Neural Network Method for Parametric Adaptation Helicopters Turboshaft Engines On-Board Automatic Control System Parameters

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Abstract

The work is devoted to the improvement of helicopters turboshaft engines closed onboard neural network automatic control system by introducing a program module for parametric adaptation with submodules of linear and custom models. A mathematical description of the problem of parametric adaptation is given, which consists in calculating a modular similarity criterion. To ensure the desired behavior of the automatic control system, dynamic compensation of the free turbine speed controller was applied and replaced with a controller of a similar structure tuned in the desired way. For parametric adaptation, PID neuroregulators are used, which are an artificial neural network of the perceptron architecture with two neurons in the hidden layer. It has been experimentally proven that the optimal neural network training algorithm for solving the parametric adaptation problem is the use of a neural network training algorithm developed on the basis of the Nelder–Mead method. Primary and secondary checks of the parametric adaptation module with submodules of linear and adjustable models were carried out, the results of which showed that the maximum improvement in the quality indicators of adaptation of transient processes in helicopters turboshaft engines closed onboard neural network automatic control system by 30 % was achieved in relation to standard regulators.

Keywords

Helicopters turboshaft engines, neural network, training, automatic control system, Nelder–Mead method, PID neuroregulators, parametric adaptation module

1. Introduction

Currently, the problem of developing automatic control systems (ACS) for dynamic objects is characterized by the transition from the adaptive control paradigm to the intelligent control paradigm, while adaptive control methods are components of intelligent ACS [1, 2]. This is caused both by the continuous complication of control objects and the conditions for their operation, the emergence of new classes of computing tools (in particular, distributed computing systems), high-performance telecommunication channels, and a sharp increase in the requirements for the reliability and efficiency of control processes under conditions of significant a priori and a posteriori uncertainty. Taking into account the above factors is possible only on the basis of the transition from "hard" algorithms of parametric and structural adaptation to the anthropomorphic principle of control formation.

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Aircraft gas turbine engines (GTE) ACS, including helicopters turboshaft engines (TE), is one of the main systems that determine their efficiency and reliability. ACS GTE engines includes a number of automatic regulation systems (ARS) designed to maintain and change controlled parameters according to a given program. ARS of modern engines are becoming more and more complex, with the inclusion of a large number of adjustable parameters and regulatory factors, more complex control programs, the implementation of which requires the introduction of a new element base [3, 4].

At present, electronic digital ACS [5, 6] are being intensively introduced, which have higher accuracy and wide opportunities for optimizing of GTE controlling process. At the same time, much attention is paid to the development and research of intelligent algorithms for monitoring and diagnostics the operational status of GTE ACS using neural network technologies [7, 8]. At the same time, due to a number of reasons (closedness of works, narrow specialization of the tasks being solved, etc.), most publications lack theoretical and practical recommendations for solving the above problems, which leaves a wide field of activity for conducting scientific research in this direction.

Within the framework of this work, an urgent scientific and practical problem is being solved to modernize the closed neural network on-board helicopters TE ACS [9, 10] by introducing a parametric adaptation module into it, which will improve the quality of control of the main control channels of helicopters TE compared to the use of standard regulators.

2. Related works

The helicopters TE reliability operating in conditions of external and internal interference is largely determined by the quality of the ACS, for the optimal implementation of the functions of which it is necessary to obtain real-time reliable information about the current engine characteristics (fuel consumption, temperature and pressure at the engine inlet / outlet subsystems, gas-generator rotor r.p.m., free turbine rotor speed rotation, etc.).

The features of onboard GTE ACS (including helicopters TE) are: high algorithmic complexity, large number of calculations, high-speed information exchange in real time, diversified requirements (reliability, functionality) for individual nodes and information transmission channels [11].

It is known [12] that the validity of the input (measured) information is important for the quality of the onboard ACS. At the same time, since the dimension of the state space of a modern aircraft GTE significantly exceeds the dimension of the vector of parameters measured on board, it is difficult to establish a deterministic one-to-one correspondence between them, and in some cases, it is impossible [13, 14].

In this regard, the solution of the issues of adapting the onboard ACS to the action of external and internal interference, as well as monitoring and diagnostics of GTE operational status, inevitably requires the use of identification methods [15, 16]. In modern digital systems for automatic control of aircraft engines, an increase in reliability in flight modes is achieved through the creation of algorithmic information redundancy using the onboard mathematical model of an aircraft gas turbine engine built into the ACS [17, 18]. At the same time, the accuracy of the engine model operating in real time under operating conditions largely determines the quality of the current identification of engine parameters and the reliability of the ACS as a whole [19, 20].

Since the developed helicopters TE closed on-board ACS [9, 10] operates in conditions of interference in the channel of the mathematical model ("noise" of the model) and in the channel of measurement ("noise" of measuring sensors), an important task is to increase the accuracy of model identification of engine parameters, taking into account current on-board measurements. This determines the relevance of the proposed study aimed at creating adaptive algorithms for monitoring helicopters TE, which make it possible to identify engine parameters with high accuracy under conditions of external and internal interference.

The scientific novelty of the proposed study lies in the further development of the solution of the problem of parametric optimization of helicopters TE closed on-board ACS of civil and military aviation, construct into the electronic controller, aimed at automatic parametric monitoring of the gas-air path of helicopters TE [21]. The advantage of the proposed approach is reliable real-time operation on board a helicopter in the event of a change in its state and the action of external interference.

3. Methods and materials

The helicopters TE closed on-board ACS was developed in [9, 10] and is shown in fig. 1, where TE – helicopter TE, TE Model – model of helicopter TE, LB – logical block, FMU – fuel metering unit, FMU model – model of fuel metering unit.

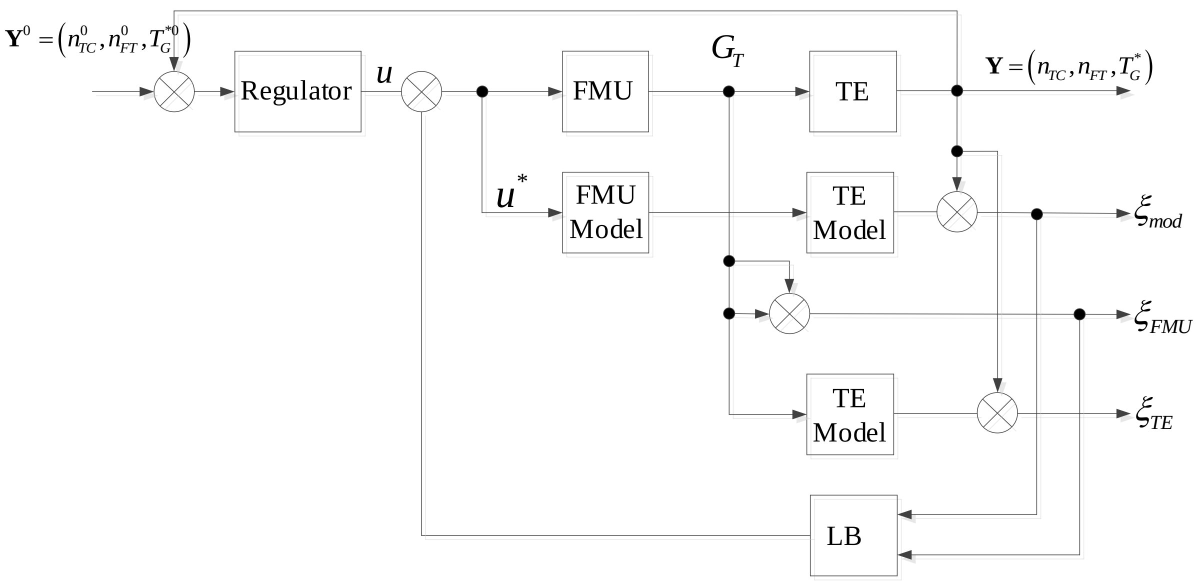


Figure 1: Helicopters TE closed on-board ACS [9, 10]

Modification of helicopters TE closed on-board ACS (Fig. 1) consists in supplementing with modified compared to [9] software modules that implement adaptive control methods:

– signal adaptation module with submodules of linear and customizable models;

– parametric adaptation module;

In this paper, using as a basis the results of Ivan Bakhirev's research for a ground-based gas turbine plant, we consider the addition of the developed helicopters TE ACS with a reference or custom model module, a parametric adaptation module (fig. 2). The vector **x** is presented in the following form: $x_1 = n_{FT}$ – free turbine speed, $x_2 = n_{TC}$ – gas generator rotor r.p.m., x_3 – gas metering regulator integrator, x_4 – n_{FT} regulator integrator, that is, the input data vector $\mathbf{Y}^0$ is supplemented with the free turbines speed parameter n_{FT} and, accordingly, is converted to the form $\mathbf{Y}^0 = \left(n_{FT}^0, n_{TC}^0, T_G^{*0}\right)$.

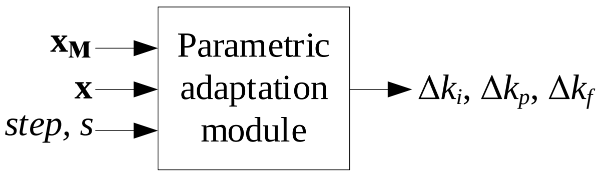


Figure 2: Parametric adaptation module

The input of the module is the step of solving differential equations that describe the dynamics of the main processes of the engine [9, 10], $\mathbf{x_M}$ – state vector of the reference or custom model, and x is the reduced state vector of the control object. Based on the obtained data, the mismatch vector is calculated. After that, the weighted sum of the mismatch vector is calculated. Then the increments of the controller coefficients Δk_i, Δk_f, Δk_p are calculated. The increments of the controller coefficients Δk_i, Δk_f, Δk_p are output variables of the module. The adaptation subsystem will work in accordance with the algorithm shown in fig. 3. Description of the modules of the custom and reference models, respectively, is given in [9].

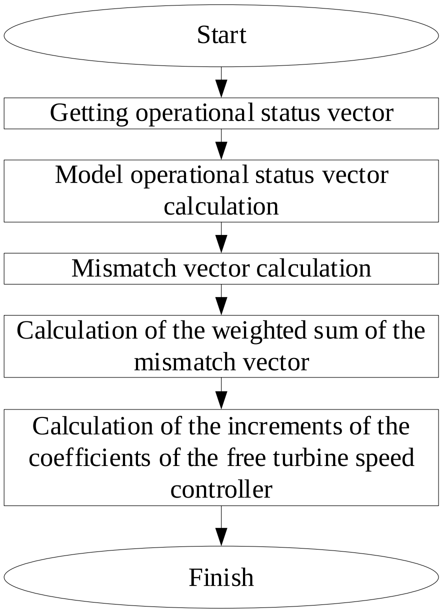


Figure 3: Block diagram of the operation algorithm of the adaptation module with parametric adaptation

The task of parametric adaptation [22] of helicopters TE closed on-board ACS is to determine the parameters of its mathematical model that provide the greatest similarity of the responses of the model and the object to the same input action. The problem is solved with the help of specialized software based on the selected similarity criterion. The simplest similarity criterion q is the modular criterion, which is determined according to the expression:

$$q(t) = \left| Y_{\exp}(t) - Y(t) \right|; \tag{1}$$

where $Y_{\exp}(t)$ – helicopters TE output parameter experimental value; $Y(t)$ – helicopters TE output parameter value.

Since the experimental values are most often presented as an array, the following notation of the similarity criterion is used:

$$q(t) = \sum_{i=1}^{n} \left| Y_{\exp_i}(t) - Y_i(t) \right|; \tag{2}$$

where $Y_{\exp_i}(t)$ – helicopters TE output parameter experimental value at the i-th time point; $Y_i(t)$ – helicopters TE output parameter value at the i-th time point; n – dimension of the experimental data array.

With a normal distribution of the random error of the experiment, the use of a quadratic criterion gives the greatest accuracy:

$$q(t) = \left(Y_{\exp}(t) - Y(t) \right)^2 = \sum_{i=1}^{n} \left(Y_{\exp_i}(t) - Y_i(t) \right)^2. \tag{3}$$

If it is necessary to highlight the significance of some points in the array of experimental results, a weighted criterion is used, which is determined according to the expression:

$$q(t) = \sum_{i=1}^{n} d_i \cdot \left(Y_{\exp_i}(t) - Y_i(t) \right)^2; \tag{4}$$

where d_i – weighting factor that determines the "weight" of the i-th time point.

In the process of helicopters TE monitoring, the parameters of all elements of a closed loop change in real time. To ensure the desired behavior, it is necessary to dynamically compensate the free turbine speed controller and replace it with a controller of the same structure, tuned in the desired way. Fig. 4 shows the dynamic compensation diagram, where:

1. Compensator parameters: W_{FTR}^{*} – free turbine speed controller transfer function with the desired settings; W_{FTR}^{-1} – transfer function compensating the free turbine speed controller.

2. Parameters of the tuned model: W_{FTR} – free turbine frequency controller transfer function; W_{GDR} – gas dispenser regulator transfer function.

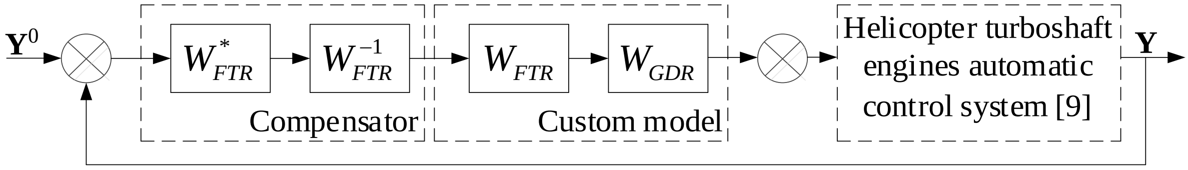


Figure 4: Dynamic compensation diagram

The transfer function compensating the free turbine speed controller is represented as:

$$W^{-1}_{FTR}\left(p\right)=\frac{1}{k_p}\cdot\frac{k_i+p}{k_i+k_f\cdot p};\tag{5}$$

The coefficients k_i, k_f, k_p are determined according to the expressions:

$$k_i=\mathbf{B}_{44};\quad k_f=\frac{1}{1+\dfrac{\mathbf{A}_{34}}{\mathbf{B}_{34}}};\quad k_p=\frac{\mathbf{B}_{24}}{k_f\cdot\mathbf{A}_{23}};\tag{6}$$

where $\mathbf{A}_{23}$, $\mathbf{A}_{34}$, $\mathbf{B}_{23}$, $\mathbf{B}_{34}$, $\mathbf{B}_{44}$ – matrices.

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 a symmetrical optimum. In this case [23], zero static error will be provided. For an open-loop system tuned to a symmetrical optimum, the transfer function has the following form:

$$W_{desired}=\frac{4\cdot T_\mu+1}{8\cdot T_\mu^2\cdot\left(T_\mu\cdot p+1\right)};\tag{7}$$

where T_μ – small uncompensated time constant.

4. Experiment

4.1. Analysis and preprocessing of input data

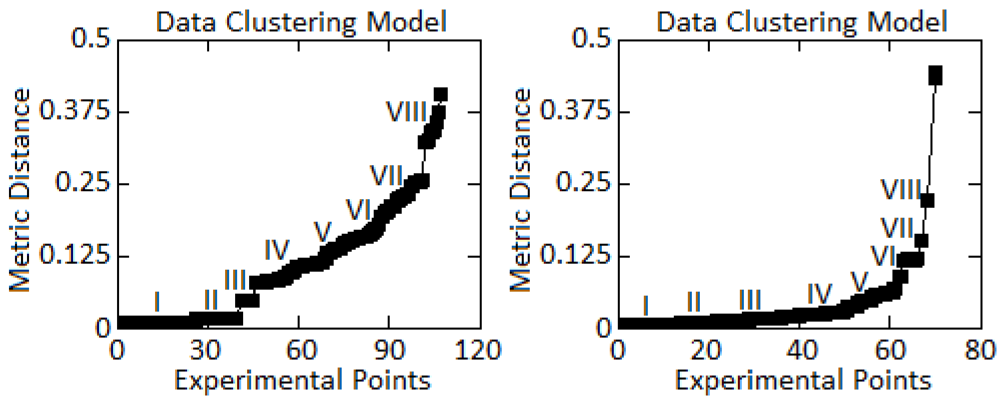
Helicopters TE mathematical model the input parameters are the atmospheric parameters values (h – flight altitude, T_N – temperature, P_N – pressure, ρ – air density). The parameters recorded on board of the helicopter (n_{TC} – gas generator rotor r.p.m., n_{FT} – free turbine rotor speed, T_G – gas 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 1). We assume in the work that the atmospheric parameters are constant (h – flight altitude, T_N – temperature, P_N – pressure, ρ – air density) [10, 22].

Table 1
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
12	0.968	0.972	0.959
…	…	…	…
256	0.953	0.973	0.981

Analysis and preprocessing of input data (table 1) are described in detail in [22]. For the purpose of establishing representativeness of the training and test samples, a cluster analysis of the initial data was performed (table 1), during which eight classes have been identified (fig. 5, *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. 5, *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 [22].



a b

Figure 5: Clustering results: a – initial experimental sample (I…VIII – classes); b – training sample [22]

An important issue is the assessment of the homogeneity of the training and test samples. To do this, we use the Fisher-Pearson criterion $\chi 2$ [24] 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 stage of statistical data processing is their normalization, which can be performed 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.

The specified statistics $\chi 2$ allows, under the above assumptions, to test the hypothesis about the representability of sample variances and covariances of factors contained in the statistical model. The area of acceptance of the hypothesis is $\chi^2 \le \chi_{n-m,\alpha}$, where α – significance level of the criterion. The results of calculations according to (8) are given in table 2.

Table 2
Fragment 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
…	…	…	…
156	0.537	0.098	0.651

Calculating the value of $\chi 2$ from 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 work, 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 3 is 22.362, which means that the hypothesis of the normal distribution law can be accepted and the samples are homogeneous [22].

4.2. Development of a neural network and the choice of an algorithm for its training

For parametric adaptation, it is proposed to use PID neuroregulators, which are an artificial neural network. The most common and simplest version for PID neuroregulators [25, 26], shown in fig. 6, was chosen as the architecture of the neural network, where N_i – neurons of the hidden layer ($i = 1…n$), w_{11}, w_{12}, …, w_{1n}, $w_{2,\,n+1}$, $w_{3,\,n+1}$, …, $w_{n+3,\,n+1}$ – weight coefficients forming weight matrix $\mathbf{W}$.

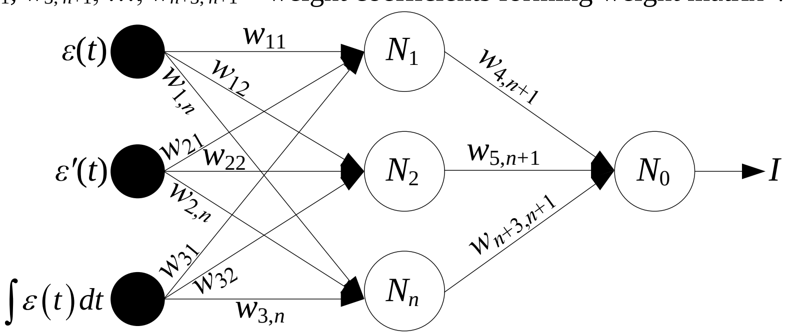


Figure 6: Neural network architecture

As an assessment of the work of helicopters TE closed on-board ACS an integral criterion of the form is adopted:

$$I(\mathbf{W}) = \int_0^\infty F\left(H\left(t,\mathbf{W}\right)\right),\varepsilon\left(t,\mathbf{W}\right)dt; \tag{10}$$

where $x(t, W)$ – system output coordinate; $\varepsilon(t, W)$ – system error; F – some convex function.

The task of helicopters TE closed on-board ACS parametric adaptation is solved using a neural network training algorithm based on the Nelder–Mead method [27], proposed by Professor Innokenty Igumnov, which requires setting the following parameters: reflection coefficient α, stretching coefficient γ, compression coefficient β.

The operator of the control object (helicopters TE) $G_p(p)$, taking into account the transfer function that compensates the free turbine speed controller, is represented as:

$$G_p\left(p\right) = \frac{1}{k_p} \cdot \frac{k_i + p}{k_i + k_f \cdot p} \cdot \frac{1}{\left(T_{\mu 1} \cdot p + 1\right) \cdot \left(T_{\mu 2} \cdot p + 1\right)} \cdot e^{-\tau_\mu \cdot p}; \tag{11}$$

where $T_{\mu 1}$, $T_{\mu 2}$ – small uncompensated time constants of the object; τ_μ – small uncompensated delay time.

The adaptation criterion is presented as:

$$I(\mathbf{W}) = \int_0^L \varepsilon^2(t, \mathbf{W})\,dt; \qquad (12)$$

where L – integration interval.

Table 3 shows a neural network training algorithm developed on the basis of the Nelder–Mead method.

Table 3

Nelder–Mead neural network training algorithm

Step	Description
1	Formation of a set of initial simplices with point coordinates *m* (n_m = 4*n*) (the number of weight coefficients, which is determined by the fact that the neural network output, taking into account the neural network architecture, reflects the response to values from a separate synaptic weight).
2	Equating to zero the value of all synaptic weights at the point *m*+1.
3	Variation of entire set synaptic weights sign of their possible values at simplices points.
4	Calculation of the values of criterion (12) in each simplex for all points; in this case, it is denoted as I_{ij}, where *i* = 1, 2, … is the number of the simplex, *j* = 1, 2, … is the point of the *i*-th simplex.
5	Definition $\hat{I}$ – characteristic number of a simplex – as $\hat{I} = \min(I_{ij})$. Below, we consider only those simplices for which $\frac{\hat{I}}{\min(\hat{I})} \le \mu$, $\mu \ge 1$.
6	Performing the main operations of the Nelder-Mead method [27] with selected simplices: "sorting", "reflection", "stretching", "compression", "truncation", "checking the fulfillment of the search terminating criterion".
7	Comparison of the results of the algorithm, which is understood as the search for points with the smallest criteria *I*, for each simplex. By finding the Euclidean distance between these points, the neighborhood of local extrema is determined, their set is formed, and among it the point with the smallest value of criterion *I* is selected. Its values of synaptic weights are considered optimal.

Thus, when the criterion for terminating the search is met, the point with the smallest value of criterion I will be considered a solution for this simplex.

The neural network of the perceptron architecture consists of two neurons in the hidden layer, this number is due to preliminary studies that showed an acceptable quality of regulation with this architecture of the neural network.

Reflection coefficient α = 1, stretch coefficient γ = 2, compression coefficient β = 0.5, truncation coefficient d = 2 [27] are parameters of the neural network training algorithm that characterize the main operations of the Neldra-Mead method.

5. Results

According to the research of Professor Innokenty Igumnov, since the neural network training algorithm developed on the basis of the Nelder-Mead method has the ultimate goal of including it in the algorithmic support of automatic systems, it is necessary to check its performance, which means the convergence of the algorithm in the range of parameters, which is determined by practice automatic regulation. In this work, such a check is based on a well-established method that uses modulation characteristics [28].

Due to the fact that γ_k – duty cycle of the k-th pulse, determined using a neural network, does not use the modulation characteristic, then, based on the foregoing, we introduce the concept of a pseudo-modulation characteristic, the meaning of which is similar to it. This characteristic is construct by feeding a control error to neural network input. Fig. 7 shows pseudomodulation characteristics for the power activation function, where 1 and 4 – pseudomodulation characteristics, each of which belongs to different initial simplices and is built from a point (a set of synaptic weights) that provides the minimum value of criterion (3); 2 – pseudo-modulation characteristic obtained as a result of the neural network training algorithm, launched from the initial simplex, which has pseudo-modulation characteristic 1 in its composition; 3 – pseudomodulation characteristic, respectively, obtained from the initial simplex, which has in its composition a pseudomodulation characteristic 4.

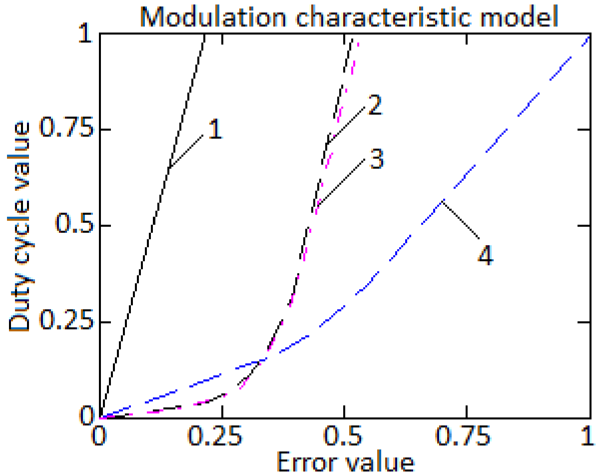


Figure 7: Modulation characteristics convergence diagram

Thus, fig. 6 shows the algorithm results convergence to one form of pseudo-modulation characteristic (pseudo-modulation characteristics 2 and 3 coincide on the interval $e \in [0, \lambda]$ with sufficient accuracy for practice). Similar results have been obtained for other activation functions.

The numbers 1' and 2' in fig. 8 represent the dependencies of I on the number of neural network training epochs, constructed from the initial simplices, which include pseudomodulation characteristics 1 and 4, respectively. The coincidence of dependencies 1' and 2' with sufficient accuracy for practice at 75 epochs of neural network training illustrates additional proof of the convergence of the algorithm.

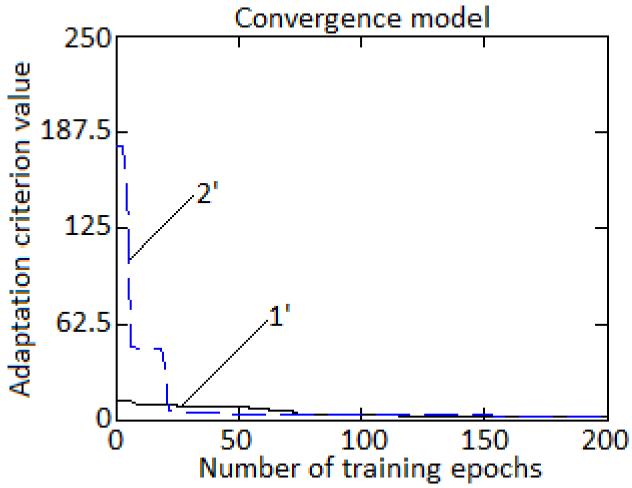


Figure 8: Simplex characteristic number convergence diagram

The researches were carried out in a fairly large range of helicopter TE parameters, for which $\frac{\tau_\mu}{T_\mu} > 1$, where $T_\mu = \max\left(T_{\mu 1}; T_{\mu 2}\right)$. As is known, with such a ratio, the acceptable quality of transient processes is provided by impulse control laws.

As an illustration, the results of the researches are given for $k_p = k_i = k_f = 1$; $T_{\mu 1} = 10$; $T_{\mu 2} = 40$; $\tau_\mu = 50$ and the pulse repetition period $T = 25$ with a master action $\lambda(t) = 0.5 \cdot 1(t)$ and restrictions under which the duty cycle γ_k obtained using the neural network lies on the segment from 0 to 1. Proceeding from Based on the literature analysis [29, 30], the following activation functions for neurons in the hidden layer were selected: logistic, power, hyperbolic tangent, sigmoidal (rational), and sinusoidal.

Based on the results of the neural network training algorithm, the values of synaptic weights were obtained, which correspond to transient processes (fig. 9, where 1 – result with a sinusoidal activation function of neurons in the hidden layer of the neural network; 2 – power activation function; 3 – activation function in in the form of a hyperbolic tangent, 4 – sigmoidal (rational) activation function, 5 – logistic activation function). The values of criterion (12) when using these activation functions are given in table 4.

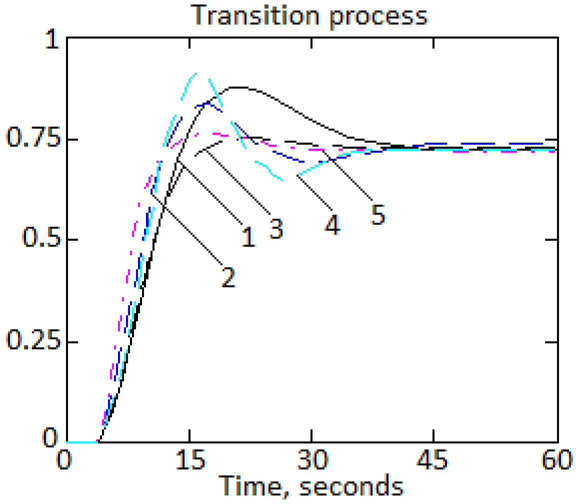


Figure 9: Transient processes obtained as a result of the work of the neural network training algorithm

Table 4
Results of adaptation criterion calculation

Number	Neuron activation function	Adaptation criterion value
1	Sinusoidal activation function	46.35
2	Power activation function	44.84
3	Activation function in in the form of a hyperbolic tangent	40.06
4	Sigmoidal (rational) activation function	37.28
5	Logistic activation function	51.92

To prove the correct choice of the number of neurons in the hidden layer and the activation function of neurons, the sigmoid, an experimental addiction $E = f(N)$ was built, shown in fig. 10.

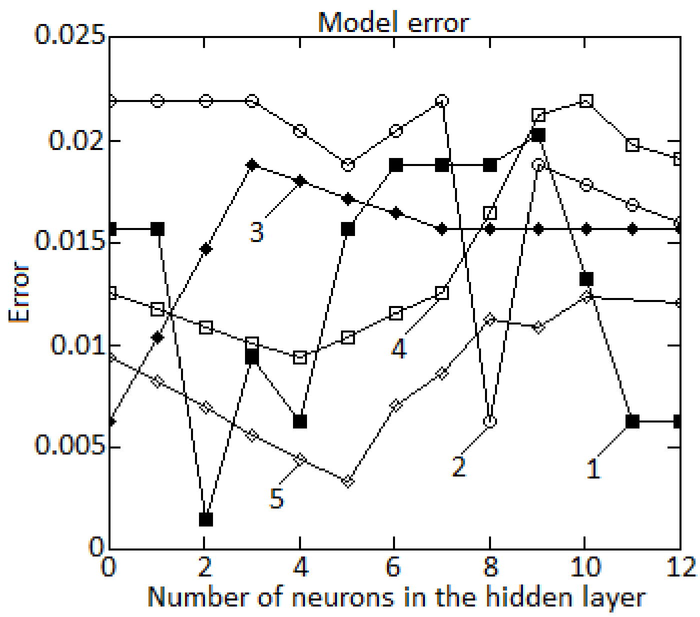


Figure 10: Dependence of neural network training error on the number of neurons in the hidden layer

Fig. 10 shown: E – neural network training error; N – number of neurons in the hidden layer, where 1 – dependence of the network training error when using the sigmoid activation function of neurons; 2 – dependence of the network training error when using the logistic function of neuron activation; 3 – dependence of the network training error when using the tangential (hyperbolic tangent) neuron activation function; 4 – dependence of the network training error when using the sinusoidal activation function of neurons; 5 – the dependence of the network training error when using the exponential activation function of neurons.

To prove the correctness of the choice of the neural network training algorithm, a comparative analysis of the results of neural network training by various methods is given (table 5). From table 5 shows that the smallest root means square error (1.86835) with the least number of training epochs of the neural network (200), as well as the smallest (given) number of neurons in the hidden layer (2) is provided by the selected neural network training algorithm developed on the basis of the Nelder–Mead method.

Table 5

Results of adaptation criterion calculation

Traning Algorithm	Root-mean-square error	Number of training epoch	Number of neurons in the hidden layer
Nelder–Mead method	1.86835	200	2
Back propagation	2.73024	220	5
Quick propagation	4.00261	240	6
Conjugate gradient	4.29965	250	8
Quasi-Newton	4.31782	280	8
Lewenberg-Marquardt	4.32009	310	8
Reverse propagation	4.88356	320	10
Fast propagation	5.01631	330	10

Thus, the expediency of using two neurons in the hidden layer, as well as the selected neural network training algorithm developed on the basis of the Nelder–Mead method, has been experimentally proven.

The conducted studies of the performance of the neural network allow us to preliminarily state:

– PID-neuroregulators can be effectively used as regulators in helicopters TE closed on-board ACS, which is confirmed by the results of the research of the convergence of modulation characteristics;

– the selected neural network training algorithm, developed on the basis of the Nelder–Mead method, solves the problem of parametric adaptation with the best accuracy for practice;

– it has been proven that the best version of the neural network in the case of using the integral quadratic criterion is the neural network of the perceptron architecture with the sigmoid activation function of neurons.

6. Discussions

Let us consider the process of parametric adaptation with a tuned model without dynamic compensation for a nonlinear model of TV3-117 aircraft engine (initial check). At the initial moment of time, the state vectors of the linear adjustable model and the nonlinear model of TV3-117 aircraft engine are equal. The transient process at the initial moment of time is due to the mismatch of the initial conditions, together with a change in the load power, which is a complex mode of operation and is similar to a change in load during the transient process.

Fig. 11 shows the transient processes, where: 1 – tuning model (using a neural network); 2 – system with a standard regulator. Fig. 12 shows the change in the values of the coefficients of the free turbine frequency controller.

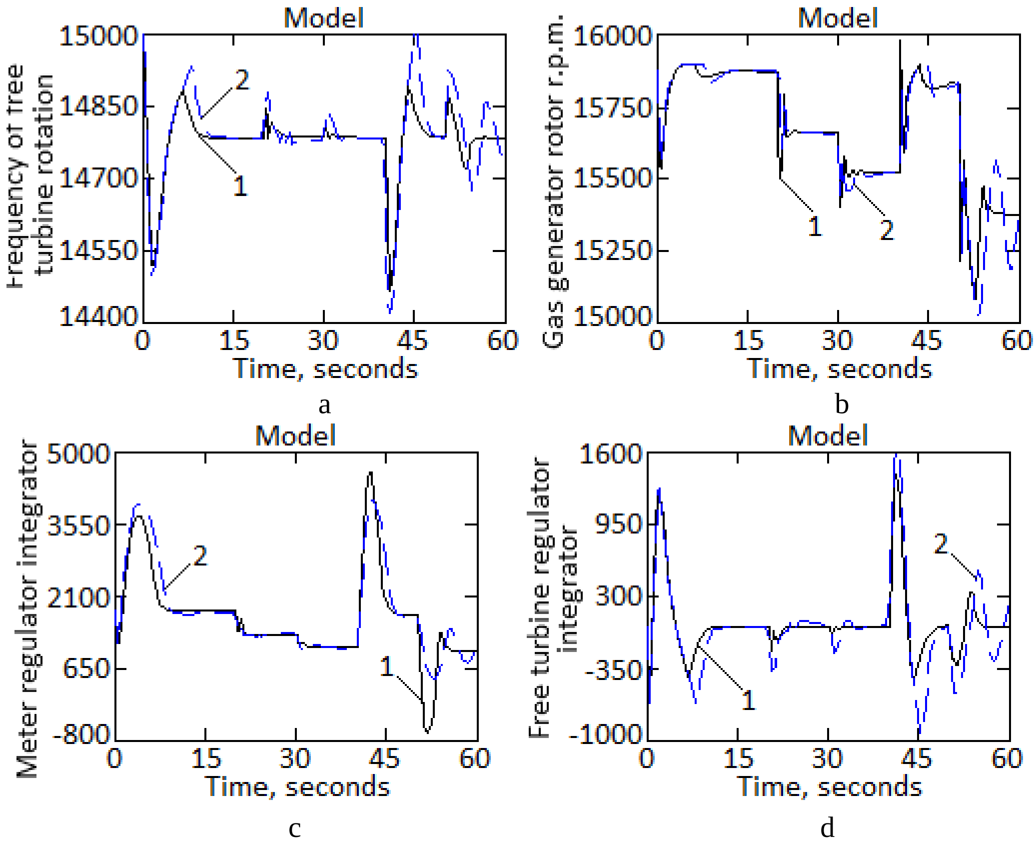


Figure 11: Diagrams of change: a – free turbine speed; b – gas-generator rotor r.p.m.; c – dispenser controller integrator; d – free turbine regulator integrator

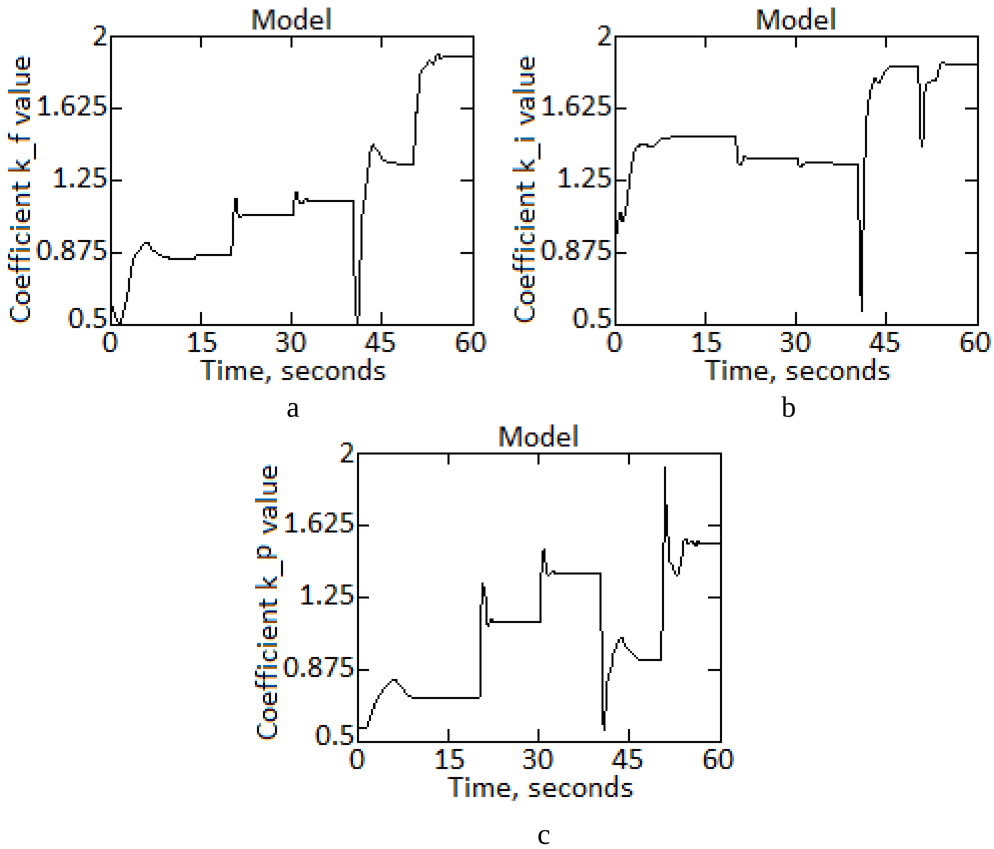


Figure 12: Diagrams of change in the values of free turbine frequency controller coefficients: a – diagrams of the change in the integral coefficient; b – diagrams of the change in the proportional coefficient; c – diagrams of the change in the forcing coefficient

By parametric tuning, quality indicators such as maximum deviation are improved. The results of improving quality indicators during transients are given in tables 6 and 7.

Table 4

Quality indicators for n_{FT} of the reference model with a signal regulator

Regulator type	Maximum deviation, rpm	Transient process time, s	Number of vibrations
Regular	2200	10.5	2
Adaptive	1320	4.3	1

Table 5

Improvement of quality indicators for n_{FT} of the reference model with a signal regulator

Improvement, %	28.35	60.92	61.37
Section of the transition process, s	40...50	50...60	50...60

Let us consider the process of parametric adaptation with a customizable model [10] for a non-linear (element-by-element) model of TV3-117 aircraft TE [31]. At the first stage, the custom and element-by-element models are compared. The element-by-element model controller coefficients are not adjusted. The mismatch of the initial conditions causes a transient process up to the 15th second. Fig. 13 shows the results of the experiment, where: 1 – element-by-element model; 2 – tuned model [10].

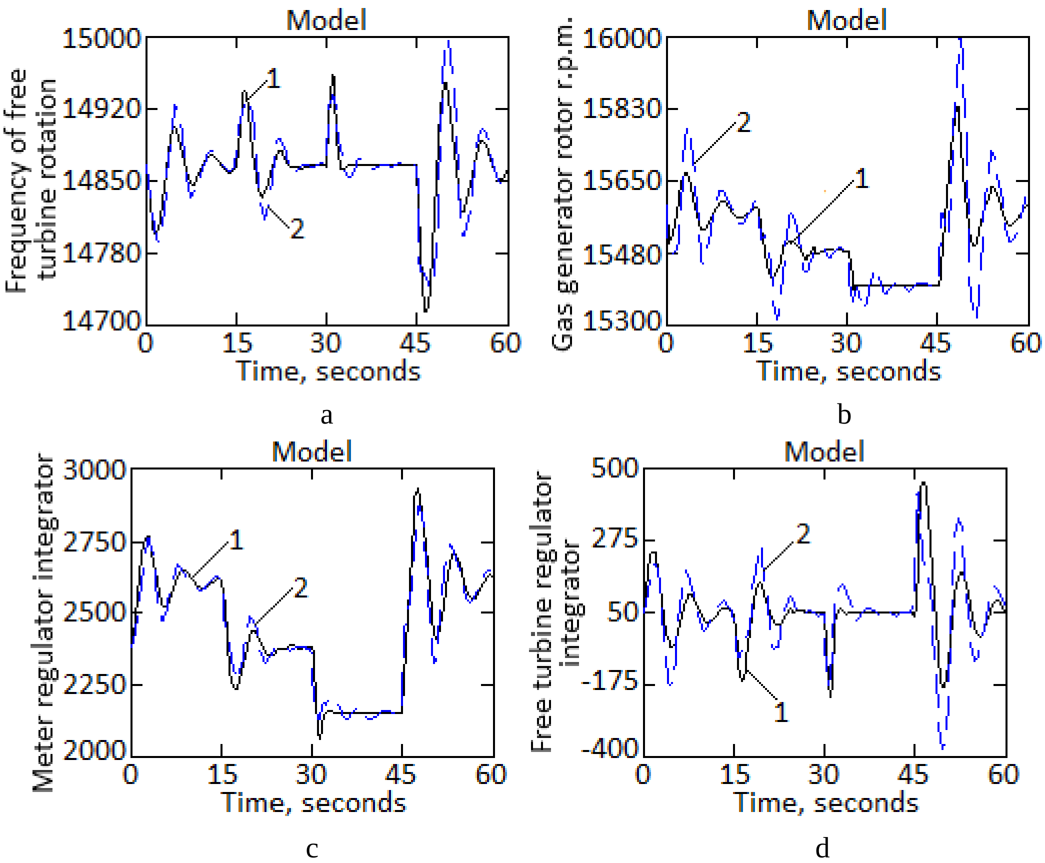


Figure 13: Diagrams of change: a – free turbine speed; b – gas-generator rotor r.p.m.; c – dispenser controller integrator; d – free turbine regulator integrator

The element-by-element model of TV3-117 aircraft TE is much more complicated than the custom model [10], so the accuracy in identifying the custom model is worse than in the previously given cases. Also, this may be due to the fact that the calculated value of the moment of inertia of the free turbine and the equivalent time constant of the linearized model turbocharger were obtained from an insufficient number of experiments, and, therefore, are not accurate enough.

At the second stage, the regulator coefficients are tuned according to the current tuned model [10]. Fig. 14 shows diagrams of transient processes, where: 1 – element-by-element model; 2 – custom model. Fig. 15 shows the change in the values of the coefficients of the free turbine frequency controller.

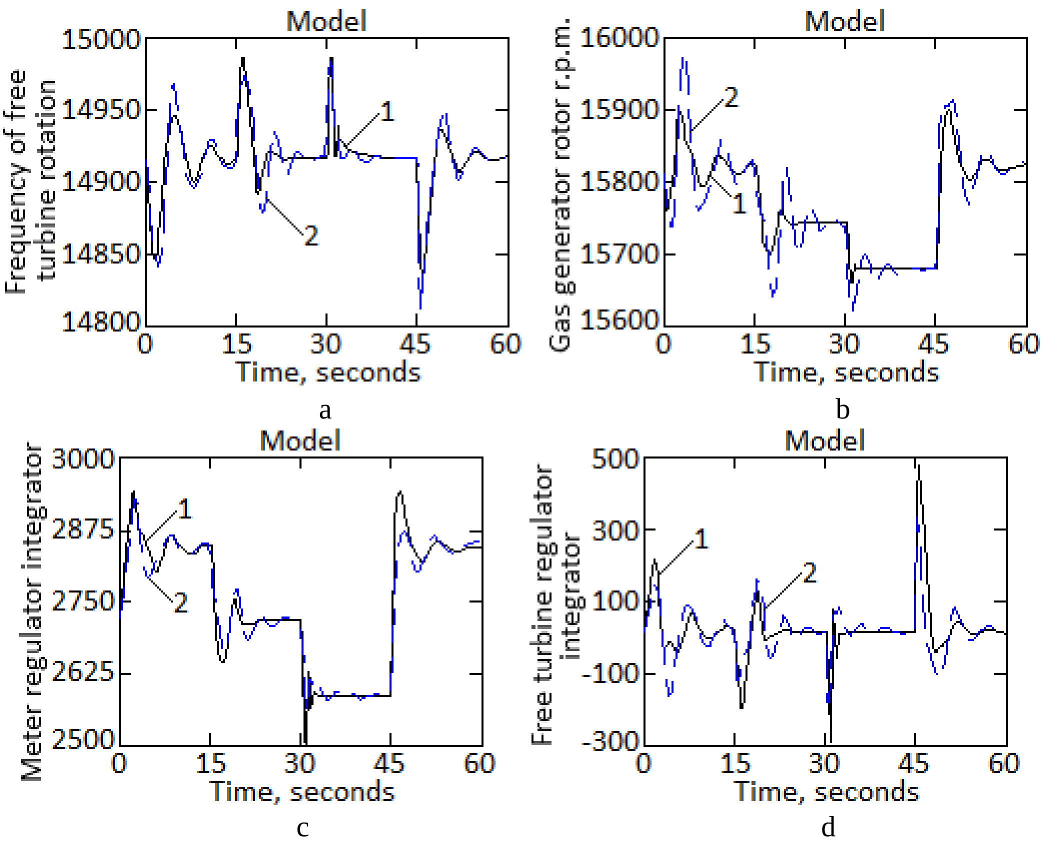


Figure 14: Diagrams of change: a – free turbine speed; b – gas-generator rotor r.p.m.; c – dispenser controller integrator; d – free turbine regulator integrator

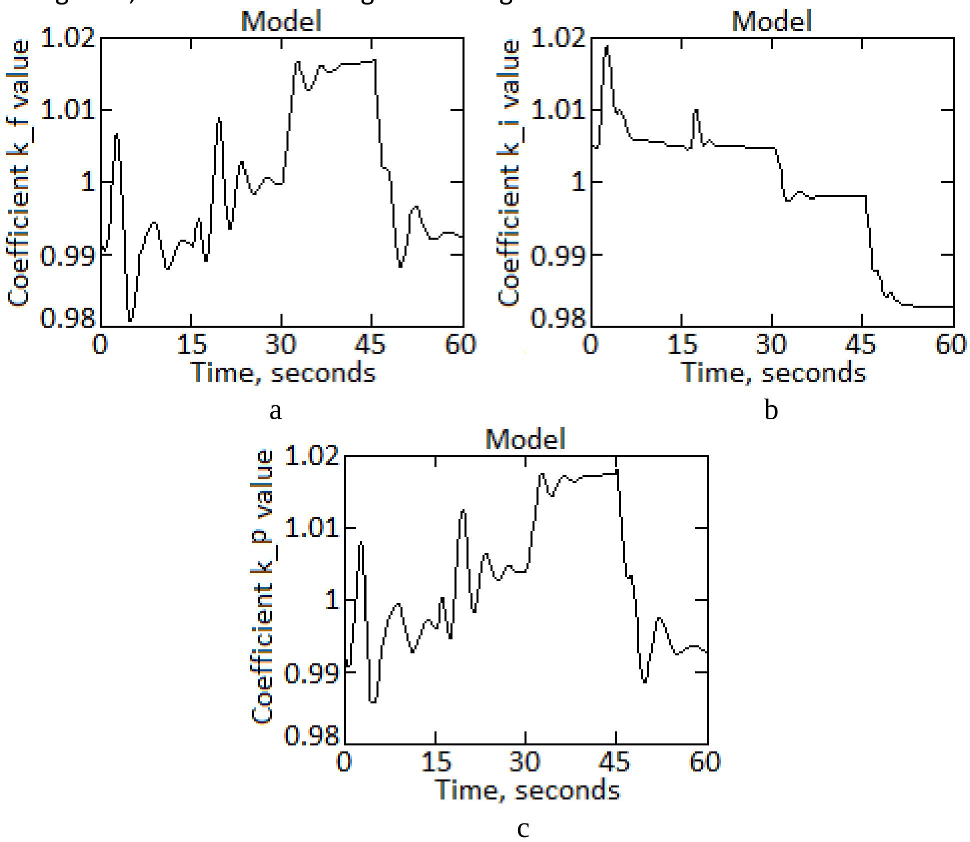


Figure 15: Diagrams of change in the values of free turbine frequency controller coefficients: a – diagrams of the change in the integral coefficient; b – diagrams of the change in the proportional coefficient; c – diagrams of the change in the forcing coefficient

The improvement in the quality indicators of transient processes occurs despite the fact that the correspondence between the adjusted model and the object (TV3-117 aircraft TE) is not as high as in the previous cases. The maximum improvement in quality indicators during transients is given in tables 8 and 9.

Table 8
Quality indicators for n_{FT} of the reference model with a signal regulator

Regulator type	Maximum deviation, rpm	Transient process time, s	Number of vibrations
Regular	380	10.8	2
Adaptive	230	3.9	3

Table 9
Improvement of quality indicators for n_{FT} of the reference model with a signal regulator

Improvement, %	47.24	64.29	–
Section of the transition process, s	50…60	50…60	50…60

As can be seen from fig. 15, the values of the coefficients k_p, k_i and k_f are close to 1, which indicates the correct choice of their values, while at $k_p = k_i = k_f = 1$, the maximum improvement in the quality indicators of adaptation of transient's processes in helicopters TE closed on-board ACS by ≈ 30 % is achieved in relation to standard regulators (tables 6 and 8).

A comparative analysis of the accuracy of the classical and neural network methods for controlling helicopters TE (on the example of the TV3-117 aircraft TE) is given in table 10, which displays the probabilities of errors of the 1st and 2nd kind in determining the optimal parameters n_{TC} and n_{FT}.

Table 10
Comparative characteristics of methods

Method of determination	Probability of error in determining the optimal parameters n_{TC} and n_{FT}, %			
	Determination of the optimal parameter n_{TC}		Determination of the optimal parameter n_{FT}	
	Type 1st error	Type 2nd error	Type 1st error	Type 2nd error
Classic (method of tolerance control)	2.19	1.21	2.12	1.92
Neural Network	0.61	0.32	0.69	0.34

7. Conclusions

1. The method of adaptive control with a customizable (or reference) model and parametric tuning has been further developed, which makes it possible to automate the process of controlling helicopters turboshaft engines at flight modes.

2. The neural network method for monitoring helicopter turboshaft engines operational status at flight modes has been improved through the use of a PID neurocontroller construct on the basis of a neural network of the perceptron architecture with two neurons in the hidden layer, which led to a decrease in errors of the first and second kind in determining the optimal engine parameters.

3. It has been proven that the use of parametric tuning units with a customizable (or reference) model in helicopters turboshaft engines closed on-board automatic control system improves the quality of recognition of transient processes by an average of 30 % compared to the use of standard regulators.

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