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**Olena Savchuk, Artem Martyniuk**

# USAGE DIAGNOSTICS TO IMPROVE THE FAULT TOLERANCE OF THE IT STRUCTURE ELEMENT BASE

The article considers the idea of obtaining information about the technical conditions of the element base with the decomposition of the IT structure. Preliminary diagnosis of the components of the element base organizes neural network technologies to increase the fault tolerance of IT structures. Classification and sorting of components according to their technical condition was carried out in the MATLAB environment.

**Key words:** fault tolerance, neural network technologies, diagnosis, element base of the IT structure.

Fig.: 3. Tabl.:1. Bibl.: 13.

**Target setting.** The process of constant improvement and updating of the modern IT structure and its element base is stochastic in nature, therefore, when diagnosing the technical condition of the studied IT structure and/or its component, greater reliability is required, by which some data about the properties of the studied object can be determined.

**Actual scientific researches and issues analysis.** In connection with the development of neural network technology, new high-tech directions were developed in the theory of reliability and diagnostics of IT structures components [1], which contributed to increasing the fault tolerance of the latter.

**Uninvestigated parts of general matters defining.** Despite the significant number works devoted to the application of neural networks for the study of IT structures, the problem of increasing the fault tolerance of the element base of IT structures remains understudies. Moreover, it is necessary to conduct a separate study and a separate selection parameters for each type of element base.

**The research objective.** The purpose of the article is to choose the type of neural networks, methods of processing accumulated data to improve the quality and reliability of diagnostic results and their research on examples of the implementation of the process of EB diagnostics of the IT structure, including integrated microcircuits (ICs). For probabilistic reasons, predict processes in it that will lead to undesirable changes in the technical state of an element of the IT structure, and remove this element.

**The statement of basic materials.**

## I. METODOLOGY FOR OBTAINING A PRIORY DIAGNOSTIC INFORMATION

For local diagnostic methods, instrumentally measurable information for the most part has the character of an image of the topographic distribution of certain properties of external environments. This allows not only to detect the presence of defects in the EB, but also to localize the location of the defects, indicating their size and orientation in space. The disadvantage of these methods is to increase the operational duration and complexity of the diagnostic process.

The emergence of non-linearity, inertia, fluctuations is related to the work processes of the investigated element to be diagnosed (IED), and has the same origin of activation. This means that the same sources of energy activation that ensure the operation of the IED during its operation are required for diagnostics. The short duration of operational diagnostics reduces its effectiveness. Diagnostic digital information often has various analog signatures [2]. Thus, it is possible to detect unfavorable malfunctions in the IED and determine its faulty operating state from the signature.

Observation of nonlinearity has specific measurement of ambiguous, since cannot a single. These are necessary functions, up the defining degrees, derivatives of higher ones. As for inertial, the corresponding inertial IEDs carried out the activation their input in the energy conversion and begin to operate. Transient integral characteristics reflect local macro-characteristics of the manifest and hidden impulse changes. The form of $\boldsymbol{g}(.)$ physical obtain during electrophysical transformation of electrical components, is an 1st a non-linear [3,4].

**General model structure.**

## II. CONVERSION OF AN INPUT VECTORS SET FOR MICROCIRCUITS DIAGNOSTICS

The transformation of the input set of vectors into eigenvectors was carried out simultaneously by Karhunen and Loeve [5-7]. Let $X$ be an $n$-dimensional random vector, then $X$ can be exactly represented by a distribution

$$X = \sum_{l=1}^{n} y_i \Phi_i = \Phi Y_i \tag{1}$$

$$\Phi = [\Phi_1 \ldots \Phi_n] \tag{2}$$

$$Y = [y_1 \ldots y_n]^{\mathrm{T}} \tag{3}$$

The matrix $\Phi$ is deterministic and consists of $n$ linearly independent column vectors:

$$|\Phi| \neq 0 . \tag{4}$$

Accordingly, linear combinations of the columns of the matrix *Φ* form an *n*-dimensional space that contains *X*. The columns of the matrix *Φ* are called basis vectors. These columns must be orthonormal, i.e

$$\Phi_i^T \Phi_j = \begin{cases} 1, i = j, \\ 0, i \neq j. \end{cases} \tag{5}$$

If the condition of orthonormality is fulfilled, then as follows:

$$yi = \Phi_i^T X, i = 1, \cdots, n. \tag{6}$$

If *m* (*m*<*n*), then following formula can be used to estimate the vector *X* (at the same time, the unknown components of *Y* are replaced by preselected constants):

$$\hat{X}(m) = \sum_{i=1}^{m} y_i \Phi_i + \sum_{i=m+1}^{n} b_i \Phi_i. \tag{7}$$

Without restriction of commonality, we can assume that only the first m components.

Each set of base vectors and values of constants corresponds to some value *ε2(m)*. It is necessary to choose them in such a way as to minimize $\varepsilon^2(m)$. The optimal selection of *bi* constants is performed as follows:

$$b_i = E\{y_i\} = \Phi_i^T E\{X\}. \tag{8}$$

$$\Sigma_x \Phi_i = \lambda_i \Phi_i. \tag{9}$$

That is, the optimal basis vectors are the eigenvectors of the covariance matrix $\Sigma_x$. Thus, the minimum root mean square error is equal to

$$\varepsilon^{-2}(m)_{opt} = \sum_{i=m+1}^{n} \lambda_i \tag{10}$$

In pattern recognition tasks, the coefficients *y1,…,yn* of this distribution are considered as features representing the observed vector *X*.

These features have the following useful properties [7].

In other words, $\Sigma z$ and $\lambda'_i$ are normalized eigenvalues. However, the transformation [7] must be justified from a physical point of view, since the statistical properties of the vector *Z*, including the covariance matrix, are completely different from the statistical properties of the vector *X*.

The study of nonlinearity was carried out for the integrated microcircuit (IMs) of the TDA2593 synchroprocessor. Dependences of nonlinearity on module and phase for IMs obtained by the method [3]. Dependencies on the components of cosine *Fc* [a2 (Uo)] and sine *Fs* [a2 (Uo)] are calculated according to the Karhunen-Loeve distribution (KLD) [4].

The number of required basic vectors m allows to determine the dimension of the space of features with a given decomposition error $\varepsilon^2(m)$. The base vectors themselves are the statistical characteristics of defective and suitable microcircuits, and the expansion coefficients are spatial coordinates.

For greater clarity, the Hilbert space is replaced by the Euclidean space. In the two-dimensional Euclidean orthonormal space ($m$ = 2, $\varepsilon^2(m)$=8%, $n$ = 100), intersections of the images of many suitable and defective chips, selected a priori based on expert data, were observed. At the same time, the KLD coefficients of suitable microcircuits were mainly located near a circle of unit radius, and defective ones shifted to the middle of the circle (Fig. 1, a).

When adding the third basis vector ($m$ = 3, $\varepsilon^2(m)$ = 2%, $n$ = 100), the orthonormal space of cosine vectors is transformed into a hemisphere on the left, and sine vectors on the right (Fig. 1, b). The points of the reflected suitable chips lie in the near-surface layer of a sphere of unit radius, and the reflections of different defective ones almost do not intersect.

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In reality, the space of non-linear basis vectors is an eight-dimensional ellipsoid. Displaying it in Euclidean space does not interfere with the natural classification of faulty and potentially unreliable microcircuits as small spheres in the middle of the main hemispheres (Fig. 1, b).

**Experiments.**

## USAGE OF NEURAL NETWORKS FOR THE MICROSERCUITS CLASSIFICATION IN MATLAB

Processing of the complex of biharmonic influence was carried out on 164 IMs [3,4]. The analog signatures were transformed into discrete vectors, then processed by the KLD method. The following algorithms were selected for training MLP in the MATLAB software package with its library Neural Network Toolbox [8-10]: Bayesian regularization or learning a function based on backpropagation of the error using Bayesian regularization [12]; gradient descent backpropagation method; back propagation; combined iterations; elastic backpropagation or inverse elastic

distribution. The results of learning neural networks: MLP, self-organized map, RBF networks are given below. International types errors - MSE, MAE, MSEREG, MAE - were used as a criterion for assessing the accuracy of training [11]

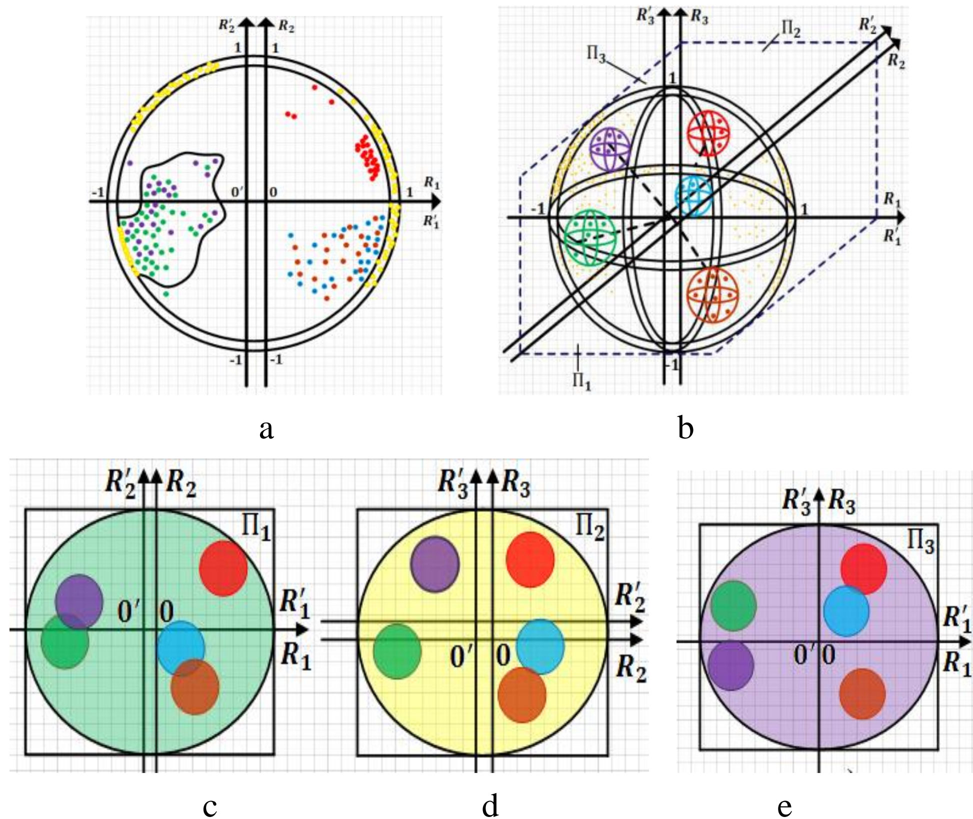
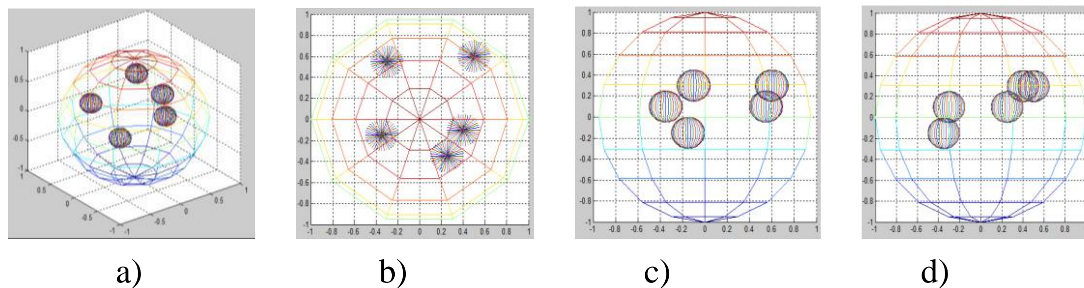



*Fig. 1.* Geometric interpretation of KLD for microcircuits [4]: a) in two-dimensional orthonormal space of vectors; b) in three-dimensional orthonormal space of vectors; c) the projection of this space onto P1 in the two-dimensional Euclidean orthonormal space (on the left – for the cosine component, on the right – for the sine component); d) projection on P2 (with overlapping axes for cosine and sine components), e) projection of this space on P3.

***Table1.*** **Training a Multiplayer Perceptron for IMs**

| **Number of classes** | **Educational function trainbr** | | | | | |
|---|---|---|---|---|---|---|
| | **logsig- logsig- logsig** | | | | | |
| | ***10E-5*** | | | | ***Epochs, unit*** | ***Learning time, s*** |
| | ***MSE*** | ***SSE*** | ***MSEREG*** | ***MAE*** | | |
| 2 | 1.4 | 4200 | 1.8 | 1100 | 52 | 24 |
| 3 | 3 | 8000 | 3 | 2100 | 62 | 33 |

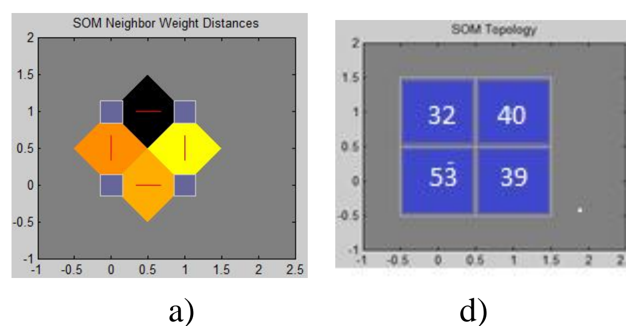
The most important advantages of probabilistic networks are that they are faster and easier to train than backpropagation networks. When training a PNN network, time is spent almost at the input. The disadvantage of the network is its size, since it actually contains all the training data and requires a lot of memory, which can reduce speed of operations [11-13].



a) b) c) d)

***Fig. 2.*** The results of RBF network training: a) spatial image of the elements of the obtained KLD matrices for microcircuits; b) projection of the received KLD matrices for microcircuits onto the XY plane; c) onto the YZ plane; d) onto the XZ plane.

When using the Kohonen map, the neurons of the active sphere have a regular structure. Such maps are often used for clustering graphic images and audio signals, as well as for rich information processing. The map is implemented as an announcement (Fig. 3).The best reliability of the microcircuits' classification (83,7%) can be achieved for gridtop topology with mandist distances and steps=30. And the best result of chip rejection is provided by MLP and RBF neural networks (pnn), when trained with a teacher (> 90%).




a) d)

***Fig. 3.*** Topology gridtop: a) the principle of forming distances between adjacent clusters: b) classification of samples with mandist distances.

**Conclusions.**The task of fault tolerance increasing using improving of electro physical methods of diagnostics with neural technologies was solved.

The Karhunen-Loeve distribution for information transformation provides a simple algorithm for learning and recognizing the technical and physical state of IT structure components using neural networks in the MATLAB environment.

The observed information signs increase the diagnostic capabilities of technical methods for diagnosing the element base of an IT structure in identifying hidden defects, potential instability and unplanned degradation processes.

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## AUTHORS

**Savchuk Olena** – associate professor, Department of Information Systems and Technologies, National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute". E-mail: savchuk_l1@ukr.net, elenasavchuk0@gmail.com

**Martyniuk Artem** – student, Department of Information Systems and Technologies National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute" E –mail: martuniukartem1123@gmail.com

## РОЗШИРЕНА АНОТАЦІЯ

**Олена Савчук, Артем Мартинюк**

# ВИКОРИСТАННЯ ДІАГНОСТИКИ ДЛЯ ПОКРАЩЕННЯ ВІДМОВОСТІЙКОСТІ ЕЛЕМЕНТНОЇ БАЗИ ІТ-СТРУКТУРИ

**Актуальність теми дослідження.** Процес постійного вдосконалення та оновлення сучасної ІТ-структури та її елементної бази (ЕБ) має стохастичний характер, тому при діагностиці технічного стану досліджуваної ІТ-структури та/або її компонента необхідна більша достовірність, за допомогою якої деякі дані про властивості досліджуваного об'єкта можна визначити.

**Актуальні наукові дослідження та аналіз проблем.** У зв’язку з розвитком нейромережевих технологій отримали розвиток нові високотехнологічні напрямки в теорії надійності та діагностики компонентів ІТ-структури, що сприяло підвищенню відмовостійкості останніх.

**Постановка проблеми. 1.** Обумовлювати в даний час і ідентифікувати внутрішній стан техніки під час виконання. 2. Відстеження місцезнаходження для несправного стану. 3. Виконати діагностику базового елемента ІТ-структури. Використати нейронні мережі для класифікації дослідженого елемента. 4. З ймовірнісних міркувань передбачити процеси в елементі ІТ-структури, які призведуть до небажаних змін технічного стану.

**Виділення недосліджених частин загальної проблеми.** Незважаючи на значну кількість робіт, присвячених застосуванню нейронних мереж для дослідження ІТ-структур, проблема підвищення відмовостійкості елементної бази ІТ-структур залишається недостатньо вивченою. Причому для кожного типу елементної бази необхідно проводити окреме дослідження і окремий підбір параметрів.

**Постановка завдання.** Вибір типу нейронних мереж, методів обробки накопичених даних для підвищення якості та достовірності результатів діагностики та їх дослідження на прикладах реалізації процесу діагностики елементної бази ІТ-структури, в тому числі інтегральних мікросхем (ІМС). З ймовірнісних міркувань спрогнозувати в ньому процеси, які призведуть до небажаних змін технічного стану елемента ІТ-структури, і видалити цей елемент, що сприяє підвищенню відмовостійкості елементної бази і всієї ІТ–структури.

**Викладання основного матеріалу**. Вирішено завдання підвищення відмовостійкості шляхом вдосконалення електрофізичних методів діагностики

нейротехнологіями. Пропоновано розподіл Карунена-Лоева для перетворення та стиснення діагностичної інформації , що забезпечує простий алгоритм для вивчення та розпізнавання технічного та фізичного стану компонентів IT-структури за допомогою нейронних мереж у середовищі MATLAB.

Спостережувані інформаційні ознаки підвищують діагностичні можливості технічних методів діагностики елементної бази IT-структури щодо виявлення прихованих дефектів, потенційної нестабільності та незапланованих процесів деградації.

**Висновки.** Розглядається ідея отримання діагностичної інформації елементної бази IT-структури. Для підвищення надійності елементів IT-структури пропонується попередньо сортувати компоненти елементної бази за технічним станом. Проведено класифікацію та сортування компонентів за технічним станом у середовищі MATLAB з використанням нейромережевої технології, що сприяє подальшому підвищенню відмовостійкості IT структури в цілому.

**Ключові слова:** відмовостійкість, нейромережеві технології, діагностування, елементна база IT-структури.

Рис.:3. Табл.:1. Бібл.:13.