Modified Searchless Method for Identification of Helicopters Turboshaft Engines at Flight Modes Using Neural Networks

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***Abstract*—This work is devoted to the improvement of the automatic control system of helicopters turboshaft engines through the introduction of a block of signal adaptation of engine parameters into it using a modified method of searchless identification. The implementation of the proposed solutions is carried out using the NEWFF multilayer neural network, which made it possible to significantly reduce the maximum absolute error compared to the least squares method.**

Keywords—helicopters turboshaft engines, neural network, searchless method, training

I. Introduction

The development of modern helicopters turboshaft engines (TE) requires better and faster troubleshooting, for this it is necessary to continuously improve the monitoring and diagnostic systems for such engines. The functioning of such systems under the conditions of "non-factors", combined with the high complexity of the processes occurring in the engine, makes it expedient to use intelligent methods to solve the problems of identifying gas turbine engines along with classical ones [1].

II. Literature review

There are a significant number of publications on the problem of TE identification with a detailed description of the methods and techniques that implement the solution of this problem [2, 3], including the use of neural network methods [4, 5]. Among the variety of identification methods, the most commonly used are: cross-correlation, stochastic approximation, maximum likelihood, maximization of a posteriori probability and least squares. Other methods are either a modification of the above, or have a narrow specialization and are applied selectively to a specific problem. Analysis of works shows that neural networks provide versatility in solving such problems. This is due to the possibility of their training and additional training as universal approximators [6, 7].

III. Mathematical description of the non-search identification method in real time

Non-search identification algorithm with an adaptive model, which is based on the method of Lyapunov functions, was developed by Stanislav Zemlyakov and Vladislav Rutkovsky, the scope of which is linear continuous objects with a description in the state space. As is known, finding Lyapunov functions for such a class of systems has no common formal methods, so the procedure remains heuristic. The simplest is the case of a linear object and model. Therefore, a modification of this method is the possibility of obtaining a linear model of a non-linear object (helicopter TE) in real time using the mathematical apparatus [8]. To do this, it is considered that at each moment of time the tuned model is a linear model corresponding to the current state of the nonlinear object, for this, at the initial moment of time, the parameters of the linear model must correspond to the nonlinear object.

A generalized description of helicopter TE and its linear model in state spaces has the following form [9]:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{g}; \tag{1}$$

$$\dot{\mathbf{x}}_\mathbf{M} = \mathbf{A}_\mathbf{M}\mathbf{x}_\mathbf{M} + \mathbf{B}_\mathbf{M}\mathbf{g}; \tag{2}$$

where $\mathbf{x}$ – helicopter TE engine state variables vector; $\mathbf{x}_\mathbf{M}$ – model state variables vector; $\mathbf{g}$ – reference signal vector, $\dot{\mathbf{x}}$ – helicopter TE derivative state variables vector; $\dot{\mathbf{x}}_\mathbf{M}$ – derivative model state variables vector.

The corresponding vectors and matrices of helicopter TE engine and the model have the same dimensions, and their deviations are as follows:

$$\Delta\mathbf{x} = \mathbf{x} - \mathbf{x}_\mathbf{M};\ \ \Delta\mathbf{A} = \mathbf{A} - \mathbf{A}_\mathbf{M};\ \ \Delta\mathbf{B} = \mathbf{B} - \mathbf{B}_\mathbf{M}. \tag{3}$$

It is believed that the vectors $\mathbf{x}$, $\mathbf{x}_\mathbf{M}$, $\mathbf{g}$, $\dot{\mathbf{x}}$, $\dot{\mathbf{x}}_\mathbf{M}$ are directly observable (measurable). Subtract (2) from (1), we find:

$$\Delta\dot{\mathbf{x}} = \Delta\mathbf{A}\mathbf{x} + \mathbf{A}_\mathbf{M}\Delta\mathbf{x} + \Delta\mathbf{B}\mathbf{g}; \tag{4}$$

where $\mathbf{A}_\mathbf{M}$ – matrix corresponding to the current model setting (assumed to be known); $\Delta\mathbf{x}$ and $\Delta\dot{\mathbf{x}}$ determined by the measured values. In this case, the observed residual signal is taken equal to:

$$\Delta\mathbf{z} = \Delta\dot{\mathbf{x}} - \mathbf{A}_\mathbf{M}\Delta\mathbf{x} = \Delta\mathbf{A}\mathbf{x} + \Delta\mathbf{B}\mathbf{g}. \tag{5}$$

The elements of the matrices $\mathbf{A}$, $\mathbf{A}_\mathbf{M}$, $\mathbf{B}$, $\mathbf{B}_\mathbf{M}$ are independent of each other. Thus, the identification process can be carried out in parallel along the rows of these matrices. Because of this, we write:

$$\Delta\mathbf{z}_\mathbf{i} = \Delta\mathbf{A}_{|\mathbf{i}|}\mathbf{x} + \Delta\mathbf{B}_{|\mathbf{i}|}\mathbf{g};\ \ i = \overline{1, n}; \tag{6}$$

where $\Delta\mathbf{A}_{|\mathbf{i}|}$, $\Delta\mathbf{B}_{|\mathbf{i}|}$ are i-th rows of matrices $\Delta\mathbf{A}$, $\Delta\mathbf{B}$.

We will look for the Lyapunov function for the *i*-th channel in the form of a positive-definite quadratic form:

$$\mathbf{V_i} = \frac{1}{2}\left(\mathbf{\Delta A_{|i|} K^{\langle i \rangle} \Delta A^T_{|i|}} + \mathbf{\Delta B_{|i|} D^{\langle i \rangle} \Delta B^T_{|i|}}\right); \qquad (7)$$

where $\mathbf{K}^{\langle i \rangle}$, $\mathbf{D}^{\langle i \rangle}$ – positive-definite diagonal matrices of given constant coefficients. For the function $\mathbf{V_i}$, we write the time derivative in the following form:

$$\dot{\mathbf{V}}_\mathbf{i} = \mathbf{\Delta A_{|i|} K^{\langle i \rangle} \Delta \dot{A}^T_{|i|}} + \mathbf{\Delta B_{|i|} D^{\langle i \rangle} \Delta \dot{B}^T_{|i|}}. \qquad (8)$$

Let

$$\begin{cases} \mathbf{\Delta \dot{A}^T_{|i|}} = -\left(\mathbf{K}^{\langle i \rangle}\right)^{-1} \mathbf{\Delta z_i x} = -\left(\mathbf{K}^{\langle i \rangle}\right)^{-1}\left(\mathbf{\Delta A_{|i|} x} + \mathbf{\Delta B_{|i|} g}\right)\mathbf{x}; \\ \mathbf{\Delta \dot{B}^T_{|i|}} = -\left(\mathbf{D}^{\langle i \rangle}\right)^{-1} \mathbf{\Delta z_i g} = -\left(\mathbf{D}^{\langle i \rangle}\right)^{-1}\left(\mathbf{\Delta A_{|i|} x} + \mathbf{\Delta B_{|i|} g}\right)\mathbf{g}; \end{cases} \qquad (9)$$

then

$$\dot{\mathbf{V}}_\mathbf{i} = -\left(\mathbf{\Delta A_{|i|} x} + \mathbf{\Delta B_{|i|} g}\right)^2. \qquad (10)$$

The asymptotic convergence of the model tuning process is confirmed by expressions (7), (9) in the event that relations (9) are satisfied, and the discrepancy value (6) vanishes identically on the implementations $x(t) \in X$; $u(t) \in U$ only when $\mathbf{\Delta A_{|i|}} = \mathbf{\Delta B_{|i|}} = 0$. Let us transform expressions (9) to the following form:

$$\begin{cases} \mathbf{\Delta \dot{A}^T_{M|i|}} = \left(\mathbf{K}^{\langle i \rangle}\right)^{-1} \mathbf{\Delta z_i x} + \mathbf{\Delta \dot{A}^T_{|i|}}; \\ \mathbf{\Delta \dot{B}^T_{M|i|}} = \left(\mathbf{D}^{\langle i \rangle}\right)^{-1} \mathbf{\Delta z_i g} + \mathbf{\Delta \dot{B}^T_{|i|}}. \end{cases} \qquad (11)$$

This algorithm for model tuning cannot be implemented exactly, because $\dot{\mathbf{A}}$ and $\dot{\mathbf{B}}$ are unknown. In cases where the gains forming the diagonal matrices $\mathbf{K}^{*\langle i \rangle} = \left(\mathbf{K}^{\langle i \rangle}\right)^{-1}$, $\mathbf{D}^{*\langle i \rangle} = \left(\mathbf{D}^{\langle i \rangle}\right)^{-1}$ are large enough or when the rate of change $\mathbf{A}$ is slow enough, members $\dot{\mathbf{A}}^\mathbf{T}_{|i|}$, $\dot{\mathbf{B}}^\mathbf{T}_{|i|}$ can be neglected. In this case, instead of (11), you can use the algorithm

$$\begin{cases} \mathbf{\Delta \dot{A}^T_{M|i|}} = \mathbf{K}^{*\langle i \rangle} \mathbf{\Delta z_i x}; \\ \mathbf{\Delta \dot{B}^T_{M|i|}} = \mathbf{D}^{*\langle i \rangle} \mathbf{\Delta z_i g}. \end{cases} \qquad (12)$$

This model tuning algorithm is realizable. Assuming that $\mathbf{K}^{*\langle i \rangle}$, $\mathbf{D}^{*\langle i \rangle}$ do not depend on *i*, we rewrite (12):

$$\begin{cases} \dot{\mathbf{A}}_\mathbf{M} = \mathbf{\Delta z}\left(\mathbf{K^* x}\right)^\mathbf{T}; \\ \dot{\mathbf{B}}_\mathbf{M} = \mathbf{\Delta z}\left(\mathbf{D^* g}\right)^\mathbf{T}. \end{cases} \qquad (13)$$

In accordance with equations (1), (2), (13) and the expression $\mathbf{\Delta z} = \mathbf{\Delta \dot{x}} - \mathbf{A_M \Delta x}$, the block diagram of the non-search identification algorithm with an adaptive model is modified, shown in fig. 1.

Since the helicopter TE is an essentially non-linear object, we will simplify the task of identification in real time using knowledge of the engine operating modes. Let us add to the linear identifiable model (2) a nonlinear part, which includes simplified static characteristics. Simplified static characteristics are obtained by approximating the static characteristics of an object based on two points corresponding to the nominal mode and idling. Thus, during the identification process, an additional assessment will appear $\dot{\mathbf{A}}$ and $\dot{\mathbf{B}}$, which makes it possible to approximate the identification process to equation (1). The equation of the nonlinear model will take the form:

$$\dot{\mathbf{x}}_\mathbf{M} = \left(\mathbf{A_M}(\mathbf{x}) + \mathbf{A_M}(\mathbf{\Delta z})\right)\mathbf{x} + \left(\mathbf{B_M}(\mathbf{x}) + \mathbf{B_M}(\mathbf{\Delta z})\right)\mathbf{g} + \mathbf{f}(t); \quad (14)$$

where $\mathbf{A_M(x)}$, $\mathbf{B_M(x)}$ – matrices representing the assessment of the nonlinear part of the model based on the physical characteristics of the object; $\mathbf{A_M(\Delta z)}$, $\mathbf{B_M(\Delta z)}$ – matrices of a linear identifiable model, changing in accordance with (13).

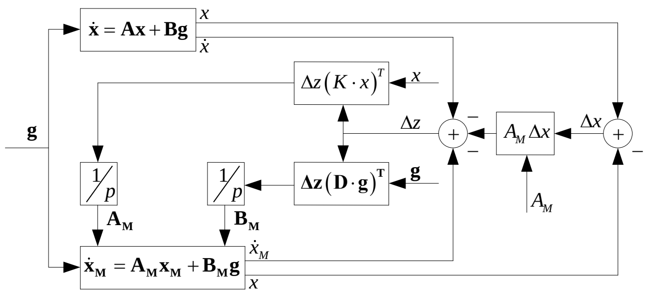


Fig. 1. Block diagram of real-time identification (developed by V. Bakhirev).

This method provides high accuracy of identification in real time. The desired indicators of the quality of transient processes are provided using the method of dynamic compensation. The improved modified method of non-search identification makes it possible to build an algorithm for an adaptive control system with a custom model of helicopter TE based on it.

When selecting parameters for the searchless identification algorithm, it should be noted that, depending on the type of turboshaft engine, the positive diagonal matrices **D** and **K** will differ. This is due to the fact that the stability of the searchless identification process is based on the Lyapunov function. Based on the experience of selecting matrices for various helicopters TE (GTE-350, TV2-117, TV3-117), the following recommendations were formed:

1. The elements of the diagonal matrices **D** and **K**, corresponding to the state variable, must be increased if the duration of the transient process of the adjustable model variable is greater than the duration of the transition process of the corresponding object variable.

2. The elements of the diagonal matrices **D** and **K**, corresponding to the state variable, must be reduced if oscillations appear in the transient process of the adjustable model variable, which are not present in the transient process of the corresponding plant variable.

3. As the initial value, the elements of the diagonal matrices **D** and **K**, it is convenient to use the number $2.25 \cdot 10^{-8}$.

IV. Helicopters Turboshaft Engines Automatic Control System Modification

Helicopters TE automatic control system (ACS) was developed in [10] (fig. 2), where TE – helicopter TE, TE Model – model of helicopter TE, LB – logical block, FMU – fuel metering unit, FMU model – model of fuel metering unit.

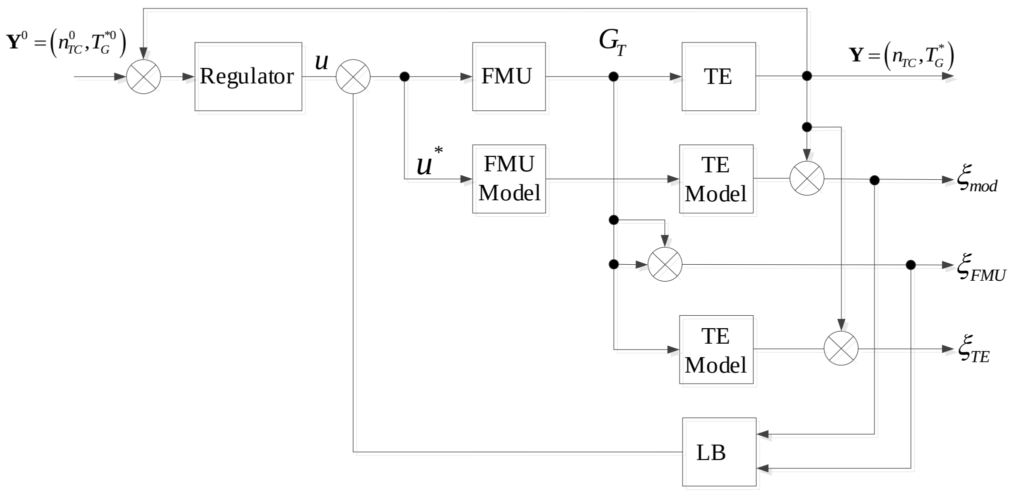


Fig. 2. Helicopters TE automatic control system [10].

The modification of the developed ACS for helicopters TE consists in supplementing with software modules that implement adaptive control methods, namely, in this work, with a signal adaptation module (fig. 3). The principle of operation of the signal adaptation module is described as follows. The input of the module receives: $\mathbf{x_M}$ –state vector of the custom model and $\mathbf{x}$ – reduced state vector of the control object. The vector $\mathbf{x}$ 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. Based on the obtained data, the mismatch vector is calculated. After that, the weighted sum of the mismatch vector is calculated. Then the signal action z is calculated. The magnitude of the signal impact z is the output variable. The input data vector $\mathbf{Y}^0$ is supplemented with the free turbine speed parameter n_{FT} and, accordingly, is converted to the form $\mathbf{Y}^0 = \left(n_{FT}^0, n_{TC}^0, T_G^{*0}\right)$.

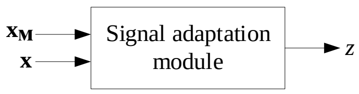


Fig. 3. Block diagram of the input and output signals of the signal adaptation module.

To create a signal adaptive ACS for helicopters TE, modules of a customizable model and signal adaptation are additionally included in the standard controller. The adaptation subsystem will work in accordance with the algorithm shown in fig. 4.

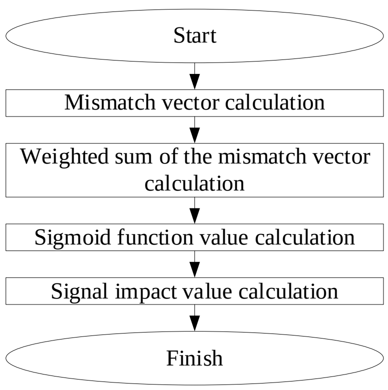


Fig. 4. Block diagram of the algorithm of the adaptation module with signal adaptation.

V. Implementation of a Non-Search Real-Time Identification Method in a Neural Network Basis

According to the review of the use of neural networks in control problems, the NEWFF multilayer neural network with forward signal transmission and error backpropagation [11], a general view of which is shown in fig. 5, in which element z delays the signal by j steps. The control signal $X(z)$ and n signal values from the output $Y(z)$ are fed to the inputs of the neural network. The value of n is determined by the order of the differential equation, which describes the operation of a helicopter gas turbine engine. When solving the control problem, the operating mode of the neural network is used, which implements the input-output mapping.

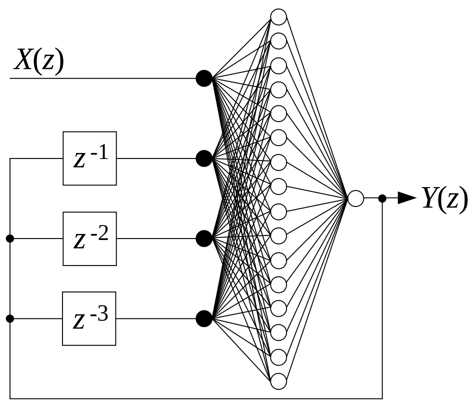


Fig. 5. Multilayer neural network NEWFF structure.

The neural network contains 16 neurons in the hidden layer with a tangential sigmoidal activation function and 1 output neuron with a linear activation function. On fig. 6 shows a neural network training scheme that minimizes the error:

$$E(t) = N(t) - Y(t); \qquad (15)$$

where $Y(t)$ and $N(t)$ – output signals of the neural network and the helicopter TE engine, respectively. In this case, two elements of the input vector are used, the current $Y(t)$ and the delayed output $Y(t - 1)$. The procedure for identifying a helicopter TE consists in setting the weight coefficients and parameters of neurons. The adjustment is made on the basis of information about the error signal $E(t)$ between the outputs of helicopter TE and the neural network.

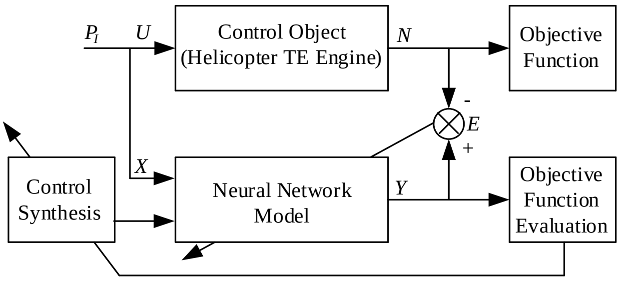


Fig. 6. Neural network training diagram.

According to fig. 6, instead of the real values of the output of the control object (helicopter TE engine) N, the model value Y is used and, accordingly, instead of the real value of the functional J, its estimate J^*.

For generalized autonomous training of a neural network, the backpropagation signals between the output and hidden layers are expressed as

$$R_k = U_k - Q_k; \quad (16)$$

where U_k – given (target) parameter of helicopter TE engine; Q_k – actual output of the neural network;

$$R_i = f'(net)\sum_k R_k W_{ki}; \quad (17)$$

where $f'(net) = \dfrac{1}{1+e^{-net}}$; W_{ki} – weights of links; R_k – outputs.

The weights of links between the input and hidden layers are adjusted according to the expression

$$\Delta W_{ji}(t+1) = g_1 R_j Q_i + g_2 \Delta W_{ji}(t) + g_3 \Delta W_{ji}(t-1); \quad (18)$$

and between the hidden and output layers – according to the expression:

$$\Delta W_{kj}(t+1) = g_1 R_k Q_k + g_2 \Delta W_{kj}(t) + g_3 \Delta W_{kj}(t-1); \quad (19)$$

where g_1 – training rate; g_2 and g_3 – instantaneous value and acceleration coefficients, respectively. Equations (18) and (19) are modified forms of the generalized delta rule [12].

In operational training, the weights of the connections of the neural network are adjusted based on the error defined as

$$E_e = \frac{1}{2}(P_I - N)^2; \quad (20)$$

where P_I and N – specified and actual outputs of helicopter TE. Thus, the output signal can be expressed as follows:

$$\delta_k^c = -\frac{\partial E^E}{\partial (net)_k^c} = -\frac{\partial E^E}{\partial Q_k^c} \cdot \frac{\partial Q_k^c}{\partial (net)_k^c}; \quad (21)$$

$$\delta_k^c = \sum_j \delta_j^E W_{ji}^E; \quad (22)$$

where Q_k^c and $(net)_k^c$ – input and output signals of neurons of the output layer.

The error signal between the hidden and input layers is expressed by the following formula:

$$\delta_j^c = Q_j^c (1 - Q_j^c) \sum_j \delta_k^c W_{kj}^c; \quad (23)$$

where Q_j^c – output signal of neurons in the hidden layer.

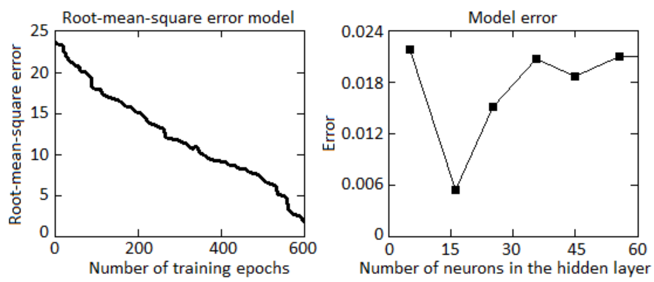
VI. Results and Discussion

The input data for training the neural network are the following parameters of the aircraft gas turbine engine of the helicopter, which are recorded on board the helicopter: n_{TC} – rotor r.p.m.; n_{FT} – frequency of free turbine rotation; T_G – gas temperature in front of the compressor turbine. All values of these parameters are reduced to absolute values according to the theory of gas-dynamic similarity developed by professor Valery Avgustinovich (table 1).

TABLE I. FRAGMENT OF THE TRAINING SAMPLE – INPUT DATA (ON THE EXAMPLE OF TV3-117 TURBOSHAFT ENGINE)

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

The neural network was trained for 600 epochs, the training accuracy characteristic is shown in fig. 7, *a*, while the steady-state root-mean-square error (RMS) is ~1.99794. According to fig. 7, *b*, the number of neurons in the hidden layer that provide the smallest training error is 16 neurons.



a b

Fig. 7. Results of training the neural network: *a* – characteristic of the accuracy of training the neural network; *b* – dependence of training error on the complexity of the neural network.

The resulting 3–16–1 architecture neural network was also trained by other known training algorithms (table 2). The results of the comparative analysis confirmed the feasibility of using the proposed training method, since it achieves the smallest training error, uses the smallest number of epochs to achieve the smallest training error, and also the smallest number of neurons in the hidden layer is sufficient to achieve the smallest training error [11].

TABLE II. RESULTS OF NEURAL NETWORK TRAINING BY VARIOUS ALGORITHMS

Training Algorithm	**Root-mean-square error**	**Number of training epochs**	**Number of neurons in the hidden layer**
Proposed algorithm	1.99794	600	16
Back propagation	2.38061	650	18
Conjugate gradient	4.35773	830	36
Quick propagation	4.14182	790	32
Quasi-Newton	3.14325	750	20
Lewenberg-Marquardt	3.07164	720	20
Delta bar delta	3.23218	770	26
Resilient propagation	3.43016	850	24
Genetic Algorithm	2.19735	630	18

Let us consider the process of signal adaptation with a tuned model (14) without dynamic compensation for a nonlinear model of TV3-117 TE (first verification). At the initial moment of time, the state vectors of the linear adjustable model and the nonlinear model of TV3-117 TE 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 load change during the transient process. Fig. 8, 9 are shows transient processes, where: 1 – tuning model (using a neural network); 2 – system with alarm setting; 3 – system with a standard regulator.

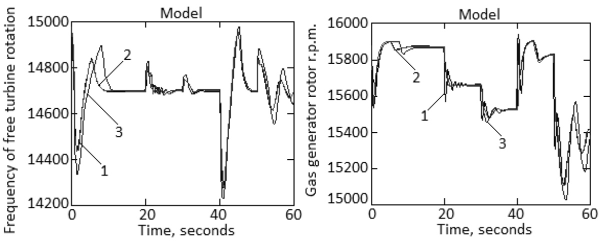


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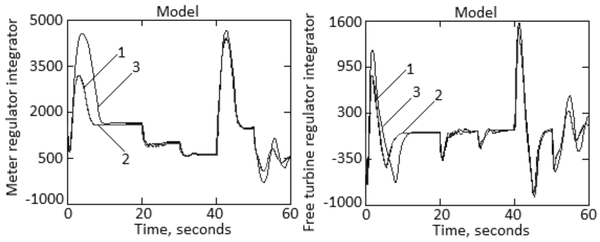
Fig. 8. Diagram of change: a – frequency of free turbine rotation; b – gas generator rotor r.p.m.



a b

Fig. 9. Diagram of change of regulator integrator: a – meter; b – free turbine

As follows from fig. 8, 9, the improvement in the quality indicators of transient processes using the tuned model of the TV3-117 TE based on a neural network is more significant compared to the model with a standard controller. This is due to the fact that dynamic compensation was not applied due to the fact that the order of the models is the same and the adjusted model demonstrates quality indicators better than the object, despite the change in parameters during the transient process. The results of maximizing performance improvement during transients are shown in tables 3 and 4.

TABLE III. QUALITY INDICATORS FOR N_{FT} OF A CUSTOM MODEL (BASED ON A NEURAL NETWORK) WITH A SIGNAL CONTROLLER

Regulator type	Maximum deviation, rev/min	Transient time, s	Number of vibrations
Regular	1380	10.1	1
Adaptive	1000	7.5	1

TABLE IV. IMPROVEMENT OF QUALITY INDICATORS FOR N_{FT} OF A CUSTOM MODEL (BASED ON A NEURAL NETWORK) WITH A SIGNAL REGULATOR

Improvement, %	26.37	26.51	27.17
Section of the transition process, s	0…20	0…20	0…20

Let us conduct an experiment of secondary verification of signal adaptation with a customizable model (14) for an element-by-element dynamic model of TV3-117 TE. At the initial moment of time, the tuned model corresponds to the nominal operating mode of the engine, since the element-by-element model is much more complicated than the tuned model, large parametric disturbances arise in the identification process, so dynamic compensation of the tuned model is applied. Fig. 10, 11 are shows transient processes, where: 1 – system with a standard controller, 2 – tuning model (using a neural network).

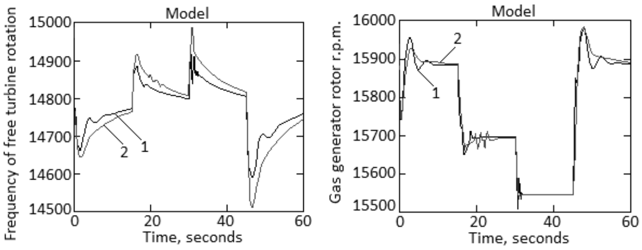


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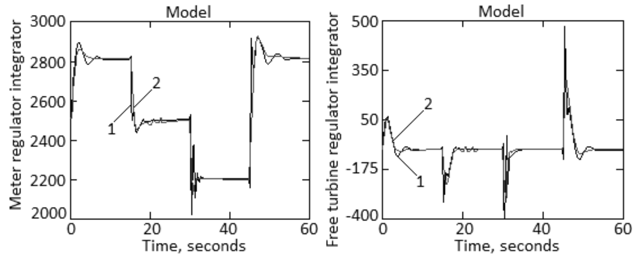
Fig. 10. Diagram of change: a – frequency of free turbine rotation; b – gas generator rotor r.p.m.



a b

Fig. 11. Diagram of change of regulator integrator: a – meter; b – free turbine

The results of maximizing performance improvement during transients are shown in tables 5 and 6.

TABLE V. QUALITY INDICATORS FOR N_{FT} OF A CUSTOM MODEL (BASED ON A NEURAL NETWORK) WITH A SIGNAL CONTROLLER

Regulator type	Maximum deviation, rev/min	Transient time, s	Number of vibrations
Regular	350	10.8	0
Adaptive	230	7.7	1

TABLE VI. IMPROVEMENT OF QUALITY INDICATORS FOR N_{FT} OF A CUSTOM MODEL (BASED ON A NEURAL NETWORK) WITH A SIGNAL REGULATOR

Improvement, %	29.14	31.32	33.03
Section of the transition process, s	30…45	30…45	10…20

As a comparative analysis of the accuracy of the neural network (NEWFF multilayer neural network) and classical (least squares method) implementations of the searchless identification algorithm for helicopters TE, it was found that the maximum absolute identification error when using the NEWFF multilayer neural network is 2.94 times less than for the polynomial eighth order regression model built using the least squares method. At the same time, the NEWFF multilayer neural network provides an identification error not exceeding 0.78 %.

The results of a comparative analysis of the accuracy of the implementation of the algorithm for searchless identification of helicopters TE of neural network and classical methods for each of the parameters of the engine model are given in table 7.

TABLE VII. COMPARATIVE ANALYSIS OF THE ACCURACY OF NEURAL NETWORK AND CLASSICAL IMPLEMENTATION METHODS OF THE SEARCHLESS IDENTIFICATION ALGORITHM

Model	Absolute error, %			
	Frequency of free turbine rotation	Gas generator rotor r.p.m.	Meter regulator integrator	Free turbine regulator integrator
Classical	2.29	2.31	2.33	2.39
Neural Network	0.75	0.76	0.74	0.78

In order to analyze the stability of neural networks to changes in input data (table 1), 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 σ_i = 0.025, that is, 2.5 % in relation to the maximum value.

The results of a comparative analysis of the accuracy of the implementation of the algorithm for searchless identification of helicopters TE of neural network and classical methods for each of the parameters of the engine model in noise environment are given in table 8.

TABLE VIII. COMPARATIVE ANALYSIS OF THE ACCURACY OF NEURAL NETWORK AND CLASSICAL IMPLEMENTATION METHODS OF THE SEARCHLESS IDENTIFICATION ALGORITHM

Model	Absolute error, %			
	Frequency of free turbine rotation	Gas generator rotor r.p.m.	Meter regulator integrator	Free turbine regulator integrator
Classical	3.46	3.52	3.59	3.67
Neural Network	1.18	1.23	1.27	1.32

Table 8 analysis shows that the identification error under the conditions of the specified noise does not exceed: when using the NEWFF multilayer neural network – 1.32 %, the least squares method – 3.67 %.

CONCLUSIONS

The modified method of signal adaptive control was further developed, which, due to the searchless identification algorithm, implemented in the neural network basis, made it possible to improve the control system of helicopters TE.

It has been established that neural networks solve the problem of implementing the searchless identification algorithm for helicopter TE more accurately than classical methods: the identification error at the output of the NEWFF multilayer neural network is 2.94 times less than that of the regression model obtained using the least squares method for the considered engine parameters, namely: frequency of free turbine rotation, gas generator rotor r.p.m., meter regulator integrator, free turbine regulator integrator.

It is shown that the error in the implementation of the searchless identification algorithm for helicopter TE using the NEWFF multilayer neural network when calculating individual engine parameters did not exceed 0.78 %, while for the classical method it is about 2.39 % for the considered engine parameters.

A comparative analysis of neural network and classical methods for implementing the searchless identification algorithm for aircraft gas turbine engines under noise conditions shows that neural network methods are more robust to external disturbances: for a noise level σ_i = 0.025, the maximum absolute error when using the NEWFF multilayer neural network increases from 0.78 to 1.32 %, and least squares method – from 2.39 to 3.67 %.

REFERENCES

[1] E. L. Ntantis, "Diagnostic methods for an aircraft engine performance", Journal of Engineering Science and Technology, 2015, vol. 8, no. 4, pp. 64–72.

[2] I. A. Krivosheev, K. E. Rozhkov and N. B. Simonov, "Complex Diagnostic Index for Technical Condition Assessment for GTE", Procedia Engineering, 2017, vol. 206. pp. 176–181.

[3] G. Musa, M. Alrashed and N. M. Muhammad, "Development of big data lean optimization using different control mode for gas turbine engine health monitoring", Energy Reports, 2021, vol. 7, pp. 4872–4881.

[4] S. Sina Tayarani-Bathaie and K. Khorasani, "Fault detection and isolation of gas turbine engines using a bank of neural networks", Journal of Process Control, 2015, vol. 36, pp. 22–41.

[5] S. Kiakojoori and K. Khorasani, "Dynamic neural networks for gas turbine engine degradation prediction, health monitoring and prognosis", Neural Computing & Applications, 2016, vol. 27, no. 8, pp. 2151–2192.

[6] S. Zhernakov and A. Gilmanshin, "New algorithms for on-board diagnostics of aircraft gas turbine engine based on fuzzy networks", Bulletin of USATU, 2015, vol. 19, no. 2 (68), pp. 63–68.

[7] M. Amozegar and K. Khorasani, "An ensemble of dynamic neural network identifiers for fault detection and isolation of gas turbine engines", Neural Networks, 2016, vol. 76, pp. 106–121.

[8] J. Zheng, J. Chang, J. Ma and D. Yu, "Performance uncertainty propagation analysis for control-oriented model of a turbine-based combined cycle engine", Acta Astronautica, 2018, vol. 153, pp. 39–49.

[9] S. M. Hosseinimaab and A. M. Tousi, "A new approach to off-design performance analysis of gas turbine engines and its application", Energy Conversion and Management, 2021, vol. 243, 114411.

[10] S. Vladov, Y. Shmelov and R. Yakovliev, "Helicopters Aircraft Engines Self-Organizing Neural Network Automatic Control System", The Fifth International Workshop on Computer Modeling and Intelligent Systems (CMIS-2022), May, 12, 2022, Zaporizhzhia, Ukraine. CEUR Workshop Proceedings, 2022, vol. 3137, pp. 28–47.

[11] P. Baldi, P. Sadowski and Z. Lu, "Learning in the machine: Random backpropagation and the deep learning channel", Artificial Intelligence, 2018, vol. 260, pp. 1–35.

[12] A. Shirilord and M. Dehghan, "Combined real and imaginary parts method for solving generalized Lyapunov matrix equation", Applied Numerical Mathematics, 2022, vol. 181, pp. 94–109.