Preventive approach to ensuring the operational reliability of aircraft components

L Papic¹, P A Iosifov² and A V Kirillin²*

¹DQM Research Center, P.O. Box 132, 32102, Čačak, Serbia
²Department of Testing and Operation Technology, Moscow Aviation Institute (National Research University), 4 Volokolamskoe highway, 125993, Moscow, Russia

Abstract. The operational safety of technical systems, especially for civil airliners, is largely dependent on the organization of their maintenance. In this case, there are two possible main approaches: service according to the standard, when the information necessary for planning the frequency of service is determined based on the analysis of series of identical products; service according to the actual state, when the state of each specific product is monitored and limit values of parameters set for the product are not exceeded, determining the quality of its functioning, including its reliability and safety. The latter approach is preventive because possible parametric failures are prevented. Using a hypothetical example, the report demonstrates the benefits of transition to condition service, provides limitations and recommendations for using this approach in the maintenance plan creation process.

1. Introduction

The operational reliability of civil airliners systems, the failures of which are associated with consequences for the safety of passengers, economic efficiency of the operation of such systems, influence on the environment, is a priority indicator of their quality [1-3]. This indicator essentially depends on the organization of the maintenance process. The theoretical basis of this process is the section of the theory of reliability: theory of recovery [4]. However, this theory deals mainly with sudden failures, and the information necessary to build models of their occurrence is collected based on the analysis of the functioning of a series of identical products.

With long-term operation of civil airliners, a large group consists of gradual or parametric failures, when degradation-aging processes lead to unacceptable change in parameters that affect the quality of the aircraft system's functioning [5]. In this case, the exit of such parameters beyond the boundaries defined for them is considered as a failure. Algorithms for detecting such anomalies in functioning are described in detail [6,7].

In this case, when planning maintenance, two main approaches are possible: constant period between services calculated according to some indicators averaged for a batch of aircraft components (maintenance according to standard) and variable period determined based on the actual condition of the component (maintenance according to the actual condition), its proximity to the limit value and thus preventing a possible failure. The actual condition of a particular component depends on its lifetime and operating conditions and may differ significantly from average values.

In addition, the measurement of parameters characterizing the actual state of the component, as a rule, is carried out with an error that is an order of magnitude smaller than the spread of values of these
parameters in a batch of components. All this determines the relevance of the transition to maintenance on condition [8-13].

The main point of the report consists in shown the effectiveness of such a transition. The second point is discussing the implementation restrictions on its implementation in servicing technical systems. Now we show the advantages of servicing by the actual state using a hypothetical example.

2. Research methodology and methods

We consider a stochastic process of measuring some parameter \( \{Y_t\} \) in time \( t \geq 0 \). If \( t = 0 \), the parameter is \( Y_0 \), if \( t \geq 0 \), \( Y_t = Y_0 + X_t \), where \( \{X_t\} \) is the really significant stochastic process with the property \( P(x_0 = 0) = 1 \). There is one-dimensional distribution function of the process \( \{Y_t\} \) \( F_t = P(Y_t \leq X) \).

The one-sided confidence area that determines no-failure operation is specified as an upper constraint \( Y_B \). The main characteristic of reliability is the random time before the onset of a gradual failure (parameter goes beyond the permissible range), called the operating time. Initializing a parameter \( Y_0 \) is recovery [3].

For a quantitative assessment of recovery process, it is necessary to have a mathematical model of the dynamics of the parameter \( Y_t \). The difference between servicing by the actual state is that it is not considered ensemble of random functions \( \{Y_t\}_{t=0}^\infty \), but individual implementations \( Y_t \).

Further the dynamics of the parameter \( Y_t \) are described by the simplest linear model:

\[
Y_t = Y_0 + V_t, \quad (1)
\]

where \( Y_t \) is the normally distributed random variable with mathematical expectation \( m_Y = Y_0 + m_v t \) and dispersion \( \sigma_Y^2 = \sigma^2 V_t \).

We consider one-sided feasible area and monotonically increasing realizations of the stochastic process \( \{Y_t\}_{t=0}^\infty \) for \( P(V \geq 0) = 1 \). The probability of failure-free operation is determined by the following ratio:

\[
F(t) = \Phi \left( \frac{Y_B - m_Y}{\sigma_Y} \right), \quad (2)
\]

where \( \Phi \) is the tabulated function of the standard normal distribution of probabilities (with zero mathematical expectation and unit variance), \( Y_B \) is the set limit of parameter change \( Y \), upon reaching which the system is restored.

From (2) taking into account (1), the value of the recovery time follows:

\[
t_B = \frac{Y_B - Y_0}{m_V + \sigma_V U_{R_1}}, \quad (3)
\]

where \( U_{R_1} \) is the quantile of the standard normal distribution for a given probability of no-failure operation \( R_1 \).

The considered approach can be generalized to any parametric aging model, with the main focus being on the identification method for this model.

When identifying the model of the dynamics of the studied system parameters, the situation is often encountered in which the variance of parameter estimates is unknown and it is estimated using the same sample. The models for changing parameters during the operation of systems are mainly empirical [5]. Therefore, the scatter of the estimate is determined not only by random measurement errors, but also by unknown fluctuations of the parameter from the model (theoretical) value. In this case, the task becomes more complicated, since the random variable of the recovery time will not have a normal probability distribution.

We consider in more detail the distribution of random variable \( z = \frac{Y_B - M(\bar{Y}_t)}{\sqrt{D(\bar{Y}_t)}} \), where \( M(\bar{Y}_t) \), \( \sqrt{D(\bar{Y}_t)} = \sigma(\bar{Y}_t) \) are sample estimates of the mathematical expectation and standard deviation of the parameter \( Y \), respectively. We represent the random variable \( z \) in the following form:

\[
z = \frac{Y_B - M(\bar{Y}_t)}{\sigma(\bar{Y}_t)}, \quad (4)
\]
The first term of the numerator is the same as the previous case:

$$\frac{Y_{RJ}-M(Y_{\bar{r}})}{\sigma(Y_{\bar{r}})} = U_{RJ},$$

(5)

The second term is a random variable with a standard normal distribution:

$$\frac{\bar{Y}-M(Y_{\bar{r}})}{\sigma(Y_{\bar{r}})} = U,$$

(6)

The denominator is a random variable $\chi_n^{2}$, where $\chi^2$ is the Pearson distribution, with $(n - m)$ degrees of freedom, where $n$ is the sample size, and $m$ is the number of estimated parameters (in our case, $m = 1$).

As a result, $z$ value has an off-center Student’s $t$-distribution with the off-center parameter $U_{RJ}$.

Using for $n \geq 5$ the normal approximation of the noncentral $t$-distribution [14], we obtain:

$$Pr\{z > k\} = \Phi\left[\frac{U_{RJ} - U}{\sqrt{n-1}} \geq k\right] = \Phi\left[\frac{U - U_{RJ}}{\sqrt{n-1}} < k\right] = Pr\{U - \chi_{k}^{2}/\sqrt{n-1} < U_{RJ}\},$$

(7)

where the random variable $U - \chi_{k}^{2}/\sqrt{n-1}$ has a normal distribution with mathematical expectation $k$ and variance $1 + k^2/(2(n - 1))$.

Therefore, choosing the confidence probability $\gamma$, we get:

$$Pr\{z > k\} = \Phi\left[\frac{U_{RJ} - k}{\sqrt{\frac{k^2}{2(n - 1)}}}\right] = 1 - \gamma,$$

(8)

i.e. $U_{RJ} - k = U_{1-\gamma} \sqrt{1 + \frac{k^2}{2(n - 1)}}$, or, taking into account that $U_{1-\gamma} = -U_{\nu}$, $k = U_{RJ} + U_{1-\gamma} \sqrt{1 + \frac{k^2}{2(n - 1)}}$, we finally have:

$$k = \frac{U_{RJ}}{1 - U_{1-\gamma}^2/2(n - 1)} \pm \frac{U_{RJ} - U_{1-\gamma}^2/2(n - 1)}{\frac{1}{1 - U_{1-\gamma}^2/2(n - 1)}},$$

(9)

The solution is greatly simplified by choosing the confidence probability $\gamma = R_3$:

$$k = \frac{2U_{RJ}^2}{1 - U_{RJ}^2/2(n - 1)}.$$

(10)

3. Results and discussion

We present the results of calculations for various $R_3$. For hypothetical numerical values (as a percentage of the nominal value characterizing wear of some aircraft component):

$$Y_{0} = 3; Y_{50 FH} = 5; Y_{p} = 13; m_{\nu} = 0.04; \sigma_{\nu} = 0.02; \sigma_{[Y_{50 FH}]} = 1,$$

(11)

the results are summarized in the table 1.

**Table 1.** Values of average recovery intervals for a batch of products.

| $R_3$ | 0.9 | 0.95 | 0.99 |
|-------|-----|------|------|
| $U_{RJ}$ | 1.28 | 1.645 | 2.32 |
| $t_{B}$ | 152 | 137 | 116 |

Dispersion $\sigma_{\nu}^2$ is determined by the spread of the parameter values in a batch of products and by the measurement error of this parameter, which is usually about 10 times less than the spread of the measured parameter [15]. In addition, in this case, the parameter is measured $Y_{p}$ with constant variance $\sigma_{\nu}^2$. $\sigma_{\nu} = 0.1$ while keeping the rest of the numeric values. The results of the corresponding calculations are summarized in the table 2.
Table 2. Values of individual recovery intervals for a single item.

| $R_3$ | 0.9  | 0.95 | 0.99 |
|-------|-------|-------|-------|
| $U_{R_3}$ | 1.28  | 1.645 | 2.32 |
| $t_B$ | 247  | 246  | 244  |

In the case of unknown variance and using its sample estimate for $n = 6$, the calculations of the values of the average recovery intervals for a batch of products are summarized in the table 3.

Table 3. Values of individual recovery intervals for a batch of products ($n = 6$).

| $R_3$ | 0.9  | 0.95 | 0.99 |
|-------|-------|-------|-------|
| $k$ | 3.066 | 4.513 | 10.104 |
| $t_B$ | 221  | 204  | 166  |

As follows from the comparison of the tables 1 and 3, the uncertainty in the estimation of variance reduces the effect of the transition to maintenance by state, which puts forward stringent requirements for the accuracy of identification of degradation aging processes during the operation of products.

In the deterministic case ($\sigma^2 = 0$) with a probability equal to 1, the value of the recovery interval will be:

$$t_B = \frac{10^{-3}}{0.04} = 250 \text{ h}, \quad (12)$$

Thus, reducing the uncertainty in the measured values $Y_i$ significantly increases the recovery interval and brings it closer to the maximum limited value. The limitations of the considered approach to maintenance are the normality condition and the linear nature of the measured parameter.

The condition for the normality of the probability distribution law within the tolerance is based on the theory of tolerances, the metrological measurement error also most often has a normal distribution [4].

A stronger limitation is the linearity of the dynamics model. However, this limitation can also be partially removed if we go to a step-by-step algorithm for calculating the duration of the recovery interval during servicing by state with a small time step allowing piecewise linear approximation.

Step 1. The speed $V_1$ defined as $\dot{V}_1 = \frac{Y_1 - Y_0}{\Delta t}$. Assuming constant speed, the predicted value can be calculated in the second step. $\ddot{Y}_2 = Y_1 + \dot{V}_1 \Delta t = 2Y_1 + Y_0$. With the same measurement variance $\sigma_0^2$ of parameter $Y_i$ in the entire range of variation $t \geq 0$, variance of predicted value $\ddot{Y}_2$ will be $\sigma_2^2 = 5\sigma_0^2$.

Step 2. The speed $V_2$ defined as $\dot{V}_2 = \frac{Y_2 - Y_1}{\Delta t}$, the predicted value for the third step will be $\ddot{Y}_3 = 2Y_2 + Y_1$ with constant variance $5\sigma_0^2$.

The calculation is terminated, if the condition is violated:

$$\varphi \left[ \frac{Y_{\theta} - Y_0}{5\sigma_0^2} \right] = R_3,$$  \quad (13)

i.e., when there is an excess $Y_{\theta} + \sqrt{5\sigma_0^2} U_{R_3} > Y_B$, herewith $t_B = n\Delta t$.

The recovery interval for state maintenance can be longer or less than normal. However, the effect of implementing the proposed approach is achieved in both cases:

- in the first case: economic;
- in the second case: increasing the reliability of technical systems by preventing possible failures.

The shown approach of predicting the time of recovery can be complementary to the main prediction methods witch used in aircraft component condition-based maintenance [16-18].

4. Conclusion

The report contains an original approach to determining the recovery time of some aircraft components. This approach allows you to estimate the required recovery time of a component based on current wear
indicators. This technique can be very useful for operators when monitoring the turnaround time of some components, as well as when planning spare parts inventory.

The prospect for the development of this topic consists in the identification of degradation processes in the components in order to clarify the assessment of their current condition.

References
[1] Grishin V M and Ko P M 2009 Optimization of reliability of aircraft control systems with active loaded redundancy. Bull. of the Mosc. Av. Inst. 16(5) 24
[2] Ahmadi R and Fouladirad M 2017 Maintenance planning for a deteriorating production process. Rel. Eng. & Syst. Saf. 159 108 https://doi.org/10.1016/j.ress.2016.11.001
[3] Liu B, Zhao X, Liu G & Liu Y 2020 Life cycle cost analysis considering multiple dependent degradation processes and environmental influence. Rel. Eng. & Syst. Saf. 197 https://doi.org/10.1016/j.ress.2019.106784
[4] Beichelt F and Franken P 1988 Reliability and maintenance. Mathematical approach (Moscow: Radio and communication) p 392
[5] Lisov A A, Chernova T A and Gorbunov M S 2018 Systematic approach to the analysis of degradation processes in electrical devices. Bull. of the Mosc. Av. Inst. 102 23
[6] Zhao W, Zhang Y, Zhu Y and Xu P 2020 Anomaly detection of aircraft lead-acid battery. Qual. and Rel. Eng. Int. 1-12 https://doi.org/10.1002/qre.2789
[7] Li Z, Wang Z, Ren Y, Yang D and Lu X 2020 A novel reliability estimation method of multi-state system based on structure learning algorithm. Maint. and Rel. 22(1) 170 https://doi.org/10.17531/ein.2020.1.20
[8] Hao S, Yang J and Berenguer C 2020 Condition-based maintenance with imperfect inspections for continuous degradation processes. Appl. Math. Mod. 86 311 https://doi.org/10.1016/j.apm.2020.05.013
[9] Chuang C, Ningyun L, Bin J and Yin X 2020 Condition-based maintenance optimization for continuously monitored degrading systems under imperfect maintenance actions. J. of Syst. Eng. and El. 31(4) 841 https://doi.org/10.23919/JSEE.2020.000057
[10] Sun J, Wang F and Ning S 2020 Aircraft air conditioning system health state estimation and prediction for predictive maintenance. Chin. J. of Aer. 33(3) 947 https://doi.org/10.1016/j.cja.2019.03.039
[11] Zhou B and Liu Z 2016 Optimizing preventive maintenance: a deteriorating system with buffers Ind. Man. & Data Syst. 116(8) 1719 https://doi.org/10.11108/IMDS-01-2016-0026
[12] Wu T, Yang L, Ma X, Zhang Z and Zhao Y 2020 Dynamic maintenance strategy with iteratively updated group information. Rel. Eng. and Syst. Saf. 197 https://doi.org/10.1016/j.ress.2020.106820
[13] Zhong J, Wang D and Li C A nonparametric health index and its statistical threshold for machine condition monitoring. Meas. 167 https://doi.org/10.1016/j.measurement.2020.108290
[14] Kobzar A I 2006 Applied Mathematical Statistics. For engineers and scientists (Moscow: Logos) p 816
[15] Aronov I Z and Aleksandrovskaya G G 2008 Safety and reliability of technical systems (Moscow: Logos) p 376
[16] Sreenuch J L and Tsourdos A 2014 Condition Based Maintenance Optimization of an Aircraft Assebley Process Considering Multiply Objectives. ISRN Aerospace Engineering 2014 13 https://doi.org/10.1155/2014/204546
[17] Feng Q, Chen Y, Sun B and Li S 2014 An Optimization Method for Condition Based Maintenance of Aircraft Fleet Considering Prognostics Uncertainty. The Scientific World Journal 2014 430190 https://doi.org/10.1155/2014/430190
[18] Gerdes M, Scholz S and Galar D 2016 Effects of condition-based maintenance on costs caused by unscheduled maintenance of aircraft. Journal of Quality in Maintenance Engineering, 22(4) 40 https://doi.org/10.1108/JQME-12-2015-0062