Algorithms of data processing for costs reducing in the aviation enterprise

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Abstract

The increase in the amount of available data to be monitored and the increase in the computational capability of information technologies have caused rapid development in the field of algorithmic support for data processing in various industries. The use of data processing algorithms makes it possible to obtain new information about the state of processes and constituent components of the industry, to increase the veracity of management decision-making, to implement artificial intelligence technologies during the realization of technological processes and the execution of certain procedures, and others. In civil aviation, data processing aims to reduce air navigation service risks related to the safety and regularity of aircraft flights, optimize aircraft routes, detect dangerous situations, and increase the level of operational efficiency of equipment. Aviation radio equipment in civil aviation is used to organize communications between the flight control and aircraft, measure aircraft coordinates, transmit useful information, and others. During the operation of aviation radio equipment, the important problems are the improvement of reliability, the saving of spending funds and costs, and the optimization of operational processes. This paper is devoted to the development of means of algorithmic support for the processes of operation of aviation radio equipment for maintenance strategies with scheduled procedures, condition-based maintenance with control of defining parameters, and condition-based maintenance with predictive control. The comparative analysis of the proposed data processing algorithms was performed by calculating the average operational costs. The results of the research can be used during the study of methodological principles for data processing in the operation systems for aviation radio equipment.

Keywords

intelligence technologies, operational cost optimization, radio equipment operation, maintenance, repair, probabilistic event model, data processing, aviation enterprise

1. Introduction

The development of new technologies, the digitalization of the industry, and the possibility of collecting and transmitting large amounts of information have caused rapid development in the field of algorithmic support for data processing in various industries [1]. Modern technologies of Industry 4.0 provide for an increase in the number of information measuring devices for all constituent components of industry and the use of measured information to increase the efficiency of management decision-making [2, 3].

Algorithmic support systems use information technologies for data processing and decision-making [4, 5]. The areas of application of these systems are aimed:

- to organize monitoring and tracking of key parameters of production processes and equipment used in them [6];
- to automate the execution of production and technological processes [7];

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- to predict future events: the occurrence of equipment failures, the appearance of inconsistencies in technological processes, an increase in the risks of possible future events with negative consequences [8];
- to optimize production and technological processes from the point of view of reducing expendable resources, choosing the best organizational management structure, determining the number of personnel, equipment, and others [9];
- to improve the quality of personnel training and adapt it to the sustainable development of technology and industry [10];
- to monitor the level of consumer satisfaction [11];
- to adapt to the changing conditions of the external environment [12];
- to harmonize the requirements of various standards, regulatory, and normative documents [13].

In civil aviation, the data processing algorithms aim to reduce the air navigation service risks related to the safety and regularity of aircraft flights, optimize possible aircraft routes, detect the dangerous situations, and increase the level of operational efficiency of equipment [14, 15].

In general, civil aviation includes a set of interconnected systems, namely: organization of transportation, ensuring the functioning of airports and airfields, dispatching service, ensuring aviation safety, flight activities, radio technical support of flights, and others [16, 17]. Aviation radio equipment (ARE) is the main element of the system of radio technical support of flights.

Aviation radio equipment in civil aviation is used to organize communications between the flight control and aircraft, measure aircraft coordinates, transmit useful information, and others. During the operation of aviation radio equipment, the important problems are the improvement of reliability, the saving of spending funds and costs, and the optimization of operational processes [18, 19].

Development of infrastructure and datahub content for the collection, processing, and use of statistical data on the functioning of the equipment and the components of its operation systems is also an urgent task for the operation of ARE. The development of datahub content involves the synthesis of data processing algorithms to solve the problems of hypothesis testing and classification, parameter estimation, signal filtering, prediction of data trends, and others [20].

The use of information technologies for data processing during the operation of ARE is a guarantee of maintaining a given level of safety in civil aviation.

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

The operation of aviation radio equipment is the main stage of its life cycle [21]. In civil aviation, at this stage, useful functions of equipment are implemented to solve specific problems of aviation enterprises and air navigation service providers [22].

The efficiency of ARE use is usually evaluated by complex indicators that take into account the tactical and technical characteristics, reliability indicators of the equipment, expendable resources for the performance of the main operational processes, indicators of the production processes of the aviation enterprise, and others [23].

Maintenance, repair, monitoring, and control of the technical condition, extension of the resource, and others can be the main processes of ARE operation [24]. These processes are usually considered from the point of view of systems approaches, so they have an internal structure, the input and output flows, an apparatus of interconnection with external production processes of the aviation enterprise, resource provision, and controlling influences [25].

The maintenance process can be carried out using different approaches to its implementation strategy. The evolution of these strategies in terms of the processing and use of statistical data includes:

1. Descriptive approach. Statistical data are used exclusively to inform about events that occur during the operation of the equipment, and conclusions about the causes of these events are not carried out.
2. Diagnostic approach. Statistical data are used to determine the causes of events during the operation of the equipment.
3. Prognostic approach. Statistical data is used to predict future events based on the use of intelligent data processing technologies, including methods of machine and deep learning.
4. Prescriptive approach. When implementing this approach, it is necessary to use artificial intelligence algorithms, as a result of which it is possible to develop a set of precautionary measures, the implementation of which will make it impossible or reduce the risk of possible events with negative consequences [26, 27].

From the point of view of the data being processed, reliability-based and condition-based maintenance (CBM) approaches can be considered [28]. The primary information for these approaches is data on the reliability of the equipment and the trends of the defining parameters, respectively.

On the one hand, condition-based maintenance is a more complex approach and can use the results of monitoring for one or a group of parameters but, on the other hand, it can contribute to greater operational efficiency by eliminating equipment failures and malfunctions, as well as minimizing operational costs. The evolution of data processing algorithms when using CBM is given in the article [29].

Maintenance is inextricably linked with the process of restoring the serviceability of the equipment (repair). The practice of operation shows the impossibility of one hundred percent elimination of the possible occurrence of failures and malfunctions. Several factors contribute to this, including the insufficient time for maintenance procedures implementation, human factors, random influences, and others [30]. At the same time, the moments of failures are random.

The processes of monitoring and control ensure the collection of primary information on the defining parameters of the equipment, perform the classification of equipment states, and implement data processing from the point of view of forecasting future states [31, 32]. The collected information is stored in the form of datasets and is the basis for processing and decision-making. The classification of states determines the dynamics of changes in all the component processes during the ARE operation. At the same time, erroneous decisions are possible, which are characterized by a confusion matrix containing the corresponding conditional probabilities of errors. The forecasting results make it possible to develop a set of preventive measures to reduce the impact of the consequences of possible negative events.

Let's perform the mathematical formulation of the problem. We will assume that the processes of ARE operation are implemented at an aviation enterprise and require the availability of a fund of expendable resources, which is described by the cost vector $\vec{C}$. The cost vector includes information on the cost of maintenance, repair, control (conventional and automated) processes, processing costs, personnel salary funds, and others. In the process of equipment use for the purpose, there is monitoring of the defining parameters, which are random and can be described by the stochastic model $SM_{y(t)}$. In the general case, this model includes the probability density function for sampling values of the defining parameter, approximate statistical characteristics, statistical characteristics of nonstationary processes, and others. The operational processes are characterized by their content, which can be described by the vector $\overrightarrow{OP}$. This vector contains information on individual procedures and technological operations, availability of resources, personnel and their qualification level, probabilistic characteristics of possible errors during the execution of individual procedures, and others. The operational processes are implemented by adopted strategy, which is determined by the developed and adopted data processing algorithms $\vec{A}$. According to the system approach, operational processes are interconnected with the environment, as a result of which additional restrictions may be imposed on them. These restrictions are described by the vector $\vec{R}$.

For simplification, we will assume that the operational efficiency is determined by the costs of the aviation enterprise. In connection with the stochastic nature of events during the implementation of ARE operation processes, it is quite natural to use the expected value of this indicator, which we denote by $E(C_\Sigma)$. Then we can write:

$$E(C_\Sigma) = \varphi\left(\vec{C}, SM_{y(t)}, \overrightarrow{OP}, \vec{A} \middle| \vec{R}\,\right). \quad (1)$$

The purpose of this research is the development and comparative analysis of data processing algorithms during the implementation of the ARE operation processes at the aviation enterprise. From a mathematical point of view, the paper solves the problem of minimizing the expected value of operational costs $E(C_\Sigma)$ concerning the vector $\vec{A}$ with the specified vectors and their components $\vec{C}$, $SM_{y(t)}$, and $\overrightarrow{OP}$ under the conditions of defined restrictions $\vec{R}$.

3. Probabilistic event model for the estimation of maintenance efficiency

A certain methodological approach must be followed to assess the effectiveness and efficiency of the processes of ARE operation. This approach includes the following basic positions:

1. Determination of how the technical condition of aviation radio equipment will be described. At the same time, it is proposed to use several defining parameters $y_i(t)$ to describe the technical condition.
2. Determination of the content of procedures and technological operations of the maintenance process.
3. Formation of data processing operator schemes.
4. Analysis of possible decisions that will be made during maintenance procedures.
5. Calculation of risks and losses during operation.
6. Development of a probabilistic event model.

The probabilistic event models (PEM) appropriately include possible events, states, risks, probabilities of their occurrence, limitations, and corresponding costs in the process of operation. At the same time, three options can be distinguished:

1. Scheduled maintenance (SM) organization system.
2. Condition-based maintenance using the automated means of monitoring the technical condition of aviation radio equipment.
3. Condition-based maintenance using automated inspections and predictive control.

During the formation of the PEM, it is advisable to take into account possible events:

1. The technical condition of ARE is determined by one defining parameter $y(t)$.
2. Trends in measured parameters are random.
3. Inspection and control of the technical condition are performed discretely.
4. The failures are independent random variables.
5. At two arbitrary moments, the measurement results of the determining parameter are independent values.
6. Expected risks can be calculated at any point of time.
7. Operational (T_{O-}, T_{O+}) and preventive (T_{P-}, T_{P+}) tolerances are known.
8. The changepoint model is linear with a random moment of occurrence and a random inclination angle.
9. After the recovery of serviceability, the trend of the defining parameter returns to the nominal value y_0.
10. The datasets being processed are independent.

According to the methodological approach, let's consider the procedure for forming decisions about the technical condition of equipment. Figure 1 and Figure 2 schematically show the process of changing ARE conditions for options with two and four thresholds.

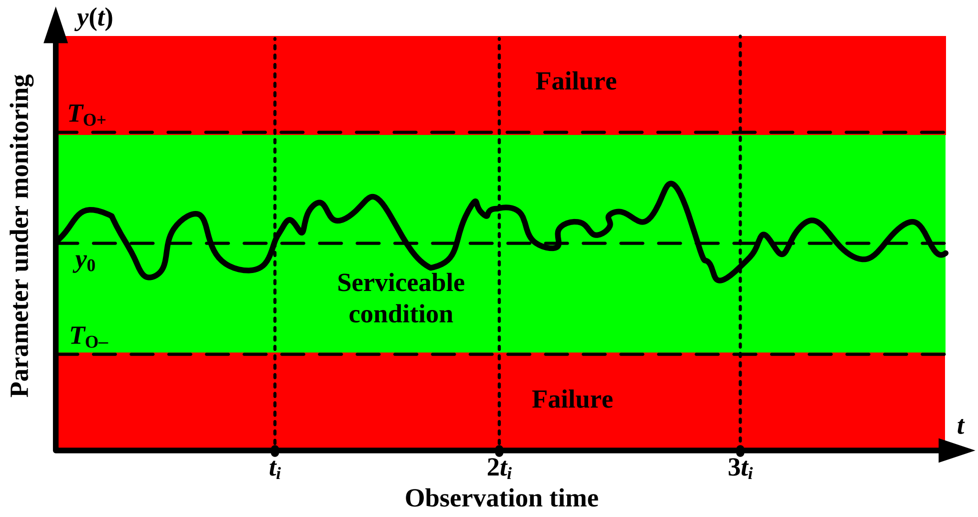

Figure 1: Defining parameter trend in the case of SM.

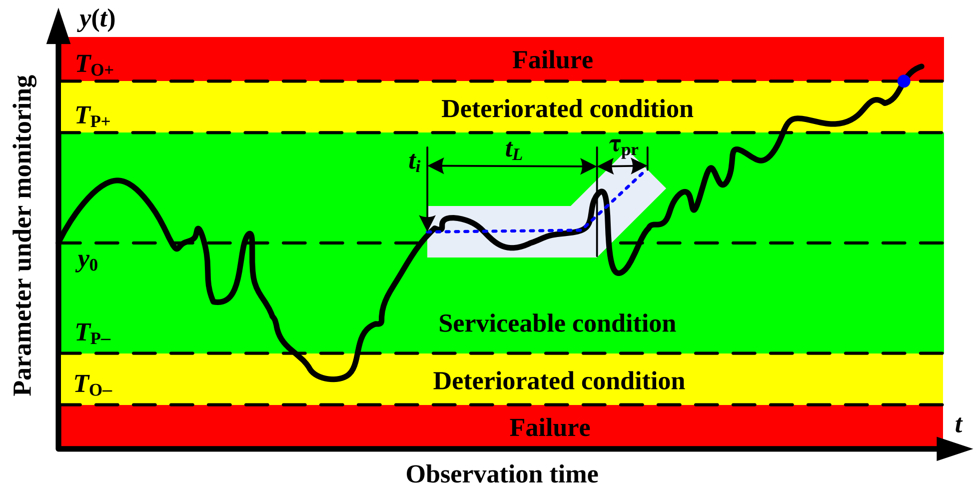

Figure 2: Defining parameter trend and condition ranges in the case of CBM.

At the same time, the defining parameter changes randomly during the inspection process. In the case of degradation of technical condition, the trend of the defining parameter becomes nonstationary, rapidly increasing or decreasing. During the degradation for the four-threshold option, the value of the defining parameter can reach threshold levels that divide the range of values into three ranges: serviceable condition, deteriorated condition, and failure.

It is known that there is no preventive threshold for the scheduled maintenance organization system since failures occur objectively and are not eliminated. At the same time, two conditions are possible (Figure 1):

– serviceable condition if $T_{O-} \leq y(t) \leq T_{O+}$;
– failure if $y(t) < T_{O-}$ or $y(t) > T_{O+}$.

In the case of CBM with the control of defining parameters, there are three possible conditions:

– serviceable condition if $T_{P-} \leq y(t) \leq T_{P+}$;

– deteriorated condition if $T_{P+} \leq y(t) \leq T_{O+}$ or $T_{O-} \leq y(t) \leq T_{P-}$;
– failure if $y(t) < T_{O-}$ or $y(t) > T_{O+}$.

Consider condition-based maintenance using automated inspections and predictive control. Figure 2 schematically shows the process of forming the forecast value of the trend of the defining parameter $y_{pr}(t_i|\tau_{pr})$, where t_i is the current time when the forecast is made, τ_{pr} is the interval of prediction. During the prediction, a training sample $\overrightarrow{t_L}$ is formed. For this sample, data processing is performed and the formation of predictive trend values at the moment of time t_i begins. During the prediction, the model of the defining parameter at the forecasting stage must be preserved according to its type (statistical distributions and their parameters). If this condition is not fulfilled, then it is necessary to solve the problems of detecting the moment of degradation and form a new training sample and, accordingly, a model based on this.

In addition, it should be noted that it is necessary to comply with the requirement that the length of the training period $\overrightarrow{t_L}$ is greater than the prediction interval τ_{pr}.

We will assume that the selection of the value of the prediction interval τ_{pr} is carried out in such a way that, during this time, preventive actions aimed at restoring the operational efficiency of the ARE are implemented, namely: regulation, preventive replacement of equipment components, nodes, boards, and others. In this case, the risk of gradual failures is reduced, which means that the costs of restoring the operational efficiency of the ARE were minimized.

Forecasting procedures are performed after a decision has been made regarding the technical condition of the ARE as a result of inspection and control procedures, i.e. when the equipment is in the serviceable or deteriorated condition.

To evaluate the efficiency of options for organizing and carrying out different types of ARE maintenance, we will use the structural diagrams of the interconnection of operators of data processing and decision-making. These schemes will reflect: 1) individual operators of data processing and decision-making, 2) ARE conditions after execution of operational processes and certain procedures and actions, 3) conditional probabilities of transition from one state to another, 4) average costs, and 5) risks associated with the execution of certain actions and decision-making.

Let’s note two features of data processing. In the first case, we can consider the implementation of operator schemes at the moment of time t_i, when a complete set of data processing algorithms is executed. Then the calculated average losses and risks can be considered as predictive estimates of expected operational costs. In the second case, it is possible to consider the processing of n values of the defining parameter $y(t)$ in a sliding window. Then, after data processing for n values, average losses (or risks) are obtained. In this case, the processing procedure is repeated iteratively, where each iteration is performed at the next measurement. That is, data processing and analysis are more complex. At the same time, correlation dependences for data from neighboring sliding windows should also be taken into account.

Let's consider the operator diagram for the system of scheduled maintenance organization. At the moment of time t_i, the staff performs technical condition control and scheduled procedures. If, based on the results of the ARE inspection and control, a decision is made regarding the serviceable condition, then the scheduled procedures are performed. At the same time, repair is performed when $y(t) < T_{O-}$ or $y(t) > T_{O+}$. Therefore, the operator scheme will include operators of inspection and control, maintenance, and restoration of operational efficiency. Possible decisions will be: 1) serviceable condition, 2) failure, and 3) continued operation. The costs of the procedures include control costs C_{con}, maintenance costs C_m, repair costs C_r. The priori probabilities of the two states at the moment t_i are as follows: the probability of the serviceable condition of the ARE P_s, the probability of failure $P_f = 1 - P_s$.

We will assume that the level of qualification of the personnel and the time of performing the procedures are sufficient to reliably determine the technical condition of the ARE. After performing the maintenance procedures, ARE will be in a serviceable condition, and no failures will be introduced by the personnel.

Taking into account the above designations and assumptions, we will present an operator scheme for performing SM (Figure 3).

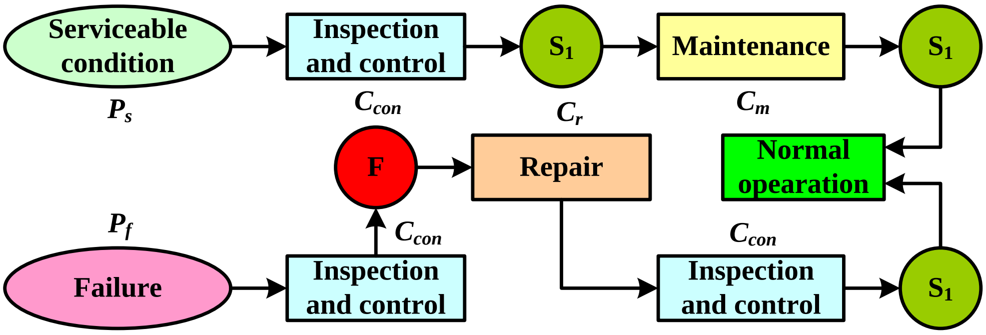

Figure 3: Operator diagram for SM.

Taking into account Figure 3, the average costs will be:

$$E(C_{\Sigma}|SM) = P_s(C_{con} + C_m) + P_f(2C_{con} + C_r). \quad (2)$$

Let's consider CBM using the automated control of the technical condition of ARE.

The expected reduction in costs for the operation of ARE is associated with the introduction of automated monitoring of ARE conditions and an expected decrease in the probability of being in the area where maintenance procedures are planned and performed. Errors in the classification of the technical condition are possible during operations for the automated control of the technical condition. In this regard, we will make several assumptions: 1) if the objectively defining parameter is in the region of serviceable condition, then it is possible to make a false decision that ARE is in the deteriorated condition; 2) if the objectively defining parameter is in the region of the deteriorated condition, then it is possible to make a false decision that ARE is in the serviceable condition or the condition of failure; 3) if the objectively defining parameter is in the region of the failure, then it is possible to make a false decision that the ARE is in the deteriorated condition. Therefore, the possible cases can be described by conditional probabilities: $(S_2|S_1)$, $P(S_1|S_2)$, $P(F|S_2)$, $P(S_2|F)$, where S_1, S_2 and F are serviceable, deteriorated, and failure conditions, respectively.

It should be noted that automated control must also be carried out after performing maintenance and repair procedures.

We emphasize that a characteristic feature of this option is the presence of preventive tolerances (T_{P-}, T_{P+}). We assume that the control of the technical condition is performed in automatic mode. Average cost of automatic control C_{ca}. Usually, $C_{ca} \ll C_{con}$. Repair costs coincide in value with the first type of maintenance, i.e. equal to C_r. If the ARE is in a deteriorated condition, then maintenance costs are C_m.

The probabilities of each of the three conditions are equal to: P_{s1}, P_{s2}, and P_f. At the same time, $P_s = P_{s1} + P_{s2}$.

Taking into account the above designations and assumptions, we will provide an operator scheme for performing CBM using the automated control of the technical condition of ARE (Figure 4).

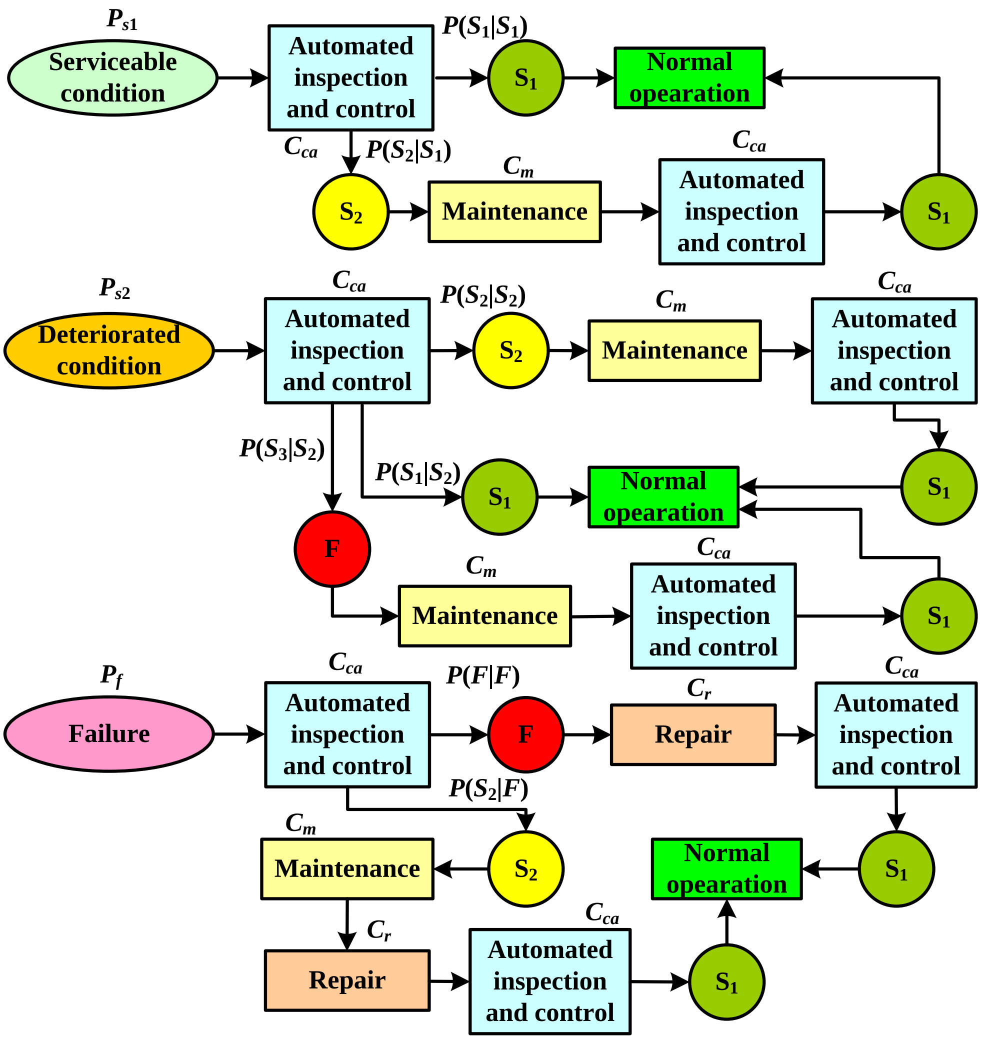

Figure 4: Operator diagram for condition-based maintenance with defining parameters monitoring.

Taking into account Figure 4, the average costs will be:

$$E(C_\Sigma|CBM_1) = P_{s1}P(S_1|S_1)C_{ca} + P_{s1}P(S_2|S_1)(2C_{ca} + C_m) + \\ +P_{s2}P(S_2|S_2)(2C_{ca} + C_m) + P_{s2}P(S_1|S_2)C_{ca} + P_{s2}P(F|S_2)(2C_{ca} + C_m) + \\ +P_f P(F|F)(2C_{ca} + C_r) + P_f P(S_2|F)(2C_{ca} + C_m + C_r). \tag{3}$$

We compare the average costs for the first and second maintenance options. That is, we will find the difference

$$\Delta = E(C_\Sigma|CBM) - E(C_\Sigma|SM). \tag{4}$$

It is desirable that $\Delta \geq 0$, then the expediency of improving maintenance will be substantiated.

To simplify the analysis, we will introduce the correlation: 1) between the costs of manual and automated control, i.e. $C_{ca} = AC_{con}$, where $A \ll 1$; 2) between the probabilities of being in the serviceable and deteriorated conditions $P_{s2} = BP_{s1}$, where $B > 0$.

Then we can simplify equation (3) to the form:

$$E(C_\Sigma|CBM_1) = P_{s1}P(S_1|S_1)AC_{con} + P_{s1}(1 - P(S_1|S_1))(2AC_{con} + C_m) + \\ +BP_{s1}P(S_2|S_2)(2AC_{con} + C_m) + BP_{s1}P(S_1|S_2)AC_{con} + \\ +BP_{s1}P(F|S_2)(2AC_{con} + C_m) + (1 - (1 + B)P_{s1}) \times \\ \times \left(P(F|F)(2AC_{con} + C_m) + (1 - P(F|F))(2AC_{con} + C_r + C_m)\right). \tag{5}$$

Consider an example of a calculation for a comparative analysis of the first and second maintenance options. We will consider the input parameters for SM: $C_{con} = 50$ USD, $C_m = 80$ USD, $C_r = 160$ USD, $P_s = 0.9$, $P_f = 0.1$. Then according to equation (2) we get

$$E(C_\Sigma|SM) = 0.9 \cdot (50 + 80) + 0.1 \cdot (100 + 160) = 143 \text{ USD}.$$

The input parameters for CBM using the automated control of the technical condition are the following parameters: $A = 0.04$, $P_{s1} = 0.45$, $B = 1$, $P_{s2} = 0.45$, $P_f = 0.1$, $P(S_1|S_1) = 0.99$, $P(S_2|S_1) = 0.01$, $P(S_2|S_2) = 0.9$, $P(S_1|S_2) = 0.05$, $P(F|S_2) = 0.05$, $P(F|F) = 0.95$, $P(S_2|F) = 0.05$.

Then according to equation (5) we get $E(C_\Sigma|CBM_{1,1}) = 55.16$ USD.

The second option of input parameters for CBM using the automated control of the technical condition is: $A = 0.04$, $P_{s1} = 0.3$, $B = 2$, $P_{s2} = 0.6$, $P_f = 0.1$, $P(S_1|S_1) = 0.99$, $P(S_2|S_1) = 0.01$, $P(S_2|S_2) = 0.9$, $P(S_1|S_2) = 0.05$, $P(F|S_2) = 0.05$, $P(F|F) = 0.95$, $P(S_2|F) = 0.05$. For this option of the data, the priori probability of ARE in the deteriorated condition increases, so the gain of CBM using the automated control will decrease. At the same time, we will get $E(C_\Sigma|CBM_{1,2}) = 65.6$ USD.

The efficiency improvement coefficients for the first and second options of CBM using the automated control compared to scheduled maintenance will be:

$$K_1 = \frac{E(C_\Sigma|SM)}{E(C_\Sigma|CBM_{1,1})} = \frac{143}{55.16} = 2.6, \qquad K_2 = \frac{E(C_\Sigma|SM)}{E(C_\Sigma|CBM_{1,2})} = \frac{143}{65.6} = 2.2.$$

At the same time, the parameter Δ according to equation (4) will be 87.84 and 77.4, respectively, which proves the efficiency of CBM using the automated control of the defining parameters.

Consider and detail the strategy of CBM using predictive control. For comparative performance analysis, several options can be explored, namely: with two thresholds (operational), with four thresholds (operational and preventive).

During the development of decision-making scenarios, we will take into account two features: 1) within what limits is the extreme value during the training period; 2) what is the confidence interval for estimating the predicted value. In the general case, the estimate of the predicted value has a probability density function. During the efficiency analysis, we can consider different variants of the trend of the defining parameter. For simplicity of research and calculations, we will assume a linear model of this trend. From the point of view of the probabilistic description of the forecasting procedure, two factors must be taken into account:

1. The tendency of the development of forecast values has an angle of inclination, which is a random value and can take a certain continuum of values.
2. Forecast values of the trend at the time of forecasting have a normal probability density function.

Let's consider the operator scheme of performing CBM using predictive control for the option with two thresholds (Figure 5).

The following assumptions and explanations should be noted when considering this maintenance strategy. The cost of predictive procedures is C_p. As a result of the implementation of the forecasting algorithm, two decisions are possible: ARE will be in the serviceable condition with conditional probability $P\left(S_1^{(pr)}\middle|S_1\right)$ and ARE will be in a failure state with conditional probability $P(F^{(pr)}|S_1)$. If deterioration with possible failure is predicted, preventive maintenance must be performed. The cost of preventive maintenance is C_{pm}. At the same time, $C_{pm} < C_m$. In the case of an erroneous decision by the automatic control system regarding the condition of failure for objectively serviceable condition, the forecaster does not fulfill the prediction, and the equipment is sent for repair. At the same time, repair procedures are not performed since the wrong decision is revealed at the stage of preventive maintenance. In the event of an objective failure and erroneous decision of the automatic control system, the predictor corrects this error and directs the ARE to carry out repair procedures.

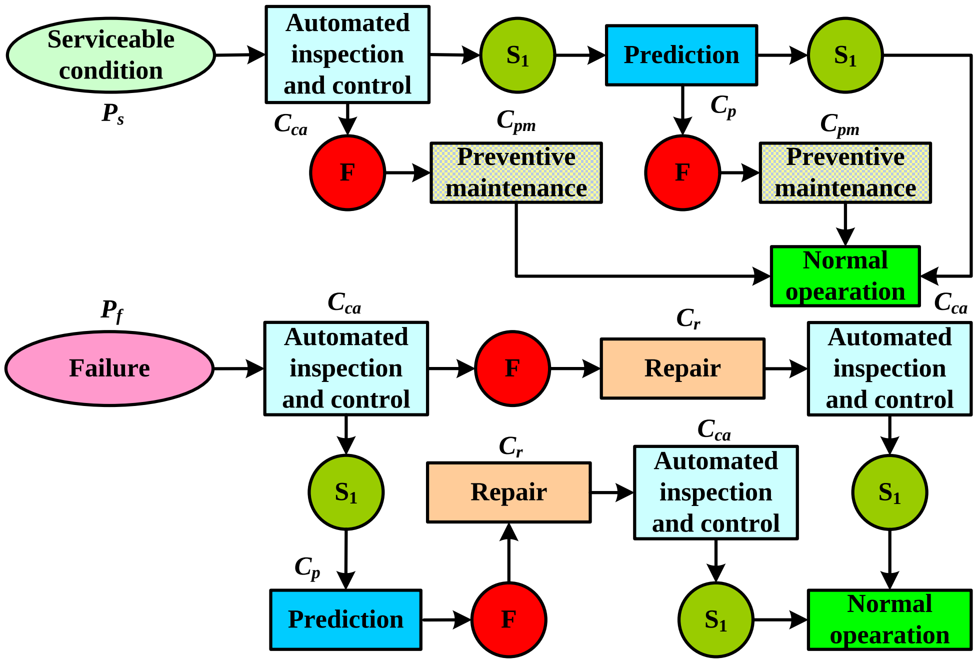

Figure 5: Operator diagram for condition-based maintenance with predictive control and two thresholds.

Taking into account Figure 5, the average costs will be:

$$E\left(C_\Sigma \middle| CBM_{2,1}\right) = P_s P(S_1|S_1) P\left(S_1^{(pr)}\middle|S_1\right)\left(C_{ca} + C_p\right) + \\ +P_s P(S_1|S_1) P\left(F^{(pr)}\middle|S_1\right)\left(C_{ca} + C_p + C_{pm}\right) + P_s P(F|S_1)\left(C_{ca} + C_{pm}\right) + \\ +P_f P(F|F)(2C_{ca} + C_r) + P_f P(S_1|F)\left(2C_{ca} + C_p + C_r\right). \quad (6)$$

We will calculate the costs for this maintenance option for the parameters from the previous example: $A = 0.04$, $P_s = 0.9$, $P_f = 0.1$, $P(S_1|S_1) = 0.99$, $P(F|S_1) = 0.01$, $P(F|F) = 0.95$, $P(S_1|F) = 0.05$, $C_r = 160$ USD. At the same time, we will additionally assume that $P\left(S_1^{(pr)}\middle|S_1\right) = 0.95$, $P\left(F^{(pr)}\middle|S_1\right) = 0.05$, $C_p = C_{ca}$, $C_{pm} = 20$ USD.

Then according to equation (6) we get $E\left(C_\Sigma \middle| CBM_{2,1}\right) = 27.45$ USD.

The parameter Δ according to equation (4) will be 115.44, and the efficiency improvement coefficient will be 5.2. This strategy also improved the level of efficiency by approximately two times in comparison with the strategy of CBM using the automated control of defining parameters.

Let's consider the operator scheme of performing CBM using predictive control for the option with four thresholds (Figure 6). Taking into account Figure 6, the average costs will be:

$$E\left(C_\Sigma \middle| CBM_{2,2}\right) = P_{s1} P(S_1|S_1) P\left(S_1^{(pr)}\middle|S_1\right)\left(C_{ca} + C_p\right) + \\ +P_{s1} P(S_1|S_1)\left(P\left(S_2^{(pr)}\middle|S_1\right) + P\left(F^{(pr)}\middle|S_1\right)\right)\left(C_{ca} + C_p + C_{pm}\right) + \\ +P_{s1} P(S_2|S_1)(2C_{ca} + C_m) + P_{s2} P(S_2|S_2)(2C_{ca} + C_m) + \\ +P_{s2} P(S_1|S_2) P\left(S_1^{(pr)}\middle|S_2\right)\left(C_{ca} + C_p\right) + P_{s2} P(F|S_2)(2C_{ca} + C_m) + \\ +P_{s2} P(S_1|S_2)\left(P\left(S_2^{(pr)}\middle|S_2\right) + P\left(F^{(pr)}\middle|S_2\right)\right)\left(C_{ca} + C_p + C_{pm}\right) + \\ +P_f P(F|F)(2C_{ca} + C_r) + P_f P(S_2|F)(2C_{ca} + C_m + C_r). \quad (7)$$

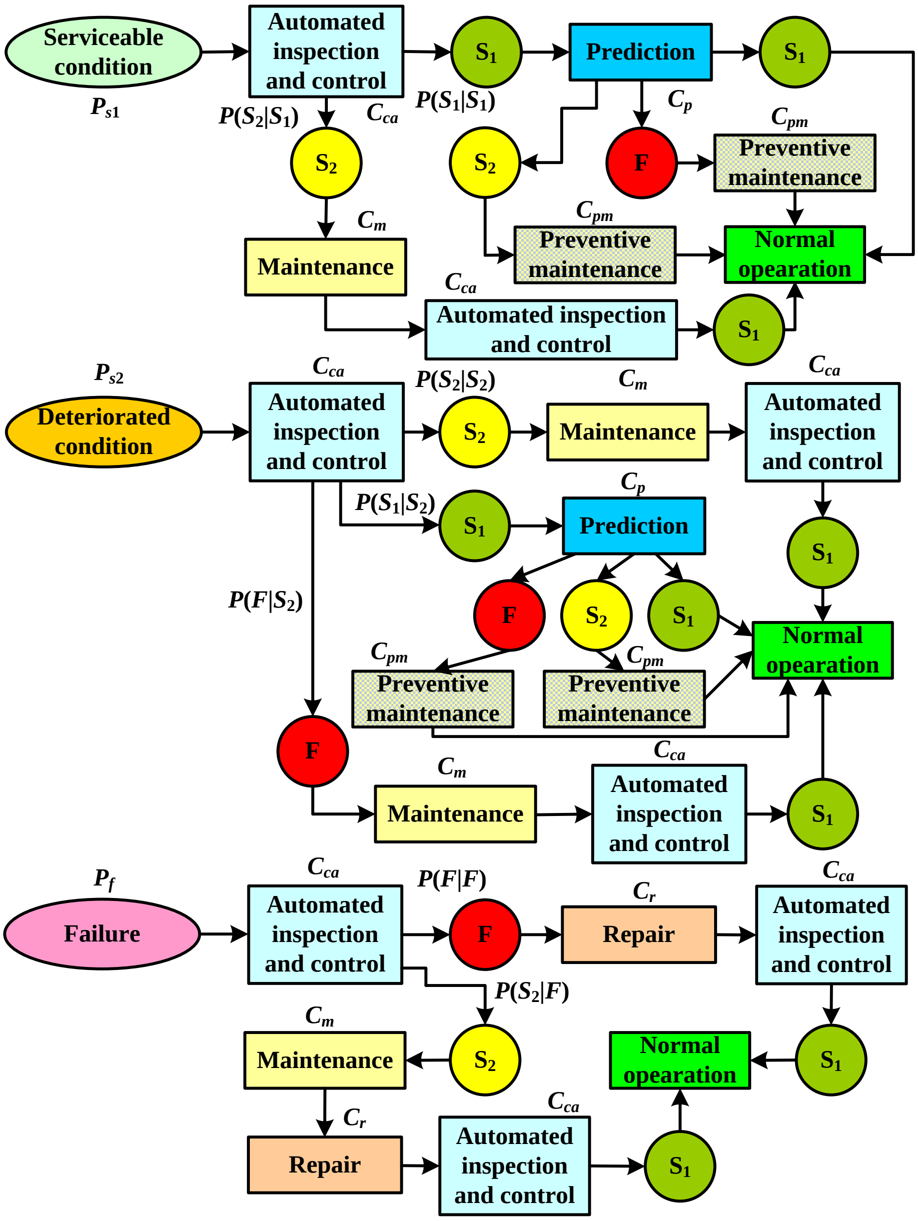

Figure 6: Operator diagram for condition-based maintenance with predictive control and four thresholds.

Equation (7) contains additional conditional probabilities of forecasting the condition of the equipment in case when it is in the deteriorated condition at the time of prediction: $P\left(S_1^{(pr)}\middle|S_2\right)$, $P\left(S_2^{(pr)}\middle|S_2\right)$, and $P\left(F^{(pr)}\middle|S_2\right)$. Obviously, the smallest of these probabilities will be the first of them.

The scheme in Figure 6 provides for the presence of two types of maintenance procedures: 1) normal, which is performed after determining the current condition of ARE by the automatic control system, and 2) preventive, which is performed based on the results of forecasting the future condition of ARE.

Calculate the average operational costs for the option with four thresholds. We will use the following initial parameters: $P_{s1} = 0.45$, $P_{s2} = 0.45$, $P_f = 0.1$, $P(S_1|S_1) = 0.99$, $P(S_2|S_1) = 0.01$, $P(S_2|S_2) = 0.9$, $P(S_1|S_2) = 0.05$, $P(F|S_2) = 0.05$, $P(F|F) = 0.95$, $P(S_2|F) = 0.05$, $C_{con} = 50$ USD, $C_m = 80$ USD, $C_r = 160$ USD, $C_{pm} = 20$ USD, $C_p = 2$ USD, $C_{ca} = 2$ USD. Conditional probabilities of future conditions during prediction: $P\left(S_1^{(pr)}\middle|S_1\right) = 0.95$, $P\left(S_2^{(pr)}\middle|S_1\right) = 0.025$, $P\left(F^{(pr)}\middle|S_1\right) = 0.025$, $P\left(S_1^{(pr)}\middle|S_2\right) = 0.05$, $P\left(S_2^{(pr)}\middle|S_2\right) = 0.55$, та $P\left(F^{(pr)}\middle|S_2\right) = 0.4$.

Then according to equation (7) we get

$$E(C_\Sigma|CBM_{2,2}) = 55.79 \text{ USD}.$$

The second option of numerical calculation for conditional probabilities of future conditions during forecasting $P\left(S_1^{(pr)}\middle|S_1\right) = 0.9$, $P\left(S_2^{(pr)}\middle|S_1\right) = 0.06$, $P\left(F^{(pr)}\middle|S_1\right) = 0.04$, $P\left(S_1^{(pr)}\middle|S_2\right) = 0.06$, $P\left(S_2^{(pr)}\middle|S_2\right) = 0.9$, and $P\left(F^{(pr)}\middle|S_2\right) = 0.04$ provides the average operational costs that equal to $E(C_\Sigma|CBM_{2,2}) = 55.87$ USD. This value is close to the results of the first example.

In this case, the parameter Δ according to equation (4) will be 87.21 and 87.13, and the efficiency improvement coefficient will be approximately 2.56.

So, the CBM using predictive control for the option with four thresholds turned out to be twice as bad in terms of efficiency compared to the option with two thresholds. Therefore, we conclude that two thresholds are sufficient during the implementation of prediction algorithm.

4. Conclusions

The paper is devoted to the issues of analyzing the efficiency of data processing algorithms during the operation of ARE by aviation enterprises. The main attention was paid to the processes of maintenance, repair, monitoring, and control of the technical condition. At the same time, four options for data processing were studied, which correspond to different strategies for the implementation of maintenance: scheduled maintenance, condition-based maintenance using automated control, and condition-based maintenance using predictive control for options with two and four thresholds. For each strategy, an operator scheme for performing data processing and decision-making procedures was developed, as well as average operational costs were calculated.

The analysis of various strategies showed the need to find the compromise between ensuring the desired level of equipment reliability and minimizing operational costs. The use of the automated control system and prediction algorithms significantly increases the efficiency of ARE operation.

The paper considers examples of numerical calculations that showed that the advantage of the implementation of condition-based maintenance is: 1) 2.2...2.6 times for the case of automated control of the defining parameters; 2) 2.5...5.2 times for the case of predictive control.

Future research will be aimed at further improving the condition-based maintenance strategy using predictive control for the two-threshold and four-threshold options (in particular, based on the multiple estimation of conditions in a sliding window), as well as developing a suitable simulation model for this strategy.

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