Neuro-Fuzzy Methods for Detecting Sensor Failures in Helicopters Turboshaft Engines

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Abstract

This work is devoted to the development of a neural network method for detecting failures of sensors of helicopters turboshaft engines under on-board operation conditions. The proposed method is based on the use of the ANFIS neuro-fuzzy network with a modified hybrid method for its training. A modification of the hybrid method of training the neuro-fuzzy network ANFIS is proposed, which, through the use of the Adam method as a gradient-based optimization algorithm, as well as the adaptive *k*-means clustering method for optimizing the shape of fuzzy membership functions, allowed reducing the number of training epochs from 400 to 50 to obtain the minimum the standard deviation of the training error is $2.646 \cdot 10^{-4}$ using the Gaussian membership function. An evolutionary system of fuzzy rules has been developed to determine the gas temperature in front of the compressor turbine sensor failure, the compressor defect, and the failure of the free turbine rotor speed sensor failure. The proposed system can be extended by adding new fuzzy rules in order to detect and identify other failures of sensors and components of helicopters turboshaft engines. An experiment was carried out, which consists of computer modeling of the gradual failure of a gas temperature sensor in front of a compressor turbine. The results of a comparative analysis of traditional and neural network methods for detecting failures in helicopters turboshaft engines sensors showed that the maximum errors of the first and second types when using neural network methods did not exceed 0.78 and 0.52 %, while for traditional methods they reached 2.48 and 1.91 %.

Keywords

Helicopters turboshaft engines, neuro-fuzzy network ANFIS, sensor failure, gas temperature in front of the compressor turbine, mathematical model, error, training

1. Introduction

The movement control of modern helicopters has to be ensured under conditions of significant and varied uncertainties in the values of their parameters and characteristics, flight modes, and environmental influences. In addition, during the flight, various emergency situations may arise, in particular, engine failures and structural damage [1].

Some of these failures and damage have a direct impact on the dynamic characteristics of the helicopter as a control object. At the same time, it is extremely difficult to foresee all possible failures and their combinations in advance. From the above it follows that the situation in which the helicopter finds itself at any given moment in time can change in a significant and unpredictable way.

In this regard, it seems appropriate from a management point of view to interpret possible sudden changes in the dynamic properties of helicopters turboshaft engines (TE) due to failures and damage as another class of uncertainty factors, the countering of which is assigned to adaptation mechanisms. They must provide fault-tolerant control, that is, control that is able to

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adapt to changes in the dynamics of the control object generated by failures or damage, providing acceptable quality of control [2, 3].

With this approach, the task of providing fault-tolerant control is divided into two parts. The first of them is related to the reconfiguration of helicopters TE control algorithms when a failure situation occurs. But in addition to reconfiguration, it is necessary to simultaneously solve the task of identifying a failure situation, its nature and source of occurrence. Helicopters TE sensors failures are a serious problem, since the information received from them is used to control the movement of the helicopter.

The use of classical failure detection methods to solve the task under consideration is associated with a number of difficulties caused by the nonlinearity of the models, inaccuracies in measuring the outputs of the control object, and the large amount of data used. In addition, classical methods work satisfactorily only for sufficiently large values of the signal-to-noise ratio, and also have high computational complexity. It is also significant that the use of classical identification methods usually involves linearization and significant simplification of the system model, which does not always correspond to the nature of the task being solved [4, 5].

Neural network methods [6] are one of the promising approaches to providing fault-tolerant control [7, 8]. Neural network tools can overcome many of these disadvantages [9, 10]. In particular, as the available research results show, neuro-fuzzy networks can provide an effective solution to identification tasks [11, 12].

Based on the above, an urgent scientific and practical task is the development of neuro-fuzzy methods for helicopters TE sensors failures detecting, since through timely detection of failures it is possible to prevent their development and the occurrence of emergency situations. In addition, a neural network failure classifier can help reduce helicopter downtime by more accurately and quickly diagnosing failures, as well as complement traditional monitoring and diagnostic methods, increasing their accuracy and efficiency.

2. Related works

The contemporary digital control system for the helicopters TE manages engine operation across all modes, maintaining stability during transitions and averting emergencies (Fig. 1). Comprising three key components – a parameter measurement control unit, an onboard monitoring and diagnostic system, and an automatic control system [13] – it guarantees smooth and safe engine performance.

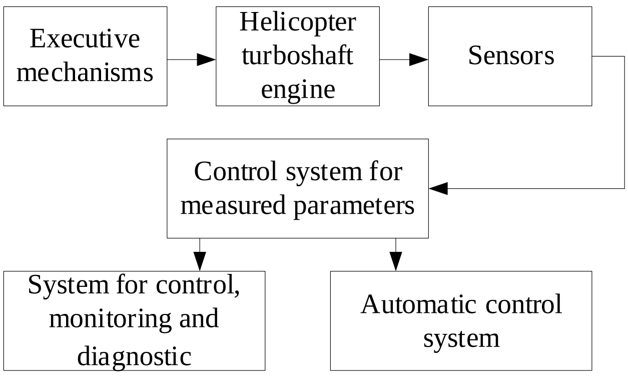


Figure 1: The overarching framework of the digital control system designed for helicopters TE [13]

At present, failures within specified thresholds are detected over time, triggering a failure assessment when these limits are exceeded. In instances of measuring channel failure, the last dependable parameter value is utilized to restore lost data [14, 15]. However, this method proves ineffective in cases of gradual or intermittent failures, especially during engine transitions, leading to low accuracy in recovered data [16, 17]. Addressing this challenge necessitates augmenting traditional monitoring and diagnostic techniques for helicopters TE with intelligent methods, which exhibit superior efficacy across all operational modes [18]. Among these methods, hybrid intelligent algorithms, combining various intelligent techniques, alongside neural networks and fuzzy logic algorithms, present promising avenues [19]. Consequently, the objective of this research is to develop an intelligent system utilizing a neural network mathematical model in tandem with a neuro-fuzzy method to address this issue [20].

In connection with the above, the purpose of the article is to develop a neural network failure classifier for helicopters TE. The following questions will be considered in the work:

1. Selection of neural network architecture. Within the framework of this task, various neural network architectures will be considered and the choice of the most suitable one for the task of failure classification will be justified.
2. Training a neural network classifier. As part of this task, methods and algorithms for training a neural network classifier will be described.
3. Evaluating the effectiveness of the neural network classifier. As part of this task, the results of assessing the effectiveness of a neural network classifier on test data will be presented.

The construction of such a model can be considered as the introduction of analytical redundancy of critical elements. As with the introduction of physical redundancy, the location of a faulty sensor is determined using a voting scheme. With this approach, the consequences of a failure situation can be countered by replacing the readings of a faulty sensor element with the output of its model.

3. Methods and materials

Traditionally, failure detection includes two main stages: identifying an abnormal situation, as well as determining its location and symptoms [21, 22]. The implementation of these stages can be interpreted as a sequential solution to the task of identifying a dynamic system and classifying the signs of a failure situation. The paper proposes a failure detection algorithm that combines solutions to these two tasks using neural network methods using neuro-fuzzy networks.

The implementation of the first stage is a typical task of monitoring a control object and measuring its outputs. A decision on the occurrence of a failure is made by comparing the current and predicted phase states of the dynamic system. If deviations reach a certain level, then a solution to the task of classifying failure signs is required. To obtain predicted phase states, a solution to the task of identifying the control object is required.

The neural network model makes it possible to assess the state of the control object at each moment in time, therefore in the proposed algorithm it is used at the stage of identifying an emergency situation for both groups of failures. Each of the failure groups has its own impact on the dynamics of helicopters TE, therefore, the proposed algorithm uses classification methods specific to each of the failure groups.

To address the aforementioned issue, an intelligent system can be employed, utilizing the FDI (Fault Detection and Identification) technique. This method relies on a neural network mathematical model of the engine in conjunction with a neuro-fuzzy classifier [20, 23]. By implementing this proposed intelligent system, it becomes feasible to detect and categorize abnormal operational states of a helicopters TE, as well as anomalies in measurement channels and actuators, all within onboard conditions (Fig. 2).

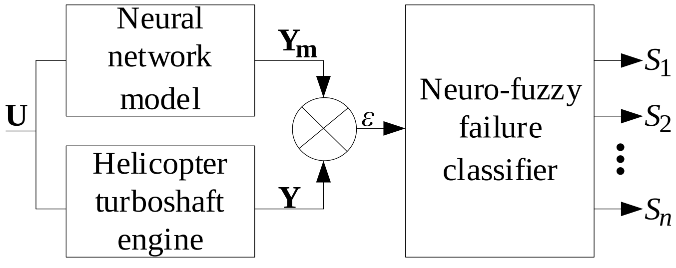


Figure 2: Helicopters TE control and diagnostic system configuration

Helicopters TE mathematical model plays the role of a reference model as part of the on-board control and diagnostic system. Comparing the calculated data of the mathematical model with the data of the measuring channels allows you to track changes in the controlled object. In addition, this model can be used to restore data in a failed measuring channel. A mathematical model must have a number of qualities, the most important of which are the following [24]: the model describes the non-stationary nature of the work processes of a helicopters TE (thus, the use of a dynamic model is necessary); the structure of the mathematical model of the helicopters TE provides the practical possibility of its functioning in combination with mathematical models of helicopter other elements.

The mathematical model, described in [25], is tailored for determining the specific fuel consumption of helicopters TE installed in helicopters, using the TV3-117 engine of the Mi-8MTV helicopter as an illustrative example. According to the insights provided in [23], the specific fuel consumption of such engines depends on factors like air intake in the combustion chamber, specific engine output, and the ratio of fuel to air consumption within the chamber, with the choice of aviation fuel exerting a direct influence.

The computation of helicopters TE thermogas-dynamic parameters, encompassing air intake in the combustion chamber, specific engine output, and the fuel-to-air consumption ratio within the chamber, is accomplished through a neural network model specifically designed for helicopters TE. This model, developed by the author and elaborated upon in [26, 27], is utilized (Fig. 3). The author performs the creation and setup of a trial version of the helicopters mathematical model using the Neural Network Toolbox, an extension package within the MATLAB environment.

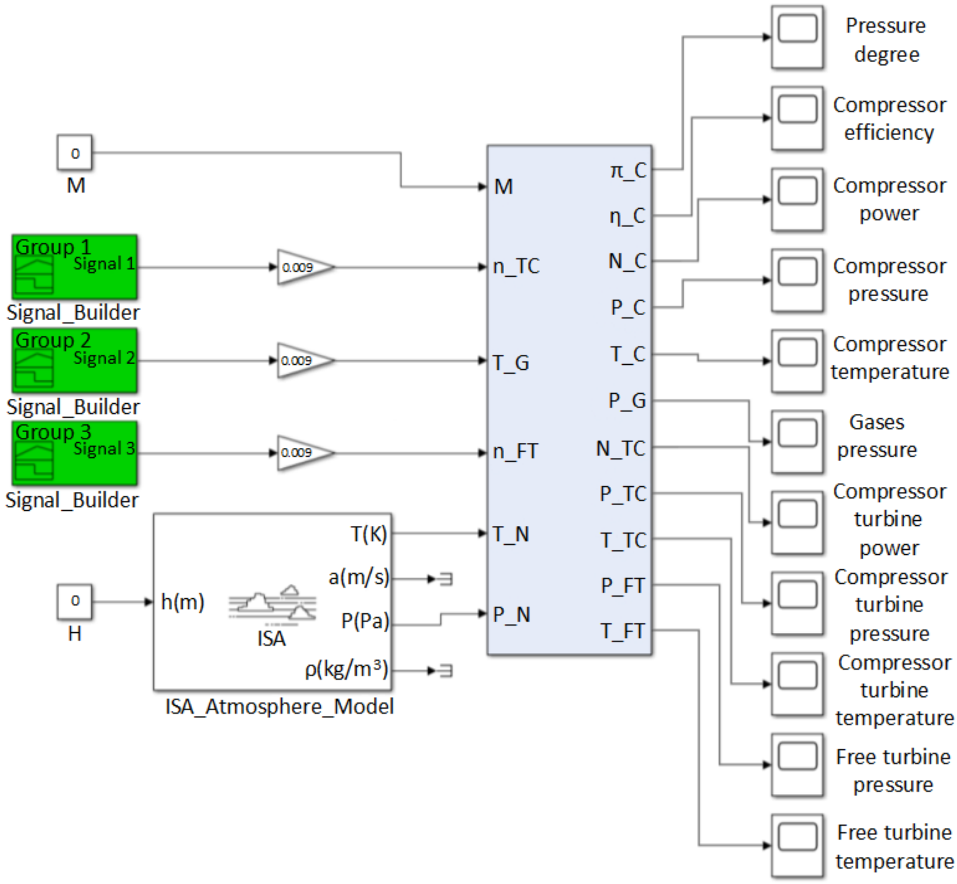


Figure 3: A fragment of the mathematical model for helicopters TE within the Matlab/Simulink environment, where 11 thermogas-dynamic parameters governing the engine's operational dynamics are calculated [26, 27]

One promising avenue in this domain involves crafting a mathematical model grounded in neural networks, renowned for their capacity to train and generalize accumulated knowledge.

This feature facilitates the adjustment of model parameters to suit the characteristics of specific engines, leveraging data derived from both bench and flight tests. Recurrent neural networks, such as Elman networks, Jordan networks, and multilayer perceptron with general feedback (NARX), fulfill these requirements for the mathematical model [28, 29].

Despite the advantages of recurrent neural networks like Elman, Jordan, and NARX networks, they also pose certain drawbacks. Chief among them is the challenge of training and fine-tuning network parameters, particularly when confronted with vast datasets or intricate nonlinear relations between input and output data. Achieving an acceptable level of model performance under such circumstances may demand significant time and computational resources. Moreover, recurrent neural networks may encounter issues like decay and gradient explosion when trained on lengthy sequences of data, leading to difficulties in consistent training and a decline in the network's generalization ability to new data.

To address these limitations, ongoing research is pivoting towards the adoption of neuro-fuzzy networks. These systems amalgamate the strengths of neural networks and fuzzy logic, rendering them more adaptable and flexible across diverse datasets and conditions. Neuro-fuzzy systems possess the capability to autonomously adapt to variations in input data and environmental factors, making them well-suited for modeling complex systems like engines, which contend with highly variable operating conditions [30, 31].

Approaches grounded in neuro-fuzzy networks enable the incorporation of uncertainty and fuzziness in data, a crucial aspect when dealing with real-world data susceptible to noise and errors. This adaptive capacity allows neuro-fuzzy networks to more effectively accommodate diverse operating conditions, furnishing more precise predictions and engine control.

Hence, the shift towards utilizing neuro-fuzzy networks represents a promising trajectory for advancing the mathematical modeling of helicopters TE, facilitating more efficient and accurate control and monitoring of their operations.

Fig. 4 shows the structure of a neural network model of a helicopter TE construct on a five-layer feed-forward network, in contrast to [20, 23], where it was proposed to use a multilayer recurrent perceptron (NARX). The adaptive neuro-fuzzy network (inference system) ANFIS (Adaptive Network-based Fuzzy Inference System) is a hybrid multilayer artificial neural network of a special structure without feedback [32]. The values of the inputs, outputs and synaptic weights of the hybrid neural network are real numbers on the interval [0, 1]. The adaptive network ANFIS in its functions is analogous to a fuzzy inference system [33]. The ANFIS network uses a hybrid training algorithm. Neurons in the ANFIS network have different structures and purposes, corresponding to the fuzzy inference system and implementing the main stages of its operation [34]:

- Fuzzification (introduction of fuzziness) using membership functions of input variables – the first layer of neurons of the network (layer 1);
- Aggregation (determining the degree of truth of conditions) by processing a base of fuzzy linguistic rules – the second layer of neurons in the network (layer 2);
- Activation (determining the degrees of truth of statements) by normalizing the activation levels of fuzzy rules – the third layer of neurons in the network (layer 3);
- Accumulation (combination of degrees of truth) using membership functions of output variables – the fourth layer of neurons in the network (layer 4);
- Defuzzification (transition to clarity) with obtaining a clear value of the output variable – the fifth layer of neurons in the network (layer 5).

The first adaptive layer of the ANFIS network contains neurons that calculate the values of the membership functions of input variables $\mu_i(G_T)$ and $\mu_j(n_{TC})$, where G_T and n_{TC} are input variables, i = 1, 2 and j = 3, 4. The adaptability of the layer is achieved by selecting type of membership functions of input variables.

The second fixed layer of the ANFIS network contains neurons that calculate the products of the values of the membership functions obtained on the first layer:

$$w_i = \mu_i\left(G_T\right) \cdot \mu_j\left(n_{TC}\right), \tag{1}$$

where w_i is the network synaptic weights.

The third fixed layer of the ANFIS network contains neurons that calculate normalized activation levels of fuzzy rules:

$$w_{average\_i} = \frac{w_i}{w_1 + w_2 + w_3 + w_4}. \quad (2)$$

The fourth adaptive layer of the ANFIS network contains neurons that calculate the values of the membership functions of the output variables, as well as the product of the values of synaptic weights and membership functions:

$$w_{average\_i} \cdot \psi_i = w_{average\_i} \cdot \psi_i \left(G_T, n_{TC}, \alpha_i, \beta_i, \gamma_i\right), \quad (3)$$

where ψ_i is the output variables membership functions values, α_i, β_i, γ_i are the parameters of the membership functions. The adaptability of the layer is achieved by selecting the type of membership functions of the output variables.

The fifth fixed layer of the ANFIS network contains a neuron that calculates the sum of the products of the values of the membership functions of the output variables and synaptic weights $Q_i = \sum w_{average\_i} \cdot \psi_i$.

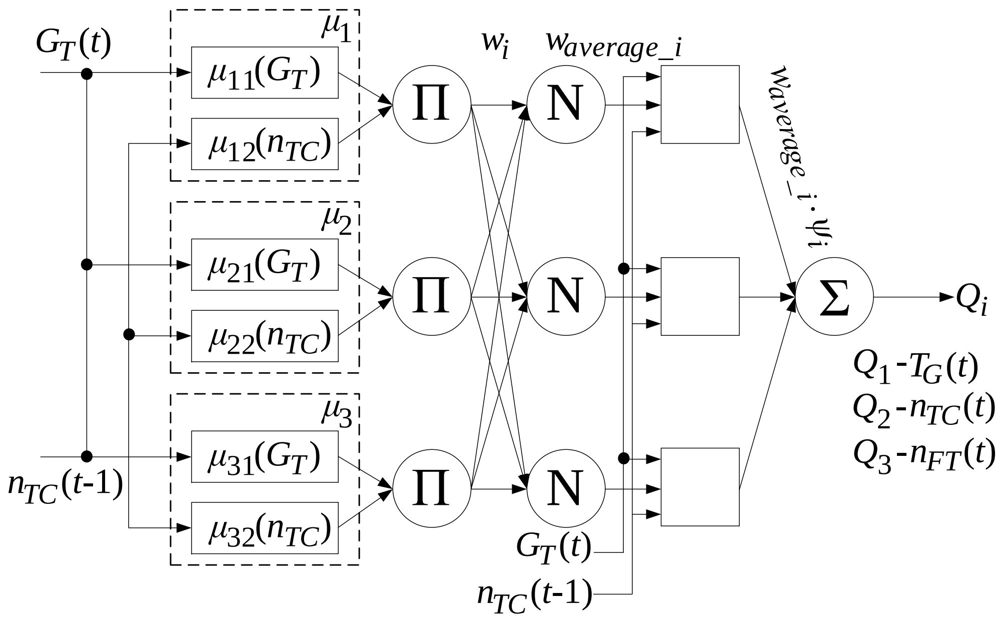


Figure 4: Helicopters TE neural network model structure in the form of adaptive neuro-fuzzy network (inference system) ANFIS

As an algorithm for training the adaptive neuro-fuzzy network ANFIS, an algorithm consisting of two stages is proposed [35]:

- first stage (algorithm direct course): we set the initial values of the parameters of the first adaptive layer, perform calculations on the second and third layers, determine the parameters of the fourth adaptive layer and calculate the value of the error function. If the value of the error function is within acceptable limits, then training of the adaptive neuro-fuzzy network ANFIS is completed, otherwise we proceed to the second stage;
- second stage (reverse algorithm): using the backpropagation method, we refine the parameters of the first adaptive layer.

At the same time, to adjust the parameters of the neuro-fuzzy network ANFIS, instead of the least square's method, it is proposed to use a more effective optimization algorithm based on gradients, for example, the Adam method [36]. To optimize the shape of fuzzy membership functions, it is proposed to use an adaptive training method, for example, the *k*-means clustering method. Thus, the use of a gradient-based optimization algorithm allows you to more accurately adjust the parameters of the ANFIS neuro-fuzzy network, and the use of the *k*-means clustering method allows you to reduce its training time.

For the mathematical description of the proposed modifications of the hybrid algorithm for training the neuro-fuzzy network ANFIS, the following notations are introduced: x is the vector of input data (G_T, n_{TC}), y is the vector of output data, w is the vector of weights of the neuro-fuzzy network, μ_i is the fuzzy membership function of the i-th rule, f_i is the output function of the i-th rule, N is the number of rules, α is the training parameter, η is the regularization parameter. The proposed modification of the hybrid algorithm for training the neuro-fuzzy network ANFIS consists of two stages:

1. Gradient-based optimization algorithm:

1.1. Initialization of weights of the neuro-fuzzy network ANFIS w.

1.2. Calculation of the gradient of the loss function $L(w)$ by weights w.

1.3. Update weights w:

$$w = w - \alpha \nabla L\left(w\right), \tag{4}$$

where w represents the parameters of a model that we're optimizing; α is the training rate, a small positive scalar that determines the step size in each iteration; $\nabla L(w)$ is the gradient of the loss function $L(w)$ with respect to the parameters w. The gradient points in the direction of the steepest increase of the function.

1.4. Repeat steps 1.1–1.3 until stopping criterion is reached.

2. Adaptive teaching method:

2.1. Clustering training data into N clusters using the k-means method.

2.2. For each cluster i, the centroid of the cluster c_i is determined, and the parameters of the fuzzy membership function μ_i are also initialized.

2.3. Training of the ANFIS neuro-fuzzy network with fixed parameters of fuzzy membership functions.

2.4. Update parameters of fuzzy membership functions:

$$\mu_i\left(x\right) = \exp\left(-\frac{\left\|x - c_i\right\|^2}{2\sigma^2}\right), \tag{5}$$

where c_i is the i-th center (centroid) in the feature space; σ is the smoothing parameter that controls the width of the Gaussian function curve; $\left\|x - c_i\right\|^2$ is the square of the distance between the input vector x and the center c_i.

2.5. Repeat steps 2.3–2.4 until stopping criterion is reached.

The root mean square error can be used as the loss function $L(w)$:

$$L\left(w\right) = \frac{1}{2}\sum_{i=1}^{N}\left(y_i - y_i\right)^2, \tag{6}$$

where y_i is the output of the ANFIS neuro-fuzzy network for the i-th example.

To prevent overfitting, Tikhonov regularization can be used:

$$L\left(w\right) = \frac{1}{2}\sum_{i=1}^{N}\left(y_i - y_i\right)^2 + \frac{\eta}{2}\sum_{j=1}^{M} w_j^2, \tag{7}$$

where M is the number of weights of the ANFIS neuro-fuzzy network; η is the regularization coefficient, which controls the importance of regularization in relation to the error.

4. Experiment

Table 1 presents a segment of the expert knowledge matrix for the neuro-fuzzy network ANFIS designed for helicopters TE. The general fuzzy rule with serial number k has the form: IF $G_T(t)$ <value> and $n_{TC}(t - 1)$ <value> THEN {1, 2, 3} <output>, where 1 is the output "gas temperature in front of the compressor turbine sensor failure", 2 is the output "gas generator defect", 3 is the output "failure of the measuring channel n_{FT}". By expanding the expert knowledge base and, accordingly, adding the number of outputs of the neuro-fuzzy network ANFIS, it is possible to identify other defects and failures of helicopters TE.

Table 1
Expert knowledge matrix

Rule number	IF <input> $G_T(t)$	$n_{TC}(t-1)$	THEN <output>	Rule weight
1	0.985	0.995	1	1
2	0.975	0.995	1	1
3	0.965	0.950	2	1
4	0.955	0.950	2	1
5	0.945	0.920	3	1
6	0.935	0.920	3	1

The input parameters for the mathematical model of helicopters TE comprise atmospheric variables (h is the flight altitude, T_N is the temperature, P_N is the pressure, ρ is the air density). These parameters, obtained from onboard recordings (n_{TC} is the gas generator rotor r.p.m., n_{FT} is the free turbine rotor speed, T_G is the gas temperature in front of the compressor turbine, G_T is the fuel consumption, calculated according [37]), are standardized to absolute values using the theory of gas-dynamic similarity (Table 1). It is assumed in this study that the atmospheric conditions remain constant (h is the flight altitude, T_N is the temperature, P_N is the pressure, ρ is the air density) [38, 39]. A thorough analysis and preprocessing of the input data are elaborated upon in [38, 39] (Table 2).

Table 2
Training sample fragment [38, 39]

Number	n_{TC}	n_{FT}	T_G	G_T
1	0.929	0.943	0.932	0.952
2	0.933	0.982	0.964	0.963
3	0.952	0.962	0.917	0.947
4	0.988	0.987	0.908	0.949
…	…	…	…	…
256	0.973	0.981	0.953	0.960

The helicopters TE operational status and its subsystems determining relies on a neuro-fuzzy network ANFIS. Its operational principle is as follows: the vector of calculated model data, denoted as $\mathbf{Y_m}$ (Fig. 5, where 1 is the n_{TC}, 2 is the n_{FT}, 3 is the T_G, 4 is the G_T), is compared element-wise with the vector of measured data $\mathbf{Y}$. Subsequently, the resulting error vector $\boldsymbol{\varepsilon}$ is inputted into the neuro-fuzzy network ANFIS. This neuro-fuzzy network ANFIS, leveraging the magnitude of errors and their temporal derivatives, generates conclusions regarding the engine's operational status or that of its subsystems. The output signals of the neuro-fuzzy classifier encompass various states, including optimal operational status (S_1), faults in measurement channels (S_2), actuator malfunctions (S_3), engine failures (S_4), and automatic control system faults (S_5).

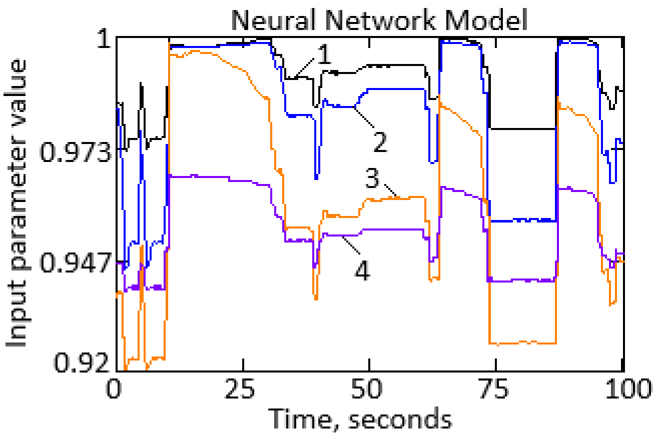
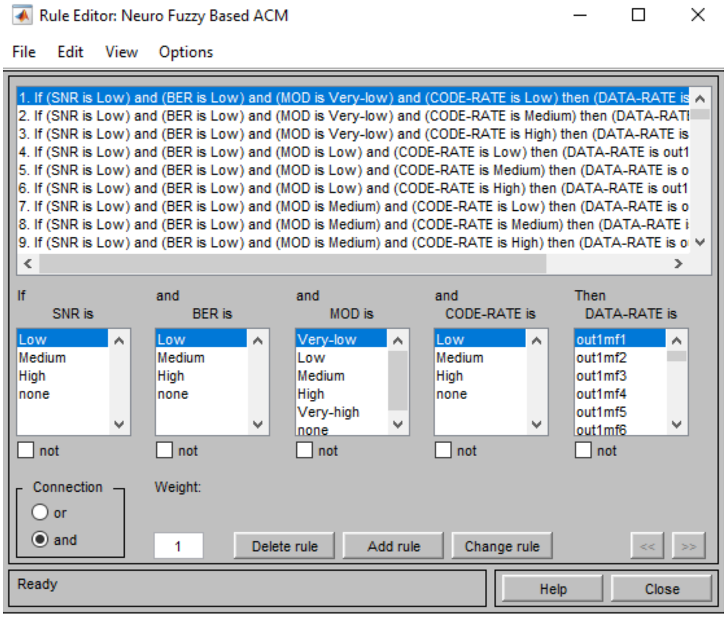


Figure 5: The computational data utilized in the neural network model for helicopters TE

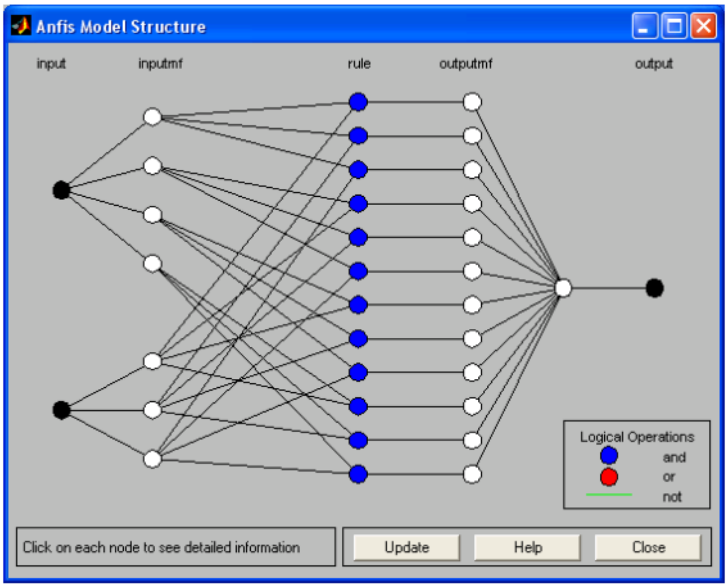
The development of the neuro-fuzzy network ANFIS involves modeling using the ANFIS editor toolkit within the MATLAB mathematical package. This process utilizes data acquired during flight tests of the helicopters TE, as well as outcomes from comprehensive modeling exercises simulating failures of the helicopters TE and its subsystems, based on a detailed mathematical model of the entire helicopters TE. The development process of a neuro-fuzzy network ANFIS comprises several key stages [20, 23]:

1. Formulating a collection of fuzzy inference rules, employing information regarding the deviation of measured data from calculated values or other anomalies.
2. Constructing a neural network, serving as the foundation for the fuzzy inference system.
3. Training the neuro-fuzzy network ANFIS utilizing a reference dataset containing input and output data, derived from experimental measurements of engine sensor channels.
4. Fine-tuning the parameters of the input membership functions.

Fig. 6, a illustrates an example of establishing fuzzy inference rules for a neuro-fuzzy network ANFIS during its debugging phase in the ANFIS editor. The structure of the neuro-fuzzy model in ANFIS is depicted as shown in Fig. 6, b.



a



b

Figure 6: Neuro-fuzzy network in ANFIS: a – rules for fuzzy inference; b – general view

To train a neuro-fuzzy network ANFIS, we employ a hybrid network training approach, which merges the Adam method with the modified inverse gradient descent method. The training process encompasses a specified number of cycles, known as epochs, set at 400 (Fig. 7, a) and 50 (Fig. 7, b). The evaluation of the model's accuracy in constructing a fuzzy inference system relied on the root mean square error (RMSE) metric [26], assessed across both training and testing datasets:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i^{train} - y_i^{calc}\right)^2}, \quad (8)$$

where y_i^{train} is the training data set; y_i^{calc} is the calculated data; n is the number of points in the training set.

Table 3

Neuro-fuzzy network ANFIS membership function type selection results

Input membership function type	Output membership function type	RMSE
Gaussian (gauss2mf)	Linear	$8.320 \cdot 10^{-5}$
Triangular (trimf)	Linear	$2.646 \cdot 10^{-4}$

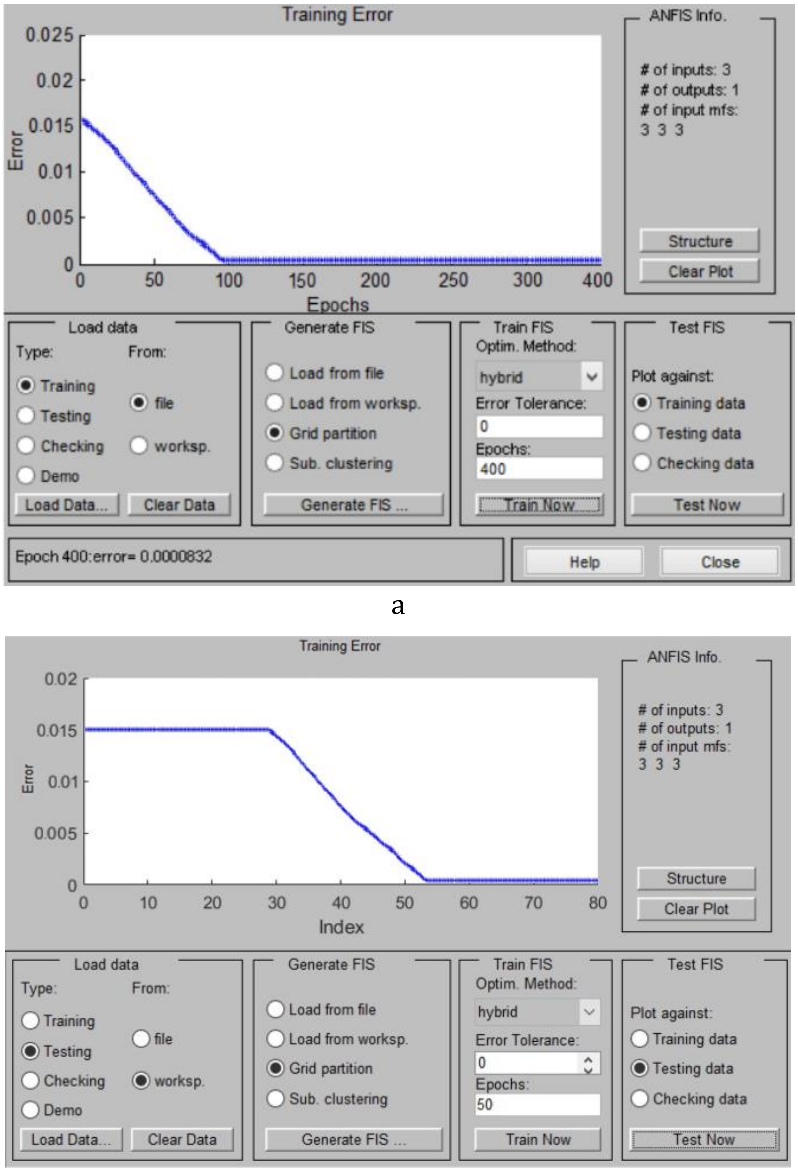


Figure 7: Neuro-fuzzy network ANFIS training results: a – with the traditional gradient method; b – with the modified inverse gradient descent method

5. Results

The work considers three types of sensor failures, which are modeled according to the following expressions [40]:

1. Additive failure:

$$S_{failure}(t) = S_{loss}(t) + \rho \cdot \eta(t), \ \ \forall t \geq t^*, \tag{9}$$

2. Multiplicative failure:

$$S_{failure}(t) = S_{loss}(t) \cdot (1 + \rho \cdot \eta(t)), \ \ \forall t \geq t^*, \tag{10}$$

3. "Freezing" sensor readings at the moment of failure:

$$S_{failure}(t) = S_{loss}(t^*) \cdot \eta(t), \ \ \forall t \geq t^*, \tag{11}$$

where $S_{loss}(t)$ is the readings of a working sensor; ρ is the parameter characterizing the magnitude of failure.

Based on the nature of changes over time, sensor failures are divided into the following types:

1. Intermittent failure:

$$\eta(t) = 1, \ \ \forall t \geq t^*, \tag{12}$$

2. Increasing failure:

$$\eta(t) = \begin{cases} \dfrac{t - t_{f_2}}{t_{f_2} - t_{f_1}}, \ t_{f_1} \leq t < t_{f_2} \\ 1, \ \ t > t_{f_2} \end{cases} \ \ \forall t \geq t^*, \tag{13}$$

where t_{f_1} and t_{f_2} are sets the start and end times of the failure, respectively.

The functioning of each sensor is determined by the mean square error between the value of the helicopters TE parameters predicted by the neural network model and the value calculated from its model. Since each neural network model describes the normal functioning of a sensor, the location of a faulty sensor is determined when its performance indicator reaches a specified threshold value. To make the system more resistant to false alarms, additional threshold values are introduced. "Upper" and "lower" sensitivity thresholds are used [41, 42].

Since failure models are specified a priori, performing an appropriate transformation of the values of the necessary parameters calculated using the helicopters TE model and predicted by neural network models allows us to determine the type and specific parameters of the failure. Recognition of signs of a failure situation is carried out by testing the corresponding hypothesis.

The work discusses an approach in which recognition of signs of a failure situation is made based on observations of the cross-correlation functions of helicopters TE parameters. The relation between pairs of parameters can be quantified and represented as a function. If a control drive fails, this relation is broken. For example, changes in the operation of one of the elevator sections causes an additional roll moment. The location of an emergency situation can be determined by changes in the corresponding cross- and autocorrelation functions of helicopters TE parameters. To classify drive failures, it is proposed to use neural network models of the cross- and autocorrelation functions of helicopters TE parameters, specified by the expression [40]:

$$R_{xy}(-m) = \begin{cases} \sum\limits_{n=0}^{N-m-1} x_{n+m} \cdot y_n^*, \ m \geq 0, \\ \overset{*}{R_{xy}}(-m), \ m < 0, \end{cases} \tag{14}$$

The output of the neuro-fuzzy network ANFIS is the norm values of the cross-correlation function between pairs of helicopters TE parameters:

$$R = \left\| R_{xy}(-m) \right\|, \tag{15}$$

where (•)* specifies the convolution operation; N = 7 is the width of the sliding window over the values of helicopters TE parameters.

Classification of failures involves determining the location and parameters of an emergency situation. The location of the sensor failure cannot be unambiguously determined when the performance indicator of only one neural network model reaches a certain threshold value. Combinations and deviation values of cross- or autocorrelation functions are combined into a rule base through which the outputs of all neural network models pass. To implement the sensor classification method, neural network models are required, for example, of the following functions: $R\left(S_{n_{TC}}, S_{T_G^*}\right)$, $R\left(S_{n_{TC}}, S_{n_{FT}}\right)$, $R\left(S_{T_G^*}, S_{n_{FT}}\right)$.

To train the neuro-fuzzy network ANFIS, training samples were compiled – input measured and calculated data of the n_{TC}, n_{FT}, T_G channels, including deviations obtained by simulating engine and sensor failures, as well as output reference data representing a signal about the corresponding failure. Fig. 8 shows a diagram of a sample of training data in which the gradual failure of the gas temperature sensor in front of the compressor turbine is modeled (1 is the T_G^* nominal values, 2 is the T_G^* values in case of sensor failure). The failure occurs at time t = 53 s, the failure is detected immediately at the moment of occurrence. When conducting a computational experiment, Gaussian noise with a standard deviation 2.5 % [43] is superimposed on the values of all observed signals.

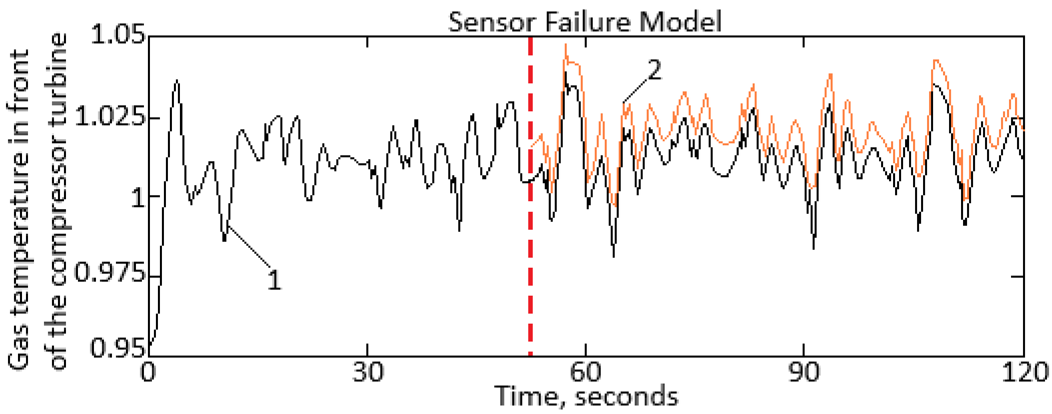


Figure 8: Diagram of the modeling result the sensor failure of helicopters TE gas temperature in front of the compressor turbine sensor failure

Fig. 9 and 10 are shows the stages of identifying and determining the location of a sensor failure of gas temperature in front of the compressor turbine (1 – performance indicator, 2 – threshold value). Since the failure is abrupt and additive, at the moment of its occurrence there is a sharp deviation from the standard behavior for the gas temperature in front of the compressor turbine. The performance indicator of helicopters TE reacts sharply to this change. There is a significant excess of the threshold value. There is also a significant excess of the "upper" sensitivity threshold for the performance indicator for the gas temperature in front of the compressor turbine.

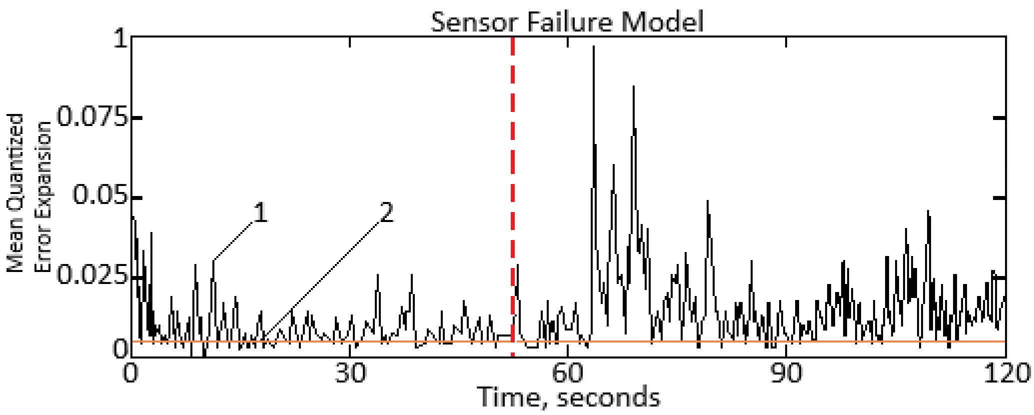


Figure 9: Diagram of the value of the performance quality indicator of helicopters TE as a diagnostic object

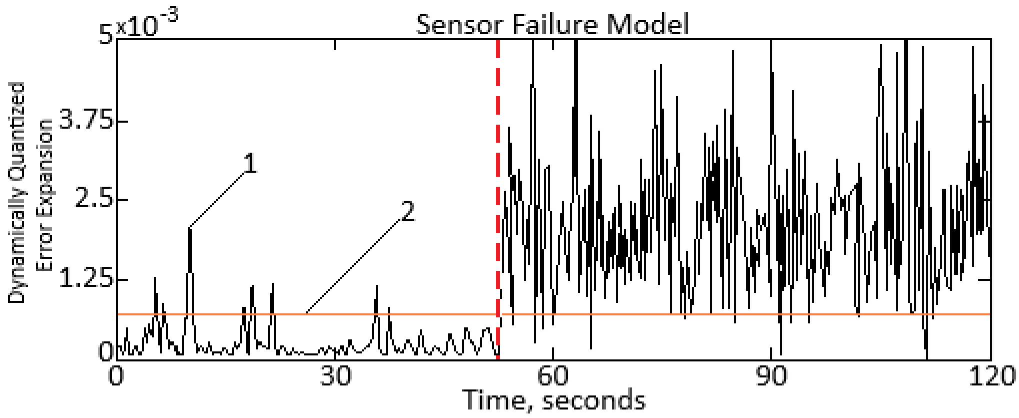


Figure 10: Diagram of the value of the performance indicator of the helicopters TE sensor gas temperature in front of the compressor turbine

Fig. 9 and 10 are shows modeling errors and the influence of noise on performance indicators. Neural network models are trained on noisy trajectories, so the influence of noise is partially suppressed by the network. To make the algorithm resistant to false positives caused by modeling errors and noise, thresholds are introduced for each neural network model according to the expression that takes into account the average value of the performance indicator and the standard deviation:

$$T = \overline{X} + k \cdot s^2, \tag{16}$$

where $\overline{X} = \frac{1}{N}\sum_{i=1}^{N} r_i$ is the sample mean; $s^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(r_i - \overline{X}\right)^2$ is the unbiased sample variance; coefficient k = 0, 1, 2, ... sets the "upper" and "lower" sensitivity thresholds [44, 45].

Since the values of the helicopters TE parameters after the occurrence of a failure and the values obtained from the neural network model of the sensor, for example, gas temperature in front of the compressor turbine, are known, the type and magnitude of the failure is determined by testing the corresponding hypothesis [46, 47].

Let's consider the detection of a "freezing" failure and a 50 % loss of efficiency by determining the current state of the engine based on the gas temperature in front of the compressor turbine. Failure occurs at t = 53 s, failure detection occurs at t = 53.2 s. Fig. 11 (1 is the T_G^* nominal values, 2 is the T_G^* values in case of sensor failure) shows the effect of failure on the norm of the cross-correlation function $R\left(S_{n_{TC}}, S_{T_G^*}\right)$. At the detection stage, the threshold value of the helicopters TE performance indicator is exceeded.

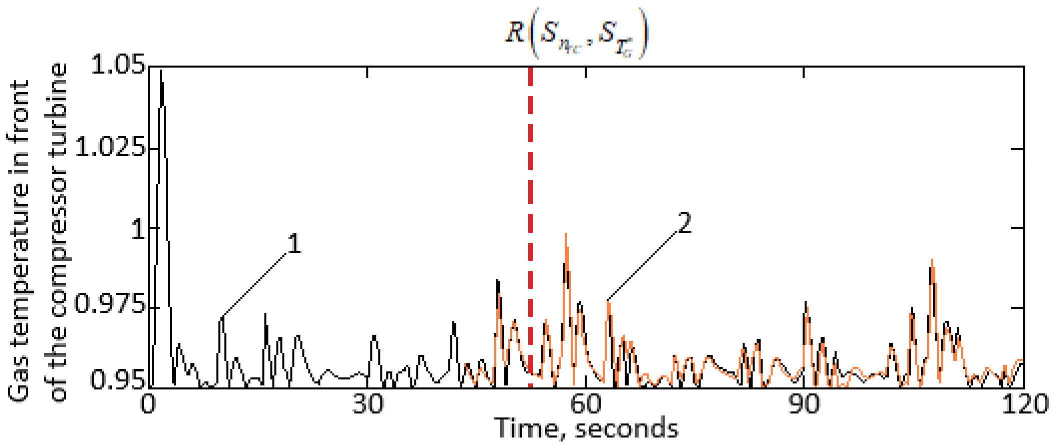


Figure 11: Diagram of the modeling result the sensor failure of helicopters TE gas temperature in front of the compressor turbine sensor failure of the cross-correlation function $R\left(S_{n_{TC}}, S_{T_G^*}\right)$

To determine the failure location, it is necessary to consider changes in the quality indicators of the functioning of neural network correlation models. Fig. 12 (1 is the indicator of quality of functioning, 2 is the threshold value) shows that the indicator of quality of functioning for the norm of cross-correlation functions exceeds the threshold value. This indicates the impact of failure on the cross-correlation functions $R\left(S_{n_{TC}}, S_{T_G^*}\right)$ and $R\left(S_{T_G^*}, S_{n_{FT}}\right)$.

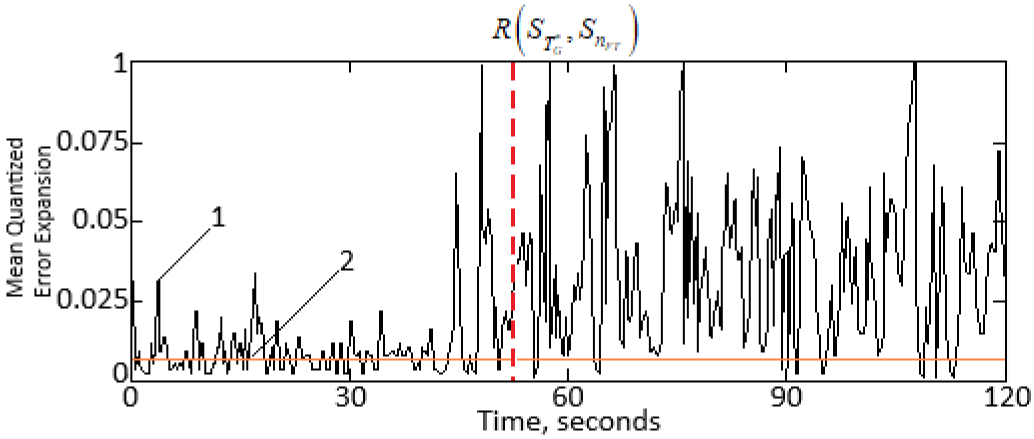


Figure 12: Diagram of the performance indicator values of the cross-correlation function $R\left(S_{n_{TC}}, S_{T_G^*}\right)$

However, Fig. 13 (1 is the performance indicator, 2 is the threshold value) shows that the autocorrelation function $R\left(S_{n_{TC}}, S_{n_{FT}}\right)$ is not affected by this failure. This allows us to determine that the failure only affects the gas temperature in front of the compressor turbine sensor.

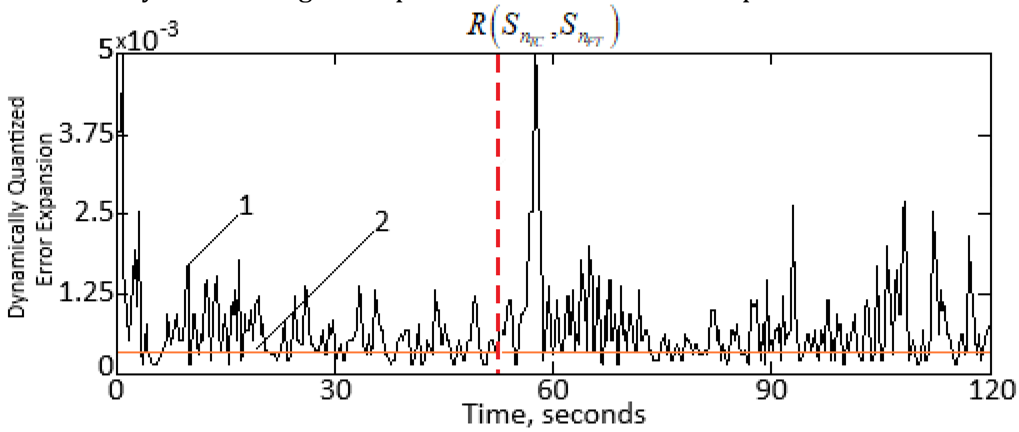


Figure 13: Diagram of the performance indicator values of the cross-correlation function $R\left(S_{T_G^*}, S_{n_{FT}}\right)$

Since the values during normal operation are specified in a Table 2, the parameters of an emergency situation are determined by testing the hypothesis about the values calculated using interpolation and obtained during a computational experiment.

6. Discussions

Tables 4–6 present a comparative evaluation of the precision of conventional and neuro-fuzzy approaches in failure classification. They illustrate the likelihoods of type 1 and type 2 errors in classifying faults, including measuring channel failure in gas temperature preceding the compressor turbine, gas generator malfunctions, and combustion chamber defects. The data provided in Tables 4–7 affirm that intelligent techniques exhibit superior effectiveness and efficiency in detecting faults within engine components and subsystems.

Table 4
The results of determining the 1st and 2nd kind errors

Controller type	The probability of error in determining the failure of the measuring channel n_{FT}	
	Type 1st error	Type 2nd error
Tolerance control	1.25	0.82
Neuro-fuzzy network ANFIS	0.43	0.26

Table 5
The results of determining the 1st and 2nd kind errors

Controller type	The probability of error in determining a gas generator defect	
	Type 1st error	Type 2nd error
Tolerance control	1.77	1.23
Neuro-fuzzy network ANFIS	0.54	0.48

Table 6
The results of determining the 1st and 2nd kind errors

Controller type	The probability of error in determining a combustion chamber defect	
	Type 1st error	Type 2nd error
Tolerance control	2.48	1.91
Neuro-fuzzy network ANFIS	0.78	0.52

Table 7
The results of determining the 1st and 2nd kind errors

Controller type	The probability of error in determining a gas temperature in front of the compressor turbine sensor failure	
	Type 1st error	Type 2nd error
Tolerance control	1.36	0.89
Neuro-fuzzy network ANFIS	0.49	0.31

To determine the reliability of the neuro-fuzzy network ANFIS method, you can use the following expressions [26]:

$$K_{error} = \frac{T_{error}}{T_0} \cdot 100\%, \tag{17}$$

$$K_{quality} = \left(1 - \frac{T_{error}}{T_0}\right) \cdot 100\%, \tag{18}$$

where K_{error}, $K_{quality}$ are the coefficients of erroneous and qualitative failure identification, respectively; T_{error} is the total time of the sections corresponding to the erroneous classification; T_0 is the duration of the test sample (in this work, T_0 = 5 s).

Table 8 shows the results of calculating the coefficients of erroneous and qualitative identification of failures and defects: gas temperature in front of the compressor turbine sensor failure, failure of the measuring channel n_{FT}, gas generator defect, combustion chamber defect.

Table 8
The results of calculating the coefficients of erroneous and qualitative

Controller type	Coefficient of erroneous, K_{error}	Coefficient of qualitative, $K_{quality}$
Gas temperature in front of the compressor turbine sensor failure	0.664	99.336
Failure of the measuring channel n_{TC}	0.676	99.324
Gas generator defect	0.673	99.327
Combustion chamber defect	0.679	99.321

As can be seen from Table 8, the coefficients of erroneous failures identification rate do not exceed 0.679 %, and the minimum coefficients of qualitative identification rate is 99.321 %.

A proposal is made to employ a neuro-fuzzy network ANFIS for helicopters TE failures utilizing a 64-bit Intel Neural Compute Stick 2 neuroprocessor. These neuroprocessors are extensively utilized in contemporary digital control systems, including aviation applications [48]. The inclusion of a multiplier-accumulator (MAC) module within the core of this microprocessor enhances algorithm calculation speed by amalgamating multiplication and addition operations with weighted summation in the neuron adder. Through experimental validation, it was substantiated that the Intel Neural Compute Stick 2 neuroprocessor is advantageous for tasks related to comprehensive monitoring and operational control of helicopters TE during flight operations. In contrast, when implementing the developed method on a 16-bit ST10F269 microcontroller from STMicroelectronics, which is commonly used in modern digital control systems, including aviation, the total code execution time for one neuron amounted to 19 microseconds, approximately 10 times greater than the calculated figure for the Intel Neural Compute Stick 2 neuroprocessor, which stood at 2.066 microseconds [20, 23].

7. Conclusions

The hybrid method of training the neuro-fuzzy network ANFIS was further developed, which, through the use of the Adam method as a gradient-based optimization algorithm, as well as the adaptive k-means clustering method for optimizing the shape of fuzzy membership functions, allowed reducing the number of training epochs from 400 to 50 to obtain the minimum standard deviation of the training error – $2.646 \cdot 10^{-4}$ using the Gaussian membership function.

An evolution system of fuzzy rules of the neuro-fuzzy network ANFIS has been developed, the use of which makes it possible to determine the sensor failure, for example, the helicopters turboshaft engine gas temperature in front of the compressor turbine, with a misidentification rate that does not exceed 0.679 %. By expanding the expert knowledge base and, accordingly, adding the number of outputs of the neuro-fuzzy network ANFIS, it is possible to identify other defects and failures of helicopters turboshaft engines.

A neural network method for helicopters turboshaft engines sensors failures identification has been developed, which is based on the use of a neuro-fuzzy network ANFIS, trained by back modified inverse gradient descent method, the use of which allows, with an accuracy higher than 99.321 %, to helicopters turboshaft engines sensors failures identification.

The technique for discerning the helicopters turboshaft engines operational status through neural network and neuro-fuzzy algorithms has undergone further refinement. This advancement enhances the diagnostic efficacy for intermittent faults, simplifies the training process, facilitates additional model refinement, and improves calculation accuracy under diverse conditions. Consequently, it enables the detection of helicopters turboshaft engines failures with a permissible error rate not surpassing 0.78 %.

The future research of investigation involves integrating the developed techniques, algorithms, and neuro-fuzzy network ANFIS method for helicopters turboshaft engines sensors failures identification into modified closed onboard helicopters turboshaft engines automatic control system [35, 36].

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