Predictive control for failure risk assessment during navigation equipment operation

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Abstract

Navigation equipment may fail during operation. As a result, this equipment becomes inoperable and risks arise related to the integrity of navigation systems and flight safety. To reduce the specified risks and losses caused by them, it is necessary to solve the problems of increasing the reliability and operational efficiency. The main methods of solving these problems are the application of various types of redundancy, the development and implementation of intelligent data processing technologies, the development of decision-making schemes regarding corrective and preventive actions, the synthesis of methods for prediction of the technical state of equipment, the development of algorithms and methods for diagnostic, and others. Prediction is an effective method of reducing failure risks. This approach is based on the determination of estimates of the future values of the determining parameters of the equipment and the formation of control influences on the prevention of exceeding the values of these parameters of the given tolerances. During the synthesis and analysis of prediction algorithms, it is advisable to determine efficiency indicators in the form of the veracity of predictive control. This paper considers the problem of predictive control procedure synthesis for decreasing the risks of equipment failure.

Keywords

risks assessment, operation, radio equipment, predictive control, veracity, decision-making

1. Introduction

Analysis of theoretical results and practice of operating modern devices of communication, navigation and surveillance (CNS) indicate the need for wide application of information technologies for processing operational data regarding the operation of these devices and further modernization of the operational system (OS) [1, 2]. Control means of modern CNS system obtain a large amount of data about their technical state (TS), but the algorithms for processing this data are not provided [3, 4]. This fact leads to the limitation possibilities of operation processes optimization for CNS devices. In addition, the real operating conditions of specific equipment are not fully taken into account [5]. That is, information technologies are practically not used to directly analyze the operation processes, which does not allow purposeful and effective improvement of the OS.

The construction of OS can be based on the implementation of system and process approaches [6, 7]. These processes must be carried out under managed and controlled conditions, which involve the performance of operations to regulate the parameters of individual means and components of their OS [8]. This action strategy is an adaptive approach to the management of operational processes. To implement adaptive operation, it is advisable to use the following measures:

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1. Identify the main factors that should be taken into account for the implementation of adaptive operation.
2. Determine the main functions of the OS of the CNS devices.
3. Justify the main actions and operations that must be performed during operation (control, adjustment, and others).
4. Analyze schemes of information interaction of individual components of OS.
5. Consider possible options for evaluating the effectiveness of the application of adaptive operation [9, 10].

The operation system includes a set of products, means of operation, performers and documentation, which establishes the rules of their interaction for the performance of operation tasks [11]. The main functions of the OS of the CNS devices are:

- organization, coordination and control of the technical operation of the facilities and means of the CNS;
- carrying out organizational and technical measures regarding modernization, maintenance of operational readiness and extension of the service life of the CNS devices;
- planning, organization, coordination and control of work on the certification of services and facilities of the CNS equipment and aviation telecommunications;
- planning, coordination and control of the flight inspections of CNS devices;
- organization and control of work on improving the qualifications of the CNS devices specialists;
- improvement and introduction of new methods of work organization, including based on the use of modern information technologies [12, 13].

One of the components of OS is the system of technical maintenance [14]. The maintenance process of CNS devices belongs to the class of complex systems. The analysis shows that maintenance processes are characterized by the presence of all the signs of a complex system [15]. Indeed, a large number of different elements interact in it, which have a single functional goal – radio technical support of the production activity of the aviation enterprise [16]. One of the areas of optimization of maintenance processes of the CNS devices is the optimization of individual components of maintenance. The main components of maintenance are:

- control of the TS of the CNS devices;
- regulation of the determining parameters of the CNS devices by the implementation of controlling influences;
- preventive replacement of blocks, nodes, elements in CNS devices [17, 18].

Because of the maintenance control, such elements of CNS devices are revealed. The condition of elements can lead to the failure of the equipment as a whole. Adjustment, regulation or replacement of such elements is carried out, thus it is possible to prevent failures. The regulation consists of the implementation of controlling influences (CI) on the determining parameters (DP) of the CNS devices based on the information about their obtained after the implementation of control operations [19]. Controlling influences should be carried out in case of reaching the DP of the limits of safety tolerances [20]. The purpose of the implementation of the CI is to bring the values of the regulated DPs, which are controlled, to the nominal values [21, 22].

It is known that long-term statistics, data on the nature of events (planned and sudden shutdowns, maintenance and repair of equipment, and others), as well as diagnostic data (measurement results on operating equipment) contain a certain amount of useful information [23, 24]. The analysis of the specified statistics allows solving a complex of tasks such as estimating the current state of the equipment and prediction the reliability of the equipment as a whole with the selection and ranking of negative factors, the elimination of which will lead to its increasing at the given operation interval.

Today it becomes necessary to apply adequate methods of processing statistical series and building special adaptive algorithms of models for making decisions on operational reliability management of specific types of the CNS devices. The implementation of modern maintenance regulations involves the application of the tools of the theory of controlled Markov random processes in the conditions of stochastic uncertainty of information about the parameters of the CNS devices, creates the necessary conditions for the development of models for evaluation and prediction the parameters of operation management [25]. The development of models, algorithms, methods, and computational procedures that use the statistical data and the results of diagnostic control of equipment allows performing calculations and prediction of probabilistic characteristics of random events flows, estimation of the criticality rank of equipment before failures, determination of the priority order of its prevention and optimization of maintenance parameters and adjustment at the considered operation interval [26].

In general, the term prediction is understood as a statement that contains an indication of a spatial or temporal interval of finite size, within which the predicted event will occur [27]. As a result of the implementation of certain algorithms for processing information about the object of research in the prediction process, an estimation of certain characteristics of the object at a biased moment in time is carried out. Data analysis in the case of predicting states or events is more complex than data analysis from previous experience.

As a result of prediction the technical state of the CNS devices, the value of the set of DPs is evaluated. At the same time, if each of the parameters determines qualitatively different properties of the object, then an independent prediction of individual parameters is carried out, the final decision about the object state is made based on a set of decisions about the state of each of the parameters [28]. If all parameters qualitatively determine one property of the object, then the vector characteristic of the suitability of the CNS devices in a certain way turns into a generalized parameter, based on the results of its control, the technical state of the CNS devices is assessed [29]. The practical application of adaptive algorithms of predictive control involves reducing the errors of making decisions about the object state in the presence of a priori uncertainty [30, 31]. The veracity of predictive control is a quantitative measure of the objectivity of decisions made as a result of prediction [32, 33]. The veracity of control depends not only on the objectivity of the actual prediction, but also on the effectiveness of the operation systems of CNS devices as a whole [20, 35].

2. Problem statement

Consider the statement of the problem for this research. There is the system that provides some services (for example, radio support of flights). During non-serviceability of this system, the risks $\overrightarrow{Risks}$ can occur related to the systems under its control. The risks can be considered from the different points of view, including social, economic, political, safety, and others. In general, risks are estimated in probability terms and for quantitative assessment it is necessary to have information on costs. In our case, we suppose that risk depends on following parameters:

- efficiency indicator (for decision-making on TS it can be the veracity) $Efficiency$;
- data processing algorithms $\overrightarrow{Algorithms}$;
- models of DPs and reliability parameters $\overrightarrow{Models}$;
- the type of prediction $\overrightarrow{TP}$;
- cost function $\overrightarrow{CF}$;
- data and their features of collecting and storage $\overrightarrow{Data}$.

Therefore, the risk can be determined as a function

$$\overrightarrow{Risks} = \vartheta(Efficiency(\overrightarrow{Algorithms}, \overrightarrow{Models}/\overrightarrow{TP}, \overrightarrow{Data}), \overrightarrow{CF}).$$

The purpose of this paper is to obtain analytical equations for estimating the efficiency of predictive control procedures for CNS devices.

3. Veracity of predictive control of navigation equipment

Let's consider the veracity indicators of the predictive control of the equipment operation. While carrying out the predictive control of the operation of navigation equipment, a decision about its TS is made at the prediction interval τ_p.

Predictive control (PrC) of product operation eliminates a significant drawback of running control (RC), which consists of the time discrepancy of making a decision about the product serviceability τ_k and the time of its use according to the purpose $\tau_k + \tau_{use}$, thereby increasing the effectiveness of control and, accordingly, the effectiveness of products use [36, 37]. The initial information for decision-making for the PrC is the results of the RC. In the technical documentation for the product, the limits of permissible values of DP $\overrightarrow{X^p}$ are established in the form of warranty tolerances $[\Omega_{Li};\ \Omega_{Hi}]$. At the same time, the event $Event(\tau_p)$, which determines the condition of product serviceability in the prediction interval, is presented in the form:

$$Event(\tau_p): \{\overrightarrow{X^p}\,(\tau_p) \in [\Omega_{Li};\ \Omega_{Hi}]\}. \qquad (1)$$

Due to the imperfection of the PrC systems, there may be errors when making the decision about the workability of the product, i.e., a serviceable product may be rejected, and an unserviceable product may be deemed suitable. At the same time, the event $Decision(\tau_p)$, which determines the conditions for making a decision about the product serviceability in the prediction interval, will be presented in the following form:

$$Decision(\tau_p): \{\overrightarrow{Y^p} \in [\Delta_{Li};\ \Delta_{Hi}]_p\}. \qquad (2)$$

Graphically, the operation of forming decisions at PrC and taking into account the above mentioned is shown in Figure 1.

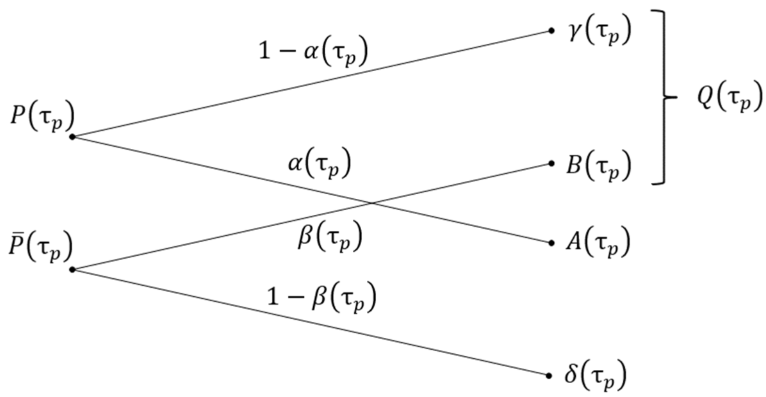

Figure 1: Graph of the forming decisions for PrC.

Figure 1 contains the following parameters:

1) $P(\tau_p) = P(Event(\tau_p))$ is the probability of serviceable state of product at the prediction interval τ_n;

2) $A(\tau_p) = P(Event(\tau_p)\overline{Decision}(\tau_p))$ is the unconditional probability of recognition of a suitable product as unsuitable based on the results of the PrC (manufacturer's risk of PrC);

3) $B(\tau_p) = P(\overline{Event}(\tau_p)Decision(\tau_p))$ is the probability of recognizing an unsuitable product as suitable based on the results of the PrC (customer risk during PrC);

4) $\gamma(\tau_p) = P(Event(\tau_p)Decision(\tau_p))$ is the probability of recognition as suitable based on the results of the PrC of a suitable product;

5) $Q(\tau_p) = P(Fvent(\tau_p))$ is the probability of recognizing the product as suitable based on the results of the PrC;

6) $\alpha(\tau_p) = P(\overline{Decision}(\tau_p)/Event(\tau_p))$ is the conditional probability of recognizing a suitable product as unsuitable based on the results of the PrC (this is the probability of the first type error during the PrC);

7) $\beta(\tau_p) = P(Decision(\tau_p)/\overline{Event}(\tau_p))$ is the conditional probability of recognizing an unsuitable product as suitable based on the results of the PrC (this is the probability of an error of the second kind during the PrC).

The probabilities of the products control results during the PrC taking into account the accepted designations and in accordance with Figure 1 are in the following equation:

$$A(\tau_p) = P(\tau_p)\alpha(\tau_p) = P(\tau_p) - \gamma(\tau_p); \tag{3}$$

$$B(\tau_p) = P(\tau_p)\beta(\tau_p) = Q(\tau_p) - \gamma(\tau_p); \tag{4}$$

$$Q(\tau_p) = P(\tau_p) - A(\tau_p) + B(\tau_p); \tag{5}$$

$$\delta(\tau_p) = \bar{P}(\tau_p) - B(\tau_p); \tag{6}$$

$$\gamma(\tau_p) = P(\tau_p) - A(p). \tag{7}$$

Let's consider possible quantitative estimation of decisions veracity during PrC. Since the task of the PrC is to make the decision about the suitability or unsuitability of products before performing tasks, during predictive control of serviceable products, there can be two such solutions: the product is considered suitable (serviceable) or a failure is observed.

Therefore, for the quantitative estimation of the veracity of the decisions made during the PrC, it is necessary to select the following characteristics, which in general have different numerical values. We will evaluate quantitatively:

– decision veracity about "suitable" state (a posteriori probability of serviceability in the prediction interval of the product determined as "suitable" according to the results of the PrC)

$$D^S(\tau_p) = \frac{\mathrm{P}(\tau_p) - \mathrm{A}(\tau_p).}{\mathrm{P}(\tau_p) - \mathrm{A}(\tau_p) + \mathrm{B}(\tau_p)}; \tag{8}$$

– the decision veracity about "unsuitable" state (a posteriori probability of unserviceability in the prediction interval of the product determined as "unsuitable" according to the results of the PrC)

$$D^F(\tau_p) = \frac{1 - \mathrm{P}(\tau_p) - \mathrm{B}(\tau_p).}{1 - \mathrm{P}(\tau_p) - \mathrm{A}(\tau_p) + \mathrm{B}(\tau_p)}; \tag{9}$$

– absolute veracity (a posteriori probability of making error-free decisions for the prediction interval according to the results of the PrC)

$$D^{\mathrm{P}}(\tau_p) = 1 - A(\tau_p) - B(\tau_p). \tag{10}$$

Analysis of equations (8) – (10) shows that the indicators of decisions veracity of the PrC are determined by the values of the manufacturer's risk $A(\tau_k)$ and customer's risk $B(\tau_k)$.

Let's consider mathematical model of the forming decisions for the preventive control of the determining parameter.

As shown above, the result of the PrC is the decision on the serviceability of the product in prediction interval. Quantitative results of the product serviceability PrC are initiate data for making decision. To describe the process forming decisions at PrC, we will use a mathematical model of PrC [20] that defines PrC as a sequence of performing individual operations with random consequences.

Let's assume that the change over time of the DP of a set of products of the same type is described by an a priori random process $\xi(\tau_k)$, statistically determined on the time interval $[0, \tau_k]$.

One of the implementations of this process, which corresponds to the change in the DP of the specific product, is observed by means of running control at discrete moments of time, $\tau_1\ \tau_2 \dots \tau_m, \tau_k$: $0 \le \tau_1 < \tau_2, \dots, < \tau_m < \tau_k$, which precede the prediction interval τ_p.

Taking into account the nature discreteness of the moments and DP observations results, the set of ordinates of its true values at the moments of changes $\tau_1, \tau_2 \dots \tau_k$ will be presented in the form of some trajectory T – changes of the true values of the DP [8]

$$T_l = \{\xi(\tau_1) \in Q_a, \xi(\tau_2) \in Q_b, \dots, \xi(\tau_k) \in Q_w\}, T_l \in L, \tag{11}$$

where L is set of trajectories of change of true DP values in observation intervals; $Q_a, Q_b, \dots, Q_w$ are indexes, in which there were true values of DP at the moments of its measurements; $a \in m, b \in$

$m, \dots, W \in m$ are discrete values of DP at the moments of measurement, m is set of parameter values distinguished by RC means. Each trajectory T_L is characterized by the probability $P_L = P(T_L)$ of existence.

Set L is characterized by the matrix. This matrix contains a series of probabilities for the existence of true DP trajectories determined by the random process $\xi(\tau)$, which is an input for the running control operation:

$$|P_{in}^{T}| = \|P_1 P_2 \dots P_l \dots P_L\|, \qquad \sum_{l \in L} P_l = 1\,. \tag{12}$$

The reliability component of the PrC, due to the errors of the RC, will be denoted by the index "t" for the considered indicator.

The set m at PrC consists of a subset ρ of serviceable states and a subset μ of non-serviceable states, $\rho \in m, \mu \in m, (\rho \cap \mu = \emptyset)$.

Quantitative results of DP measurements $y(\tau_1), y(\tau_2) \dots y(\tau_k)$ are transformed by RC means into the numbers of its various states $g_a, g_b, \dots g_w$, $a \in m, b \in m, \dots, w \in m$, based on the set $g_a, g_b, \dots g_w$ obtained in the observation interval $[\tau_1, \tau_2 \dots \tau_k]$. The control system (CS) with the help of its prediction tool forms the prediction result $g(\tau_n) = \Psi(g_a, g_b, \dots g_w)$, which belongs to many V possible states and represents some characteristic of the posterior random process $\xi(\tau)/g_a, g_b, \dots g_w$, which describes possible changes in the values of the DP in the prediction interval given its initial values.

Then the CS determines the membership of the prediction result to the set $\upsilon, (\upsilon \subset V)$, that corresponds to the results “Suitable”. The PrC based on this definition with the correspondingly chosen decision rule gives a conclusion about the operability of the object instance according to the measured parameter in the prediction interval.

We will distinguish between $I\{T_S\}; s = \overline{I, S}$ trajectories formed based on the results of observations by RC means on the variable DP in the observation interval:

$$T_S = \{y(\tau_1) \in g_a, y(\tau_2) \in g_b, \dots, y(\tau_k) \in g_w\};\; T_S \in S. \tag{13}$$

Each trajectory T_S is characterized by the probability of existence $P_d = P(T_S)$. As a result of the error of the selected RC means, obtained at the moment of observation, the numbers of DP states $g_a, g_b, \dots g_n$, in the general case, differ from $Q_a, Q_b, \dots Q_n$, numbers, distinguishable true DP values at the indicated moments of time. In this regard, any l-th trajectory of changes in the true values of DP – T_l with the probability $W_{ls} = \{T_s/T_l\}$ can be perceived as any S-th of the trajectories formed based on the results of observations by RC means according to changing the DP.

Conditional probabilities of transitions based on RC results of true trajectories into observed ones form a matrix of transition probabilities of RC operations, which is presented in the following form:

$$|W_{trs}^{\mathrm{T}}| = \left\| \begin{matrix} \omega_{11} & \omega_{12} & \cdots & \omega_{1s} & \cdots & \omega_{1S} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \omega_{l1} & \omega_{l2} & \cdots & \omega_{ls} & \cdots & \omega_{lS} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \omega_{L1} & \omega_{L2} & \cdots & \omega_{Ls} & \cdots & \omega_{LS} \end{matrix} \right\|, \tag{14}$$

where: $\sum_{s \in S} w_{lS} = 1, l = \overline{I, L}$.

The row matrix at the output of the enlarged RC operation is the result of the multiplication of matrices (12) and (14) and contains as its elements the probabilities of the observations trajectories existence of the set S:

$$|P_S^T| = |P_L^T||W_{trs}^T| = \|P_1 P_2 \dots P_s \dots P_S\|,$$
$$\sum_{s \in S} P_S = 1\,, P_S = \sum_{l \in L} P_l P_{lS}. \tag{15}$$

Predictive control of the operations composition differs from RC in the presence of elementary prediction operations, the resulting joint action of which, as for RC, can be replaced by one enlarged prediction operation. Consider the probabilistic characteristics of this operation, which differs from the enlarged RC operation in that the input information for it is not the probabilities of these operations, but the probabilities of combinations of these probabilities at discrete moments of observation. Since the used combinations are characterized by the probabilities of the trajectories of the set L, which are input to the prediction the enlarged operation, then the probabilistic characteristics of this operation form a transition probability matrix:

$$\left|W_{trs}^{p}\right| = \left\| \begin{matrix} \omega_{11}(\tau_p) & \omega_{12}(\tau_p) & \cdots & \omega_{1j}(\tau_p) & \cdots & \omega_{1V}(\tau_p) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \omega_{s1}(\tau_p) & \omega_{s2}(\tau_p) & \cdots & \omega_{sj}(\tau_p) & \cdots & \omega_{sV}(\tau_p) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \omega_{S1}(\tau_p) & \omega_{S2}(\tau_p) & \cdots & \omega_{Sj}(\tau_p) & \cdots & \omega_{SV}(\tau_p) \end{matrix} \right\|, \tag{16}$$

where $\sum_{j\in V} w_{sj}(\tau_p) = 1;\ w_{sj}(\tau_p) = P\{g(\tau_p) \in j/T_S\}, s \in S$ is transition probability of transition S-th trajectory in j-th state in prediction interval.

Multiplying matrices (15) and (16), we obtain the matrix-line of probabilities $|Q(j,\tau_p)|,\ j = 1{,}2$ at the output of the enlarged prediction operation:

$$\left|Q(j,\tau_p)\right| = |P_{out}^{T}|\,\left|W_{trs}^{p}\right| = \left\|Q(1,\tau_p)Q(2,\tau_p)\right\|. \tag{17}$$

Let's consider the probabilistic characteristics of PrC. For example, the probability of obtaining a "suitable" result is based on the formula:

$$Q(\tau_p) = Q(1,\tau_p) = \sum_{l\in L}\sum_{S\in R} P_l P_{lS} P_{Si}(\tau_p), \tag{18}$$

where $R = \{g_a \in \rho, g_b \in \rho, \ldots\ g_w \in \rho\}$.

The considered mathematical model of PrC in the form of a system of matrices describing the probabilistic characteristics of sequentially performed control operations essentially represents a Markov model. In this model, the "non-Markovity" of the dependencies of the future values of the parameter (the predicted value of the parameter in general depends not only on its TS at the present moment, but also on a number of states at past moments of time) is artificially eliminated by introducing into the model probabilistic characteristics of the trajectory of values changes controlled parameter. This introduction made it possible to simplify the calculation of PrC veracity indicators, and using the generalized mathematical model of object classification [20], to link the characteristics of RC and PrC.

Let's consider the characteristics of the decision veracity at the predictive control of the serviceability of according to the controlled parameter.

During serviceability control, the RC means distinguishes a set of states of the controlled parameter, which consists of a subset ρ of serviceable states and a subset μ of non-serviceable states, ($\rho \cap \mu = \emptyset$), $\rho + \mu = M$. There are such subsets of trajectories $M, R \in S$ that pass only through subsets of states ρ of DP. Trajectories are characterized by their own probabilities $P_M = P(T_M)$ and $P_R = P(T_R)$ of existence. The change in the parameters of the same type of objects set in the considered time interval $[\tau_p, \tau_k + \tau_{use}]$ is described by the random process $\xi(\tau)$, which determines, in particular, the probability of suitable $\mathrm{P}[Decision(\tau_p)]$ and unsuitable $\mathrm{P}[\overline{Decision}(\tau_p)]$ object states in the prediction interval τ_p.

Let's determine the characteristics of the decision-making veracity for the next decisive rule of the RC, which is identical to the rule most common in the practice of product serviceability control [20]:

$$\begin{gathered} \xi(\tau_p) \in \rho, \text{ if } g(\tau_p) \in \Omega(\tau_p), j = 1 \text{ – decision "Suitable"}, \\ \xi(\tau_p) \overline{\in} \rho, \text{ if } g(\tau_p) \overline{\in} \Omega(\tau_p), j = 2 \text{ – decision "Unsuitable"}. \end{gathered} \tag{19}$$

The most common is the PrC algorithm, in which the product, recognized as unsuitable according to the RC results, is not subject to prediction and is excluded from the RC process. The exclusion criterion is the fulfillment of the condition $T_S \overline{\in} \rho$.

In accordance with the total probability formula [24], we replace the probability $P(\tau_p)$ with the sum of probabilities $P_l^{\rho}p(\tau_p)$, each of which represents the probability of the coexistence of trajectories and the passage of its continuation in the prediction interval τ_p through the subset of the states ρ :

$$P(\tau_p) = \sum_{l\in L} P_L^{\rho}(\tau_p), \tag{20}$$

where $P_L^{\rho}(\tau_p) = P\{T_l;\ \xi(\tau_p)\ \in \rho\}$.

Similarly replace

$$\bar{P}(\tau_p) = \sum_{l\in L} P_L^{\mu}(\tau_p), \tag{21}$$

where $P_L^{\mu}(\tau_p) = P\{T_l;\ \xi(\tau_p)\ \in \mu\}$.

Thus, $P_L^{\rho}(\tau_p) +\ P_L^{\mu}(\tau_p) = P_L$.

With this replacement, the probability of existence of each true trajectory is divided into 2 parts. One part characterizes the potential possibility for the continuation of the trajectory $T_l, l\ =\ \overline{1, M}$ to end up in a serviceable state, the second – in a non-serviceable state in the prediction interval. As a result, two new matrices can be formed, the elements of which are functions of the argument τ_p:

$$|\ P_L^{\rho}(\tau_p)| =\ \|P_1^{\rho}(\tau_p)P_2^{\rho}(\tau_p)\ \dots\ P_l^{\rho}(\tau_p)\ \dots\ P_L^{\rho}(\tau_p)\|; \tag{22}$$

$$|\ P_L^{\mu}(\tau_p)| =\ \|P_1^{\mu}(\tau_p)P_2^{\mu}(\tau_p)\ \dots\ P_l^{\mu}(\tau_p)\ \dots\ P_L^{\mu}(\tau_p)\|. \tag{23}$$

Some l-th trajectory, $T_l \in \rho$, to which the probabilities $P_L^{\rho}(\tau_p)$ correspond, due to the errors of the RC operation, may be mistakenly accepted by the RC product as the S-th trajectory of the observation results, and will be excluded from RC. This leads to the manufacturer's risk $\mathrm{A}^{(\mathrm{T})}(\tau_p)$ at PrC caused by RC errors

$$\mathrm{A}^{(\mathrm{T})}(\tau_p)\ =\ P\{T_S \,\overline{\in}\, R;\ \xi(\tau_p) \in\ \rho\}\ =\ \sum_{S\in S/R} P_l^{\rho}\, P_{ls}\,; \tag{24}$$

$$\alpha^{(\mathrm{T})}(\tau_p) = P\{T_S \,\overline{\in}\, R/\xi(\tau_p) \in \rho\} = \mathrm{A}^{(\mathrm{T})}(\tau_p)/P(\tau_p) = \mathrm{A}^{(\mathrm{T})}(\tau_p)/\sum_{l\in L} P_l^{\rho}\,(\tau_p)\,. \tag{25}$$

On the other hand, l-th trajectory, T_l, to which the probability $P_l^{\mu}(\tau_p)$ corresponds, can be mistakenly accepted by the CC product as the S-th trajectory, T_S, which leads to the customer's risk $B(\tau_p)$ at PrC due to RC errors

$$B^{(\mathrm{T})}(\tau_p) = P\{T_S \in R;\ \xi(\tau_p) \in \mu\} = \sum_{l\in L}\sum_{s\in R} P_l^{\rho}\,(\tau_p)P_{ls}\,; \tag{26}$$

$$\beta^{(\mathrm{T})}(\tau_p) = P\{T_S \in R/\xi(\tau_p) \in \mu\} = B^{(\mathrm{T})}(\tau_p)/\bar{P}(\tau_p) = B^{(\mathrm{T})}(\tau_p)/\sum_{l\in L} P_l^{\mu}\tau_p). \tag{27}$$

Similarly, the components of the probabilities $\gamma^{(\mathrm{T})}(\tau_p)$, $\delta^{(\mathrm{T})}(\tau_p)$ are found, which characterize the part of correct decisions in the PrC of serviceable and no serviceable products according to the DP, respectively, in the prediction interval τ_p

$$\gamma^{(\mathrm{T})}(\tau_p) = P\{T_S \in R;\ \xi(\tau_p) \in \rho\} = \sum_{l\in L}\sum_{s\in R} P_l^{\rho}\,(\tau_p)P_{ls}\,; \tag{28}$$

$$\delta^{(\mathrm{T})}(\tau_p) = P\{T_S \,\overline{\in}\, R;\ \xi(\tau_p) \in \mu\} = \sum_{l\in L}\sum_{s\in S} P_l^{\mu}\tau_p)P_{ls}. \tag{29}$$

On the one hand, some l-th trajectory, $T_l \in \rho$, to which the probability $P_l^{\rho}\,(\tau_p)$ corresponds, accepted by the RC as S-th trajectory of the results of observations, $T_S \in M$, may be falsely rejected due to errors of the prediction operation. This leads to the manufacturer's risk $A^p(\tau_p)$, due to the errors of the prediction operation at RC. By analogy with (24), we have:

$$A^p(\tau_p) = P\begin{Bmatrix} g(\tau_p) \in j = 2; \\ T_S\ \in M;\ \xi(\tau_p)\ \in\ \rho \end{Bmatrix} = \sum_{l\in L}\sum_{s\in R}\sum_{j=\frac{V}{v}} P_l^{\mu}(\tau_p)\, P_{lS}P_{sj}(\tau_p). \tag{30}$$

On the other hand, some l-th trajectory, $T_l \in M$, to which the probability $P_l^{\mu}(\tau_p)$ corresponds, accepted by the RC product as the S-th trajectory of the observation results, $T_S \in R$, due to the errors of the prediction operation, can be rejected with probability $\delta(\tau_p)$. By analogy with (29), we have:

$$\sigma_p(\tau_p) = P\begin{Bmatrix} g(\tau_p) \in j = 1; \\ T_S\ \in R;\ \xi(\tau_p)\ \in\ \mu \end{Bmatrix} = \sum_{l\in L}\sum_{s\in R}\sum_{j=\frac{V}{v}} P_l^{\mu}(\tau_p)P_{lS}P_{sj}(\tau_p). \tag{31}$$

Graphically, the operation of forming a decision at PrC in accordance with [20], Figure 1 and taking into account the above mentioned is presented in the form of the probability graph in Figure 2.

The graph uses the following notations:

1) $\alpha^{(p)}(\tau_p) = P(g(\tau_p) \bar{\in} \rho \,/\, T_S \in R)$ is the conditional probability of recognizing a suitable product as unsuitable based on the results of the PrC, due to the errors of the prediction operation - the probability of an error of the first kind, due to the errors of the prediction operation.

2) $\beta^{(p)}(\tau_p) = P(g(\tau_p) \in \rho \,/\, T_S \bar{\in} R)$ is the conditional probability of recognizing an unsuitable product as suitable based on the results of the PrC, due to the errors of the prediction operation – the probability of an error of the second kind, due to the errors of the prediction operation.

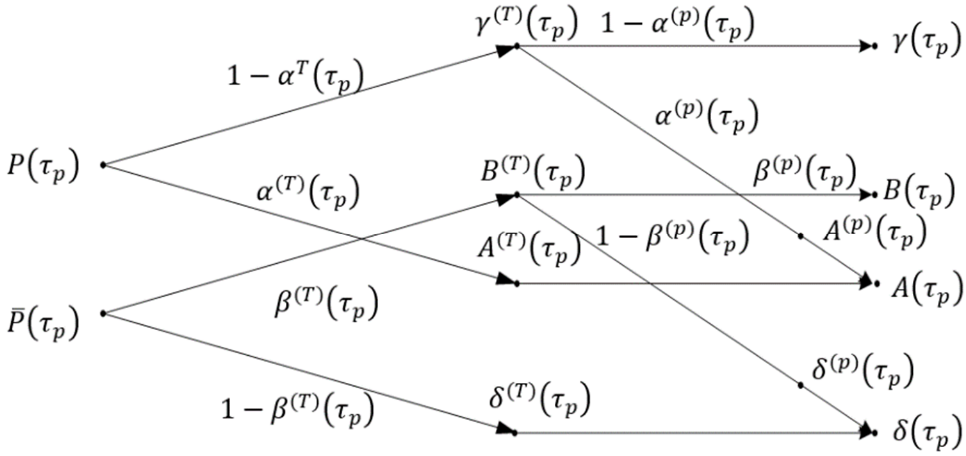

Figure 2: Graph of decision-making during RC taking into account the possible probabilities of making erroneous decisions.

Characteristics of the solutions veracity at the RC of the serviceability products, taking into account the accepted designations and in correlation with Figure 2 are in the following relationship:

$$\begin{aligned} A(\tau_p) &= A^T(\tau_k) + A^p(\tau_p); \\ B(\tau_p) &= B^T(\tau_k) - \delta^p(\tau_k); \\ \gamma(\tau_p) &= \gamma^T(\tau_k) - A^p(\tau_p); \\ \delta(\tau_p) &= \delta^T(\tau_k) + \delta^p(\tau_p). \end{aligned} \tag{32}$$

Substituting (20), (21), (24), (26), (28), (29) into formula (32) we get:

$$A(\tau_p) = \sum_{l=1}^{L}\sum_{s\in\delta} P_l^{\rho}(\tau_p)P_{ls} + \sum_{l\in L}\sum_{s\in R}\sum_{j=\frac{V}{v}} P_l^{\rho}(\tau_p)\,P_{ls}P_{sj}(\tau_p); \tag{33}$$

$$B(\tau_p) = \sum_{l\in L}\sum_{s\in R}\sum_{j=v} P_l^{\mu}(\tau_p)\,P_{ls}P_{sj}(\tau_p); \tag{34}$$

$$\alpha(\tau_p) = \sum_{l=1}^{L}\sum_{s\in R}\sum_{j\in\vartheta v} P_l^{\rho}(\tau_p)P_{ls}P_{sj}(\tau_p); \tag{35}$$

$$\delta(\tau_p) = \sum_{l=1}^{L}\sum_{s\in\frac{S}{R}} P_l^{\mu}(\tau_p)P_{ls} + \sum_{l=1}^{L}\sum_{s\in R}\sum_{j=\frac{V}{v}} P_l^{\mu}(\tau_p)P_{ls}P_{sj}(\tau_p). \tag{36}$$

Figure 2 and formula (32) shows that the effect of RC operations with this RC algorithm affects to subtraction a part that equal to $\delta(\tau_p)$ from the risk component $B^T(\tau_k)$, the addition of a part, that equal to $A^p(\tau_p)$ to the manufacturer's risk component $A^T(\tau_k)$. As a result, the total risk of the manufacturer $A(\tau_p)$ increases, and the risk of the customer $B(\tau_p)$ decreases in comparison with similar components caused by errors of RC operations.

4. Conclusions

While operating navigation equipment we can observe failures. This causes the equipment inoperable and gives rise to risks concerning the integrity of navigation systems and flight safety. To mitigate these risks and minimize associated costs, it is essential to address issues related to increasing reliability and operational efficiency. Key methods for resolving these challenges include implementing various forms of redundancy, developing and applying intelligent data processing technologies, establishing decision-making frameworks for corrective and preventive actions, synthesizing techniques for prediction of equipment's technical state, and creating algorithms and methods for diagnostics, and others. Prediction emerges as the effective strategy for reducing the risks of equipment failure. This approach relies on estimating future values of DPs and implementing control measures to prevent these values from exceeding specified tolerances. When synthesizing and analyzing prediction algorithms, it is advisable to determine efficiency indicators, such as the veracity of predictive control.

The paper is devoted to the study of issues related to the features of the application of predictive control and estimation of the veracity of decision-making as a result of prediction. At the same time, mathematical equations are given that characterize the process of classifying the technical state during prediction and further estimation of the veracity of decision-making.

The results of the research can be used for the development and modernization of systems for the operation of navigation devices.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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