Algorithms of data processing for aviation equipment reliability estimation

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Abstract

The reliability of the equipment affects the quality of performance of the functions assigned to it. Reliability is a complex indicator. It is influenced by a significant number of random factors, which include the equipment components aging, changes in operating weather conditions, the human factor, untimely procedures of maintenance and repair, lack of redundancy, and others. The issue of equipment reliability is especially important in the aviation industry and other industries, where the key task is to ensure the safety of human life and health. Statistical methods and data processing algorithms are usually used to estimate reliability indicators. The basis of their application is a priori information about the type of statistical model of the collected data on the operating time between failures and the operating time between restores. During the operation of the equipment, violations of its functioning modes are possible. These violations are associated with the deterioration of the technical condition. In such cases, the statistical model of the data is significantly complicated, which leads to difficulties in reliability estimation. This paper is devoted to the synthesis and analysis of a data processing algorithm under the assumption of deterioration of the technical condition of the equipment. The tasks ware solved analytically. The obtained results were verified on the basis of statistical simulation.

Keywords

statistical data processing, reliability, aviation equipment, operation, efficiency analysis, statistical simulation

1. Introduction

Today we live in a rapidly changing world. The development of electronics, computer technology, and the nascence of new intelligent data processing algorithms became the keys to the emergence of the concept of Industry 4.0 [1]. Electronic devices of the Internet of Things have made it possible to measure information and generate large datasets about equipment parameters, environment, production processes, user needs, and others [2]. The modern means of data and information transmission has become another aspect of sustainable development in the field of digitization [3]. The increase in the speed of data transmission due to the broadband of fiber optic networks and the capabilities of communication channels of the fifth and higher generations allow timely collection of datasets in the appropriate data warehouses [4].

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Big datasets can now be processed because of increased computer power and capability. This is explained by the possibility of implementing and using complex and sophisticated data manipulation procedures that allow extracting useful information for the user from unprocessed arrays [5].

Modern data processing technologies are a key factor in improving the constituent components of any industry. Data processing technologies make it possible to solve the following tasks:

- identifying trends characterizing the presence of useful information or a sudden or gradual change in the state of equipment, production processes, the psychological and physical state of a person, and others [6, 7];
- determining regularities and building on their basis mathematical models of the interdependence of a group of parameters to be measured [8, 9];
- estimation of key parameters that characterize the quality of production processes, the use of equipment as intended, the efficiency of the functioning of the constituent components of the industry, and others [10, 11];
- forecasting future states, failures, malfunctions, occurrence of dangerous situations, and future trends of monitoring indicators [12, 13];
- data-driven management decision-making [14, 15].

The specified tasks can be considered within the framework of classification and prediction problems, which are constituent components of the modern theory of data processing based on artificial intelligence. Data processing methods are based on machine and deep learning tools, including statistical classification, regression analysis, statistical estimation, clustering, neural networks, and others.

Data processing algorithms are currently becoming very important in the aviation industry. They can be used during surveillance and aeronautical support, security control, airport activity monitoring, logistics, route planning, and others. Nowadays, the data processing algorithms are associated with increasing the efficiency of civil aviation, primarily by reducing the risks of catastrophic and dangerous situations [16], reducing operational costs of aviation enterprises [17], and increasing the level of aviation equipment reliability [18].

In addition to the synthesis and analysis of data processing algorithms, an important problem in civil aviation is the development of the structure of hubs for the collection and use of statistical data, the purpose of which is algorithmic support of equipment operation processes.

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

The reliability of the equipment affects the quality of performance of the functions assigned to it. Reliability is a complex indicator. It is influenced by a significant number of random factors, which include the equipment components aging, changes in operating weather conditions, the human factor, untimely procedures of maintenance and repair, lack of redundancy, and others [19, 20].

The issue of equipment reliability is especially important in the aviation industry and other industries, where the key task is to ensure the safety of human life and health.

The main indicators of reliability are: the mean time between failures, the mean time between restores, the probability of failure-free operation, the probability of failure, the availability function, the steady-state availability, the coefficient of technical use, and others [21].

High levels of reliability indicators are associated with the high-quality performance of equipment functions and the efficiency of operational processes.

The estimation of the reliability of aviation equipment is usually performed at the stage of implementation of the main operational processes, which include maintenance, control, monitoring, diagnosis, repair, and others [22, 23]. In addition, ensuring the required level of reliability is associated with the involvement of additional material resources, which affects the level of costs of the aviation enterprise [24, 25]. Due to the random nature of failure occurrence, reliability indicators are described using statistical models, or they can also be estimated based on statistical data processing algorithms [26, 27].

The article [28] presents a comprehensive overview of machine learning methods used for structural reliability analysis in civil engineering and mechanical engineering. The authors focus on various machine learning models, including artificial neural networks, support vector machines, and Bayesian methods. The article considers the analysis of efficiency and accuracy during reliability analysis, reducing the computational complexity of classical methods. The authors present procedures for Monte Carlo simulation and problems of processing the probabilities of rare events.

The article [29] deals with the approach to the analysis of reliability and availability of the system based on the consideration of the time series of failures and repairs during the occurrence of dependent failures. The article notes that while traditional research assumes a constant number of failures, real systems rarely meet this assumption, especially in environments with cumulative shock and damage processes. The authors use numerical methods and modeling methods to analyze the reliability of these systems. The article contains an example of the implementation of the proposed methodology for studying the reliability of the mechanical system in a special vehicle.

The article [30] focuses on a detailed study of how reliability changes during the life cycle of a system. The authors emphasize the importance of continuous reliability monitoring, which is crucial for early detection of potential system failures and ensuring a given level of efficiency. The article presents theoretical models with practical examples, demonstrating how data-driven methods and algorithms can optimize service strategies. Based on the application of statistical methods and real-time data, the article highlights approach to increasing system reliability. The article also examines the complex interplay between design, operation and maintenance phases, emphasizing that system reliability is not a static property but one that changes over time.

The article [31] investigates the reliability analysis of systems with several components based on stochastic methods. The authors consider systems with redundancy, in which backup groups are included only after the failure of the main group. The article provides detailed comparisons of life expectancy distributions in such systems. The authors used modern mathematical models and distribution functions to evaluate the effectiveness of the system.

Statistical methods and data processing algorithms are usually used to estimate reliability indicators. The basis of their application is a priori information about the type of statistical model of the collected data on the operating time between failures and the operating time between restores. During the operation of the equipment, violations of its functioning modes are possible [32]. These violations are associated with the deterioration of the technical condition. In such cases, the statistical model of the data is significantly complicated, which leads to difficulties in reliability estimation.

We assume that one sample of aviation equipment be under monitoring. This equipment has a certain structure described by a vector $\overrightarrow{S(I)}$ that depends on the hierarchical level I of consideration. In general, the quality of aviation equipment functioning can be described by a vector of reliability indicators $\vec{R}$. Data processing algorithms $\vec{A}$ are used to estimate the numerical values of these indicators. The set of algorithms is also determined by statistical models $\vec{M}$ of the trends of the diagnostic parameters $\vec{D}$, which can flow in a stationary and nonstationary mode. The choice of the processing algorithm is influenced by the applied methods of ensuring reliability $\vec{E}$, for example, the redundancy option, the periodicity of maintenance, and others. Both financial and computing resources $\vec{C}$ are spent on the synthesis and implementation of data processing algorithm. Estimation of reliability indicators is performed under conditions of certain limitations $\vec{L}$. Then the reliability indicator is estimated according to the transformation:

$$\vec{R} = \vec{A}\left(\overrightarrow{S(I)}, \vec{C}, \vec{M}(\vec{D}), \vec{E} \middle| \vec{L} \right). \tag{1}$$

The purpose of this research is the synthesis and analysis of data processing algorithm under the assumption of deterioration of the technical condition of the aviation equipment. From a mathematical point of view, the paper solves the problem of finding the best data processing algorithm $\vec{A}$, which can be implemented for diagnostic parameters $\vec{D}$ with given statistical model $\vec{M}$ for certain type of aviation equipment with structure $\overrightarrow{S(I)}$ under the conditions of assumed limitations $\vec{L}$.

3. Materials and methods

Let's consider the procedure for evaluating the reliability of aviation equipment. As aviation equipment, we will choose an airfield radar. This radar contains three channels: primary, secondary, and weather channel. To increase the level of reliability, redundancy of primary and secondary channels was provided at the design stage.

When developing the reliability data processing algorithm, we will assume about the following limitations:

1. Devices of individual channels of equipment are characterized by an exponential model of the failure occurrence. The failure rates of the primary, secondary, and weather channels are λ_p, λ_s, and λ_w respectively. The failure rates of redundant groups are the same as those of the basic group.
2. In case of failure of the main channel, the aviation equipment switches to the redundant channel with a probability equal to one. The redundant group is in an unloaded mode.
3. During the functioning of the equipment, deterioration of the technical condition occurs. The degradation model corresponds to the step-function. After degradation, regardless of the channel type, the failure intensity is set at the level λ_d. In general case, we suppose that $\lambda_d > \lambda_p$, $\lambda_d > \lambda_s$, and $\lambda_d > \lambda_w$. The moments of deterioration in each channel are independent. At the same time, we will assume that the deterioration is possible in only one channel of radar during the observation period. The moment of deterioration corresponds to the observed failure or malfunction with the number k. In general, N failures or malfunctions were observed during the observation period.
4. The recovery process is characterized by an exponential model with the recovery rate λ_r. Procedures for restoring serviceability are performed only after the loss of functioning of one of the radar channels.

The structural diagram of the radar is shown in Figure 1.

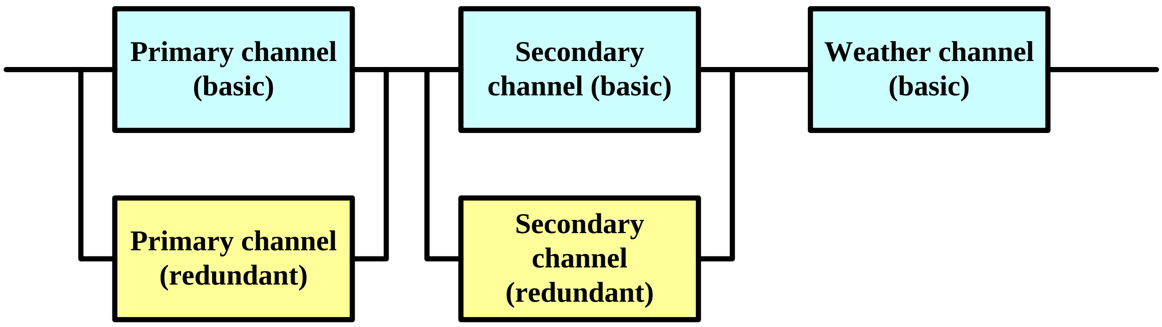

Figure 1: The structural diagram of the radar.

The probability of failure-free operation of individual radar channels (without redundancy) will be determined by the equations:

$$R_p(t) = e^{-\lambda_p t}, t > 0;$$
$$R_s(t) = e^{-\lambda_s t}, t > 0; \quad (2)$$
$$R_w(t) = e^{-\lambda_w t}, t > 0.$$

The probability of failure:

$$Q(t) = 1 - R(t). \tag{3}$$

The probability density function of failure times:

$$f(t) = \frac{dQ(t)}{dt}. \tag{4}$$

To simplify the mathematical representation, we will assume that $\lambda = \{\lambda_p, \lambda_s, \lambda_w\}$. Then we will get:

$$R(\lambda, t) = e^{-\lambda t}, t > 0. \tag{5}$$

$$Q(\lambda, t) = 1 - e^{-\lambda t}, t > 0. \tag{6}$$

$$f(\lambda, t) = \lambda e^{-\lambda t}, t > 0. \tag{7}$$

To form the data processing algorithm regarding reliability, we will determine the main indicators during taking into account redundancy. For this purpose, we will use the methods of functional transformation of random variables. We will assume that redundancy corresponds to the parallel connection of elements. However, we take into account that the redundant blocks are in an unloaded mode. Then the first failure in such a system occurs in the basic unit (let it be at the time t_1). The second failure occurs in the redundant equipment at the moment of time t_2. Then the moment of occurrence of the failure $t = t_1 + t_2$.

Then, for one radar channel (primary or secondary), the probability density function of failure times is found as for the sum of two independent random variables. At the same time, we can get:

$$f_{red}(\lambda, t) = \int_0^t f(\lambda, t_1) f(\lambda, t - t_1) dt_1. \tag{8}$$

Let's consider two cases of calculation. The first case corresponds to the absence of deterioration of the technical condition. Then:

$$f_{red}(\lambda, t) = \int_0^t f(\lambda, t_1) f(\lambda, t - t_1) dt_1 = \int_0^t \lambda e^{-\lambda t_1} \lambda e^{-\lambda(t - t_1)} dt_1 = \lambda^2 \int_0^t e^{-\lambda t_1} e^{-\lambda(t - t_1)} dt_1 =$$
$$= \lambda^2 \int_0^t e^{-\lambda t} dt_1 = \lambda^2 e^{-\lambda t} \int_0^t dt_1 = \lambda^2 t e^{-\lambda t}.$$

The second case corresponds to the occurrence of deterioration of the technical condition. Then:

$$f_{red}(\lambda, t) = \int_0^t f(\lambda_d, t_1) f(\lambda, t - t_1) dt_1 = \int_0^t \lambda_d e^{-\lambda_d t_1} \lambda e^{-\lambda(t - t_1)} dt_1 =$$
$$= \lambda \lambda_d \int_0^t e^{-\lambda_d t_1} e^{-\lambda(t - t_1)} dt_1 = -\frac{\lambda \lambda_d}{\lambda_d - \lambda} e^{-\lambda t} e^{-t_1(\lambda_d - \lambda)} \Big|_0^t = \frac{\lambda \lambda_d}{\lambda_d - \lambda} \left(e^{-\lambda t} - e^{-\lambda_d t}\right).$$

The probability of failure in the case of deterioration absence:

$$Q_{red}(\lambda, t) = \int_0^t f_{red}(\lambda, t) dt = \int_0^t \lambda^2 t e^{-\lambda t} dt = \lambda^2 \int_0^t t e^{-\lambda t} dt = -\lambda t e^{-\lambda t} \Big|_0^t + \lambda \int_0^t t e^{-\lambda t} dt =$$
$$= -\lambda t e^{-\lambda t} - e^{-\lambda t} \Big|_0^t = 1 - e^{-\lambda t} - \lambda t e^{-\lambda t}.$$

The probability of failure in the case of deterioration occurrence:

$$Q_{red}(\lambda, t) = \int_0^t f_{red}(\lambda, t) dt = \int_0^t \frac{\lambda \lambda_d}{\lambda_d - \lambda} \left(e^{-\lambda t} - e^{-\lambda_d t}\right) dt =$$
$$= \frac{\lambda \lambda_d}{\lambda_d - \lambda} \int_0^t \left(e^{-\lambda t} - e^{-\lambda_d t}\right) dt = \frac{\lambda \lambda_d}{\lambda_d - \lambda} \left(-\frac{1}{\lambda} e^{-\lambda t} + \frac{1}{\lambda_d} e^{-\lambda_d t}\right) \Big|_0^t =$$
$$= \frac{\lambda_d}{\lambda_d - \lambda} \left(1 - e^{-\lambda t}\right) - \frac{\lambda}{\lambda_d - \lambda} \left(1 - e^{-\lambda_d t}\right) = 1 - \frac{\lambda_d}{\lambda_d - \lambda} e^{-\lambda t} + \frac{\lambda}{\lambda_d - \lambda} e^{-\lambda_d t}.$$

The probability of failure-free operation will be:

$$R_{red}(\lambda, t) = e^{-\lambda t} + \lambda t e^{-\lambda t};$$
$$R_{red}(\lambda, t) = \frac{\lambda_d}{\lambda_d - \lambda} e^{-\lambda t} - \frac{\lambda}{\lambda_d - \lambda} e^{-\lambda_d t}.$$

Three channels of the radar from the point of view of reliability can be represented as a series connection of elements. Then for whole radar we can write for the case of deterioration absence:

$$R_\Sigma(t) = R_{red}(\lambda_p, t) R_{red}(\lambda_s, t)\, R(\lambda_w, t) = \left(e^{-\lambda_p t} + \lambda_p t e^{-\lambda_p t}\right)\left(e^{-\lambda_s t} + \lambda_s t e^{-\lambda_s t}\right) e^{-\lambda_w t} =$$
$$= e^{-\Lambda t} + \lambda_p t e^{-\Lambda t} + \lambda_s t e^{-\Lambda t} + \lambda_p \lambda_s t^2 e^{-\Lambda t} = \left(1 + \lambda_p t + \lambda_s t + \lambda_p \lambda_s t^2\right) e^{-\Lambda t},$$

for the case of deterioration occurrence in the primary channel:

$$R_\Sigma(t) = R_{red}(\lambda_p, t) R_{red}(\lambda_s, t)\, R(\lambda_w, t) =$$
$$= \left(\frac{\lambda_d}{\lambda_d - \lambda_p} e^{-\lambda_p t} - \frac{\lambda_p}{\lambda_d - \lambda_p} e^{-\lambda_d t}\right)\left(e^{-\lambda_s t} + \lambda_s t e^{-\lambda_s t}\right) e^{-\lambda_w t} =$$
$$= \frac{\lambda_d}{\lambda_d - \lambda_p}(1 + \lambda_s t) e^{-\Lambda t} - \frac{\lambda_p}{\lambda_d - \lambda_p}(1 + \lambda_s t) e^{-\Lambda_1 t},$$

and for the case of deterioration occurrence in the secondary channel:

$$R_\Sigma(t) = R_{red}(\lambda_p, t) R_{red}(\lambda_s, t)\, R(\lambda_w, t) =$$
$$= \left(e^{-\lambda_p t} + \lambda_p t e^{-\lambda_p t}\right)\left(\frac{\lambda_d}{\lambda_d - \lambda_s} e^{-\lambda_d t} - \frac{\lambda_s}{\lambda_d - \lambda_s} e^{-\lambda_s t}\right) e^{-\lambda_w t} =$$
$$= \frac{\lambda_d}{\lambda_d - \lambda_s}(1 + \lambda_p t) e^{-\Lambda t} - \frac{\lambda_s}{\lambda_d - \lambda_s}(1 + \lambda_p t) e^{-\Lambda_2 t},$$

where $\Lambda = \lambda_p + \lambda_s + \lambda_w$, $\Lambda_1 = \lambda_d + \lambda_s + \lambda_w$, and $\Lambda_2 = \lambda_p + \lambda_d + \lambda_w$ are total failure rates for three considered cases.

To determine the probability density function we can use equation (3) and (4). However, of greater interest is the value of the mean time between failures, which can be found according to the equation:

$$MTBF = \int_0^\infty t f(t) dt. \tag{9}$$

Omitting mathematical calculations, we obtain the following densities for three cases: absence of deterioration:

$$f_\Sigma(t) = \left(\lambda_w + \left({\lambda_p}^2 + {\lambda_s}^2 + \lambda_p \lambda_w + \lambda_s \lambda_w\right) t + \left({\lambda_p}^2 \lambda_s + \lambda_p {\lambda_s}^2 + \lambda_p \lambda_s \lambda_w\right) t^2\right) e^{-\Lambda t},$$

deterioration in the primary channel:

$$f_\Sigma(t) = \left(\frac{\lambda_s \lambda_d - \lambda_d (1 + \lambda_s t)\Lambda}{\lambda_p - \lambda_d}\right) e^{-\Lambda t} - \left(\frac{\lambda_p \lambda_s - \lambda_d (1 + \lambda_s t)\Lambda_1}{\lambda_p - \lambda_d}\right) e^{-\Lambda_1 t},$$

and deterioration in the secondary channel:

$$f_\Sigma(t) = \left(\frac{\lambda_p \lambda_d - \lambda_d (1 + \lambda_p t)\Lambda}{\lambda_s - \lambda_d}\right) e^{-\Lambda t} - \left(\frac{\lambda_p \lambda_s - \lambda_d (1 + \lambda_p t)\Lambda_2}{\lambda_s - \lambda_d}\right) e^{-\Lambda_2 t}.$$

The mean time between failures for three cases: absence of deterioration

$$MTBF = \frac{6\lambda_p \lambda_s + 2\left({\lambda_p}^2 + {\lambda_s}^2 + \lambda_p \lambda_w + \lambda_s \lambda_w\right) + \lambda_w \Lambda}{\Lambda^3}, \tag{10}$$

deterioration in the primary channel:

$$MTBF = \frac{\lambda_p (2\lambda_s + \lambda_w + \lambda_d)}{(\lambda_d - \lambda_p){\Lambda_1}^2} - \frac{\lambda_d (2\lambda_s + \lambda_w + \lambda_p)}{(\lambda_d - \lambda_p)\Lambda^2}, \tag{11}$$

and deterioration in the secondary channel:

$$MTBF = \frac{\lambda_s (2\lambda_p + \lambda_w + \lambda_d)}{(\lambda_d - \lambda_s){\Lambda_2}^2} - \frac{\lambda_d (2\lambda_p + \lambda_w + \lambda_s)}{(\lambda_d - \lambda_s)\Lambda^2}. \tag{12}$$

The mean time between restores can be obtained as follows:

$$MTBR = \int_0^\infty t f_r(t) dt = \int_0^\infty t \lambda_r e^{-\lambda_r t} dt = \frac{1}{\lambda_r}. \tag{13}$$

The information obtained with the help of formulas (10) – (13) can be used for the purpose of evaluating the steady-state availability of the radar. For this, we will use the equation:

$$A = \frac{MTBF}{MTBF + MTBR}. \tag{14}$$

The parameters included in equation (14) are random variables. The following equations can be used to find their estimates based on the collected dataset:

$$MTBF = \frac{1}{N}\sum_{i=1}^{N} t_i ; \quad (15)$$

$$MTBR = \frac{1}{N}\sum_{i=1}^{N} t_{ri}. \quad (16)$$

The statistical distributions of estimates (15) and (16) have a complex form. For example, for an exponential model, they can be described by the chi-square distribution. In the case of large datasets, these distributions can be considered normal with average value calculated according to the formulas (10) – (12).

In the general case, the steady-state availability distribution can be defined as:

$$f_A(x) = \frac{1}{(1-x)^2}\int_0^{\infty} x f_{MTBF}\left(\frac{xt}{(1-x)}\right) f_{MTBR}(x)dx. \quad (17)$$

4. Results and discussions

This section contains the results of numerical calculations of reliability indicators of radar for the proposed methodology. Mathematical modeling was performed for the initial data:

- $\lambda_p = 10^{-3}$;
- $\lambda_s = 5 \cdot 10^{-4}$;
- $\lambda_w = 5 \cdot 10^{-4}$;
- $\lambda_d = 5 \cdot 10^{-3}$.

The dependencies for probability of failure-free operation, the probability density function of operating time between failures, and the mean time between failures are shown in Figure 2, Figure 3, and Figure 4.

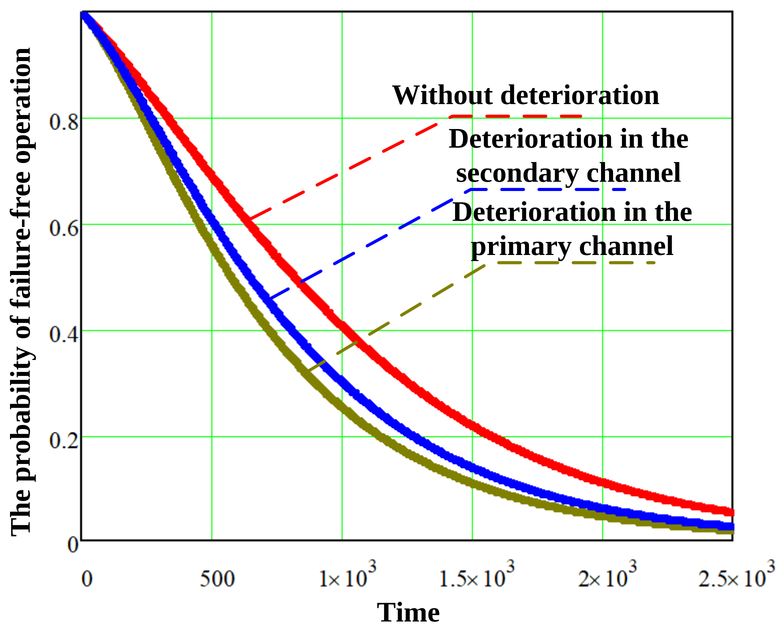

Figure 2: The probability of failure-free operation.

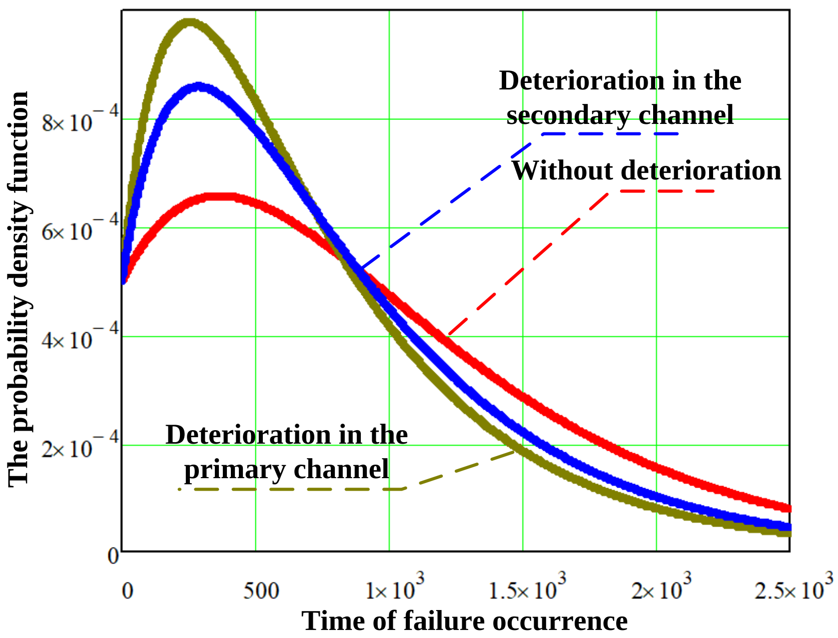

Figure 3: The probability density function of operating time between failures.

Analysis gives possibility to conclude that for this case deterioration occurrence decreases the mean time between failures approximately by 40 %. Deterioration in the primary and secondary channels has same influence on reliability of whole radar. Figure 5 shows the histogram of availability estimates. The availability was calculated for initial parameters $\lambda_p = 0.05$, $N = 10$, and the number of iterations $M = 1000$. The obtained distribution is asymmetric.

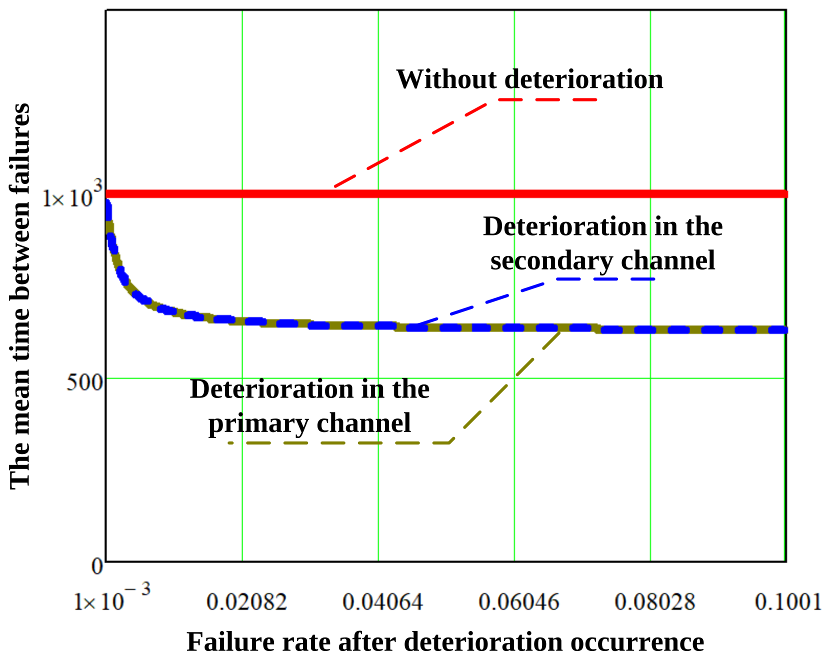

Figure 4: The mean time between failures.

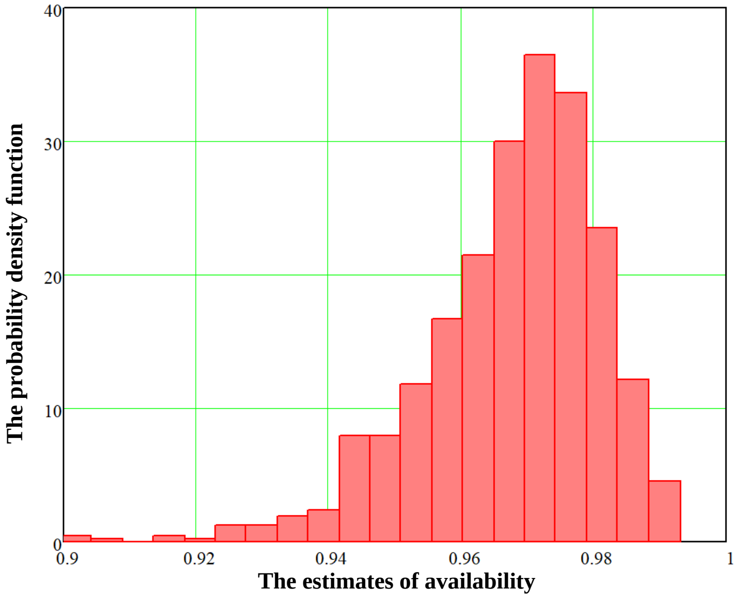

Figure 5: The probability density function of availability estimates.

5. Conclusions

The paper considers the issue of developing the algorithm for estimating the reliability of aviation equipment in case of deterioration of the technical condition of one of its components. The proposed approach is illustrated on the example of the operation of the radar containing three channels, two of which are with redundancy in an unloaded mode. The reliability estimation algorithm involves the analysis of the structural connections of the components, the calculation of the probability of failure-free operation, the mean time between failures, and steady-state availability. Obtaining calculation formulas became possible due to the use of mathematical statistics methods. The results of the calculations confirm the need to monitor reliability indicators in the event of a possible deterioration in the technical condition of the equipment.

Future research will be aimed at: synthesis of detector of deterioration of technical condition, research of multistage deterioration process, operational costs analysis in the case of deterioration, improvement of algorithmic support of operation system of aviation equipment.

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