Information technologies of data processing for linear deterioration process during aviation equipment operation

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Abstract

Aviation radio equipment is used for the information support of civil aviation flights. The stability of information support is determined by the reliability and efficiency of operational processes. The reliability of the equipment depends on external factors, the environmental conditions (temperature, pressure, humidity, radiation level, electromagnetic compatibility), processes of electronic radio components aging, wire and contact connections, personnel skills, and accuracy class of control and measuring equipment. In general, reliability tends to deteriorate over the life cycle of the aviation equipment. Signs of deterioration include an increase in the number of failures, non-stationary trends in the change of diagnostic parameters and reliability indicators, an increase in the number and complexity of maintenance and repair procedures, and others. The random nature of the deterioration of the technical condition of the aviation equipment leads to a decrease in the remaining useful life of this equipment. The tasks of detecting the deterioration of the technical condition are solved through the use of information technologies, which include methods of statistical data processing based on elements of probability theory, mathematical statistics, statistical decision theory, artificial intelligence, and others. This paper is devoted to the synthesis and analysis of the procedure for detecting changepoint in the diagnostic parameter trend for a linear model of deterioration of the technical condition of aviation radio equipment.

Keywords

information technologies, aviation radio equipment, operation, data processing, reliability, linear model of deterioration, diagnostic variable

1. Introduction

Aviation radio equipment is used for the information support of civil aviation flights [1]. The stability of information support is directly related to the safety, availability, and regularity

CMSE'24: International Workshop on Computational Methods in Systems Engineering, June 17, 2024, Kyiv, Ukraine
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of flights and the efficiency of the implementation of operational processes in aviation enterprises [2].

The main process of aviation equipment life cycle is the process of operation [3]. This process is the longest and it realizes the useful properties of the equipment that were planned at the design stage [4, 5]. The total cost of operational process implementation far exceeds the initial cost of aviation radio equipment [6]. This feature necessitates optimization of the organizational structure and operation processes in terms of improving the control and preventive measures, applying information technology for data processing, implementing best practices of domestic and foreign domains, harmonizing regulatory and technical documentation, training and professional development of personnel, and introducing production process automation systems based on robotics and artificial intelligence [7, 8].

One of the main tasks during the implementation of the operation processes is to ensure and maintain the proper level of equipment reliability [9]. The reliability of aviation radio equipment depends on external factors, the environmental conditions (temperature, pressure, humidity, radiation level, electromagnetic compatibility), processes of electronic radio components aging, wire and contact connections, personnel skills and qualifications, and an accuracy class of control and measuring equipment [10, 11]. Some of these factors are objective and cannot be studied and eliminated [12]. The other part can be investigated, analyzed, and taken into account in terms of when, what, and who should take corrective and preventive actions [13].

Reliability may deteriorate over time, which is manifested in the form of:

- An increase in the number of failures.
- The occurrence of non-stationary trends in the change of diagnostic parameters and reliability indicators.
- Increase in the number and complexity of maintenance and repair procedures and their content, and others [14, 15].

The basis for ensuring the efficiency of the operation system is solving the problems of failure and fault detection and estimation of trend parameters of the diagnostic parameters and reliability indicators after detection. This makes it possible to predict future failures, the remaining useful life of aviation radio equipment, and optimize the processes of extending the equipment's life [16].

The tasks of detecting deterioration in the technical condition and estimating the parameters of relevant trends can be solved by using information technologies, which include methods of statistical data processing based on elements of the probability theory, mathematical statistics, statistical decision theory, regression analysis, and artificial intelligence [17].

This approach to studying the deterioration processes is an improvement of the known condition-based maintenance strategy, the reliability-centered maintenance strategy, and the new maintenance strategy with the use of modern artificial intelligence tools. The new maintenance strategy with the use of modern artificial intelligence can be based on machine and deep learning methods.

2. State of the art and the statement of the problem

State and enterprise standards for the operation of civil aviation equipment usually use condition-based maintenance strategies [18]. According to these strategies, the reliability indicators and diagnostic parameters are monitored and measured [19]. It should be noted that these strategies do not use modern information technology to process data and make complex decisions based on the results of processing. In other words, there are no operators for prediction, decision-making, detection of inconsistencies, facts of the beginning of a malfunction, and others.

These circumstances have a negative impact on the overall level of uncertainty in the technical condition of the equipment and therefore do not allow for timely corrective and preventive actions [20, 21]. According to the second law of thermodynamics, the entropy level of an arbitrary system is constantly increasing, but this means that there is a need to conduct a thorough analysis of the diagnostic parameters and reliability indicators and thus eliminate this negative effect. The concepts of modern Industry 4.0 are shaped by the tasks of comprehensive application of advanced information technologies, including those aimed at reducing the level of uncertainty [22, 23].

A modern trend during the use of data processing information technologies can be considered the analysis of datasets with changepoint. The changepoint corresponds to objective phenomena and patterns of change in the technical condition of equipment, when the data trends can be considered as non-stationary random processes [24, 25].

The changepoint is a process that has several intervals of quasi-stationarity or non-stationarity. The transition from one interval to another usually occurs at a random moment of time. The trends in monitoring indicators for different intervals of quasi-stationarity (non-stationarity) are generally characterized by different probability density functions (PDFs) [26]. In the most complicated cases, the parameters of these probability density functions, in turn, may also be random, so the parameters also can be described by the corresponding probability densities. Such circumstances necessitate the synthesis and analysis of complex data processing schemes that combine a variety of statistical processing methods and artificial intelligence technologies, which are largely based on the use of a heuristic approach [27, 28].

The following methods are promising in the case of a priori uncertainty:

1. The sequential approach (also known as A. Wald's method). This approach is based on the use of samples with a random observation volume. This approach is effective in terms of decision-making time and saving of sample sets, which is very important, especially in the context of expensive measurements. In general, the procedures for detection, estimation, and forecasting should be sequential. On the other hand, this approach is characterized by complex mathematical relationships in terms of determining the stopping rule, finding decision thresholds and truncation, studying the use of training datasets, and analyzing the effectiveness of a particular developed method [29].

2. Nonparametric procedures. These procedures allow to synthesize distribution-free statistical classification algorithms. However, in terms of efficiency, these procedures are slightly worse than their parametric counterparts [29].
3. Sliding window processing. These procedures allow to reduce the volume of observation, providing flexibility to the conditions of observation and increase the accuracy of statistical processing procedures in the case of observation of different intervals of quasi-stationarity. The peculiarities of applying this approach are the difficulties in optimizing the size of the sliding window and forming appropriate sample sets [30].
4. Adaptive approach. This approach is versatile, as it involves the ongoing evaluation of the data model, the parameters of the PDF, and the selection of the best processing method for a particular model in the space of possible options. However, to implement this approach, it is necessary to have the means to design under uncertainty for the populations to be analyzed [31].
5. Machine learning and deep learning methods. This approach involves the use of regression analysis, classifiers, estimators, predictors, clustering techniques, heuristic approaches, and neural network technologies. This approach requires significant computer power (in terms of GPU) and time-consuming training procedures [32].

Let's formulate the problem at the level of generalized functionalities. Let the generalized efficiency indicator Ψ depends on the data processing algorithm A, the model of the diagnostic parameter or reliability indicator P, the PDF model of the input data M (for signal and noise components), sliding window parameters W, parameters L that impose constraints and limitations. In general, the algorithm is defined by the operators O that determine the sequence of actions within a certain strategy S of processing and decision-making and their interconnection.

The efficiency indicators are:

– probability of correct detection D,
– delay in making a decision,
– bias and variance of estimates,
– accuracy and veracity of the predictive value.

Then we can write

$$\Psi = \varphi(A(O(S), W) | M, P, L).$$

To solve the problem of synthesis and analysis of data processing algorithms during the study of processes with changepoint during the operation of aviation radio equipment, it is necessary to implement the following set of steps:

– determine the model of the PDF and the relevant parameters,
– make assumptions and impose restrictions,
– determine the processing strategy,
– justify the parameters of the sliding window,
– develop a processing flowchart,

– obtain analytical ratios for efficiency indicators,
– conduct a statistical simulation to confirm the correctness of the calculations,
– conduct a comparative analysis with existing processing methods,
– formulate conclusions and recommendations.

Thus, the aim of this paper is to synthesize and analyze information technologies for data processing in case of deterioration of the technical condition of aviation radio equipment within the framework of the formed list of procedures.

3. Materials and methods

This section considers the synthesis of the procedure for detecting the deterioration of the technical condition of aviation radio equipment during its operation. To simplify the synthesis procedure, we will make several assumptions:

1. One diagnostic parameter of aviation radio equipment is the subject to monitoring. We believe that equipment failures and faults are directly associated with this parameter. Thus, there is a certain operational threshold, after which a failure occurs.
2. The trend of the diagnostic parameter is a mixture of information and noise components. The information component is described by a deterministic law. The noise component, due to the influence of a large number of random factors, can be characterized by a normal law with zero average value and a given standard deviation σ.
3. The deterioration of the technical condition of aviation equipment is characterized by a random moment of occurrence t_{det} and a linear increasing dependence after its occurrence with a random value of the tangent of the slope angle a of this linear dependence. It should be also noted that the linear nature of the deterioration leads to a violation of the stationarity of the trend of change in the diagnostic parameter.
4. The processing is performed in a sliding window with the given volume n of observations.

The synthesis of the deterioration detection procedure will be performed using a well-known method based on the Neyman-Pearson criterion. This procedure will test a simple hypothesis against a simple alternative.

Let's define the hypothesis H_0 is no deterioration in the technical condition. Then the alternative H_1 is the occurrence of deterioration. In accordance with the assumptions made, we write the PDFs of the values of the diagnostic parameter for the hypothesis and the alternative:

$$f_{H_0}(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-m)^2}{2\sigma^2}}, \quad (1)$$

$$f_{H_1}(x,t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-m-a(t-t_{det})\varphi(t-t_{det}))^2}{2\sigma^2}}, \quad (2)$$

where m is the normative average value of the diagnostic parameter, $\varphi(t)$ is the Heaviside function, which is included after the deterioration occurs, adding non-stationarity to the initial model.

Since the processing will be performed in a sliding window, the choice of its location is very important. Figure 1 shows three realizations of the diagnostic parameter for the width of the sliding window containing a dataset of 40 measurements. In this case, the sliding window is configured in such a way that the moment of deterioration coincides with the window center.

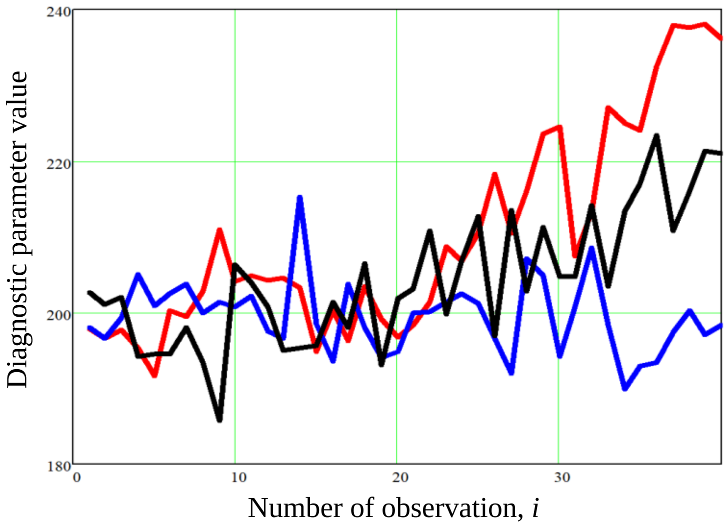

Figure 1: The realizations of diagnostic parameter trend in sliding window.

The blue line in Figure 1 corresponds to a situation where there is no deterioration in the technical condition. The red and black lines have two intervals: stationary – before the 20th value of the sample and non-stationary – after the 20th value.

An important task of synthesis is to choose the size of the sliding window and its location relative to the changepoint origin. Small sizes of the sliding window worsen the accuracy of detection. At the same time, large sizes of the sliding window led to delays in decision-making and greater inertia of the data processing system.

To simplify the mathematical calculations and check the feasibility of applying sliding window processing, we assume that the sliding window is placed so that its start coincides with the moment of the changepoint occurrence. Then, having information about the sampling interval of measurements Δ and the number of measurements i in the sliding window, it is possible to simplify the equation for the PDF of the diagnostic parameter in the case of the alternative:

$$f_{H_1}(x_i, i) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x_i - m - ai\Delta)^2}{2\sigma^2}}. \tag{3}$$

The likelihood functions for the hypothesis and the alternative will be:

$$\gamma_{H_0}(x) = \prod_{i=1}^{n} f_{H_0}(x_i) = \left(\frac{1}{\sigma\sqrt{2\pi}}\right)^n e^{-\sum_{i=1}^{n}\frac{(x_i - m)^2}{2\sigma^2}}, \tag{4}$$

$$\gamma_{H_1}(x) = \prod_{i=1}^{n} f_{H_1}(x_i, i) = \left(\frac{1}{\sigma\sqrt{2\pi}}\right)^n e^{-\sum_{i=1}^{n}\frac{(x_i-m-ai\Delta)^2}{2\sigma^2}}. \quad (5)$$

The likelihood ratio:

$$\Lambda(x) = \frac{\gamma_{H_1}(x)}{\gamma_{H_0}(x)} = \frac{\left(\frac{1}{\sigma\sqrt{2\pi}}\right)^n e^{-\sum_{i=1}^{n}\frac{(x_i-m-ai\Delta)^2}{2\sigma^2}}}{\left(\frac{1}{\sigma\sqrt{2\pi}}\right)^n e^{-\sum_{i=1}^{n}\frac{(x_i-m)^2}{2\sigma^2}}} = e^{-\sum_{i=1}^{n}\frac{(x_i-m-ai\Delta)^2}{2\sigma^2}+\sum_{i=1}^{n}\frac{(x_i-m)^2}{2\sigma^2}} =$$

$$= e^{-\sum_{i=1}^{n}\frac{(x_i-m-ai\Delta)^2}{2\sigma^2}-\frac{(x_i-m)^2}{2\sigma^2}} = e^{-\sum_{i=1}^{n}\frac{(x_i-m)^2}{2\sigma^2}-\frac{2ai\Delta(x_i-m)}{2\sigma^2}+\frac{(ai\Delta)^2}{2\sigma^2}-\frac{(x_i-m)^2}{2\sigma^2}} =$$

$$= e^{-\sum_{i=1}^{n}\frac{(ai\Delta)^2}{2\sigma^2}-\frac{2ai\Delta(x_i-m)}{2\sigma^2}}.$$

To simplify the calculations, let us take $\Delta = 1$ and move on to the logarithm of the likelihood ratio:

$$\ln\Lambda(x) = \ln e^{-\sum_{i=1}^{n}\frac{(ai)^2}{2\sigma^2}-\frac{2ai(x_i-m)}{2\sigma^2}} = -\sum_{i=1}^{n}\frac{(ai)^2}{2\sigma^2} - \frac{2ai(x_i-m)}{2\sigma^2} =$$

$$= \frac{a}{\sigma^2}\sum_{i=1}^{n} ix_i - \frac{am}{\sigma^2}\sum_{i=1}^{n} i - \frac{a}{2\sigma^2}\sum_{i=1}^{n} i^2.$$

Information about the values of the diagnostic parameter is contained only in the first term of the logarithm of the likelihood ratio. Therefore, we rewrite this formula in the following form:

$$\ln\Lambda(x) + \frac{am}{\sigma^2}\sum_{i=1}^{n} i + \frac{a}{2\sigma^2}\sum_{i=1}^{n} i^2 = \frac{a}{\sigma^2}\sum_{i=1}^{n} ix_i.$$

So, we get

$$\sum_{i=1}^{n} ix_i = \frac{\sigma^2}{a}\ln\Lambda(x) + m\sum_{i=1}^{n} i + 0{,}5\sum_{i=1}^{n} i^2.$$

Let's take the expression as the decisive statistic:

$$\Theta(x_i, n) = \sum_{i=1}^{n} ix_i. \quad (6)$$

According to the Neyman-Pearson criterion, the logarithm of the likelihood ratio $\ln\Lambda(x)$ must be compared with the threshold of decision-making on the truth of the hypothesis or the alternative. In the case under consideration, we obtain a modified threshold of the following form:

$$V = \frac{\sigma^2}{a}\ln\Lambda(x) + m\sum_{i=1}^{n} i + 0{,}5\sum_{i=1}^{n} i^2. \quad (7)$$

Then the decision-making algorithm will be described by the formula:

$$Decision = \begin{cases} \text{Normal operation}, & \text{if } \Theta(x_i, n) < V, \\ \text{Deterioration}, & \text{if } \Theta(x_i, n) \geq V. \end{cases} \quad (8)$$

Let's consider the procedure for determining the decision threshold. To do this, it is necessary to determine the PDF of the decisive statistics for the cases of the hypothesis and the alternative. The calculation of these PDFs is possible by applying the central limit theorem of probability theory and the tools of functional transformations of random variables and processes. In accordance with formula (6), a linear combination of normal distributions occurs. Therefore, the distribution of the decisive statistics will also be normal. So, we get

$$f_{H_0}(\Theta) = \frac{1}{\sigma\sqrt{2\pi}\sum_{i=1}^{n}\sqrt{i}} e^{-\sum_{i=1}^{n}\frac{\left(\Theta - m\sum_{i=1}^{n} i\right)^2}{2\left(\sigma\sum_{i=1}^{n}\sqrt{i}\right)^2}}, \qquad (9)$$

$$f_{H_1}(\Theta) = \frac{1}{\sigma\sqrt{2\pi}\sum_{i=1}^{n}\sqrt{i}} e^{-\sum_{i=1}^{n}\frac{\left(\Theta - m\sum_{i=1}^{n} i - a\sum_{i=1}^{n} i^2\right)^2}{2\left(\sigma\sum_{i=1}^{n}\sqrt{i}\right)^2}}. \qquad (10)$$

Figure 2 and Figure 3 show the results of statistical simulation to confirm the validity of the obtained formulas (9) and (10). The graphs were plotted for the following values of the initial parameters: the normative value of the diagnostic parameter $m = 200$, standard deviation of the noise $\sigma = 5$, width of the sliding window $n = 40$, number of epochs repetition $N = 2000$.

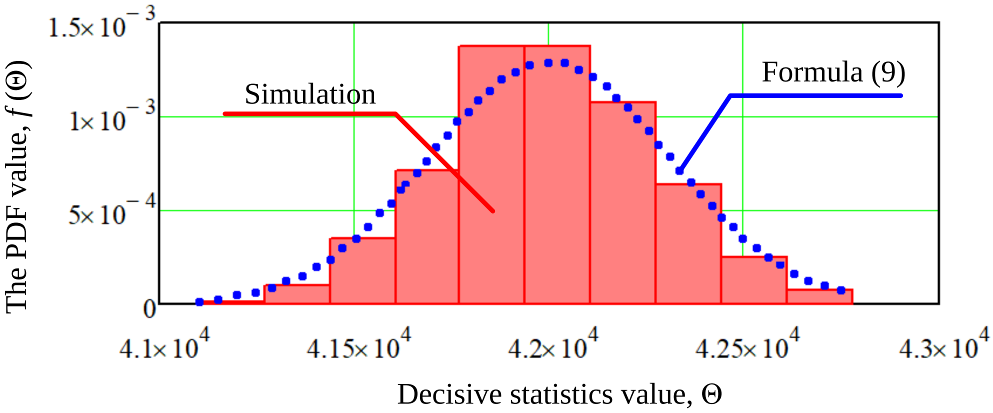

Figure 2: The PDF of decisive statistics in case of hypothesis.

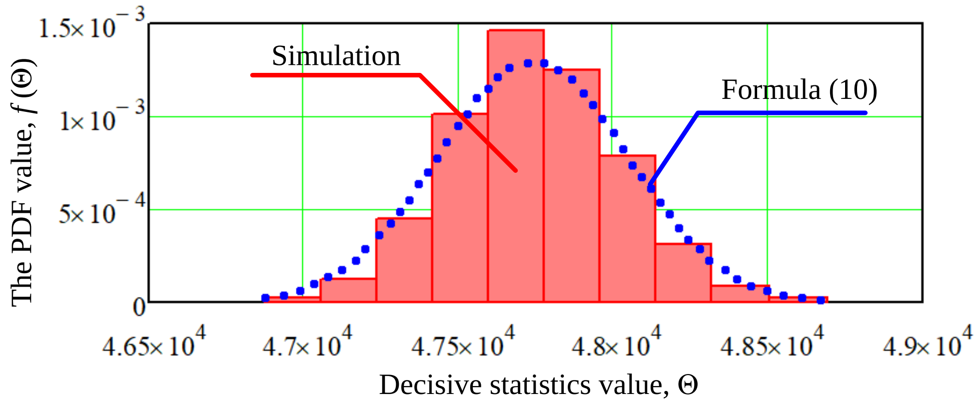

Figure 3: The PDF of decisive statistics in case of alternative.

A visual analysis of the graphs allows to conclude that the results of the Monte Carlo simulation methods coincide with the analytical equations (9) and (10) proving the correctness of formulas.

The calculation of the decision threshold in this research was performed for a given probability of a first-type error α. It is known that

$$\alpha = \int_V^\infty f_{H_0}(\Theta) d\Theta. \tag{11}$$

Taking into account (9), we obtain

$$\alpha = \int_V^\infty \frac{1}{\sigma\sqrt{2\pi}\sum_{i=1}^n \sqrt{i}} e^{-\sum_{i=1}^n \frac{\left(\Theta - m\sum_{i=1}^n i\right)^2}{2\left(\sigma\sum_{i=1}^n \sqrt{i}\right)^2}} d\Theta = 1 - \Phi\left(\frac{V - m\sum_{i=1}^n i}{\sigma\sum_{i=1}^n \sqrt{i}}\right),$$

where $\Phi(\cdot)$ is the probability integral.

From here we get

$$V = m\sum_{i=1}^n i + \sigma\Phi^{-1}(1-\alpha)\sum_{i=1}^n \sqrt{i}, \tag{12}$$

where $\Phi^{-1}(\cdot)$ is the inverse function of the probability integral.

Thus, the algorithm for detecting a linear trend in the deterioration of the technical condition of aviation radio equipment consists of calculating the decisive statistics (6) for the values of the diagnostic parameter observed in the sliding window and comparing it with the decision threshold (12).

4. Results and discussions

This section is devoted to the analysis of the algorithm for detecting a linear trend in the deterioration of the technical condition of aviation radio equipment.

As the efficiency indicator of the processing algorithm, the probability D of correct detection of technical condition deterioration of the aviation radio equipment. It is known that

$$D = \int_V^\infty f_{H_1}(\Theta) d\Theta. \tag{13}$$

Taking into account (10), we obtain

$$D = \int_V^\infty \frac{1}{\sigma\sqrt{2\pi}\sum_{i=1}^n \sqrt{i}} e^{-\sum_{i=1}^n \frac{\left(\Theta - m\sum_{i=1}^n i - a\sum_{i=1}^n i^2\right)^2}{2\left(\sigma\sum_{i=1}^n \sqrt{i}\right)^2}} d\Theta = 1 - \Phi\left(\frac{V - m\sum_{i=1}^n i - a\sum_{i=1}^n i^2}{\sigma\sum_{i=1}^n \sqrt{i}}\right).$$

Then, according to (12), we finally get

$$D = 1 - \Phi\left(\frac{\sigma\Phi^{-1}(1-\alpha)\sum_{i=1}^n \sqrt{i} - a\sum_{i=1}^n i^2}{\sigma\sum_{i=1}^n \sqrt{i}}\right). \tag{14}$$

Formula (14) can be used to build the detection characteristic. In the case under research, this characteristic will be the dependence of the probability of correct detection on the tangent of the slope of the linear deterioration trend, i.e., the dependence $D(a)$. To verify the correctness of the obtained formulas, let's calculate the probability of correct detection in the case of changepoint absence:

$$D(a=0) = 1 - \Phi\left(\frac{\sigma\Phi^{-1}(1-\alpha)\sum_{i=1}^{n}\sqrt{i} - a\sum_{i=1}^{n} i^2}{\sigma\sum_{i=1}^{n}\sqrt{i}}\right)\Bigg|_{a=0} =$$

$$= 1 - \Phi\left(\frac{\sigma\Phi^{-1}(1-\alpha)\sum_{i=1}^{n}\sqrt{i}}{\sigma\sum_{i=1}^{n}\sqrt{i}}\right) = 1 - \Phi\left(\Phi^{-1}(1-\alpha)\right) = 1 - 1 + \alpha = \alpha.$$

Thus, the correct result is that in the absence of deterioration, the probability of correct detection turns into the probability of the first-type error.

An example of calculating the decisive statistic and comparing it with the decision threshold to determine the probability of correct detection is shown in Figure 4.

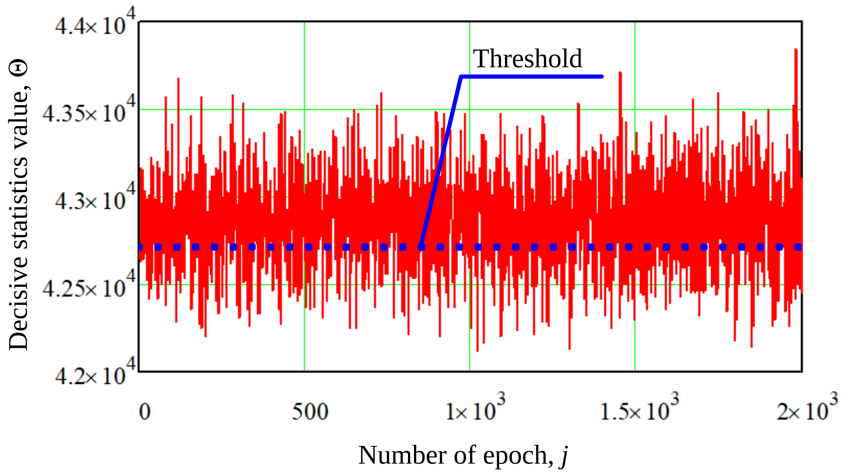

Figure 4: Decisive statistics calculation for 2000 epochs of simulation.

Figure 5 shows the detection characteristic of the developed algorithm. This characteristic was plotted for the following values of the initial parameters: the normative value of the diagnostic parameter $m = 200$, standard deviation of the interference $\sigma = 5$, width of the sliding window $n = 40$, probability of the first-type error $\alpha = 0.01$, number of repetition epochs $N = 2000$.

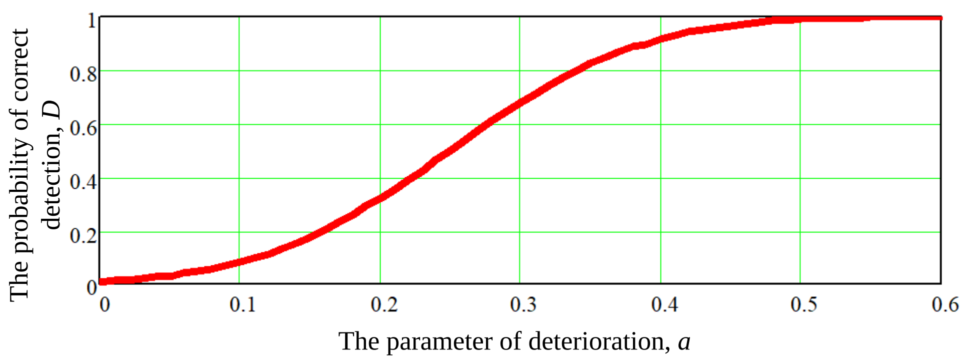

Figure 5: The operating characteristic of detection.

As can be seen, the developed algorithm has good detection quality, providing the probability of correct detection of more than 0.9 for slope angles of the linear deterioration trend of more than 20 degrees.

5. Conclusions

Aviation radio equipment plays an important role in ensuring the safety and regularity of aircraft flights, as well as the efficiency of the production activities of the structural units of aviation enterprises. Significant resources are spent to maintain the reliability of radio equipment during its operation. Some of them can be reduced by optimizing the implementation of corrective and preventive actions. It can be assumed that the basis of the content of such actions is the algorithms for processing data on the diagnostic parameters and reliability indicators.

Practice shows that data are usually random. The nature of data trends can also be non-stationary. In such cases, we can speak about changepoint for which there are intervals with random durations, where the data are described by different PDFs. The literature analysis has shown that there are currently insufficient of methods for processing data on the diagnostic parameters and reliability indicators in the event of changepoint. This, in turn, reduces the efficiency of the equipment's intended use. The large number of parameters characterizing statistical models of trends in the diagnostic parameters and reliability indicators of radio equipment does not allow to immediately solve all the problems of designing new algorithmic support for operation systems. One of the possible approaches to solving such problems is the use of machine learning and deep learning methods of artificial intelligence with a harmonious combination of methods of statistical decision theory, statistical estimation theory, mathematical statistics, and others.

This paper solves the problem of synthesis and analysis of information technologies for data processing in the case of linear model of deterioration of the technical condition of aviation radio equipment. The paper describes a new algorithm for detecting the deterioration of the technical condition of aviation radio equipment and derives analytical equations for calculating and constructing the detection characteristic. The results of the statistical simulation have confirmed the correctness of the analytical calculations.

In general, the obtained results can be used in design organizations and operational enterprises during the modernization and creation of new systems for the operation of aviation radio equipment.

Acknowledgements

This research is partially supported by the Ministry of Education and Science of Ukraine under the project “Methods of building protected multilayer cellular networks 5G / 6G based on the use of artificial intelligence algorithms for monitoring country’s critical infrastructure objects” (# 0124U000197). Also, this project has received funding through the EURIZON project, which is funded by the European Union under grant agreement No. 871072 (Project EU #3035 EURIZON “Research and development of Ukrainian ground network of navigational aids for increasing the safety of civil aviation”).

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