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RESEARCH ARTICLE

Localization of structural defects of printed circuit board assembly by vibration diagnostics

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Abstract

Objectives. Structural defects may arise during the production and operation of printed circuit board assemblies (PCBAs) installed in radio-electronic assemblies (REAs) due to manufacturing imperfections or the influence of external factors. Of particular concern are latent defects that cannot be detected after the PCBA has been manufactured and which may lead to failures during operation. The typical installation in sealed enclosures of modern PCBAs, which are characterized by a high density of electronic components, significantly complicates the use of conventional inspection and diagnostic methods. This study aims to improve the reliability of detecting and classifying latent defects in PCBAs in sealed blocks based on their mechanical amplitude-frequency characteristics (AFCs) using a deep neural network.

Methods. The paper proposes a vibration diagnostics method based on the numerical modeling of mechanical processes, experimental vibration testing, and the application of an artificial neural network for technical condition classification. Diagnostics involves analyzing the obtained mechanical AFCs using an accelerometer mounted on the enclosure and comparing them with a database of calculated AFCs generated for various technical states of the PCBA.

Results. To verify the proposed method experimentally, a PCBA mock-up was fabricated and installed inside an enclosure with various structural defects introduced into its design. A database of calculated mechanical AFCs was formed for both healthy and faulty states. After obtaining experimental AFCs, they were compared with the calculated data, and the introduced defects were identified using a deep neural network.

Conclusions. The developed vibration diagnostics method enables the highly accurate detection and classification of latent defects arising in radio-electronic equipment during production and operation. This improves the reliability of technical condition assessment of PCBAs.

Keywords: diagnostics, vibrational loading, radio-electronic equipment, PCBA, DNN

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НАУЧНАЯ СТАТЬЯ

Локализация дефектов конструкций печатных узлов методом вибродиагностики

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Резюме
Цели. В процессе производства и эксплуатации печатных узлов (ПУ), устанавливаемых в блоках радиоэлектронных средств (РЭС), могут возникать конструктивные дефекты, обусловленные технологическими погрешностями или воздействием внешних эксплуатационных факторов. Наибольшую опасность представляют латентные дефекты, которые невозможно выявить после изготовления ПУ, но которые способны привести к отказам в процессе эксплуатации. Современные ПУ характеризуются высокой плотностью компоновки электрорадиоэлементов и, как правило, размещаются в герметичных блоках, что существенно затрудняет применение традиционных методов контроля. Целью работы является повышение достоверности выявления и классификации латентных дефектов конструкций ПУ в герметичных блоках по механическим амплитудно-частотным характеристикам (АЧХ) с использованием глубокой нейронной сети.
Методы. Предложен метод вибродиагностики, основанный на численном моделировании механических процессов, экспериментальных вибрационных испытаниях и применении искусственной нейронной сети для классификации технического состояния. Диагностирование осуществляется путем анализа механических АЧХ, полученных с помощью акселерометра, установленного на корпусе блока, и их сравнения с базой расчетных АЧХ, сформированной для различных технических состояний ПУ.
Результаты. Для экспериментальной проверки метода изготовлен макет ПУ внутри блока, в конструкцию которого вносились различные дефекты, и сформирована база расчетных механических АЧХ для исправного и неисправных состояний. После получения экспериментальных АЧХ выполнено их сравнение с расчетными данными, и с использованием глубокой нейронной сети определены виды внесенных дефектов.
Выводы. Разработанный метод вибродиагностики ПУ позволяет с высокой точностью выявлять и классифицировать латентные дефекты, возникающие в РЭС в процессе производства и эксплуатации, и повышает достоверность оценки технического состояния ПУ.

Ключевые слова: диагностирование, вибрационные воздействия, радиоэлектронное средство, печатный узел, DNN

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INTRODUCTION

A typical diagnostic system comprises a unit under test (UUT), as well as the various tools and methods for determining its technical condition. The tools are defined as a set of hardware and software devices used to measure and analyze diagnostic data obtained from the UUT at all stages of its lifecycle. Depending on how the UUT interacts with the diagnostic tool, different functional and testing techniques may be employed. Functional techniques are used to diagnose the UUT during operation, employing sensors to gather information regarding its technical condition. In this case, the diagnostic tools do not interfere with the UUT. Testing techniques involve applying a signal or set of signals are applied to the UUT input to trigger processes that provide information about its technical state [1].

Diagnosis of the technical condition of radio-electronic assemblies (REAs) constructed as modular units with printed circuit board assemblies (PCBAs) involves analyzing their mechanical amplitude-frequency characteristics (AFCs) under vibration conditions. This technique has been widely used in technical diagnostics [2–4]. Design defects in a device can lead to changes in its resonant frequencies as compared to those of a well-functioning device [5]. Based on this, a methodology can be developed for diagnosing PCBA structures that detects and classifies defects in devices during manufacturing and operation without affecting their structure.

Within the scope of this study, the authors are investigating the development of a non-destructive diagnostic technique. This includes the creation of models and algorithms for automatically detecting and identifying types of latent defects in a structure. These defects can affect the mechanical AFC of a block design, but the research does not consider failures resulting from the electrical parameters of electronic components. To enhance the reliability of the technique, a mechanical simulation process is applied to the UUT, taking into account variations in structural parameters.

1. METHOD OF DIAGNOSING PCBA STRUCTURES IN CASE OF VIBRATION EFFECTS

Most design defects in PCBA that occur during manufacture and operation are caused by mechanical factors, such as shock, harmonic vibration, and acoustic noise. These include missing or deformed electronic components, cracks in the structure, loosening of fasteners, inhomogeneity of the PCBA material, and other issues. However, defects that occur during equipment operation cannot be directly detected when using the device for its intended purpose [6], as current methods require shutting down the equipment, or compromising the structural integrity of the unit containing the controller, which is undesirable for sealed units.

Such defects may occur during the manufacture or operation of the units. To detect and identify the type of these latent defects, we propose a diagnostic method that compares the experimentally obtained AFC on the external surface of the blocks at a designated control point with a set of calculated AFCs for different technical conditions of the PCBA structure at the same control point [7]. Based on this comparison, it is possible to determine the technical condition of the device and take an appropriate action. The use of this technique can reduce labor expenses, diagnostic time, and financial costs associated with the monitoring and diagnosis of PCBA structures [8, 9].

With the use of modern modeling techniques and AFC analysis, it is possible to accurately identify the relationship between a specific type of defect and a corresponding diagnostic feature. In order to collect diagnostic data and subsequently analyze it, the following series of steps should be taken:

- conversion of physical phenomena into diagnostic signals by measuring the AFC using an accelerometer;
- collection of characteristics from this signal and analysis thereof through modeling of various technical conditions;
- comparison of the analytical results with values defined in technical documentation;
- use of an artificial intelligence (AI) algorithm for decisions-making regarding the technical condition.

The structural diagram of the proposed method is presented in Fig. 1.

In order to diagnose the technical condition of the PCBA structure based on the design documentation (Block 1), it is necessary to develop a model that enables the analysis of mechanical processes (Block 2). At the same time, the design model for the block with PCBA must accurately describe its geometric structure along with the physical and mechanical properties of its materials, as well as the mechanical characteristics of each electronic component of the simulated PCBA. In other words, the model must accurately reflect the data specified in the product's design documentation.

A computer-aided design (CAD) system can be utilized to simulate mechanical processes within the unit to determine the AFC at specific points when the device is subjected to vibrational mechanical forces. The described technique uses the *Solidworks*[1] software tool.

[1] https://www.solidworks.com/. Accessed March 23, 2026.

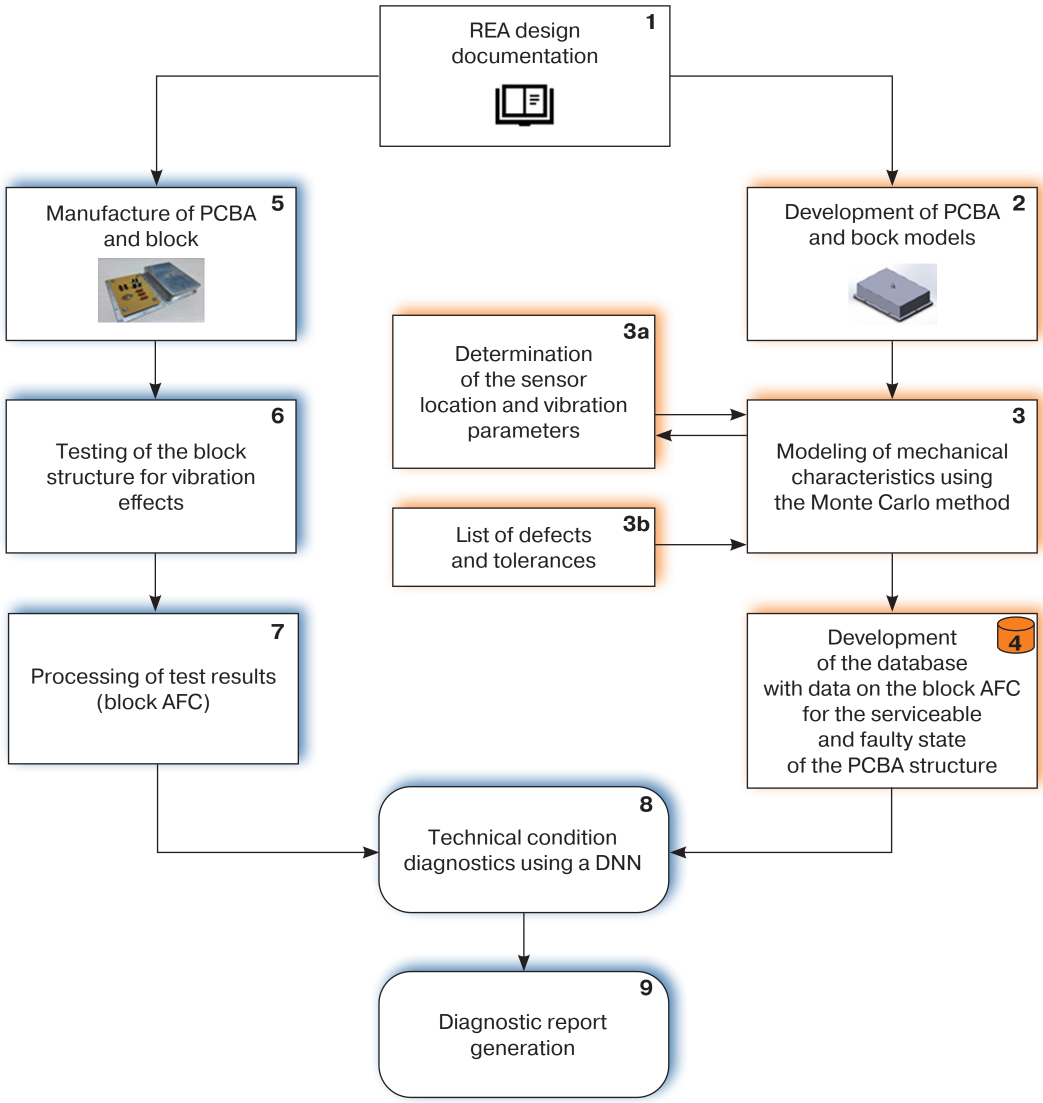

Fig. 1. Method for vibration-based diagnostics of PCBA

The AFC of the block, which is derived from the analysis of mechanical processes, depends on the selection of a reference point for calculating the AFC, as well as on the parameters of the applied mechanical vibrations, such as the amplitude and frequency of harmonic vibrations (Block 3a). The position of the reference point used to determine the AFC is chosen based on the peak amplitude of the vibrations; in this case, the center of the enclosure cover is the preferred option. During diagnostics, the amplitude of the harmonic vibrations should not exceed the theoretical maximum value of $A_{\text{max theor}}$ at which mechanical failure of the block and PCBA may occur, nor should it be significantly lower than the actual value of $A_{\text{min actual}}$ that can be detected by the sensor. Therefore, the minimum and maximum values of the harmonic oscillation amplitude at a monitoring point, denoted as $A_{\text{min effect}}$ and $A_{\text{max effect}}$, respectively, must meet the following condition[2]:

$$[A_{\text{min effect}}; A_{\text{max effect}}] \in [A_{\text{min actual}}; A_{\text{max theor}}].$$

In order to obtain information on the mechanical characteristics of the block structure under different PCBA technical conditions, it is necessary to simulate mechanical processes in both good PCBA conditions and in the presence of various defects. A list of potential defects is provided in Block 3b. The greater the number of defects considered in the simulation process, the more accurate the results of the technical condition diagnosis will be.

[2] Lu Ngoc Tien. *Acoustic Emission Method of Control of Multilayer Printed Circuit Boards of Radio-Electronic Devices*: Cand. Sci. Thesis (Eng.). Moscow: 2024.

The physical and mechanical properties (γ_i) of real PCBA structures often vary within a certain range, typically between 3% and 10%. To account for this variation, statistical Monte Carlo simulations are performed (Block 3) [10]. Based on this analysis, a set of AFCs is calculated for various combinations of the physical and mechanical PCBA design parameters that fall within acceptable ranges. In this scenario, it is assumed that the distribution of these parameter values follows a normal distribution:

$$f(\gamma_i) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(\gamma_i - \mu)^2}{2\sigma^2}\right),$$

where $f(\gamma_i)$ is the probability density function for the distribution of the γ_i physical and mechanical parameter; μ is the expected (or nominal) value of this parameter; σ is its standard deviation.

For the kth iteration of the Monte Carlo simulation, the ith physical and mechanical parameter is calculated using the following formula:

$$\gamma_i = \gamma_i^{\text{nom}}(1 + \xi_k \delta_i),$$

where γ_i is the value of the ith parameter in the kth iteration of the Monte Carlo simulation; γ_i^{nom} is the nominal value of the ith physical and mechanical parameter; δ_i is a relative tolerance for the ith physical and mechanical parameter; $\xi_k \sim N(-1, 1)$ is a random variable following a standard normal distribution [11, 12].

A database of calculated AFCs (Block 4) for various PCBA design conditions was developed using *Microsoft Excel*. The database is used to make a final conclusion about the PCBA's technical condition by comparing the AFCs obtained from field testing.

To determine the technical condition of the PCBA during the production or operation of devices manufactured in accordance with the design documentation (Block 5), a mechanical AFC test is carried out on the device using a vibration testing apparatus (Block 6). In order to obtain AFC data during these tests, a sensor is installed at the same reference point at which the calculated AFC was obtained during simulation. In this study, the VP-32 model manufactured by IMV Corporation (Japan) is used as the vibration sensor. This highly sensitive piezoelectric accelerometer, which converts vibration acceleration into an electrical charge, has a wide operating frequency range (up to 10 kHz) and is highly resistant to shock loads, making it suitable for use in vibration analysis under conditions of intense mechanical stress. The main element of the sensor is a quartz crystal that converts vibration into a proportional electrical voltage. The sensitivity of the sensor is expressed in pC/g, where pC is the unit of charge known as the picocoulomb, and g is the acceleration due to gravity, expressed in m/s^2. The sensor's measurement range falls within the linear portion of its AFC curve [13].

The experimentally obtained mechanical AFC of the block design (Block 7) is converted into a data table containing amplitude and frequency values. This data is then compared with the stored mechanical AFC in the database (Block 4) using an artificial neural network (Block 8) to detect and classify any defects. In this process, a deep neural network (DNN) is employed. Based on the comparison between the experimental and simulated mechanical AFCs, a report is generated regarding the PCBA technical condition (Block 9).

2. OBTAINING CALCULATED MECHANICAL AFC

When designing a block with PCBA, it is essential to simulate mechanical processes under the influence of vibration-induced mechanical stresses. This simulation, which is a critical component of the proposed approach, significantly impacts the accuracy of the diagnostic outcomes. The simulation is conducted for different technical conditions of the device. The more diverse the technical states considered for the structure, the more accurate the final conclusions based on the diagnostic results will be.

When diagnosing the PCBA structure, a list of potential latent defects is compiled and the mechanical characteristics of the device are simulated to obtain the calculated AFC at a control point of the unit. This corresponds to each identified defect. The experimental AFC is then measured on a physical prototype to identify potential defects by comparing the experimental and calculated AFCs for each possible technical condition. This comparison establishes whether the PCBA is functioning properly or has a defect.[3]

An algorithm has been developed to identify a list of potential defects in a PCBA. Its scheme is presented in Fig. 2 below.

This algorithm can be used to determine the likelihood of detecting a particular defect in the PCBA structure. Based on the AFC analysis control panel, a decision is made as to whether to include the relevant defect in the list of detected defects (Block 3b in Fig. 1).

The *SolidWorks Simulation* package is used to calculate mechanical characteristics under vibrational influences for the analysis of mechanical processes. The resonant frequencies of the structural block are calculated for input effects in the form of harmonic vibrations ranging from 0 to 2000 Hz.

[3] Malpass L. *SolidWorks 2009 API – Advanced Product Development*. 2009, 246 p.

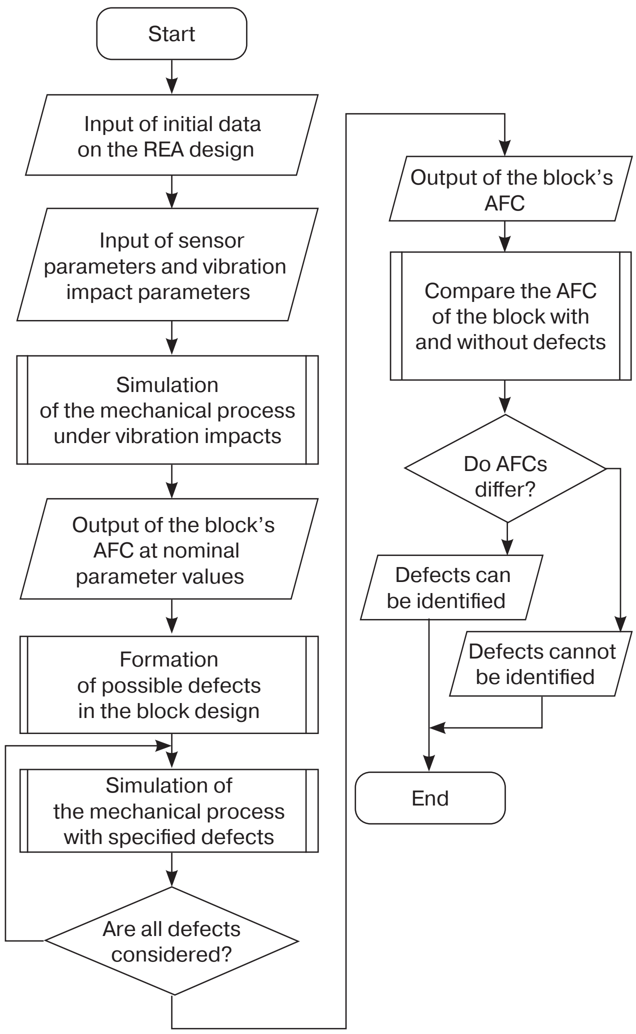

Fig. 2. Algorithm for identifying potential defects in a PCBA

The UUT is a power amplifier, whose electrical circuit and PCBA design model are presented in Fig. 3. The prototype PCBA is as depicted in Fig. 4. This prototype device for simulating the distribution of electronic components on a printed circuit has been designed solely for this study, which includes mechanical and vibration testing of the device's design. However, this model does not take into account the electrical parameters of the electronic components, since this study focuses on the mechanical characteristics and dynamic response of the structure, rather than the electrical performance of the device.

The mechanical AFC of a tested prototype in good working condition (Fig. 5) exhibits resonant frequencies at f_1 = 878.1 Hz, f_2 = 1089.5 Hz, and f_3 = 1405.7 Hz.

In cases where the tested prototype exhibits one or more of the identified defects, the resonant frequencies of the device vary as follows:

- Defect A (absent electronic component): f_1 = 878.3 Hz, f_2 = 1092.6 Hz, and f_3 = 1409.5 Hz (Fig. 6).
- Defect B (PCBA fastener loosening): f_1 = 878.2 Hz, f_2 = 1090.6 Hz, f_3 = 1428.8 Hz (Fig. 7).
- Defect C (electronic component deformation): f_1 = 878.1 Hz, f_2 = 1091.5 Hz, f_3 = 1403.6 Hz (Fig. 8).
- Defect D (layout and placement violations of an electronic component on the printed circuit): f_1 = 878.4 Hz, f_2 = 1090.2 Hz, f_3 = 1424.2 Hz (Fig. 9).
- Defect E (installation of an electronic component that does not correspond to the design documentation (Fig. 10).
- Defect F (heterogeneity of the printed circuit material structure): f_1 = 842.4 Hz, f_2 = 878.4 Hz, f_3 = 951.5 Hz (Fig. 11).

The overall AFC for all defects listed above is shown in Fig. 12.

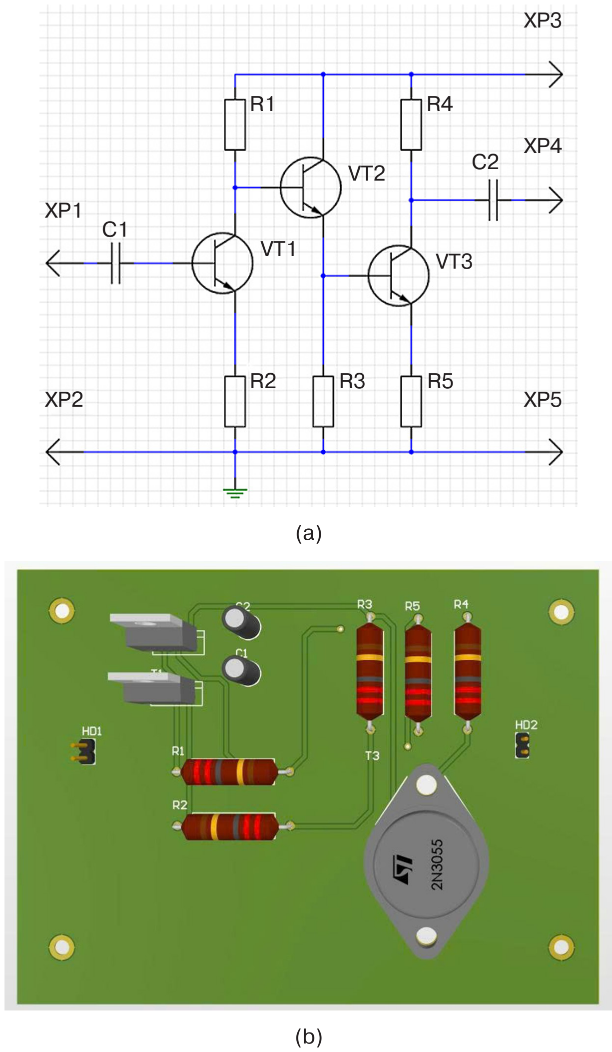

Fig. 3. Electrical circuit (a) and design model of control unit (b) for the studied object. Designations of circuit elements correspond to those adopted in GOST 2.710-81[4]

[4] GOST 2.710-81. Interstate Standard. *Unified system for design documentation. Alpha-numerical designations in electrical diagrams*. Moscow: Izd. Standartov; 1985 (in Russ.).

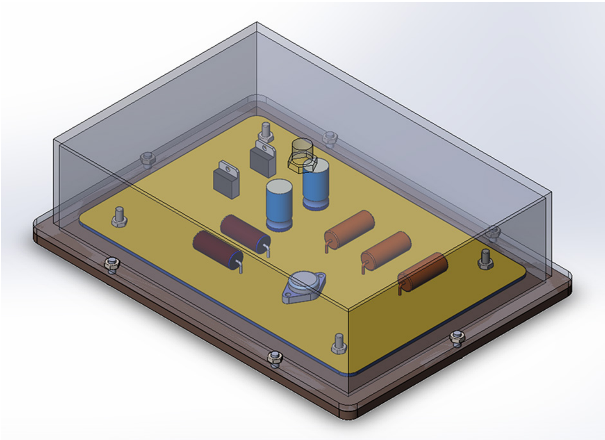

Fig. 4. Design model of a block with PCBA

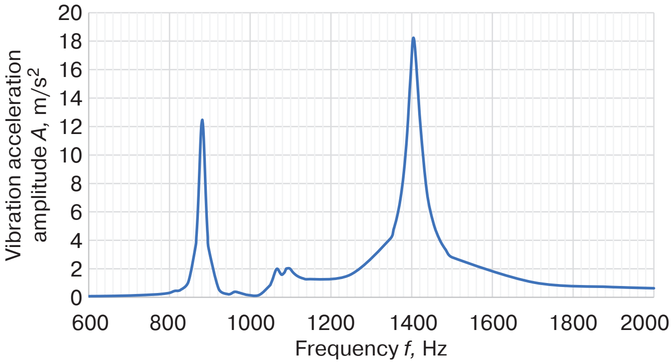

Fig. 5. AFC of the prototype in good operating condition

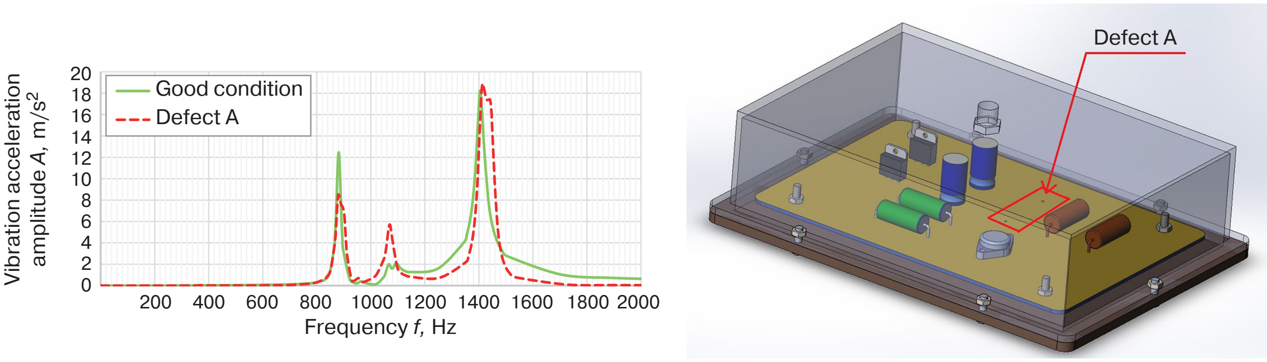

Fig. 6. AFC of the prototype with defect A

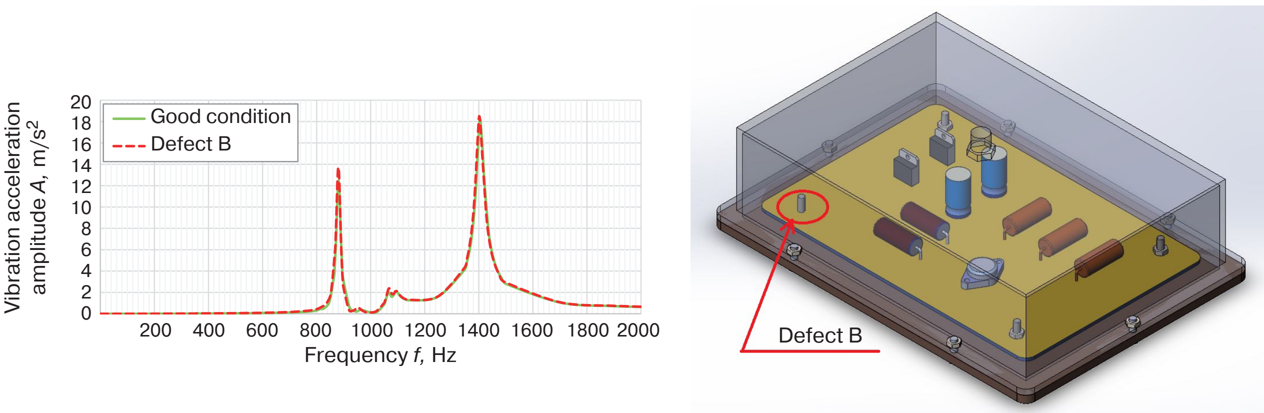

Fig. 7. AFC of the prototype with defect B

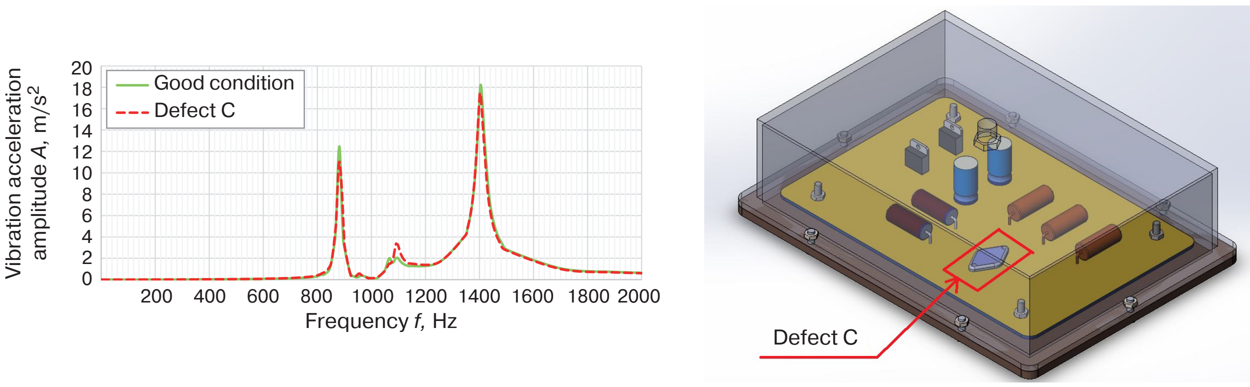

Fig. 8. AFC of the prototype with defect C

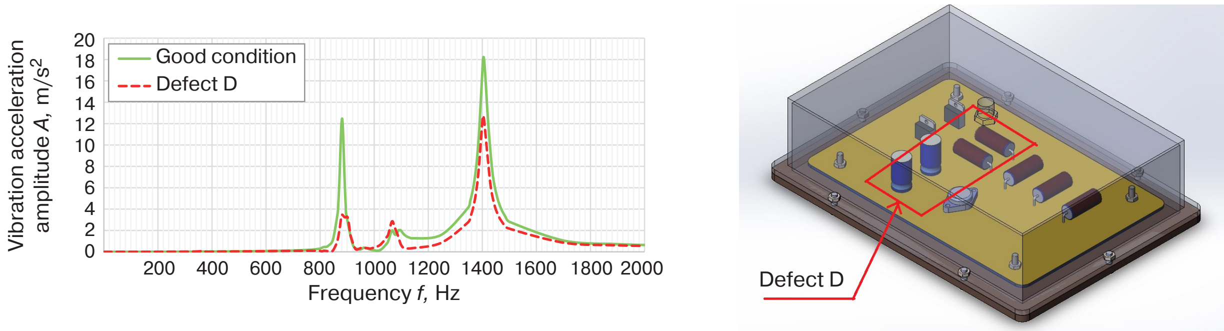

Fig. 9. AFC of the prototype with defect D

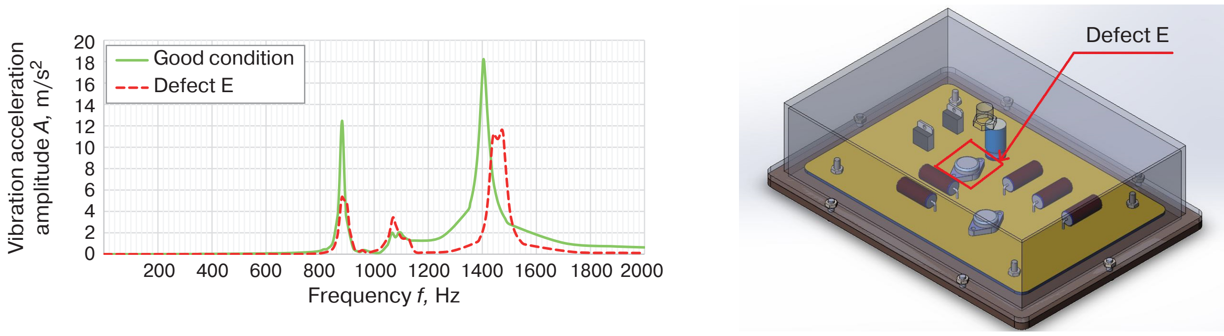

Fig. 10. AFC of the prototype with defect E

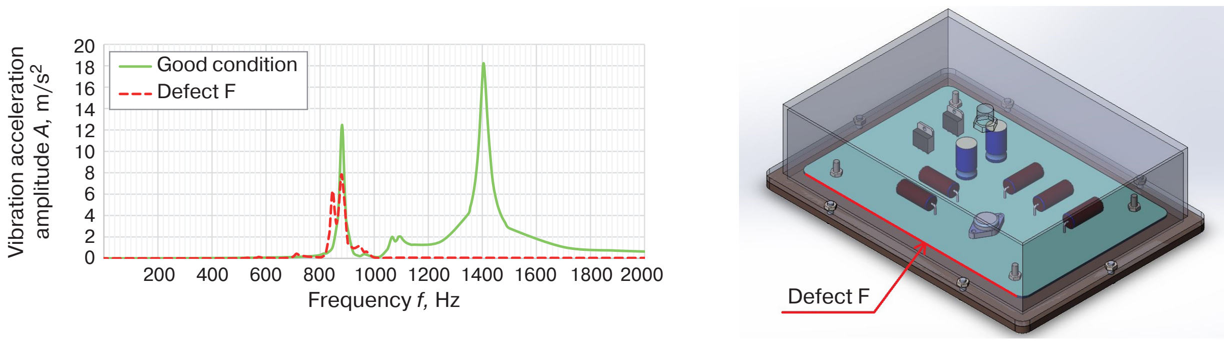

Fig. 11. AFC of the prototype with defect F

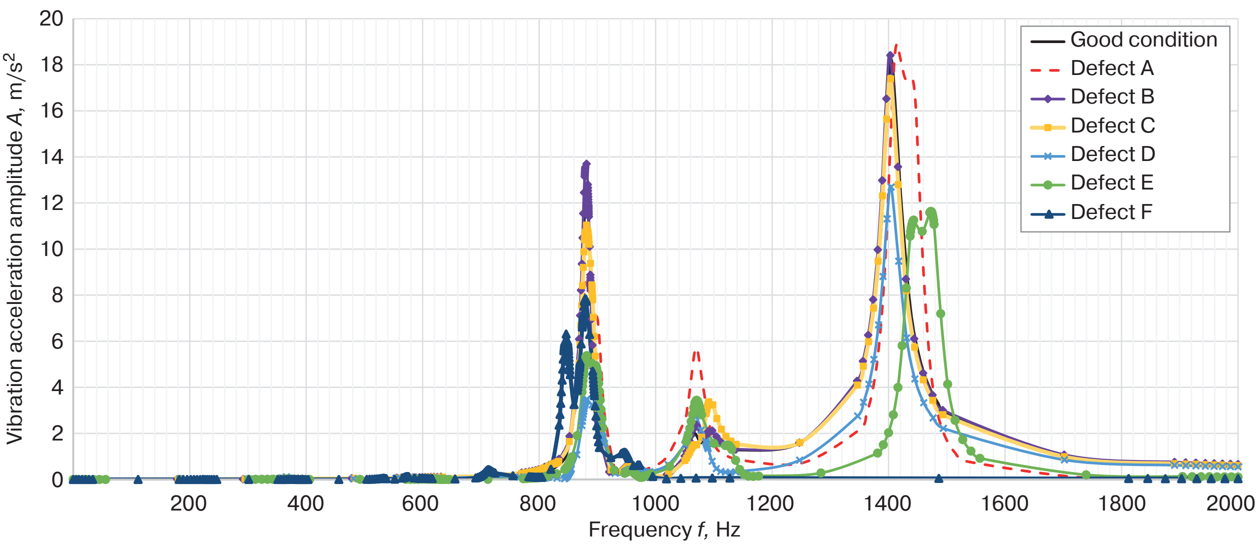

Fig. 12. The overall AFC of the tested prototype with various defects

Table. Frequency and amplitude values of vibration acceleration for various technical conditions of PCBA design during the modeling process

Good condition		Defect A		Defect B		Defect C		Defect D		Defect E		Defect F	
Frequency, Hz	Amplitude, m/s^2	Frequency, Hz	Amplitude, m/s^2	Frequency, Hz	Amplitude, m/s^2	Frequency, Hz	Amplitude, m/s^2	Frequency, Hz	Amplitude, m/s^2	Frequency, Hz	Amplitude, m/s^2	Frequency, Hz	Amplitude, m/s^2
$1.59\cdot10^{-6}$	$3.68\cdot10^{-19}$	$1.59\cdot10^{-6}$	$1.02\cdot10^{-20}$	$1.59\cdot10^{-6}$	$4.42\cdot10^{-19}$	$1.59\cdot10^{-6}$	$3.76\cdot10^{-19}$	$1.59\cdot10^{-6}$	$4.31\cdot10^{-19}$	$1.59\cdot10^{-6}$	$7.53\cdot10^{-20}$	$1.59\cdot10^{-6}$	$6.72\cdot10^{-20}$
9.5	$1.32\cdot10^{-5}$	8.1	$2.62\cdot10^{-7}$	7.8	$1.06\cdot10^{-5}$	7.9	$9.19\cdot10^{-6}$	8.0	$1.08\cdot10^{-5}$	8.0	$1.92\cdot10^{-6}$	4.9	$6.26\cdot10^{-7}$
19.1	$5.27\cdot10^{-5}$	16.5	$1.10\cdot10^{-6}$	15.9	$4.43\cdot10^{-5}$	16.1	$3.85\cdot10^{-5}$	16.3	$4.54\cdot10^{-5}$	16.5	$8.05\cdot10^{-6}$	9.9	$2.62\cdot10^{-6}$
28.6	0.0001	25.4	$2.60\cdot10^{-6}$	24.5	0.000105	24.8	$9.13\cdot10^{-5}$	25.1	$1.08\cdot10^{-4}$	25.3	$1.91\cdot10^{-6}$	15.3	$6.21\cdot10^{-6}$
……	……	……	……	……	……	……	……	……	……	……	……	……	……
1952.5	0.6712	1962.0	0.0426	1959.0	0.6948	1959.0	0.6303	1959.1	0.5700	1964.1	0.1149	1929.4	0.03589
1968.3	0.6591	1975.3	0.0414	1973.3	0.6839	1973.4	0.6202	1973.4	0.5618	1976.7	0.1127	1954.1	0.0356
1984.2	0.6476	1987.9	0.0403	1987.0	0.6741	1987.0	0.6111	1987.0	0.5550	1988.6	0.1107	1977.6	0.0354
2000	0.6368	2000	0.0393	2000	0.6652	2000	0.6028	2000	0.5478	2000	0.1090	2000	0.0352

The presence of any defect in the PCBA design can cause changes in its AFC. Therefore, defects are detected by comparing the AFC of a given prototype with those of previous responses corresponding to various possible defects in the PCBA design. This is an effective method of monitoring and determining the technical condition of the PCBA [14, 15].

In order to compare AFCs, a table is created containing vibration acceleration amplitude values for different technical conditions of the block design at a specific point, measured at various vibration frequencies ranging from 0 Hz to 2000 Hz.

3. EXPERIMENTAL VERIFICATION OF THE PCBA DEFECT DETECTION USING A VIBRATION TESTING APPARATUS

In order to obtain the experimental AFC of the studied prototype in both good and defective PCBA conditions, a benchmark test is performed using a testing setup consisting of a vibration testing apparatus and a computer equipped with specialized software for signal analysis installed. The setup comprises:

- A vibration testing apparatus M030/MA1 manufactured by IMV Corporation (Japan), which is used to generate mechanical harmonic vibrations at a specific amplitude and frequency that are set for the experiment. In this case, the UUT is subjected to harmonic vibration with an acceleration amplitude of 10 m/s^2 at frequencies ranging from 0 to 2000 Hz [15].
- The accelerometer comprises a VP-32 sensor that measures vibration acceleration on the UUT enclosure cover (maximum recorded acceleration of 500 m/s^2 over the operating frequency range of 2 to 10000 Hz).
- A personal computer (PC) operates a vibration testing apparatus to generate harmonic vibrations, and then records and displays the AFC measured using an accelerometer.

The UUT design is a prototype block (Fig. 13) having an aluminum body measuring 3 mm in thickness and a base measuring 5 mm. A hole has been created in the enclosure cover for the to be installation of the accelerometer. Inside the enclosure, there is a printed circuit prototype containing electronic components, which is fastened with screws 10 m away from the base.

Fig. 13. The design of the prototype block

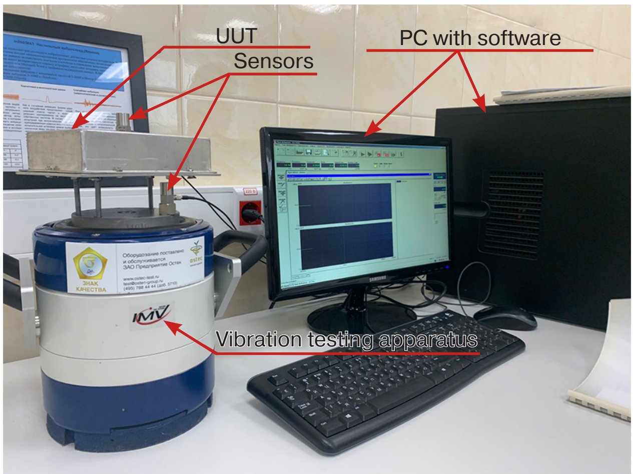

Fig. 14. The laboratory and experimental setup for vibration diagnostics

The laboratory and experimental setup for analyzing the mechanical AFC to vibration is shown in Fig. 14.

Figure 15 shows the mechanical AFC of the prototype obtained through field testing under vibration conditions.

Based on the experimental measurements, the prototype is found to have a satisfactory mechanical AFC. This response is measured in the presence of the aforementioned defects in both good and faulty conditions. In future, this AFC will be converted into a suitable format for comparison with the results of simulations. This will enable the technical condition of the prototype block to be assessed and the defects to be classified.

4. APPLICATION OF DEEP MACHINE LEARNING FOR THE CLASSIFICATION OF DEFECTS IN PCBA

Deep machine learning is a subfield of machine learning that uses artificial neural networks and algorithms to mimic the way the human brain works. This approach enables the independent learning by systems from large amounts of data to identify hidden patterns within them. Although the concept of deep learning dates back to the 1960s, it has only become widely used in practice with the development of computing technologies and big-data analysis methods, which have significantly boosted the efficiency of neural networks [16].

DNNs are used to recognize the complex, nonlinear relationships between the shape and parameters of the AFC, as well as the type of defect. This is not possible with simple perceptron models. The use of a DNN enables stable convergence and high classification accuracy.

A DNN is a type of artificial neural network consisting of multiple interconnected layers. The depth of the network is determined by the number of hidden layers and the complexity of its structure [17, 18].

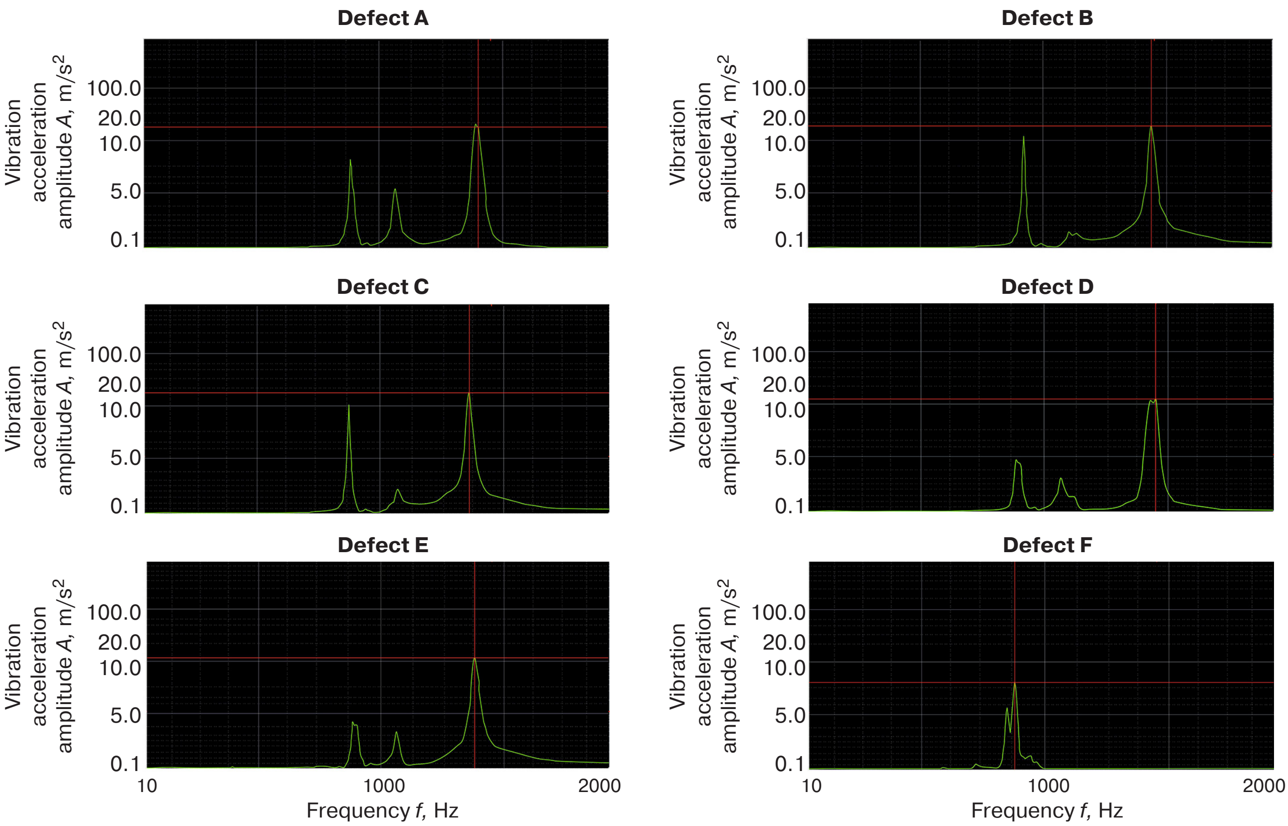

Fig. 15. Mechanical AFC of the prototype design obtained during field testing for vibration effects

Each layer processes data and passes the results to the next layer, enabling problems of high computational complexity to be solved.

The main components of the DNN are:

- the input layer, which receives the initial model data in the form of a two-dimensional numerical matrix containing vibration acceleration amplitude values and their corresponding frequencies for different technical conditions;
- the hidden layer, which processes the data and transfers information between layers;
- the output layer, which makes the final decision about the condition of the unit (good or defective).

The activation function provides a nonlinear approximation of the dependencies between the AFC characteristics and the types of defects in the PCBA design.

Weight coefficients and biases are adjustable network parameters that allow for its adjustment to the training data.

Figure 16 illustrates the structure of an artificial neuron used in a DNN. Here, x_i represents the neuron's input signals, w_{ki} represents the weight coefficients of the corresponding inputs; b_k represents the bias; Σ represents the summation operation; u_j is the linear combination of the neuron's inputs (also called the weighted sum or net input); j is the number of network input signals, depending on the frequency range and $\varphi(.)$ represents the activation function.

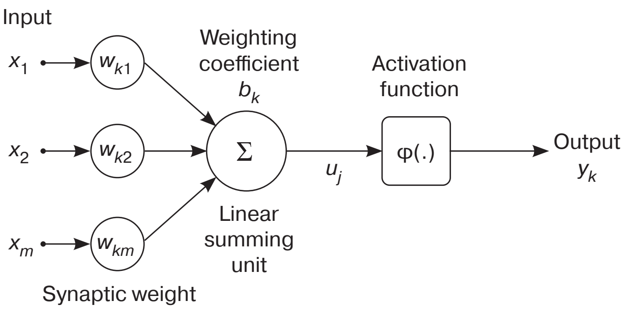

Fig. 16. Structure of an artificial neuron in a DNN

The study involves creating a database of design defects for the UUT, with a sample size of n = 1000. This corresponds to 1000 different implementations of each state, as obtained using the Monte Carlo simulation technique. The output layer consists of seven neurons, with each neuron corresponding to one functional state and six types of potential design defect in the studied PCBA.

The network architecture implemented during modeling is as follows (Fig. 17):

- input layer: combined frequencies and amplitudes;
- hidden layer: neurons with a rectified linear unit (ReLU) activation function:

$$f(x) = \max(0, x);$$

- output layer: nodes with a softmax activation function:

$$p_i = \frac{e^{z_j}}{\sum_{j=1}^{7} e^{z_j}}, \ i = \overline{1,7}; \tag{1}$$

where z_j is a linear combination of the inputs at the output layer and p_i is the probability of belonging to class i.

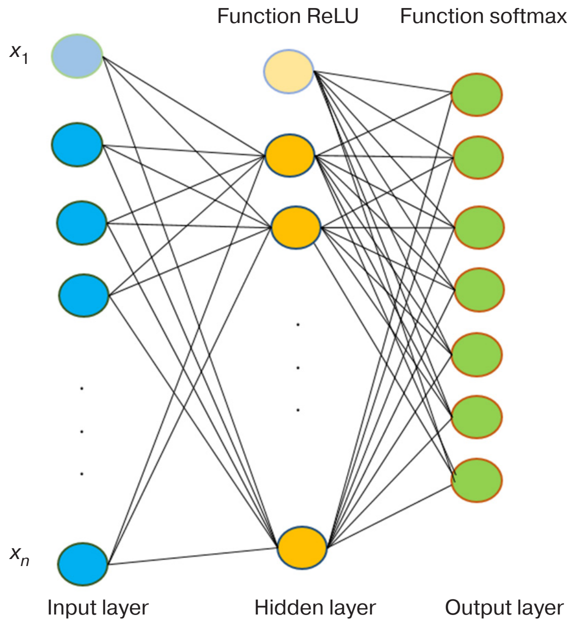

Fig. 17. Architecture of the developed DNN model

The activation function plays a key role in the operation of a neural network by ensuring its nonlinearity and modeling the process of signal transmission between neurons.

Due to its straightforward implementation and high training efficiency, ReLU is one of the most common activation functions. In addition, it has several advantages over sigmoid and tanh functions:

- provides faster convergence (training speed is six times higher than tanh);
- requires less computational effort;
- prevents the gradient saturation effect, thereby increasing training stability.

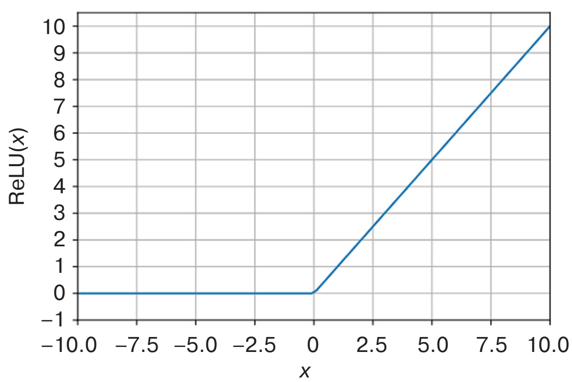

Fig. 18. Graph representing the ReLU function

By using the ReLU function in the defect classification task, the model's convergence rate can be significantly increased, as has been observed during training with *epoch* = 10. Here, *epoch* refers to the number of complete training cycles of the model on the entire dataset, with the weights of the neurons updated each time.

The technical condition is classified using a DNN implemented in Python with the Keras library. The model input comprises data arrays representing the AFC in the form of "frequency–amplitude" numerical pairs, which are formed based on the modeling and field test results. Training uses the cross-entropy loss and the Adam optimizer with 10 epochs.

The accuracy value of the model, as calculated when executing the DNN code in Python, is shown in Fig. 19.

Based on the training results, the model has an accuracy of 99.57%, indicating the high effectiveness of the proposed approach.

The classification and identification results obtained are presented in the form of histograms (Figs. 20–25), which reflect the percentage distribution of defect detection probability, calculated using formula (1).

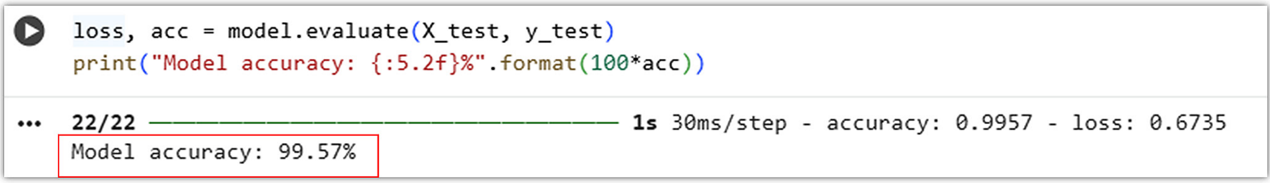

Fig. 19. Screenshot of the DNN model accuracy calculation results in the *Google Colab*[5] environment

Fig. 20. Report on the technical condition of the tested model with defect A

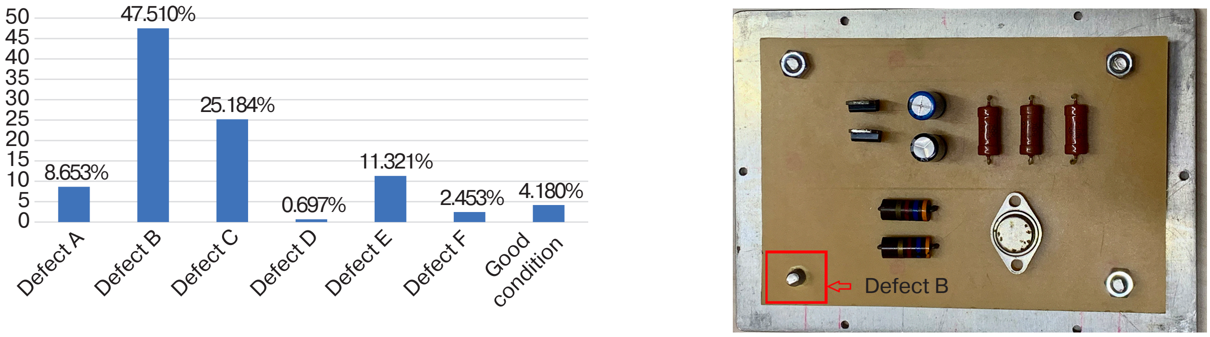

Fig. 21. Report on the technical condition of the tested model with defect B

[5] https://colab.google/. Accessed March 23, 2026.

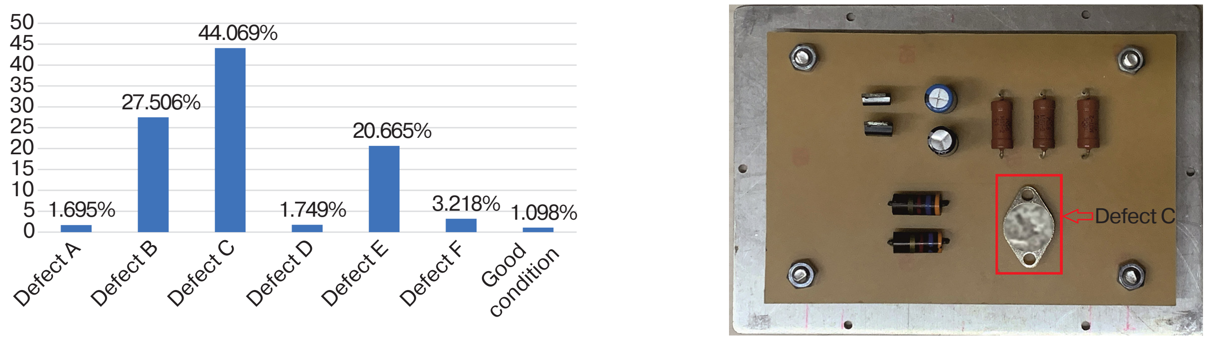

Fig. 22. Report on the technical condition of the tested model with defect C

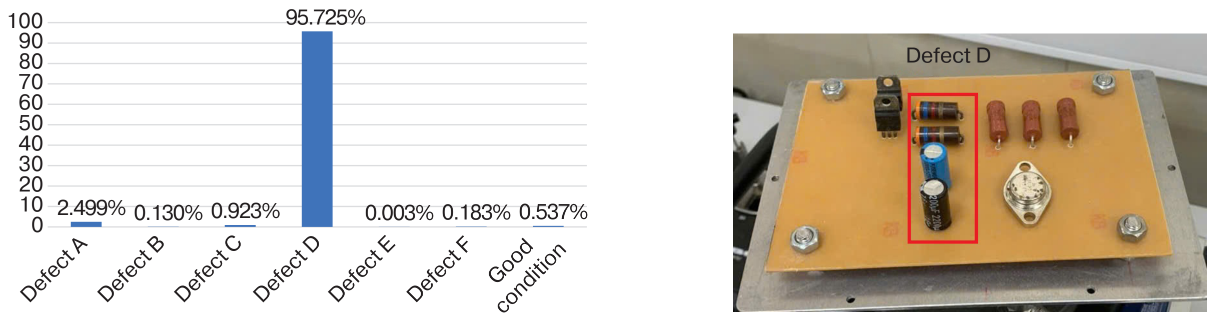

Fig. 23. Report on the technical condition of the tested model with defect D

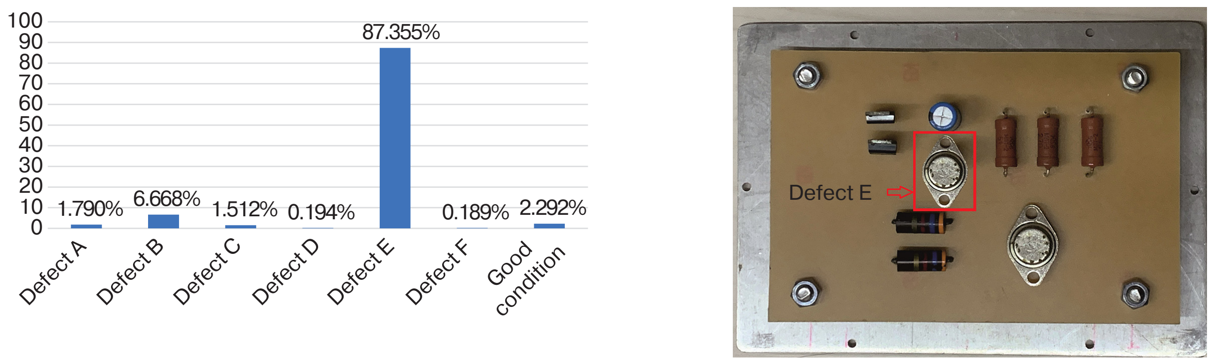

Fig. 24. Report on the technical condition of the tested model with defect E

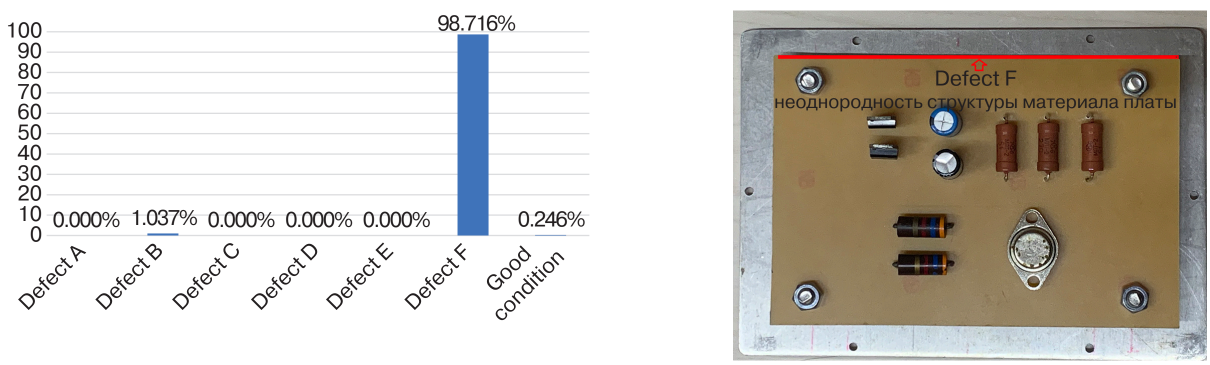

Fig. 25. Report on the technical condition of the tested model with defect F

The defect classification results show that the DNN model can recognize each type of defect in the PCBA design with a fairly high probability:

- defect A: 93.7%;
- defect B: 47.5%;
- defect C: 44.1%;
- defect D: 95.7%;
- defect E: 87.4%;
- defect F: 98.7%.

The developed DNN model has therefore confirmed the possibility of accurately identifying hidden defects in the PCBA design through analysis of the mechanical AFC of the block obtained during vibration testing.

CONCLUSIONS

The paper presents a vibration-based diagnostic method for PCBA structures that has been developed and experimentally tested. This approach involves analyzing the mechanical AFC of the block and using DNN to classify defects.

The key findings of the study are as follows:

- Numerical and field experiments have confirmed that the mechanical AFC of block structures under vibration stress is affected by the design defects listed in Section 2.
- A vibration diagnostics method for PCBA structures has been developed that integrates numerical modeling of mechanical processes with field testing. This enables latent defects in PCBA to be detected and classified with high accuracy.
- A DNN model has been implemented that achieves 99.6% accuracy in defect classification.
- The feasibility of applying the proposed method for PCBA diagnostics during the manufacturing and operational stages, without opening the sealed enclosures, has been demonstrated.

Thus, the proposed method for diagnosing the effects of vibration on PCBA can be used to make the diagnostic process more efficient by improving the accuracy with which the technical condition is determined. Using numerical modeling and artificial neural networks automates the procedure for analyzing mechanical AFC characteristics. The results obtained in this study can form the basis for further scientific research and development into vibration diagnostic methods for PCBA structures.

Authors' contribution. All authors contributed equally to the research work.

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