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CLASSIFICATION METHOD FOR LINEAR MODEL OF FAULTS IN ALTERNATOR DIAGNOSTIC

PH.D., D.SC., ENG. KONRAD SKOWRONEK
M.SC., ENG. ARTUR WOZNIAK

Abstract: *The paper presents an attempt to implement the classification method for linear model of faults in alternator diagnostic. Method basis on the signal feature extractions, with the use of frequency methods, with reduction of the variables basis on Principal Component Analysis (PCA) and linear discrimination analysis (LDA). The consideration has been carried out on the grounds of the faults of a bridge-rectifier. Comparison with other classification methods was presented.*

Key words: *linear model, diagnostic, classification*

INTRODUCTION

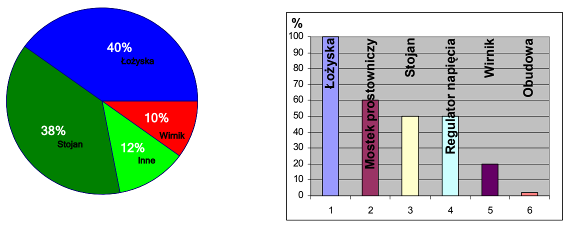
The topic of the alternator diagnostics is a subject of many books and publications devoted to the automotive industry. The method most common in practice is a so-called "oscilloscope method" that consists in comparing the sample patterns to the ones obtained for the considered alternator.

The present work presents the method of classification of the defects of a motor-car alternator, based on the analysis of a reduced dataset in the frequency domain, with the use of the method of multi-dimensional data analysis.

The use of the frequency analysis for diagnostic purposes is described in [1]. The items [2,3] indicate the meaning of the analysis in the sphere of alternator diagnostics, although usefulness of the method was noticed already in 1979 [4]. At that time a diode defect was detected with the help of a surveying filter by appearance of a definite frequency component.

1 THE DEFECTS

While developing the classification method it was proposed to join the approach to the diagnostic task performed in the manner characteristic for a typical electric machine, with the approach appropriate for the electric equipment of a vehicle. Consideration of the percent share of particular defects of an electric machine (Fig. 1a) and alternator (Fig. 1b) [5] indicates that the most frequent defects are related to bearings. Another common alternator defect concern the bridge-rectifier. The present paper verifies the proposed method with regard to the defect of the bridge-rectifier.



a) b)

Fig.1: The defects of: a) electric machines, b) alternators

2 THE FFT-PCA-LDA CLASSIFIER

Let us consider a set of N samples in n-dimensional space and assume that each of the pictures belongs to one of K classes $\{C_1, C_2, \ldots, C_K\}$. Let us assume too that in the class C_j, $u_j = (1/N_j)\sum_{x\in C_j} x$ is an average picture of the C_j class, $u = (1/N)\sum_{j=1}^{K}\sum_{x\in C_j} x$ being an average picture of all the samples. Then, the within-class scatter matrix is defined as:

$$(1)\quad S_w = (1/N)\sum_{j=1}^{K}\sum_{x\in C_j}(x-u_j)(x-u_j)^T = \Phi_w\Phi_w^T$$

The between-class scatter matrix is defined as:

$$(2)\quad S_b = (1/N)\sum_{j=1}^{K} N_j(u_j-u)(u_j-u)^T = \Phi_b\Phi_b^T$$

The total-class scatter matrix is defined as:

(3) $$S_t = (1/N)\sum_{j=1}^{K}\sum_{x \in C_j}(x-u)(x-u)^T = \Phi_t \Phi_t^T = S_w + S_b$$

In case the S_w matrix is not singular, the LDA attempts to find a $W_{opt}=(w_1, w_2, \ldots, w_L)$ projection that meets the Fisher's criterion:

(4) $$W_{opt} = \arg\max_w \frac{|W^T S_b W|}{|W^T S_w W|},$$

where: $w_1, w_2, \ldots, w_L$ are the eigenvectors of $S_w^{-1}S_b$ corresponding to L (≤K-1) largest eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_L$.

In case the matrix S_w is singular and its inverse matrix does not exist, the PCA method may be used in order to project the vector of variables on the space of smaller size, thus avoiding the singularity.

Analysis of principal components assists searching a large number of the data that are correlated each with other, thus reducing dimension of the variables and allowing for more efficient interpretation of the measurement results. This, in turn, enables developing the models of damage location directly based on the measurement data, making no allowance for the object inputs and outputs [6,7]. Once the vector of x random variables p is given, the aim of the PCA analysis consists in rearranging the correlated to uncorrelated variables, with the use of covariance matrices or correlation matrices. The first stage of the procedure consists in finding a linear function $\alpha_1^{'}x$ from the x elements of maximal variation, where α_1 is a vector of p constants $\alpha_{11}, \alpha_{12}, \ldots, \alpha_{1p}$, and a' is for such a transposition that:

(5) $$\alpha_1^{'}x = \alpha_{11}x_1 + \alpha_{12}x_2 +, \ldots, +\alpha_{1p}x_p = \sum_{j=1}^{p}\alpha_{1j}x_j$$

Then a linear function $\alpha_2^{'}x$ of maximal variance, uncorrelated with $\alpha_1^{'}x$ is sought, up to the $\alpha_k^{'}x$ element [8].

Proposed method was realized in 2 stages: training model and inference. In described method complies states generating base on real measurements. The classifier is referred to as linear taking into account the methods of describing the relationships between the variables, making use of linear functions (PCA and LDA). The trend of defects found in result of the analysis based on the covariance matrix is of linear character too.

Analyses of the system and methodological solutions give evidence that the codes inform only of several defect types (Table 1). Taking into account that the systems of on-board diagnostics are not provided in proper hardware and software solutions that would allow explicit detection of the alternator defect type, an attempt was made aimed at finding a new approach to alternator diagnostics to be used for purposes of the on-board vehicle diagnostics. Its main assumptions are as follows:

- the use of signal frequency analysis;
- diagnosis based on the voltage or current signal of alternator;
- construction of a statistical model with the use of multi-dimensional data analysis in order to reduce the dimensions of the variables and to recognize the fault patterns;
- minimization of the number of signal acquisition points (so as to avoid invasion into the alternator structure).

Code	Defect description	System
1117	The load signal coming from the DF alternator terminal	VAG
1209	Rotational velocity signal – alternator terminal	VAG

Tab. 1: Codes of alternator defects

Another important element consists in distinguishing various kinds of bridge-rectifier defects based on the input signals – current or voltage. Formerly such a distinction was impossible in the oscilloscope method (Fig. 2). For this purpose voltage of the stator zero-point had to be taken into account necessarily.

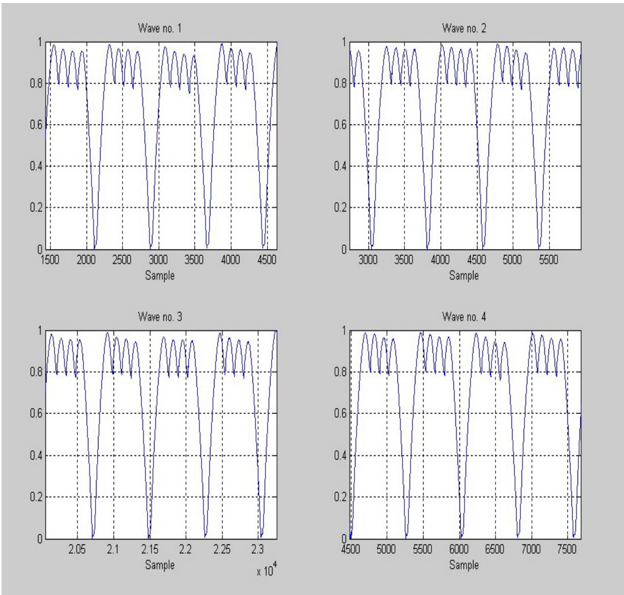


Fig.2: Time patterns in case of the defects: A(+), A(-),B(+),B(-), the defect in one diode

Similarly, the sole FFT analysis used in order to make comparisons, gives no expected results (Fig. 3).

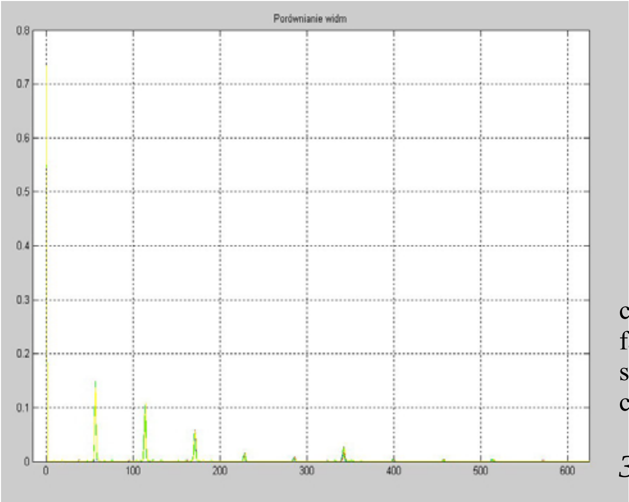


Fig.3: The FFT analysis of the defects: A(+), A(-),B(+),B(-) the defect in one diode

3 MEASUREMENTS AND VERIFICATION RESULTS

In order to verify the classifier the tests have been carried out, by simulation of the bridge-rectifier defect, for one and two diodes. The defect patterns for 4000 samples have been collected from a time-window, and the FFT analysis was performed on 250 points. The samples were collected for 800 and 1000 r.p.m.

The defects were divided into the sets, with learning patterns selected for:

– the defects in particular phases;
– the defects of positive and negative diodes;
– the defects for particular phases and polarity.

3.1 Defect discrimination of one diode at the polarity level, for the velocity of 800 r.p.m.

Results of the defect analysis of the alternator bridge-rectifier taking into account only the polarity for the velocity of 800 r.p.m. are shown below. Fig. 4 presents projection of the main components on 3D space. It may be noticed that particular samples are arranged along the lines.

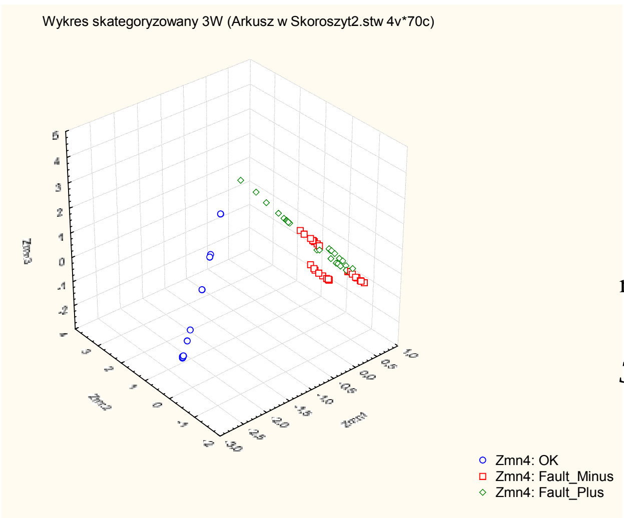


Fig.4: Categorized 3D plot of main components

Status	Percent
OK	100,00
Fault_Minus	66,67
Fault_Plus	90,00
Total	81,43

Tab. 2: Percent classification quality

For the case of the considered sample the classification gave 81.43%. Table 2 shows that only the faultless samples have been properly classified. The samples of negative polarity gave the smallest rate of correct classifications.

3.2 Defect discrimination of one diode at the phase level, for the velocity of 800 r.p.m.

Results of classification of the samples collected for the velocity of 800 r.p.m. are shown below. They were divided into faultless and faulty samples, the last ones with discriminated phases where the defect occurred.

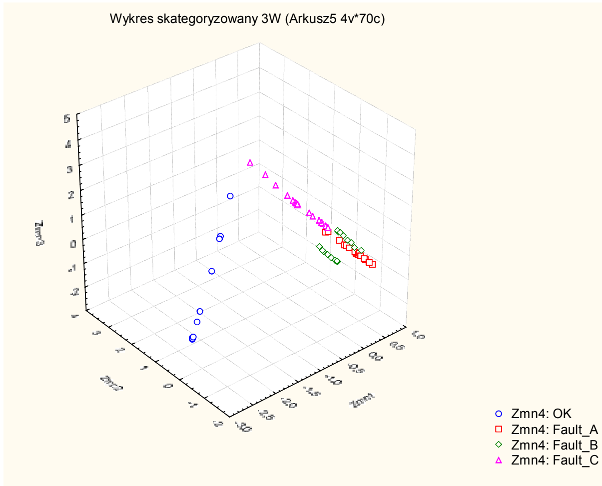


Fig.5: Categorized 3D plot of main components

Status	Percent
OK	100,00
Fault_A	90,00
Fault_B	50,00
Fault_C	90,00
Total	80,00

Tab. 3: Percent classification quality

Similarly like for the previous analysis, correct results are obtained only in case of the faultless samples.

3.3 Defect discrimination of one diode at the polarity and phase levels, for the velocity of 800 r.p.m.

Another analysis trial was related to the samples referring to the bridge defects both for the phases and polarity. They were recorded for the velocity of 800 r.p.m.

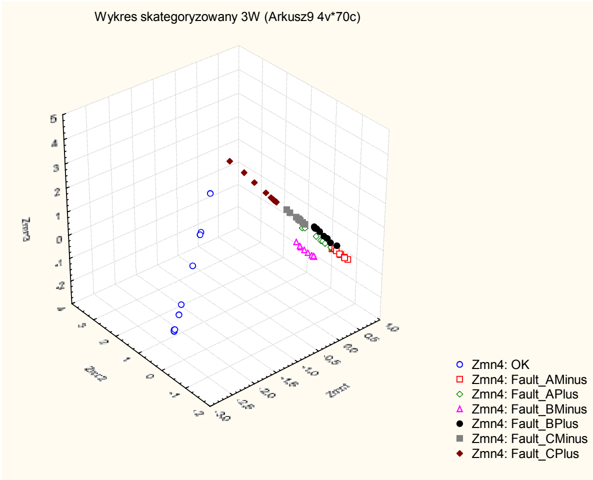


Fig.6: Categorized 3D plot of main components

Status	Percent
OK	100,00
Fault_AMinus	100,00
Fault_APlus	70,00
Fault_BMinus	100,00
Fault_BPlus	90,00
Fault_CMinus	100,00
Fault_CPlus	100,00
Total	94,28

Tab. 4: Percent classification quality

Similarly like for previous analyses, the faultless samples have been correctly classified. On the other hand, in case of the A and B phases and positive polarity the classification gave 70 and 90 percent, respectively. Nevertheless, the final result amounting to 94.28 of all the samples was satisfying.

3.4 Defect discrimination of two diodes for the same phase, for the velocity of 800 r.p.m.

Results of the samples collected for the velocity of 800 r.p.m. with simulated defect of 2 diodes are shown below.

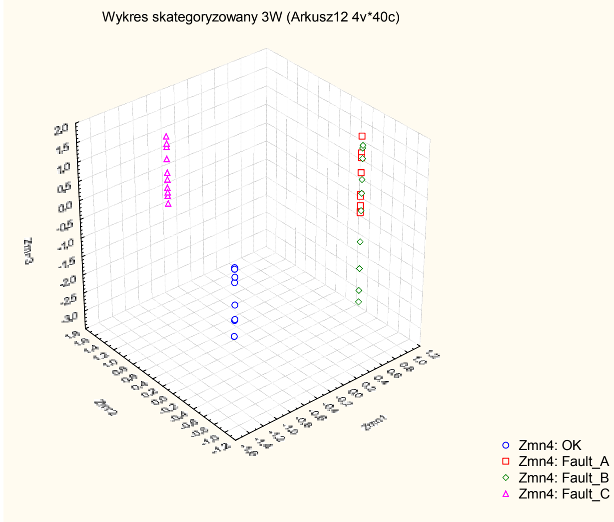


Fig.7: Categorized 3D plot of main components

Status	Percent
OK	100,00
Fault_A	100,00
Fault_B	100,00
Fault_C	100,00
Total	100,00

Tab. 5: Percent classification quality

All the samples have been correctly classified in spite of the fact that projections of the main components in the samples A and B on the 3D plane (Fig. 7) are located very near each to other.

3.5 Defect discrimination of one diode at the polarity level, for the velocity of 1000 r.p.m.

In order to check operation of the classifier for various velocities of rotation the analysis for the case of 1000 r.p.m. has been performed.

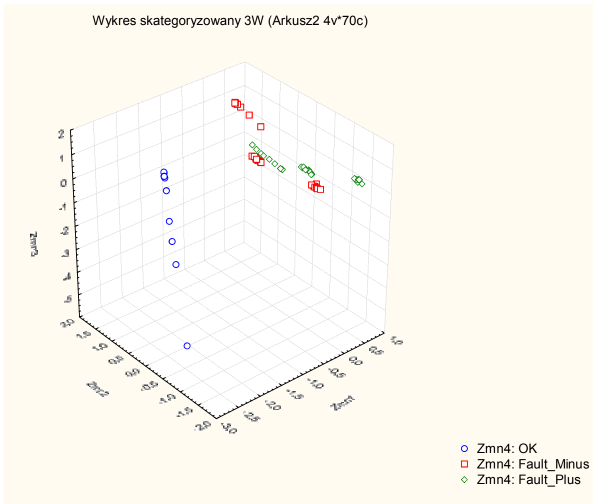


Fig.8: Categorized 3D plot of main components

Status	Percent
OK	100,00
Fault_Minus	66,67
Fault_Plus	66,67
Total	71,43

Tab. 6: Percent classification quality

The classifier operates similarly like for 800 r.p.m. Only in case of positive polarity the result was worse.

3.6 Defect discrimination of one diode at the phase level, for the velocity of 1000 r.p.m.

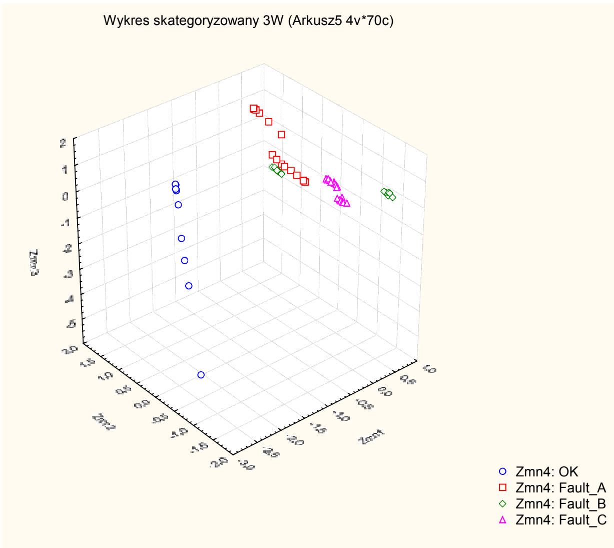


Fig.9: Categorized 3D plot of main components

Status	Percent
OK	100,00
Fault_A	70,00
Fault_B	30,00
Fault_C	55,00
Total	58,57

Tab. 7: Percent classification quality

The result is worse than for 800 r.p.m. (80 percent of correctly classified ones). Only the faultless samples have been correctly classified.

3.7 Defect discrimination of one diode at the polarity and phase levels, for the velocity of 1000 r.p.m.

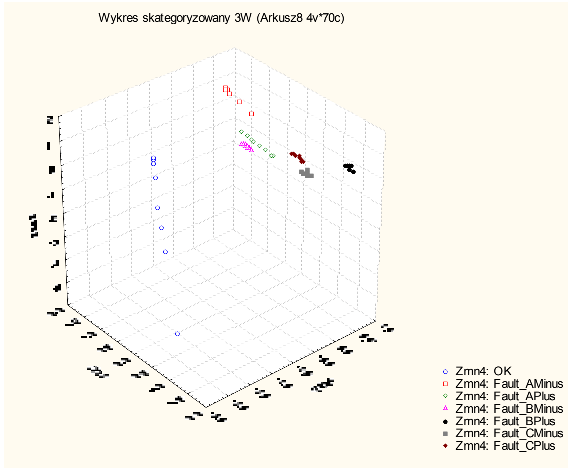


Fig.10: Categorized 3D plot of main components

Status	Percent
OK	100,00
Fault_AMinus	100,00
Fault_APlus	100,00
Fault_BMinus	100,00
Fault_BPlus	100,00
Fault_CMinus	100,00
Fault_CPlus	100,00
Total	100,00

Tab. 8: Percent classification quality

The result is equal to the one obtained for 800 r.p.m. All the samples have been correctly distinguished.

3.8 Defect discrimination of two diodes for the same phase, for the velocity of 1000 r.p.m.

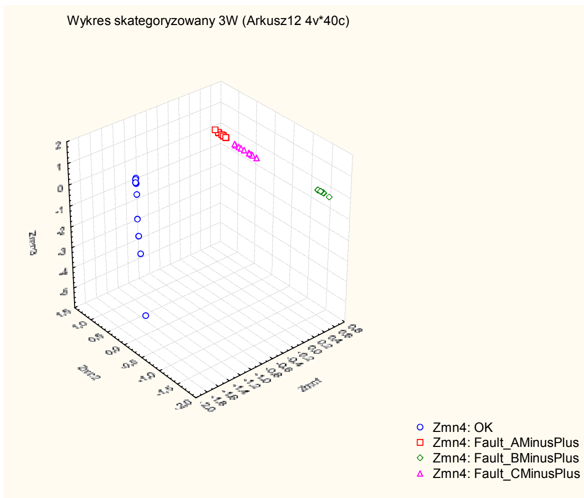


Fig.11: Categorized 3D plot of main components

Status	Percent
OK	100,00
Fault_A	100,00
Fault_B	100,00
Fault_C	100,00
Total	100,00

Tab. 9: Percent classification quality

Also for the case of the data dividing the samples into faultless and faulty ones correct results have been obtained in all the groups.

4 CLASSIFICATION RESULTS OBTAINED WITH OTHER METHODS

4.1 Artificial neural networks

In order to compare the proposed classifier with other methods the classifications have been made with the method of artificial neural networks for several net types: a linear, PNN, RBN, three-layered perceptron, and four-layered perceptron ones. The trials have been carried out for 20 network types in various configurations and for the cases of the sets with non-reduced and reduced variables. The tables contain the results sorted starting from the networks characterized with the best results.

For the non-reduced set of 250 variables, the case of a defect of one diode at the polarity and phase levels, the best result was obtained for the linear network 248:248-7:1. The learning quality: 1.000000; validation quality 0.705882, testing quality 0.823529; the learning error: 0.000000; validation error 2.254002, testing error 2.254002. Diagram of the best network is shown in Fig. 20.

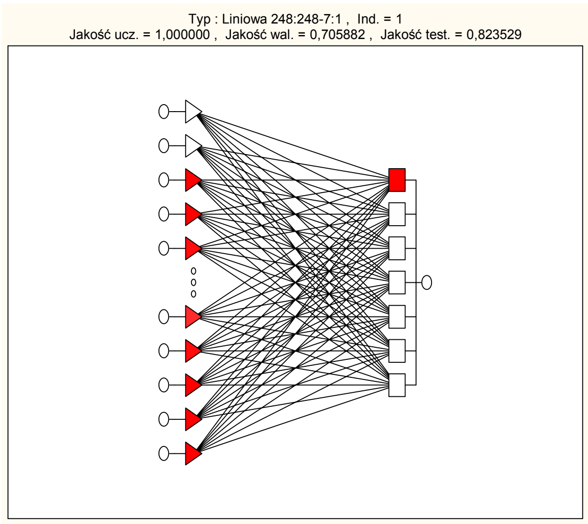


Fig.12: Diagram of the linear network

For the case of a reduced set, having 3 variables (the main components) the case of a defect of one diode at the polarity and phase levels, the best result was obtained for the MLP network 3:3-9-9-7:1. The learning quality: 1.000000; validation quality 0.941176, testing quality 1.000000; the learning error: 0.042153; validation error 2.763365, testing error 0.048920. Diagram of the best network is shown in Fig. 21.

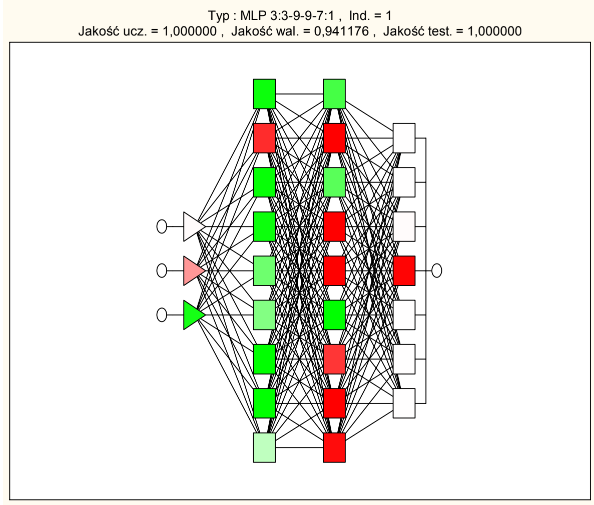


FIG.13: Diagram of the MLP network

For the case of a reduced set, having 3 variables (the main components) the case of a defect of one diode at the phase level, the best result was obtained for the RFB network 3:3-7-4:1. The learning quality: 0.888889; validation quality 0.823529, testing quality 0. 823529; the learning error: 0.232214; validation error 2.030926, testing error 5.351756. Diagram of the best network is shown in Fig. 22.

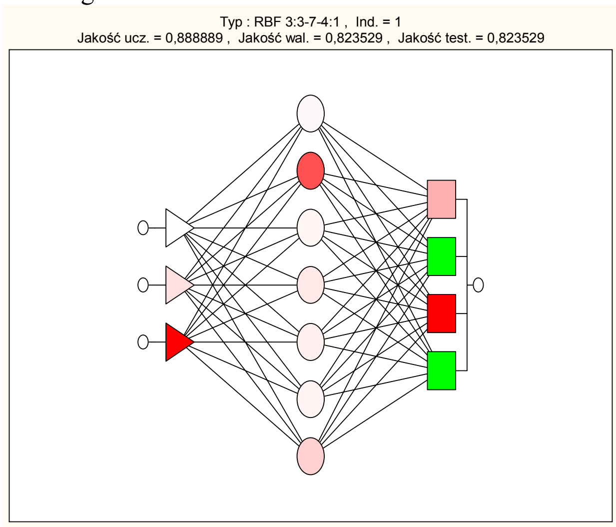


Fig.14: Diagram of the RBF network

4.2 Grouping with the method of k-averages

The classification has been performed for a reduced set of variables – having 3 variables (the main components). For 70 cases particular trials were interconnected with method of k-averages. Missing data have been completed with the cases. Seven concentrations have been selected, the solution was found upon 2 iterations. The results are presented in the Table.

Concentration number	Number of the cases
1	20
2	3
3	10
4	2
5	20
6	8
7	7

Tab. 10: Results of the assignment

5 SUMMARY

At present most of the diagnostic systems, not only of vehicle type, are based on artificial neural networks that very reliably cope with the regression and classification problems. The paper presents the FFT-PCA-LDA classifier that has shown good discrimination ability in the case of the defects of linear trend, having considerably simpler tuning process. The classifier allows for reduction of the number of variables to 3, maintaining correct operation. The classifier has shown the highest number of erroneously classified data for generalized defects in groups (e.g. the defects occurring in particular phases). Nevertheless, in case of all the defects the data have been correctly assigned to proper classes. The results so obtained enable further analysis. The test shall be repeated for a complete alternator, as for purposes of the present tests the alternator had no voltage controller. The classifier should be necessarily verified for various values of rotational velocity and load. The work shall be aimed at taking into account correlation of mechanical and electric signals of the alternator.

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Ph.D., D.Sc., Eng. Konrad Skowronek, M.Sc., Eng. Artur Wozniak, Poznan University Of Technology, Institute Of Electrical Engineering And Electronic, 60-965 Poznan, Piotrowo 3A street, Poland, E-mail: konrad.skowronek@put.poznan.pl, artur.wozniak@put.poznan.pl