Neuro-Fuzzy System for Detection Fuel Consumption of Helicopters Turboshaft Engines

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Abstract

The work is dedicated to the development of a neuro-fuzzy system for detection and control the fuel consumption of helicopters turboshaft engines at flight modes. The realization of the developed system was performed on the basis of ANFIS – an adaptive neuro-fuzzy system that implements the Sugeno fuzzy inference system in the form of a five-layer neural network of direct signal propagation, the first layer of which contains terms of input variables (helicopters turboshaft engines thermogas-dynamic parameters current values and their delayed values). In the process of forming the model, the sample of initial data was divided into two parts: training and testing. To estimate the effectiveness of using the ANFIS network for intelligent control of the specific fuel consumption of helicopter gas turbine engines, a training sample was used. The sample contains data on air consumption in the combustion chamber, specific engine power, the ratio of fuel and air consumption in the combustion chamber, calculated (in absolute units) using a helicopters turboshaft engines neural network model. It has been experimentally proven that for adapting the neuro-fuzzy network ANFIS and the Sugeno zero-order fuzzy inference system to solving the problem of control the fuel consumption of helicopters turboshaft engines, it is effective to use a hybrid training method, 2...3 delayed inputs and two two-way Gaussian membership functions. It was found that the two-sided Gaussian membership function provides the smallest network training error, equal to $3.28 \cdot 10^{-3}$, compared to others, which give the largest neural network training error – 0.138. Increasing the number of outputs of the ANFIS neuro-fuzzy network and expanding the base of fuzzy rules makes it possible to improve the decision-making logic and, as a result, expand the range of calculation of activity levels of the rules. Prospects for further research is the introduction of the developed neuro-fuzzy system for detection and control the fuel consumption into a closed on-board neural network control system for helicopters turboshaft engines.

Keywords

neuro-fuzzy network, helicopters turboshaft engines, fuel consumption, ANFIS neuro-fuzzy network, Gaussian membership function, thermogas-dynamic parameters, Sugeno fuzzy inference system

1. Introduction

To effectively manage the quality of intricate technical entities [1, 2], such as helicopter turboshaft engines, a thorough investigation into the phenomena occurring at each stage is essential. This is crucial for establishing the correlation between operational factors and the inherent characteristics of the engines.

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An essential concern in helicopter flight operation is the selection of optimal flight modes to enhance fuel efficiency [3, 4]. The most rational approach in this context involves the utilization of theoretical methods, particularly numerical modeling and intelligent information technologies [5, 6]. To implement such an approach, having a mathematical model of helicopter dynamics, which incorporates a module for determining fuel consumption, is necessary.

A promising avenue for advancing tools for controlling helicopter operation involves integrating components of artificial intelligence, such as production rules [7], fuzzy logic [8], artificial neural networks [9], hybrid neuro-fuzzy architectures [10], and genetic algorithms [11].

Analysis of patent materials and recent publications indicates that considerable attention is given internationally to creating intelligent control methods for complex technical entities [12, 13]. The methodological approach to synthesizing intelligent systems relies on the technology of distributed expert and neural network systems. A fundamental aspect of developing intelligent methods, particularly those incorporating elements based on neural network structures, is the formulation of principles for constructing an identification block and a knowledge base.

Hence, enhancing economic efficiency and maintaining a high level of operational reliability for helicopters in special operational situations, through the development of theoretical foundations, methods, and intelligent management means, constitutes a pressing scientific and applied challenge.

2. Related works

It is recognized that the control of helicopter operation heavily relies on the continuous monitoring of its engine's operational status. The engine is a complex nonlinear dynamic system influenced by the interplay of gas-dynamic and thermophysical processes in its various units (air inlet section, compressor, combustion chamber, compressor turbine, free turbine, exhaust unit) [14].

To regulate these intricate processes, the prevalent approach involves employing a mathematical framework, specifically in the form of artificial neural networks. A literature review indicates that neural networks are widely applied to tackle diverse tasks, demonstrating notable accuracy, particularly in modeling and detecting complex technical systems [15].

In [16, 17], the development of a neural network model for a small-sized gas turbine engine is discussed, utilizing a recurrent neural network, along with the simulation results.

In [18, 19], the specifics of constructing a real-time neural network model for operating gas turbine engines are outlined, accompanied by an evaluation of the model's effectiveness.

However, a survey of the literature regarding neural network methods for controlling gas turbine engines, including helicopter turboshaft engines, reveals the absence of current methods and models for controlling specific fuel consumption. Hence, addressing this gap is the pertinent objective addressed in this research.

3. Proposed technique

The mathematical model, outlined in [20], is designed for calculating the specific fuel consumption of turboshaft engines in helicopters, taking the TV3-117 engine as an example, which forms part of the power plant for the Mi-8MTV helicopter. As per the findings in [20], the specific fuel consumption of turboshaft engines in helicopters is contingent upon factors such as air consumption in the combustion chamber, specific engine power, and the ratio of fuel to air consumption in the combustion chamber. This particular parameter is directly influenced by the type of aviation fuel in use.

The computation of thermogas-dynamic parameters for turboshaft engines in helicopters, including air consumption in the combustion chamber, specific engine power, and the ratio of fuel to air consumption in the combustion chamber, is performed utilizing a neural network model for helicopters turboshaft engines developed by our team of authors, as detailed in [21, 22] (fig. 1).

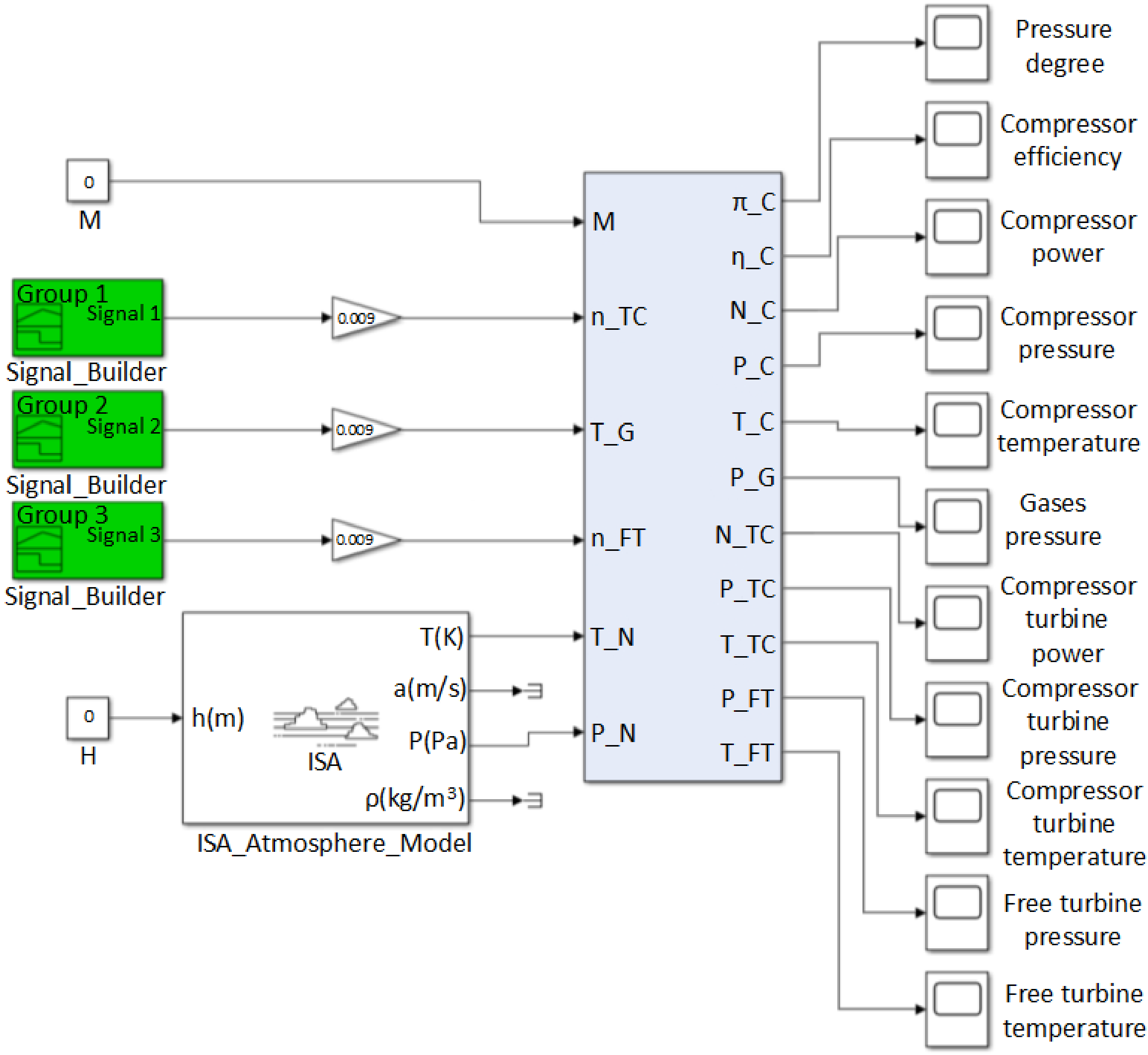


Figure 1: An overview of a segment of the mathematical model for turboshaft engines in helicopters within the Matlab/Simulink program, wherein 11 thermogasdynamic parameters of the engine operating process are computed [21, 22]

Addressing the challenge of intelligent control over the specific fuel consumption of helicopter turboshaft engines through neural networks holds promise and is timely. However, selecting a neural network architecture that aligns seamlessly with the quality requirements for controlling the specific fuel consumption of these engines constitutes an independent challenge, contingent upon the unique aspects of the problem at hand. Thus, the resolution of this challenge involves the following sequence of actions: computing thermogas-dynamic parameters of helicopter turboshaft engines (including air consumption in the combustion chamber, specific engine power, and the ratio of fuel to air consumption in the combustion chamber); determining fuel consumption values; and classifying the extent of deviation of fuel consumption from the norm. These tasks are intricately interconnected and can be functionally segmented, necessitating the development (or refinement) of appropriate methods and tools implemented through various neural network models. Schematically, this progression appears as follows: task – functions – methods (tools) – implementation.

Currently, the integration of neural networks with fuzzy logic has the potential to significantly enhance the effectiveness of automatic control systems employing neuro-fuzzy networks. This is attributed to the fact that the drawbacks inherent in one technology are offset by the advantages of the other [23]. Specifically, neural networks demonstrate a strong training capability, albeit with a complex training process. On the other hand, systems utilizing fuzzy logic provide clear explanations for conclusions but have limitations on the number of input variables. Consequently, the development of neuro-fuzzy networks becomes feasible, wherein conclusions are drawn based on fuzzy logic, and membership functions are adjusted using a neural network. The advantage of such systems is evident: the constructed structure not only utilizes a priori information but also has the capacity to acquire new knowledge while maintaining logical transparency [24].

Presently, a variety of hybrid neuro-fuzzy networks exist, exhibiting diverse architectures, capabilities, and methodologies [23]. A comprehensive analysis reveals several key properties, including the ability to automatically generate decision rules, the flexibility to employ different training algorithms, the option for online training during data reception, the capability to modify the structure, and the preservation of knowledge within the system through parametric optimization or training new rules. In [25], essential characteristics of various hybrid neuro-fuzzy systems are outlined, accompanied by recommendations for their selection based on the nature of the problem at hand. According to the data presented in [25], it is recommended to employ an adaptive neuro-fuzzy inference system (ANFIS), such as the Adaptive Network-based Fuzzy Inference System, for developing a process control system. Compared to alternative methods, ANFIS stands out for its rapid training, algorithmic simplicity, and optimal integration with the MatLab mathematical modeling system. In the ANFIS system, conclusions are drawn using fuzzy logic apparatus, and membership function parameters are adjusted through the error backpropagation algorithm or a hybrid method during neural network training. This approach facilitates the identification of patterns and the discovery of new dependencies. Following the recommendations mentioned in this study, simulations were conducted in the MatLab environment using the Fuzzy Logic Toolbox extension package. Within the Fuzzy Logic Toolbox package of the MatLab system, the ANFIS adaptive neuro-fuzzy inference system is characterized as a hybrid network – a multilayer neural network with a unique structure and no feedback. This network utilizes standard (non-fuzzy) signals, weights, and activation functions, employing fixed T-norm, T-conorm, or another continuous operation for summation. In this context, the values of inputs, outputs, and weights in the hybrid neural network fall within the real number range [0, 1].

Commonly recognized inference algorithms, such as Mamdani, Sugeno, Tsukamoto, and Larsen, can serve as solutions for the inference algorithm [26]. These algorithms implement fuzzy logical inference in varying manners, yet they do not exhibit significant differences. However, the precision of the resulting control signal can be enhanced by selecting an appropriate output algorithm. A comparative analysis of these algorithms, as indicated in [25], reveals that, all else being equal, the error in function approximation using the Sugeno algorithm is somewhat lower than when using the Mamdani algorithm. Furthermore, the Sugeno algorithm is computationally simpler than the Mamdani algorithm and requires 50 to 100 times less computation time. Therefore, for constructing a fuzzy controller for the control system of helicopter turboshaft engines, the Sugeno algorithm is employed [26]. The ANFIS network training technique for determining the parameters of the membership functions in Sugeno-type fuzzy inference systems can utilize either the backpropagation algorithm or a hybrid training algorithm. Let's conduct a comparative analysis of training a four-layer neuro-fuzzy network with different membership functions using both the backpropagation method and the hybrid method. The training of an ANFIS network can follow typical neural network training procedures since it employs only differentiable functions. This usually involves a combination of gradient descent in the form of backpropagation and least squares.

The backpropagation algorithm adjusts the parameters of the antecedents of the rules, specifically the membership functions. Meanwhile, the coefficients for rule conclusions are determined through the least square’s method, given their linear relationship to the network output. The tuning procedure comprises two steps during each iteration. In the initial phase, a training sample is inputted to the network, and optimal parameters for the nodes of the fourth layer are determined using the iterative least squares method, based on the residual between the desired and actual network behavior. Subsequently, in the second stage, the residual discrepancy is propagated from the network output to the inputs, and the parameters of the nodes in the first layer are modified using the error backpropagation method. It's crucial to note that the rule conclusion coefficients identified in the first stage remain unchanged. This iterative tuning process persists until the residual surpasses a predetermined threshold.

Based on the aforementioned information, the system developed was implemented using ANFIS, an adaptive neuro-fuzzy system that employs the Sugeno fuzzy inference system in the structure of a five-layer neural network with direct signal propagation (see Figure 2). The initial layer of this network encompasses terms related to the input variables, representing both the current values of thermogas-dynamic parameters of helicopter turboshaft engines and their delayed values. During the model formation, the initial dataset was partitioned into two segments: one for training and another for testing.

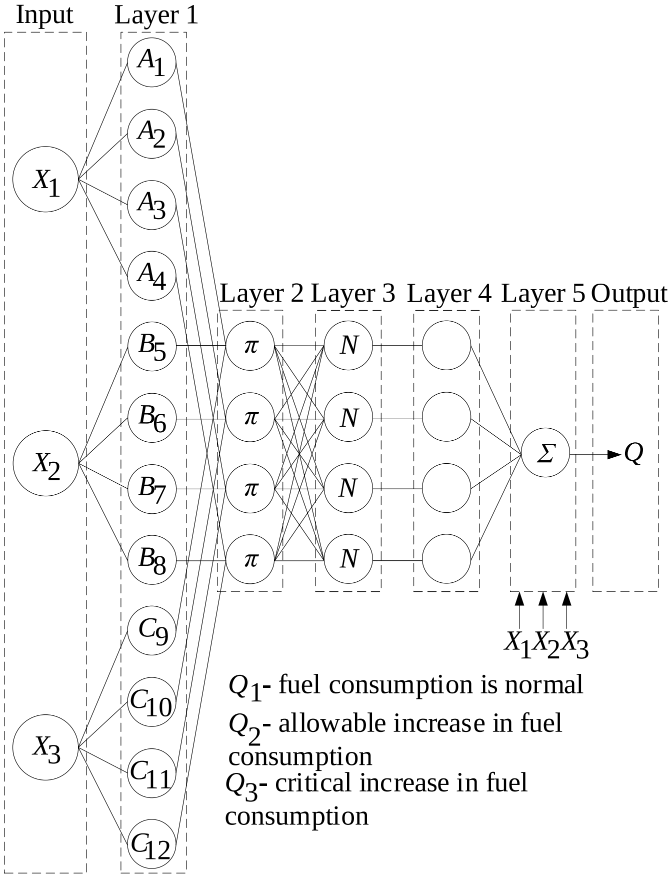


Figure 2: A five-layer neural network utilizing the Sugeno fuzzy inference system with direct signal propagation

To assess the efficacy of employing the ANFIS network for intelligent control of the specific fuel consumption of helicopter turboshaft engines, a training sample was utilized. This sample comprises data on air consumption in the combustion chamber, specific engine power, and the ratio of fuel to air consumption in the combustion chamber. These values were calculated in absolute units using a neural network model for helicopter turboshaft engines, as per [21, 22].

In the proposed neuro-fuzzy system, the transformation performed by a typical neuron with two inputs has the form $y = \left(\omega_1 x_1 + \omega_2 x_2\right)$, where $f\left(\bullet\right)$ – sigmoid function. In order to generalize it, you need to imagine that the weight of the neuron does not necessarily have to be multiplied by the value of the corresponding input, but some other operation can be used here. Further, the summation of effects can also be replaced by some other action. Finally, instead of the sigmoid function, the potential of the neuron can be transformed in some new way. In fuzzy logic, the multiplication operation is replaced for Boolean variables by the AND operation, and for numerical ones by the operation of taking the minimum (min). The summation operation is replaced, respectively, by OR operations and taking the maximum (max).

If we perform the corresponding changes in the transformation carried out by the neuron we know, and put $f\left(z\right) = z$ (linear output) in it, then we will get the so-called fuzzy OR-neuron:

$$y = \max\left\{\min\left(\omega_1, x_1\right)\min\left(\omega_2, x_2\right)\min\left(\omega_3, x_3\right)\right\}. \tag{1}$$

For fuzzy neurons, it is assumed that the values of the inputs and weights are in the interval [0, 1], so the output of the OR neuron will also belong to the same interval. Using the opposite substitution (multiplication max), (addition min) we get a transformation characteristic of a fuzzy AND-neuron:

$$y = \min\left\{\max\left(\omega_1, x_1\right)\max\left(\omega_2, x_2\right)\max\left(\omega_3, x_3\right)\right\}. \tag{2}$$

The architecture of the proposed neuro-fuzzy system is an isomorphic fuzzy knowledge base. It uses differentiable implementations of triangular norms (multiplication and probabilistic OR), as well as smooth membership functions. This makes it possible to use fast neural network training algorithms based on the method of inverse error propagation to adjust neural fuzzy networks. The proposed neuro-fuzzy system implements Sugeno fuzzy inference system in the form of a five-layer neural network of direct signal propagation. The purpose of the layers is as follows: first layer – terms of the input variables; second layer – antecedents (premises) of fuzzy rules; the third layer – rules fulfillment degrees normalization; fourth layer – rules conclusions; fifth layer – aggregation of the result obtained according to different rules, wherein 2 terms are used for linguistic evaluation of input variables x_1, x_2, x_3 [27]. The general fuzzy rule with serial number k has the form:

$$R_k : \text{If } x_1 = a_{1,k} \text{ and } x_2 = a_{2,k} \text{ and } x_3 = a_{3,k} \text{ then } y = b_{0,k} + b_{1,k}x_1 + b_{2,k}x_2 + b_{3,k}x_3; \tag{3}$$

where m – rules number, $k = \overline{1,m}$; $a_{i,k}$ – fuzzy term with a membership function $\mu_k(x_i)$, used for linguistic evaluation of a variable x_i in the k-th rule ($k = \overline{1,m}$, $i = \overline{1,n}$); $b_{q,k}$ – real numbers in the conclusion of the k-th rule ($k = \overline{1,m}$, $q = \overline{0,n}$).

The proposed neuro-fuzzy system functions as follows.

Layer 1. Each unit in the first layer represents one term with a Gaussian membership function. The network inputs are connected only to their terms. The number of units in the first layer is equal to the sum of the cardinalities of the term sets of the input variables. The output of the unit is the degree to which the value of the input variable belongs to the corresponding fuzzy term:

$$\mu_k(x_i) = \frac{1}{1 + \left| \frac{x_i - C}{A} \right|^{2B}}; \tag{4}$$

where A, B and C – configurable parameters of the membership function.

Layer 2. The number of units in the second layer is m. Each node in this layer corresponds to one fuzzy rule. The node of the second layer is connected to those nodes of the first layer that form the antecedents of the corresponding rule. Therefore, each node in the second layer can receive from 1 to n input signals. The layers output is the degree of rule realization, which is calculated as the product of the input signals. Let us denote the outputs of the nodes of this layer by τ_k ($k = \overline{1,m}$).

Layer 3. The number of units in the third layer is also m. Each unit of this layer calculates the relative degree of fulfillment of the fuzzy rule:

$$\tau_k^* = \frac{\tau_k}{\sum\limits_{j=\overline{1,m}} \tau_j}. \tag{5}$$

Layer 4. The number of units in the fourth layer is also m. Each unit is connected to one unit in the third layer, as well as to all network inputs. The fourth layer node calculates the contribution of one fuzzy rule to the network output:

$$y_k = \tau_k^* \left(b_{0,k} + b_{1,k}x_1 + b_{2,k}x_2 + b_{3,k}x_3 \right). \tag{6}$$

Layer 5. A single unit in this layer summarizes the contributions of all rules:

$$y = y_1 + \ldots + y_k + \ldots + y_m. \tag{7}$$

4. Experiment

The authors group conducted the analysis and initial processing of the input data, as detailed in [28, 29]. The input parameters for the mathematical model of helicopter turboshaft engines include atmospheric values (h – flight altitude, T_N – temperature, P_N – pressure, ρ – air density). Parameters measured on board the helicopter (n_{TC} – gas generator rotor speed, n_{FT} – free turbine rotor speed, T_G – gas temperature in front of the compressor turbine) were converted to absolute values using the theory of gas-dynamic similarity developed by Professor Valery Avgustinovich (refer to table 1). In this work, we assume that atmospheric parameters remain constant (h – flight altitude, T_N – temperature, P_N – pressure, ρ – air density) [28, 29].

Table 1

Part of training set (author's development, described in [28, 29])

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

Ensuring the homogeneity of the training and test samples is a crucial consideration in the evaluation process. To address this, we employ the Fisher-Pearson criterion χ^2 with degrees of freedom equal to $r - k - 1$ [28, 29]:

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

where θ – represents the maximum likelihood estimate determined from the frequencies m_1, …, m_r; n – denotes the number of elements in the sample, and $p_i(\theta)$ – refers to the probabilities of elementary outcomes up to a certain indeterminate k-dimensional parameter θ.

The concluding step in the statistical data processing involves normalization, which can be accomplished using the following 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.

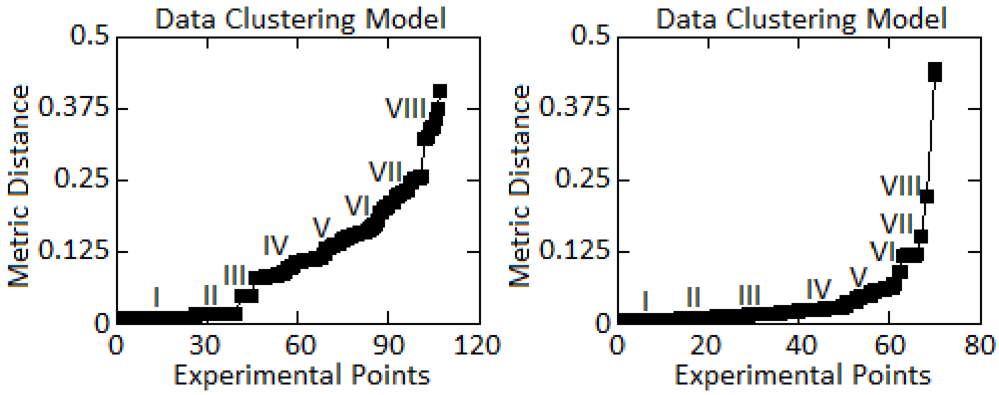
The χ^2 statistics mentioned above, given the stated assumptions, enable the testing of the hypothesis regarding the representability of sample variances and the covariance of factors within the statistical model. The domain for accepting the hypothesis is defined as $\chi^2 \le \chi_{n-m,\alpha}$, where α – denotes the significance level of the criterion. The computed results based on equation (8) are presented in table 2

Table 2

Part of the training sample during the operation of helicopters TE (on the example of TV3-117 TE) (author's development, described in [28, 29])

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

To assess the representativeness of the training and test samples, an initial data cluster analysis was conducted (table 2), revealing the identification of eight classes (fig. 3, *a*). Subsequently, following a randomization procedure, the actual training (control) and test samples were chosen in a 2:1 ratio, corresponding to 67 % and 33 %, respectively. The clustering process applied to both the training (fig. 3, *b*) and test samples indicated that, like the original sample, each contains eight classes. The distances between the clusters closely match in each of the examined samples, affirming the representativeness of both the training and test samples [28, 29].



a b

Figure 3: Clustering results: a – initial experimental sample (I…VIII – classes); b – training sample (author's development, described in [28, 29])

A fragment of the expert knowledge matrix for intelligent control of helicopters TE specific fuel consumption is given in table 3.

Table 3

Expert knowledge matrix for intelligent control of helicopters TE specific fuel consumption (on the example of the TV3-117 engine)

Rule number	IF <input>			THEN <output>	Rule weight
	air flow in the combustion chamber	specific engine power	ratio of fuel and air consumption in the combustion chamber		
1	0.985	0.995	0.990	1	1
2	0.975	0.995	0.985	1	1
3	0.965	0.995	0.980	1	1
4	0.940	0.980	0.975	2	1
5	0.930	0.980	0.970	2	1
6	0.920	0.980	0.965	2	1
7	0.895	0.960	0.960	3	1
8	0.875	0.960	0.955	3	1
9	0.855	0.960	0.950	3	1

First, the neuro-fuzzy network was trained using the error backpropagation algorithm (fig. 4). After 2200 training epochs, the training error was $\delta = 5.86 \cdot 10^{-4}$. According to the results of training by the hybrid method (fig. 5), the training error after 20 epochs was $\delta = 1.29 \cdot 10^{-4}$, that is, 4.53 times less than when training with the backpropagation algorithm.

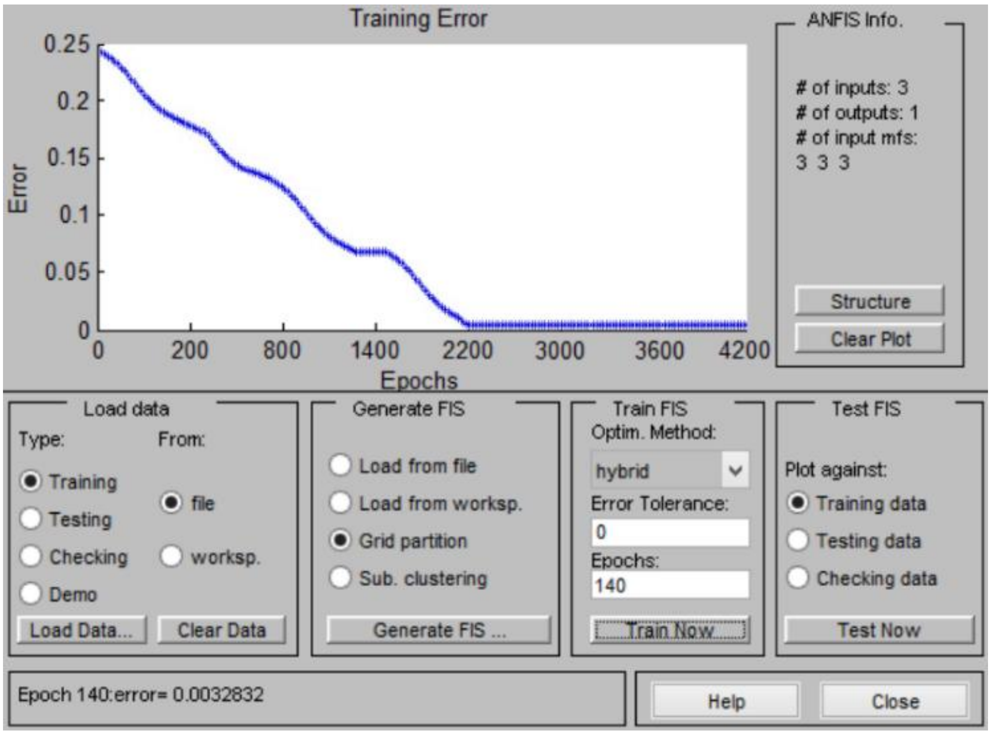


Figure 4: Diagram of the results of training a neuro-fuzzy network by the backpropagation algorithm

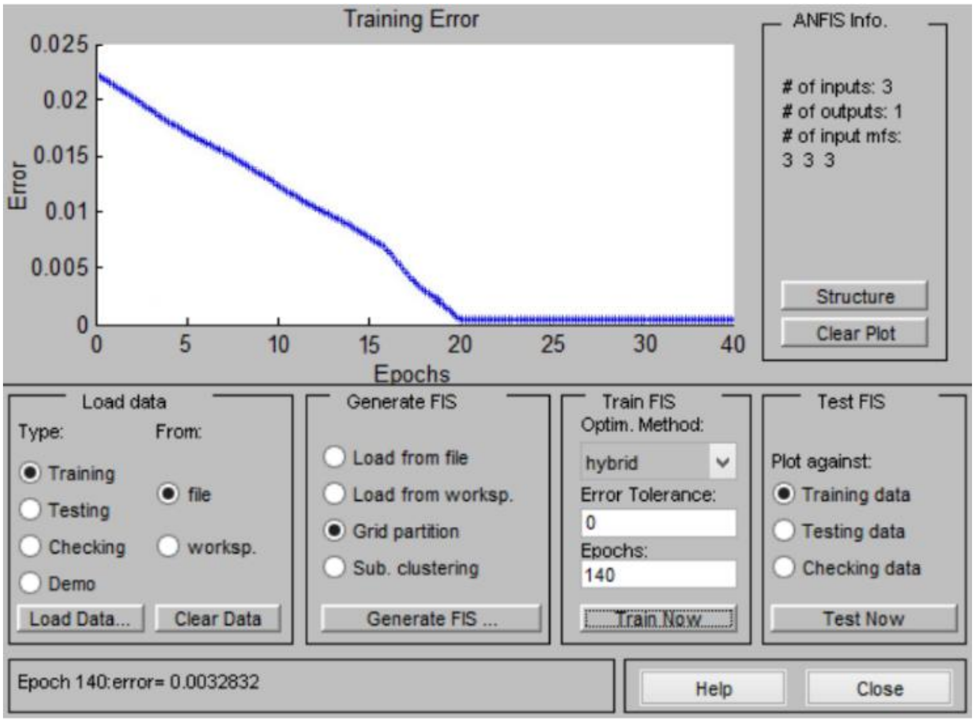


Figure 5: Diagram of training results for a neuro-fuzzy network by the hybrid method

Fig. 4 and 5 indicate that the hybrid method requires 105 times fewer epochs to train the network compared to the error backpropagation algorithm. Consequently, the hybrid method was employed for training the neural network in this work.

In the development of a neuro-fuzzy network, the selection of the membership function holds significant importance. Table 4 displays the network training error achieved for various membership functions during the network training using the hybrid method.

Table 4
Neural network training error obtained with different membership functions

Membership function name	Training error	Number of epochs	Training time, seconds
triangular (trimf)	0.007418	25	5.4715
trapezoidal (trampf)	0.018642	45	6.3604
generalized bell-shaped (gbellmf)	0.000216	28	5.2499
symmetrical gaussian (gaussmf)	0.000367	20	5.1689
two-sided gaussian (gauss2mf)	0.000129	20	5.1837
membership function as difference between two sigmoid functions (dsigmf)	0.002436	80	7.6352
product of two sigmoid membership functions (psigmf)	0.002277	80	7.9781

The result of tuning the membership functions in the case of two and three terms of input variables [30] is shown in fig. 6.

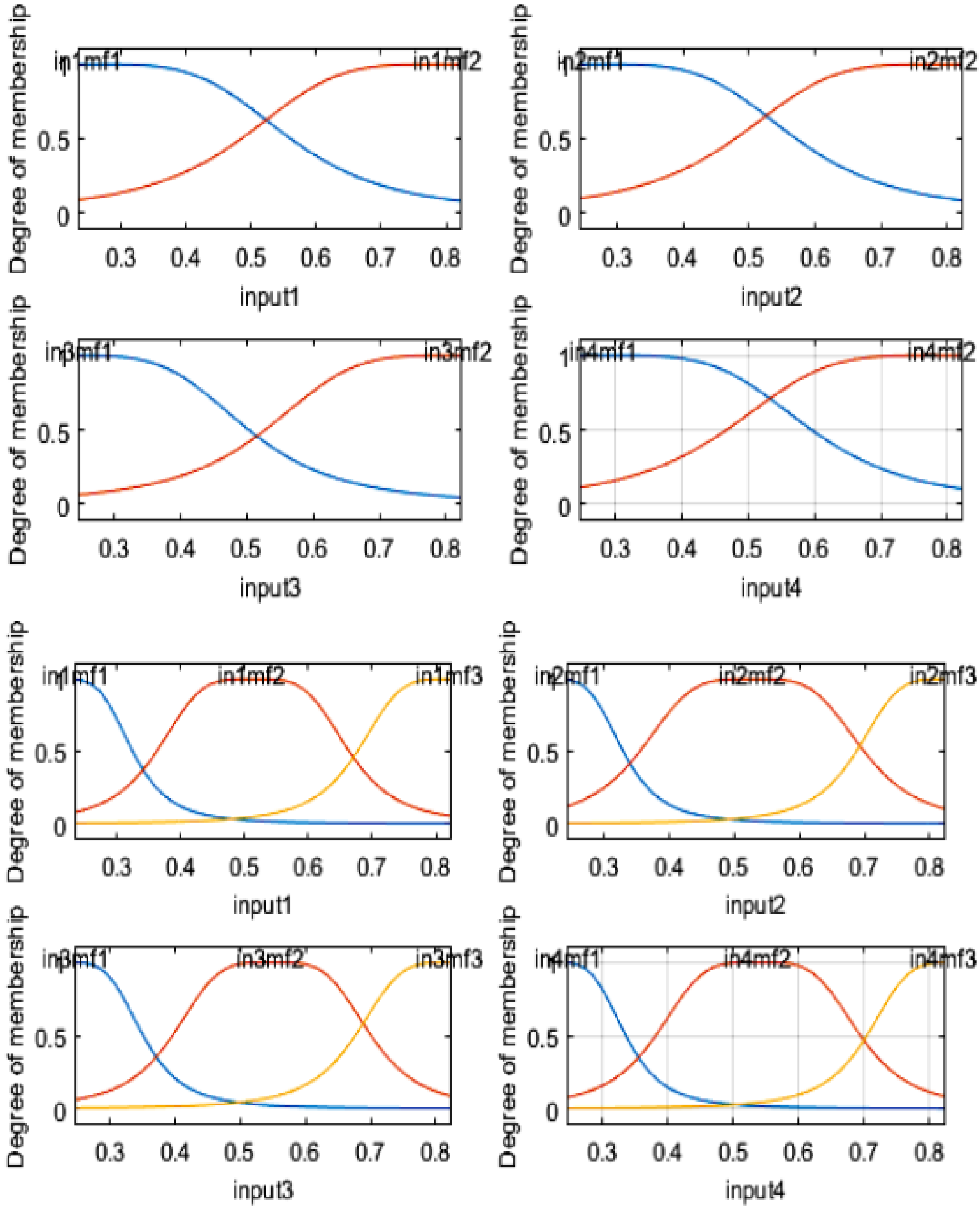


Figure 6: Membership functions of terms of input variables [30]

In the course of the study, it was observed that the two-sided Gaussian membership function yields the smallest training error (fig. 7 [30]), with $\delta = 1.29 \cdot 10^{-4}$ and $N = 20$ epochs. This is in comparison to the symmetric Gaussian membership function, which results in an error of $\delta = 3{,}67 \cdot 10^{-4}$ with $N = 20$ epochs, and the trapezoidal membership function, which produces the highest training error of $\delta = 1.86 \cdot 10^{-2}$ with N = 45 epochs. Therefore, when adapting a neuro-fuzzy network to address a control task, it is recommended to use a two-sided Gaussian membership function.

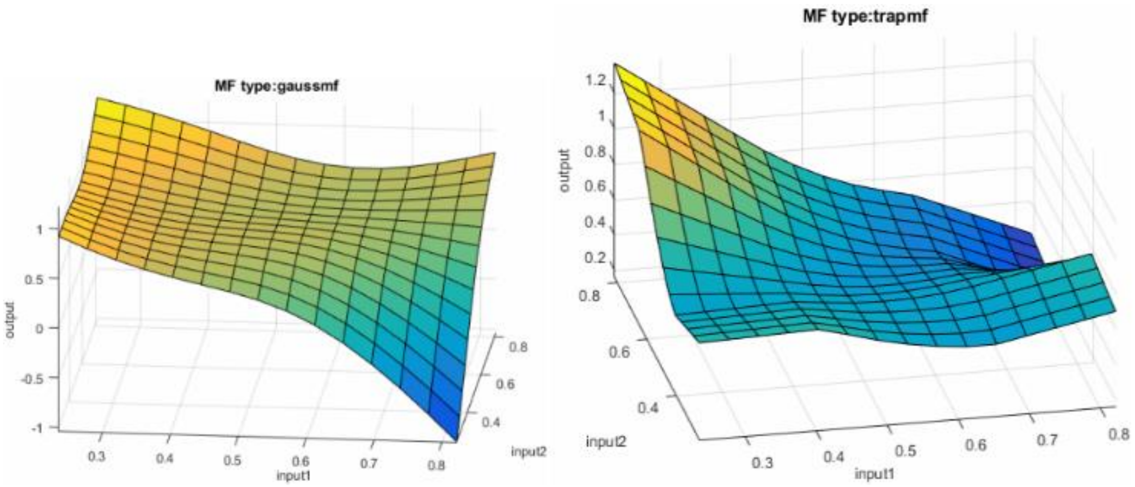


Figure 7: Type of fuzzy inference surfaces for different types of membership functions [30]

Table 5 presents the outcomes of evaluating the impact of the number of membership functions on the performance indicators of the task being addressed [30].

Table 5
Neural network training error obtained with different membership functions

Number of membership functions	Training error	Execution time, seconds
1	0.000129	5.46
2	0.000367	48.92
3	0.000492	1566.08

The investigation into the impact of the number of delayed inputs on the efficiency indicators of identification [29] revealed, as shown in table 6, that the optimal results are attained with 2 to 3 delayed inputs.

Table 6
Neural network training error obtained with different membership functions

Number of inputs	Training error	Training time, seconds
1	0.000326	3.18
2	0.000129	8.44
3	0.000156	17.56
4	0.000286	49.35
5	0.000422	77.93
6	0.000575	185.72

5. Results

In order to implement the above proposed method, a universal program (fig. 8) was created for generation according to the given values of the knowledge base matrix for the fuzzy controller. This program works as follows:

– saved matrix of elements is called;
– largest modulo values of each of the inputs and outputs are determined;
– range of values (from –max to +max) of each input and output is divided into terms with a step specified by the user;
– according to the affiliation of the variable values (from the resulting matrix), at each step, “input–output” rules are formed to one or another term;
– rules are combined if the output does not change its values when the inputs change;
– same rules are also combined;
– after executing this method, a rule base is formed.

To load the knowledge base that is necessary for the operation of the neuro-fuzzy system, we used the command fuzzy2=readfis('fuzzy2777').

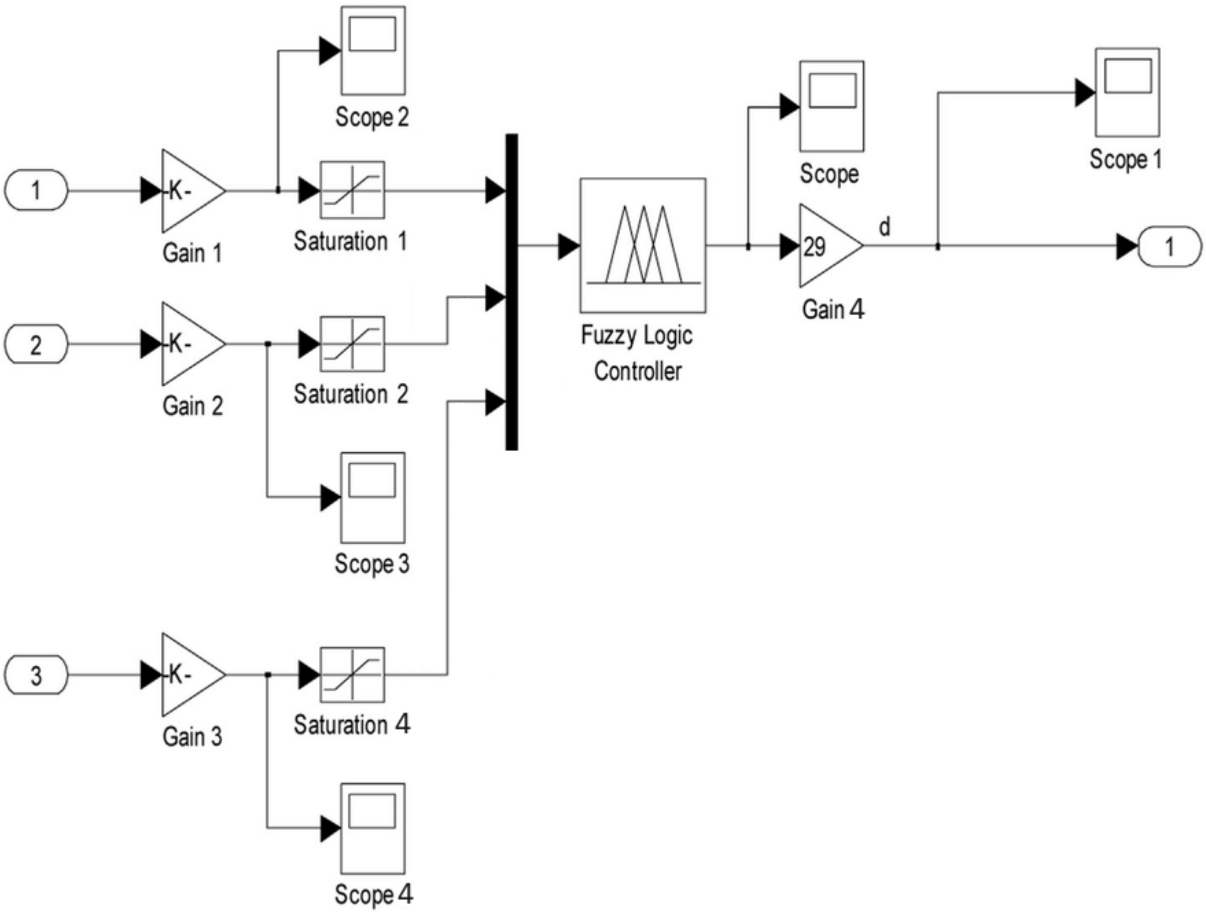


Figure 8: A universal program structure

We accept X_1 – air flow in the combustion chamber; X_2 – specific engine power; X_3 – ratio of fuel and air consumption in the combustion chamber. Fig. 9 shows the response curves of the FIS block for generating variables X_1, X_2, X_3. The combined diagram of the initial data and the results of controlling the specific fuel consumption, as well as the control error, are shown in fig. 10 and 11. Fig. 12 – 14 shows scatter diagrams of the output parameters: fuel consumption on the training sample in the interval from 0 to 5 seconds, fuel consumption on the test sample in the interval from 0 to 5 seconds; resulting training error of the neuro-fuzzy system in the interval from 0 to 5 seconds, respectively.

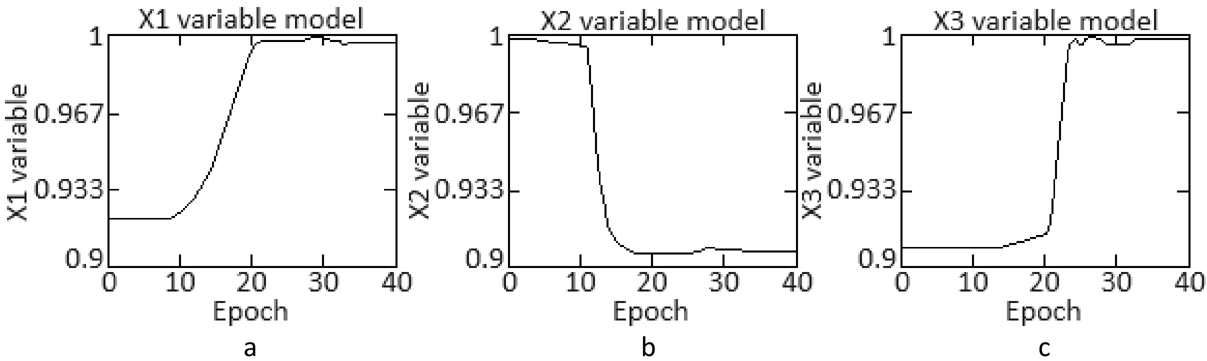


Figure 9: Response curves of the variable generation block: a – X_1; b – X_2; c – X_3

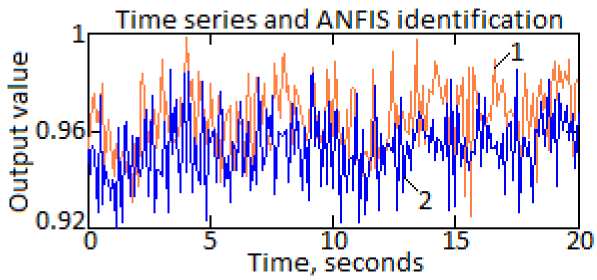


Figure 10: The result of checking the model on train (1) and test (2) data

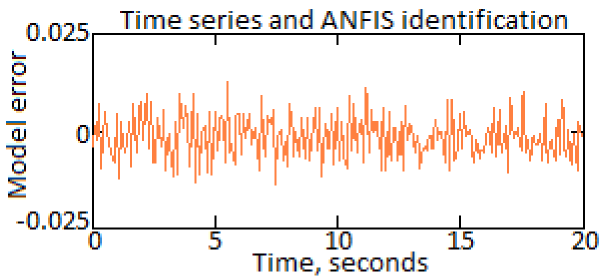


Figure 11: Model error result

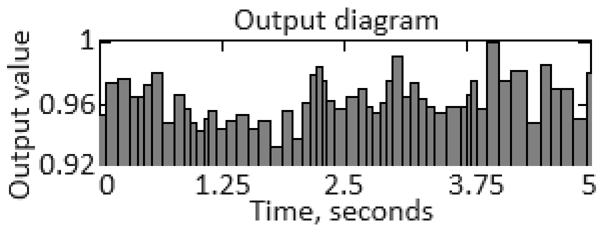


Figure 12: The scatter diagrams on training data

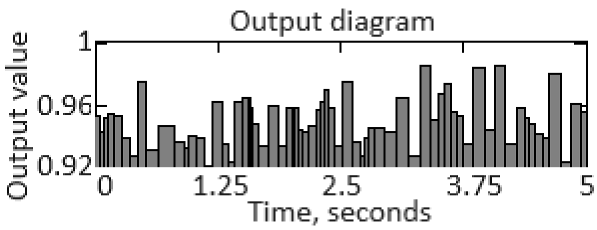


Figure 13: The scatter diagrams on test data

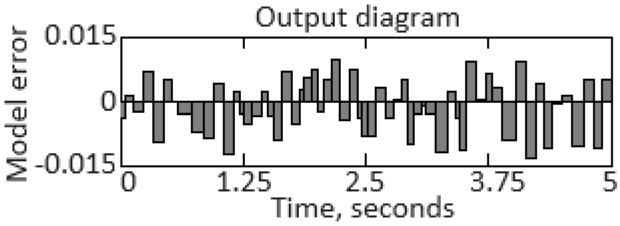


Figure 14: The scatter diagrams model error

Also, using the neuro-fuzzy system developed above, data on specific fuel consumption in various operating modes of the TV3-117 engine at $H = 0$, $V = 0$ were obtained. The initial data for the calculation were taken from [32], where the engine's nameplate data is also presented, with which the calculation results were compared. The calculation results and passport data are summarized in table 7 and are presented in fig. 15 (curve 1 – calculated data, curve 2 – passport data, curve 3 – calculated data obtained in [31]).

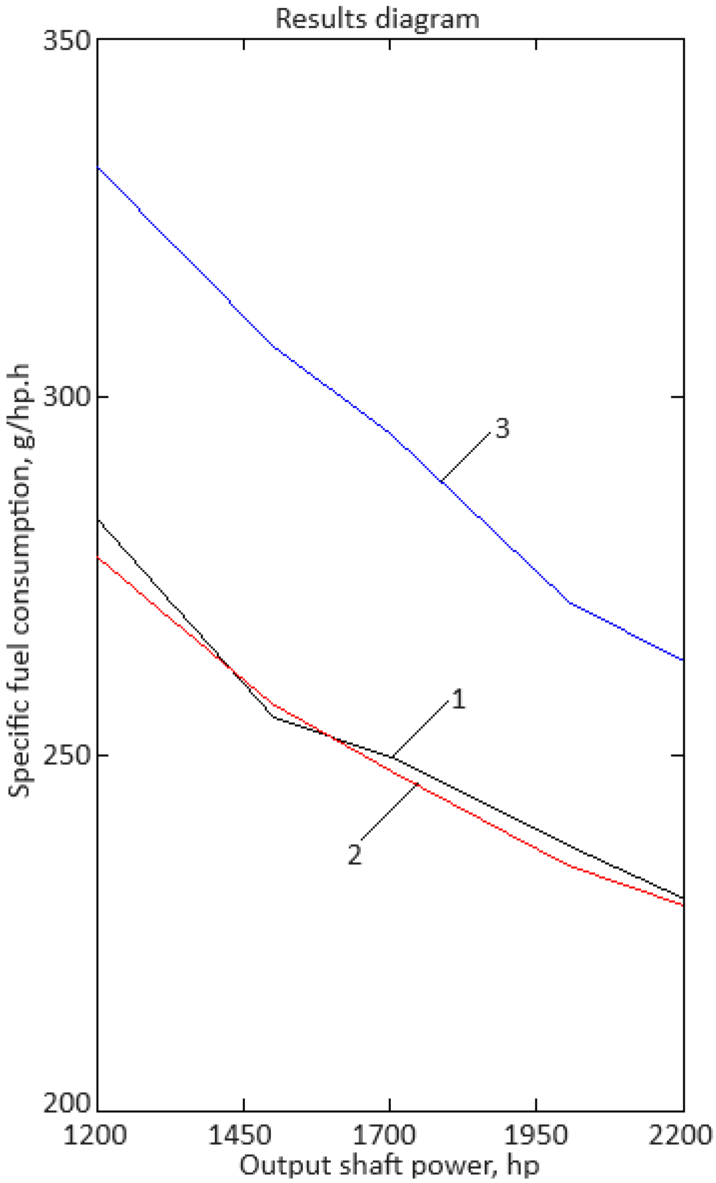


Figure 15: Comparison of the obtained values of specific fuel consumption of the TV3-117 engine with the passport characteristics and results obtained in [31]

Table 7
Comparison of the obtained values of specific fuel consumption of the TV3-117 engine with the passport characteristics and results obtained in [31]

Engine operating mode	Output shaft power, hp	Specific fuel consumption, g/hp.h		
		Calculated	Passport	[31]
Emergency	2200	232	230	263
Takeoff	2000	235	236	272
Nominal	1700	249	248	295
I cruising	1500	260	258	307
II cruising	1200	280	278	330

The adequacy of a mathematical model is determined by its accuracy and consistency with experimental data [31]. In terms of consistency, it can be argued that the considered mathematical model of specific fuel consumption does not contradict the passport data, since the nature of the calculated dependence and the dependence constructed from the passport data coincide. In terms of accuracy, we can note the presence of a systematic error, the reasons for which will be investigated further.

6. Discussions

During the experiment, the accuracy of the ANFIS neuro-fuzzy control algorithm was assessed in comparison to other machine learning techniques, including Random Forest, ExtraTree, and the Multilayer Perceptron Classifier (MLP) [32] (table 8).

Table 8
Results of a comparative analysis of the effectiveness of control methods

Methods	Accuracy	F1-measure	Completeness
ANFIS	0.992	0.905	0.976
Random Forest	0.862	0.754	0.811
ExtraTree	0.975	0.907	0.977
MLP	0.723	0.698	0.634

The overall performance of the ANFIS neuro-fuzzy control system demonstrated commendable generalization capabilities compared to MLP. However, the ExtraTree algorithm exhibited an advantage in terms of the F1-measure, given its ensemble nature. The outcomes detailing errors of the 1st and 2nd kind concerning the fuel consumption of helicopter turboshaft engines are provided in table 9.

Table 9
The results of determining errors of the 1st and 2nd kind

Neural networks architectures	Probability of error in determining the optimal value of fuel consumption	
	Type 1st error	Type 2nd error
ANFIS (proposed)	0.76	0.47
Multilayer perceptron	1.04	0.63
Radial basis function network	1.05	0.66
Hopfield neural network	1.38	0.82
Elman neural network	1.77	1.01
Jordan neural network	1.96	1.12
Hamming neural network	2.13	1.25
LSTM-network	2.69	1.43
Kohonen network	3.17	1.84
Adaptive resonance network	3.93	2.36

The comparative analysis of the results obtained (table 9) affirms that the developed neuro-fuzzy method for controlling fuel consumption in helicopter turboshaft engines achieves the minimum error in addressing the task during helicopter flight operations.

The results of comparison of the obtained results of the specific fuel consumption of the TV3-117 engine with the passport data, as well as with studies conducted in [31] (table 7) are presented in table 10.

Table 10
The comparative analysis results

Engine operating mode	Specific fuel consumption absolute error, g/hp.h	
	Results obtained with passport data	Results obtained with results obtained in [31]
Emergency	2	31
Takeoff	1	37
Nominal	1	46
I cruising	2	47
II cruising	2	50

As can be seen from table 10, the developed neuro-fuzzy system most accurately determines the specific fuel consumption of the TV3-117 engine in various modes of its operation.

7. Conclusions

1. For the first time, an on-board method for neuro-fuzzy control of the fuel consumption of helicopters turboshaft engines has been developed, which, through the use of an adaptive neuro-fuzzy system that implements the Sugeno fuzzy inference system in the form of a five-layer neural network of direct signal propagation, allows control the fuel consumption of helicopters turboshaft engines in real time with an accuracy of 99.2 %.

2. It has been experimentally proved that in order to adapt the ANFIS neuro-fuzzy network and the zero-order Sugeno fuzzy inference system to solving the problem of controlling the fuel consumption of helicopters turboshaft engines, it is effective to use a hybrid training method, 2...3 delayed inputs and two two-sided Gaussian membership functions.

3. The implementation of the neuro-fuzzy method for control the fuel consumption of helicopters turboshaft engines provides a decrease in errors of the first and second kind compared to other neural networks architectures from 1.34 to 5.17 times and also that the hybrid method training the neural network for the number of epochs 105 times less than the backpropagation algorithm.

4. It has been established that the two-sided Gaussian membership function provides the smallest network training error, equal to $1.29 \cdot 10^{-4}$, compared with others that give the largest neural network training error $5.86 \cdot 10^{-4}$.

5. Increasing the outputs number of the ANFIS neuro-fuzzy network and expanding the base of fuzzy rules makes it possible to improve the decision-making logic and, as a result, expand the range of rule activity levels calculating.

6. The prospect of further research is the introduction of the developed methods and algorithms into a modified closed onboard helicopters turboshaft engines automatic control system [28, 29].

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