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FFT-PCA-LDA CLASSIFIER IN A.C. GENERATOR DIAGNOSTICS

KLASYFIKATOR FFT-PCA-LDA W DIAGNOSTYCE ALTERNATORA*

The methods of A.C. generator diagnostics are discussed. The need of developing new methods is justified. A new classification method is presented that is used for diagnostics of A.C. generator damages. Features of the method are specified. Functioning of the method is analyzed based on examination of damages of A.C. generator diodes. The method is compared with other methods of electric machine diagnostics used in practice.

Keywords: *A.C. generator diagnostics, classification, hybrid method.*

Omówiono metody diagnostyki alternatorów. Uzasadniono konieczność konstrukcji nowych metod. Zaprezentowano nową metodę klasyfikacyjną wykorzystaną do diagnostyki uszkodzeń alternatora. Przedstawiono cechy metody. Działanie metody przeanalizowano na podstawie badania uszkodzeń diod alternatora. Metodę porównano z metodami diagnostyki maszyn elektrycznych stosowanymi w praktyce.

Słowa kluczowe: *diagnostyka alternatora, klasyfikacja, metoda hybrydowa.*

1. Introduction

The problem of A.C. generator diagnostics has a topical meaning, taking into account the needs of automotive industry and motor car users. In the first case the diagnostics is aimed at assessing the product during manufacturing process, in the other – during its operation.

In practice the A.C. generator diagnostics in the vehicle or beyond it is carried out with the following methods [12]:

- comparative,
- oscilloscopic,
- voltmetric,
- with the use of specialized diagnostic devices, for example an indicator device.

In the comparative method the degree of compliance of the measured and standard characteristics of the generator is checked. It is a laborious and inaccurate method. It is rather an individual solution that enables evaluation of the A.C. generator, nevertheless, it does not allow to identify the type and place of the damage. It is equivalent to consideration of the machine as a "black box", without visualization of the connections and without access to the terminals. Statistics of recorded cases does not enable concluding, for example on the type of the manufacturing error.

The most common practical method is a so-called oscilloscopic method. It consists in comparison of standard signal oscillograms with the signal patterns obtained for the considered A.C. generator. This method enables identifying both the locations of manufacturing errors and damages, as for example short-circuits of stator winding to earth. The main signals are usually the output, phase, and interphase voltages. The signals are measured in various points, according to the generator type, in particular in the points where measuring probe access is possible. Therefore, the method itself is not general enough. Moreover, it does not allow to discern single damages and manufacturing errors.

In the voltmetric method the same signals that are estimated in the oscilloscopic method are measured with voltmeter. Therefore, it has the same bad and good points.

The use of specialized diagnostic devices is delimited to a given A.C. generator type. Usually, the access to definite generator terminals should be accessible, particularly to the phase windings ones. This simple method may be easily used even by imperfectly trained workers and, at the same time, it ensures detection of the damages and errors but does not allow to discern them.

As opposed to diagnostics of induction motors, the literature delivers rather few information on more sophisticated diagnostic methods related to A.C. generators. For example in [5] a computer analysis of A.C. generator is proposed, with the use of artificial neural network. Good identification results have been achieved only for some types of errors and damages. Literature delivers no works on:

- proposals of algorithms that allow for assessing the state based on many signals, under dynamic changes of operation conditions;
- proposals of algorithms that perform the classification and regression tasks in the state assessment;
- proposals of algorithms that operate correctly even in extremely different cases;
- adaptation of the model used for the assessment to various tasks: in the frequency and time domains (adaptation of the number of variables and model parameters);
- proposals of a method of forecasting the pattern of selected parameters of the device operation.

Therefore, a proposal of a new method of A.C generator diagnostics, at the assembly belt or located in vehicle, is considered to be purposeful. Such a method should be universal, should be able to

(*) Tekst artykułu w polskiej wersji językowej dostępny w elektronicznym wydaniu kwartalnika na stronie ***www.ein.org.pl*** detect and classify both the groups of the damages and single damage, allowing, at the same time, to indicate their locations.

2. Analysis of possible solutions

In order to automate and standardize the assessment of the state of new and used A.C. generators the diagnostic results should be free of the components that depend on non-objective factors. At the same time, the method should be sufficiently elastic, which means that it should allow for formulating objective standards of deviations from rated patterns. For example, the damage standard patterns should be possible to formulate. In this sense among the most important methods the ones that make use of random description of the signals are reckoned.

There are many diagnostic methods [2]. Among the most general ones the statistical classification methods should be mentioned, as PCA, ICA, LDA, B&B, SFS, SBS, SFFS&SBFS, SVM, Bayes, LDC, k-NN, and others. In order to analyze large data files recorded during the measurements many methods are used, e.g. the ones used for teaching the patterns [9]. Common distinction between the teaching with or without supervision is made. The first ones includes, among others, PCA, PP, SOM (Kohonen maps) etc. The others are usually classified among the calibration, discrimination, and classification ones, according to the considered problem.

In the discussed case, i.e. in A.C. generator diagnostics, a large number of strongly correlated data must be searched, due to physical structure and the place of operation of these devices. Therefore, preliminary comparative study of selected methods has been carried out. For this purpose the identification of the state of the object or estimation of the values of its operation parameters has been carried out with the use of the following methods: PCA (principal component analysis), LDA (linear discriminant analysis), SVM (support vector method), SNN (artificial neuron networks), MARSPlines (multivariate adaptive regression with the use of splines).

For purposes of searching large data files the PCA method (principal component analysis) appears to be optimal. PCA is a typical teaching method without supervision, based on linear algorithm of feature extraction, with reduction of the data files.

On the other hand, LDA method (linear discriminant analysis) appears to be optimal in case of classification of data groups. The linear discriminant analysis is reckoned among the most frequently used in engineering. It serves for formulating linear discriminant functions. They are created for the samples of a model file. The samples formulate the initially defined groups. The discriminant functions created for them are used for classifying new "virtual" samples for one of the considered groups.

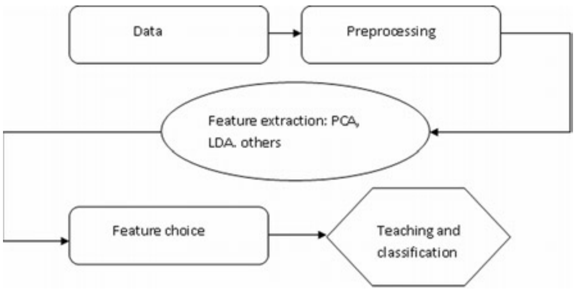

Fig. 1. The stages of statistical classification

Both above mentioned methods (their location with regard to the chain of diagnostic events is shown in Fig. 1) are particularly useful for the data distinguished by Gaussian distribution. Effectiveness of simultaneous use of both these methods for processing of the sample files was noticed, among others, in [11].

One of possible ways of formulating a method distinguished by the above mentioned advantages consists in joining both methods at various classification stages and, at the same time, supplementing it by an algorithm allowing for easier formulating of the standards. This goal may be attained e.g. by wavelet transformation or Karhunen-Loeve transformation. Taking into account common use of FFT algorithms, implementation the Fourier transformation was used in the present paper.

Hence, a new hybrid method FFT-PCA-LDA of damage classification of automotive alternator is proposed, based on the analysis of a reduced data of variables in frequency domain, with the use of multi-dimensional data analysis method. The frequency analyses used in diagnostics are described, for example, in [3, 6, 7, 8, 10]. The paper [7] presents detection of diode damage with the help of a filter tracing appearance of a definite frequency component. Nevertheless, they are distinguished by important constraints. Moreover, as it was mentioned above, large data files must be then analyzed. Therefore, the data should be initially examined with a view to optimize the quantity and contents of the information.

Summarizing, formulation of the new method was carried out with consideration of the diagnostic methods used for typical electric machines, and, at the same time, with the use of the methods applied in diagnostics of the vehicle electric equipment. Such an approach has not been proposed before in the literature related to these problems.

The most frequent damages of A.C. generators and other electric machines are the damages of bearings. Another damage that relatively often occurs in A.C. generator is the damage of the bridge-rectifier. Taking it into account the classification method proposed in the present paper is verified for the bridge-rectifier damages.

2. FFT-PCA-LDA Classifier

In the on-board diagnostic systems the hardware and software solutions are missing, that could clearly determine the generator damage type. The codes delivered by manufacturer or another economical units provide the information on barely several damages (Table 1). Therefore, an attempt is made aimed at a new approach to A.C. generator diagnostics that may be used at measuring stand or for purposes of vehicle on-board diagnostics.

The following assumptions are made:

- the use of signal frequency analysis;
- concluding based on voltage or current signal of the A.C. generator;
- construction of a statistical model using multi-dimensional data analysis for reducing variable dimensions and recognizing the damage standards;
- minimization of the signal acquisition points (non-invasive for the A.C. generator structure.

Table 1. Example codes of A.C. generator damages

Code	Damage description	System
1117	Load signal from DF terminal of A.C. generator	VAG
1209	Rotation signal – A.C. generator terminal	VAG

It should be noticed that various types of the bridge-rectifiers should be discerned only based on output signals: e.g. voltage or current. For comparison – in case of the oscilloscopic method such a discernment is impossible (Fig. 2), since the zero point voltage of generator stator would be necessary for this purpose. Moreover, according to Fig. 2, knowledge of generator structure or, at least, standard course of the signal, would be required.

Similarly, FFT analysis with comparison of the signals does not provide expected results (Fig. 3). According to the measurements

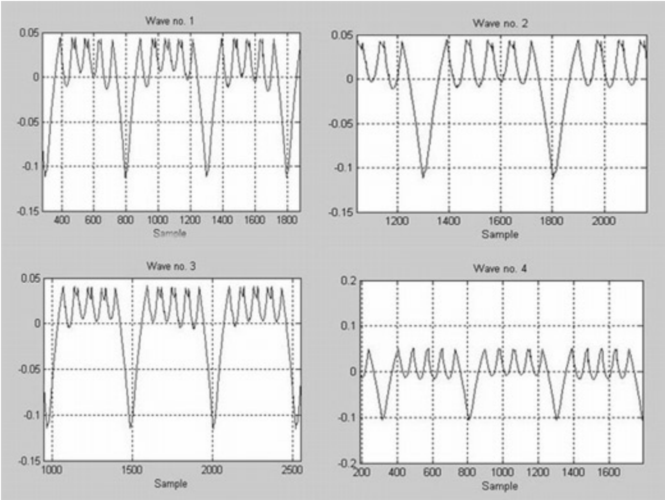

Fig. 2. Voltage time patterns of the damages: A(+), A(−), B(+), and dB(−), the damage of one diode

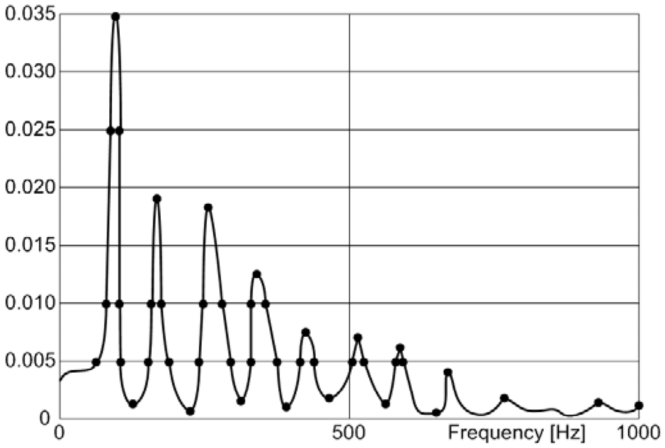

Fig. 3. FFT analysis of the damages: A(+), A(-), B(+), and dB(-), the damage of one diode

(Fig. 2) discernment of the damage types (and even the damage states only) remains impossible in this case. The above problems may be also related to clear randomness of measured patterns of all the signals (Fig. 4).

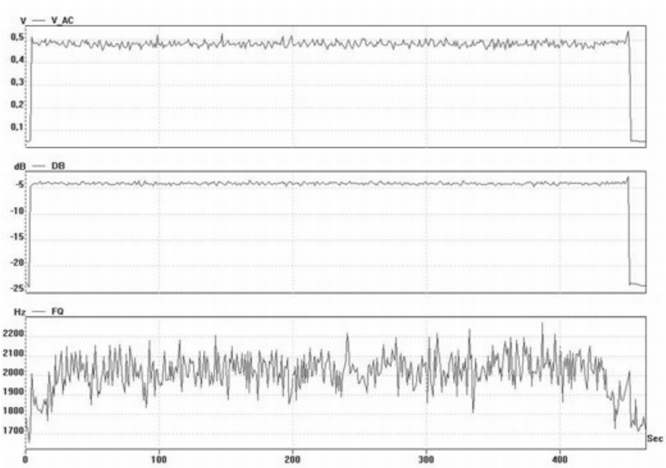

Fig. 4. True A.C. generator signals: from top to bottom: voltage, noise, and frequency

During classification with the method of linear discriminant analysis (LDA) with preliminary extraction of signal features, with the use of principal component analysis (PCA), the vector of variables is automatically chosen. This vector is then considered as a basis for classification of the object to a definite group of standard states. A file of N-samples in n-dimensional space is considered and it is assumed that every image belongs to one of K-classes $\{C_1, C_2, ..., C_K\}$. N_j is the sample number within the class C_j, $u_j = (1/N_j)\sum_{x \in C_j} x$ is the average of the image from the class C_j, $u = (1/N)\sum_{j=1}^{K}\sum_{x \in C_j} x$ is the average of the image from all the samples. The dissipation matrix in the class is given in the form:

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

On the other hand, the dissipation matrix between the classes is defined as:

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

The dissipation matrix has a form:

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

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

$$W_{opt} = \arg\max_w \frac{\left|W^T S_b W\right|}{\left|W^T S_w W\right|}, \tag{4}$$

where $w_1, w_2, \ldots, w_L$ is the vector of eigenvalues $S_w^{-1}S_b$ with reference to L (≤K−1) the biggest eigenvalues $\lambda_1, \lambda_2,\ldots, \lambda_L$.

In case the S_w matrix is singular its inverse does not exist. The PCA method [6] is then used for projection of the vector of variables on the space of lower dimension in order to remove the singularity.

Principal component analysis (PCA) consists in the use of a statistical algorithm with a view to separate a small number of coefficients that represent the best a large number of properties of extremely large datafile. It is at present very often used, e.g. in MatLab packages, since it enables graphical approximate assessment of datafile structures. In the PCA method the principal components (PC) are generated, that make a part of optimal linear combinations representing the weighted sums of the input data. The combinations result from gradual transforming of the coordinated system with regard to consecutive decreasing values of data variations. These consecutive coordinate axes make a file of further principal components.

The proposed method is performed in two steps: training of the model and concluding. The classifier is called a linear one, taking into account the methods of description of the relationships between the variables, that make use of linear functions (PCA and LDA). The trend of the damages in the analysis carried out based on the covariance matrix is also of linear character. Finally, the PCA ensures maximization of the variation while LDA – separation of the classes. Proper application of LDA method occurs, when [9]:

- distribution of the objects within each sample group approximates the normal distribution;
- the sample groups are linearly separable;

- the variance-covariance matrices of each of the sample groups are comparable;
- total number of the objects must be at least three times as large as the number of the variables.

It was found that the above assumptions correspond to the conditions of data collecting in case of A.C. generator tests.

In order to generate the standards the FFT analysis has been used, with narrowed frequency windows. Analysis of the initial "raw" data consists only in collecting the damage standards with the help of FFT analysis with rectangular window. Preliminary processing is made by multiplying the obtained signal with the Hanning window and, additionally, averaging of the values so obtained for particular frequency components for restricted number of the windows with restricted number of points.

4. Measurements and verification results

The proposed classifier was verified during the tests on the measurement stand shown in Fig. 5. It was provided, among others, with a 4-channel music card ESI Quata Fire 610, measurement converter SENSOR AMP-4ICP, vibration sensor DYTRAN, and the A.C. generator testing stand. A bridge-rectifier damage was simulated for 1 diode and 2 diodes. The damage patterns from the time window for 4000 samples have been collected. The time window was obtained based on FFT analysis for 250 points. The samples were collected for the speeds 800 and 1000 rpm of the A.C. generator shaft.

Fig. 5. Measurement stand of the A.C. generators

The damage cases were classified into groups and files. The teaching standards were formulated for the damages in particular stator phases, for the damages of positive and negatives diodes, and the damages of particular phases and polarity. It was found during the tests that eigenvalues of the covariance matrix for each of examined cases approximated each to other and were distributed similarly as in the case presented in Fig. 6.

It was found during the tests of discernment of one diode damage at the level of polarity and with varying speed, that the results are good. Nevertheless, correctness of classification significantly depends

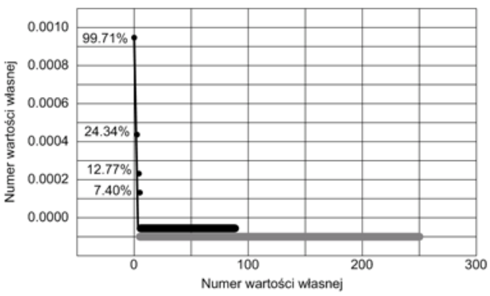

Fig. 6. Eigenvalues of the covariance matrix for one damaged diode at the speed equal to 800 rpm

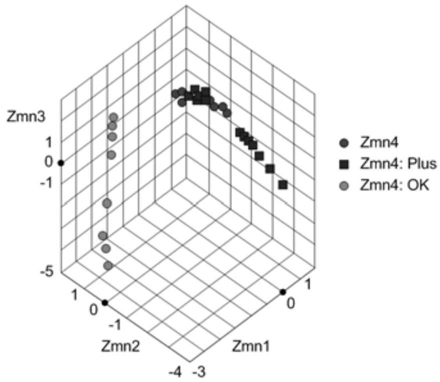

Fig. 7. Categorized 3D plot of principal components for one damaged diode at the speed equal to 800 rpm

Table 2. Percent quality of classification for one damaged diode at the speed equal to 800 rpm

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

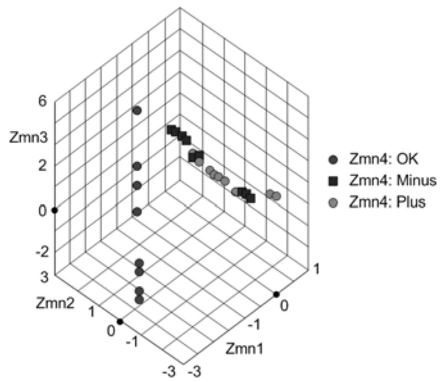

Fig. 8. Categorized 3D plot of principal components for one damaged diode at the speed equal to 1000 rpm

Table 3. Percent quality of classification for one damaged diode at the speed equal to 1000 rpm

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

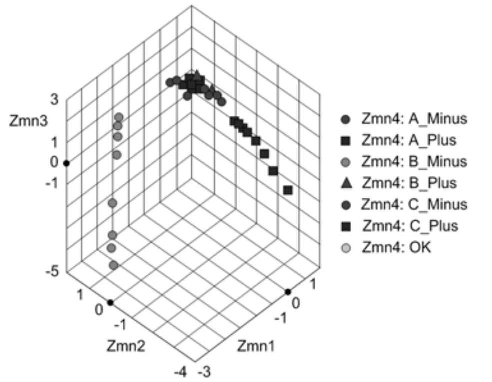

Fig. 9. Categorized 3D plot of principal components for one diode damaged at polarity and phases level at the speed equal to 800 rpm

Table 4. Percent quality of classification for one diode damaged at polarity and phases level at the speed equal to 800 rpm

State	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

on the speed (Figs 7 and 8). On the other hand, in all tested cases the trend for the variables processed with FFT-PCA-LDA was clear.

Taking into account unsatisfactory classification results (Tables 2 and 3) with the use of polarity or phase only, the damages were classified with simultaneous consideration of both these signals. In consequence, it appeared that effectiveness of classification grew significantly. For example, Fig. 9 and Table 4 present the results of discernment tests of a damage of one diode at polarity and phases level at the speed equal to 800 rpm.

Interesting results have been obtained in examination of the damages of more than one element in the same phase. In all these cases 100-percent effectiveness was achieved, that is shown, for example, in Fig. 10 and Table 5.

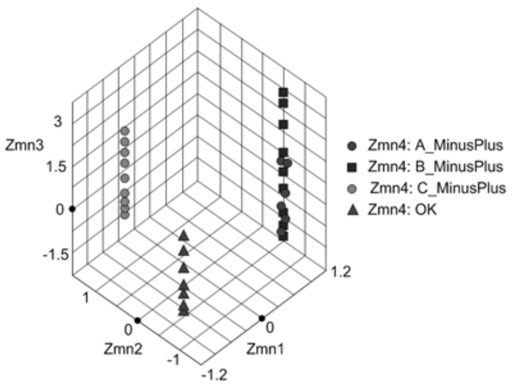

Fig. 10. Categorized 3D plot of principal components for 2 diodes damaged for the same phase at the speed equal to 800 rpm

Table 5. Percent quality of classification for 2 diodes damaged for the same phase at the speed equal to 800 rpm

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

It was found that the best results are obtained with the use of the FFT-PCA-LDA classifier for the signals referring to polarity and phase for more than one damage.

5. Classification results obtained with other methods

5.1. Artificial neural networks

In order to confirm good quality of the proposed classifier similar tests have been carried out for other selected classification methods.

Comparison of the classification process was performed for the following network types: linear, PNN, RBN, three-layer perceptron, and four-layer perceptron. The tests have been made for 20 of these network types and for the cases of the files including non-reduced and reduced variables. For the non-reduced file – 250 variables – with one diode damaged at the polarity and phases level, the best result was achieved for linear network 248:248-7:1, with teaching quality 1.000000; validation quality 0.705882; testing quality 0.823529; teaching error 0.000000; validation error 2.254002; testing error 2.254002. Diagram of the winning network is shown in Figure 11.

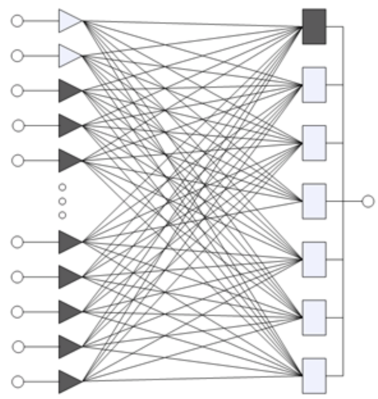

Fig. 11. Diagram of linear network

For the reduced file – 3 variables (principal components) – with one diode damaged at the polarity and phases level, the best result was achieved for the network MLP 3:3-9-9-7:1, with teaching quality 1.000000; validation quality 0.941176; testing quality 1.000000; teaching error 0.042153; validation error 2.763365; testing error 0.048920. Diagram of the winning network is shown in Figure 12

For the reduced file – 3 variables (principal components) – with one diode damaged at the phase level, the best result was achieved for the network RBF 3:3-7-4:1, with teaching quality 0.888889; validation quality 0.823529; testing quality 0.823529; teaching error 0.232214; validation error 2.030926; testing error 5.351756. Diagram of the winning network is shown in Figure 13.

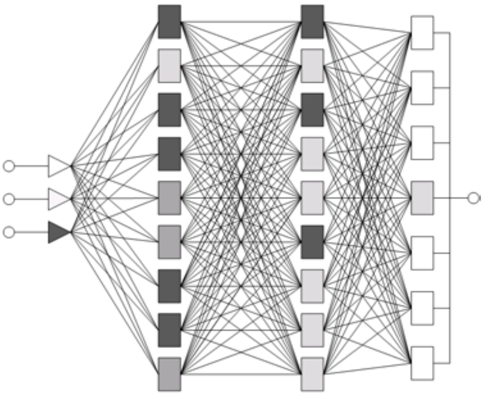

Fig. 12. Diagram of MLP network

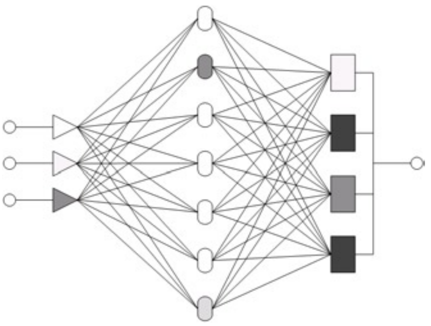

Fig. 13. Diagram of RBF network

Table 6. Results of assignment

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

5.2. Grouping with k-average method

Classification for a reduced datafile – 3 variables (principal components) was carried out for 70 cases. The cases were interrelated with k-average method, missing data were complemented with the cases. 7 concentrations were separated, while the solution was found after 2 iterations. The results are shown in Table 6.

6. Summary

Automotive A.C. generator is an electric machine operating in specific conditions that vary cyclically during the operation, similarly to the device load. The methods that enable accurate identification of the generator state may be applied only after its disassembly from the vehicle.

Preliminary results of the tests and measurement analysis with the use of FFT analysis of the output voltage signal of the generator and with data mining show that the hierarchical FFT-PCA-LDA classifier is very effective in discernment of the damages of the generator bridge-rectifier. These damages are distinguished by linear trend in 3D space of principal components for the damage samples.

The data mining methods allow for using "former" data, many times analyzed before. At present most of the diagnostic systems, aimed not only at vehicle diagnostics, are based on the use of artificial neural networks, that are very successful in the regression or classification problems. The proposed hybrid FFT-PCA-LDA classifier, that is characterized by good discretization ability of the damages distinguished by a linear trend, with remarkably more simple adjusting process as compared to other classifiers. The classifier enables reducing the number of the variables down to 3, maintaining accurate operation. The highest number of the data erroneously classified by this classifier occurred for the damages converted to the groups (e.g. the damages in particular phases). In case of all the damages the data have been correctly assigned to particular classes. The results obtained enable further analysis. The classifier should be checked for various values of rotational speed and load, since increased number of the signals improved the classification quality. Further tests will be aimed at the use of correlation of mechanical and electrical signals of the A.C. generator. The number and type of the signals will depend, among others, on the fact whether the A.C. generator is to be tested at the assembly belt or in vehicle. In the first case detection of possibly large number of faults is important, while in the other – stating its fitness for use.

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