DOI: 10.17587/mau.23.496-503

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Accepted on June 14, 2022

Planning of a Group of Dynamic Systems Operation Program Based on the Failure Time Prediction

Abstract

The article is devoted to the justification of group of dynamic systems (DS) operation program based on the failure time prediction. The following assumptions are made: the group includes DS operating under the same conditions, but having different service life; the composition of the DS includes a number of potentially faulty elements with similar values of reliability indicators; for each element a number of parameters are measured and the failure of the DS occurs when at least one of the controlled parameters leaves the tolerance range. The use of a piecewise linear regression model of parameter drift corresponding to the life cycle of DS is justified. The rule of correction of the linear model is formed based on the results of last measurements of the controlled parameters. A unified algorithm for calculating the reliability characteristics in a group of DS based on the drift of controlled parameters is proposed. At the first step, the probability of failure-free operation for a given time and a gamma-percent resource is calculated for one controlled parameter. At the second step, the time moment of a DS failure (which is assumed to happen when at least one controlled parameter leaves the tolerance range) is calculated. At the third step, the reliability characteristics of a group of DS are predicted using a mixture of distributions. The realization of a random variable corresponding to a random mixture is modeled as follows: first, DS is selected at random, then a random variable is modeled in accordance with its distribution function. The mixture distribution function is expressed as a weighted sum of the component distribution functions. Model examples allowing to rank the considered DS according to the predicted failure time with subsequent adjustment of the operation program are considered.

Keywords: *technical condition forecast, parameter drift, regression model, gamma-percent resource*

Acknowlegements: The research was carried out at the expense of a grant from the Russian Science Foundation No. 22-29-00708

For citation:

Buryak Yu. I., **Skrynnikov A. A.**, **Khrulin S. V.**, **Shaginova E. S.** Planning of a Group of Dynamic Systems Operation Program Based on the Failure Time Prediction, *Mekhatronika, Avtomatizatsiya, Upravlenie*, 2022, vol. 23, no. 9, pp. 496—503.

DOI: 10.17587/mau.23.496-503

УДК 519.718

DOI: 10.17587/mau.23.496-503

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Планирование программы эксплуатации группы динамических систем на основе прогнозирования времени отказа

Статья посвящена обоснованию программы эксплуатации группы динамических систем (ДС) на основе прогноза времени их отказа.

Принимаются следующие допущения: группа включает ДС, функционирующие в одинаковых условиях, но имеющие разные сроки эксплуатации; в состав ДС входит ряд потенциально отказных элементов с близкими значениями показателей безотказности; для каждого элемента проводятся измерения ряда параметров, причем отказ ДС наступает в случае, когда хотя бы один из контролируемых параметров выйдет из поля допуска.

Предложен единый алгоритм расчета характеристик безотказности в группе ДС по данным дрейфа контролируемых параметров. На первом шаге проводится расчет вероятности безотказной работы в течение заданного времени и гамма-процентного ресурса применительно к одному контролируемому параметру. На втором шаге рассчитывается отказ ДС при условии выхода из поля допуска хотя бы одного контролируемого параметра. На третьем шаге проводится прогноз характеристик безотказности группы ДС с использованием смеси распределений. Реализация случайной величины, соответствующей случайной смеси, моделируется следующим образом: сначала наугад выбирается ДС, затем в соответствии с ее функцией распределения моделируется случайная величина. Функция распределения смеси выражается в виде взвешенной суммы функций распределения компонент.

Рассмотрены модельные примеры, позволяющие ранжировать рассматриваемые ДС по прогнозируемому времени отказа с последующей корректировкой программы эксплуатации.

***Ключевые слова:** прогноз технического состояния, дрейф параметров, регрессионная модель, гамма-процентный ресурс*

Introduction

To ensure the safe operation of a group of homogeneous dynamic systems (DS), it is necessary to organize the entire complex of necessary technological operations, including planning their logistics.

The complexity of planning the operation program of the DS group is due to the following circumstances [1]:

— the composition of the DS includes a known set of potentially faulty elements with similar values of reliability indicators;

— the DS that make up the group have different values of the commissioning time, i.e. different operating periods.

The existing approach to the planning of the DS operation program is based on periodic measurements of the controlled parameters of the elements that can be faulty, and forecasting the drift (degradation) of the parameter to the next control point. The element must be replaced if the predicted value of the parameter exceeds the permissible values. The obvious disadvantage of this approach is the need to organize an excess stock of spare parts for all elements; the need to minimize it requires solving the problem of predicting the moment of failure.

For practical purposes of engineering prediction of parameters degradation, the following models are most often used:

— statistical (regression, autoregression, exponential smoothing, etc.);

— structural (neural networks, Markov chains, classification trees, etc.).

Within the framework of the proposed classification, we will consider a number of works related to the field of operation of technical systems. First of all, it should be noted that the methodological aspects of the problem under consideration, including: the basic definitions related to forecasting, methods of modeling failure and the corresponding criteria for the occurrence of failure, as well as methods for assessing the residual life of machine components are deeply elaborated in regulatory documents [2, 3]. In particular, the document [3] offers a mathematical description of a technical condition parameter change process, assuming the monotonous nature of its deterioration

In a number of works, the structure of time series describing the operational parameters of industrial facilities is analyzed, and their stationarity, predictability and irregularity are considered as criteria for the predictability of time series [4, 5]

Quite interesting results on the comparative analysis of the features and functionality of several methods for predicting changes in a vehicle and estimating the residual life of marine power-mechanical equipment (statistical forecasting method, extrapolation method) when choosing the scope of their application were obtained in [6].

In [7], when studying the problem of forecasting the technical condition of radio-electronic equipment in real operating conditions, the choice of an analytical forecasting method using a set of trend models that requires less statistical data on changes in parameter values while ensuring equal reliability of the forecast is justified.

In [8, 9], a new method for predicting the probability density of a random process based on a shortened data set is mathematically justified and an algorithm for obtaining an optimal density estimation by the criterion of forecast accuracy is developed.

In [10], to provide operational solutions for the management of an object, an algorithm is proposed for predicting its technical condition, which is described by a set of indicators represented as a time series scheme. An adequate mathematical model is constructed using adaptive regression modeling. The predicted values of the indicators are analyzed by fuzzy logic methods, and the predicted state of the object is output in the form of a fuzzy term.

To solve the problem of predicting the time drift of critical parameters of on-board equipment, which is characterized by significant uncertainty and incompleteness of information, a hybrid approach has been developed in [11]. The integrated use of artificial intelligence tools and spline approximation makes it possible to obtain estimates with an accuracy acceptable for practical use.

Quite a lot of publications are devoted to the study of systems [12, 13] including degradation processes of constituent elements, which can be functionally interconnected or related to different subsystems (executive, measuring, etc.). The results obtained suggest, basically, a significant simplification of the incoming processes, or the use of complex modeling complexes.

Without pretending at all to the completeness of the analysis, we can however conclude that single-mode processes with variable load intensity were mainly considered in the literature before. In this case, in order to increase the accuracy of the results obtained, the necessity of complicating the applied mathematical apparatus is justified. At the same time, much less attention is paid to the practical application of more complex models to improve the prediction of the state in a group of homogeneous technical systems in a complex life cycle (multi-mode load), where the parameters of their components are monitored.

In this paper, methodological issues of planning the operation program of a group of DS are developed based on the forecast of the expected failure time, and the DS of the group are in a complex life cycle and have different operating times.

Problem statement

We consider a set of DS, which we will denote by S. Each DS includes n elements. Each element has a set of measured parameters. The number of measured parameters of the element number $1 \leqslant j \leqslant n$ depends on j and will be denoted by l_j. For the k-th measured parameter of the j-th element, $1 \leqslant k \leqslant l_j$, there is a limit value, which we will denote by $\max_{jk}$. When the parameter value exceeds the limit value, the element is considered faulty. For each DS $a \in S$, a set of time points is a set $T_a = (t_1, ..., t_{N(a)})$ at which the parameter values were measured. The value of the k-th parameter, of j-th element of the DS at a time t_i we will denote by $v_a(t_i, j, k)$. Based on the values $v_a(t_i, j, k)$ the function $\Gamma_{a,j,k}(\gamma)$, $0 \leqslant \gamma \leqslant 1$, called the gamma-percent resource, is constructed, the value of which is equal to such a number $t \geqslant 0$ that the probability that during the time t the value of the k-th parameter of the j-th the element of the DS $a \in S$ will not exceed the permissible limit is equal to γ. Denote by $\xi_{a,j,k}(t)$, $t \geqslant 0$, the inverse function, that is, $\xi_{a,j,k}(t)$ is equal to the probability that the k-th parameter of the j-th element of the DS will not exceed the permissible limit during the time t. We assume that the operating time before going beyond the permissible limit for this parameter is a random variable, and for various a, j, k the resulting random variables are independent. Thus, the number

$$\xi_a(t) = \prod_{1 \leqslant j \leqslant n} \prod_{1 \leqslant k \leqslant l_j} \xi_{a,j,k}(t)$$

is equal to the probability that all elements of the DS $a \in S$ will be serviceable during the time t. The gamma-percent resource of the DS $a \in S$ is given by the function $\Gamma_a(\gamma)$ that is equal to the inverse to the function $\xi_a(t)$. With a given probability value γ, the function $\Gamma_a(\gamma)$ allows one to rank the DS of the group by the time of operation to failure. The gamma-percent resource $\Gamma_a(\gamma)$ of the entire DS group is calculated as the function inverse to the function

$$\xi(t) = \prod_{a \in S} \xi_a(t).$$

The law of distribution of the time when controlled parameter reaches the limit value

Let's consider the solution of this problem in the example of the operation of a group of aircrafts (AC) as typical representatives of the DS. During the operation of aircraft, the values of the controlled parameters of the elements are measured at a specified frequency and their compliance with the requirements is assessed [14]. The initial moment of time corresponds to the moment of putting the aircraft into operation, therefore, regardless of the calendar time, the control time points can be designated t_1, ..., t_n.

Consider the i-th controlled parameter. The value X_{ij} — the value of the i-th controlled parameter at a time t_j — is a random value, its implementation will be denoted as x_{ij}. Thus, according to the n measurement results, there are data x_{ij}, $j = \overline{1, n}$.

Assuming a constant wear rate, we will adopt a piecewise linear model [1] for approximating the controlled parameters as part of a subset of linear sections and transition conditions between them. Let's assume that at the initial moment of time for the linear section of the parameter drift process the drift value is zero.

Then, to describe the drift of the i-th parameter of the aircraft under consideration, one can use a linear regression model

$$X_{ij} = \beta_{1i} t_j + \varepsilon_{ij}$$

where β_{1i} is a parameter of the model; ε_{ij} are random errors having mathematical expectation $M[\varepsilon_{ij}] = 0$ and variance $D[\varepsilon_{ij}] = \sigma_i^2$; values ε_{ik} and ε_{il} for $k \neq l$ are uncorrelated [14—21]. The direct line $\beta_{1i} t_j$ determines the expected value of the i-th controlled parameter X_i at a time t_j, i.e.

$$M[X_{ij}] = \beta_{1i} t_j. \tag{1}$$

Using the least squares method, we find an expression for estimate β_{1i}^* of the parameter β_{1i}:

$$\beta_{1i}^* = \frac{\sum_{j=1}^{n} x_{ij} t_j}{\sum_{j=1}^{n} t_j^2}. \tag{2}$$

Since the parameter β_{1i} estimates a function of random variables X_{i1}, X_{i2}, ..., X_{in}, then it is itself a random variable. Then the estimate β_{1i}^* obtained by formula (2) for realizations x_{ij} is the realization of a random variable B_{1i}. Since the parameter β_{1i} estimate is a linear combination of observations x_{ij}, it is easy to find its mathematical expectation. Let us use the theorems on numerical characteristics [22] and, taking into account (1), we obtain:

$$M[B_{1i}] = M\left[\frac{\sum_{j=1}^{n} X_{ij} t_j}{\sum_{j=1}^{n} t_j^2}\right] = \frac{1}{\sum_{j=1}^{n} t_j^2} M\left[\sum_{j=1}^{n} X_{ij} t_j\right] =$$

$$= \frac{\sum_{j=1}^{n} M[X_{ij}] t_j}{\sum_{j=1}^{n} t_j^2} = \frac{\sum_{j=1}^{n} \beta_{1i} t_j^2}{\sum_{j=1}^{n} t_j^2} = \beta_{1i} \frac{\sum_{j=1}^{n} t_j^2}{\sum_{j=1}^{n} t_j^2} = \beta_{1i},$$

that is, the parameter β_{1i} estimate is unbiased

$$M[B_{1i}] = \beta_{1i} \tag{3}$$

where β_{1i} — is the true, unknown to us value of the parameter. Similarly, we find the variance of the parameter β_{1i} estimate:

$$D[B_{1i}] = D\left[\frac{\sum_{j=1}^{n} X_{ij} t_j}{\sum_{j=1}^{n} t_j^2}\right] = \frac{1}{\left(\sum_{j=1}^{n} t_j^2\right)^2} D\left[\sum_{j=1}^{n} X_{ij} t_j\right] =$$

$$= \frac{1}{\left(\sum_{j=1}^{n} t_j^2\right)^2} \sum_{j=1}^{n} D[X_{ij} t_j] = \frac{\sum_{j=1}^{n} t_j^2 D[X_{ij}]}{\left(\sum_{j=1}^{n} t_j^2\right)^2} = \frac{D[X_{ij}]}{\sum_{j=1}^{n} t_j^2}.$$

But $D[X_{ij}] = D[\varepsilon_{ij}]$, where $\varepsilon_{ij} = X_{ij} - \beta_{1i}^* t_j$. The variance $D[\varepsilon_{ij}]$ estimate is determined by the formula

$$D^*[\varepsilon_{ij}] = \frac{1}{n-1} \sum_{j=1}^{n} (x_{ij} - \beta_{1i}^* t_j)^2. \tag{4}$$

In the denominator of expression (4), the number of degrees of freedom is equal to the difference between the sample size and the number of parameters estimated from the sample (in this case, there is only one parameter, it is β_{1i}). Then estimate of the variance B_{1i} of a random variable is defined by the expression

$$D^*[B_{1i}] = \frac{\sum_{j=1}^{n} (x_{ij} - \beta_{1i}^* t_j)^2}{(n-1)\sum_{j=1}^{m} t_j^2}. \tag{5}$$

Thus, the estimation β_{1i}^* of the parameter β_{1i} of the linear regression model (1) is the realization of a normally distributed random variable B_{1i} with numerical characteristics $m_{1i} = \beta_{1i}$ and $\sigma_{1i} = \sqrt{D[B_{1i}]}$.

The parameter β_{1i} estimate obtained from the control results is a random variable B_{1i} with the distribution density

$$f(b_{1i}) = \frac{1}{\sqrt{2\pi}\sigma_{1i}} \exp\left\{-\frac{(b_{1i} - m_{1i})^2}{2\sigma_{1i}^2}\right\} \tag{6}$$

where $m_{1i} = \beta_{1i}$ (true, unknown value to us), but $\sigma_{1i} = \sqrt{D[B_{1i}]}$. I.e. the distribution law of the estimate β_{1i}^* depends on the unknown parameter β_{1i} itself. To construct the estimation β_{1i}^* distribution law, we use the following approximate technique [22]: replace in the expression $f(b_{1i})$ the unknown parameters m_{1i} and σ_{1i} by their point estimates $m_{1i} = \beta_{1i}^*$ and $\sigma_{1i} = \sqrt{D^*[B_{1i}]}$, calculated by formulas (2) and (5), respectively.

Now let's find the law of time distribution T_i — the time when the i-th controlled parameter reaches the limit value $x_{\lim i}$. It can be defined as the distribution law of the function of a random argument [22].

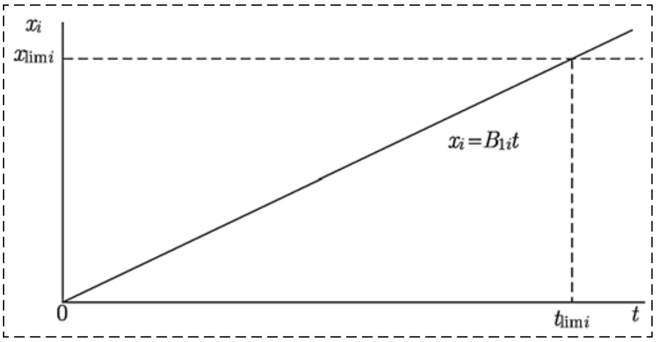

Fig. 1. Scheme for determining the time $t_{\lim i}$ when the parameter reaches the limit value

Denote $x_{\lim i} = \varphi(B_{1i}) = B_{1i}t$ (see Fig. 1), then the inverse function $\psi(t) = B_{1i} = x_{\lim i}/t$. The probability density $g_i(t)$ is determined by the formula

$$g_i(t) = f(\psi(t))\left|\psi'(t)\right|.$$

The derivative $\psi'(t_{\lim i})$ is equal to

$$\frac{d\psi(t)}{dt} = -\frac{x_{\lim i}}{t^2}$$

and the absolute value of the derivative is

$$\left|\psi'(t)\right| = \frac{x_{\lim i}}{t^2}.$$

Then

$$g_i(t) = \frac{1}{\sqrt{2\pi}\sigma_{1i}} \exp\left\{-\frac{\left(\frac{x_{\lim i}}{t} - m_{1i}\right)^2}{2\sigma_{1i}^2}\right\} \frac{x_{\lim i}}{t^2}. \quad (7)$$

The integral distribution function $G_i(t)$ has the form

$$G_i(t) = 1 - \Phi^*\left(\frac{x_{\lim i}}{\sigma_{1i}t} - \frac{m_{1i}}{\sigma_{1i}}\right), \quad (8)$$

where $\Phi^*(\cdot)$ is the distribution function of a standard normally distributed random variable:

$$\Phi^*(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z} e^{-\frac{1}{2}t^2} dt.$$

Expressions (7), (8) can be applied for the case when the range of practically possible values of a random variable B_{1i} is greater than zero.

The type of distribution density $g_i(t)$ and distribution function $G_i(t)$ graphs is shown in Fig. 2. As it can be seen from the figures, the distribution $g_i(t)$ has a positive coefficient of asymmetry.

The forecast of the time when a separate parameter reaches its limit value

The distribution function $G_i(t)$ determines the probability that the i-th parameter will leave the tolerance range during the time t, i.e.

$$P(T_i < t) = G_i(t).$$

From (8) it is possible to obtain an expression for calculating the gamma-percent resource, i.e. the value of the total operating time during which the

Fig. 2. Distribution density $g_i(t)$ (*a*); distribution function $G_i(t)$ calculated for the following parameter values: m_{1i} = 0,5; σ_{1i} = 0,1; $x_{\lim i}$ = 10 (*b*)

i-th parameter does not reach the limit state with a probability γ expressed as a percentage:

$$t_{\gamma i} = \frac{x_{\lim i}}{m_{1i} + \arg\Phi^*(1-\gamma)\sigma_{1i}},$$

where $\arg\Phi^*(\cdot)$ is the inverse function of the normal distribution function $\Phi^*(\cdot)$.

So, for example, with the values of the parameters for which the distribution function $G_i(t)$ is constructed in Fig. 2, the gamma-percent resource for various probability γ values is: $t_{0,8} = 17{,}12$; $t_{0,9} = 15{,}92$, $t_{0,95} = 15{,}05$ units of time.

In the absence of sharp outliers, with an increase in the number of observations of an individual object, the variance of the estimate of the time when the i-th controlled parameter reaches the limit value decreases. An illustration of this is the result of calculations of the distribution density $g(t_{\lim i})$ carried out sequentially in 5, 6 and 7 measurements (Fig. 3).

In the conditions of a multimode model of aircraft operation, there may be an effect of changes in the intensity of wear on the amount of time for a separate parameter to reach its limit value. To verify this assumption, it is necessary to determine the significance of the difference in the estimate β^*_{1i} when using all **n** data ($\mathbf{X}_{i1}$, ..., $\mathbf{X}_{in}$) measurements and β^{**}_{1i} for **k** last $\mathbf{X}_{i,n-k}$, ..., $\mathbf{X}_{in}$.

We formulate the main H_0 and alternative H_1 statistical hypotheses H_0: H_1: $\beta^*_{1i} \neq \beta^{**}_{1i}$. The solution of the problem of the equality of the mathematical expectation of two samples is well known [23], so we will not present it.

The rule of statistical inference will be formulated as follows:

— if the resulting difference between a pair of implementation numbers does not exceed the significance level, then it can be assumed that the hypothesis H_0: $\beta^*_{1i} = \beta^{**}_{1i}$; is considered not to contradict experimental data and is accepted, and the value of the gamma-percent resource is calculated based on all **n** data ($\mathbf{X}_{i1}$, ..., $\mathbf{X}_{in}$) measurements.

— otherwise, the hypothesis H_1 is accepted: $\beta^*_{1i} \neq \beta^{**}_{1i}$ and the value of the gamma-percent resource is calculated based on the **k** last $\mathbf{X}_{i,n-k}$, ..., $\mathbf{X}_{in}$ measurements.

Forecast of the failure time of the aircraft

When monitoring the aircraft at time points t_j, measurements of m parameter values are made. The limit values $x_{\lim i}$ are known. According to the measurement data x_{ij}, $i = \overline{1,m}$, $j = \overline{1,n}$, for each i-th controlled parameter there are numerical characteristics m_{1i} and σ_{1i}, and knowing them distributions $G_i(t)$ can be found. The AC will fail when at least one of the controlled parameters leaves the tolerance range.

Since $G_i(t)$ determines the probability that the i-th parameter will leave the tolerance range during the time $t_{\lim}$, the probability that the AC will fail is determined by the expression

$$G_c(t) = 1 - \prod_{i=1}^{m}(1 - G_i(t)). \qquad (9)$$

Fig. 4 shows an example of calculations of distribution densities and distribution functions $G_i(t)$ for three controlled parameters, as well as the probability $G_c(t)$ of aircraft failure at the parameter values m_{1i}, σ_{1i}, $x_{\lim i}$ shown in the figure.

The calculation of the gamma-percent resource for the aircraft is associated with the need to solve the equation $G_c(t) = 1 - \gamma$ by an iterative method, where $G_c(t)$ is calculated using the expression (9).

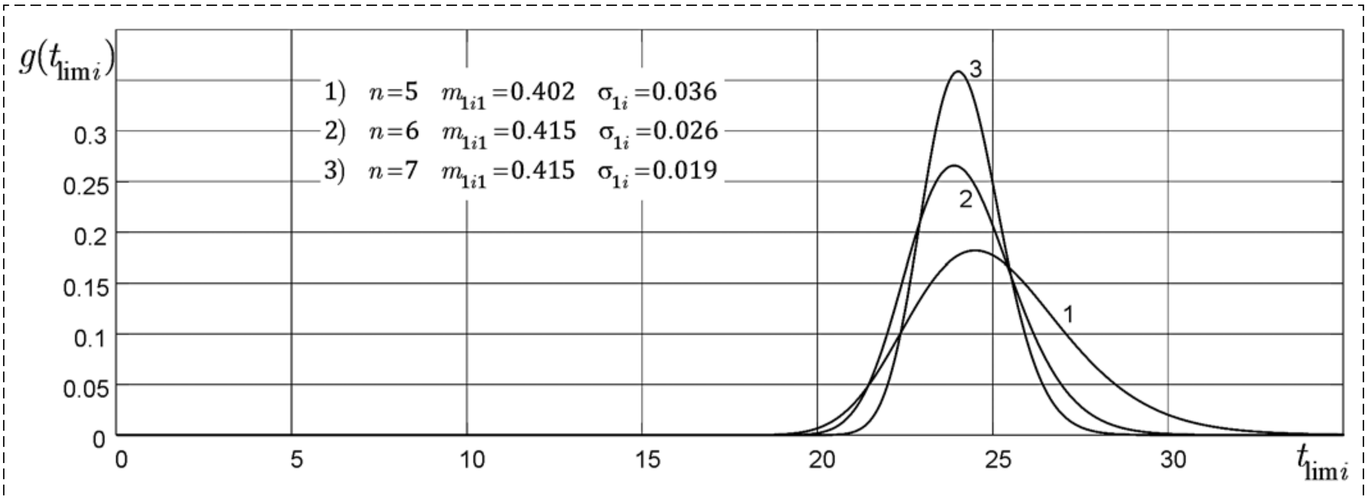

Fig. 3. Example of a change in the distribution density $g(t_{\lim i})$ with an increase in the number of measurements

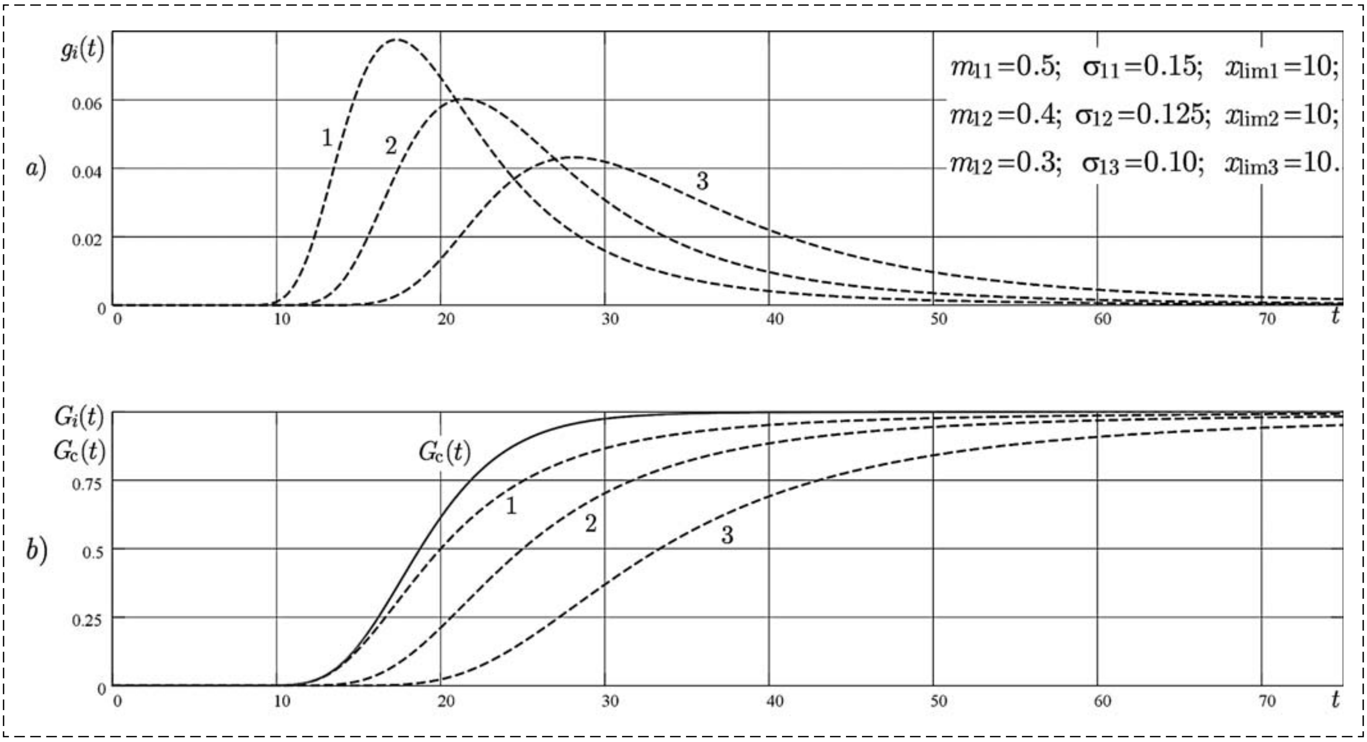

Fig. 4. Distribution density $g_i(t)$ (*a*); distribution functions $G_i(t)$ and $G_c(t)$ (*b*)

Forecast of residual resource characteristics for a group of similar aircrafts

According to the control data of the parameters of the same type of K aircrafts, it is possible to build dependences on the time of the probability of failure of each aircraft $G_{ck}(t)$, where $k = \overline{1, K}$.

The number of measured parameters is the same for all similar aircrafts. But the number of measurements for each aircraft can be different, because the dates of commissioning of the aircrafts are different. Assuming that all other things are equal, the variance of the estimate of the predicted failure time decreases when the number of checks increases.

To predict the reliability characteristics for a series of aircrafts according to their control data, one can use a mixture of distributions. The realization of a random variable corresponding to a random mixture is modeled as follows: first, a random variable is selected at random, then a random variable is modeled in accordance with its distribution function. The distribution function of the mixture is expressed as a weighted sum of the distribution functions of the components, then the dependence on the time of the probability of failure of a randomly taken aircraft from the series has the form:

$$G_{\text{ser}}(t) = \frac{1}{K}\sum_{k=1}^{K} G_{ck}(t). \qquad (10)$$

In this case, in order to find the gamma-percent resource, the equations $G_{\text{ser}}(t) = 1 - \gamma$ must be solved by the iterative method.

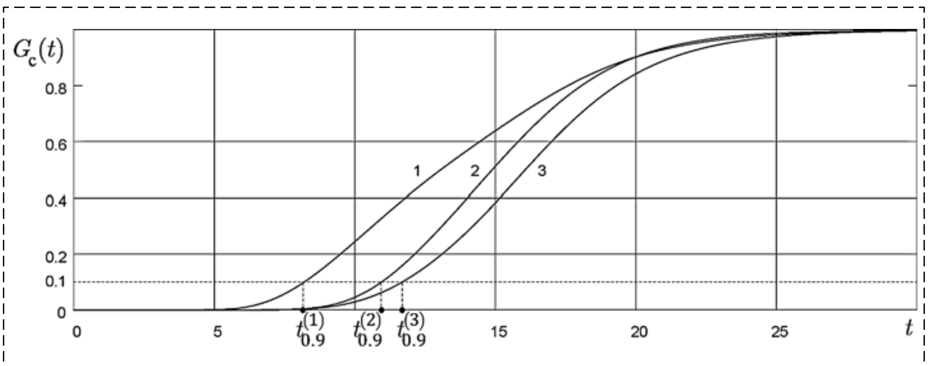

Fig. 5. Scheme for calculating the gamma percentage resource

Fig. 5 shows an example of calculating the value of the gamma-percent resource for three similar AC for $\gamma = 0{,}9$. The results obtained allow us to rank these aircrafts according to the predicted failure time — the least reliable aircraft is AC No. 1, and the most reliable is No. 3.

Ultimately, the results obtained make it possible to make appropriate adjustments to the operation program, providing a given level of readiness necessary to fulfill the objectives of the aircraft group. In terms of retrospective analysis, the developed methods will allow us to form objective assessments of changes in the quality of aircraft production in different time periods.

Conclusion

The article develops methodological issues of planning the operation program of a group of similar aircrafts based on the calculation of their reliability characteristics according to the drift of controlled parameters. It is assumed that the failure of an aircraft occurs when at least one of the controlled parameters leaves the tolerance range. The drift of the parameters is described by a piecewise linear regression model corresponding to the life cycle of the aircraft. The rule of correction of the linear model based on the use of the results of the last measurements is proposed. The methods of calculating the probability of trouble-free operation for a given time and calculating the gamma-percent resource in relation to one controlled parameter, to the aircraft as a whole, as well as to a series of similar aircrafts commissioned at different times are consistently considered. The prediction of the reliability characteristics of the aircraft group is carried out using a mixture of distributions. The mixture distribution function is expressed as a weighted sum of the component distribution functions.

The results obtained can be used in planning the operation of grouping other dynamic systems.

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