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Надійшла до редколегії 12.11.2024

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UDC 004.4:656.7:629.7 DOI: 10.30837/0135-1710.2024.183.014

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COMPONENT MODELS OF DEGRADATION ASSESSMENT FOR RECOVERY OF AVIATION EQUIPMENT DURING ITS MAINTENANCE

The study set and solved the task of creating models that allow planning actions to ensure the required level of reliability of aviation equipment (AE) and extend its service life. A component model has been developed, based on which it is possible to determine the impact of degradation processes on the state of AE. The model uses a multi-level representation of the component architecture of an AE sample and system decomposition. The proposed model allows making decisions regarding the replacement or repair of components that are subject to degradation. The modeling of maintenance processes during airport operation is carried out. The relationship between agents of the proposed multi-agent model of AE restoration at the airport is investigated. A model for optimizing the selection of a supplier of AE components to the airport has been proposed, which will reduce the duration and cost of maintenance of the AE in operation.

1. Introduction

During operation, aviation equipment (AE) is exposed to various climatic, mechanical, electromagnetic external influences that accelerate internal degradation processes, which, in turn, reduce the life of the AE or lead to gradual failures of the technical system as a whole or its components. Failure is an event that consists in violating the operational state of a technical product. During the operation of the AE, there is a need to predict the occurrence of failures. During maintenance (aircraft maintenance, AM), an analysis of changes in parameters that characterize the ability of the product to perform certain functions is carried out. The occurrence of possible failures is associated with the process of wear, corrosion, creep of materials, etc.

AM planning consists in determining, even at the stages of the development of the AE, the requirements for the composition and frequency of scheduled maintenance work, the implementation of which provides an assessment of the level of reliability and safety of the AE. For each AE product, a warranty resource and service life are established. After the expiration of at least one of them, the manufacturer's warranty is terminated.

AM is carried out by the forces and means of operating organizations in accordance with operational documentation and with the aim of maintaining the operability or serviceability of products. Although, in some cases, AM is allowed to be performed by the forces and means of enterprises that produce AE on the basis of relevant agreements.

A tool for assessing the actual values of characteristics is monitoring of operation processes, during which data on high-tech products, the condition of its components and actual operating conditions are collected. In the monitoring process, data on the operation of the technical system, reliability (failure-free, durability), labor intensity and duration of maintenance work, actual costs of material resources, total maintenance costs, etc. are collected, statistically processed and analyzed. To structure and accumulate such information, there is a need to create special information technologies that will help optimize the forecasting of maintenance needs and unscheduled repairs [1], [2].

2. Analysis of the latest researches and publications

During the operation of complex technical products, failures inevitably occur and gradually, as the resource decreases, reliability decreases and the quality of system operation deteriorates. Often, the cause of failures can be the influence of technical degradation processes on the product. These circumstances necessitate product repair (current, medium or capital) or component replacement to eliminate emerging malfunctions or restore the current resource [3]. One of the processes of AM and repair of AE is the forecasting of needs for service and spare parts [4].

A number of publications [5], [6] consider the issue of predicting the performance of technical systems that are subject to aging during operation. To solve this problem, a top-down approach using statistical analysis and machine learning can be used. Therefore, for assessing the aging of a technical system, it is quite important to have a sufficient amount of statistical information [7]. The necessary information can be accumulated through the use of Industry 4.0 data collection systems [8] involving cloud storage [9]. To predict the aging process of technical systems, the publication [8] proposes to use a mathematical model based on the theory of Markov processes. The organization of safety due to the aging of complex technical systems covers all stages of the life cycle of a complex product [10]. There is a need to identify and analyze the facts that have an impact on the degradation processes of a technical system. During operation, not only individual technical products are subject to aging, but also the technical base of large manufacturing enterprises [11], the slow modernization of which affects the quality of the products created. Predictive maintenance is a promising solution for maintaining long-term operation of industrial systems with high reliability and low cost. A predictive maintenance model can consist of four stages: degradation modeling, maintenance effect modeling, maintenance policy development, and efficiency assessment [12]. The publication proposes models of degradation processes that can be applied to complex industrial systems at the maintenance stage and are aimed at varying degrees of reducing the degradation level or virtual age of the technical system [13]. The article [14] considers the maintenance stage for system aging depending on operating conditions. The publication [15] proposes models for managing the operation of technical systems that take into account the deterioration of product quality under the influence of degradation processes. It is worth noting that the AE coating is subject to degradation both during active use of aircraft for their intended purpose at the operation stage and during downtime [16].

When considering warranty service projects, it is worth noting that manufacturers of complex technical systems use the most profitable strategy to solve warranty service issues [17]. The price of the product depends on the duration and capabilities of the warranty. In addition, the warranty may cover preventive maintenance [18] or be limited to system failures. The maintenance policy applied to aircraft is regulated by a combination of airworthiness rules and the choice of suppliers and users. This allows airlines to use different strategies to minimize total maintenance costs [19]. At the same time, one of the most priority criteria in the organization of AM is competitiveness and increasing customer satisfaction [20]. The actual operation of aircraft consists of several complex methods of achieving not only safety as a basic element, but also many commercial factors that lead to protecting the value of the aircraft and ensuring the operation of the airline in an economically productive state. When finding a balance between safety and operational profitability, it is very difficult to manage the appropriate settings. These calculations depend on many factors. The importance of maintenance reserves to maintain profitability is one of the key factors for airlines [21]. The optimal combination of warranty, reliability and price is achieved by maximizing the total expected profit over the entire life of the products [22].

After-sales service is a service that allows for the repair of a previously purchased product from a manufacturer or an authorized dealer. When the factory warranty expires, a contract is concluded with the client. As part of the agreement, a person may receive the right to repair the product under the same conditions that were already in effect [23]. After-sales service also has its own characteristics and can be organized in the form of different maintenance packages. The cost of different after-sales service packages may depend on the non-financial risk reduction factor for assessing the effectiveness of the maintenance task and the value added indicator [24].

One of the important issues in the aviation industry is the continuity of service. Accordingly, attention should be paid to spare parts management. In the aviation industry, a reliable supply of spare parts is essential for the continuous operation of the aircraft. High-value spare parts are repaired and returned to the warehouse after being removed from the aircraft, forming a closed supply chain. Current methods of planning suppliers for maintenance, repair and overhaul, as well as the results of research published to date, do not meet the requirements of the commercial aviation industry. Currently, there is a transition from post-failure and preventive repair strategies to a strategy of preventive and predictive aircraft maintenance [25]. Typically, spare parts management in most aviation companies is aimed at achieving a high level of customer service with minimal inventory and minimal investment in inventory [26]. Aviation companies can achieve this goal by creating special spare parts management systems. For the Air Force, an inventory management system is a vital tool that can reduce operating costs while improving fleet readiness, aircraft availability, and availability. In addition, the system itself improves inventory management in the military aviation industry and provides reports that improve supply chain and logistics management, allowing for the minimization of component inventories [27].

Modern publications are mainly aimed at solving individual issues of maintenance and repair. It is worth noting that the element base used to create AE is potentially high reliability. But under the influence of time, various factors and operating conditions, both the product itself and its components age. Economic instability, martial law, globalization of the economy require the search for new approaches to the organization of AE operational processes. Therefore, there is a need for a comprehensive consideration of the technical condition of AE at the operation stage. Based on the analysis of existing publications, we can conclude that a fairly frequent cause of failures There are degradation processes in a complex system, the analysis of which is not given enough attention. Therefore, during periodic maintenance of the AE, there is a need to forecast the need for spare parts and the occurrence of failures, the cause of which may be the aging of the AE.

It is advisable to study and improve the organization of service (technical) maintenance of AE at the operation stage, which is based on the active use of applied information technologies. Obtaining information about the course of degradation processes of components of a complex technical product using these technologies makes it possible to predict the occurrence of failures. Therefore, the main problem of this study is proposed to consider the development of a number of models for assessing the level of degradation impact on AE samples for their restoration during maintenance. To solve this problem, it is proposed to use a component approach, which involves assessing degradation processes based on the analysis of the state of the multi-level component architecture of an AE sample subject to periodic maintenance [28].

3. The purpose and objectives of the research

The aim of the research is to develop a component model for determining the level of influence of degradation processes on the condition of AE during its AM and repair. Such a definition is necessary for predicting the needs for AM and spare parts, by implementing the created multi-agent model of AM at the airport. The multi-agent model is based on the application of models for determining the level of influence of degradation processes on the condition of AE and optimizing the choice of suppliers of aircraft components, which further ensures a reduction in the duration and cost of AM.

To achieve this goal, the following tasks are solved:

– to develop a component model for determining the level of influence of degradation processes on the condition of AE;

– to build a multi-agent model of actions for the restoration of AE at the airport;

– to develop a model for optimizing the selection of a supplier of AE components to the airport.

4. Research materials and methods

The operation of complex technical systems involves the introduction of a certain redundancy (backup connections) so that after the occurrence of local damage there is an alternative load transfer path and a temporary reserve necessary to eliminate the damage. Such systems are able to function for a certain time in the presence of local damage. In this case, these local damage must be identified during maintenance and be eliminated by repair and replacement.

By system degradation we mean the physical process of accumulation of failures due to deterioration of the characteristics of the components of the object being diagnosed. The presence of a failure consists in the values of the parameters of the product components going beyond the established limits.

High requirements for the reliability of AE do not allow considering it in the context of limited operability, which prompts a more detailed consideration of the issues of degradation and malfunctions of such a system. The reliability of an AE consists in its ability to maintain over time, within established limits, the values of all parameters that characterize the ability to perform the necessary functions in the specified modes and conditions of use, maintenance, repair, storage and transportation, that is, to perform the necessary functions during operation. Reliability is a complex property, and certain indicators are used to assess it. They allow assessing the reliability of an object in different conditions and at different stages of operation. AE reliability indicators by the number of properties can be both single (failure-free, durability, maintainability, etc.) and complex. For example, durability is the property of an object to maintain operability until the onset of a limiting state with an established AM and repair system. Durability characteristics are resource and service life. The following durability characteristics are established for AE:

– warranty resource, usually 15-30 % of the service life between repairs. If a failure or damage occurs on a sample of the AE during the warranty life, through no fault of the operating organization, then a complaint report is drawn up for this sample, on the basis of which the sample is restored by the capacities and at the expense of the manufacturing enterprise;

– the designated service life until the first repair (the calendar duration of operation established in the regulatory documentation from the commissioning of the AE sample until its referral for the first repair, regardless of the technical condition);

– the designated service life between repairs (the calendar duration of operation of the AE sample from the completion of the repair until its referral for the next repair, regardless of its technical condition, is established in the regulatory documentation);

– the designated service life before retirement or the full service life (the calendar duration of operation established in the regulatory documentation from the commissioning of the AE sample to its final decommissioning, regardless of its technical condition).

Instead of operating hours (in hours), for some AE samples, the resource is set by the number of activations, switching on, landings, starts, etc. All types of resources for AE are used simultaneously and, moreover, are equivalent, that is, the operation of the AE sample is terminated if at least one of these resources is completely exhausted.

During operation, the built-in resource decreases, thus the product ages (is exposed to degradation processes). The longer the resource (service life) of the object before the limit state occurs, the greater its durability. The occurrence of the limit state can be slowed down by rationally organized maintenance of the product during its operation.

4.1. Component model for determining the level of influence of degradation processes on the state of aviation equipment

Degradation processes are caused by certain mechanical, physical, and chemical processes. The change in the physical state, properties, and characteristics of the components of the AE is usually caused by the influence of energy and consists in the conversion of one type of energy into another. The most important types of energy corresponding to the degradation processes are mechanical, thermal, electrical, chemical, and electromagnetic. Most degradation processes are thermally activated processes that accelerate depending on temperature.

The proposed model is based on a component approach, which allows for the analysis of the aging of a complex system, considering its multi-level component architecture at certain levels of decomposition. Different types of degradation processes (failure mechanisms) of AE components are influenced by the corresponding types of energy. For example, mechanical and chemical energy can lead to the processes of mechano-chemical wear of components, multi-cycle fatigue of components (subsystems), crack formation, creep, etc. Thermal and electrical energy can activate such degradation processes of components as electrochemical corrosion, electrodiffusion, crystallization, oxidation, etc.

The proposed model for assessing the level of degradation impact on the state of the system uses a priori information. As a priori information about the degradation processes, the model uses such characteristics as activation energy, fractional participation in the degradation process (relative, normalized by the sample size, number of failures), and coefficient of variation. The assessment of the degradation impact is carried out during the sequential decomposition of the AE sample.

Components of a complex technical product are usually subjected to several almost uncorrelated degradation processes simultaneously. Therefore, the generalized degradation process of a component (subsystem, assembly, unit in etc.) at a certain level of decomposition is a combination of these processes.

Any possible failure of a product can be identified by one or another process of degradation of its components, and any distribution of failures at the qualitative level is a set of subsets of failures with a characteristic P_{ik}^{j} that is a dimensionless quantity is the fraction of failures by the k-th degradation process (relative, normalized by the sample size, the number of failures), which affects the i-th component, at the j-th level of AE decomposition:

$$\sum_{k=1}^{t} P_{ik}^{j} = 1, \tag{1}$$

where t is the number of degradation processes affecting the i-th component of the j- th level of decomposition of AE .

The components of a component are subject to degradation processes, in general, at different rates. It is quite difficult to obtain information about the degradation rate of each component of the component under consideration, and sometimes it is impossible at all. Therefore, it is proposed in the model to determine the average degradation rate of the component as a whole, for a specific *s*-th degradation process. Thus, the components of the system considered at a given decomposition level *j* can be combined into sets based on the occurrence of the same degradation process. Therefore, all components at the *j*-th decomposition level can be structured in the form of subsets corresponding to certain degradation processes, due to which the components lose their resource at a certain rate during the operation of the AE. Degradation processes can be represented in the following form:

$$M^j = \left\{M^j_{1D_1}, M^j_{1D_2}, \ldots M^j_{2D_1}, M^j_{2D_3}, \ldots, M^j_{yD_s}, \ldots\right\},$$
$$M^j_{yD_s} = \left\{K^j_1, K^j_i, \ldots\right\},\ M^j_{yD_s} \in M^j, \tag{2}$$

where $M^j_{yD_s}$ is the set that includes the components of K^j_i the j- th decomposition level; D_s is the type of degradation process related to the *y*-th set of components, $s = \overline{1,n}$, *n* is the number of degradation processes affecting on the i-th component of the j- th level of decomposition of AE; $y = \overline{1,q}$, *q is* the number of sets.

Therefore, the product at each level of decomposition can be represented as a set of subgroups related to degradation processes.

The rate of the generalized degradation process for the i-th composite component can be represented as follows:

$$f_{general} = \left(\sum_{k=1}^{n} f_k^2\right)^{\frac{1}{2}}. \tag{3}$$

The share of each degradation process P^j_{ik} for the i-th component at the j-th decomposition level is used as the rates of degradation processes affecting the i-th component. Then, the coefficient of variation of the generalized degradation process for the i-th component at the j-th decomposition level is calculated as follows:

$$V_i^j{}_{general} = \left(\sum_{k=1}^{n} \frac{V_k^2 * \left(P^j_{ik}\right)^2}{\sum\limits_{k=1}^{n}\left(P^j_{ik}\right)^2}\right)^{\frac{1}{2}}. \tag{4}$$

Within the framework of the model, it is proposed to determine, in addition to the coefficient of variation of the generalized degradation process of the component, also the relative operating time indicator, which characterizes the working out of the resource (service life) of the component (subsystem, unit in etc.) $\overline{t^j_i}$:

$$\overline{t^j_i} = \frac{t^j_i}{T_i}, \tag{5}$$

where t^j_i is actual operating time (service life) of the i-th component of the j-th decomposition level; T_i is established resource (before the first repair; between-repair resource; full service life).

To determine the resource (service life) of the system as a whole (subsystem), the relative average operating time of the components is used $t_{general}$:

$$t_{i\,general}^{j} = \frac{\sum_{j=1}^{r} \frac{\sum_{i=1}^{m} \overline{t_i^j}}{m}}{r}, \tag{6}$$

where $j = \overline{1, r}$, r is the number of decomposition levels at which the components were considered.

Calculations can be made both based on the resource in hours (hydropneumatic system, aircraft control systems, liquid cooling systems, etc.), in landings (landing gear), and based on the service life in years.

In this study, it is proposed to assess the aging process of the AE by taking into account the number of failed components of the same type, which allows determining the level of reliability of the equipment being operated during AM. This characteristic is the failure rate. The failure rate is the proportion of components that failed in the (d+1)-th interval from the number of components, that have worked flawlessly before the start of this interval:

$$\mu_i^j(\tau_{d+1}) = \frac{\Delta b_{i,d+1}^j}{B_{i,d}^j * \Delta\tau}, \tag{7}$$

where $B_{i,d}^j$ is the number of i- th components of the j- th decomposition level, operating before the beginning of the d-th time interval; $\Delta b_{i,d+1}^j$ is the number of i-th components of the j-th decomposition level that failed at the (d+1)-th interval; $\Delta\tau$ is the time interval.

So, failure rate is a conditional probability component failure rate per unit of time (1/h). The value $\mu_i^j(\tau_{d+1})$ is calculated based on statistical data obtained during the operation of the AE. Monitoring the change in this reliability parameter during operation is very important, since its growth with increasing operating time may indicate the aging of individual components of the system or the entire product as a whole as a result of wear.

The failure rate during operation varies. At the beginning of the operation of a new product, the failure rate increases slightly. This is due to the possible presence in the system of components with undetected defects, after the elimination of which the failure rate decreases. In addition, at the initial stage of operation, design errors may manifest themselves, which also lead to failures. After the detection and elimination of defects and errors, a second period occurs, when the failure rate during operation decreases and remains approximately at the same level. The third period of operation of a complex technical product is associated with its degradation. After a certain period of product operation, the failure rate begins to increase.

Therefore, the model for determining the level of degradation impact on the state of components of a multi-level architecture of the AE involves the calculation of three indicators: coefficient of variation of the generalized degradation process, indicator of the relative service life of the component and the intensity of component failures, which is determined if there is a sufficient amount of statistical data on previous failures of components of a certain type.

Further qualitative assessment of the obtained results is carried out by expert means based on estimates of the state of the system according to three a indicators. Fig. 1 schematically presents three levels of decomposition of the component architecture of the AE sample. The sample itself is located directly at the zero decomposition level. For each component of a certain decomposition level, after performing calculations of the coefficient of variation of the generalized degradation process of the component, the indicator of the relative operating life of the component and the intensity of component failures, it is proposed to determine the level of component performance S, which depends on its degradation. In this case, the component can be at one of five levels of performance:

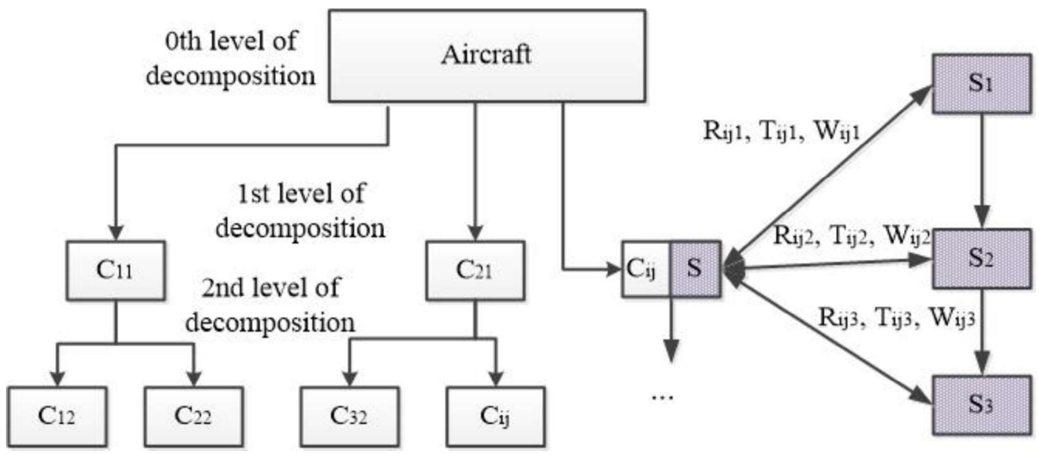

Fig. 1. Fragment of a multi-level architecture of the aviation equipment with determination of the level of component performance

S_0 – fully functional state of the component;

S_1 – the first degradation group (working condition with minor deviations of the normalized characteristics of the components);

S_2 – the second group of degradation (a state with some deviations in characteristics, from which it is possible to return to the S_0 state with small resource costs);

S_3 – the third degradation group (a state from which it is possible to return to the S_0 state with high costs associated with rather resource-intensive maintenance);

S_4 – the fourth degradation group, for which it is impossible to restore the component's performance.

It is assumed that as a complex technical system degrades, the duration of the inspection, the time and cost of restoration increase, and the reliability decreases. Thus, the transition from the level of operability S_1 of the component C_{ij} on The level of operability S_0 can be achieved by taking into account the cost of repair W_{ij1}, the duration of component repair T_{ij1} and the risk of the component not meeting the requirements after repair R_{ij1}. The same indicators are calculated for other levels of component operability W_{ij2}, T_{ij2} , R_{ij2} , W_{ij3} , T_{ij3} , R_{ij3}.

The level of component performance can be determined depending on each of three indicators: the coefficient of variation of the generalized degradation process, the component's operating time, and the intensity and failure rate of the component:

$$S\left(V_{i\,general}^{j}\right)=\begin{cases} V_{i\,general}^{j}=0\%, & S_0 \\ V_{i\,general}^{j}<10\%, & S_1 \\ 11\%<V_{i\,general}^{j}<25\%, & S_2 \\ V_{i\,general}^{j}>25\%, & S_3 \end{cases}, \quad (8)$$

where $V_{i\,general}^{j}$ is coefficient of variation of the generalized degradation process for the i-th component at the j-th decomposition level; $S\left(V_{i\,general}^{j}\right)$ is the level of component performance depending on the coefficient of variation of the generalized degradation process.

The values of the indicators of the relative component life and failure intensity are relative values. Therefore, the level of operability of the i-th component at the j-th decomposition level is determined based on values for these indicators, obtained by expert means. After determining the level of component performance for each of the possible indicators, the average value of the component performance level avg S_{index} is calculated. The calculation is carried out by finding the arithmetic mean of the indices at the values of the performance levels for each of the three indicators. Depending on the obtained average value of the component performance level, it is possible to determine the approximate cost of the transition W_{ij1} (W_{ij2} or W_{ij3}) from the current average performance level average S_{index} in level S_0; duration of component repair T_{ij1} (T_{ij2} or T_{ij3}) and risk of component non-compliance with requirements after repair R_{ij1} (T_{ij2} or T_{ij3}). Based on the information received, an expert decision is made on repair or replacement of a component that has been affected by degradation processes. Usually, if the rounded index of the average level of component performance is $avg\ index > 2$, then component replacement is recommended (Table 1). Definition $avg\ index$ is carried out according to the formula:

$$avg\ index = \frac{\sum_{f=1}^{3} index^{S(f)}}{3}, \tag{9}$$

where $avg\ index$ is index of the average level of component performance; $index^{S(f)}$ is index of the component's performance level for each of the three indicators: the coefficient of variation of the generalized degradation process ($index^{S(1)}$), the indicator of the component's relative operating life ($index^{S(2)}$), and the component's failure intensity ($index^{S(3)}$).

Table 1

Making a decision to replace or repair components due to degradation

i	j	Component name	$S\left(V_{i\,general}^{j}\right)$	$S(t_{i\ general}^{j})$	$S\left(\mu_i^j\left(\tau_{d+1}\right)\right)$	avg S_{index}
1	1	C_{11}	S_1	S_2	S_1	$S_{1,33}$
2	1	C_{21}	S_2	S_1	S_2	$S_{1,66}$
1	2	C_{12}	S_0	S_1	S_1	$S_{0.66}$
2	2	C_{22}	S_2	S_2	S_3	$S_{2.33}$
i	j	W_{ij}	T_{ij}	R_{ij}	Repair	Replace-ment
1	1	W_{111}	T_{111}	R_{111}	+	
2	1	W_{212}	T_{212}	R_{212}	+	
1	2	W_{121}	T_{121}	R_{121}	+	
2	2	W_{222}	T_{222}	R_{222}		+

4.2. Development of a multi-agent model for the recovery of aviation equipment at the airport

During maintenance of the AE sample, the technical condition of the system is monitored and, if necessary, current repairs are carried out, taking into account identified faults and analysis of the impact of degradation processes. Repair is a set of operations to restore the serviceability or performance of products and restore the resources of products or their components . During current and average repairs, products are not removed from operation. Therefore, these types of repairs belong to the stage of product operation. Major repairs, due to their specific features in organization and implementation, are sometimes allocated to a separate stage of the life cycle.

To perform a number of maintenance and repair works on the AE, appropriate tools are required, the characteristics of which must correspond to the parameters of not only the AE sample in general, but also a list of its constituent elements (subsystems, units, equipment blocks) to ensure the technological possibility of performing maintenance and repair work, including access to the objects being serviced and the convenience of performing work, mechanization and automation of maintenance processes, transportation of the AE and its components. Repair of the technical system is an integral part of maintenance, which involves resolving issues related to assessing the overall need for spare parts and materials for scheduled and unscheduled maintenance for the period of operation.

The AE maintenance management system is quite specific due to the huge number of parts and devices. Of these, 20% are replaced during the entire period of operation. The functions of aircraft equipment management include: purchasing, repair, rental (or borrowing), storage, planning, customs clearance and monitoring of the activities of the repair business provider , etc. Large airlines are trying to improve management systems by involving special units and departments, and are also trying to create their own management systems to control all aspects of aviation resources and processes. Very often, aircraft repair and replacement of spare parts is carried out directly on the airport territory.

From the airport's perspective, the maintenance process can be verbally described as follows: AE samples arrive at the airport at the scheduled time, after which each of them undergoes maintenance, as a result of which AE is diagnosed. If the aircraft is in good condition, it leaves the airport immediately after maintenance in order to continue flights. If during maintenance of the aircraft a need for repair or replacement of parts is detected, the loaders search for the necessary spare parts in the airport warehouse. After the necessary parts are found, they are delivered to the maintenance station. Then the aircraft are repaired and the aircraft are sent on flights. If the parts required for repair are not in the warehouse, it is necessary to organize the supply of spare parts from production (or other warehouses). For formalized presentation of the process described above in the study is proposed by multi-agent model of airport AE restoration. The proposed agent representation of measures and actions for AE maintenance and repair allows for effective management in real time and through regular monitoring of the AE status. The structural scheme of the proposed multi-agent model of airport AE restoration is presented in Fig. 2.

Models created using a multi-agent approach have their own advantages. Each type of agent has an independent structure, properties and behavior, which can be described by agent activity diagrams. Despite the fact that agents of the same type have the same structure, they are not dependent on each other. Due to this, agents of the same type can be given individual properties.

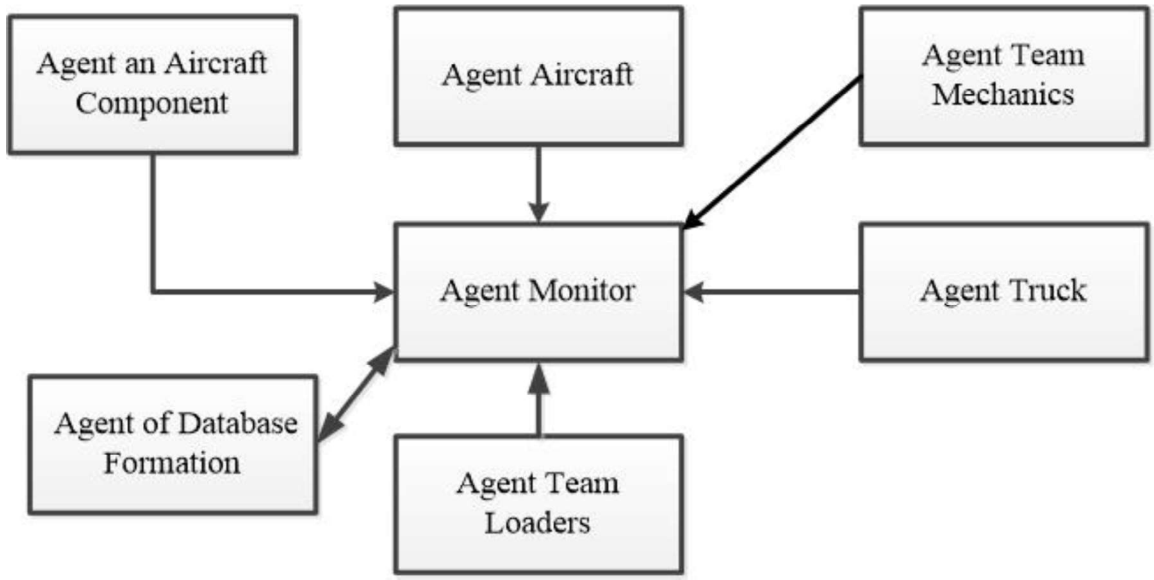

Fig. 2. Structural scheme of a multi-agent model for the recovery of aviation equipment at the airport

The study proposes to describe the behavior and relationship of the model agents in the form of a diagram of airport agent activities, which is presented in Fig. 3.

It should be noted that the «AE Component Agent» describes the structure and properties of each component of the AE sample at a certain level of decomposition. The component may be in working condition or require replacement or repair. Therefore, the behavior of each of the components considered during maintenance is proposed to be described in the form of a UML component state diagram, the scheme of which is presented in Fig. 4.

Activity diagram of airport agents assumes the need to purchase and transport components that are not available at the airport warehouse. That is why this study has developed a choice optimization model supplier of aircraft components to the airport.

4.3. Model for optimizing the selection of an aircraft component supplier to an airport

Important tasks of maintenance are the logistical support of its processes, which include the processes of production or purchase of new components, repair of the AE, restoration of the operability of failed AE parts, storage and transportation of spare parts. Management of the logistical support of these processes requires the development of an appropriate mathematical apparatus that performs adequate analysis, comprehensive quality assessment and optimization of decisions made.

The main disadvantage of the traditional procurement system is the need for a warehouse complex with its inherent administrative and labor costs. The main costs of maintaining warehouses include: depreciation of warehouse facilities; costs of preventive maintenance; costs of heating and electricity; wages of warehouse workers.

At the stage of development of the aviation industry, the problem of increasing the efficiency of the use of AE is associated with with high cost of transportation of spare parts and consumables for repair aircraft enterprises. Therefore, within the framework of the study, a model for optimizing the selection of a supplier of missing components of an airline to the airport is proposed. By implementing the developed model, the risks of failure to timely replace components are reduced, the cost of delivery is reduced, and the duration of cargo delivery is reduced by optimally selecting a supplier of aircraft components to the airport.

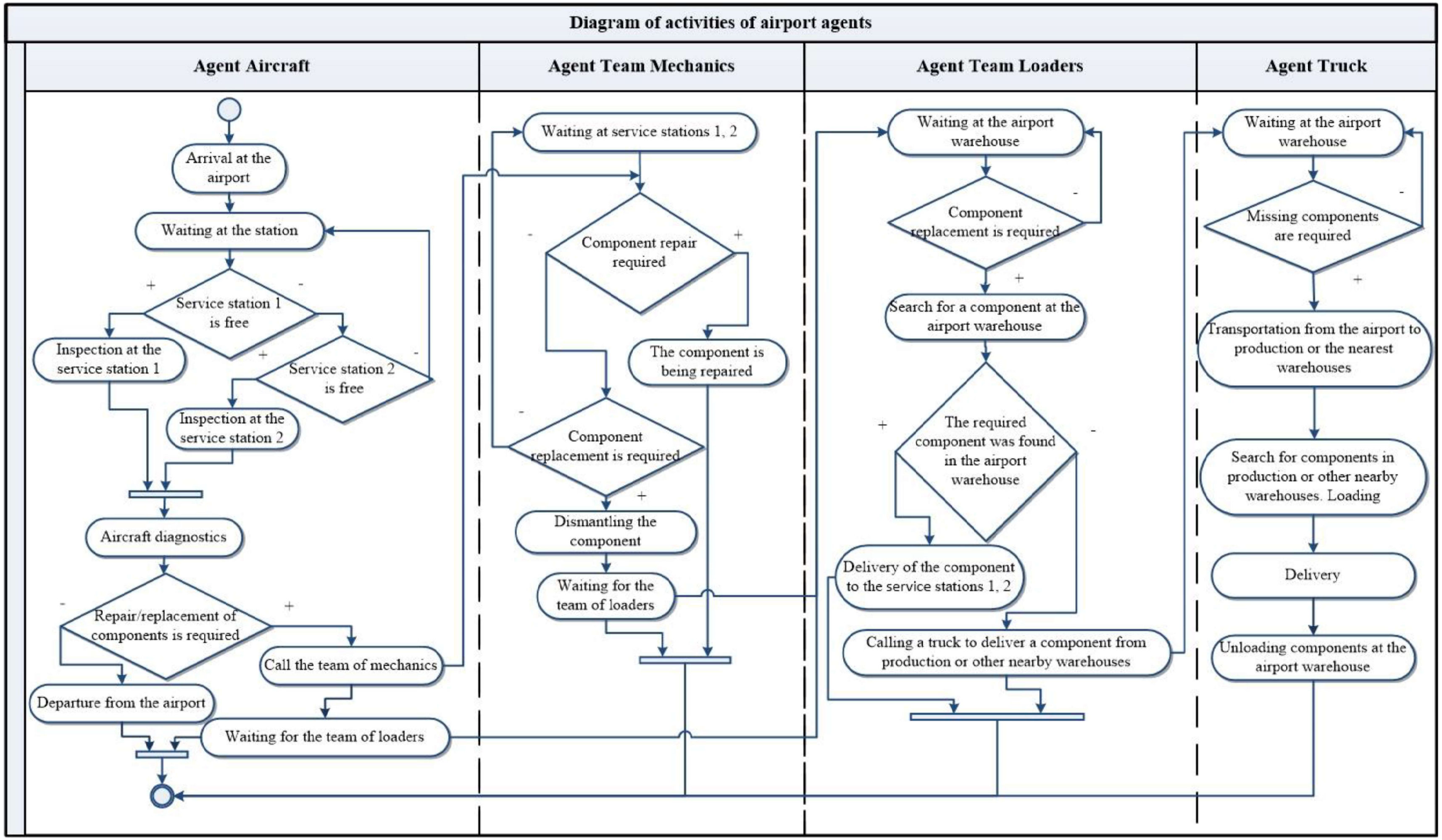

Fig. 3. Diagram of activities of airport agents

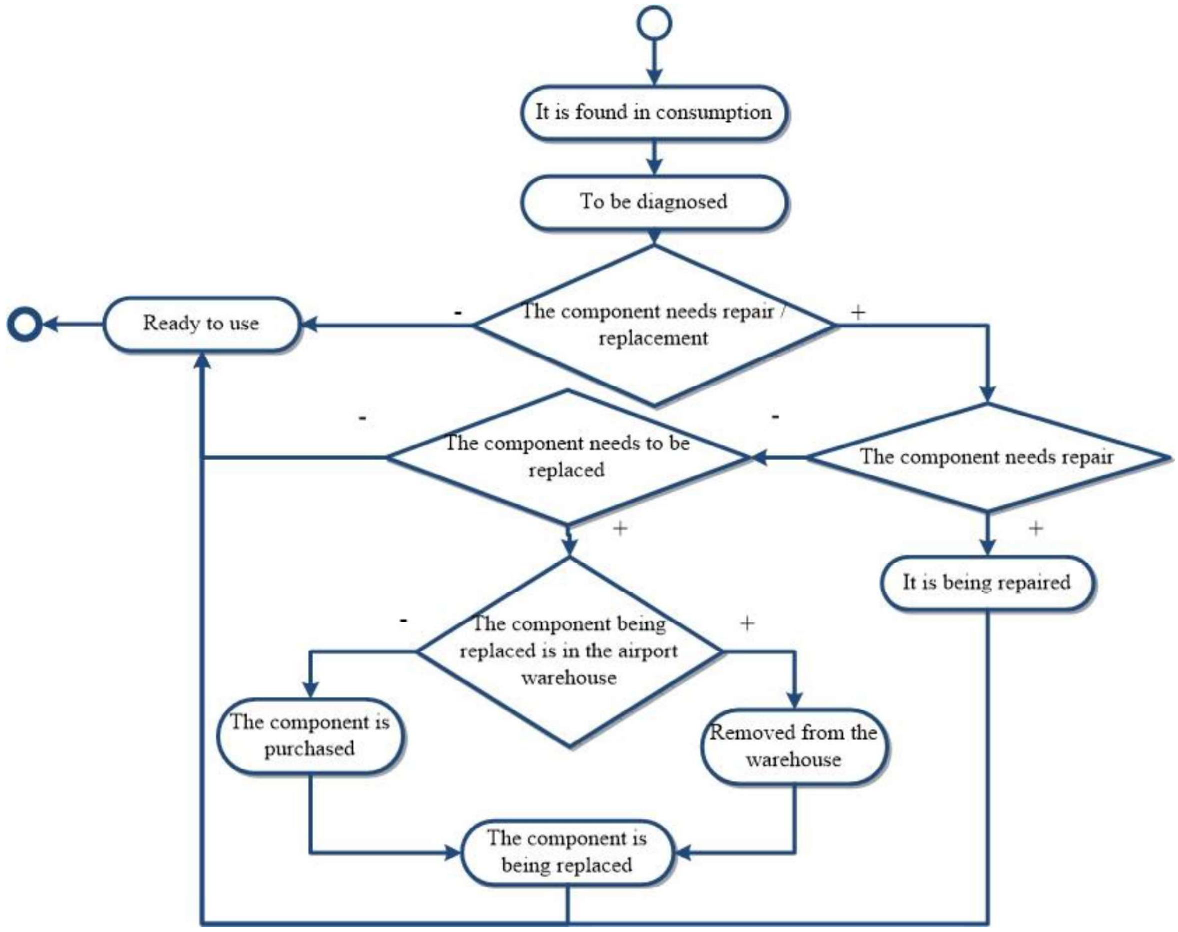

Fig. 4. Component state diagram during maintenance

To determine the optimal choice of a component supplier, it is necessary to form the logistics of the selection and method of cargo delivery, criteria for optimizing the airport supply process, and also to compile a matrix of selected supplier selection criteria (Table 2).

Table 2

Supplier selection criteria matrix

j	i	ϑ_1	w_1	s_1	t_{ij}	w_{ij}	r_{ij}
1	1	ϑ_1^1	w_1^1	s_1^1	t_{11}	w_{11}	r_{11}
1	2	ϑ_1^2	w_1^2	s_1^2	t_{21}	w_{21}	r_{21}
1	3	ϑ_1^3	w_1^3	s_1^3	t_{31}	w_{31}	r_{31}
2	1	ϑ_1^1	w_1^1	s_1^1	t_{12}	w_{12}	r_{12}
2	2	ϑ_1^2	w_1^2	s_1^2	t_{22}	w_{22}	r_{22}
…	…	…	…	…	…	…	…
n	k_n	ϑ_1^{kn}	w_1^{kn}	s_1^{kn}	$t_{k_n n}$	$w_{k_n n}$	$r_{k_n n}$

The logistics supply chain can be represented as a transport network graph, the edges of which are modeled passage of cargo flow (components and consumables). Within the framework of the developed model of enterprise selection for the purchase of missing components, it is proposed to determine indicators for optimal decision-making and set restrictions for each indicator. Let us define these restrictions.

Cargo restrictions:

– the volume of cargo that can be accommodated by each vehicle intended for transporting components, v_1;

– carrying capacity of each vehicle, m_1.

The presented multi-agent model of airport AE restoration (see Fig. 2) involves the use of trucks to supply the necessary components.

Time limit:

– speed of vehicles on a given section of the route, ϑ_1;

– vehicle range taking into account the fuel tank capacity, t_1;

– time spent on refueling and driver rest, t_2.

Minimum spending restrictions:

– cost of the component, w_1;

– average cost of one liter of fuel, w_2;

– distance between cities (manufacturing enterprises, warehouses of aviation products), s_1;

– fuel consumption of each vehicle unit per 100 km, w_3 etc.

Let us introduce a Boolean variable x_{ij} that shows the choice of the i-th alternative as a manufacturing enterprise or a warehouse of aviation products for the purchase of the j-th component for replacement at the airport. In this case:

$$x_{ij} = \begin{cases} 1, & \text{selection of the i-th enterprise (warehouse)} \\ & \text{to purchase the j-th component;} \\ 0, & \text{otherwise (no choice).} \end{cases}, \tag{10}$$

where $i=\overline{1,k_j}$, k_j is the number of alternatives as a manufacturing enterprise or warehouse of aviation products for purchasing the missing j -th component at the airport warehouse ; $j=\overline{1,n}$, n is the number of components that need replacement.

In addition, it is necessary to take into account

$$\sum_{i=1}^{k_j} x_{ij} = 1, \tag{11}$$

which means a mandatory choice of one of the alternatives. Then the risks of not replacing components in time are as follows:

$$R_{ij} = \sum_{j=1}^{n}\sum_{i=1}^{k_j} r_{ij} * x_{ij}, \tag{12}$$

where r_{ij} is the risk of failure to replace the j-th component in a timely manner when choosing the ith alternative component supplier.

Costs for replacing missing components:

$$W_{ij} = \sum_{j=1}^{n}\sum_{i=1}^{k_j} w_{ij} * x_{ij}, \tag{13}$$

where w_{ij} is spend on replacing the j- th component in time when choosing the i-th alternative component supplier

$$w_{ij} = w_1 + \left(\frac{s_1^i}{100} * w_3 * w_2 \right) * 2. \tag{14}$$

Costs may vary depending on the volume of the shipment and the weight of the component or components to be delivered.

Delivery time for missing components:

$$T_{ij} = \sum_{j=1}^{n} \sum_{i=1}^{k_j} t_{ij} * x_{ij}, \tag{15}$$

where t_{ij} is the duration of supply for replacing the jth component on time when choosing the i-th alternative component supplier.

$$t_{ij} = \frac{\left(\frac{s_1^i}{100} * w_3 \right)}{t_1} * t_2 * 2. \tag{16}$$

For the smooth operation of the airport, it is necessary to minimize delays to scheduled flights due to repair activities. Therefore, in the model for optimizing the selection of a supplier of aircraft components, it is proposed to minimize the duration of the supply of components necessary for replacement:

$$\min T_{ij},\ T_{ij} = \sum_{j=1}^{n} \sum_{i=1}^{k_j} t_{ij} * x_{ij}, \tag{17}$$

at the same time

$$R_{ij} \le R'_{ij},\ R_{ij} = \sum_{j=1}^{n} \sum_{i=1}^{k_j} r_{ij} * x_{ij}, \tag{18}$$

$$W_{ij} \le W'_{ij},\ W_{ij} = \sum_{j=1}^{n} \sum_{i=1}^{k_j} w_{ij} * x_{ij}, \tag{19}$$

where R'_{ij} is the acceptable value of the risk of not replacing components on time ; W'_{ij} is planned costs for replacing missing components.

We minimize the risks of not replacing components on time:

$$\min R_{ij},\ R_{ij} = \sum_{j=1}^{n} \sum_{i=1}^{k_j} r_{ij} * x_{ij}, \tag{20}$$

when fulfilling the constraints $T_{ij} \le T'_{ij}$, $W_{ij} \le W'_{ij}$, where T'_{ij} is the permissible duration of supply of components .

Next, we minimize costs for replacing missing components:

$$\min W_{ij},\ W_{ij} = \sum_{j=1}^{n} \sum_{i=1}^{k_j} w_{ij} * x_{ij}, \tag{21}$$

when fulfilling the constraints $T_{ij} \le T'_{ij}$, $R_{ij} \le R'_{ij}$.

Next, multi-criteria optimization is performed to ensure the optimal choice of supplier. For this, we introduce a complex criterion in the form of a sum of individual indicators:

$$F_{ij} = \alpha_{T_{ij}} \hat{T}_{ij} + \alpha_{W_{ij}} \hat{W}_{ij} + \alpha_{R_{ij}} \hat{R}_{ij}, \tag{22}$$

where $\alpha_{T_{ij}}$, $\alpha_{W_{ij}}$, $\alpha_{R_{ij}}$, is weight coefficients, respectively, for $\hat{T}_{ij}$, $\hat{W}_{ij}$, $\hat{R}_{ij}$, obtained through expert assessment of their importance. In this case:

$$\begin{gathered} 0 \le \alpha_{T_{ij}} \le 1,\ 0 \le \alpha_{W_{ij}} \le 1,\ 0 \le \alpha_{R_{ij}} \le 1, \\ \alpha_{T_{ij}} + \alpha_{W_{ij}} + \alpha_{R_{ij}} = 1. \end{gathered} \tag{23}$$

Selection indicators $\hat{T}_{ij}$, $\hat{W}_{ij}$, $\hat{R}_{ij}$, are normalized (converted to a dimensionless scale $[0,1]$):

$$\hat{T}_{ij} = \frac{T_{ij} - T^*_{ij}}{T'_{ij} - T^*_{ij}},\ \hat{W}_{ij} = \frac{W_{ij} - W^*_{ij}}{W'_{ij} - W^*_{ij}},\ \hat{R}_{ij} = \frac{R_{ij} - R^*_{ij}}{R'_{ij} - R^*_{ij}}, \tag{24}$$

where T^*_{ij}, W^*_{ij}, R^*_{ij} is extreme values of indicators obtained by local optimization.

It is necessary to minimize the complex criterion taking into account the requirements for selecting a supplier of missing components:

$$\min\ F_{ij}, \tag{25}$$

$$F_{ij} = \alpha_{T_{ij}} \hat{T}_{ij} + \alpha_{W_{ij}} \hat{W}_{ij} + \alpha_{R_{ij}} \hat{R}_{ij} = \alpha_{T_{ij}} \frac{T_{ij} - T^*_{ij}}{T'_{ij} - T^*_{ij}} + \alpha_{W_{ij}} \frac{W_{ij} - W^*_{ij}}{W'_{ij} - W^*_{ij}} + \alpha_{R_{ij}} \frac{R_{ij} - R^*_{ij}}{R'_{ij} - R^*_{ij}}, \tag{26}$$

when fulfilling the requirements $T_{ij} \le T'_{ij}$, $W_{ij} \le W'_{ij}$, $R_{ij} \le R'_{ij}$.

The solution of such a multi-criteria problem can be carried out on the basis of single-criteria optimization methods, including functional-cost analysis, the ideal point method, the lexicographic method, etc. Each of these methods has its own certain advantages, disadvantages and scope. The above methods take into account the reduction to one criterion, and also allow preliminarily solve optimization problems as single-criteria.

Functional-cost analysis involves minimizing resource consumption in the production process by improving product design, improving methods of manufacturing parts, rationalizing technology and using effective materials. Economic, technical and design information is used to conduct the analysis. The proposed study does not consider the rationalization of manufacturing of missing components.

The idea of the ideal point method is based on the existence of an «ideal point» for solving a problem in which the extremum of all criteria is achieved. Since the ideal point, in the absolute majority of cases, is not among the permissible ones, the problem arises of finding the point that is «closest» to the ideal point and belongs to the set of permissible solutions. To solve a multi-criteria optimization problem using the ideal point method, it is necessary, first of all, to determine its coordinates, and then to determine the metric by which the distance to the optimal point could be measured. The model proposed in the study does not provide for the definition of the metric.

The lexicographic method is based on the primary ranking of partial optimization criteria according to their relative importance. Then, single-criteria optimization problems are gradually solved, starting with the most important criterion. The criteria can be evaluated by experts, which requires a mechanism for coordinating assessments. The possible solution obtained using the lexicographic method and the ideal point method may be somewhat subjective and inaccurate.

In the proposed supplier selection model, the multi-criteria optimization problem is transformed into a single-criteria one using the method based on the construction of a generalized criterion. The search for the extremum of the generalized (complex) criterion is carried out by applying the coordinate descent method. In model (26), three main criteria are distinguished for finding the optimal solution: the duration of the supply of missing components T_{ij}; the risks of failure to replace components on time R_{ij}; the costs of replacing missing components W_{ij}, which are combined into one integral (complex) criterion, which must be minimized taking into account the requirements for selecting a supplier of missing components. As a result, the original multi-criteria problem is reduced to a single-criteria optimization problem. The relative importance of the criteria is taken into account using weight coefficients, which can be changed in the process of studying the effectiveness of the resulting solution. The number of criteria is insignificant, therefore, using this approach, the exact optimal solution for selecting a supplier of missing airline components for the airport will be determined.

All current information obtained as a result of using the models proposed in the study is stored and accumulated in the database (DB) by involving the «DB Formation Agent» (see Fig. 2). The conceptual scheme of the formed DB is presented in Fig. 5.

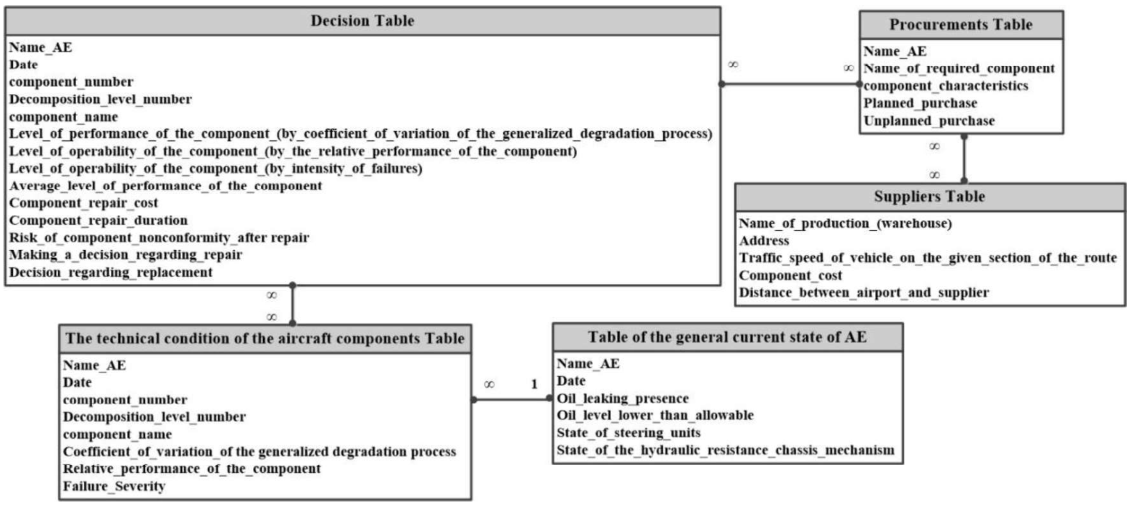

Fig. 5. Conceptual scheme of the maintenance database

The conceptual scheme of the database shown in Fig. 5 can be expanded to provide storage of information about vehicles (trucks) transporting components; the team of mechanics and loaders involved in a specific aircraft; the availability of all components in the airport warehouse, etc.

5. Research results

The experiment was conducted on the example of determining the impact of degradation processes on an unmanned aerial vehicle (UAV) during maintenance using the component model proposed in the work for determining the level of impact of degradation processes on the state of the AE.

The assessment of the impact of degradation was carried out during the sequential decomposition of the UAV sample. The aircraft itself was located at the zero level of decomposition. Therefore, the fragment of the decomposed component structure of the UAV, for which the impact of degradation processes was assessed, had the form shown in Fig. 6:

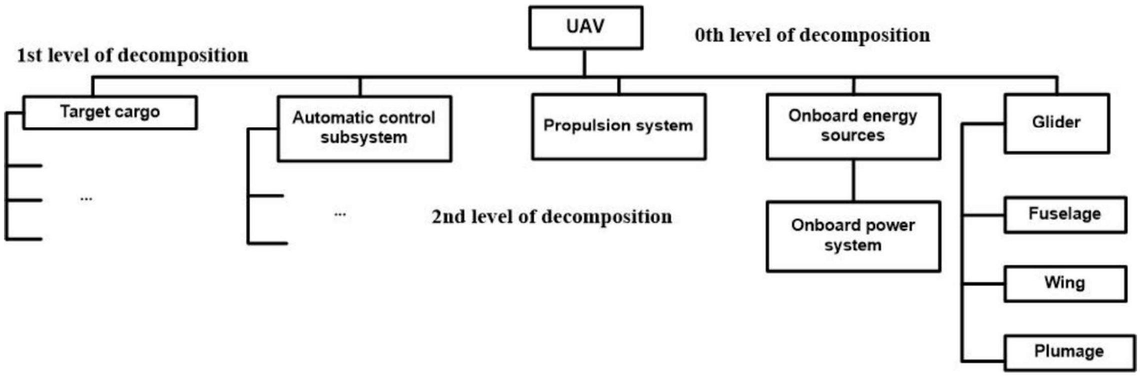

Fig. 6. Fragment of the decomposed component architecture of an unmanned aerial vehicle

An assessment of the impact of degradation on the second-level decomposition component «Onboard power system» after several years of UAV operation was carried out. The model for determining the level of impact of degradation on the state of the components of the multi-level AE architecture involves the calculation of three indicators: coefficient of variation of the generalized degradation process, indicator of the relative component life and component failure rate. The result of calculations regarding The coefficient of variation of the generalized degradation process has the following form: $V_{1\ general}^{2} = 18\%$, therefore $S\left(V_{1\ general}^{2}\right) = S_2$, according to formula (8).

The calculation of the relative component lifetime indicator is carried out as follows: $t_1^2 = \frac{200}{250} = 0.8$, which indicates a high level of lifetime. Therefore, as a result of expert assessment of the component's performance level according to this indicator, the value S_3 was obtained.

The component failure rate was calculated based on available statistical information about previous component failures of the same type: $\mu_1^2(150,\ 200\ \text{год.}) = \frac{5}{31*50} \approx 0.0032\ (1/\text{год})$. The obtained result was evaluated by experts and the level of component performance was determined as S_2 according to this indicator.

Further, based on the results of assessing the level of component performance by three indicators, the average level of component performance is determined according to formula (9): $avg\ index = 2.33$, $(avg\ index > 2)$. The results of a comprehensive assessment of the impact of degradation on the component under consideration are given in Table 3.

Table 3

Making a decision to replace or repair the «Onboard power system» due to degradation

i	j	Component name (subsystems)	$S\left(V_{i\ general}^{j}\right)$	$S(t_{i\ general}^{j})$	$S\left(\mu_i^j\left(\tau_{d+1}\right)\right)$	avg S_{index}
1	2	Onboard power system	S_2	S_3	S_2	$S_{2.33}$
i	j	W_{ij}	T_{ij}	R_{ij}	Repair	Replacement
1	2	3000 $	168 hours	0.75		+

As a result of all calculations, a decision was made to replace the «Onboard Power System» for this UAV in order to ensure high-quality and coordinated performance of its tasks during operation.

6. Discussion of the research results

The selection of components when assessing the degradation of the AE can be implemented on the basis of the proposed model of multi-level component fault finding in diagnosing the AE [4]. Therefore, the selection of components of a certain level of decomposition to assess the impact of degradation on them is carried out based on the complete or partial failure of the component or within the framework of preventive maintenance of a high-tech product.

The study proposes a multi-agent model for AM at the airport. A detailed description of the behavior and relationship between model agents is provided in the form of an airport agent activity diagram. Agents of the same type have the same structure, but they can be given individual properties, which makes the multi-agent model flexible and adaptive to changes in the composition of agents. Among the shortcomings of the proposed model, one can single out the fact that the needs for the number of agents of a certain type for specific situations are not calculated within the model. In the process of assessing the impact of degradation on the AE sample, an analysis of the multi-level component architecture is carried out at certain levels of product decomposition. The behavior of each component considered during maintenance is described in the form of a component state diagram.

The component model developed in the study for determining the level of influence of degradation processes, unlike existing solutions, provides an assessment of degradation at different levels of the multi-level architecture of the AE sample and involves taking into account three indicators: coefficient of variation of the generalized degradation process, the indicator of the relative operating life of the component, and the intensity of component failures. Due to this, using the component model proposed in the study for determining the level of influence of degradation processes on the condition of the AE during its maintenance and repair, an objective forecast of maintenance and spare parts needs is carried out, which further ensures a reduction in the duration and cost of maintenance by applying a multi-agent model of aircraft restoration at the airport and a model for optimizing the selection of aircraft component suppliers.

The research is aimed at further development of information technology based on the proposed set of models. Information technology will allow to automatically solve the tasks of maintenance and repair of AE. The limitation in the application of the developed set of models is that the models are highly specialized and can be used only for the aviation industry and cannot be used for other types of high-tech products except AE.

The models proposed in the study are used at the stage of operation of the AE. The end of the operation stage is considered to be the moment of documenting the decision on the impossibility or inexpediency of further operation of this product due to its technical condition, due to moral or physical obsolescence, significant material costs and other factors. The decommissioned product can not only be sent for repair, but also converted into educational equipment, converted for use not for its intended purpose, or disposed of. One of the promising areas of further research is the processes of utilization of AE.

7. Conclusions

Operation of such complex products as AE is usually carried out for a long time. During the operation period, some design, technological and operational shortcomings are revealed, in addition, malfunctions occur in the system, which must be identified, their causes determined and eliminated. One of the significant reasons for failures is degradation processes in a complex technical system. The development of a new product requires significant financial costs, resources and time, therefore, after a certain period of operation, there is a need to extend the period of trouble-free operation of the product and improve the level of performance of its components by repairing or replacing individual components of the product. Deterioration of the characteristics of the product components leads to time and resource costs required to restore the AE and bring it into working condition.

The study considered the operation phase for the purpose of optimizing maintenance processes and reducing the duration and cost of assessing the impact of degradation processes on AE and repairs during maintenance. In this study, it was considered and resolved the following tasks.

1. In order to determine the assessment of the impact of degradation processes on aircraft during maintenance, a component model for determining the level of impact of degradation processes on the AE is proposed. The assessment of the level of impact of degradation processes on the airframe is carried out on the basis of a component approach, which involves considering the impact of degradation processes on components of certain levels of decomposition of the product architecture. In addition, the assessment of the impact level is comprehensive. It involves taking into account three degradation indicators: the coefficient of variation of the generalized degradation process, the component lifetime and the component failure intensity , which ensures the accuracy of the assessment of the level of impact of degradation on the AE and allows, with the involvement of experts, to make a decision on replacement or repair of product components during maintenance.

2. A multi-agent model of actions for the restoration of AE at the airport, carried out during the maintenance of AE by replacing or repairing its components, was built. The relationship between the agents of the proposed model was formed and the sequence of actions of the airport agents was described in the form of an activity diagram of the model components.

3. To solve the problem of optimal search and transportation of components missing from the airport warehouse in order to restore AE during AM, a model for optimizing the selection of a supplier of aircraft components was proposed. The implementation of the developed model for optimizing the selection of a supplier of components necessary for maintenance to the airport will significantly reduce the costs of transporting cargo to the airport, reduce the time of cargo delivery by forming a rational route, ensure uninterrupted supply of spare parts to the airport, as well as make informed decisions regarding purchases and maintain a high level of service.

The set of models proposed in this study is aimed at further developing applied information technology, which will allow for automated solutions to the processes of maintenance and repair of AE at the operation stage, as well as ensuring the necessary level of reliability and extending the service life of AE.

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Надійшла до редколегії 14.11.2024 р.

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УДК 004.8 DOI: 10.30837/0135-1710.2024.183.035

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ДОСЛІДЖЕННЯ АРХІТЕКТУР НЕЙРОННИХ МЕРЕЖ ДЛЯ ПІДВИЩЕННЯ ТОЧНОСТІ ПРОГНОЗУВАННЯ ПОПИТУ НА ПРОДУКЦІЮ

Розглянуто використання різних архітектур нейронних мереж для задач прогнозування попиту на продукцію. Проаналізовано основні виклики та сучасні проблеми в області прогнозування, що виникають при роботі з великими обсягами даних і сезонними коливаннями. Особливу увагу приділено порівнянню архітектур нейронних мереж за кількома ключовими характеристиками, зокрема, Accuracy, F1-Score, Logarithmic, середньою абсолютною помилкою, коренем середньоквадратичної помилки та AUC-ROC. На основі детального аналізу та проведеного експерименту було визначено архітектуру нейронної мережі, яка забезпечує найвищу точність прогнозування при прогнозуванні попиту на продукцію.

1. Вступ

Прогнозування попиту на продукцію є важливою складовою успішної діяльності будь-якого підприємства, оскільки якість та достовірність прогнозів безпосередньо впливає на ефективність планування виробничих та логістичних процесів. Неточні прогнози можуть призвести до виникнення надлишкових запасів, що збільшує витрати на зберігання, або до нестачі продукції, що може спричинити зниження рівня обслуговування клієнтів і втрату доходу. У сучасних умовах, коли обсяги даних значно зросли, з’явилися нові можливості для застосування передових технологій аналізу, зокрема нейронних мереж. Використання нейронних мереж дозволяє підприємствам виявляти приховані закономірності в історичних даних, прогнозувати зміни попиту та формувати точніші прогнози, що допомагає підприємству своєчасно адаптуватися до ринкових умов [1].

Однак вибір архітектури нейронної мережі є складним завданням, оскільки різні архітектури мають свої переваги та недоліки в залежності від умов застосування. Наприклад, деякі архітектури можуть давати точніші результати при обробці великих обсягів історичних даних, тоді як інші краще справляються з задачами прогнозування в реальному часі або за нестандартними умовами. Незважаючи на значний прогрес у використанні нейронних мереж для задач прогнозування, питання вибору архітектури нейронної мережі, що надає точний результат, залишається недостатньо вивченим. Важливим напрямом сучасних досліджень є вивчення та вдосконалення існуючих архітектур для досягнення найкращих результатів у специфічних умовах, зокрема у виробничих і логістичних процесах, де попит на продукцію може змінюватися сезонно або