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S.F. Telenyk, O.V. Savchuk, E.O. Pocrovskyi, O.M. Morgal, K.S. Krivenko, I.O. Latash
Dept. of Automation and Control in Technical Systems NTUU "Igor Sikorskyi KPI" Kyiv, Ukraine
41, Polytechnic str., kor.18, fl. 528, Kyiv, 02056

ON SOME PROBLEMS OF NEURAL NETWORK TECHNOLOGIES IN ELECTRIC COMPONENTS DIAGNOSING

С.Ф. Телeник, О.В. Савчук, Є.О. Покровський, О.М. Моргаль, К.С. Кривенко, І.О. Латаш
Кафедра автоматики та управління в технічних системах "КПІ ім. Ігоря Сікорського", Україна
вул. Політехнічна, буд. 41, кор. 18, кв. 528, м. Київ, 02056

ПРО ДЕЯКІ ПРОБЛЕМИ НЕЙРОМЕРЕЖЕВИХ ТЕХНОЛОГІЙ В ДІАГНОСТИЦІ ЕЛЕКТРИЧНИХ КОМПОНЕНТІВ

The paper describes an idea of getting electric components diagnostic information and its transformation using the discrete Karhunen-Loeve expansion. Presorting of elements by their physical and technical states is proposed to operate with the MLP, self-organized and RBF- neural networks in the MATLAB environment. The paper investigates the possibility of using neural network technologies for improving electric components diagnosing by integral effects for increasing reliability of complex technological systems. The statistical and individual classification and presorting of elements according to their physical and technical states for work with the use of neural network technologies is proposed.

Key words: neural network technologies; diagnosing; integral effects; electric components.

У статті описується ідея отримання діагностичної інформації про електричні компоненти та її перетворення за допомогою дискретного розкладання Карунена-Лоева. Запропоновано визначення фізичних та технічних станів елементів за допомогою MLP, самоорганізованих та RBF-нейронних мереж в середовищі MATLAB. У роботі досліджується можливість використання нейронних мережевих технологій для поліпшення діагностики електричних компонент за інтегральними ефектами для підвищення надійності складних технологічних систем. Запропоновано статистичну та індивідуальну класифікацію та сортування елементів відповідно до їх фізичних і технічних станів для роботи з використанням нейронних мережевих технологій.

Ключові слова: нейросетеві технології; діагностика; інтегральні ефекти; електричні компоненти.

I. Introduction

Recently more definition is need in diagnosing physical condition of technical products by which it is possible to determine some data about properties of physical environment of the object being investigated. It depends on the type of hidden or overt defects and performance degradation or various destructive processes (fatigue, wear, corrosion, erosion, destruction, etc.) in electric components (EC). All these processes lead to the possibility of changing technical condition that explains rapid development of appropriate diagnosing methods of technologic forecasting by identifying relevant characteristics of changes in their physical environment.

Thus, using the methods and means of technical diagnostics the relevant problems may be solved:

1. To determine the type of technical state in which the object of diagnostics is located that can be characterized as an appropriate check of its status relative to perform working functions.
2. To trace or get the place of fault localization or determine the cause of transition into the inactive status.

3. To forecast changes in the technical state of the object to determine the causes of the probability of such changes or to determine the length of time after which it may begin the processes that lead to the unwanted changes of the product for its technical condition.

These problems are associated with using diagnostics during technical products operation. But using diagnostics for various problems to improve technical level of modern technology would also be appropriate to the stage of products development and their replication. Especially, it is important for diagnosis and analysis of the changes causes in the technical state with fixing the place and time of the unit malfunction and the type of failure that caused appearance of the faults.

In modern production and operation of the most critical technologies there is a special system failure analysis (SFA) which constantly helps monitoring failures and faults and establishing their causes. Such an analysis is carried out to develop more sophisticated designs of technical products and further improve processes with ability to avoid overt and hidden defects. Thus, it appears improving quality and reliability of products during their operation.

Weighty importance in analysis of failures, malfunctions, defects, and breakages has products operating conditions that lead to faults appearance. Thus, it takes place increasing functional efficiency of product and its technical reliability and eliminating the possibility of emergent or catastrophic situation. In the SFA systems failure analysis of technical products in conjunction with other methods plays an effective feedback between various stages of the product's life cycle in order to improve quality and reliability of industrial production at these stages.

The objective of the paper is to investigate the possibility of using the neural network technologies for improving electric radio components diagnosing by the integral effects for increasing reliability of complex computerized systems (CCS).

Comprehensive computerization of production processes, increasing requirements for reliability and diagnosis of CCS need to transform their diagnostic software with experiment informational technology to the neural network predictive analysis.

The direction of the problem solution is to test the possibility of using the neural network technology to improve electro-physical methods of diagnosing EC by integral effects to increase reliability of CCS.

II. Problems

The problems to be solved:

- usage of the electro-physical methods based on the integral physical effects of inertia and non-linearity of electric components for getting primary diagnostic information;
- compression and intellectual analysis of a posteriori information using neural networks for electric components being studied by their physical condition in the software package MATLAB and its library Neural Network Toolbox. Informational opportunity of electro-physical diagnosis methods for integral physical effects may be explained by the Black Box method as a closed system. The Black Box term is commonly defined as environment knowledge which can be obtained using only input and output signals/information.

III. Methoodlogy for getting apriori diagnostic information about electric components status

When utilizing the integrated methods for physical diagnosing and getting diagnostic information some integrated physical effects are used that are observed at physical environments of different nature [1-4]. These generally recognized effects include the integral non-linearity effects, the effects of inertia, and the effects of fluctuations.

Emergence of these effects is associated with workflows in the Object to be Diagnosed (OD) and it has the same excitement origin. This means that for observability of the integrated effects it is required the same energy activation sources that provide OD working operation during its operation. If units are of electrical nature, it needs for integrated methods of diagnosing to use electricity energy of the same level as for the workflows. If there are mechanical products, they require mechanical energy, etc. In all these cases there is no need to apply any additional conditions for operating personnel protection in addition to implementation of safety rules during operation [5]. The main advantage of the integrated diagnostic methods is their high efficiency due to the low operational diagnosis lifetime with the reduced operational complexity and the operational costs for the diagnosis process. Signals of diagnostic information more often have a kind of the analogue signatures. Therefore, these methods are well suited for rapid diagnosis in unfavourable conditions to identify not only the obvious defects that cause appearance of the faults in OD but also to detect the hidden defects that trigger the sudden and gradual failures with loss of the OD working condition state.

Non-linearity is the phenomenological property of the object physical environment that appears in disproportionate and ambiguous nature of its response to activating the physical quantity action depending on its changes meaning and direction. This property is fundamental as in nature and in man-made products. It is caused by action of a large number of direct and back-end connections between the dynamic and dissipative subsystems of physical environments which may have very different thresholds of the energy activation in solids.

Manifestation of non-linearity for intrinsic properties of OD physical environment is nonlinear change of the favourable function at the physical layer or of the transfer function at the analytical descriptive level. In this regard, all kinds of OD functional characteristics have signs of nonlinearity (as significant and insignificant) relatively the object operating functions and can be used to determine the OD technical condition.

But observation of non-linearity in the form of physical effects have two features. First, there is no particular dimension (or metric scale) of nonlinearity as a physical quantity that conveys a quantitative idea of the properties in this object. Secondly, in a quantitative sense nonlinearity is quite multivalued because this property can’t be sufficiently identified by one feature of functional characteristics. We have to use several features of nonlinearity which will already make a range of the determining variables (degree polynomials, derivatives of different orders, curvature of the first and highest orders, etc.).

With respect to the inertia property, relevant manifestation of inertia effects is associated with the OD transition and impulse response characteristics. Their registration is made by action of activating physical quantities at the OD entrance in the form of a pulse jump or duble jump. In this case, mechanisms of energy conversion start acting in the dissipative subsystems of the physical environment and mechanisms of energy dissipation into the environment. In the language of physics, in the physical environment it takes place transition from the adiabatic state to the isothermal state that affects the transient characteristics of the active medium physical system. The transient integral characteristics reflect local physical environment macrocharacteristics at time intervals. Thus, obvious and hidden defects cause some transient or pulse characteristics changes. Measurement of these characteristics is realised as the analogue signatures that reflect diagnostic information about physical condition of the unit.

Observability of the corresponding OD state at the transition process in action after the energy jump when applying the test excitation is caused by the difference of the character time scale change or the relaxation time in the dissipative excitation subsystems. Therefore, it is possible to display and lead out certain dissipative processes at their character time scales in the form of the constant time or relaxation time. In this case, the individual parameters of the transition process are used that is fixed by the time you change the membership function or the transfer function.

To determine the OD physical condition at its transient or pulse characteristics it is also possible to compare these characteristics as the size continuum of physical quantity, that varies over time, with the standard characteristics or the analogue signatures of the same type. The fluctuation-dissipative processes occur in the thermodynamic systems of any type. This gives rise to the stochastic temporal changes of physical quantities in the form of fluctuations around the equilibrium state. These fluctuations generate the stochastic signals-noises reflecting the random functions of the spontaneous oscillatory processes in the OD physical environment.

IV. Getting primary diagnostic information

Consider a model in a black box which is defined as

$$Y(t) = g(\cdot)U(t), \qquad (4.1)$$

where U (t) - input function; Y (t) - output function; t - time.

For physical dynamic objects $g(\cdot)$ is the susceptibility function – the complex environment function.The susceptibility function manifests integrated physical effects: non-linearity, inertia (describes dynamics), fluctuations (own noise) [6]. Let us consider the susceptibility function components:

$$g(\cdot) = const(g(\cdot)) + \mathrm{var}(g(\cdot)). \qquad (4.2)$$

For physical objects the function $g(\cdot)$ is a complex function of environment

$$g(\cdot) = const\, R_0[g(\cdot)] + var\, Re[g(\cdot)] + J\{const\, Im[g(\cdot)] +$$

$$+var\, Im[g(\cdot)], \qquad (4.3)$$

where Re - the real part of the function; Im - the imaginary part; *const*- the fixed part; *var* -the variable part.

Integral physical effects of nonlinearity, inertia, and fluctuations are used for getting diagnostic information in carrying out electro-physical diagnostics. According to (4.3) and using the Taylor conversion [1] for obtained EC characteristics it’s possible to describe, say, integrated circuit by its dynamic resistance as the 1-st derivative of the nonlinear Ampere-Volt characteristic:

$$R_g(I) = R_g + \sum_{i=1}^{\infty} b_{(R)_i} I^i, R_g = const\, Re[g(\cdot)],\ var\, Re[g(\cdot)] = \sum_{i=1}^{\infty} b_{(R)_i} I^i. \qquad (4.4)$$

The Volt – Farad characteristic (dynamic capacity):

$$C_g(U) = C_0 + \sum_{i=1}^{\infty} b_{(C)_i} U^i, C_0 = const\ Im[g(\cdot)], var\ Im[g(\cdot)] = \sum_{i=1}^{\infty} b_{(C)_i} U^i. \qquad (4.5)$$

The Ampere - Henry characteristic (dynamic inductance):

$$L_g(I) = L_0 + \sum_{i=1}^{\infty} b_{(L)_i} I^i, L_0 = const\ Im[g(\cdot)], var\ Im[g(\cdot)] = \sum_{i=1}^{\infty} b_{(L)_i} I^i. \qquad (4.6)$$

The general approach to hardware support of technical diagnostic methods is sufficiently described in [1-4]. Synchronous and parallel development of electro-physical methods allow to accumulate knowledge that determines the methodology of intellectual diagnostic devices and sensors which are intellectual aids for accumulation of new diagnostic knowledge.

To diagnose resistive structures by the inertia effect some options and features of TTC are used. That is a resistor reaction as a complex object under influence of the electric jump with maximally non-destructive value [3]. Informational opportunity of electro-physical methods by the integral non-linearity effect and a common approach to hardware of technical diagnostic methods is sufficiently provided in [4].

V. Processing and compression of diagnostic information

Compression of primary diagnostic information about the state of ERC can be accomplished by using the discrete Karhunen-Loeve expansion (DKLE) which is expansion of the initial vectors ensemble by own vectors of the covariance matrix [6,7]. Termal transient characteristics (TTC) of different types of resistors from 10 Om to 1MOm were examined and processed with using DKLE in number of 800 units.

Research of non-linearity was done for integrated microcircuit series K174XA11 (analog TDA2593) in number of 160 units on representative samples. Complex dependencies of quadratic non-linearity by absolute value and phase which were gained with using method of difference frequency separately for fit and defect probes. These dependencies were transformed on cosine $F_c[a_2(Uo)]$ and sinus $F_s[a_2(Uo)]$ components and calculated by DKLE.

Depending on an error resistor orthonormal space consists of two basic coordinates. That means it is a plane. For circuits which space has three coordinates the number of matrixes will increase to 5. The total number of vectors is 160 (32 samples for each matrix). Items of the received orthonormal matrixes depicted in space are shown in Fig.1.

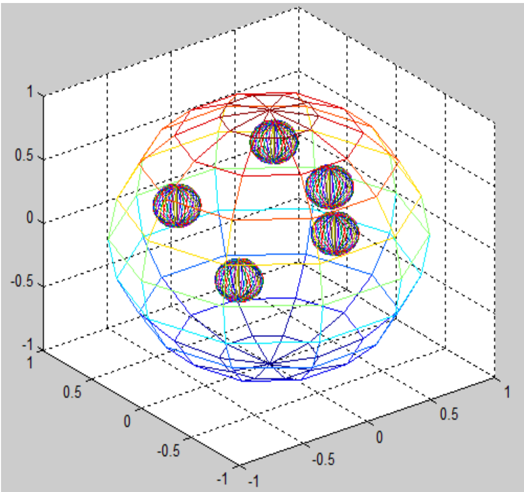

Fig.1. The canonical decomposition forms of the orthonormal Euclidean space (three dimensional X, Y, Z space)

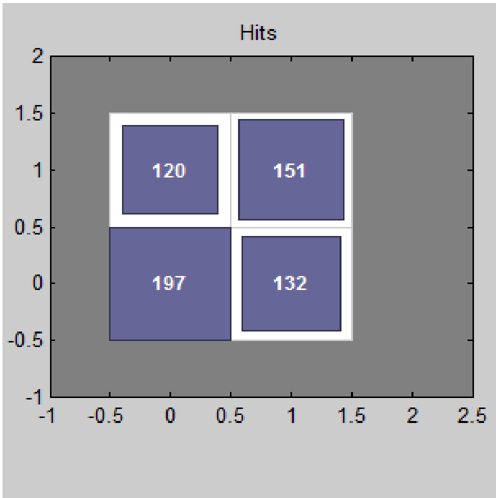

Fig. 2. Results of classification on the self-organized map: recognition accuracy for the “gridtop” topology with the“mandist” distance

Research of the multidimensional information processing principles has allowed selecting and justifying validity of the Karhunen-Loeve expantion as a mathematical tool for processing diagnostic information of EC. It is proposed for practical realization to process diagnostic information with integral physical effects at using modern neural network technology (multilayer perceptron, Kohonen maps, radial-basis networks).

VI. Experimental results

For practical implementation of processing diagnostic information with integrated physical effects it was proposed to use modern neural network technologies (multilayer perceptron, Kohonen maps, radial-basis networks) [8]. For training MLP the following algorithms in the MATLAB environment were selected: Bayesian regularization or function training based on the inverse error propagation using the Bayesian regularization; the gradient descent back propagation method or the method of gradient descent; the gradient descent method with adaptive back propagation; the Powell-Beale back propagation or gradient method coupled with the Powell-Beale repetitions; the resilient back propagation method or the method of inverse elastic distribution.

As the criterion for assessing the training accuracy it was used the international types of error - MSE, MAE and others. For multilayer perceptron procedure training it was obtained the best accuracy result for resistors (Table 1).

Table 1. Comparative results for resistors classification

Neural network type	Obtained classification accuracy, %	Training time, s
RBF-network	99.96	2
Kohonen map	84	2
MLP	98.75	39

Table 2. Results for classification resistors precision for multilayer perceptron

Educational function	Activation functions of hidden layers logsig- logsig- logsig					
	Error type				k_{ep}, unit	t_{tr}, s
	MSE	SSE	MSEREG	MAE		
MLP	0.0000004	0.00092	0.00000034	0.00025	83	39

As clear from tables 1 and 4 the probabilistic radial basis neural networks have higher classification accuracy than the neural network with radial basic elements and given zero error. For classification of microcircuits using orthonormal space decomposition it is enough to perform classification into two or three classes (Table 3).

Table 3. The best results for accuracy of the classification using multilayer perceptron

	№ of classes	Activation functions of the hidden layer					
		Error type, 10^{-7}				k_{ep}, unit	t_{tr}, s
		MSE	SSE	MSEREG	MAE		
MLP	2	1.4	4200	1.8	1 100	52	24
	3	3	8000	3	2 100	62	33

Table 4. Comparing the best results for all training types of neural network for microcircuits

Neural network type	Classification accuracy, %	Training time, s	Classification accuracy , %	Training time, s
	Two classes		Three classes	
RBF-network (pnn)	99.96	2	99,96	2
RBF-network (newrbe)	82.81	2	70,83	2
MLP	99.23	24	99.05	33

Thus the best results again were shown by neural network with activation function of each hidden layer. The data sample size is 64 samples. Further study was carried out on the self-organized maps (Table 5).

Table 5. Dependence of the accuracy classification on the self-organized map setting parameters

Topology	Hextop			
Distance type between adjacent clasters	Linkdist	Dist	Mandist	Boxdist
Correctly classified samples, %	83.33	83.5	61	70.67
Topology	Gridtop			
Distance type between adjacent clasters	Linkdist	Dist	Mandist	Boxdist
Correctly classified samples, %	61	61	83.67	83.33
Number of training periods	200			
Average training time, s	2			

The results in the Table 5 topology have the best performance with the "gridtop" topology at using the distance between the "mandist" clusters. And moreover impact on the classification accuracy of the step parameter used to estimate distance between the neighboring clusters is not significant (Table 6).

Table 6. Influence of the step parameter on the classification accuracy

"Gridtop" topology, distance between adjacent "mandist"clusters							
Step size	10	30	50	70	80	90	100
Probability of correct classification	0.61	0.84	0.837	0.597	0.603	61	0.837

Self-organized (Kohonen) network (excluding teachers) do not require submission outputs on neural network training set. This algorithm is a neural network algorithm known analogue *K* medium. At each step of the training input vector network served and sought another neuron whose weight differs least from this vector. Found declared the winner neuron and its weights vector *W* is updated as follows:

$$w_i(k+1)= w_i(k)+ \eta(x_n-w_i(k))+aw_i(k)(1-||w_i||^2), \tag{6.1}$$

which parameter η is responsible for setting the rate of learning and change its value in the interval (0,1). All training vectors are processed one by one until they will fail to stabilize or other condition stops. The applied technique traingd (gradient descent backpropagation) and / or penalty functions. Recognition results on the Kohonen map are shown in Fig. 2.

For solving probability problems a special type of neural network PNN (Probabilistic Neural Networks) is using. PNN network architecture is based on the architecture of radial basis function network, but as a second layer uses so-called rival layer which calculates the probability input vector belonging to a particular class and compares the vector of the class whose probability of belonging to above.

The main difference between RBF networks and conventional multilayer networks of direct distribution is a function of the hidden layer neurons. In a conventional multi-layer network, each neuron of the working layer implements a hyperplane in multidimensional space and RBF-neuron implements a hypersphere. In problems where the formation of data are close to the circular symmetry, it can reduce the number of neurons.

When MATLAB modeling the weight matrix of the first layer IW11 (net.IW) formed using vectors from the training set input in the form of a matrix P'.When a new entry is submitted, the unit $||\mathrm{dist}||$ calculates the proximity to the new vector of vectors of the training set, then the calculated distance multiplied by bias and fed to the input function activation *radbas*. The vector of the training set, which is closest to the entrance, to be submitted in output vector a_1. Number of a_1 close to 1.

Weight matrix of the second layer LW21 (net.LW) meets the connectivity matrix T built for this training sequence. This operation can be performed using M-function *ind2vec*, which converts vector of targets in a matrix of connectivity T. The product $T * a_1$ defines the elements of a vector a_1 corresponding to each of the K classes. As a result the competing activation function of second layer *compet* forms the output value equal to 1 for most largest element of the vector n_2 and 0 otherwise. Thus, the network PNN performs the input vector classification by K classes.

Classification and presorting of elements according to their physical and technical states were performed on neural networks in the MATLAB environment [9,10]. For EC presorting the probabilistic neural networks were used. In fact, the network is trained to assess the probability density function. According to the Bayesian statistics to minimize error the model with the greatest probability density is being chosen. The resulting data for chips and resistors confirm the highest accuracy 99.96% and speed training time 2 hours at using the probabilistic (pnn) RBF networks compared with the neural networks with the radial- basis elements and given zero error (newrbe).

Conclusion

The observed identification features increase diagnostic possibilities of technical methods for diagnostics electric components in exposing hidden defects, potential instability and unplanned degradation processes. The discrete Karhunen-Loeve expansion for information compression provides easy algorithm for neural network training and classifying with usage neural networks in MATLAB environment.

For the further development of this problem area the fuzzy logical deduction on real data may be proposed. This approach will allow to perform synthesis of the new type neural network that will help to explore larger data samples with less time and more accuracy in the overall problem of increasing reliability and diagnosis of complex infrastructures.

References

1. Сердюк Г.Б., Усатенко В.Г., Миненко А.П. Автоматизированные комплексы для электро-физического диагностирования ИС и других изделий электронной техники по критериям качества и надежности. К.:КПИ: НПП АМАТЕК, 1992.- С. 55-59.
2. Володарський Є.Т., Кухарчук В.В., Поджаренко В.О., Сердюк Г.Б. Метрологічне забезпечення вимірювань і контролю. Навчальний посібник. – Вінниця: ВДТУ, 2001. – 219 с.
3. А.С.№ 1667118.СССР. Устройство для распознавания динамических характеристик объектов/ Сердюк Г.Б.,Савчук Е.В., Усатенко В.Г., Попова Н.С., Шерстюк И.В., Свистунов А.Я. Приоритет от 17.05.1988, БИ №28, 1991
4. Патент № 1056 на винахід (Україна). Спосіб відбраковки потенційно ненадійних та нестабіль-них мікросхем / В.Г. Усатенко, Г.Б. Сердюк, С.Н. Сазонов. - G 01 R 31/27. - 1993.

5. Теленик С.Ф., Ролік О.І., Ясочка М.В., Моргаль О.М. Нечітке оцінювання в задачах управління рівнем обслуговування // В кн.: Наукові записки Українського науково-дослідного інституту зв'язку. — 2011.— №2(18).— С. 29—42.
6. Castrillon-Candas J., Amaratunga K. – Fast estimation of continuous Karhunen-Loeve eigenfunctions using wavelets. – IEEE: IEEE Signal Processing Society. – 2002. – pp.78-86.
7. Солодовщиков А.Ю., Платонов А.К. Исследование метода Карунена-Лоэва. – М.:РАН, 2006. – 29 с.
8. Telenyk S., Savchuk O., Pocrovskyi E., Morgal O., Krivenko K., Latash I. On Searching of Type and Optimizing of Neural Network in Electric Component Diagnosis // Proceedings of the IV Congress on «Automatic Control and Information Technology», (ICACIT 2017), Cracow, Poland, 14 - 16 of December, 2017, pp.147-159.
9. Дияконів В., Круглов В. Математичні пакети розширення MATLAB. Спеціальний довідник. - Спб.: Питер, 2001. - 480 с.
10. Yakimenko O. Engineering computations and modeling in MATLAB/Simulink. – Monterey, California: American Institute of Aeronautics and Astronautics, INC., 2011. – 938 p.

References

1. Serdyuk G.B., Usatenko V.G., Minenko A.P. Avtomatizirovannyie kompleksyi dlya elektro-fizicheskogo diagnostirovaniya IS i drugih izdeliy elektronnoy tehniki po kriteriyam kachestva i nadezhnosti. K.:KPI: NPP AMATEK, 1992.- S. 55-59.
2. Volodarskyi Ye.T., Kukharchuk V.V., Podzharenko V.O., Serdiuk H.B. Metrolohichne zabezpechennia vymiriuvan i kontroliu. Navchalnyi posibnyk. – Vinnytsia: VDTU, 2001. – 219 s.
3. A.S.# 1667118.SSSR. Ustroystvo dlya raspoznavaniya dinamicheskih harakteristik ob'ektov/ Serdyuk G.B.,Cavchuk E.V., Usatenko V.G., Popova N.S., Sherstyuk I.V., Svistunov A.Ya. Prioritet ot 17.05.1988, BI #28, 1991.
4. Patent № 1056 na vynakhid (Ukraina). Sposib vidbrakovky potentsiino nenadiinykh ta nestabil-nykh mikroskhem / V.H. Usatenko, H.B. Serdiuk, S.N. Sazonov. - G 01 R 31/27. - 1993.
5. Telenyk S.F., Rolik O.I., Yasochka M.V., Morhal O.M. Nechitke otsiniuvannia v zadachakh upravlinnia rivnem obsluhovuvannia // V kn.: Naukovi zapysky Ukrainskoho naukovo-doslidnoho instytutu zviazku. — 2011.— №2(18).— S. 29—42.
6. Castrillon-Candas J., Amaratunga K. – Fast estimation of continuous Karhunen-Loeve eigenfunctions using wavelets. – IEEE: IEEE Signal Processing Society. – 2002. – pp.78-86.
7. Solodovschikov A.Yu., Platonov A.K. Issledovanie metoda Karunena-Loeva. – M.:RAN, 2006. – 29 s.
8. Telenyk S., Savchuk O., Pocrovskyi E., Morgal O., Krivenko K., Latash I. On Searching of Type and Optimizing of Neural Network in Electric Component Diagnosis // Proceedings of the IV Congress on «Automatic Control and Information Technology», (ICACIT 2017), Cracow, Poland, 14 - 16 of December, 2017, pp.147-159.
9. Dyiakoniv V., Kruhlov V. Matematychni pakety rozshyrennia MATLAB. Spetsialnyi dovidnyk. - Spb.: Pyter, 2001. - 480 s.
10. Yakimenko O. Engineering computations and modeling in MATLAB/Simulink. – Monterey, California: American Institute of Aeronautics and Astronautics, INC., 2011. – 938 p.

РЕЗЮМЕ

С.Ф. Теленик, О.В. Савчук, Є.О. Покровський, О.М. Моргаль, К.С. Кривенко, І.О. Латаш

Про деякі проблеми нейромережевих технологій у діагностиці електричних компонентів

У статті розглядається інформаційна можливість електофізичних методів діагностування електричних компонентів за інтегральними ефектами інерційності та нелінійності, описується ідея отримання діагностичної інформації про електричні компоненти.

Надається модель чорної скриньки, внутрішній зміст якої описується комплексною функцією сприйнятливості. Використано перетворення Тейлора для отримання моделі за інтегральним ефектом нелінійності для різних електричних компонентів, таких як резистори, індуктивності, конденсатори, а також для мікросхем у вигляді двохполюсника, що підключений до шини живлення.

Інтелектуальний аналіз та перетворення діагностичної інформації про електричні компоненти виконано за допомогою дискретного розкладання Карунена-Лоева, що є розкладанням ансамбля початкових векторів за власними векторами коваріаційної матриці. Експериментально доведено, що для електричних компонентів цей простір складається з двох, трьох або шести компонентів в залежності від похибки обчислень.

У роботі досліджується можливість використання нейронних мережевих технологій для поліпшення діагностики електричних компонент за інтегральними ефектами інерційності та нелінійності для підвищення надійності складних технологічних систем. Запропоновано визначення фізичних та технічних станів елементів за допомогою MLP, самоорганізованих та RBF-нейронних мереж, а також наведений алгоритм моделювання вагових матриць в середовищі MATLAB. Найкращий результат за точністю класифікації 99.96 % отриманий для RBF-нейронних мереж.

Запропоновані статистична та індивідуальна класифікація та сортування електричних компонентів відповідно до їх фізичних і технічних станів з використанням нейронних мережевих технологій.

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