ІНФОРМАЦІЙНІ ТЕХНОЛОГІЇ

S.I. VLADOV
Kremenchuk Flight College of
Kharkiv National University of Internal Affairs
ORCID: 0000-0001-8009-5254

K.G. KOTLIAROV
Kremenchuk Flight College of
Kharkiv National University of Internal Affairs
ORCID: 0000-0002-6097-9084

S.A. HRYBANOVA
Kremenchuk Flight College of
Kharkiv National University of Internal Affairs
ORCID: 0000-0001-5831-2363

O.V. HUSAROVA
Kremenchuk Flight College of
Kharkiv National University of Internal Affairs
ORCID: 0000-0002-9823-0044

I.G. DEREVYANKO
Kremenchuk Flight College of
Kharkiv National University of Internal Affairs
ORCID: 0000-0003-0116-1378

S.D. GVOZDIK
Kremenchuk Flight College of
Kharkiv National University of Internal Affairs
ORCID: 0000-0002-5754-2949

NEURO-MECHANICAL METHODS OF CONTROL AND DIAGNOSTICS OF THE TECHNICAL STATE OF AIRCRAFT ENGINE TV3-117 IN FILM REGIONS

The subject of the study in the article is the modes of operation of the aircraft engine TV3-117 and methods of their control and diagnostics. The purpose of the work is to develop methods of control and diagnostics of the technical condition of the aircraft engine TV3-117 on the basis of neural network technologies in real time. The following tasks are solved: substantiation of the preconditions of the use of neural networks in the task of control and diagnostics of the technical condition of the aircraft engine TV3-117, construction of the generalized neural network and the choice of the algorithm for its training, the solution of the task of controlling the parameters of the technical condition of the aircraft engine TV3-117 with the use of neural networks. The following methods are used: methods of probability theory and mathematical statistics, methods of neuroinformatics, methods of the theory of information systems and data processing. The following results were obtained: The feasibility of using neural networks in the task of controlling and diagnosing the technical condition of the aircraft engine TV3-117 was substantiated. The expediency of developing neural networks based on the NN Predictive Controller. The expediency of using the gradient method of teaching neural networks is substantiated, as well as the method of training a neuro-regulator based on a neuro-modulator with the use of the method of reverse error propagation. The expediency of using the gradient method of teaching neural networks is substantiated, as well as the method of training a neuro-regulator based on a neuro-modulator with the use of the method of reverse error propagation. The solution of the task of controlling the parameters of the technical condition of the aircraft engine TB3-117, which confirms the expediency of using neural networks in the task of control and diagnostics of the technical condition of the aircraft engine TV3-117, is obtained. Conclusions: The application of neural network technologies is effective in solving a wide range of poorly formalized tasks, one of which is the task of controlling the technical condition of the aircraft engine TV3-117. The advantage of neural networks in their application in the tasks of control and diagnostics of the technical condition of the aircraft engine TV3-117 is the possibility of working with small training samples, the appointment of soft tolerances, using the experience of experts to assess the technical condition of the aircraft engine TV3-117, which is important in the condition's information incompleteness.

Keywords: engine, neural network, technical condition, control and diagnosis.

С.І. ВЛАДОВ
Кременчуцький льотний коледж
Харківського національного університету внутрішніх справ
ORCID: 0000-0001-8009-5254

К.Г. КОТЛЯРОВ
Кременчуцький льотний коледж
Харківського національного університету внутрішніх справ
ORCID: 0000-0002-6097-9084

С.А. ГРИБАНОВА
Кременчуцький льотний коледж
Харківського національного університету внутрішніх справ
ORCID: 0000-0001-5831-2363

О.В. ГУСАРОВА
Кременчуцький льотний коледж
Харківського національного університету внутрішніх справ
ORCID: 0000-0002-9823-0044

І.Г. ДЕРЕВ'ЯНКО
Кременчуцький льотний коледж
Харківського національного університету внутрішніх справ
ORCID: 0000-0003-0116-1378

С.Д. ГВОЗДІК
Кременчуцький льотний коледж
Харківського національного університету внутрішніх справ
ORCID: 0000-0002-5754-2949

НЕЙРОМЕРЕЖЕВІ МЕТОДИ КОНТРОЛЮ І ДІАГНОСТИКИ ТЕХНІЧНОГО СТАНУ АВІАЦІЙНОГО ДВИГУНА ТВ3-117 У ПОЛЬОТНИХ РЕЖИМАХ

Предметом дослідження в статті є режими роботи авіаційного двигуна ТВ3-117 та методи їх контролю і діагностики. Мета роботи – розробка методів контролю і діагностики технічного стану авіаційного двигуна ТВ3-117 на основі нейромережевих технологій у режимі реального часу. В статті вирішуються наступні завдання: обґрунтування передумов застосування нейронних мереж у задачі контролю і діагностики технічного стану авіаційного двигуна ТВ3-117, побудова узагальненої нейронної мережі та вибір алгоритму її навчання, розв'язок задачі контролю параметрів технічного стану авіаційного двигуна ТВ3-117 із застосуванням нейронних мереж. Використовуються такі методи: методи теорії ймовірностей і математичної статистики, методи нейроінформатики, методи теорії інформаційних систем та обробки даних. Отримано наступні результати: Обґрунтовано доцільність застосування нейронних мереж у задачі контролю і діагностики технічного стану авіаційного двигуна ТВ3-117. Обґрунтовано доцільність розробки нейронних мереж на базі на базі нейрорегулятора NN Predictive Controller. Обґрунтовано доцільність застосування градієнтного методу навчання нейронних мереж, а також розроблено метод навчання нейрорегулятора на основі нейромодулятора із застосуванням методу зворотного поширення помилки. Отримано розв'язок задачі контролю параметрів технічного стану авіаційного двигуна ТВ3-117, який підтверджує доцільність застосування нейронних мереж у задачі контролю і діагностики технічного стану авіаційного двигуна ТВ3-117. Висновки: Застосування нейромережевих технологій э ефективним при розв'язку широкого кола погано формалізованих задач, однією з яких є задача контролю технічного стану авіаційного двигуна ТВ3-117. Перевагою нейронних мереж при їх застосуванні у задачах контролю і діагностики технічного стану авіаційного двигуна ТВ3-117 є можливість роботи з малими навчальними вибірками, призначенням м'яких допусків, використанням досвіду експертів для оцінки технічного стану авіаційного двигуна ТВ3-117, що є важливим в умовах неповноти інформації.

Ключові слова: авіаційний двигун, нейронна мережа, технічний стан, контроль і діагностика.

С.И. ВЛАДОВ
Кременчугский летный колледж
Харьковского национального университета внутренних дел
ORCID: 0000-0001-8009-5254
К.Г. КОТЛЯРОВ
Кременчугский летный колледж
Харьковского национального университета внутренних дел
ORCID: 0000-0002-6097-9084
С.А. ГРИБАНОВА
Кременчугский летный колледж
Харьковского национального университета внутренних дел
ORCID: 0000-0001-5831-2363
О.В. ГУСАРОВА
Кременчугский летный колледж
Харьковского национального университета внутренних дел
ORCID: 0000-0002-9823-0044
И.Г. ДЕРЕВЯНКО
Кременчугский летный колледж
Харьковского национального университета внутренних дел
ORCID: 0000-0003-0116-1378
С.Д. ГВОЗДИК
Кременчугский летный колледж
Харьковского национального университета внутренних дел
ORCID: 0000-0002-5754-2949

НЕЙРОСЕТЕВЫЕ МЕТОДЫ КОНТРОЛЯ И ДИАГНОСТИКИ ТЕХНИЧЕСКОГО СОСТОЯНИЯ АВИАЦИОННОГО ДВИГАТЕЛЯ ТВ3-117 В ПОЛЕТНЫХ РЕЖИМАХ

Предметом исследования в статье являются режимы работы авиационного двигателя ТВ3-117 и методы их контроля и диагностики. Цель работы – разработка методов контроля и диагностики технического состояния авиационного двигателя ТВ3-117 на основе нейросетевых технологий в режиме реального времени. В статье решаются следующие задачи: обоснование предпосылок применения нейронных сетей в задаче контроля и диагностики технического состояния авиационного двигателя ТВ3-117, построение обобщенной нейронной сети и выбор алгоритма ее обучение, решение задачи контроля параметров технического состояния авиационного двигателя ТВ3-117 с применением нейронных сетей. Используются следующие методы: методы теории вероятностей и математической статистики, методы нейроинформатики, методы теории информационных систем и обработки данных. Получены следующие результаты: Обоснована целесообразность применения нейронных сетей в задаче контроля и диагностики технического состояния авиационного двигателя ТВ3-117. Обоснована целесообразность разработки нейронных сетей на базе на базе нейрорегулятора NN Predictive Controller. Обосновано целесообразность применения градиентного метода обучения нейронных сетей, а также разработан метод обучения нейрорегулятора на основе нейромодулятора с применением методп обратного распространения ошибки. Получено решение задачи контроля параметров технического состояния авиационного двигателя ТВ3-117, подтверждающее целесообразность применения нейронных сетей в задаче контроля и диагностики технического состояния авиационного двигателя ТВ3-117. Выводы: Применение нейросетевых технологий является эффективным при решении широкого круга плохо формализованных задач, одной из которых является задача контроля технического состояния авиационного двигателя ТВ3-117. Преимуществом нейронных сетей при их применении в задачах контроля и диагностики технического состояния авиационного двигателя ТВ3-117 является возможность работы с малыми учебными выборками, назначением мягких допусков, использованием опыта экспертов для оценки технического состояния авиационного двигателя ТВ3-117, что является важным в условиях неполноты информации.

Ключевые слова: авиационный двигатель, нейронная сеть, техническое состояние, контроль и диагностика.

Problem statement

Operation of the aircraft engine TV3-117 takes place with the continuous change of the technical state of attachments, units and parts due to inevitable aging processes, characterized by a constant change in their properties in general in the direction of deterioration. This happens under the influence of internal and external factors, either having a rather strict deterministic, or a random unpredictable manifestation. In conditions of increased load on the attachments and units of the engine, increasing the safety of its operation is achieved on the basis of using the management strategy of operation in actual technical condition. This involves using along

with classical approaches and new intellectual methods that allow efficiently and qualitatively to carry out the process of control and diagnostics of the technical condition of the aircraft engine TV3-117 taking into account the incompleteness of measured information, noise measurements, the presence of constructive, parametric and expert uncertainty in evaluating its parameters. The basis for the operation of the aircraft engine TV3-117 is the subordination of the objectives of the operation of its on-board information technology control and operation management purposes for the operation of the aircraft engine, which defines the rules and procedures for processing comprehensive information in accordance with the conditions of its operation.

Despite the considerable amount of research in this field [1–3], information technology for control and diagnostics of the technical condition of aviation engines is not perfect for a number of reasons: on the one hand, weak information "link", lack of elements of "intelligence", allowing to rapidly, efficiently and effectively support responsible decision-making and, as a consequence, reduce the total time spent on maintenance of aviation engines; on the other hand, the unsteadiness of physical processes in the aviation engine, the complexity of their mathematical description, the dependence of its technical characteristics on external conditions of work, the limited composition of the measured parameters, their technological spread, etc. These factors lead to the need to automate the decision-making process on the technical condition of the aircraft engine under uncertainty.

The main directions determining the efficiency of on-board information technology for control and diagnostics of the technical condition of aviation engines should be considered intellectualization of information processing processes involving neural network methods that are capable of improving the quality of on-board algorithms for monitoring and diagnosing the technical condition of aviation engines under the influence of the above-mentioned factors of uncertainty.

Thus, the creation of on-board information technology for monitoring and diagnosing the technical condition of the aircraft engine TV3-117 involves the development of appropriate methods, techniques, algorithmic and software that can improve the efficiency and quality of the solution of tasks of control and management of the operation of the aircraft engine TV3-117.

Recent research and publications analysis

At present, the problems of information diagnostics of aviation technology are actively engaged scientists of the Moscow State Technical University of Civil Aviation, among which one should highlight the work of Professor Oleg Mashoshin [4–6], in which different methods of determining the malfunction of aviation equipment, including aviation engines. Much attention was paid to the methods of diagnostics of aviation technology from the standpoint of informativeness and information provision processes of its diagnosis. It is also worth noting the work of Professor Serhii Gernakov (Ufa State Aviation Technical University) [7–9], devoted to the control and diagnostics of the technical state of aviation gas turbine engines on the basis of intelligent data analysis. But their work is devoted to the development of information systems for controlling the technical condition of aviation engines in conditions of bench testing only. Thus, the development of the on-board control system for the technical condition of the aircraft engine TV3-117 (including local tasks) is relevant.

Materials and results

The basis of the ideology of the information system for monitoring and diagnosing the technical condition of the engine TV3-117 is the use of the FDI (Fault Detection and Identification) method, which is based on a comparison of the results of measurements of gas-dynamic indicators in real-time with formular [10] (fig. 1).
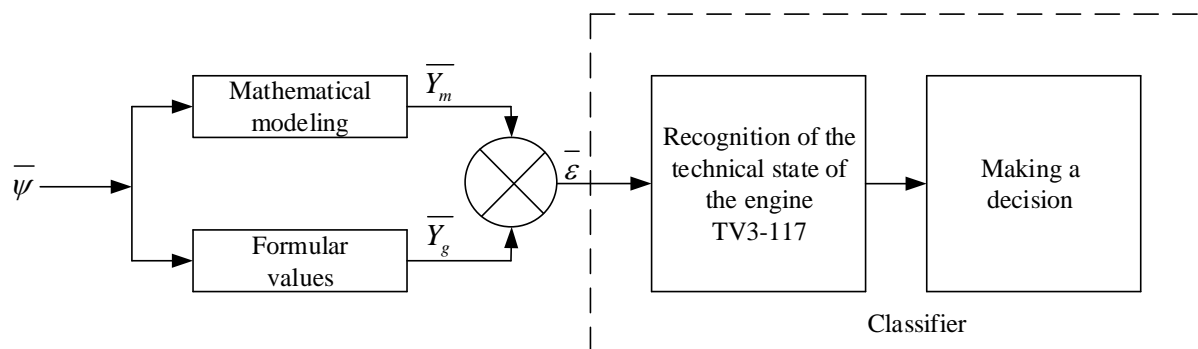

Fig. 1. Realization of FDI-method

In fig. 1 is indicated: $\overline{\psi}$ – vector of control effects; $\overline{Y_m}$ – vector of parameters obtained on the basis of mathematical modeling of gas-dynamic processes in real time; $\overline{Y_g}$ – vector of formular values of gas-dynamic indicators; $\overline{\varepsilon} = \overline{Y_g} - \overline{Y_m}$ – non-binding, obtained in the process of component comparison of vectors $\overline{Y_g}$ and $\overline{Y_m}$.

Implementation of the FDI-method allows to take into account as much as possible the individual features of the aviation engine TV3-117 by using a mathematical model that adapts to the individual characteristics of the latter, obtained during its operation. When using neural networks to solve the problems of controlling and diagnosing the state of the aviation engine TV3-117, available information is presented to the neural network in the form of ready-made solutions (tasks), on the basis of which the process of its training (learning) is carried out. When assessing the quality of the network's network, its input is the data from the test sample, on the basis of which it calculates the vector of deviations (the difference between the output of the neural network and the desired characteristics).

In addition, neural networks have a number of undeniable advantages:

– they are able to solve problems poorly formalized by traditional mathematical methods, including control and diagnostics of the technical state of the engine TV3-117 and the classification of its information-identification features by classes of functional states;

– the solution of these tasks is possible in real time due to the high speed of the neural network, which is especially important for the onboard system;

– given the diversity of connections in the neural network, its reliable work is possible even after damage some of them;

– in the process of its work, the neural network is able to learn itself in accordance with the variable parameters in the process of operation of the engine.

Creation of an on-board system for monitoring and diagnosing the technical state of the engine on the basis of neural network technologies, the structural-logic scheme of which is shown in fig. 2, includes the following steps:

– identification of systems and units, and aviation engine TV3-117, i.e. the creation of a neural network (which includes the choice of its type and architecture), the input values of which are the functional parameters of the engine, recorded by the sensors, and the output – the parameters that determine its condition, with the possibility self-training and correction of their parameters in the process of exploitation of a particular unit;

– creation of a training sample for the neural network on the basis of statistical information on the functional parameters of the engine in all modes of operation and the most likely failures of operation experience (for already operated engines) or bench test results (for those engines being developed or upgraded);

– training of the neural network using the training sample;

– verification of the adequacy and correctness of the created and trained neural network by modeling the operating modes and failures of engines not included in the training sample;

– hardware implementation of the developed neural network in electronic circuits, integrated into the system of automatic control of the engine.

Proceeding from the fact that the parameters of the technical condition of the aircraft engine TV3-117 are as follows: air pressure at the engine inlet (x_1), air temperature at the inlet to the engine (x_2), fan speed (x_3), compressor air pressure (x_4), compressor rotation frequency (x_5), the temperature of the gas behind the turbine (x_6), the gas pressure behind the turbine (x_7), the oil level in the oil system (x_8), the presence of chips in oil (x_9), fuel combustion in the combustion chamber (x_{10}), temperature fuel at the inlet to the engine (x_{11}), fuel pressure at the inlet to the engine (x_{12}), oil temperature at the engine inlet (x_{13}), oil pressure on the entrance of the engine (x_{14}), the diameter of the critical intersection of the nozzle (x_{15}), the vibration of the engine housing (x_{16}), engine propagation (x_{17}) [11], it is assumed that these parameters form a multilayered neural network with $n = 17$ inputs and one output (fig. 3). Each i-th neuron of the first layer ($i = 1, 2, ... m = 17$) has $n = 17$ inputs, which are written with weights $w_{1i}, w_{2i}, ... w_{ni}$.

By inputting any numbers $x_1, x_2, ... x_{17}$, we get at the output the value of some function $Y = F(x_1, x_2, ... x_{17})$, which is the answer (response) of the network. It is known that the response of the network depends both on the input signal and on the values of its internal parameters – the weights of the neurons, that is:

$$F\left(x_1, x_2, ..., x_{17}\right) = \sum_{i=1}^{m=17} v_i \sigma\left(\sum_{j=0}^{n=17} x_j w_{ji}\right); \qquad (1)$$

where $F(x_1, x_2, ... x_{17})$ is any continuous function defined on a bounded set; $\sigma(s) = \dfrac{1}{1 + e^{-\alpha s}}$ – sigmoidal function.

Applying Kolmogorov's theorem $F\left(x_1, x_2, ..., x_n\right) = \sum_{i=1}^{2n+1} g_i\left(\sum_{j=1}^{n} h_{ij}\left(x_j\right)\right)$, where g_i and h_{ij} – are continuous functions, and h_{ij} does not depend on the function F, for 17 variables, it is found that for the implementation of the function 17 variables are sufficient operations of summation and composition of the function of one variable.
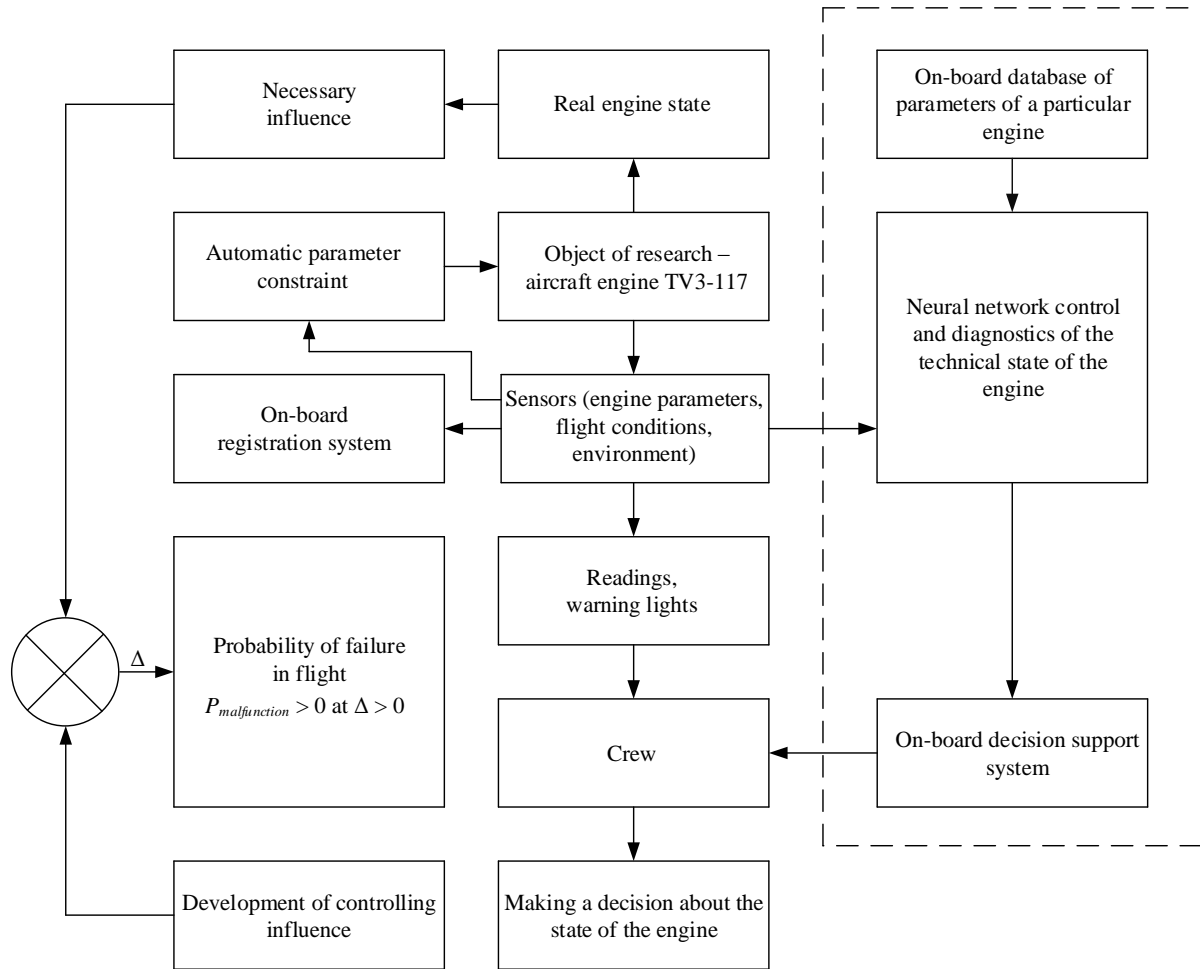
**Fig. 2. Structural-logical scheme of the control and diagnostics system
of aircraft engine TV3-117 technical condition in flight modes**
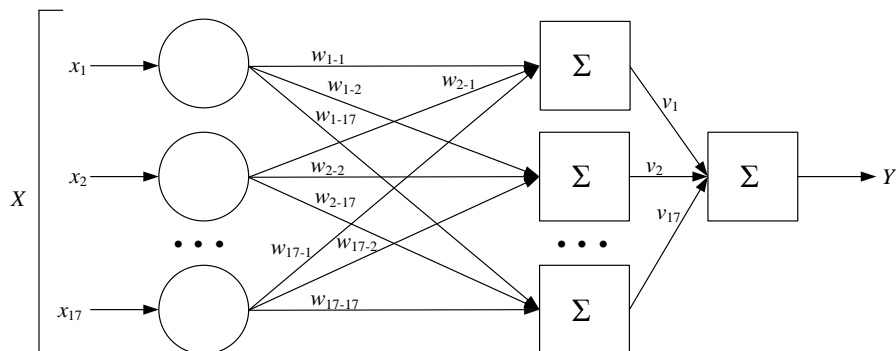

Fig. 3. Structure of the generalized neural network

In the work, the synthesis of the neural network system was carried out using the application package Neural Network Toolbox MATLAB system, which implemented three neuro regulators: NN Predictive Controller Forecast; Regulator based on autoregressive model with sliding middle NRAMA-L2 Controller; Regulator based on reference model Model Reference Controller.

NN Predictive Controller is most effective in solving the problem. The controller uses the model of the managed object as a neural network in order to predict its future behavior. In addition, the controller calculates a control signal that optimizes the behavior of the object at a predetermined interval of time. Consequently, the design of a neuro-regulator consists of two stages: the stage of identification of the controlled object and the stage of the synthesis of the control law. At the first stage, a model of a controlled object is developed in the form of a neural network, which is used in the next step for the synthesis of the regulator [12].

Fig. 4 shows a structural diagram of the proposed neural network system for monitoring and diagnostics of the technical condition of the aircraft engine TV3-117, developed in Simulink. This structure includes a subsystem control unit and a NN Predictive Controller, as well as generators of a standard random variable amplitude generator Random Reference, a chart construction block.
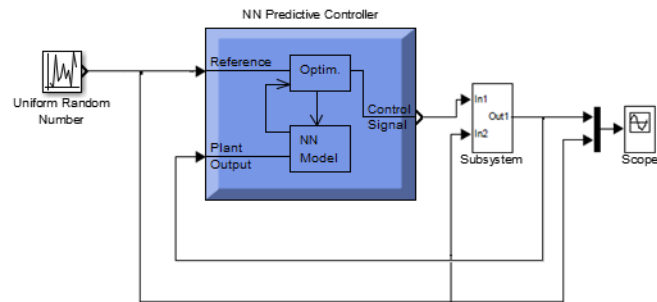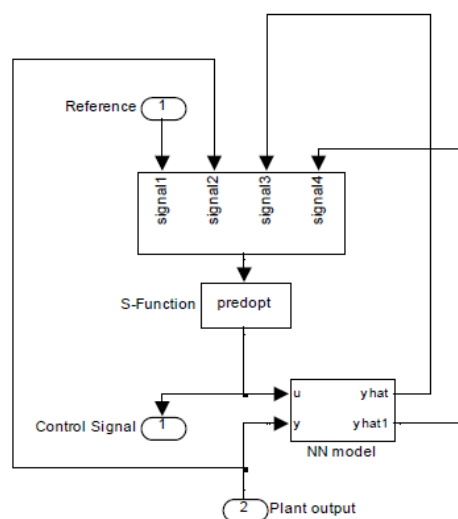

Fig. 4. Scheme of control system based on NN Predictive Controller

Scheme of the model of the control object is shown in fig. 5 and the structural scheme of the neuro regulator NN Predictive Controller – in fig. 6.
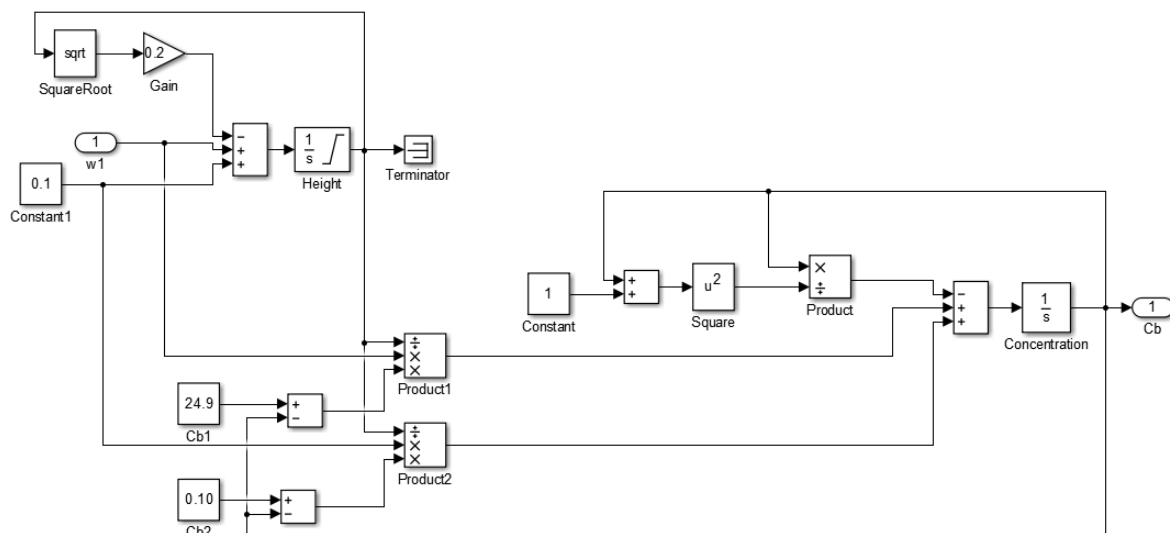
Fig. 5. Schematic of the management model (subsystem)

Fig. 6. Structural scheme of the NN Predictive Controller neuroregulator [12]

The feature of this system is that, before installing a separate neuro-regulator, the identification of the controlled object, namely, the aviation engine TV3-117, is carried out, that is, the construction of its neural network model is underway. The identification procedure allows constructing a neural network that will simulate engine dynamics and is used by the S-function to calculate the optimal control signal on the engine. The training sequence generation program generates training data by influencing a number of random stepped signals on the simulink model of the controlled object (engine). After the network is established, the process of its learning begins. The input vectors are represented as numerical sample arrays, which corresponds to a group representation of the data.

After the construction of the neural network model is completed, the Neural Network Predictive Controller returns to the window (Fig. 4) and the optimization parameters are set:

1. Const Horizon (N_2) – the upper limit of summation with the quality indicator N_2, the lower limit N_1 is fixed and equal to 1;

2. Control Horizon (N_u) – the upper limit of summation when evaluating power management N_u;

3. Control Weighting Factor (ρ) – the weight factor for power management;

4. Search parameter (α) – jne-dimensional search parameter setting the threshold for quality reduction;

5. Minimization Routine – select a one-dimensional search procedure;

6. Iterations Per Sample Time – the number of iterations per 1 bit of discretion.

When identifying an engine, the most important issue is the choice of the number of neurons of the hidden layer S. With a small number of neurons, the network cannot perform the task, but with a large observed phenomenon of retraining and increasing the volume of computing.

Since the most important property of neural networks is their ability to study on the basis of data on the aircraft engine TV3-117 and, as a result of training to increase its functionality, it is proposed to apply the adaptive step of training the neural network, which is realized in the form of a gradient method [13], in which the weight change is described by dependence:

$$\overrightarrow{w_{k+1}} = \overrightarrow{w_k} + \eta_k \overrightarrow{p_k};$$ (2)

where η_k – is the step size for the k-th iteration, and the vector p_k specifies the direction of motion and is calculated by the formula:

$$\overrightarrow{p_k} = \overrightarrow{g_k} + \sum_{i=1}^{\min(k-1,m)} \beta_i \overrightarrow{g_{k-1}};$$ (3)

where vector g_j specifies the direction of the anti-gradient on the j-th iteration; β_i – coefficient which determines the weight of the i-th gradient; m defines the number of memorable gradients; k – serial number of the current iteration.

The gradient learning method for (3) is obtained for $m = 0$, and the methods of the combined gradients, which are most often used in the training of neural networks, are obtained by summing all previous directions (при $m = \infty$). The general algorithm of the adaptive method is [13]:

1. Beginning;

2. Select a starting point with some coordinates (x_0; y_0; ...);

3. Verification of the stop criterion (number of iterations, mean square error, etc.);

4. Calculation of the anti-gradient at the current point $\overrightarrow{g_j}$ (at the first iteration of the starting point);

5. Enter the current direction to the stack directions;

6. Calculating the vector direction by (3);

7. Moving the calculated p_k to a new point;

8. Returning to step 2. If the stop criterion is positive, then finish the algorithm, if not – go to step 3;

9. End of the algorithm. We have a point close to the minimum of the function.

This training method minimizes human interference in the training of neural networks, which makes it attractive, since not every user of neural network technologies has knowledge of optimization techniques. In addition, the method is flexible and tailored to the learning sample by learning.

The training of the same neural network with a constant step is carried out with the help of the Hebb's rule, which consists in the fact that learning occurs as a result of strengthening the binding force (synaptic weight) between simultaneously active neurons. Proceeding from this, often used in the network of communication intensified, which explains the phenomenon of learning through repetition and addiction. The Hebba teaching rule is written as follows [14, pp. 39–40]:

$$w_{ij}(t + 1) = w_{ij}(t) + x_i y_j;$$ (4)

it is assumed that $w_{ij}(0) = 0$, where t – time; x_i and y_j are respectively the initial value of the i-th and j-the neurons.

The continuous training of the neural network is also implemented through the Rosenblatt training (learning perceptron), which is characterized by the fact that the weighting coefficients of the neural network change only if the initial response of the network y does not coincide with the reference d and contains the learning speed a and not changes weight coefficients if the output signals of the network coincide with the reference ones. The Rosenblatt training rule in general form has the form [14, pp. 42–45]:

$$W(t + 1) = W(t) - a(y - t)X = W(t) + a(t - y)X. \tag{5}$$

For the solution of the problem of recognition or approximation of functions of multilayer direct propagation networks, weighting coefficients must be corrected. This correction is based on known methods of training neural networks, which consist of three types [15–17]:

1. Teaching with a teacher. Put a set of training vectors – input values and desired results of the neural network. Weights in the process of learning are selected in such a way that the results obtained are as close as possible to the desired results.

2. Training with evaluation. Initially, the desired vector of output signals is not given, but according to the results of the neural network receives a positive or negative rating.

3. Exercise without a teacher. A set of input data vectors is established that are processed on the basis of self-organization laws, which leads the neural network to a state in which it is capable of solving tasks.

The circuit of the neural network control with the emulator and the controller is shown in fig. 7. In this case, the neuro regulator learns on the reverse pattern of the control object, and the neuromodulator learns from the real model of the control object (engine).

The neurocontroller is trained on the basis of a neuromodulator, which learns by the method of reverse error propagation. To teach a neuro-emulator, a multilayered direct-propagation network with randomly selected weights and a training set consisting of the pairs of the network input – the desired output $\{X, D\}$, as well as the output value of the network Y, are determined.
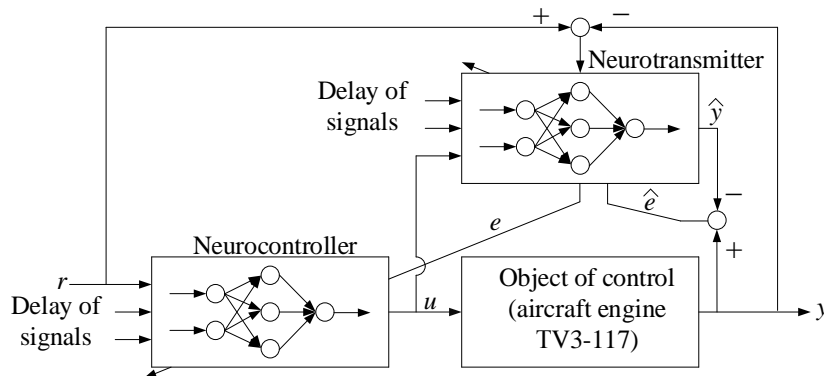

Fig. 7. The scheme of neural network control with the emulator and controller

The task of training the neuroregulator is to select weighting factors to minimize some target function – the sum of squares of network errors on examples from the training set, that is

$$E(w) = \sum_{j,p} \left(y_{j,p}^{(N)} - d_{j,p} \right)^2; \tag{6}$$

where $y_{j,p}^{(N)}$ – the real output of the N-th output layer of the network for the p-th neuron in the j-th study example, $d_{j,p}$ is the desired output.

To find the minimum and determine the weight coefficients that are included in the $y_{j,p}^{(N)}(x)$ function of the method of fastest descent [18], in which at each step of the training change the weight coefficients in accordance with the expression:

$$\Delta w_{ij}^{(n)} = -\eta \frac{\partial E}{\partial w_{ij}^{(n)}}; \tag{7}$$

where $w_{ij}^{(n)}$ is the weighting factor that convenes the *j*-th neuron *n*-th layer and *i*-th neuron (*n*–1) layer, η is the learning speed parameter.

To do this, the obtained weighting coefficients of the network need to determine the partial derivatives of the target function *E*:

$$\frac{\partial E}{\partial w_{ij}^{(n)}} = \frac{\partial E}{\partial y_j^{(n)}} \frac{\partial y_j^{(n)}}{\partial s_j^{(n)}} \frac{\partial s_j^{(n)}}{\partial w_{ij}^{(n)}}; \tag{8}$$

where $y_j^{(n)}$ – output, $s_j^{(n)}$ – sum of inputs of *j*-th neuron of *n*-th layer. Knowing the activation function can be calculated $\frac{\partial y_j^{(n)}}{\partial s_j^{(n)}}$. For sigmoidal function $\frac{\partial y_j^{(n)}}{\partial s_j^{(n)}}$ will be equal to:

$$\frac{\partial y_j^{(n)}}{\partial s_j^{(n)}} = \alpha y_j^{(n)} \left(1 - y_j^{(n)}\right). \tag{9}$$

Output of *i*-th neuron (*n*–1)-th layer $\frac{\partial s_j^{(n)}}{\partial w_{ij}^{(n)}}$ can be represented as:

$$\frac{\partial s_j^{(n)}}{\partial w_{ij}^{(n)}} = y_j^{(n-1)}. \tag{10}$$

Thus, by differentiating (8) $y_j^{(N)}$ with respect to (10) and Kolmogorov's theorem, we calculate the partial derivatives of the objective function by the weights of the initial layer neurons:

$$\frac{\partial E}{\partial w_{ij}^{(n)}} = \left(y_j^{(N)} - d_j\right) \frac{\partial y_j^{(N)}}{\partial s_j^{(N)}} y_j^{(N-1)}. \tag{11}$$

Entering in (11) substitution $\delta_j^{(n)} = \frac{\partial E}{\partial y_j^{(n)}} \frac{\partial y_j^{(n)}}{\partial s_j^{(n)}}$, we obtain the value of neurons in the output layer:

$$\delta_j^{(N)} = \left(y_j^{(N)} - d_j\right) \frac{\partial y_j^{(n)}}{\partial s_j^{(n)}}. \tag{12}$$

To find $\alpha y_j^{(n)}$ of the weight coefficients of the neurons of the inner layers, we represent (8) in the following form:

$$\frac{\partial E}{\partial y_j^{(n)}} = \sum_k \frac{\partial E}{\partial y_k^{(n+1)}} \frac{\partial y_k^{(n+1)}}{\partial s_k^{(n+1)}} \frac{\partial s_k^{(n+1)}}{\partial y_j^{(n)}} = \sum_k \frac{\partial E}{\partial y_k^{(n+1)}} \frac{\partial y_k^{(n+1)}}{\partial s_k^{(n+1)}} w_{jk}^{(n+1)}. \tag{13}$$

Note that $\delta_k^{(n+1)} = \sum_k \frac{\partial E}{\partial y_k^{(n+1)}} \frac{\partial y_k^{(n+1)}}{\partial s_k^{(n+1)}}$, what allows (6) to express the values $\delta_j^{(n)}$ of *n*-th layer neurons by means of neurons (*n*+1)-th $\delta_k^{(n+1)}$ layer. The value $\delta_j^{(n)}$ for all neurons of all layers can be obtained through the recursive formula for the last layer $\delta_j^{(N)}$:

$$\delta_j^{(n)} = \left(\sum_k \delta_k^{(n+1)} w_{jk}^{(n+1)}\right) \frac{dy_j}{ds_j}. \tag{14}$$

Thus, (7) for the correction of weight coefficients takes the form of:

$$\Delta w_{ij}^{(n)} = -\eta \delta_j^{(n)} y_j^{(n-1)}. \tag{15}$$

Teaching a neuroregulator with the help of the algorithm of re-distribution occurs in several stages:

1. Assigning arbitrary initial values of the weight coefficients of the neural network and obtaining the values of the target function at given values.

2. The input of the neural network is provided by the vector of the training set, and then the values at the output of the neural network are calculated, which form the vector of memory from the values of each neuron.

3. Calculate the values $\delta_j^{(N)}$ of the neurons in the original layer for (12), and the recursive formula (14) calculates the values $\delta_j^{(n)}$ with the help of neurons (*n*+1)-th $\delta_k^{(n+1)}$ layer, and then after (15) the weight of the neural network changes.

4. Adjustment of weighting coefficients of the network: $w_{ij}^{(n)} = -w_{ij}^{(n)} + \Delta w_{ij}^{(n)}$.

5. The target function for (6) is calculated, and if it is relatively small, we can assume that the neural network has successfully passed the training procedure. Otherwise, we proceed to step 2.

Let's consider the solution of the task of controlling the technical condition of the aircraft engine TV3-117 with the use of neural network technologies [19]. It is believed that all possible states of the engine can be divided into two classes S_o and $\overline{S_o}$, which combine some states close to each other according to certain integral indicators. Here, the S_o class includes all the proper states of the engine, and the class $\overline{S_o}$ combines all the faulty states that are characterized by the presence of at least one defect in its work. It is necessary by the results of a limited number of measurements of the vector of the initial parameters of the engine $Y(t_i)$, $t_i \in T$ (where t_i – discrete moments of time; T – interval of observation), to make a decision on the belonging of the engine to one of the specified classes of states.

The solution of this problem in general is reduced to finding a separate function (hypersurface) in the space of controlled parameters of the engine. To solve this problem we apply an approach based on the construction of this decisive rule with the help of a neural network.

The basis of the proposed method is the construction of reference (averaged) model of the engine obtained by the results of flight (or bench) tests of the engine, which is stored in the neural network basis as its information "portrait". In the process of controlling the technical condition of the aviation engine the measurement of its parameters is carried out; Then the metric describes the difference in the characteristics of a particular (individual) engine and reference (neural network) engine model, and the size of this metric is made decision about the actual state of the engine under investigation.

The idea of the investigated algorithm for controlling the technical state of the engine is as follows: the engine state is a point in the space of controlled parameters $y_1, y_2,\ldots, y_n$ (in this work, n = 4). To assess the engine's efficiency, that is, the conformity of its characteristics to the requirements, it is necessary to calculate the distance from this point to the reference point corresponding to the reference (normal) engine. If this distance is zero, the technical state of the engine coincides with the reference; the larger the value of the specified distance, the greater the difference between the characteristics of the controlled and reference engines.

As estimates of the metric distance (metric), known in the literature on mathematical statistics and cluster analysis, one can distinguish the following:

1. The Euclidean metric:

$$d = \sqrt{\sum_{i=1}^{n} \left(y_i - y_i^{ref} \right)^2}; \tag{16}$$

where y_i – measured value of the *i*-th parameter of the engine; y_i^{ref} – reference value of this parameter, calculated using the neural network.

2. Metropolitan Chebyshev:

$$d = \max \left| y_i - y_i^{ref} \right|. \tag{17}$$

The physical meaning of the metric (16) consists in the fact that it characterizes the mean square deviation in the exits space between the object and its reference model, and the metric (17) characterizes the greatest deviation between these outputs.

Let's consider the features of the solution of the task of controlling the technical condition of the aircraft engine TV3-117. As the initial data are considered such as, data obtained during the flight test of the engine at various temperature values T_0, K and pressure P_0, mm of mercury environment. Table 1 shows the parameters of the reference (well-known service) engine, which are brought to relative (dimensionless) values; $\overline{T_0} = 1$ and $\overline{P_0} = 1$ correspond to the parameters $T_0 = 288\ K$ and $P_0 = 760$ mm of mercury.

Table 1

Parameters of the reference engine

$\overline{T_0}$	$\overline{P_0}$	$\overline{n}$	$\overline{T_3^*}$	$\overline{P_2^*}$
1,000	0,951	0,867	0,749	0,255
1,012	1,011	0,894	0,787	0,305
1,005	0,974	0,930	0,809	0,312
1,026	0,974	1,000	0,894	0,353
1,000	0,990	0,858	0,743	0,271
1,022	0,973	0,798	0,721	0,209

Table 2 shows the data of engine flight tests, which are further processed by the neural network and the results of their processing, the last decision on the results of control of the aircraft engine is made.

Table 2

A fragment of the engine TV3-117 test data, analyzed using a neural network

№	$\overline{T_0}$	$\overline{P_0}$	$\overline{n}$	$\overline{T_3^*}$	$\overline{P_2^*}$
1	1,029	0,993	0,827	0,766	0,238
2	1,029	0,995	0,826	0,766	0,239
3	1,022	0,997	0,816	0,748	0,234
4	1,015	0,980	0,819	0,743	0,230
5	1,040	1,041	0,829	0,755	0,250
6	1,008	1,023	0,797	0,740	0,240
7	1,000	1,016	0,796	0,712	0,237
8	0,995	1,015	0,805	0,711	0,243
9	1,000	1,031	0,825	0,726	0,262
10	1,000	0,997	0,844	0,743	0,272

The results of the conducted research show that in order to construct a standard model based on the neural network, the structure of the neural network, the three-layer perceptron (fig. 8), which has two inputs (values of environmental parameters − T_0 and P_0), optimal for complexity is required, 12 neurons in the hidden layer and 3 neurons at its output.
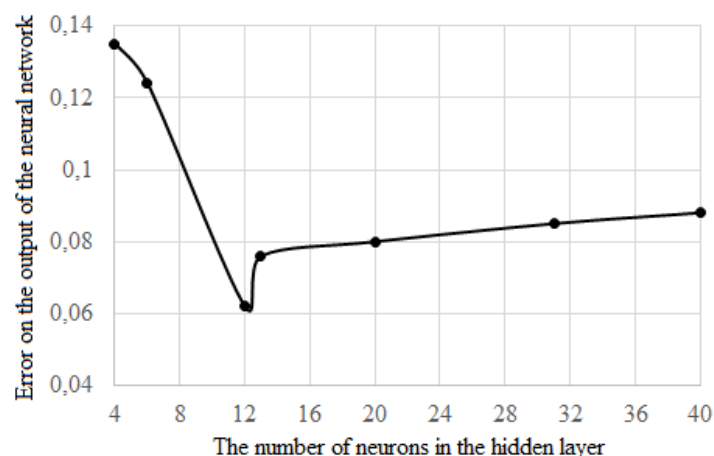

**Fig. 8. Graph of the dependence of the error of training the neural network
on the number of neurons in the hidden layer**

When solving a given problem, the calculation of the metric distance for (16) and (17) as a function of the development of aviation engine, in order to assess the degree of performance of its performance compared with the reference engine, throughout the test time.

The received schedule of change of the metric distance d depending on the progress of the aircraft engine TV3-117 is shown in fig. 9, where 1 is the Euclidean distance calculated by (16); 2 – Chebyshev distance, calculated in accordance with (17).
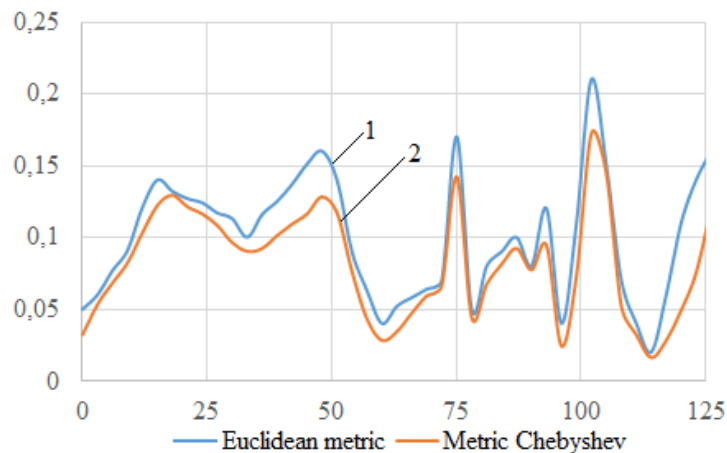

Fig. 9. Results of control of technical condition of aircraft engine TV3-117

The decision-making process on the technical state of the engine as a result of controlling its parameters can be carried out on the basis of fuzzy logic, while the functions of accessory (fig. 10) are appointed expertly; R – the decision on the serviceability of the engine is issued in the form of coefficients of confidence.
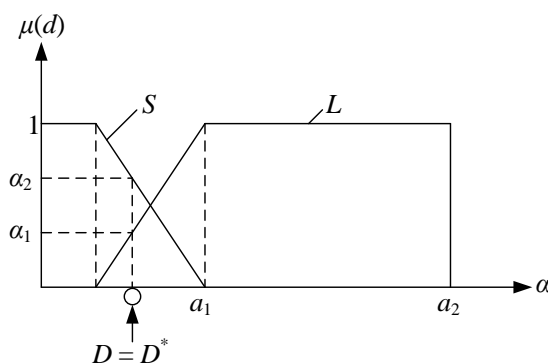

Fig. 10. Functions of the belonging of the linguistic variable D

The decisive rule, on the basis of which the decision is made on the correctness of the engine, has the following form:

$$R = \begin{cases} S_o, \text{ if } d = S\,(\text{Small}); \\ \overline{S_o}, \text{ if } d = L\,(\text{Large}). \end{cases} \tag{18}$$

The final decision on the technical condition of the aircraft engine is taken by the expert taking into account the values of the confidence coefficients (for example, in fig. 10, the value of α_1 means the confidence coefficient of implementing rule 1 in (18); α_2 is the same value for the 2nd rule).

Conclusions

Thus, based on the obtained results, we can make the following conclusions:

1. The application of neural network technologies is effective in solving a wide range of poorly formalized tasks, one of which is the task of controlling the technical condition of the aircraft engine TV3-117.

2. The advantage of neural networks in their application in the tasks of control and diagnostics of the technical condition of the aircraft engine TV3-117 is the ability to work with small training samples, the

appointment of soft tolerances, using the experience of experts to assess the technical condition of the aircraft engine TV3-117, which is important in conditions of incompleteness of information.

References

1. S. Kiakojoori and K. Khorasani, "Dynamic neural networks for gas turbine engine degradation prediction, health monitoring and prognosis", Neural Computing & Applications, vol. 27, no. 8, 2016, pp. 2151–2192.
2. E. L. Ntantis, "Diagnostic Methods for an Aircraft Engine Performance", Journal of Engineering Science and Technology, review 8(4), 2015, pp. 64–72.
3. A. M. Pashayev, D. D. Askerov, C. Ardil, R. A. Sadiqov and P. S. "Abdullayev Complex Condition Monitoring System of Aircraft Gas Turbine Engine", International Journal of Aerospace and Mechanical Engineering, vol. 1, no. 11, 2007, pp. 689–695.
4. O. Mashoshin and G. Zontov, "Diagnostics of aviation gas turbine engine on the presence of harmful impurities in the air conditioning system", Scientific Bulletin of the Moscow State Technical University of Civil Aviation, no 205, 2014, pp. 44–48.
5. O. Mashoshin, "Assessment of the diagnostic value of information in solving problems in the field of aircraft operation", Scientific Bulletin of the Moscow State Technical University of Civil Aviation, no 219, 2015, pp. 53–56.
6. O. Mashoshin, M. Karmyzov and V. Makarov, "Algorithm for estimating the vibration state of gas turbine engines using elements of the theory of mathematical statistics", Scientific Bulletin of the Moscow State Technical University of Civil Aviation, no 135, 2008, pp. 28–33.
7. S. Gernakov, "Determination of the trend of aircraft engine parameters by an active expert system", Aviation industry, no. 4, 2004, pp. 24–28.
8. S. Gernakov, "Application of expert systems with neural networks of knowledge to diagnostics and control of aircraft engine devices", Information Technology, no. 12, 2000, pp. 37–44.
9. S. Gernakov, "Active expert system for diagnostics and control of GTE parameters", Information Technology, no. 2, 2001, pp. 34–39.
10. Y. Shmelov, S. Vladov, A. Khebda and K. Kotlyarov, "Application of the rules of urban logic in the problem of identification of the technical state of the aviation engine TV3-117", Scientific notes of V. I. Vernadsky Taurida National University, Series Technical Sciences, vol. 30 (69), no. 3, 2018, pp. 34–40.
11. Y. Shmelov, S. Vladov, S. Boiko, Y. Klimova and S. Vyshnevskyi, "Diagnostics of the state of the Mi-8MTV helicopter using neural networks", Herald of Khmelnytskyi national university: Technical sciences, no. 3, 2018, pp. 165–170.
12. T. Vasylets, O. Varfolomiiev, R. Tiutiun, Yu. Alforov and A. Vlasov, "Synthesis of the NN Predictive Controller for the three-mass electromechanical system", Information Processing Systems, no. 3 (149), 2017, pp. 88–95.
13. S. Vladov and Y. Klimova, "Application of adaptive neural network training method for diagnostics of the engine of the Mi-8MTV helicopter", The International Theoretical and Practical Conference "Participating in European Scientific, Scientific and Engineering and Innovation Programs and the Integration of Ukraine with the European Research Space", 16–18 May, Kharkiv, National Technical University "Kharkiv Polytechnic Institute", part 1, p. 14.
14. V. Govovko, Neural networks: training, organization and application 4th ed., Moscow, Publishing house "IPRZHR", 2001, 256 p.
15. D. Shanin, V. Pshikhopov and M. Medvedev, "Neural network adaptive controller for the task of helicopter model control through global feedback", News of South Federal University. Technical science, no. 11 (88), 2008, pp. 107–110.
16. D. Shanin, V. Pshikhopov, V. Chikin and M. Medvedev, "Application of a neural network adaptive controller to control an object with uncertainty", News of South Federal University. Technical science, no. 7 (84), 2008, pp. 136–140.
17. D. Shanin, V. Pshikhopov and M. Medvedev, "Construction of neural network regulators for the synthesis of adaptive control systems", Information-measuring and control systems, no. 3, vol. 6, 2008, pp. 48–52.
18. Y. Shmelov, S. Vladov, Y. Klimova and M. Kirukhina, "Expert system for identification of the technical state of the aircraft engine TV3-117 in flight modes", System Analysis & Intelligent Computing: IEEE First International Conference on System Analysis & Intelligent Computing (SAIC), 08–12 October 2018, Kiev, National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", pp. 77–82.
19. Y. Shmelov, S. Vladov, A. Kryshan and S. Gvozdik, "Application of neural network technologies in the technical state control system of the aircraft engine TV3-117 in flight modes", Radiotekhnika, no. 194, 2018, pp. 147–154.