The object of the study is the quality of helicopter maintenance based on digital diagnostic tools. To ensure the required quality, quantitative risk assessment models for the in-depth and express diagnostics system of helicopter gas turbine engines in a neural network environment are proposed. The assessment of diagnostic efficiency is based on the analysis of probable control risks by standard deviations, which distinguishes the proposed approach from the traditional one. Two diagnostic modes are considered: rapid diagnostics exemplified by vibration diagnostics, and in-depth diagnostics, including both vibration diagnostics and pyrometric control. These diagnostic methods make it possible to implement a remote monitoring system at aircraft repair facilities, which significantly reduces maintenance labor intensity. As a result, it was found that control risks depend not only on the metrological level of measuring instruments but also on a combination of the statistical nature of control agents in their system composition according to the following characteristics: statistical parameters of the controlled indicator, distribution laws, and values of uncertainty of measuring instruments, as well as the uncertainty of control standards (tolerances). In the modeling process, risks were assessed as a function of the ratio of uncertainties of measuring instruments to the uncertainty of the controlled parameter, with varying values of the standard (tolerance). This approach will allow, in practice, the creation of a more effective system for monitoring and collecting statistical information on the operational reliability of the Mi-8 helicopter engine, where the quality of control is predicted to a greater extent based on the metrological indicators of the measuring instruments and methods

Keywords: helicopter engine, Digital Twin (DT), risk management, neural network, simulation model

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DEVELOPMENT OF A NEURAL NETWORK APPROACH FOR RISK MANAGEMENT IN HELICOPTER TECHNICAL CONDITION DIAGNOSTICS

Kayrat Koshekov
Doctor of Technical Science, Professor*
Ildar Pirmanov
Master, PhD Student*
Saltanat Kenbeilova
Corresponding author
PhD*
E-mail: s.kenbeilova@agakaz.kz
Abay Koshekov
PhD
Department of Aviation Technique and Technologies**
Rustam Togambayev
Master, PhD Student
Division of Telematics
Transport and Telecommunication Institute
Lauvas str., 2, Riga, Latvia, LV-1019
Beglan Toiganbayev
Master, PhD Student*
*Department of Science**
**Civil Aviation Academy
Akhmetova str., 44, Almaty, Republic of Kazakhstan, 050039

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1. Introduction

Based on the analysis of decisions made by government bodies in Kazakhstan and assessing the current state of the country's technical policy and economy, it was concluded that one of the key factors in accelerating the development of the Republic of Kazakhstan and improving the quality of life of its population lies in transitioning the economy to a fundamentally new development trajectory – based on digital transformation, following the example of technologically successful countries.

In 2017, the "Digital Kazakhstan" State Program (No. 827) was developed, which was followed by a new Digital Transformation Program (No. 311) in 2022. Currently, several strategic documents, such as the National Development Plan of the Republic of Kazakhstan until 2025 and the Concept for Digital Transformation, outline tasks and measures that focus on artificial intelligence as a fundamental direction.

According to the 2023 Government artificial intelligence (AI) Readiness Index by Oxford Insights, Kazakhstan ranks 72nd among 193 countries and 3rd in regional rankings for South and Central Asia, following India and Turkey [1]. Fig. 1 shows the percentage of readiness for the implementation of artificial intelligence in Republic of Kazakhstan.

An advantage of Republic of Kazakhstan is its high level of digitalization. According to the United Nations, Kazakhstan ranks 28th in the "E-Government Development Index" and 8th in the "Online Services Index". Kazakhstan ranks 15th in the E-Participation Index (EPI), one of the highest positions globally [1]. Currently, the number of scientific publications in the field of AI is 1,016. The International Data Corporation estimates that by the end of 2023, global spending on AI systems, including software, hardware, and related services, will reach $154 billion with an average annual growth rate of 42 % over the last decade.

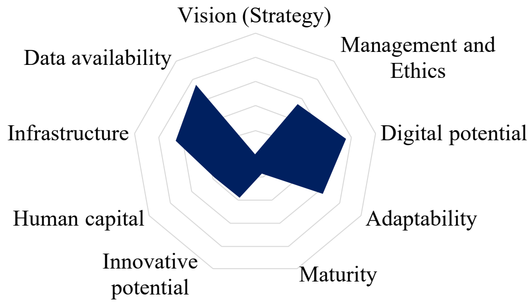


Fig. 1. Kazakhstan's readiness to implement artificial intelligence [1]

All of these external factors, driven by the digital transformation of the country's socio-economic environment and competition within the aviation maintenance and repair services niche, create strong preconditions for innovative development in this field and among individual enterprises.

2. Literature review and problem statement

The paper [2] presents the results of studies on diagnostic methods for wind turbine gearboxes based on the vibration method. In this study, diagnostics were based on an intelligent approach for assessing gearbox faults. The value of dispersion entropy was chosen as the fault criterion. To establish a diagnosis in the empirical measurement results, the vibration spectrum was restructured, regression smoothing was performed, and a function was obtained for predicting the fault trend. The proposed method, as a general approach to diagnosing gearboxes, is applicable, but the quantitative results for helicopter gearboxes will differ significantly from those for wind equipment because they have completely different design solutions. The use of the "least squares method" in smoothing is not a new achievement to specifically note in the work, since all regressions use this method. The effectiveness of the diagnostic results in quantitative measurements was also not reported. Remote monitoring is a common advantage of the vibration methods.

The paper [3] presents a diagnostic method using a control quality assessment algorithm based on fuzzy logic. Fuzzy approaches in control processes are currently widely used by fuzzy chips, produced in a wide range by industry, which significantly reduces the labor intensity of the technical implementation of diagnostics and the cost of such systems. However, a significant drawback is the low accuracy of such control algorithms, as the basis of the fuzziness of any estimate is subjective. The basis of modeling and algorithmization of control processes of fuzzy systems is a linguistic approach, where already at the first stage of "fuzzification", the number of terms is determined subjectively, the purpose of the significance of each term is also set subjectively, the parameters of the term in its mathematical interpretation are also determined by experts. Therefore, these systems are used for rough qualitative assessment and decision-making and are acceptable for some systems. In the subject area studied by the author of this work, a research system consisting of a personal computer and an external interface based on a microcontroller (Microchip PIC16C73A) was proposed. The obtained data (stored in the *.dat files) is calculated and analyzed in the frequency domain of the signal by the SPTOOL processing tool of the Matlab5 package. Only system imbalance was diagnosed.

In [4], a systematic review of the current methods of using vibration for machine monitoring and diagnostics was presented. It includes data collection, applied tools such as analyzers and sensors, feature extraction, and fault-recognition methods. This study proposes the use of artificial intelligence (AI). This paper presents a forecast of future vibration level development. The author concludes that in the future, a combination of statistical functions in the time domain and deep learning approaches will be widely used for this purpose, where fault characteristics can be automatically extracted from raw vibration signals. This paper notes that the use of various sensors and communication devices in new intelligent machines will create a huge new problem in vibration monitoring and diagnostics. However, the author does not specifically consider future technical, metrological, and organizational problems in this study, which reduces the quality of recommendations for choosing directions in practical diagnostics.

The paper [5] presents a method for online diagnostics of faults in real time for a turbine gearbox. This paper presents data on the evolution of the vibration signal level using an example of a gearbox. The proposed method decomposes the signal spectrum into a Fourier series. In this case, the following operations are performed: extraction of time-domain characteristics and frequency-domain characteristics, and extraction of nonlinear characteristics of the principal component from the time-domain and frequency-domain characteristics. This paper proposes the use of a neural network approach with training by using a pre-trained principal component analysis model of a neuron kernel, calculating the SPE statistics of the degree of deviation from the principal component model of the kernel based on the characteristics of the nonlinear principal components. In this case, a decision is made that the state of the gearbox is normal if the statistics of the degree of deviation from the principal component model of the kernel are less than a specified threshold; otherwise, a judgment is made that the state of the gearbox is abnormal. The advantages of the proposed method are the simplicity and ease of obtaining the required data, as well as the high efficiency of fault diagnostics and the smaller amount of required sample data of characteristic data. The disadvantage of this work is the lack of information about the type and number of sensors, the location of the sensors, the need for a reference working object for comparison and decision-making, and most importantly, the accuracy of the diagnosis. This approach for some procedures and solutions has already been used and described in the literature [3].

The ISO 31000 standard regulates the mandatory quantitative assessment of the risk of any project or innovative work [6]. The main reason for risk is the parametric uncertainty of management agents and statistical uncertainty of data. In many studies, the conditions of statistical uncertainty are called risk conditions.

The paper [7] presented one of the first formulations, as well as the connection of risk categories with uncertainties. According to Knight's concept, risk is a measurable uncertainty: an entrepreneur can "foresee" or "guess" some basic parameters (results, conditions) of his business in the future. The question arises: What is objective "measurability" if uncertainty is assessed subjectively ("foresee" or "guess")? At present, for forecasting (foreseeing), many methods and mathematical tools have been developed [4, 5].

Recently, the concept of uncertainty has been studied from different points of view in many areas of science, technology, and economics. Thus, [8] proposed a structural model for classifying uncertainties "by the method of assessment and the method of expression". Methodologically, the measurement uncertainties in this case are divided into the uncertainty of category A and uncertainty of category B. Type A is based on statistical estimates. Using the expression method, a distinction is made between standard (mean square deviation), total, expanded, and relative uncertainties. In many countries, this approach has achieved the status of a generally accepted standard. When assessing uncertainty by type B, the only information available is often that the measured value lies in a certain interval, and information of this type can be formalized as a uniform probability distribution.

Uncertainty gives rise to risk. In 2016, the International Organization for Standardization (ISO) developed a special section within the ISO 31000 standard called "Risk Management" where four new normative documents appeared: ISO Guide 73 "Risk Management. Vocabulary: ISO 31000 "Risk Management [6, 9]. Principles and Guidelines"; ISO/TR 31004 "Risk Management. Guide for the Implementation of ISO 31000"; IEC 31010 "Risk Management. Risk Assessment Practices". In these documents, an important fact and difference of the new edition is that the modified standard uses a requirement for risk assessment (risk-based thinking, ed.) for the entire risk-management process chain. This addition increases the importance of the risk control system, which makes quantitative risk measurement mandatory.

The quantitative assessment and forecasting of risks in a control system were studied in [10]. This study presents analytical expressions for assessing and forecasting risks using nondeterministic standards. Normative restrictions are represented by lower and upper restrictions, respectively. The tolerance limits were approximated using normal distribution laws. The controlled parameter has an equally probable distribution. The selected composition of statistical distribution laws is encountered in practice, as the author of the paper notes, when monitoring the parameters associated with flight hazards.

The paper [11] presents the results of the formalization of the robust control system of the VLC object under conditions of statistical uncertainty of the parameters of the decision-making process. An agent-based nine-screen model of system dynamics is proposed for the system description of the subject of this study, which reduces risks. This paper also develops and proposes a new modified approach to expert integrated assessment of the result, which reduces the subjective component of this method. To move from a quantitative assessment of the result to a final qualitative assessment, the Harrington curve is proposed. The principle of VLC information transmission in aircraft maintenance systems proposed in this study, along with high electromagnetic immunity, depends on optical interference, which significantly reduces its applicability in practice. This paper proposes probabilistic estimates of the "producer risk" and "consumer risk". However, the proposed expressions can only be used with the "lower" limit standards, and in real diagnostic practice, "upper" limits and tolerance formats of standards are often used. Therefore, the proposed mathematical support has limited application.

Based on the literature review conducted, it can be concluded that modern control and diagnostic systems face issues related to low control efficiency, a lack of consistency, and insufficient integration in decision-making. Additionally, in the diagnostics of helicopter engine conditions, there is no integrated approach or criteria for assessing the technical condition of the engine, nor is there a methodology for quantitatively evaluating the quality of control and associated risks-especially since control errors impact flight safety. Improving decision-making quality and risk reduction systems in the face of parametric uncertainty and fuzzy data necessitates a strong reliance on integrated multiparametric systems and neural network technologies.

3. The aim and objectives of the study

The aim of the study is to develop a neural network approach to risk management in a diagnostic system of the technical condition of helicopter equipment. This will significantly enhance the efficiency and reliability of the control process in the helicopter engine maintenance system.

To achieve this aim, it is necessary to solve the following objectives:

– to develop models for quantitative risk assessment of the express diagnostics system of helicopter gas turbine engines in a neural network environment;

– to develop models for quantitative risk assessment of in-depth diagnostics of helicopter gas turbine engines in a trained neural network environment;

– to implement a computer experiment, analyze the results of the experiment, and propose recommendations for effectively maintaining the operational reliability of helicopters.

4. Materials and methods

The object of the study is the quality of technical maintenance for helicopter equipment based on digital diagnostic tools for assessing helicopter components. The main hypothesis of the study is that the quality of helicopter maintenance, utilizing digital diagnostic tools, can be significantly enhanced through the quantitative assessment of diagnostic risks within a neural network environment. The study suggests that the quality of helicopter maintenance can be enhanced by utilizing digital diagnostic tools and risk assessment models. The effectiveness of these diagnostics is evaluated by analyzing potential control risks using standard deviations, which yields more accurate results than traditional methods. The study adopted the following simplifications: risk assessment models utilize standard deviations, enabling a simpler analysis and calculation of risks compared to more complex methods. It is assumed that the assessment system can function at various levels of uncertainty in measurement instruments and controlled parameters, thereby reducing the complexity of accounting for all possible factors.

The methodological basis of this research was a systematic approach. The main idea of the systems approach is that the management and decision-making agents are statistical in nature and are integrated into the control process in the form of stochastic compositions that affect the quality of management. The quality of management is determined by the risks generated by parametric fuzziness and data uncertainty. Uncertainty is estimated by the standard deviations of the statistical characteristics of the control and management agents. To study these theoretical assumptions, probabilistic models have been developed for assessing and forecasting control risks and modeling reliability. The quality of the modeling was checked using the well-known generally accepted F and t criteria using the "Statistica" statistical package. The compliance of the theoretical assumptions with practical data was assessed by means of a computer experiment and visualization of the results in a 2D graphical format. The final conclusions were based on the modeling results.

The hardware used was a standard set of control and measuring equipment, including a programmable digital oscilloscope S2800 and special diagnostic equipment: a diagnostic stand FSA 560 from BOSCH, a piezoelectric vibration assessment module, and pyrometric sensors of the MG30 type. The patent complex, "Software for instrumental quality control of VLC systems", was used to calculate errors and control risks. The neural principle of constructing a control system was used in the modeling process. Documents of the Aircraft Maintenance Program of the JSC EURO-ASIA AIR were used as a regulatory framework. An MI-8 helicopter was used as the object of the study.

5. Results of the study on express diagnostics of helicopter equipment conditions

5. 1. Development of model express diagnostics for helicopter gas turbine engines

The proposed neural network in this study is constructed based on a system analysis of data that will be structured according to a mixed principle: using local onboard databases and "historical" information accumulated in Big Databases. Such data are accessed as needed, for example, when constructing a time trend of controlled diagnostic information and the results of periodic processing. In diagnostic systems, the data represent the current values of the controlled diagnostic parameter x_i. In modern systems, information comes from the "Digital Twin" [12–16]. As a structural and functional idea of the neural network in this study, we propose the use of the Rosenblatt multi-layer perceptron (MLP) model with variable weights at each of the inputs.

One of the problems in the use of neural network technologies is the parametric uncertainty of the parameters of the neural model agents. For this purpose, we consider an example of a typical structural-functional model, shown in Fig. 2, which was proposed in [7].

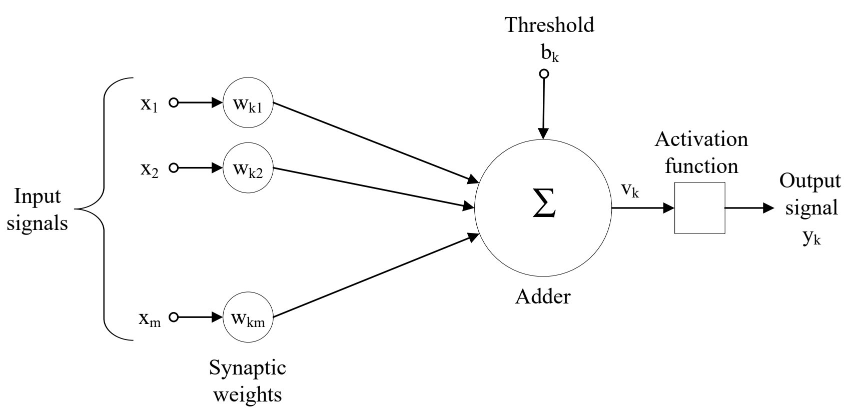


Fig. 2. Structural and functional model of a neuron [6]

In this model, adder Σ receives a vector of weighted diagnostic information (from the control sensors) $X_1, X_2 ... X_m$. The weight w_{km} of each signal X_m is interpreted as the information significance of the diagnostic signal. The adder generates a quantitative value of the sum of the weighted signals and compares the resulting sum with the standard level – threshold b_k, and if the threshold is exceeded, a general conclusion is generated, for example, – "good" – "bad", and also starts the activation function φ(.), which can estimate the integrated error (risk) of decision-making for each control channel and differentiated the same for each channel. In this paper, as in many similar ones, the question remains unanswered: how are the weights of the w_{km} signals found? If we assume that expert methods are used, an additional error appears, and what is its magnitude? Next, it would be necessary to imagine what a "threshold" is. As a rule, in many studies, the hypothesis of a deterministic threshold value – the standard – is accepted. However, in practice, its statistical nature is revealed, which leads to another error.

The weight variables are formed by considering new information that arises during the current diagnostic session, replenishing the local and large database, which allows for the implementation of the system training process. The number of hidden layers is assumed to be greater than two, which allows us to discuss "deep learning". The structural and functional models of the first hidden layer are shown in Fig. 3.

Signals from the external sensors of the digital twin are fed to the inputs of the first hidden layer of the perceptron, which integrates all the diagnostic information, as shown in Fig. 3, in the format of the vectors X_1, $X_2 ... X_k$. Fig. 3 shows: $S_1, S_2 ... S_k$ – vibration piezoelectric quartz sensors of the digital twin, installed in the engine's-controlled K_i points; piezoelectric sensor signal amplifiers; ADC – analog-to-digital conversion unit of diagnostic parameters; evaluation of the "weight" of the diagnostic parameter – W_i and expression of the weighted value of the diagnostic parameter $w_k X_k$. Piezoelectric quartz sensors were used in a set with magnetic connections, supplied in a set with the device in industrial production.

Vibroacoustic monitoring can be performed using the statistical average value of the vibration signal and the maximum vibration signal level in the digital sample for a certain time interval, both in automatic and manual measurement modes.

The monitored time interval and selection of the monitoring mode were performed by the diagnostic operator. The selection of the maximum value of the vibration signal in the time digital sample was performed using software. The first hidden layer comprises the instruments and software of the monitoring system. The control and measuring channels of the monitoring system must have an autonomous on-board computer.

Because the level of the useful signal of the piezoelectric sensor is extremely low, and the integration link at the input of the measuring channel additionally reduces the signal, the signal from the sensor output must be amplified. In this case, special requirements are imposed on the first amplifier cascade: ultra-high input resistance, low level of intrinsic noise and high thermal stability. Ultra-high resistance in piezoelectric transducers in some cases is necessary to highlight the low-frequency trend that is present in the vibration information.

Regardless of the technical implementation of the hidden layer, the economic component of the diagnostic system was determined by measuring the entire set of diagnostic parameters. If a separate sensor is installed at each diagnostic vibration control point, in addition to financial costs, switching sensors with the measuring hardware arises. A branched switching cable network is required, which complicates the measuring system as a whole, increases the financial costs, complicates the circuitry of the system, and reduces the manufacturability and reliability of the system.

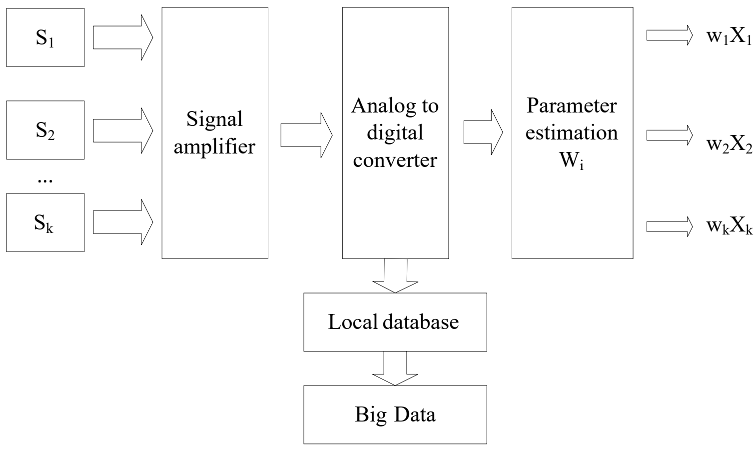
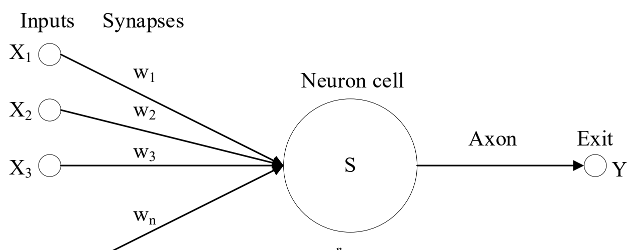


Fig. 3. Structural and functional model of the first hidden layer

The express diagnostics system offers a single-channel system of measurement with one sensor, which is sequentially reinstalled by the operator, and the result with the code number of the control point in the form of a digital file is stored in the RAM of the device and subsequently uploaded to Big Data. In Big Data, the information in the coded file acts as a virtual sensor. In accordance with the adopted computing technology implemented in the software, this information was fed to the inputs of the first neural layer.

While the hidden neural layer performed technical and technological functions of collecting and primary processing of diagnostic information, the next first neural layer, according to the generally accepted methodology, performs computational functions. The signal at the output of a hidden (input) neuron is functionally related to the weighted sum of signals at its input.

The first neural layer is based on the model proposed in this study, as presented in Fig. 4 [15].



$$S=\sum_{i=1}^{n} X_i \cdot w_i$$

Fig. 4. Neural model of object control [15]

The presented neuron model is considered as an adaptive adder, to the input of which information is received in the form of a data vector (or signals) $X_1...X_n$. In this study, we propose to store these data in a local database for current diagnostics and duplicate them, as defined above, in big data. In big data, diagnostic information should be replenished and stored for each engine during operation throughout the life cycle of the object. This information should be differentiated into separate arrays for each checkpoint. In reality, the neuron under consideration, like all subsequent ones, is a software agent object, and in stochastically programmable systems it has the nature and characteristics of a precedent. The connections between the virtual "inputs" $X_1...X_n$ and cell S are called the synapses. Each synapse has a certain "weight" W_i. Cell S is an adaptive adder of $\Sigma w_i X_i$, weighted inputs. The output of the adder is called an axon, which can be connected to the input of the next agent – a neuron or hidden layer.

The weighted sum in the cell of the neuron (S) is subjected to a nonlinear transformation, which is "shortly called the functional" $Y=F(S)$ or an algorithm.

The known basic model in this study was transformed in accordance with the task as follows.

In the applied version of the studied subject topic, the input vector $X_1...X_n$ (Fig. 4) will be physically represented by a set of sensors $S_1...S_k$ (Fig. 3), and quantitatively, by an informational virtual vector in a local database or Big Data, in the form designated as $Y_1...Y_k$. Core S (Fig. 4) forms a weighted sum $\Sigma w_i X_i$. In the expression of this sum, a serious scientific and technical problem is the definition of the "weight" quantitative values w_i.

At present, acceptable objectivity and statistical significance methods for the quantitative assessment of "weight" indicators have not been noted in the literature. In practice, the values of w_i are presumably established by a group of experts during the first diagnostic session of a new engine, and are modified with each subsequent diagnostic session of the object.

This study proposes a new method for substantiating the standard (threshold) values of vibration signals – based on the statistical nature of the energy and operating processes in existing helicopter engines. The following criteria were used: arithmetic mean of the vibration signal in the control sample, standard deviation, maximum value of the vibration signal in the digital selective control and measuring quantitative vector. It is assumed that the quantitative diagnostic parameters of engine performance have a statistical distribution approximated by Gaussian law. If the maximum value of $Y_{\max}$ is selected as the key diagnostic parameter, it can vary within the range of $Y_{average}\pm 3$ sigma. Subsequently, the permissible level and threshold of the maximum value of the vibration signal are estimated based on the following calculation:

$$Y_{\max}=\frac{Y_{average}}{3}+Y_{average}. \tag{1}$$

The value of w_i is estimated using the Harrington curve from the following expression:

$$w_i==\frac{Y_{\max}-Y_{measured}}{Y_{\max}}. \tag{2}$$

Then, if $Y=0$, then w_i is equal to 1.

The second suggestion is to consider the importance of the operational reliability of the diagnosed unit according to technical and economic assessments – by introducing the coefficient K_e. This coefficient within the range of 0 to 1 is estimated expertly. Then, the working value of the synapse "weight" coefficient will be equal to:

$$W_i=w_i \cdot K_e. \tag{3}$$

The functional $Y=F(S)$ realizes the operation of comparing the value of S with the norm (threshold) using the second neural layer.

The functionality of the second hidden layer involves two tasks. The first task involved calculating the statistical characteristics and distribution laws of the key diagnostic parameter Y_{max}. The following statistical characteristics were calculated: arithmetic mean, standard deviation, regression model and distribution law. The Weibull law is studied as the distribution law, as it is the most acceptable for managing the reliability of objects. Statistical data are extracted from big data, since it is the use of the entire sample taking into account "historical" data that allows recalculating all statistical characteristics and regression model coefficients, which increases the reliability of the forecast and the statistical reliability of conclusions and decision-making. This procedure of adapting formal tools to the current situation is called the "training" process in neural network technologies.

The second task consisted of threshold control of the Y_{max} value with an acceptable limit of $Y_{average}+Y_{average}/3$. If the threshold is exceeded, a warning is given in audio and visual form and saved as big data.

The task of the second neural layer is to formalize the process of managing the quality of diagnostics of helicopter engines according to the criteria of the quantitative assessment of control errors in the conditions of statistical uncertainty of the agents of the entire system. The solution of the named problem is carried out on the example of vibroacoustic express diagnostics of the operational reliability of helicopter gas turbine engines. The diagnostic process is organized in the form of a digital twin on a neural network platform. The goal of formalizing the control process in the diagnostic system is achieved by constructing a probabilistic model consisting of two functionals: quantitative assessment and prediction of the error of a false failure and the error of an undetected failure. Previously, a similar problem was considered in the diagnostics of automobile engines, but in other systems, organizational, technical and information conditions, as well as a different instrumental, measuring and technological environment. A significant difference between the known traditional organizational and technological solutions and the proposed solution is the absence of a learning process, which reduces the reliability of the diagnostic results.

The neural model of the functional for calculating the diagnosis error – false refusal P_{FR} and normal refusal P_{NR} is shown in Fig. 5.

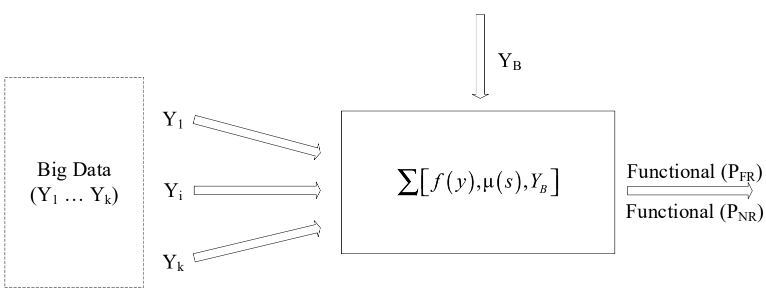


Fig. 5. Neural model of the second layer

For the integral assessment of the quality of the control and measuring system, an indicator of reliability is often used, which is the main characteristic of the quality of control. Control reliability is the degree of confidence that the measured values truly reflect the state of the object.

Because the measurement process is accompanied by errors, control errors occur. There are three types of errors: systematic, random and gross errors, called blunders.

Systematic errors remain constant or change according to a certain law. They can be studied, and a correction is introduced into the measurement result.

Random errors cannot be eliminated from the measurement results by introducing corrections. However, by conducting a series of repeated measurements, using mathematical statistics, it is possible to refine the measurement results.

The measurement results in the presence of misses are not considered in this case. In this paper, only random errors are considered. Analytically, the reliability is calculated using the formula:

$$D=1-(\text{sum of probable errors}). \tag{4}$$

In the process of diagnostics, there are control errors that occur, which are usually divided into errors called false and undetected faults. In reliability theory, the same errors are called false and undetected failures. Quantitatively, these errors are estimated by their respective probabilities, in this case, P_{FR} is the probability of a false failure and P_{NR} is the probability of an undetected failure.

Thus, initially there is a general task of developing new mathematical models, or using known acceptable models with necessary modification and adaptation to current conditions and requirements. The most acceptable variant among the known model analogs is the work [11]. In this work it was found that the reliability of control is not evaluated unambiguously by the measurement error, but is a function depending on the system composition of statistical characteristics of all components of the multi-agent model: measurement error, norms and statistical laws of distribution of all control agents. In all known works it was considered that normative values are deterministic. This hypothesis is also accepted in the present research. Then formula (4) takes the following form:

$$D=1-\left(P_{FR}-P_{NR}\right). \tag{5}$$

In the process of modeling the concept of full probability was used, where the calculation algorithm repeats the following events, for example, event A is the case when the current value of the controlled parameter is in some delta range $Y_i \div Y_{i+1}$, and event B is the case when the measurement result (instrument indications) turns out to be higher than the limit value of the parameter. Then the probability of event A will be determined by the following equation:

$$P_i(A)=\int_{Y_i}^{Y_{i+1}} f(Y)\,\mathrm{d}Y. \tag{6}$$

The probability of event B is calculated by the formula:

$$P_i(B)=\int_{-\infty}^{Y-Y_N} \mu(Y)\,\mathrm{d}Y. \tag{7}$$

The probability of error P_{iFR} is the probability of simultaneous realization of events A and B, which is called the probability of false failure and is calculated by the formula:

$$P_{iFR}=\int_{Y_i}^{Y_{i+1}} f(Y)\,\mathrm{d}Y \cdot \int_{-\infty}^{Y-Y_N} \mu(Y)\,\mathrm{d}Y. \tag{8}$$

Considering these events over the whole field of random values of the controlled parameter and summarizing the products according to the formula of total probability we obtain the following formulas:

$$P_{FR}=\sum\nolimits_{t=1}^{n}\frac{1}{\sqrt{2\pi}}\int_{t_i}^{t_{i+1}}e^{-\frac{t^2}{2}}\mathrm{d}t\cdot\frac{1}{\sqrt{2\pi}}\int_{z_i}^{+3}e^{-\frac{z^2}{2}}\mathrm{d}z. \qquad (9)$$

Similarly, we obtain an equation for P_{NR} estimation, which will have the following form:

$$P_{NR}=\sum\nolimits_{t=1}^{n}\frac{1}{\sqrt{2\pi}}\int_{t_i}^{t_{i+1}}e^{-\frac{t^2}{2}}\mathrm{d}t\cdot\frac{1}{\sqrt{2\pi}}\int_{-z_i}^{-3}e^{-\frac{z^2}{2}}\mathrm{d}z. \qquad (10)$$

In the expressions (9) and (10) there is a well-known transition to a new variable t, called centered and normalized random variable:

$$t=\frac{S-S_{average}}{\sigma_S}. \qquad (11)$$

Centering and normalizing the variables allows further use of tabulated data of numerical values of the probability integral or use of programming languages such as Python.

The functionals (9), (10) allow for the quantitative assessment of control errors (risks) only in cases of single-threshold limits. In [13], models for tolerance limits of the controlled parameter from below and above are proposed. It is suggested to use the Weibull distribution as the statistical law for the controlled parameter, which significantly expands the practical application of the developed model, as studies in reliability theory have found that approximately 60 % of all statistics are accounted for by the Weibull distribution [17]. The Weibull distribution also has the property of modeling other distributions at various values of the shape parameter.

For instance, with a value of $\beta=0.5$, it approximates the exponential distribution, with $\beta=2.5$, it approximates the Rayleigh distribution, and with $\beta=3.25$, the shape of the Weibull distribution is close to the normal distribution. The probability density function of the Weibull distribution is given as follows:

$$f(S,\alpha,\beta,\gamma)=\frac{\beta}{\alpha}\left(\frac{S}{\gamma}\right)^{\beta-1}\cdot e^{-\frac{\left(\frac{S}{\gamma}\right)^{\beta}}{\alpha}},\ S\geq\gamma, \qquad (12)$$

where α – scale parameter, β – shape parameter, γ – location parameter.

Unlike the normal distribution, the Weibull distribution has an analytical form of the cumulative distribution function:

$$F(S)=1-e^{-\frac{\left(\frac{S}{\gamma}\right)^{\beta}}{\alpha}}. \qquad (13)$$

Using the cumulative function of the Weibull distribution $F(S)$, the final expression for calculating the probability P_{FR} is as follows:

$$P_{FR}=\sum\nolimits_{i=1}^{k}\left(e^{-\frac{S_i^{\beta}}{\alpha}}-e^{-\frac{S_{i+1}^{\beta}}{\alpha}}\right)\left[\begin{array}{l}\dfrac{1}{\sigma_y\sqrt{2\pi}}\displaystyle\int_{S_l}^{S_i-3\sigma_y}e^{-\frac{y^2}{2}}\mathrm{d}y+\\+\dfrac{1}{\sigma_y\sqrt{2\pi}}\displaystyle\int_{S_u}^{S_i+3\sigma_y}e^{-\frac{y^2}{2}}\mathrm{d}y\end{array}\right]. \qquad (14)$$

The expression for P_{NR} will be represented by two components [14]:

$$P_{NR}=\sum\nolimits_{i}^{k}\left(e^{-\frac{S_i^{\beta}}{\alpha}}-e^{-\frac{S_{i+1}^{\beta}}{\alpha}}\right)\cdot\frac{1}{\sigma\sqrt{2\pi}}\int_{S_l}^{S_i-3\sigma_y}e^{-\frac{y^2}{2\sigma_y^2}}\mathrm{d}y+$$
$$+\sum\nolimits_{i}^{k}\left(e^{-\frac{S_i^{\beta}}{\alpha}}-e^{-\frac{S_{i+1}^{\beta}}{\alpha}}\right)\cdot\frac{1}{\sigma\sqrt{2\pi}}\int_{S_u}^{S_i+3\sigma_y}e^{-\frac{y^2}{2\sigma_y^2}}\mathrm{d}y. \qquad (15)$$

To investigate the impact of statistical characteristics in the model parameters (9)–(15) on the values of probable errors P_{FR} and P_{NR}, software was developed and integrated into the overall neural network algorithm.

The neural model can be further enhanced by calculating integrated diagnostic quality assessments, not only for the current session but also for building trends and forecasting the development of engine technical condition indicators.

The functionality of the third neural layer realizes the construction of predictive models by three indicators: validity of control – D; control error – P_{FR}; control error – P_{NR}. Control errors are interpreted in the object management system as risks and have different social and economic significance, which is determined at the first stage by a link of experts, and at the second stage by the modeling. In addition to making decisions based on the results of the current one-time act of diagnostics, it is important to predict changes in individual indicators of engine operational reliability by statistical "history", which is formally expressed and built on the basis of large data in the form of regression models.

Then, if the regression functionals are denoted as $F(D)$, $Z(Y_{\max})$, $Q_1(P_{FR})$, $Q_2(P_{NR})$, then the neural network model for predicting the operational reliability of helicopter engines as a function of control risks can be generally represented by Fig. 6.

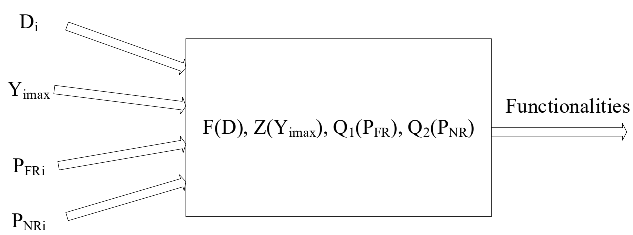


Fig. 6. Neural network model for predicting operational reliability of helicopter engines in control risks

To calculate empirical functions of reliability indicators of helicopter engines and quality of the diagnostics system, marked as $F(D)$, $Z(Y_{\max})$, $Q_1(P_{FR})$, $Q_2(P_{NR})$ (Fig. 6), it is recommended to use ready-made tools such as: Data Mining, Big Data, Data Science.

5. 2. Development of a model for the advanced diagnostics of gas turbine helicopter engines

After express diagnostics, if some of the control results exceed the established standard levels, there is a need to conduct a more in-depth diagnostics of both individual engine units and the entire facility as a whole [18]. In this paper, the following solution to this scientific and practical problem is proposed using a neural network approach and a digital transformation platform.

In order to implement the tasks of in-depth diagnostics of gas turbine engines, an analysis of the available works on this issue was preliminarily carried out. As the most acceptable option for the operating conditions and tasks solved in this study, the work [19] should be noted. During in-depth diagnostics in some cases there is a need to measure diagnostic parameters at hard-to-reach control points (CP) of the engine, where it is impossible to install piezo or vibration sensors. In such a situation, two measuring channels are used. The first channel uses laser technology, in the form of a portable laser vibrometer of increased sensitivity. Laser vibrometry is a "modern, qualitatively new level of measuring the parameters of mechanical vibrations of objects". The unique physical features of laser methods are that qualitatively new technological capabilities appear in diagnosing engines: the most important technological opportunity is remote contactless measurement of vibration parameters; there is no reaction to the resonance phenomena of objects; there is no need for preliminary preparation of the surface of the object; it has become possible to measure vibrations in hard-to-reach points of an object. In a laser vibrometer, the working technological distance from the device to the test object can be from 1.5 to 10 m. The supply voltage of the vibrometer is 12 V. DC from a portable battery or from a power source connected to a 220 V (50 Hz) AC network. Power consumption is 15–20 W (depending on the operating mode). The next advantage is that the microprocessors included in the laser vibrometer perform digital processing and analysis of vibration signals. The results in the form of spectrograms or oscillograms are displayed on the screen of an external computer connected via RS-232 or USB channels, the connectors of which are located on the control panel of the device. Measurement error is 10 %. The second measuring channel of this system allows for temperature pyro control at any point of the engine. Temperature control is performed in the infrared range.Taking into account the listed control and measuring capabilities of existing devices, this complex is modified and adapted to the current operating conditions by means of additional functional-technical, mathematical and software-algorithmic solutions. The new solution is based on neural network technology and special technical, mathematical in combination with information and organizational-methodological system support.

The structural and functional model of neural in-depth diagnostics and training using helicopter engines as an example is shown in Fig. 7.

In Fig. 7, the laser channel is represented by controlled points $CPCL_1$–$CPLC_n$. The infrared measurement channel is represented by pyrometric control points $CPPN_1$–$CPPN_k$. This block in the general system of in-depth diagnostics with training on the neural network principle is the first hidden layer. The measurement results, as follows from Fig. 7, are duplicated in Big Data.

It is recommended to use the MG30 as a pyrometric sensor, which has high sensitivity in the infrared region.

The functionality of the first neural layer in this system with training implements two tasks. The first task involves calculating the statistical characteristics and identifying the distribution laws of the following diagnostic parameters: $f(x)$ and $f(y)$ are the density functions of the distribution of the approximated laws; the maximum value of the diagnostic parameters $X_{\max}$ and $Y_{\max}$; the arithmetic mean X_{avg} and Y_{avg}; the root mean square S_x and S_y; regression models for forecasting $F(x)$ and $F(y)$. The Gaussian and Weibull laws are studied as distribution laws, as the most suitable for the problems of managing the reliability of helicopter engines and units. Statistical data are extracted from Big Data, since it is the use of the entire sample, taking into account the "historical" precedent data, that allows recalculating all statistical characteristics and coefficients of the regression model. This procedure for adapting the formal characteristics and control indicators to the current situation is called the "training" process in neural network technologies.

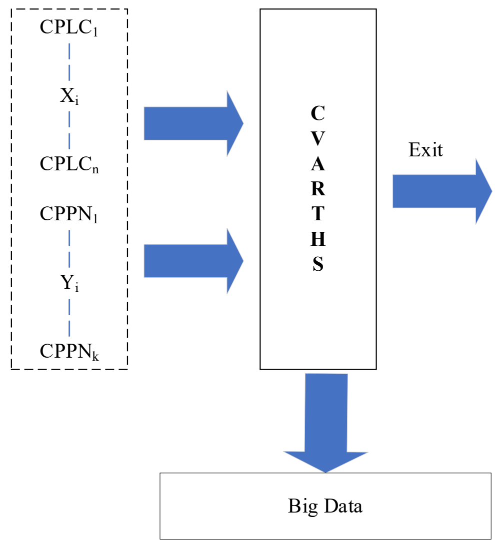


Fig. 7. Structural-functional model of the first hidden neural layer of the in-depth diagnostics system for gas turbine engines

The neural model of the first neural layer of the system with training is shown in Fig. 8.

In this layer, statistical processing and threshold control are performed, where the measured values are compared with the threshold limits equal to: ($X_{average}$+$X_{average}$/3) and ($Y_{average}$+$Y_{average}$/3). This processing is carried out on a computer in the diagnostic system loop (Fig. 8). If the threshold is exceeded, a warning is issued in both audio and visual forms and stored in Big Data.

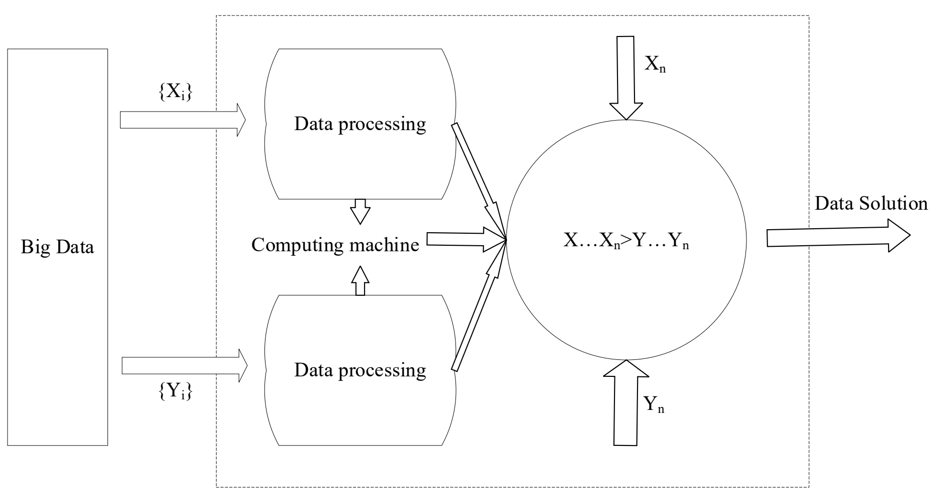


Fig. 8. Neural model of the first neural layer of the system with training

The task of the second neural layer is to formalize the process of quality control of diagnostics of helicopter engines according to the criteria of quantitative assessment of errors of control in conditions of statistical uncertainty of agents of the entire system. The solution of the named task is carried out on the example of vibroacoustic and pyrometric diagnostics of the operational reliability of helicopter gas turbine engines.

The diagnostic process is organized in the form of a digital twin on a neural network precedent platform. The goal of formalizing the control process in the diagnostic system is achieved by constructing a probabilistic model consisting of two functionals of quantitative assessment and prediction of the false failure error and the error of undetected failure. Previously, a similar problem was considered using examples of diagnosing automobile engines, but in other system organizational, technical and information conditions, as well as a different instrumental, measuring and technological environment.

A significant difference between the known traditional organizational and technological solutions and the proposed solution was the absence of a learning process, which reduced the reliability of the diagnostic results. The neural model of the functional for calculating the diagnostic error – false and undetected failures is shown in Fig. 9. For an integral assessment of the quality of the control and measuring system, the indicator – reliability is quite often used, which is the main characteristic of the quality of control. Reliability of control is the degree of confidence that the measured values truly reflect the state of the object.

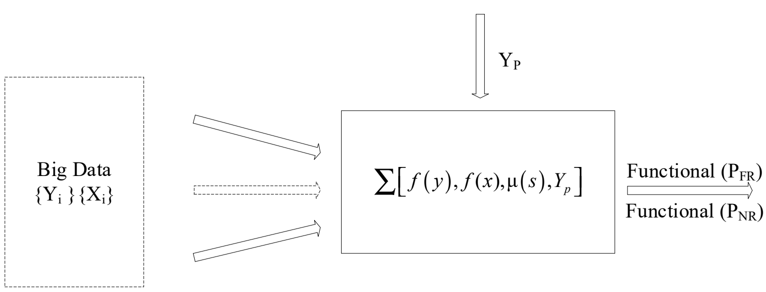


Fig. 9. Neural model of the second layer of the system of in-depth diagnostics of gas turbine engines

During the diagnostics process in the advanced diagnostics system of gas turbine engines, control errors occur in two channels of measurement – laser and pyrometric channels. The resulting control errors, which, as noted above, are usually divided into errors of false and undetected failures in this system are estimated both separately for each channel and integrated – as a total error. Control errors can be considered as control uncertainty [9]. Then the expression for the reliability of control in the laser and pyrometric channels takes the following form:

$$\begin{cases} D_x = 1 - \left(Px_{FR} - Px_{NR}\right), \\ D_y = 1 - \left(Py_{FR} - Py_{NR}\right). \end{cases} \tag{16}$$

The two channels for data collection and processing, each associated with different diagnostic parameters are shown in Fig. 10. The visualization highlights the interaction of all elements aimed at improving the accuracy and reliability of the diagnostics.

The analytical probabilities of control errors for each channel will be quantitatively estimated using expressions (9), (10) and (14), (15). Software applications have been developed for the quantitative estimation of these probabilities.

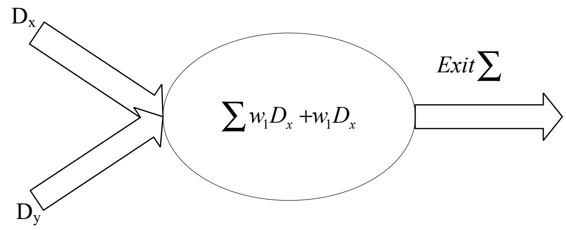


Fig. 10. Neural model of integrated expression of reliability of in-depth diagnostics of gas turbine engines in a two-channel version

The process of training the neural network system consists in the fact that the technology of decision-making and conclusions is based on a two-stage algorithm. The first stage uses current control data. Then the current data are "attached" to the historical Big Data, and the entire procedure of neural network calculations, final conclusions and decision-making is repeated. In this case, not only integrated assessments of the diagnostic quality are calculated, but also formal constructions of trends and forecasts of the development of indicators of the technical condition of the engine are carried out.

5. 3. Computer-aided study of statistical properties and assessment of control risks

In conclusion of the theoretical studies, a computer experiment was implemented. The purpose of the computer experiment was to study the influence of parametric uncertainties of control agents on the magnitude of management risks. The parametric agents of uncertainty were: S_{avg} – arithmetic mean value of the controlled parameter; σ_S – standard deviation of the controlled parameter; σ_μ – standard deviation of the error of the measuring channel; S_P – threshold value of the controlled parameter. In the process of modeling, the values of the probability of occurrence of a false failure P_{FR}, and the values of the probability of an undetected failure P_{NR} as a function of the ratio σ_μ/σ_S were calculated, with varying the value of the threshold S_P (standard).

The threshold value was changed in increments: $S_P=S_{avg}+\sigma_S$; $S_P=S_{avg}+2\sigma_S$; $S_P=S_{avg}+3\sigma_S$. Here: S_{avg} – arithmetic mean value of the controlled parameter; σ_S – mean square deviation of the distribution law of the controlled parameter. The simulation results are given in Tables 1, 2. The values of the probability of occurrence of a false failure P_{FR} are given in Table 1 and the values of the probability of an undetected failure P_{NR} are given in Table 2.

The calculated data are presented in Fig. 11, 12 in 2D graphical format.

Table 1

Values of the probability of false failure occurrence P_{FR}

Probability of false failure (P_{FR})	Relative uncertainty (σ_μ/σ_S)				
	0.2	0.4	0.6	0.8	1
$S_P=S_{AVG}+3\sigma_S$	0	0	0	0.0012	0.046
$S_P=S_{AVG}+2\sigma_S$	2.2	3.9	5.9	9.6	13.2
$S_P=S_{AVG}+\sigma_S$	4.1	9.2	14.1	20	24.9

Table 2

Values of the probability of undetected failure P_{NR}

Probability of undetected failure (P_{NR})	Relative uncertainty (σ_μ/σ_s)				
	0.2	0.4	0.6	0.8	1
$S_P=S_{AVG}+3\sigma_S$	0	0	0	0.00025	0.031
$S_P=S_{AVG}+2\sigma_S$	1.1	1.6	2	2.15	2.4
$S_P=S_{AVG}+\sigma_S$	3.3	6	7.8	9.1	10

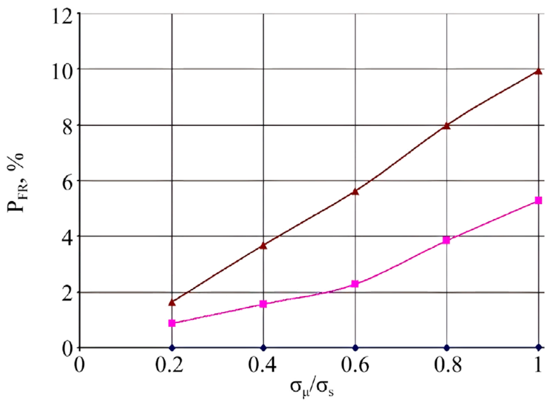


Fig. 11. Graphical model of the probability of false failure occurrence P_{FR}

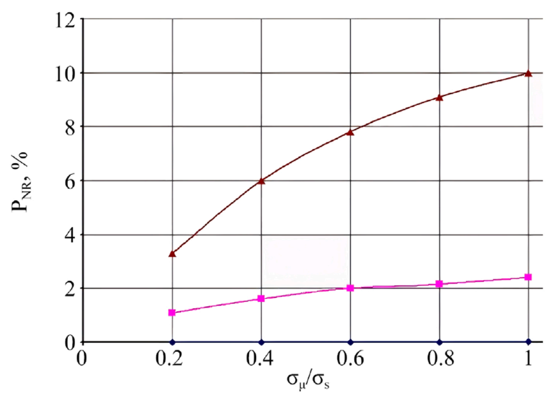


Fig. 12. Graphical model of the probability of occurrence of undetected failure P_{NR}

Thus, having obtained graphical models of the probabilities (risks) of false and undetected failures, it is possible to visually and quantitatively assess, as well as predict the reliability and probable risks of control when making technological diagnoses. Studying Fig. 11, 12, it can be concluded that the maximum risk is associated with a "false failure" and can reach 25 %.

6. Discussion of the results of the study on neural network quality control based on diagnostic risk criteria

In the organizational and technical plan for completing the research objectives presented above, the first stage of the work envisaged studying the current state of helicopter maintenance and repair systems in the Republic of Kazakhstan, identifying shortcomings, and proposing new technical solutions based on government documents on the digital transformation of the state. JSC Aircraft Repair Plant No. 405, a leading certified and licensed enterprise with a unique repair and technical base, a sufficiently high level of digitalization, and personnel support, was selected as the base enterprise for solving the task set.

The second stage involved studying the statistical material on this subject area available in the reporting materials of Aircraft Repair Plant No. 405. As a result of preliminary statistical processing of the material, using the STATISTICA* environment, it was found that in the scientific practice of the enterprise, there is no factor and correlation analysis of statistical data, and there is a complete absence of a prognostic methodology using historical data. The choice of instrumental diagnostic tools according to metrological criteria was carried out according to the price principle, without considering functional performance. At the same time, it was already revealed in previous works [14, 15] that the accuracy parameters of the devices have a close compositional analytical connection with the regulatory framework, and in conditions of parametric fuzziness and uncertainty of data, they quantitatively determine the risks of control. The second significant drawback was that decision-making in the control system was carried out based only on the current measurement results with a complete lack of predictive analytics. Based on this, the tasks presented above were formed to improve the system for maintaining the reliability of helicopter equipment using the example of the JSC Aircraft Repair Plant No. 405. Formal support for the control system and practical implementation were based on neural network approaches that provide differentiated approaches to two measuring channels: a vibro-acoustic channel and a pyrometric channel. On this basis, two technologies were planned and implemented: express diagnostics technology based on vibration control data, and in-depth diagnostics based on vibration and pyrometric control. In the case of in-depth diagnostics, the results of vibration and pyrometric monitoring were integrated in the form of a weighted sum, which was used to evaluate the quality level of the entire diagnostic system. In this express diagnostics solution, vibration diagnostics was chosen owing to its technological effectiveness and acceptable diagnostic accuracy, which was confirmed by the studies cited above. The neural model for the express diagnostics contained three hidden layers (Fig. 3, 4, 6), and two open layers for implementing the functionality of monitoring, assessing, and predicting the quality of monitoring, assessed by the risk level. The first hidden layer, which is the most complex, implements preliminary technical standardization of information from vibration sensors and statistical processing of this information.

The third stage involved statistical processing, including calculation of basic statistical characteristics, identification of distribution laws, and assessment of the statistical homogeneity of the data.

In the fourth stage, the second neural layer, based on the results of statistical processing, calculates the reliability of control, probable risks of false and undetected control, which are interpreted as the risk of the manufacturer (in this case, the manufacturer of control and measuring works), and the risk of the consumer of work (the customer of work). These risks determine the socio-economic losses of production and, ultimately, the safety of flights for air transport users.

The fifth stage provides a quantitative assessment of the risks of in-depth diagnostics of gas turbine helicopter engines in a trained neural network environment. In-depth diagnostics are solved by creating a second additional channel for the pyrometric control of the local thermal sections of the engine. Pyrometric control provides measurements in the infrared region. Technologically, this control is performed remotely, which greatly simplifies the diagnostic process. As a structural and functional idea of the neural network, this study suggests using the Rosenblatt multilayer perceptron model (multilayer perceptron, MLP) with variable weights at each of the inputs. Variable weights are formed by considering new information that arises during the current diagnostic session, replenishing the local and large databases, which allows the implementation of the system training process. The structural and functional model of the in-depth diagnostic process contained one hidden layer (Fig. 7) and three open layers (Fig. 8–10). The calculated analytical functionals of producer and consumer risks generated by the model (Fig. 9) are presented in (14), (15).

The methodology for substantiating normative (threshold) values is an important agent and new scientific and practical result. The substantiation of standards is an extremely complex stage in any decision-making system. In this study, a similar methodology for substantiating the normative (threshold) values of the vibration signals was proposed. The proposed methodology uses the statistical nature of the energy and operating processes in existing helicopter engines. The following were used as normative criteria: the arithmetic mean of the vibration signal in the control sample, the standard deviation, and the maximum value of the vibration signal in the digital selective control and measuring quantitative vector. It is assumed that the quantitative diagnostic parameters of engine performance have a statistical distribution approximated by Gaussian law. If the maximum value of $Y_{\max}$ is selected as the key diagnostic parameter, it can vary within the range of $Y_{mean}\pm3$ sigma. Then, the permissible level and threshold of the maximum value of the vibration signal should be estimated from Equation (1). The value of weight w_i is estimated using the Harrington curve from equation (2). If $Y_{measured}=0$, w_i is equal to one. The second proposal is to consider the importance of the technical and economic assessments of the operational reliability of the diagnosed unit by introducing the coefficient K_e. This coefficient was estimated expertly within the range of 0–1. Then, the working value of the synapse "weight" coefficient is estimated by (3). The functional $Y=F(S)$ was used to compare the value of S with the standard (threshold) of the second neural layer.

The structural and functional model of in-depth neural diagnostics and training using helicopter engines as an example is shown in Fig. 7. The system was implemented in a two-layer format (Fig. 8, 9). The training process of the neural network system is that the technology of decision-making and conclusions is based on a two-stage algorithm. The first stage uses the current control data. Then, the current data are "attached" to the historical big data, and the entire procedure of neural network calculations, final conclusions, and decision-making are repeated. In this case, not only are integrated assessments of the quality of diagnostics calculated, but formal constructions of trends and forecasts of the development of engine technical condition indicators are also carried out. A neural model of the integrated expression of the reliability of in-depth diagnostics of a gas turbine engine in a two-channel version (Fig. 10) was implemented to assess the overall reliability of a two-channel system in the form of a weighted sum of the reliability of the vibration and pyrometric channels.

The limitations of this study include the reliance on the accuracy of the initial data and the quality of the measurement instruments used, which may restrict the applicability of the proposed models under conditions with an insufficiently high metrological level. Additionally, despite the use of a neural network environment, the influence of complex environmental factors and operating conditions is not fully accounted for, which may impact the applicability of the solutions in real-world situations. Future developments of this study could involve expanding the analysis by employing more complex models that consider nonlinear interactions and external factors, such as climatic conditions and operating modes. Furthermore, incorporating more advanced methods of machine learning and artificial intelligence could enhance the accuracy of forecasting and diagnostics. This advancement is crucial, as it will facilitate the creation of more adaptive and resilient control and monitoring systems that respond to changing conditions, ultimately increasing the reliability of helicopter maintenance and ensuring operational safety.

7. Conclusions

1. A neural model of risk assessment in the express diagnostics system of the technical condition of helicopter units was built. In the express diagnostics system for monitoring the operability of helicopter units, a vibroacoustic method is used, which physically involves installing vibration sensors at experimentally selected control points. Monitoring provides for a one-time assessment and a monitoring mode with multiple control and accumulation of information in a special database. Statistical processing of current and historical information makes it possible: to carry out control by average values of diagnostic parameters and by sharply distinguished values; to build regression models and automatically predict the dynamics of processes; to calculate control risks.

2. For in-depth diagnostics, the involvement of remote control of pyrometric information using laser technology is provided. The conclusion regarding the operability of the object is differentiated for each measurement channel as well as integrally for the weighted sum of the measurement results. Risks were calculated separately for each control channel.

3. A combination of all statistical properties and the integral influence of these properties on the final result (i.e., control risks) was investigated using a computer experiment based on experimental data. The study revealed that the quality of control, as assessed by the level of risks, depends more on the standard for the controlled parameter than on the metrology, specifically the uncertainty of measuring instruments. Additionally, the computer experiment showed that the risk of false failure (enterprise risk) significantly exceeds consumer risk.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

The manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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