Helicopters Turboshaft Engines Intelligent Control Algorithms Synthesis, Taking into Account Required Quality Provision

Serhii Vladov[a], Yurii Shmelov[a], Ruslan Yakovliev[a], Tatyana Kozlovskaya[a] and Maryna Petchenko[b]

[a] *Kremenchuk Flight College of Kharkiv National University of Internal Affairs, Peremohy street 17/6, Kremenchuk, 39605, Ukraine*
[b] *Kharkiv National University of Internal Affairs, L. Landau Avenue 27, Kharkiv, 61080, Ukraine*

Abstract

The work is devoted to the development of a reconfigured modified closed onboard helicopters turboshaft engines automatic control system, which is based on the use of a hybrid neuro-fuzzy network, which takes into account the main indicators of the automatic control system: overshoot and subsystem regulation time. The trained hybrid neuro-fuzzy network allows you to select the parameters of helicopters turboshaft engines automatic control system, taking into account the required quality indicators, which makes it possible to adjust the automatic control system operation when operating conditions change. A system of fuzzy knowledge base rules is proposed, which takes into account the threshold values of the main helicopters turboshaft engines thermogas-dynamic parameters and, thereby, allows to prevent overshoot. The use of bell-shaped membership functions of linguistic variables is proposed to describe the helicopters turboshaft engines thermogas-dynamic parameters registered on board helicopters, as well as the linguistic expression "about" in a fuzzy knowledge base, which made it possible to correct their values in case of random changes (uncertainties) associated due to errors, conditions helicopter flight, helicopter operational status etc. The results of training a hybrid neuro-fuzzy network indicate the stability of control, that is, the tendency for the training error indicator (residuals) to approach zero and does not exceed 0.4 %. Prospects for further research are the development of a software product that allows for instant reconfiguration of modified closed onboard helicopters turboshaft engines automatic control system in the conditions of on-board implementation for continuous monitoring of helicopters turboshaft engines operational status.

Keywords 1

Helicopters turboshaft engines, automatic control system, hybrid neuro-fuzzy network, transient processes, thermogas-dynamic parameters, membership functions, linguistic expression, residuals

1. Introduction

Aircraft gas turbine engine (GTE), including a helicopter turboshaft engine (TE), is a complex dynamic system (DS) consisting of many interacting elements and subsystems, progressive strategies. The efficiency of helicopter TE operation is mainly associated with an increase in their reliability, an increase in service life, and a reduction in maintenance and repair costs [1, 2].

At the helicopters TE automatic control system (ACS) operation mode, after solving the problem of ensuring stability, the problem arises of ensuring the required indicators of the quality of transient processes: overshoot, control time, and others. Often, these requirements are contradictory, which is

CITI'2023: 1st International Workshop on Computer Information Technologies in Industry 4.0, June 14–16, 2023, Ternopil, Ukraine
EMAIL: ser26101968@gmail.com (S. Vladov); nviddil.klk@gmail.com (Yu. Shmelov); ateu.nv.klk@gmail.com (R. Yakovliev); kozlovskaya5819@gmail.com (T. Kozlovskaya); marinapetcenko@gmail.com (M. Petchenko)
ORCID: 0000-0001-8009-5254 (S. Vladov); 0000-0002-3942-2003 (Yu. Shmelov); 0000-0002-3788-2583 (R. Yakovliev); 0000-0002-6106-5524 (T. Kozlovskaya); 0000-0003-1104-5717 (M. Petchenko)

primarily due to the peculiarities of the functioning of systems [3, 4]. For example, when the overshoot decreases, the regulation time increases and vice versa; thus, these two quantities have an inverse relationship. It is impossible to represent the indicated dependence for helicopters TE ACS as complex systems in mathematical form, which is explained by the peculiarities of each class of systems and subsystems included in the system, however, to solve the synthesis problem, it is necessary to determine such parameters so that the system meets the specified requirements.

One of the promising directions for the development of helicopter TE controls is the use of artificial intelligence components in their composition: production rules [5], fuzzy logic [6], artificial neural networks [7], hybrid neuro-fuzzy architectures [8], genetic algorithms [9]. Therefore, increasing the economic efficiency and maintaining a high level of reliability of the operation of helicopters TE at the stage of operation in conditions of special operational situations based on the development of theoretical foundations, methods and means of intelligent control of its modes is an urgent scientific and applied task.

2. Related Works

Modern approaches to the implementation of the main strategies for GTE development – operation on condition and ensuring system safety – involve the "intellectualization" of GTE all subsystems and information integration with the engine control, monitoring and diagnostics system (FADEC) in order to reliably assess the state, identify failures and ensure normal operation engine due to FADEC reconfiguration [10].

It should be noted that hybrid systems for GTE operational status classifying are currently widespread, which are used in the structure of fuzzy logic parts and neural networks. Hybrid systems compare the actual GTE operational status in terms of vibration velocity and vibration acceleration with possible typical operational status that are stored in the "knowledge base" of the system, which will make it possible to classify the current GTE operational status and predict its further changes. The disadvantage of hybrid systems is the need for a large amount of initial data for training an intelligent diagnostic system, as well as the difficulty of monitoring the correctness of the diagnostics [11, 12].

In [13, 14], the structure of an intelligent automatic system for diagnostics and reconfiguration of the GTE control was developed and synthesized, based on a combination of a neural network of radial basis functions (RBF) and fuzzy logic elements. The developed system provides the ability to configure such systems for diagnostics and reconfiguring the control of GTE different types during their operation, which helps to increase the reliability of classification and predicting of the residual life, and also prevents the transition of an emergency situation into a catastrophic one with an accuracy of 0.92 ... 0.96, which is insufficient. in the conditions of flight operation of an aircraft (helicopter, aircraft). The limitation of this system lies in the fact that it classifies the GTE operational status only by the vibrational state.

A modified closed onboard helicopters TE ACS developed by this authors group (fig. 1) [15, 16], which is supplemented with plug-in software modules that implement adaptive control methods: signal adaptation module; parametric adaptation module; linear model submodule; custom model submodule. Also, an important distinguishing feature of the developed modified closed onboard helicopters TE ACS 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.

Each block of the developed modified closed onboard helicopters TE ACS is implemented using neural network technologies, which have shown high efficiency and stability in the research of transient's processes in the helicopters TE [17, 18]. However, the use of linear neural networks did not solve the problem of overshooting the system.

Therefore, the paper proposes an alternative approach of "intelligent description" of the developed modified closed onboard helicopters TE ACS using neuro-fuzzy modeling using hybrid neuro-fuzzy networks, on the basis of which fuzzy inference systems are generated.

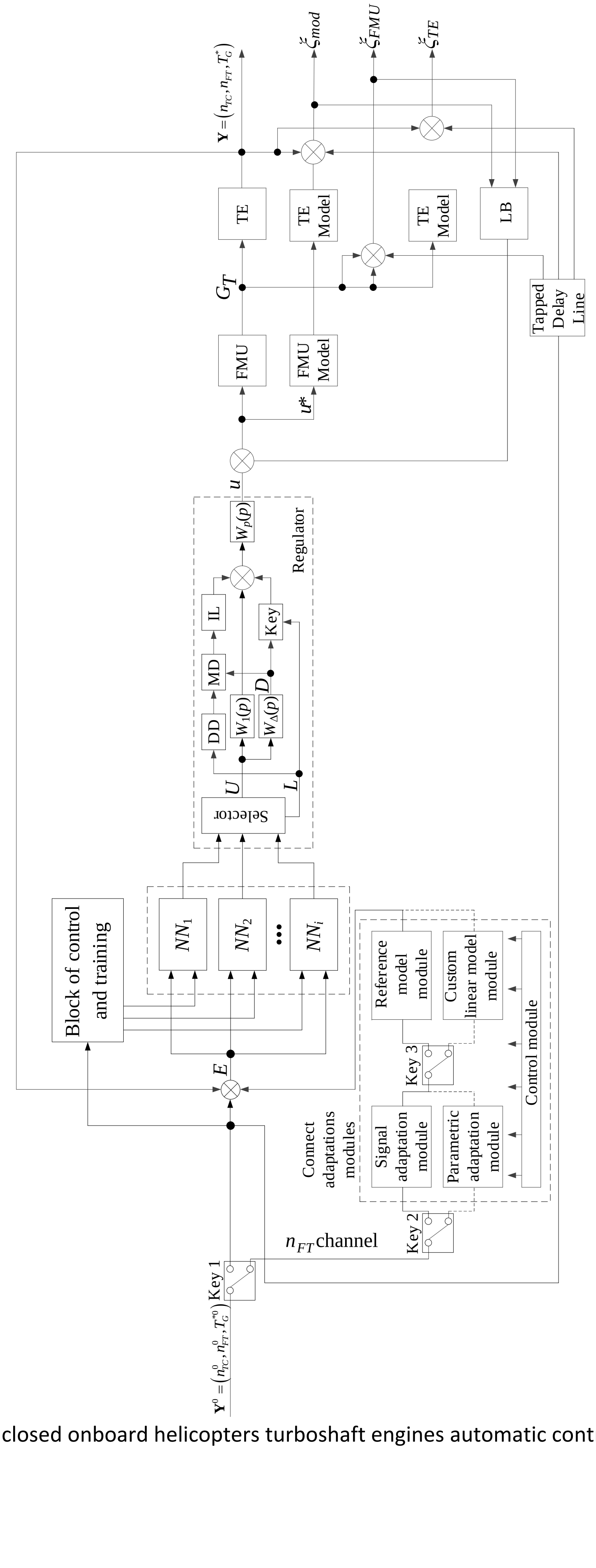


Figure 1: Modified closed onboard helicopters turboshaft engines automatic control system [15, 16]

3. Proposed technique

Fuel regulation is carried out according to the gas generator rotor r.p.m. n_{TC}. The gas generator rotor r.p.m. n_{TC} value, which was at the moment when the idle speed was reached, is selected as the gas generator rotor speed setting.

Experts, based on information regarding the operation of gas-generating pumping units over the past 10 years, have established that their failure is more associated with the following problems [19, 20]: device design errors; defects made during the production of the unit and its assembly, as well as installation; defective materials.

The helicopter TE ACS should have three levels, each of which solves its own task. The tasks of local control of TE and control of TE as part of a helicopter power plant seem to be the most closely related. These tasks should be solved by a decentralized system, at the lower level of which there are the same type of local TE ACS, the number of which coincides with the number of TE in the helicopter power plant (most helicopters use two engines as part of the power plant). From the point of view of mathematical software, the problem of local control of helicopters TE is quite trivial; it is solved by classical PI and PID controllers [21]. Nonlinearity and multidimensionality of helicopters TE as control objects lead to the need to introduce several feedback loops, sometimes with variable (adaptive) gain factors [22].

In [23], a description of complex dynamic systems is proposed through the characteristics of subsystems and multidimensional elements of communication between them. As an individual characteristic of a separate subsystem, its transfer function is considered in the control mode, when the subsystem operates in a state isolated from other subsystems.

When designing ACS, the next task after achieving stable operation is the task of fulfilling the specified indicators of the quality of transient processes [24]. The dependence of the quantities under consideration on the parameters of the synthesized system can be represented as a system of equations:

$$\begin{cases} q_1\left(\{k_1\},\{\tau_1\},\{T_1\}\right) = f_1\left(\{k_1\},\{\tau_1\},\{T_1\}\right); \\ q_2\left(\{k_2\},\{\tau_2\},\{T_2\}\right) = f_2\left(\{k_2\},\{\tau_2\},\{T_2\}\right); \\ \ldots \\ q_i\left(\{k_i\},\{\tau_i\},\{T_i\}\right) = f_i\left(\{k_i\},\{\tau_i\},\{T_i\}\right); \end{cases} \quad (1)$$

where q_1, …, q_i – quality indicators of the transient processes under consideration; $\{k_i\}$, $\{\tau_i\}$, $\{T_i\}$ – variable system parameters sets (gain factors, time constants, etc.); $f_1(\bullet)$, …, $f_i(\bullet)$ – functions expressing the dependence of system quality indicators on the parameters of synthesized controllers.

Let us consider the overshoot and the time of regulation of subsystems as the main indicators of the quality of systems. Then the system of equations (1) will take the form:

$$\begin{cases} t_{reg1} = f_1\left(\{k_1\},\{\tau_1\},\{T_1\}\right); \\ \sigma_1 = g_1\left(\{k_1\},\{\tau_1\},\{T_1\}\right); \\ \ldots \\ t_{reg\_i} = f_i\left(\{k_i\},\{\tau_i\},\{T_i\}\right); \\ \sigma_i = g_i\left(\{k_i\},\{\tau_i\},\{T_i\}\right); \end{cases} \quad (2)$$

where σ_1, …, σ_i – overshoot, t_{reg1}, …, t_{reg_i} – control time of transient processes of subsystems.

The performance indicators required for each subsystem may differ depending on the functional purpose and mode of operation of the system. When constructing a logical multiply connected controller for each mode, the synthesis of parameters is carried out separately for the purpose of subsequent merging.

The constructed mathematical models of helicopters TE are difficult for the analysis and synthesis of regulators, in this regard, when designing, methods of data mining are used: methods for recognizing and assessing the technical condition of an object [25], intelligent control methods [26], nonlinear control methods [27], methods of the theory of multiply connected ACS [28], the theory of artificial intelligence systems [29].

It is very difficult to represent the dependence of the quality indicators of system functioning on the subsystems parameters and the relationships between them in mathematical form, which is explained by the peculiarities of each class of systems and subsystems included in a complex system. The indicators of overshoot and regulation time have an inverse relation, and the mutual influence of subsystems on each other also affects. However, there are various methods to solve the task.

Data analysis tools such as neural networks, fuzzy logic, machine learning, evolutionary calculations, genetic algorithms, etc. can be used as tools for synthesizing ACS parameters by complex objects. According to the goal of the work, it is proposed to use the method of synthesis of ACS using hybrid neuro-fuzzy networks (HNFN).

The quality of training of the developed HNFN directly depends on the number of examples – the size of the training sample, and how fully the examples describe this task. All information used by a HNFN to build a fuzzy inference system is contained in a set of training samples. At the same time, the membership functions of the synthesized systems are tuned (trained) in such a way as to minimize deviations between the results of fuzzy modeling and experimental data [30].

HNFN combine the advantages of fuzzy inference systems and neural networks. On the one hand, they allow developing and presenting system models in the form of fuzzy production rules, which are visual and easy to interpret, and on the other hand, neural network methods are used to build fuzzy production rules, which is a more convenient and less time-consuming process for designers. The algorithm described in [31, 32] is used when constructing a HNFN that implements decision-making on the choice of system parameters in order to satisfy the given overshoot indicators. The choice is made according to several criteria: gain factors and time constants in nonholonomic cross-couplings. Fig. 2 shows the structure of the fuzzy inference system under consideration.

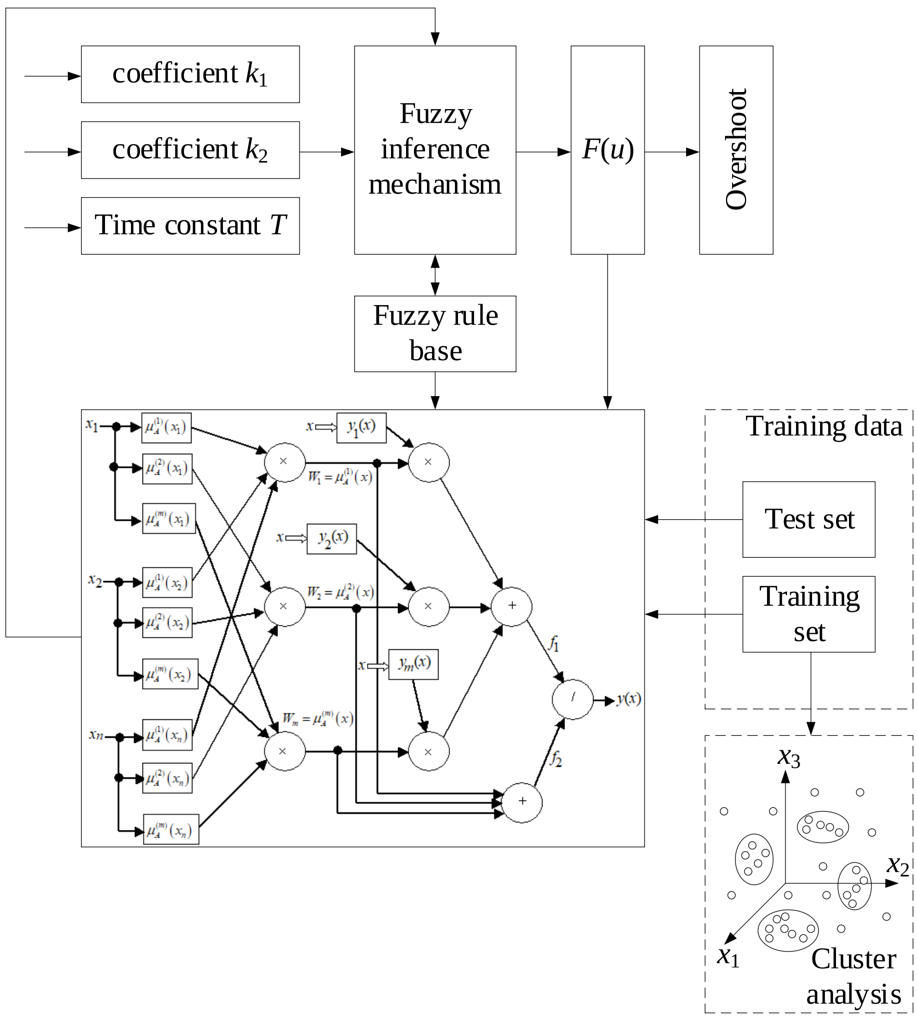


Figure 2: Fuzzy inference system structure (author's development)

To build a HNFN, the application of the MatLab software package, the ANFIS editor, is used in the work, with the help of which a neuro-fuzzy network is automatically synthesized. The sequence of the HNFN model development process is as follows:

1) preparation of a training sample;
2) loading training data;
3) building the structure of the fuzzy inference system;
4) visualization of the hybrid network structure.

The results of HNFN training are exported to the MatLab workspace and then applied in the Simulink package by loading into the Fuzzy Logic Controller block, which acts as the coordinating part of the neuro-fuzzy controller [33]. The location of the coordinating part in the block diagram of the multiply connected helicopters TE ACS is shown in fig. 3.

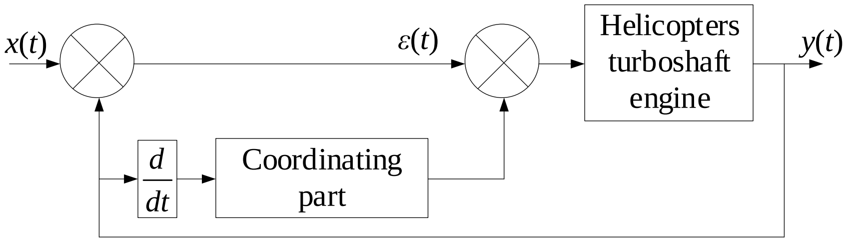


Figure 3: The coordinating part of the neuro-fuzzy controller in the block diagram of helicopters turboshaft engine multi-connected automatic control system (author's development)

The trained HNFN allows you to select the helicopters TE ACS parameters, taking into account the required quality indicators, which makes it possible to adjust the operation of the system when the operating conditions change.

In HNFN, logical conclusions are made using the fuzzy logic apparatus, and the corresponding membership functions (MF) are tuned using the neural network training algorithm – backpropagation error (BPE) [34, 35], that is, the description of the research object is performed by fuzzy logic methods, and the tuning this model – by artificial neural network methods, to obtain a more accurate correspondence to the considered model of the helicopter TE. The main subsystem is a fuzzy inference system with an output variable of a discrete type (fig. 4).

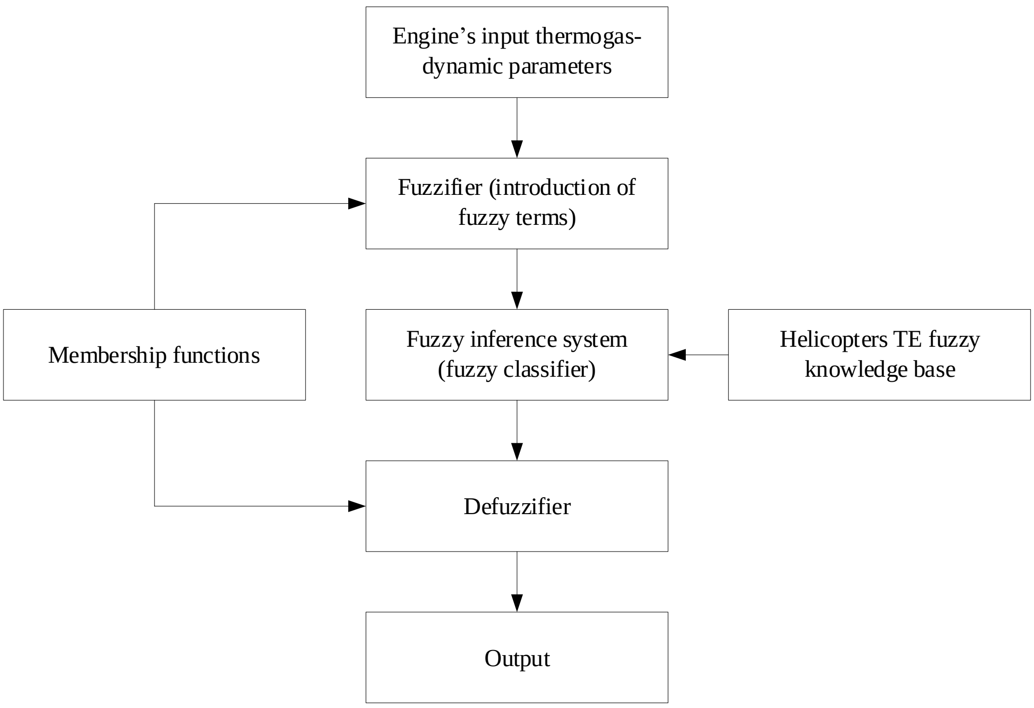


Figure 4: Fuzzy inference system (author's development, based on [36])

Fuzzy inference is an approximation of the "inputs – output" dependence based on linguistic statements "IF–THEN" and logical operations on fuzzy sets [36], that is, a variation of neuro-fuzzy inference with a discrete output.

The input signals vector $X = \{x_1, x_2, ..., x_n\}$ defines a set of engine's input thermogas-dynamic parameters that objectively describes the engine, and the discrete output variable values $y – d_j$ represent the class of the output variable, one of the possible values – d_j of which is associated with a reference sample known in the fuzzy knowledge base.

The main condition for helicopters TE ACS is that the fuzzy knowledge base should contain a complete set of reference samples for possible values of input signals (engine's thermogasdynamic parameters). At the same time, the structure of the fuzzy inference system for helicopters TE ACS contains modules common to the fuzzy logic apparatus.

To build a fuzzy knowledge base, the work uses the zero-order Takagi-Sugeno-Kang (TSK) algorithm [37], the output variable of which is a linear combination of input parameter values, that is:

$$\begin{aligned}
&\text{Rule № 1: IF } x_1 = x_1^{etalon_1} \text{ and } x_2 = x_2^{etalon_1} \text{ and } \ldots \text{ and } x_n = x_n^{etalon_1}\text{, THEN } y = y_1;\\
&\text{Rule № 2: IF } x_1 = x_1^{etalon_2} \text{ and } x_2 = x_2^{etalon_2} \text{ and } \ldots \text{ and } x_n = x_n^{etalon_2}\text{, THEN } y = y_2;\\
&\ldots\\
&\text{Rule № } m\text{: IF } x_1 = x_1^{etalon_m} \text{ and } x_2 = x_2^{etalon_m} \text{ and } \ldots \text{ and } x_n = x_n^{etalon_m}\text{, THEN } y = y_m.
\end{aligned} \tag{3}$$

For the j-th rule in the TSK algorithm, the value is the i-th output variable and is determined according to the expression:

$$y = y_j + \sum_{i=1}^{n} a_i^j \cdot x_i^{etalon_j}. \tag{4}$$

The use of the zero-order TSK algorithm according to [37, 38], which coincides with the modified Mamdami algorithm when building a knowledge base, significantly simplifies the procedure for choosing the parameters of a fuzzy inference system, since there is no need to calculate the coefficients a_i^j in expression (4). Since the fuzzy inference machine (fig. 4) for solving the classification problem is implemented as the ratio of input parameters to the value of the reference sample from the knowledge base, this fuzzy knowledge base is defined as:

$$\left(\bigcap_{i=1}^{n} x_i = x_i^{etalon_j}\right) \rightarrow y = y_j; \tag{5}$$

where ∩ – operation; t – norms (realization of logical "AND").

Then the classified engine's thermogas-dynamic parameter belonging degree to the reference sample is determined as:

$$\mu_j(x) = \bigcap_{i}^{n} \mu_{ji}(x_i); \tag{6}$$

where $\mu_{ji}(x_i)$ – belonging degree of the i-th parameter of the classified object to the j-th parameter of the reference object.

As a solution to helicopters turboshaft engine control task, a solution with the maximum degree of the membership function is chosen [39, 40]:

$$y^* = \arg_{y_1, y_2, \ldots, y_k} \max\left(\mu_1\left(x^*\right), \mu_2\left(x^*\right), \ldots, \mu_k\left(x^*\right)\right). \tag{7}$$

The fuzzy inference system aggregates with the neural network. As a result, an HNFN of the ANFIS type [36, 41] is obtained, the adjustable parameters of which are the MF parameters – $\mu_{ji}(x_i)$ (HNFN block diagram is shown in fig. 5).

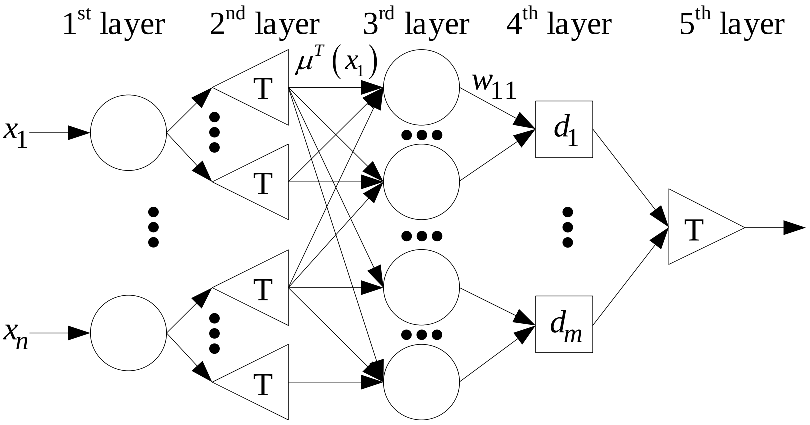
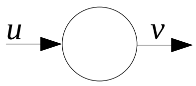
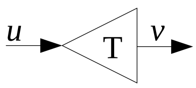
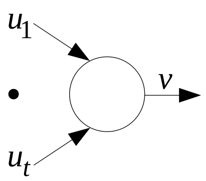
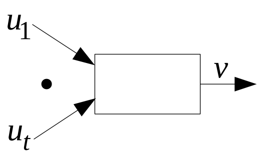
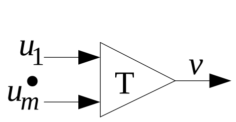


Figure 5: ANFIS type hybrid neuro-fuzzy network structural diagram (author's development, based on [36])

Unit's functions (analogues of neurons in a conventional neural network) of the HNFN block diagram shown in fig. 5 are reflected in table 1 according to [36].

Table 1
Hybrid neuro-fuzzy network unit's functions [36]

Unit	Name	Functions
	Input	$v = u$
	Fuzzy term	$v = \mu^T(u)$
	Fuzzy rule	$v = \prod_{i=1}^{l} u_i$
	Rule class	$v = \sum_{i=1}^{l} u_i$
	Defuzzification	$v = \dfrac{\sum_{j=1}^{m} u_j \cdot \overline{d}_j}{v = \sum_{j=1}^{m} u_j}$

As can be seen from fig. 5 ANFIS type HNFN contains 5 layers:
1) 1st layer – inputs of the studied nonlinear object;
2) 2nd layer – layer of fuzzy terms that are used in helicopters TE fuzzy knowledge base;
3) 3rd layer – fuzzy knowledge base conjunction lines (fuzzy rules);
4) 4th layer – classes of the output variable d_j;
5) 5th layer – defuzzification layer, i.e., converting a fuzzy output to a crisp number.

The number of units (neurons) in each HNFN layer is determined as follows [41, 42]:
1) in the 1st layer by the number of object inputs;
2) in the 2nd layer by the number of fuzzy terms of the input variables of the fuzzy knowledge base;

3) in the 3rd layer by the number of conjunction lines in the fuzzy knowledge base;

4) in the 4th layer by the number of classes of the output variable d_j.

Thus, the resulting model is a fuzzy knowledge base about the object under study (helicopters TE), built by an expert, which corresponds to the "rough" tuning of the model, and also has a "fine" tuning apparatus, which consists in training the HNFN using a method similar to backpropagation algorithm for neural networks [41, 42].

So, with the direct passage of signals in the network, expressions appear to determine the input signals values belonging degree to the linguistic terms of the fuzzy knowledge base of the description of the modeled object (helicopters TE) [36]:

$$\mu^{jp}\left(x_i\right)=\frac{1}{\left(1+\frac{x_i-b_i^{jp}}{c_i^{jp}}\right)^2}; \tag{8}$$

where b and c – parameters of the bell-shaped membership function, the form of which is shown in fig. 6.

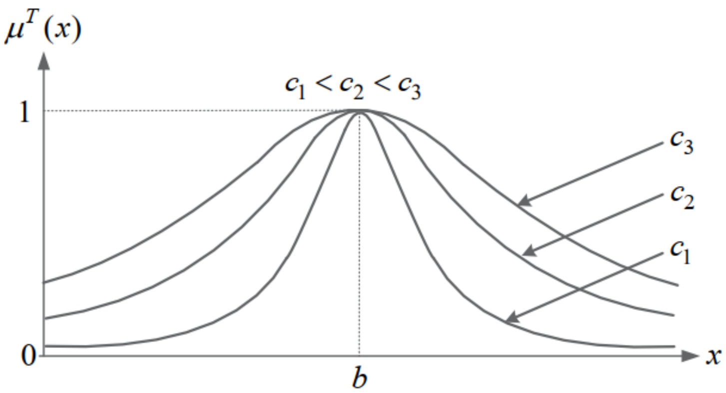


Figure 6: Diagrams of the bell-shaped membership function depending on the parameter values [36]

The analytical expression of the bell-shaped membership function according to [36] has the form:

$$\mu^T\left(x\right)=\frac{1}{1+\left(\frac{x-b}{c}\right)^2}. \tag{9}$$

The output signal belonging degree to the corresponding classes of the output variable is determined according to the expression [36]:

$$\mu^{dj}\left(y\right)=\max\left\{w_{jp}\left(\min\mu^{jp}\left(x_i\right)\right)\right\}. \tag{10}$$

The model value, which corresponds to the mathematical expectation operation in the random process's theory, the output variable y is calculated by defuzzification according to the expression:

$$y=\frac{y_0\mu^{d_1}\left(y\right)+y_1\mu^{d_2}\left(y\right)+...+y_{m-1}\mu^{d_m}\left(y\right)}{\mu^{d_1}\left(y\right)+\mu^{d_2}\left(y\right)+...+\mu^{d_m}\left(y\right)}. \tag{11}$$

Then the HNFN error value is determined according to the expression [36]:

$$E_t=\frac{\left(y_{tm}-y_t\right)^2}{2}; \tag{12}$$

where y_{tm} – HNFN output model value at the i-th training step; y_t – experimental output value of the engine thermogas-dynamic parameter.

By analogy with the error backpropagation algorithm for neural networks in a neuro-fuzzy network, backtracking procedures are performed in HNFN each segment to estimate the error. Determination of the rate of change of the network error when the value of the output variable changes:

$$\frac{\partial E_t}{\partial y}=\varepsilon_1=y_{tm}-y_t. \tag{13}$$

At the last stage of the neural fuzzy network training algorithm, the HNFN parameters are modified, similar to the error backpropagation method for neural networks [36]:

$$w_{jp}\left(t+1\right)=w_{jp}\left(t\right)-\eta\frac{\partial E_t}{\partial w_{jp}\left(t\right)}; \tag{14}$$

$$c_i^{jp}\left(t+1\right)=c_i^{jp}\left(t\right)-\eta\frac{\partial E_t}{\partial c_i^{jp}}; \tag{15}$$

$$b_i^{jp}\left(t+1\right)=b_i^{jp}\left(t\right)-\eta\frac{\partial E_t}{\partial b_i^{jp}}. \tag{16}$$

4. Experiment

The analysis and preliminary processing of the input data was carried out by this authors group and described in detail in [16, 18]. 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 2). We assume in the work that the atmospheric parameters are constant (h – flight altitude, T_N – temperature, P_N – pressure, ρ – air density) [16, 18].

Table 2
Part of training set (in absolute units) (author's development, described in [16, 18])

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
…	…	…	…
256	0.953	0.973	0.981

Valuation is an important issue of the homogeneity of the training and test samples. To do this, we use the Fisher-Pearson criterion $\chi 2$ [43] with $r - k - 1$ degrees of freedom [16, 18]:

$$\chi^2=\min_{\theta}\sum_{i=1}^{r}\left(\frac{m_i-np_i\left(\theta\right)}{np_i\left(\theta\right)}\right); \tag{17}$$

where θ – maximum likelihood estimate found from the frequencies m_1, …, 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:

$$y_i=\frac{y_i-y_{i\min}}{y_{i\max}-y_{i\min}}; \tag{18}$$

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 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 (17) are in table 3 [16, 18].

Table 3
Part of the training sample during the operation of helicopters TE (on the example of TV3-117 TE) (author's development, described in [16, 18])

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

For the purpose of establishing representativeness of the training and test samples, a cluster analysis of the initial data was performed (table 2), during which eight classes have been identified (fig. 7, *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. 7, *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 [16, 18].

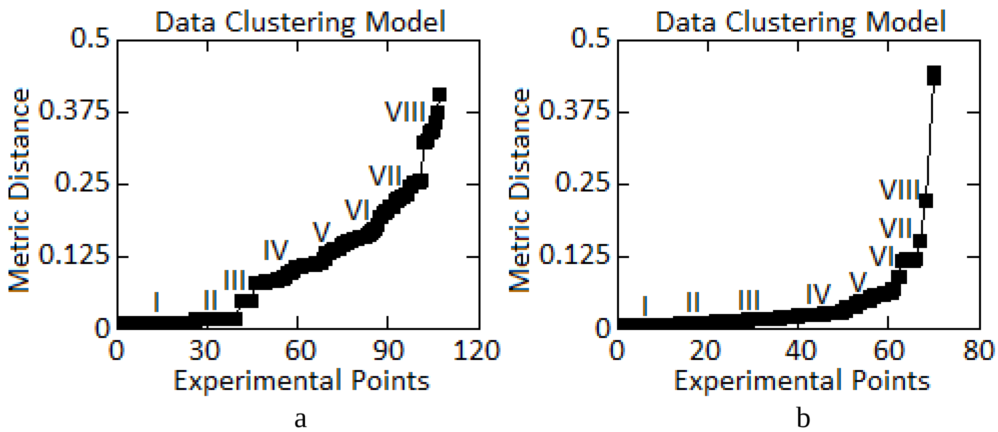


Figure 7: Clustering results: a – initial experimental sample (I…VIII – classes); b – training sample (author's development, described in [16, 18])

As an example of the development of helicopters TE thermogas-dynamic parameters ACS recorded on board a helicopter, which are key in modified closed onboard helicopters TE ACS [15, 16], let us consider the applied algorithm using HNFN. Carrying out the process of helicopters TE monitoring at flight mode, it is required to describe it using the input parameters of the fuzzy knowledge base – x_1, x_2, ..., x_n and possible classes of the output variable – y_1, y_2, ..., y_m, which are defined in the knowledge base as helicopters TE thermogas-dynamic parameters reference values. For this example of the use of HNFN, the input variables (in the terminology of the fuzzy logic apparatus are called linguistic terms) are n_{TC} – gas generator rotor r.p.m., n_{FT} – free turbine rotor speed, T_G – gas temperature in front of the compressor turbine. As a result of the experiments on the development of the HNFN structure, the HNFN diagram was obtained, shown in fig. 8, where:

1) layer 1 – three input variables, the parameters of which uniquely determine the helicopters TE thermogas-dynamic parameters values;

2) layer 2 – three terms for each ACS input;
3) layer 3 – three rules of fuzzy knowledge base;
4) layer 4 – three classes of the output variable;
5) layer 5 – the result is defuzzified.

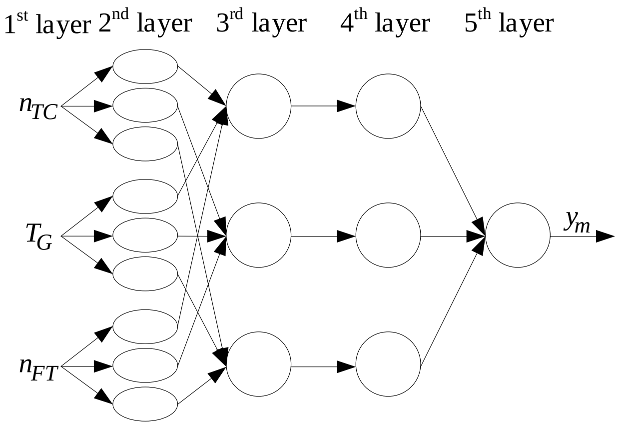


Figure 8: ANFIS type hybrid neuro-fuzzy network diagram (author's development, based on [36])

The fuzzy knowledge base is defined by three rules:
Rule № 1: If n_{TC} near 0.905 and T_G near 0.900 and n_{FT} near 0.900 then $y = y_1$;
Rule № 2: If n_{TC} near 0.950 and T_G near 0.995 and n_{FT} near 0.900 then $y = y_2$;
Rule № 3: If n_{TC} near 0.900 and T_G near 0.900 and n_{FT} near 0.995 then $y = y_3$;
where the class of the output variable y is represented by the following values: y_1 – parameter n_{TC} override; y_2 – parameter T_G override; y_3 – parameter n_{FT} override.

The linguistic expressions "about" selected by the expert method in the fuzzy knowledge base most fully reflect the essence of helicopters TE thermogas-dynamic parameters recorded on board the helicopter. On the one hand, at each moment of time, the values of the terms n_{TC} – gas generator rotor r.p.m., n_{FT} – free turbine rotor speed, T_G – gas temperature in front of the compressor turbine are certain numbers, but at other times the values of these terms change randomly (indefinitely) due to errors, flight conditions, helicopter's operational status etc.

The essence of the linguistic expression "about" most fully reflects the bell-shaped membership functions, which are also selected by the expert method from among the most popular membership functions: triangular, trapezoidal and bell-shaped [44]. The bell-shaped membership functions for the fuzzy knowledge base specified by the specified rules, chosen for our example of the work of the HNFN (before training the ANFIS network), are shown in fig. 9.

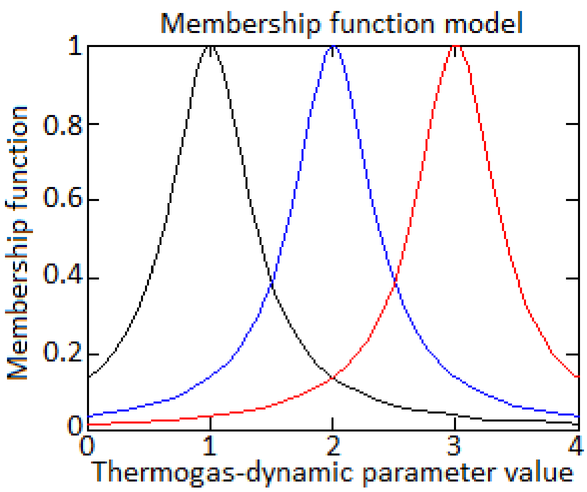


Figure 9: Diagram of the bell-shaped membership function before HNFN training (author's development, based on [36])

The developed model, corresponding to the considered example of creating a reconfigured modified closed onboard helicopters TE ACS, is shown in fig. 10, where the designations of the units of the developed model and the terms of the HNFN theory are shown in fig. 5 and in table 1. For the exact solution of this problem, the methods of training HNFN (13) – (16), similar to artificial neural networks, are applied, similarly to [36]. As a result of training the developed HNFN network according to the algorithms described above, an object model was obtained with parameters *b* and *c* of membership functions and weights of fuzzy rules, which are given in table 4 and 5.

Table 4
The values of the parameters of the bell-shaped membership function before and after HNFN training (author's research based on [36])

Parameters		Values	
Before HNFN training			
b	0.10	0.10	0.10
c	0.25	0.50	0.75
After HNFN training			
b	0.12	0.11	0.13
c	0.29	0.53	0.76

Table 5
Rule weights before and after HNFN training (author's research based on [36])

Parameters		Values	
Before HNFN training			
w	1.0	1.0	1.0
After HNFN training			
w	0.999	0.997	0.998

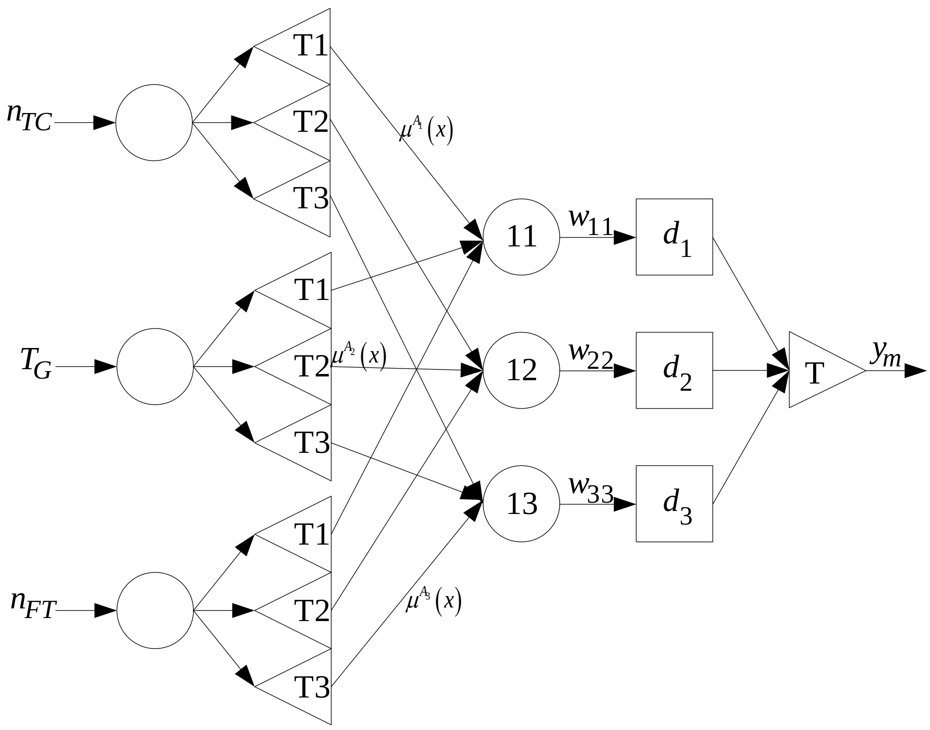


Figure 10: The developed model corresponding to the considered example of reconfigured modified closed onboard helicopters TE ACS development (author's development, based on [36])

Diagrams of membership functions and parameters of bell-shaped membership functions after HNFN training are shown in fig. 10 and table 4, where *c* – bell-shaped membership functions contraction coefficient, *b* – bell-shaped membership functions maximum coordinates. Similarly [36], as a result of training the HNFN network, new values of the parameters of the bell-shaped membership functions were obtained (table 4, fig. 11) and the weights of the rules of the fuzzy knowledge base were changed (table 5), which corresponds to the stage of "fine" tuning of the fuzzy model of the research object – reconfigured modified closed onboard helicopters TE ACS.

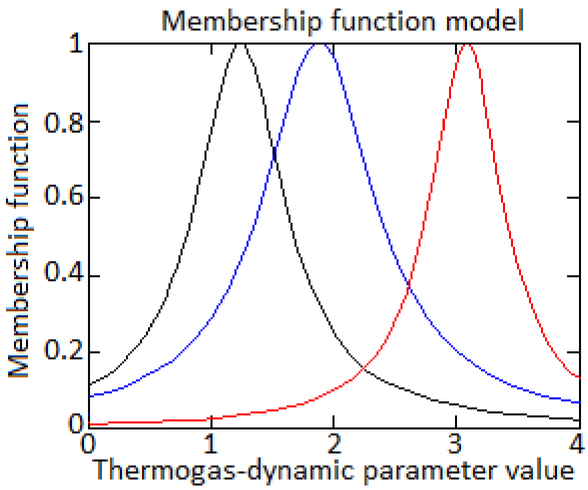


Figure 11: Diagrams of the resulting bell-shaped membership function after HNFN training (author's development, based on [36])

5. Results

Let us consider the problem of ensuring the specified quality indicators in one of the modes of operation of helicopters TE (for example, in the nominal mode). For the considered mode, the requirements for the indicators of transient processes are set in the following form: $\{t_{reg}\} = \{1.5; 1.5\}$, $\{\sigma_{reg}\} = \{0.1; 0.1\}$.

As a result of modeling the dynamics of changes in helicopters TE thermogas-dynamic parameters according to the training sample (table 2), depending on the model time, the obtained results presented in fig. 12, where *a* – parameter n_{TC} change, *b* – parameter T_G change, *c* – parameter n_{FT} change, while curve 1 corresponds to the experimental values of helicopters TE thermogas-dynamic parameters recorded on board the helicopter, curve 2 corresponds to the model (corrected using the reconfigured modified closed onboard helicopters TE ACS) values of helicopters TE thermogas-dynamic parameters.

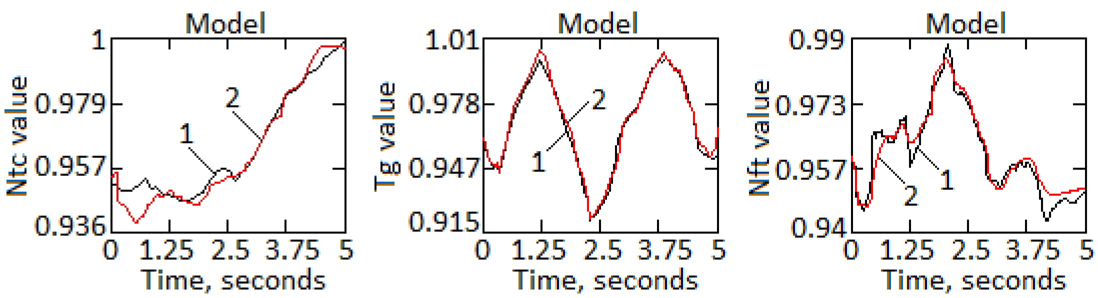


Figure 12: The results of modeling the dynamics of changes in helicopters turboshaft engines thermogas-dynamic parameters (author's development)

The value of the change in residuals after control $\varepsilon(t) = x_1(t) + x_2(t) + x_3(t) - y(t)$ does not exceed the allowable deviation of helicopters TE thermogas-dynamic parameters, which is 0.004. The dynamics of changes in helicopters TE thermogas-dynamic parameters values after control $\varepsilon(t)$, shown in fig. 13, indicates the stability of control, that is, the tendency for the indicator $\varepsilon(t)$ to approach zero [45].

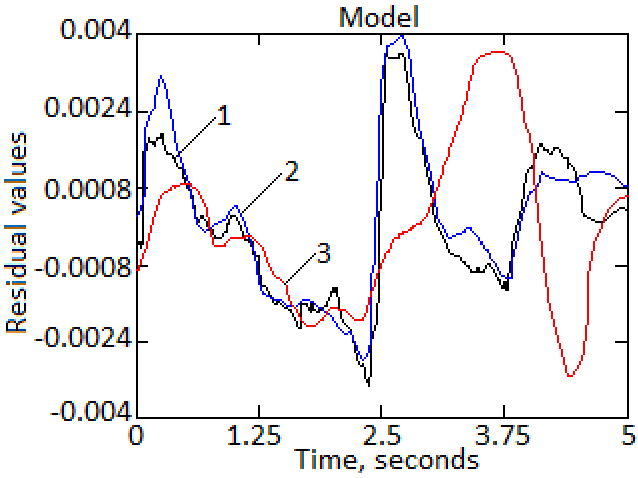


Figure 13: Diagram for determining residuals: 1 – by parameter n_{TC} (black line), 2 – by parameter T_G (blue line), 3 – by parameter n_{FT} (red line) (author's development)

Fig. 14–16 shows the calculation results of the fuel consumption parameter G_T (in absolute units) for precise (modified closed onboard helicopters TE ACS [15, 16]), fuzzy and neuro-fuzzy control (reconfigured modified closed onboard helicopters TE ACS developed in this work), respectively, for given values of helicopters TE thermogas-dynamic parameters according to table 2 and a step change in the required fuel consumption G_T. On fig. 14–16 marked: 1 – reference fuel consumption value G_T (step action), 2 – real fuel consumption value G_T.

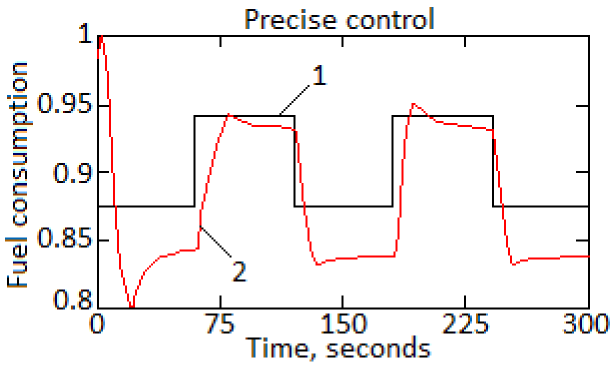


Figure 14: Diagram for the precise control transient process (author's development)

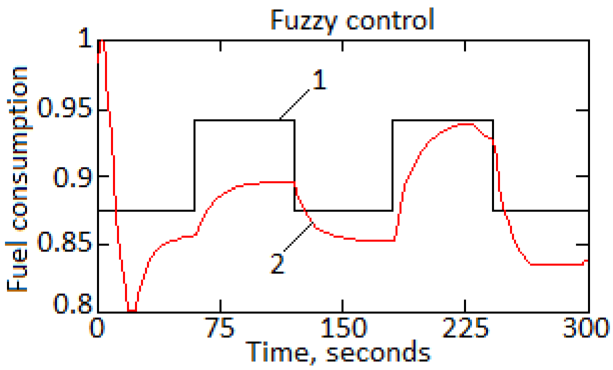


Figure 15: Diagram for the fuzzy control transient process (author's development)

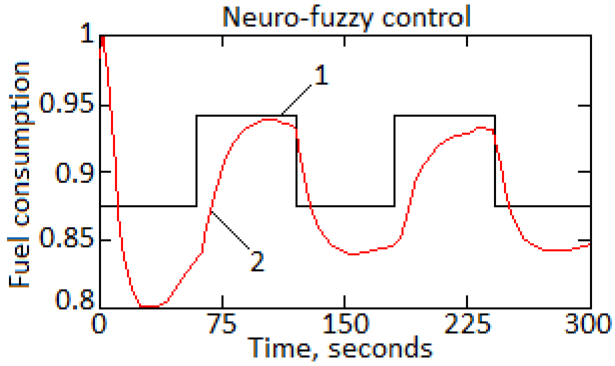


Figure 16: Diagram for the neuro-fuzzy control transient process (author's development)

To compare the quality of control in all three control modes (clear, fuzzy and neuro-fuzzy control), transient diagrams were superimposed for these control modes, shown in fig. 17.

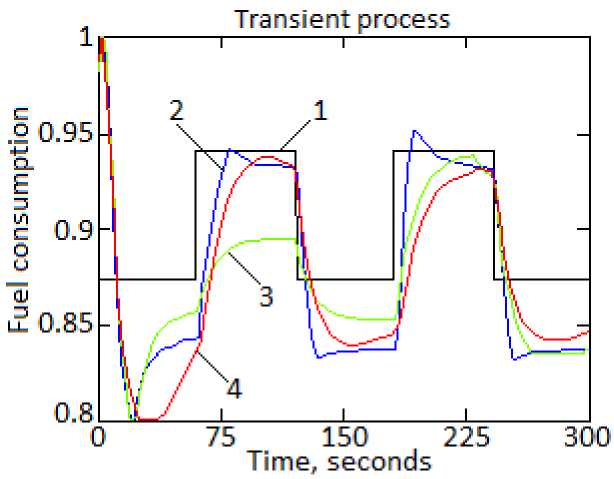


Figure 17: Diagram for the precise, fuzzy and neuro-fuzzy control transient process: 1 – reference value, 2 – precise control, 3 – fuzzy control, 4 – neuro-fuzzy control (author's development)

As can be seen from the presented diagrams of transient processes control, the quality of control (the duration of the transient process and the maximum deviation of the controlled variable) for the considered types of control (clear, fuzzy and neuro-fuzzy) is approximately the same.

As can be seen from fig. 11–16, the synthesized system has the specified quality indicators t_{reg}, σ_{reg} that is, the overshoot and control time satisfy the requirements.

Thus, the use of the reconfigured modified closed onboard helicopters TE ACS makes it possible to increase the operational reliability of helicopters TE.

It should be noted that automatic control systems can also be implemented both on the basis of traditional clear-cut approaches, for example, on the basis of PID controllers, and on the basis of fuzzy logic and artificial neural networks, and neural networks can be used both for setting the parameters of precise control systems (for example, PID controllers), and as control systems based on fuzzy neural networks, combining the methods of artificial neural networks and systems based on fuzzy logic.

6. Discussions

The results of a comparative analysis of helicopters TE control task solution (on the example of determining fuel consumption) using various of neural networks architectures are presented in table 6. The results of determining errors of the 1st and 2nd kind according to the main helicopters TE thermogas-dynamic parameters are presented in table 7.

Table 6
The results of a comparative analysis of helicopters TE control task solution (author's research)

Number	Neural networks architectures	Training sample		Test sample	
		Error number	Error percentage	Error number	Error percentage
1	Multilayer perceptron	10	2.05	45	9.23
2	Hopfield neural network	10	2.05	38	7.79
3	Hamming neural network	10	2.05	30	6.15
4	Hybrid intelligent system [13, 14]	10	2.05	18	3.69
5	Reconfigured modified closed onboard helicopters TE ACS	10	2.05	11	2.23

Table 7
The results of determining errors of the 1st and 2nd kind (in percentages) (author's research)

Neural networks architectures	Error probability in determining the optimal parameters n_{TC}, T_G, n_{FT} and G_T %							
	Parameter n_{TC}		Parameter T_G		Parameter n_{FT}		Parameter G_T	
	Type 1st error	Type 2nd error	Type 1st error	Type 2nd error	Type 1st error	Type 2nd error	Type 1st error	Type 2nd error
Multilayer perceptron	1.13	1.08	1.14	1.06	1.10	1.05	1.17	1.12
Hopfield neural network	1.02	0.98	1.00	0.87	1.01	0.88	1.03	0.99
Hamming neural network	0.97	0.86	0.94	0.83	0.96	0.85	0.94	0.82
Hybrid intelligent system [13, 14]	0.75	0.64	0.76	0.65	0.74	0.63	0.74	0.65
Reconfigured modified closed onboard helicopters TE ACS	0.38	0.18	0.35	0.16	0.36	0.17	0.35	0.15

A comparative analysis of the obtained results (table 6 and table 7) confirms that the developed reconfigured modified closed onboard helicopters TE ACS provides the minimum error in solving helicopters TE control task during operation.

7. Conclusion

The method of constructing helicopters turboshaft engines automatic control systems gained further importance, which, due to the reconfiguration of automatic control systems by using hybrid neuro-fuzzy networks of the ANFIS type with a zero-order Takagi-Sugeno-Kang training algorithm, made it possible to provide the specified stability indicators (overshoot, control time of transient processes of subsystems) at a given specific mode.

The method of adapting the apparatus of hybrid neuro-fuzzy networks has gained further importance, which, by taking into account the main indicators of automatic control systems quality, namely, the overshoot and the time of regulation of automatic control systems subsystems, allows solving the helicopters turboshaft engines control task at the helicopter flight mode with a minimum control error, which is not exceeds 0.004 (0.4 %).

For the first time, the use of bell-shaped membership functions of linguistic variables was proposed to describe the helicopters turboshaft engines thermogas-dynamic parameters recorded on board helicopters, as well as the linguistic expression "about" in a fuzzy knowledge base, which made it possible to correct their values in case of random changes (uncertainties) associated due to errors, helicopter flight conditions, helicopter operational status, and so on, with an accuracy of 99.6 % (the maximum control error does not exceed 0.4 %).

It is shown that the errors of the 1st and 2nd implementations of the adaptation method of hybrid neuro-fuzzy networks apparatus in the reconfigured modified closed onboard helicopters turboshaft engines automatic control system did not exceed 0.38 % and 0.18 %, respectively, while for other neural networks architectures they amounted to 0.74 % and 0.63 % minimum respectively. The obtained results prove that the application of the developed neural network method will allow solving the problem of helicopters turboshaft engines control at the helicopter flight mode 2.5 times more accurately.

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