Modified Neural Network Fault-Tolerant Closed Onboard Helicopters Turboshaft Engines Automatic Control System

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Abstract

The work is devoted to the modernization of closed onboard helicopters turboshaft engines automatic control system through the use of a selectable block of neural network controllers in front of the control channel selector – gas generator rotor r.p.m. and gases temperature in front of the compressor turbine. To ensure the principle of minimal complexity of the neural network controller, a three-layer perceptron with two neurons in the input layer, three neurons in the hidden layer, and one neuron in the output layer was chosen as a neural network. It is proved that in order to fulfill the small gain theorem, which was applied to determine the fault tolerance of the automatic control system, the optimal neural network training algorithm is backpropagation error algorithm with regularization, which includes a quadratic criterion for determining the neural network training error. The results of the research showed that with the use of the developed automatic control system for helicopters turboshaft engines, the time diagrams of thermo-gas-dynamic parameters of engine control – gas generator rotor r.p.m. and gases temperature in front of the compressor turbine show more stable values compared to the standard automatic control system, in which the spread of parameters reaches several percent, which for helicopters turboshaft engines is critical, and indicates the indication of a false engine defect.

Keywords

Helicopters turboshaft engines, automatic control system, neural network regulator, transient processes, gas generator rotor r.p.m., gases temperature in front of the compressor turbine

1. Introduction

Currently, neural network technology is one of the most dynamically developing areas of artificial intelligence. It has been successfully used in various fields of science and technology, such as pattern recognition, diagnostic systems for complex technical objects, ecology and environmental science (weather forecasts and various cataclysms), the construction of mathematical models that describe climatic characteristics, biomedical applications, etc. in the field of operation of aircraft gas turbine engines (GTE), in particular, helicopters (aircraft gas turbine engines with a free turbine (TE)), it is relevant to create a unified methodology for the development of algorithms for designing and training various types of neural networks to solve problems of managing the operation of engines operational status, including: the development of algorithms and software for the neural network control method operation of an engine that provides a higher probability of detecting defects in GTE compared to existing methods; verification of the effectiveness of the neural network method on the example of specific aviation gas turbine engines; identification the architectures of neural networks that are most effective for managing the operation of GTE [1, 2].

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It is known that among the malfunctions and failures of GTE, a significant part is parametric, consisting in the discrepancy between the values of the parameters controlled on the engine and the technical specifications. To control and prevent such failures, parametric diagnostic methods are used, based on special processing and analysis of the values of thermo-gas-dynamic and other parameters measured on a running engine during its operation.

The assessment of helicopters TE operational status, in the conditions of their flight operation, is carried out, as a rule, according to a limited amount of information, due to the small number of standard controlled parameters. This significantly limits the effectiveness of parametric methods based on the identification of mathematical models of engine workflows. Therefore, it is relevant to conduct research to improve the efficiency of onboard methods for helicopters TE operational status monitoring, including the method of neural networks [3, 4].

2. Related Works

2.1. Literature review

Modern helicopters TE are complex nonlinear dynamic systems with the mutual influence of gas-dynamic and thermophysical processes occurring in its nodes. To simulate such processes, it is proposed to use a mathematical apparatus in the form of artificial neural networks. A review of the literature shows that neural networks are used to solve various problems and show high accuracy, including in the tasks of modeling and identification complex technical systems [5, 6]. In [7, 8], a dynamic neural network for monitoring and predicting gas turbine engine operational status was developed. In [9, 10], neural network methods for diagnostics of GTE parameters were developed using a semi-alternative optimization strategy.

At the same time, the analysis of modern literature [11, 12] devoted to neural networks and neural network control systems shows that, despite the ongoing active developments in this area, many issues related to the development of algorithms and methods for identification nonlinear objects based on neural network models, synthesis of the structure and adaptation (training) algorithms for the parameters of neural network controllers [13, 14], features of their implementation in multi-mode control systems for nonlinear dynamic objects. All of the above fully applies to such a dynamically complex class of control objects as helicopters TE.

Thus, the task of synthesizing a neural network controller for helicopters TE characteristics identification and their elements in helicopters TE onboard automatic control system (ACS) is relevant.

2.2. Research problem statement

In the process of designing GTE ACS, they are subject to strict and often conflicting requirements. The scope of these requirements is usually limited to a given set of internal and external parameters of the control system. The use of artificial intelligence methods, and, in particular, neural networks, allows you to expand and tighten these requirements by removing restrictions on the area of change of these parameters. Additional requirements for GTE ACS include:

– adaptation of GTE ACS characteristics to changing operating modes and flight conditions, individual characteristics of a particular engine;

– predicting the behavior of the system in order to quickly adjust control algorithms in a changing environment;

– ensuring the stability of work processes and the operability of GTE ACS both in design and emergency modes associated with failures of actuators, sensors, information input-output devices, strong external disturbances at the input of GTE, etc.

At present, the greatest progress in the design of intelligent control systems has been achieved for control systems that have the property of “intelligence in small things” [15]. This means, first of all, that the control system uses knowledge in the course of its functioning (to achieve its goals) as a means of overcoming the uncertainty of input information, the behavior of the controlled object, and the state of the system elements.

In [16], an onboard helicopters TE ACS is described, which, within the framework of the global monitoring task, solves such particular problems: classification of engine operation modes, identification of direct, inverse and dynamic engine models, engine operational status control, diagnostics and prediction, engine parameters debugging (regulation), trend analysis and others.

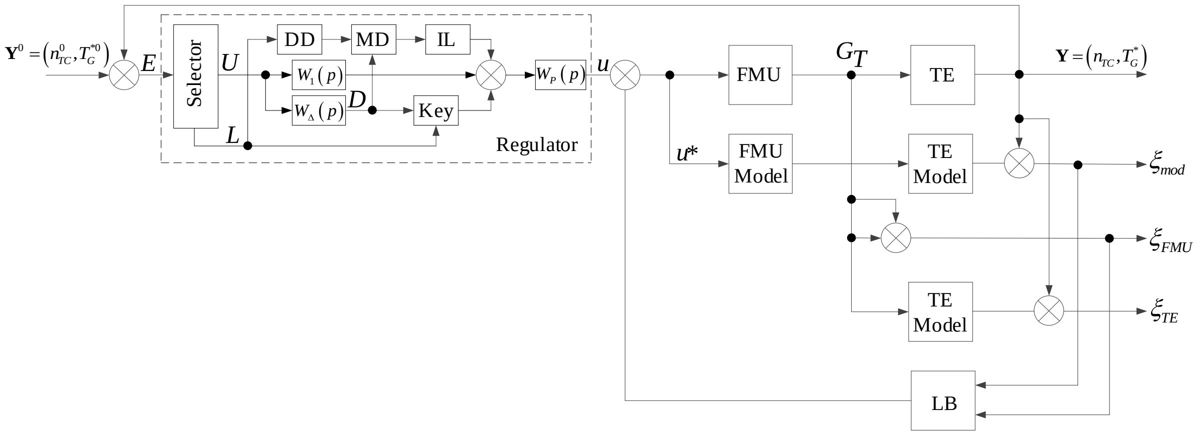


Figure 1: Helicopters TE automatic control system [16]

The developed helicopters TE on-board intelligent ACS is essentially non-linear, therefore, the issues of modification control and monitoring algorithms, as well as studying the stability of this system in a wide range of changes in its operating modes, remain open and require research.

3. Methods and materials

3.1. Implementation of a general approach to ensuring the fault tolerance of the onboard helicopters turboshaft engines automatic control system with a neural network controller

Modern helicopters TE (for example, TV3-117), operating under parametric conditions and structural uncertainty, require the use of new approaches to ensuring the fault tolerance of ACS. Decision-making algorithms based on fuzzy logic can be used as a basis for developing a fault-tolerant intelligent ACS. The presence of a rule base of the "IF-THEN" type allows using expert knowledge to solve this problem.

The fuzzy system for control, diagnostics, prediction and reconfiguring the ACS can be represented in this case as a supervisor, whose control signals are used to change the structure of the main neural network controller. This controller must contain a certain functional redundancy (for example, additional control programs or duplicating simplified NN_i algorithms (i = 1, …, m).

The control and training algorithm are a system of rules:

if $E = S$ and $\Delta E = S$ and … $u = S$, then choose NN_1;

if $E = M$ and $\Delta E = M$ and … $u = M$, then choose NN_2;

…

if $E = L$ and $\Delta E = L$ and … $u = L$, then choose NN_i;

where E, ΔE, u – inputs and outputs of the controller; S, M, L – values of the linguistic variable corresponding to the sets "Small", "Medium", "Large" (fig. 2). Accordingly, a membership function is constructed for each parameter. Further, using the inference mechanism, the value of the output parameters of the control and training unit is calculated, which are control signals that connect the currently required neural network controller NN_i to the actuators.

A distinctive feature of the above approach from the existing one, first proposed by professor Volodymyr Vasiliev, is the use of Gaussians to describe a linguistic variable, and not a function of a triangular type. This is explained by the fact that the Gaussian curve has a narrower distribution, and the membership of the parameter is close to the given value, compared to the triangular function.

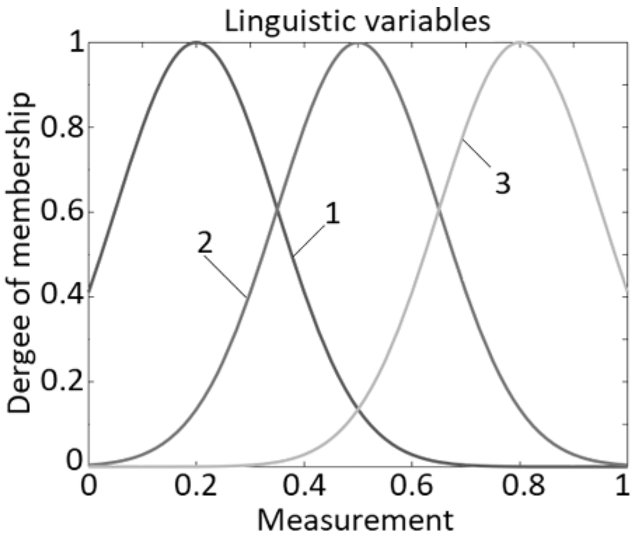


Figure 2: Membership functions general view: 1 – "Small", 2 – "Medium", 3 – "Large"

As an effective way to ensure fault tolerance, you can use the so-called active approach based on the reconfiguration of the neural network controller using a selector (fig. 3) in case of emergency situations in the operation of the ACS.

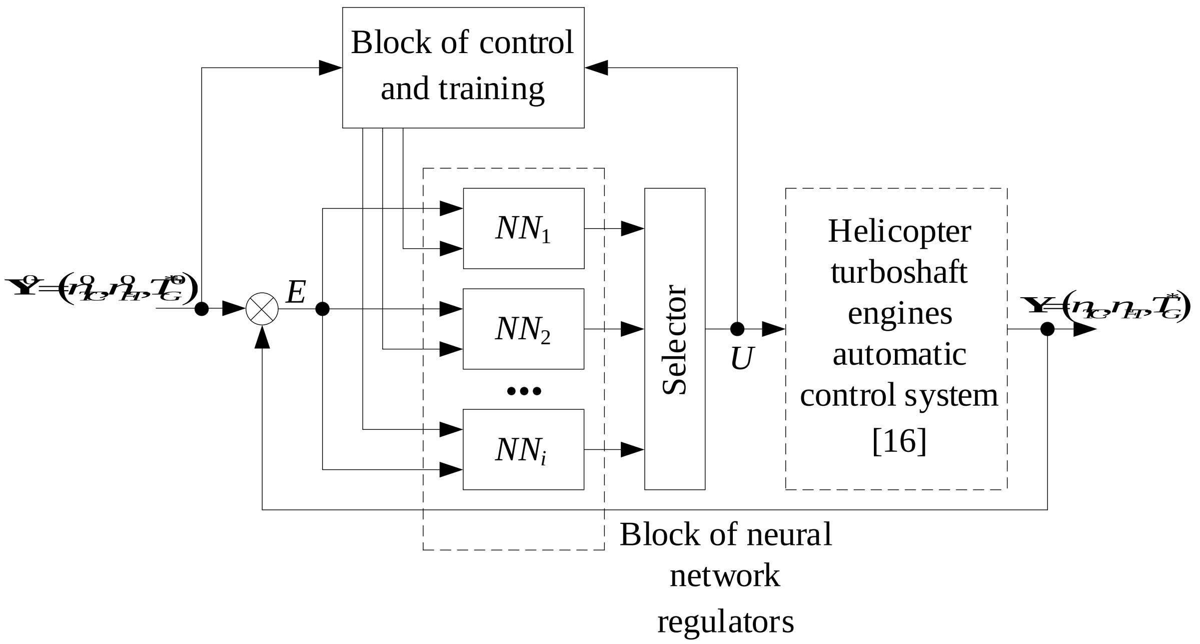


Figure 3: Diagram of the project of a fail-safe helicopters turboshaft engines automatic control system with a selectable block of neural network controllers

3.2. Synthesis of a supervisory neural network approximating the coefficients of the PID controller

According to the developed block diagram of the onboard helicopters TE ACS [16], as well as the generalized one (the most common option for including a neural network in helicopters TE ACS), in Fig. 4 shows a diagram of a closed-loop helicopters TE ACS, in which a supervisory neural network is used to tune the parameters of a linear PID controller depending on the engine operational status and external conditions. Compared to the classical (tabular) method of approximating the coefficients, the neural network approximator provides more flexible adaptation (training) to changes in external conditions and GTE parameters.

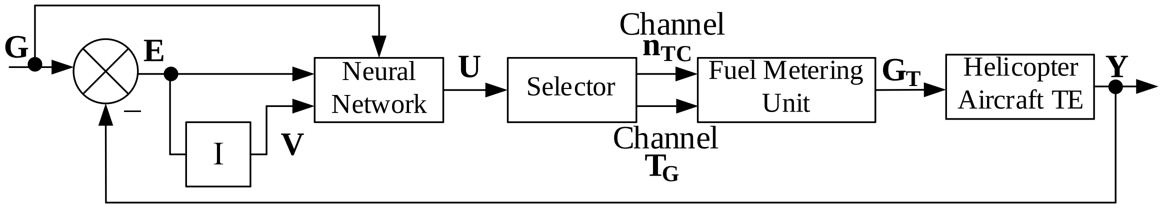


Figure 4: Generalized diagram for switching on a neural network controller in helicopters turboshaft engine automatic control system

The neural network performs the functions of a nonlinear multi-mode controller, providing the formation of the required control actions on the helicopters TE actuators based on the training procedure. The structural redundancy embedded in the neural network implies increased noise and fault tolerance compared to classical algorithms.

To construct a training sample containing the required values of the coefficients of the linear controller in different modes, various methods can be used, of which the sequential simplex search method is the most effective for solving the problem posed [17]. The essence of this method is that the movement towards the optimum in the *n*-dimensional space of variable parameters (in our case, the coefficients of the PID controller) is carried out by successive reflection (relative to one of the faces) of the vertices of the simplex. A simplex is a figure in *n*-dimensional space formed by (n + 1) vertices that do not belong to any of the spaces of lower dimension.

To solve the approximation problem, we chose a neural network based on a perceptron with three neurons in the hidden layer, three neurons in the output layer, and a logistic sigmoid activation function for neurons in the hidden layer. The search was carried out in six engine operating modes under constant external conditions, which are the training sample for the initial training of the neural network. The input data for training are the values of the setting (setting action) $\mathbf{Y}^0$ at the basic modes of helicopters TE operation. To train the neural network, we used the error backpropagation algorithm (method of moments) with regularization. Fig. 5 shows the dependence of the coefficients of the PID controller on the value of the control setpoint (in relative terms).

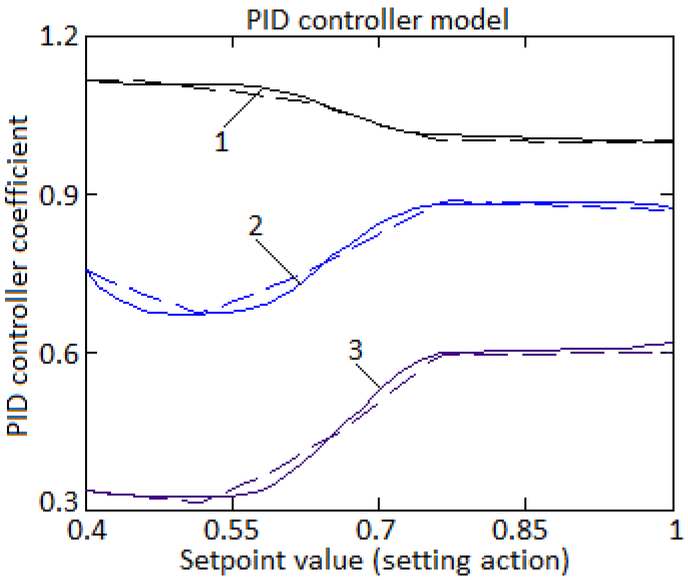


Figure 5: Diagram of dependence of the PID controller coefficients on the value of the control setpoint: 1 – proportional coefficient; 2 – integral coefficient; 3 – differential coefficient (the solid line shows the values obtained using the neural network; the dotted line shows the values obtained using the piecewise linear approximation)

Fig. 6 shows diagram of transients when testing the operation of a neural network as part of a closed onboard helicopters TE ACS, where 1 – desired transients (output of the reference model); 2 – transients on the frequency of gas generator rotor r.p.m., obtained for successive 5 % increases in the setpoint signal.

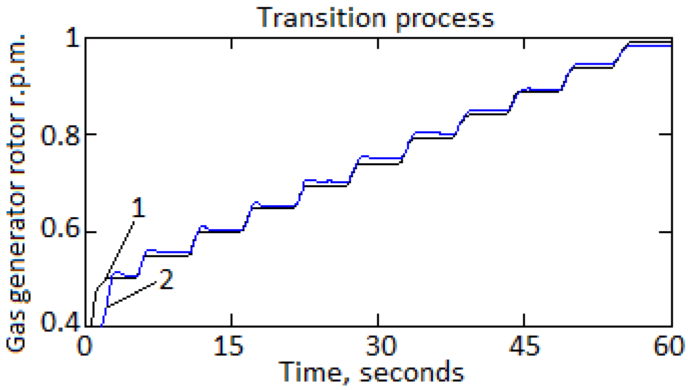


Figure 6: Diagram of transient processes by gas generator rotor r.p.m.

The analysis of the obtained transients shows that the set requirements for the quality indicators of the control processes of helicopters TE are met.

For the synthesis of a multi-mode neural network controller, the technique proposed in [18, 19], synthesized and systematized by professor Volodymyr Vasiliev, was applied, and includes the following steps:

1) choosing a method for including a neural network as a regulator in the GTE control system;

2) choice of architecture (structure) of the neural network;

3) determining the composition of the training sample for training the neural network controller as part of a closed onboard helicopters TE ACS;

4) selection of criteria and algorithm for training the parameters of helicopters TE neural network controller.

The inclusion of the neural network controller, which is a non-linear PI controller, the weight coefficients of which are adjusted from the condition of obtaining the specified quality indicators in all operating modes of the system, is carried out before the selector of the channels of gas generator rotor r.p.m. (free turbine rotor speed) and the gas temperature before the compressor turbine (fig. 2). According to the minimum complexity criterion, the simplest possible solution in this case is to use a perceptron that has three neurons in the hidden layer.

To train the neural network, it is necessary to determine the steady-state values of the inputs and outputs of the PI controller in one of helicopters TE ACS operating modes and use these values as a training sample. After receiving the training sample for the neural network controller, preliminary training (initialization) of the neural network is carried out using any optimization method.

After preliminary initialization of the neural network, it is possible to proceed to the training of the neural network controller as part of closed onboard helicopters TE ACS. To do this, at each of the specified basic helicopters TE operating modes, a small setpoint deviation is applied to the ACS input, the mismatch between the helicopters TE output parameter and the output of the reference model (desired ACS response) is calculated, after which the neural network weights are adjusted in the direction of decreasing the mismatch. These actions are repeated until the mismatch (training error) reaches the specified value.

According to [17], the method of sequential simplex search showed high efficiency in the process of training a neural network. The variable parameters in this case are the values of the weights of the synaptic connections of the neural network. For the correct operation of the algorithm, it is necessary to preprocess the initial data to construct the initial simplex, since the weights of the pretrained neural network have values that vary in a wide range – from tens to hundredths of a unit. For each neuron, the maximum values of its weights were determined, the corresponding weights were normalized in the range [–1, 1]. As a criterion for training the neural network in this case, according to the requirements for closed onboard helicopters TE ACS, a quadratic criterion was used:

$$E(k)=\sum_i \sigma n_i^2 + 10\sum_i \sigma T_{G_{OVER}}^2; \qquad (1)$$

where k – iteration number; σn_i^2 – value of the control error on the channel of gas generator rotor r.p.m. n_{TC} (free turbine rotor speed n_{FT}); $\sigma T_{G_{OVER}}^2$ – value of overshoot on gas temperature before the compressor turbine T_G channel.

Fig. 7 shows diagrams of transients when testing the operation of a neural network controller as part of closed onboard helicopters TE ACS: 1 – transients in terms of gas generator rotor r.p.m. n_{TC} when using a pre-initialized neural network controller; 2 – transients in terms of gas generator rotor r.p.m. n_{TC} in a system with a neural network controller trained in the entire range of operating modes for successive 5% increases in the setpoint signal.

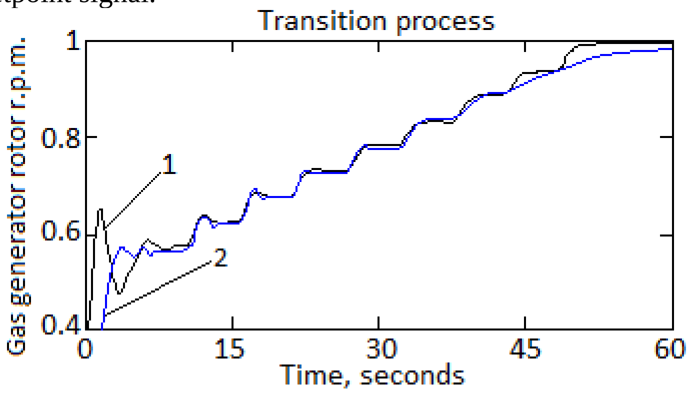


Figure 7: Diagram of transient processes by gas generator rotor r.p.m.

A distinctive feature of the developed helicopters turboshaft engines automatic control system from the existing ones is the division into separate links, respectively, turboshaft engines and actuating mechanism – fuel metering unit (FMU). This modification of the classic ACS of complex dynamic objects is associated with the neglect of dynamic processes in the fuel system – in helicopters turboshaft engines, transient processes in the fuel metering unit and the engine itself occur almost simultaneously.

The main elements of the developed ACS are: comparison element (CE), regulator, FMU and TE. The CE input receives the initial value of gas generator rotor r.p.m. n_{TC} and gas temperature in front of the compressor turbine T_G and the obtained values of the number of these parameters. At the output of the ACS, an inconsistency of the incoming parameters is formed and a system error ξ is formed, which is fed to the input of the controller, the signal u is generated at the output, which is fed to the input of the FMU, the fuel consumption signal G_T is generated at the output, which is fed to the input of the gas turbine engine and, respectively, the signal $\mathbf{Y}$, entering the CE [16].

An analysis of the obtained transients in closed onboard helicopters TE ACS shows that the set requirements for the quality indicators of control processes are met and the use of the proposed procedure for training the parameters of the TE multi-mode neural network controller is effective. The general diagram of the closed onboard helicopters TE ACS is shown in fig. 8, where: TE – helicopter TE; TE Model – model of helicopter TE; LB – logical block; FMU – fuel metering unit; FMU model – model of fuel metering unit [16].

In the logical block (LB) the input signals are analyzed as follows: a knowledge base is built on the basis of experimental data and conclusions. In relation to it, membership functions are formed for the input parameters of the LB, as well as output signals. Having formed the necessary change, the LB sends response signals to the input of the comparison element, forming a control signal that is fed to the input of the FMU and its model. The LB receives two signals: the inconsistency of the FMU and TE models with the FMU and TE models – model error (ξ_{mod}) and the inconsistency of the FMU with the FMU model – FMU error (ξ_{FMU}). As practice shows, the TE error is small and is not taken into account in the course of the research [16].

The regulator is designed on the basis of the ACS diagram with channel regulators after the selector (developer by professor Valery Petunin), where one of the channels is a control channel, which can be considered a channel for controlling the gas generator rotor r.p.m. n_{TC}, and the other channel is a limitation channel, for example, a channel for controlling the gases temperature before the compressor turbine T_G.

The TE model is presented as a self-adjusting neural network control system with interconnected coordinates. The control error vector after the comparison elements is fed to the input of the neural network and the weight correction block, in which, depending on the control error signal, the weight coefficients of the neural network are corrected at each discrete time point. The output signal vector of the neural network is a control vector and is fed to the input of the control object (helicopters TE). The neural network is multilayered with one intermediate layer containing N_0 neurons in the input layer and N_2 neurons in the output layer, while $N_2 = N_0 = n$. The network is characterized by the number of neurons N_1 in the inner layer. The input layer (layer 0) consists of nodes – signal receivers – control error vector, and the output layer – of neurons – signal sources [16].

For the purpose of signal or parametric adaptation, the developed modified closed onboard helicopters TE ACS is supplemented with connect adaptation modules that implement adaptive control methods:

– signal adaptation module;
– parametric adaptation module;
– linear model submodule;
– customizable model submodule.

The adaptive control subsystem is developed as a software module in accordance with the developed algorithm [20], then the resulting software module is directly integrated into the standard selective modified closed onboard helicopters TE ACS.

Key 1 performs the function of enabling or disabling connect adaptation modules, key 2 – switching signal or parametric adaptation models, key 3 – switching submodules of the reference or customizable models.

As a result, an improvement in the quality indicators of regulation was obtained for the channel of the free turbine speed n_{FT} of onboard helicopters TE ACS introduced into the developed helicopters TE ACS by an average of 3...5 % in terms of the maximum deviation and by 20...30 % with the standard onboard helicopters TE ACS, the time spent (by 2...2.5 times or more) on setting the regulators of onboard helicopters TE ACS was reduced due to the use of an adaptive control module connected in parallel with the regulators of onboard helicopters TE ACS.

To check the calculated parameters and the correspondence of the code to mathematical expressions, the developed modules were supplemented with a module of models and controllers of helicopters TE and a control module that allows you to set: simulation time, simulation step, initial load value, load change time, new load value. As a result, a software package for preliminary adjustment of the adaptive module was obtained.

The desired behavior of the system over the entire operating range is ensured by adjusting the regulators. Optimization methods, fitting methods, and other methods can be used to tune the custom and reference models. The structure of the custom and reference models allows you to tune them to the symmetric optimum [21]. In this case [22], a zero static error will be provided. For an open-loop system tuned to symmetric optimum, the transfer function has the following form:

$$W_{desired} = \frac{4 \cdot T_\mu + 1}{8 \cdot T_\mu^2 \cdot \left(T_\mu \cdot p + 1\right)}; \tag{2}$$

where T_μ – small uncompensated time constant.

The software package for pre-configuring modules allows you to check modules both individually and together. The main task of this software package is to check the software implementation of adaptive control algorithms.

Algorithms for adaptive control of helicopters turboshaft engines based on a reference model and a customizable model are implemented in the form of an adaptive control module and are used as part of developed closed onboard helicopters turboshaft engines automatic control system, which makes it possible to conduct computer tests of closed onboard helicopters turboshaft engines automatic control system in real time, predict the engine operational status, which, ultimately, affects the current management process.

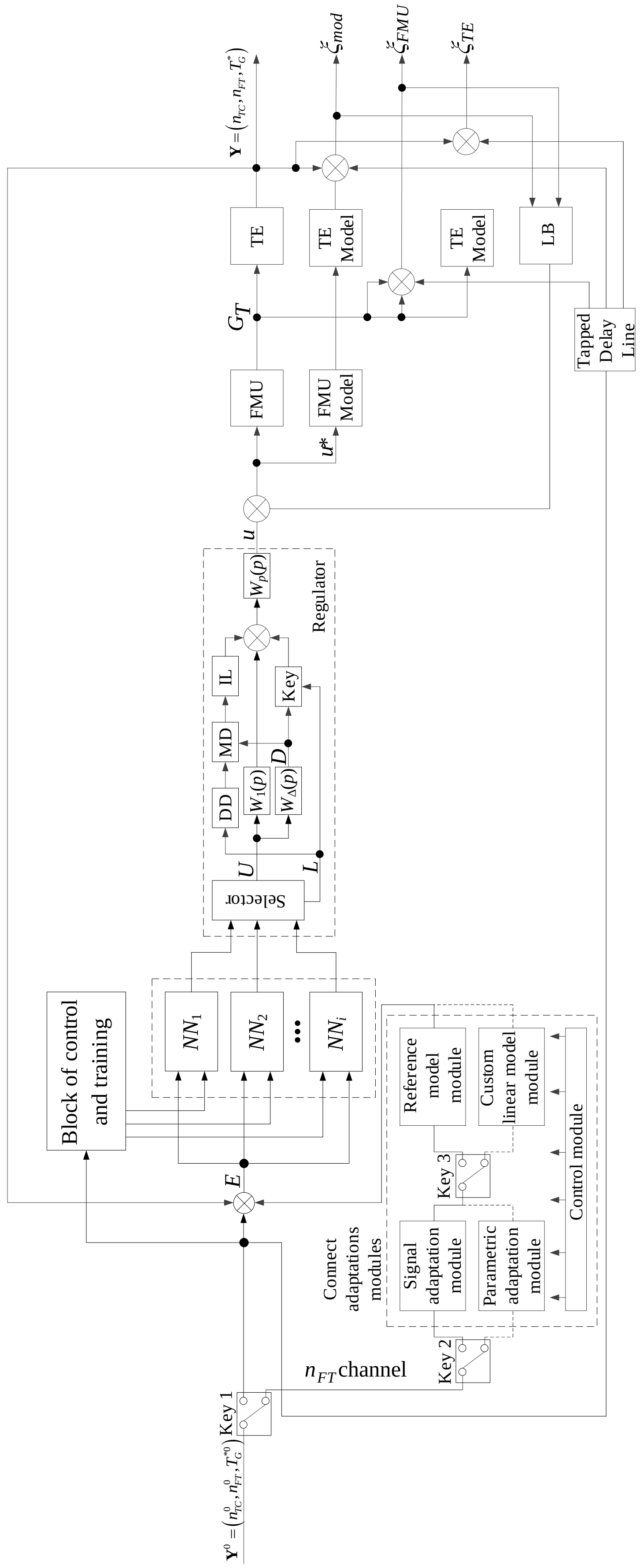


Figure 8: Modified closed onboard helicopters turboshaft engines automatic control system

3.3. Analysis of modified closed onboard closed helicopters turboshaft engine automatic control system stability

Since the synthesized modified closed onboard helicopters TE ACS with a neural network controller is essentially non-linear, the question of the stability of control processes in this system during the development of external disturbances remains open.

In the general case, various methods are used to study the stability of nonlinear ACS: the first and second methods of Oleksandr Lyapunov, the circular stability criterion of Volodymyr Yakubovich, etc. In this paper, we propose an approach to studying the stability of ACS with a neural network controller using the theorem on low gain [23, 24].

According to the methodology developed by professor Volodymyr Vasiliev it is assumed that in the basic (steady) helicopters TE operating modes (taking into account the dynamics of the actuator) is described by transfer functions of the form:

$$W_{TE}^{(r)}(s)=\frac{N_{TC}(s)}{G_T(s)}=\frac{a(s)}{b(s)}=\frac{a_0^{(r)}s^m+...+a_m^{(r)}}{b_0^{(r)}s^n+...+b_n^{(r)}}; \tag{3}$$

where $N_{TC}(s)$ and $G_T(s)$ – Laplace images for variables n_{TC} and T_G; r – helicopters TE operation mode number, r = 1…M, $m < n$. The coefficients $a_0^{(r)}...a_m^{(r)}$ and $b_0^{(r)}...b_n^{(r)}$ transfer functions depend on the specific mode of operation of the engine.

Fig. 9 shows a typical equivalent block diagram of a non-linear closed onboard helicopters TE ACS obtained by equivalent transformations of the onboard ACS (fig. 8), where $y = (e, V)^T$, x – vectors of the output coordinates of the linear part (LP) and the output of the non-linear element (NE) dimensions 2x1 and mx1, respectively; u – NE scalar output; $u = \Phi(x)$ – neural network "input-output" characteristic; $W_{LP}(s)=W_{TE}^{(r)}(s)\cdot\left(1,s^{-1}\right)^T$ – matrix transfer function of LP size 2x1; $f_1 = f_1(t)$ and $f_2 = f_2(t)$ – external influences on the system, limited in magnitude.

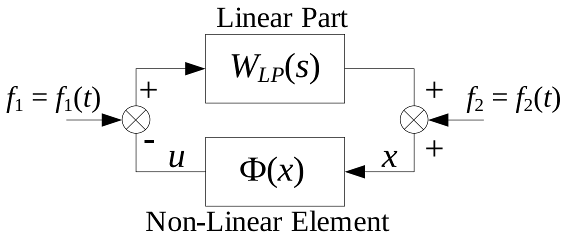


Figure 9: Equivalent block diagram of a non-linear closed onboard helicopters TE ACS

In accordance with the small gain theorem, control processes in a given system are stable if it is possible to find such a linear feedback control law $u = C_x$ and a positive number r for which the following conditions are satisfied:

1) the boundary gain of the nonlinear mapping $\Phi(x) - C_x$ must be less than the slope of the cone r:

$$\sup_{x\neq 0}\frac{\left\|\Phi(x)-C_x\right\|}{\left\|x\right\|}\leq r; \tag{4}$$

2) the closed linear system obtained by replacing $\Phi(x)$ with C_x and described by the matrix of transfer functions $H(s)=\dfrac{W_{LP}(s)}{I+CW_{LP}(s)}$, is stable;

3) the product of the linear system gain H given by its matrix frequency response $H(j\omega)$ and the cone slope r must be less than 1:

$$\sup_{\omega}\overline{\sigma}\left\{H(j\omega)\right\}\cdot r<1; \tag{5}$$

With regard to the aircraft TE TV3-117 considered in this paper, which is part of the power plant of the Mi-8MTV helicopter and its other modifications, the transfer function coefficients $W_{TE}^{(r)}(s)$ for various engine operating modes are given in table 1.

Table 1
Transfer function coefficient values

Mode	a_0	a_1	b_0	b_1	b_2	b_3	b_4
1	1.93	2.26	0.12	1.54	6.35	5.65	2.73
2	2.04	3.11	0.12	1.82	9.21	1.21	4.11
3	1.79	8.97	0.12	2.93	35.73	60.09	1.57

A multilayer neural network of the perceptron architecture with three neurons in the hidden layer and one neuron in the output layer is taken as a neural network controller (fig. 10). The total number of weights of synaptic connections (configurable parameters of the neural network controller) – 9; type of neuron activation function – tangential sigmoid.

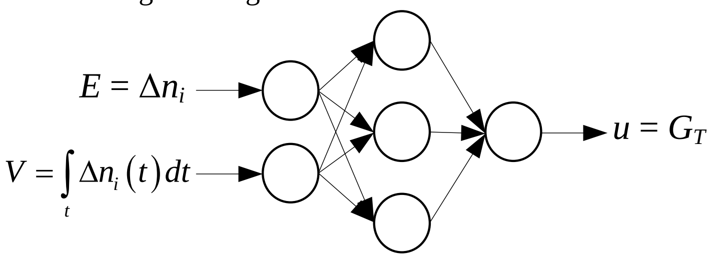


Figure 10: Multi-mode neural network controller modified structural diagram

For the synthesized neural network controller, the "input-output" characteristic of the neural network $u = \Phi(e, V)$ was develop, for which the dependence $u = 0.5e + 0.5V$ was chosen as the linearizing characteristic $u = C\mathbf{x}$, that is, $C = (0.5; 0.5)$. For this method of approximation of the operator $\Phi(x)$, we obtain for the ranges $e \in [-1,1]$ and $V \in [0,1]$ the value of the coefficient $r = 0.392$.

Matrix eigenvalue calculation

$$H(s) = \frac{W_{LP}(s)}{I + CW_{LP}(s)} = \frac{s \cdot W_{TE}^{(r)}(s)}{s + 0.5(s+1) \cdot W_{TE}^{(r)}(s)} \cdot \left(1; s^{-1}\right)^T \tag{6}$$

carried out according to the rule:

$$\sup_{\omega \ge 0} \bar{\sigma}\{H(j\omega)\} = \max_{\omega \ge 0} \sqrt{H^*(j\omega) \cdot H(j\omega)} = \max_{\omega \ge 0} \sqrt{\frac{\left(\omega^2+1\right) \cdot \left|W_{LP}^{(r)}(j\omega)\right|^2}{\left|0.5 \cdot (1 + j\omega) \cdot W_{LP}^{(r)}(j\omega) + j\omega\right|^2}} = 2.471; \tag{7}$$

where $H^*(j\omega)$ is the transfer function matrix conjugate to $H(j\omega)$.

Thus, the product of the boundary values of the LP and NE gains in this case is equal to:

$$\sup_{\omega \ge 0} \bar{\sigma}\{H(j\omega)\} \cdot r = 0.392 \cdot 2.471 = 0.969 < 1;$$

i.e., the conditions of the small gain theorem are satisfied. Consequently, all forced processes in the studied ACS, corresponding to the limited setting action (setpoint) $g(t)$ and other external perturbations acting during the helicopter TE operation, are asymptotically stable in general, which is a necessary condition for the performance of the synthesized modified closed onboard helicopters TE ACS.

3.4. Rationale for choosing a neural network training algorithm

When choosing an algorithm for implementing the proposed training diagram, one should consider methods of sequential training of a neural network with a high convergence rate, such methods primarily include first and second order gradient descent methods.

As a diagram algorithm in this paper, we adopted the error backpropagation algorithm (method of moments) with regularization [25], due to the simplicity of its implementation and low computational costs. At the same time, it is proposed to use a variable training rate parameter for each layer of the neural network as a function of the error of neurons of the corresponding layer. The diagram algorithm is a set of actions shown in table 2.

Table 2
Steps of backpropagation algorithm with regularization

Step	Description
1	Initialization of weights W with random small values, choice of initial η_0 and maximum training rate η_{max}, control errors δ.
2	Zero initialization of the initial values of the change in weights ΔW.
3	Definition of error $E(k)$ according to (1). The use of a quadratic criterion when calculating the training error of a neural network allows you to increase the accuracy of closed onboard helicopters TE ACS parameters identification by reducing root-mean-square error.
4	If the result is satisfactory, namely $\|E(k)\| \le \delta$, then network training is not implemented; otherwise, go to step 5.
5	Calculation of the value of the gradient of the loss function $\nabla E(k)$ at the current iteration.
6	Determining the training rate parameter for the i-th layer according to the expression: $$\eta_i = \eta_{\max} \cdot 1 + e^{-\|\mathbf{G}_i\|};$$ where η_{max} – maximum training rate; $\|\mathbf{G}_i\| = \frac{\sum_{j=i+1}^{l} \mathbf{x}_{(i+1)l}}{i}$ – arithmetic mean value of the error for the i-th layer of the network; l – number of neurons in the j-th next relative to the i-th layer; x – network error matrix, where $\dim(\mathbf{x}) = [m_{\max} \times d]$, m_{max} – maximum value of neurons among all layers of the neural network; d – number of layers of the neural network. In this case, we consider the network inputs as the first layer.
7	Calculation of parameter change according to the expression: $$\Delta W(k) = \eta \cdot (E(k) + \rho \cdot W(k-1)) + \mu \cdot \Delta W(k-1);$$ where η – coefficient characterizing the training rate; ρ – regularization coefficient; $\Delta W(k-1)$ – weight change at the previous iteration; μ – moment coefficient; $W(k-1)$ – value of the weight coefficients at the previous iteration.
8	Network weight adjustment:
9	Go to step 3

4. Experiment

The input parameters of helicopters TE mathematical model are the values of atmospheric parameters (h – flight altitude, T_N – temperature, P_N – pressure, ρ – air density). The parameters recorded on board of the helicopter (n_{TC} – gas generator rotor r.p.m., n_{FT} – free turbine rotor speed, T_G – gas temperature in front of the compressor turbine) reduced to absolute values according to the theory of gas-dynamic similarity developed by Professor Valery Avgustinovich (table 3). We assume in the work that the atmospheric parameters are constant (h – flight altitude, T_N – temperature, P_N – pressure, ρ – air density) [26].

Table 3
Part of training set

Number	T_G	n_{TC}	n_{FT}
1	0.932	0.929	0.943
2	0.964	0.933	0.982
3	0.917	0.952	0.962
4	0.908	0.988	0.987

5	0.899	0.991	0.972
6	0.915	0.997	0.963
7	0.922	0.968	0.962
8	0.989	0.962	0.969
9	0.954	0.954	0.947
10	0.977	0.961	0.953
11	0.962	0.966	0.955
…	…	…	…
256	0.953	0.973	0.981

Table 4 shows a comparative analysis of the training results of the developed three-layer perceptron The reverse propagation algorithm was chosen as the training algorithm, which ensures high convergence velocity and accuracy of the training process.

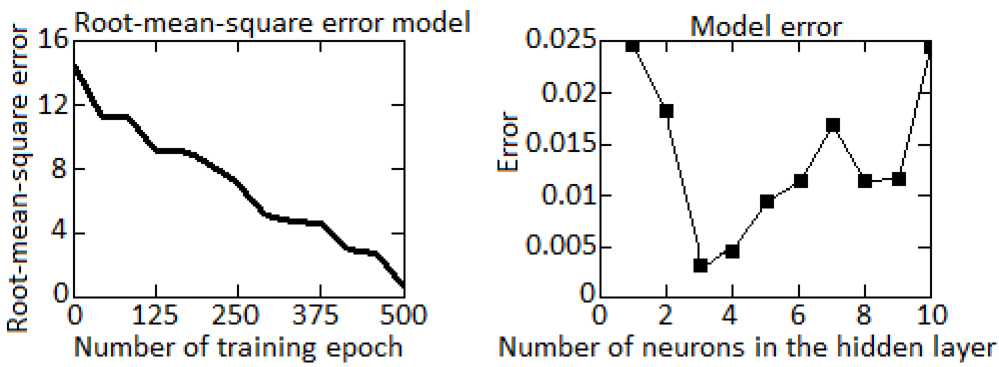
Table 4
The training results of neural network perceptron

Traning Algorithm	Root-mean-square error	Number of training stages	Number of neurons in the hidden layer
Reverse propagation with regularization	0.597	500	3
Reverse propagation	0.936	600	5
Fast propagation	2.374	750	6
Conjugate gradient	2.991	750	10
Quasi-Newton	2.038	700	8
Lewenberg-Marquardt	1.628	600	5

In this article [27], the sigmoid neuron activation function of the form $f(x)=\frac{1-e^{-x}}{1+e^{-x}}$, is used as the activation functions of neurons for a three-layer perceptron.

To determine the optimal number of neurons in the hidden layer, an experimental addiction $E = f(N)$ was built, shown in fig. 11, where E – neural network training error; N – number of neurons in the hidden layer (it is assumed that the number of neurons in the input layer – 2, in the output layer – 1).

The neural network was trained for 500 stages, the training accuracy characteristic is shown in fig. 11, *a*, while the steady-state root-mean-square error (RMS) is ~0.597. In accordance with fig. 11, *b*, the number of neurons in the hidden layer that provide the smallest training error is 3 neurons.



a b

Figure 11: Neural network training results: a – characteristic of the accuracy of neural network training; b – addiction of training error on the complexity of the neural network

As you can see from fig. 11, with 3 neurons in the hidden layer, the smallest training error of the neural network is achieved, that is, the optimal structure of the neural network is 2–3–1.

Valuation is an important issue of the homogeneity of the training and test samples. To do this, we use the Fisher-Pearson criterion $\chi 2$ [28] with $r - k - 1$ degrees of freedom:

$$\chi^2 = \min_{\theta} \sum_{i=1}^{r} \left(\frac{m_i - np_i(\theta)}{np_i(\theta)} \right); \tag{8}$$

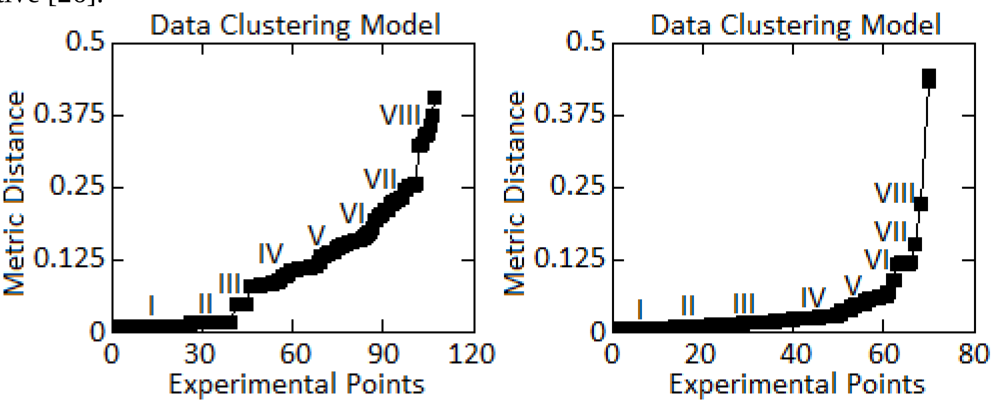
where θ – maximum likelihood estimate found from the frequencies $m_1, \ldots, m_r$; n – number of elements in the sample; $p_i(\theta)$ – probabilities of elementary outcomes up to some indeterminate k-dimensional parameter θ.

The final phase of statistical data processing is their normalization, which can be executed according to the expression:

$$y_i = \frac{y_i - y_{i\min}}{y_{i\max} - y_{i\min}}; \tag{9}$$

where y_i – dimensionless quantity in the range [0; 1]; $y_{i\min}$ and $y_{i\max}$ – minimum and maximum values of the y_i variable.

For the purpose of establishing representativeness of the training and test samples, a cluster analysis of the initial data was performed (table 3), during which eight classes have been identified (fig. 12, *a*). Following the randomization procedure, the actual training (control) and test samples were selected (in a ratio of 2:1, that is, 67 % and 33 %). The process of clustering the training (fig. 12, *b*) and test samples shows that they, like the original sample, contain eight classes each. The distances between the clusters practically coincide in each of the considered samples, therefore, the training and test samples are representative [26].



a b

Figure 12: Clustering results: a – initial experimental sample (I…VIII – classes); b – training sample [26]

The above mentioned statistics $\chi 2$ permits, under the above assumptions, to check the hypothesis about the representability of sample variances and covariance of factors contained in the statistical model. The field of hypothesis acceptance is $\chi^2 \leq \chi_{n-m,\alpha}$, where α – significance level of the criterion. The results of calculations in accordance with (7) are in table 5.

Table 5

Part of the training sample during the operation of helicopters TE (on the example of TV3-117 TE)

Number	$P(T_G)$	$P(n_{TC})$	$P(n_{FT})$
1	0.561	0.109	0.652
2	0.588	0.155	0.574
3	0.542	0.128	0.515
4	0.612	0.147	0.655
5	0.644	0.121	0.612
…	…	…	…
256	0.537	0.098	0.651

Calculation of the $\chi 2$ value based on the observed frequencies m_1, …, m_r (summing line by line the probabilities of the outcomes of each measured value) and comparing it with the critical values of the distribution $\chi 2$ with the number of degrees of freedom $r - k - 1$. In this article, with the number of degrees of freedom $r - k - 1 = 13$ and $\alpha = 0.05$, the random variable $\chi 2 = 3.588$ did not exceed the critical value from table 4 is 22.362, which means that the hypothesis of the normal distribution law can be accepted and the samples are homogeneous [26].

5. Results

From the point of view of adaptive and optimal control, the minimized functional plays a key role. Often, this functional is presented in the form of a generalized work functional (GWF) [29], proposed by academician A.A. Krasovsky. Computer simulation of various variants of the ACS by the extraction cascade has established that the root-mean-square deviation of the gas generator rotor r.p.m. n_{TC} (free turbine rotor speed n_{FT}) and gases temperature in front of the compressor turbine T_G, which does not exceed 1 % of the set value, ensures stable engine operation. Therefore, in the system (see fig. 8), the goal of control is to stabilize the gas generator rotor r.p.m. n_{TC} (free turbine rotor speed n_{FT}) and gases temperature in front of the compressor turbine T_G. This means that the GWF written in the following form can act as the target functional:

$$J_{Y^0} = \sum_{i=}^{k+he} \varepsilon_i^2 + \sum_{i=}^{k+hu} \left(u_i - u_k\right)^2; \tag{10}$$

where $k = 1, 2, …, \infty$; ε_i – control error of gas generator rotor r.p.m. n_{TC} (free turbine rotor speed n_{FT}) and gases temperature in front of the compressor turbine T_G; u_i – control action; he is the interval of optimization by control error; *hu* – control optimization interval. In this paper, it is proposed to split the GWF (9) into four parts:

$$J_{n_{TC}} = \sqrt{\frac{\sum_{i=k}^{k+he-1} \varepsilon_i^2}{he-1}} \le \Delta n_{TC};\ \Delta n_{TC} = 1\ \%; \tag{11}$$

$$J_{n_{FT}} = \sqrt{\frac{\sum_{i=k}^{k+he-1} \varepsilon_i^2}{he-1}} \le \Delta n_{FT};\ \Delta n_{FT} = 1\ \%; \tag{12}$$

$$J_{T_G} = \sqrt{\frac{\sum_{i=k}^{k+he-1} \varepsilon_i^2}{he-1}} \le \Delta T_G;\ \Delta T_G = 1\ \%; \tag{13}$$

$$J_u = \sqrt{\frac{\sum_{i=k}^{k+he-1} \left(u_i - u_k\right)^2}{hu-1}} \le \Delta u;\ \Delta u \approx 1\ \%; \tag{14}$$

where Δn_{TC}, Δn_{FT}, ΔT_G – permissible standard deviation of gas generator rotor r.p.m. n_{TC} (free turbine rotor speed n_{FT}) and gases temperature in front of the compressor turbine T_G; Δu – allowable root-mean-square change in the control action over the control optimization interval. The value of Δu was determined experimentally in order to achieve the goals (11–14) and the acceptable performance of the system.

In this paper, the process of controlling the rotor speed loop of gas generator rotor r.p.m. n_{TC}. At various operating points of gas generator rotor r.p.m. n_{TC} (table 3), a parametric synthesis of a neural network controller was carried out using the following methods: optimal modulus, Kuhn, Kopelovich, Kopelovich–Sharkov, aperiodic stability, dynamic compensation. At each operating point, from the obtained parameters of the neural network controller, parameters were selected that provide the best direct indicators of control quality (control time, dynamic control coefficient) and coarseness. Thus, grid functions $k_i^p\left(n_{TC}\right)$, $T_i^i\left(n_{TC}\right)$, $T_i^d\left(n_{TC}\right)$ were obtained. In order to improve the accuracy of control, amplification $k_i^p\left(n_{TC}\right) = 8.5 \cdot k_i^p\left(n_{TC}\right)$ was performed. Using these grid functions, training data was obtained for a neural network of size $n = 256$.

It was experimentally established that the error in the approximation of tabular given dependencies using neural networks [30, 31], reduced to the range of their change, did not exceed 0.025 %.

From the one shown in fig. 13, fig. 14 of the transient process it follows that the automatic control system with a neural network controller provides the best quality of control: the dynamic control coefficient is 6 times less, the control time is 2 times less compared to a system based on a PID controller with constant settings. Fig. 15 shows gas generator rotor r.p.m. n_{TC} signal timing diagram with continuous disturbances and the operation of gas generator rotor r.p.m. n_{TC} ACS with and without neural network adaptation (fig. 3).

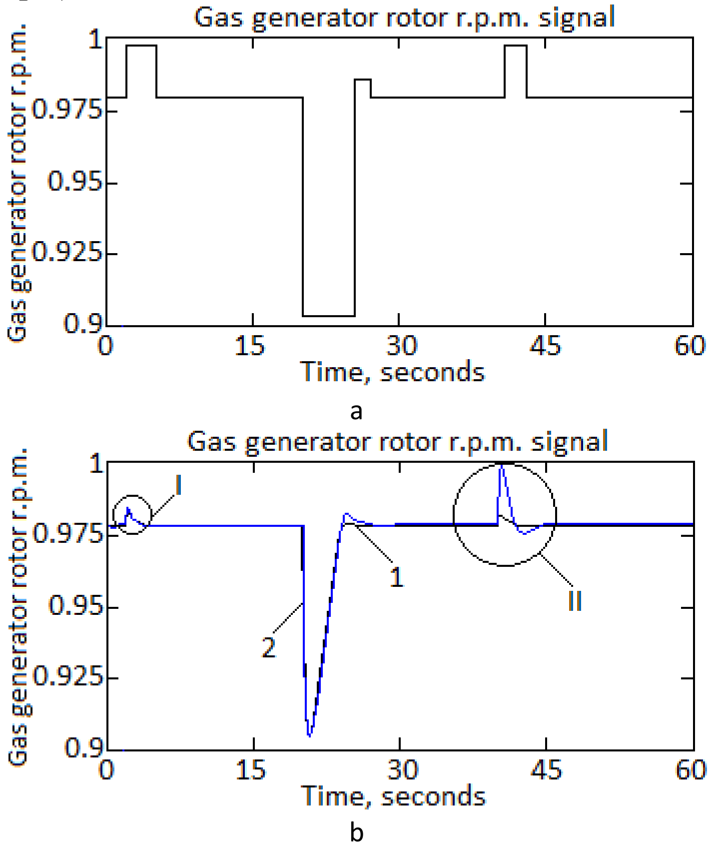


Figure 13: Transient processes diagrams in modified closed onboard helicopters TE ACS (gas generator rotor r.p.m. n_{TC} channel): a – input signal; b – real transient processes (1 – with neural network regulator (fig. 3); 2 – without neural network regulator)

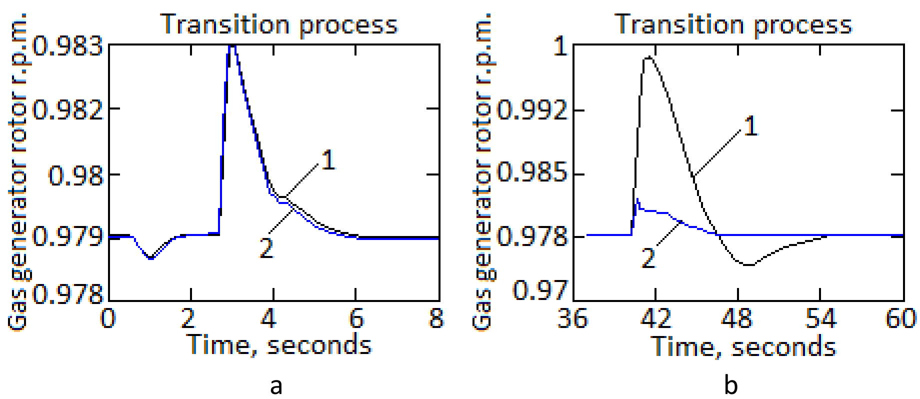


Figure 14: Transient processes diagrams in modified closed onboard helicopters TE ACS (gas generator rotor r.p.m. n_{TC} channel): a – sector I in fig. 13, b; sector II in fig. 13, b (1 – with neural network regulator (fig. 3); 2 – without neural network regulator)

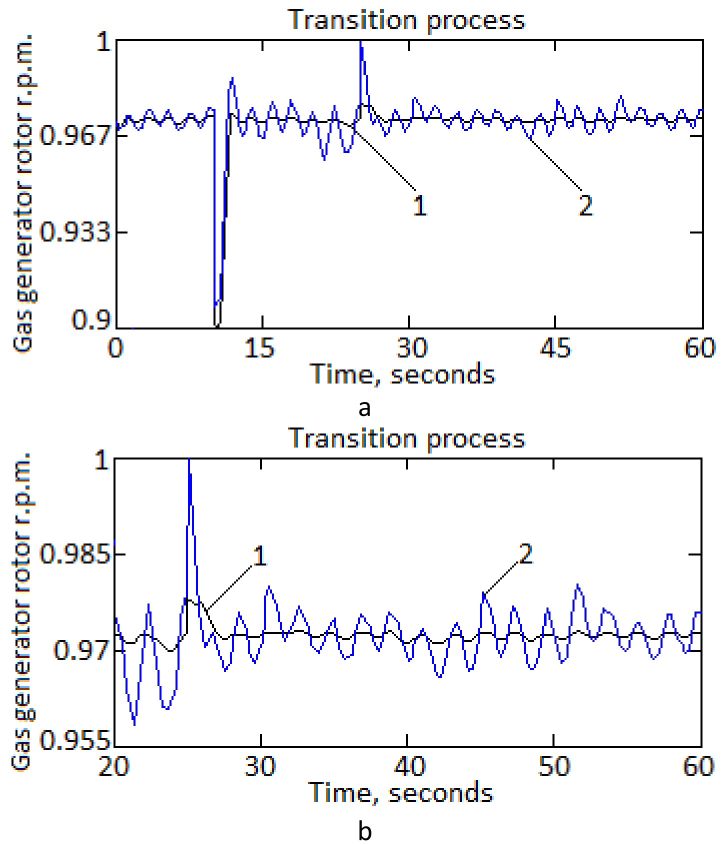


Figure 15: Signal timing diagram (gas generator rotor r.p.m. n_{TC} channel): 1 – with neural network regulator (fig. 3); 2 – without neural network regulator

6. Discussions

As a result of a comparative analysis of neural network accuracy (perceptron (fig. 10), RBF, modular neural network) and classical methods: least squares method (LSM) and group argument accounting method (GAAM) of identifying the ACS controller by three engine parameters (table 6), it was found that the maximum identification error when using the perceptron neural network is 2.14 times less than for the 12th order polynomial regression model built using LSM and 1.85 times less than the GAAM, and less for the modular neural network and for the RBF, respectively 1.29 and 1.25 times. At the same time, the perceptron provides an identification error not exceeding 0.441 %; modular neural network – 0.732 %; neural network RBF – 0.755 %; GAAM – 0.817 %; LSM – 0.942 %.

Table 6

Results of identifying a neural network controller

Calculation method	Parameter		
	T_G	n_{TC}	n_{FT}
Classical methods:			
least squares method	0.887	0.844	0.942
group argument accounting method	0.663	0.701	0.817
Neural network methods:			
perceptron (fig. 10)	0.267	0.318	0.441
modular neural network	0.499	0.535	0.732
RBF network	0.542	0.573	0.755

In order to analyze the stability of neural networks to changes in input data (table 3), additive noise was added to them in relation to the current value of each of the parameters in the form of white noise with zero mathematical expectation and $\sigma_i = \pm\, 0.01$ (table 7).

Table 7
Results of identifying a neural network controller under conditions of additive noise (M = 0, σ_i = ± 0.01)

Calculation method	Parameter		
	T_G	n_{TC}	n_{FT}
Classical methods:			
least squares method	2.999	3.717	5.866
group argument accounting method	2.618	2.962	1.957
Neural network methods:			
perceptron (fig. 10)	0.535	0.604	0.695
modular neural network	1.184	1.198	1.215
RBF network	1.305	1.308	1.324

The results of the analysis of the identification accuracy of an ACS controller by three engine parameters under noise conditions showed the following results: neural network perceptron (fig. 10) – 0.695 %; modular neural network – 1.215 %; RBF network – 1.324 %; GAAM – 1.957 %; LSM – 5.866 %.

Thus, the paper considers a promising approach that makes it possible to increase the efficiency of automatic control of complex technological objects [32, 33] (helicopters turboshaft engines at flight modes) in the conditions of limited computing capabilities of control controllers [33, 34], which is the use of neural network controllers in ACS.

7. Conclusions

1. An improved approach has been improved to improve the efficiency of automatic control of helicopters turboshaft engines in conditions of limited computing capabilities of control controllers through the use of a reconfigured neural network controller in front of the engine control channel selector and an adaptive control subsystem, which was a connect adaptation modules.

2. Neural network control algorithms for gas turbine engines based on multilayer perceptron’s have been further developed, which, due to the use of a quadratic training error criterion for a neural network in a modified error backpropagation algorithm with regularization, provide the required indicators of the quality of transient processes of helicopters turboshaft engines thermo-gas-dynamic parameters at flight modes in a given range of mode changes engine operation.

3. The algorithm for analyzing the stability of a neural network control system based on the low gain theorem was further developed, which, due to the use of a reconfigured neural network controller in front of the engine control channel selector, as well as the Gaussian form of linguistic variables in the system of rules for the control and training algorithm of the neural network controller, guarantees the absolute stability of helicopters turboshaft engines automatic control system at flight modes for an arbitrary range of driving and disturbing influences.

4. The use of the proposed adaptive modified closed onboard helicopters turboshaft engines automatic control system at flight modes can significantly reduce the influence of the human factor due to more significant roughness and stability compared to classical automatic control systems based on PID controllers.

5. It was found that the error in identification the ACS controller using the perceptron neural network did not exceed 0.441 %; modular neural network – 0.732 %; RBF network – 0.755 %; GAAM – 0.817 %; LSM – 0.942 %.

6. It has been experimentally confirmed that neural network methods are more robust to external disturbances: for the noise level σ_i = ± 0.01, the error in identifying the ACS controller increased from 0.441 to 0.695 % using the perceptron neural network; modular neural network – 0.732 to 1.215 %; RBF network – from 0.755 to 1.324 %; GAAM – from 0.817 to 1.957 %; MNC – 0.942 to 5.866 %.

7. The conducted experimental studies have shown the feasibility of using a multi-stage neural network controller in modified closed onboard helicopters turboshaft engines automatic control system.

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