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Modified Neural Network Method for Classifying the Helicopters Turboshaft Engines Ratings at Flight Modes

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***Abstract*— This work is devoted to the modification of neural network method for classifying the helicopters turboshaft engines ratings at flight modes using neural network technologies, which, through the use of a new hybrid network of ART-1 and BAM, made it possible to improve the quality of recognition of operating modes to almost 100 %. The hybrid network ART-1 and BAM training process was modified, which made it possible to adapt the network without adding a new class and train it to recognize existing classes when the incoming data only slightly differs from those recorded in long-term memory. This makes it possible to associate non-identical data with one identifier vector, which makes it possible, when using the classifier in helicopters turboshaft engines automatic control system, to correctly respond to the presented data.**

Keywords—helicopters turboshaft engines, neural network, classifying, ratings, training

I. Introduction

Aircraft turbine engines (TE), including helicopter TE (turboshaft engine), as recoverable objects during their service life, require continuous monitoring of its current state in real time (aircraft flight), the complexity of which depends on the level of receiving processes automation, processing, storing, documenting information and intellectualization of information processing processes about the current state, the sequence and methods of implementation determine the information technology of monitoring [1, 2]. At present, the main directions that determine the improvement of the quality of information technologies for monitoring of helicopters TE technical state should be considered the intellectualization of information processing processes using methods of intelligent data analysis, including, neural networks, that can improve the quality of recognition of helicopters TE operating modes during operation, the above uncertain factors, as well as the integration of distributed local databases and knowledge into the global database and knowledge [3, 4]. Thus, the classification and recognition of the classes of states of helicopters TE are necessary to coordinate the optimal control strategy of the helicopter in the flight mode.

II. Analysis of Existing Methods of Classification and Recognition of Aircraft TE Technical State and Work Goal Formation

It is assumed that the behavior of TE as a complex dynamic object can be represented in the form of equations [5, 6]:

$$\dot{X}(t) = F\left(X(t), U(t), V(t), A(t)\right); \tag{1}$$

$$Y(t) = G\left(X(t), U(t), V(t)\right); \tag{2}$$

where $X(t)$ – vector of state variables of TE; $U(t)$ – control actions vector; $V(t)$ – external disturbing influences vector; $Y(t)$ – observed (output) coordinates vector; F, G – nonlinear vector functions. Then the main reasons for the change in the states of the TE can be considered the change in the vectors $U(t)$ and $V(t)$, the parameters of TE $A(t)$, as well as the change in the operators F and G during its operation. Fig. 1 are shows an oriented graph describing the process of changing the operating modes (classes of states) of TE [5, 6].

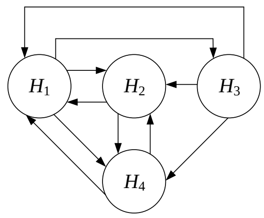


Fig. 1. Model of the process of changing the classes of GTE states: H_1 – steady-state modes class, for which $U(t)$ = const, $A(t)$ = const, $F(t)$ = const; H_2 – class of modes accompanied by a linear trend of parameters, for which $U(t)$ = const, $A(t)$ = var, $F(t)$ = var; H_3 – class of transient modes of operation (states), for which $U(t)$ = var, $A(t)$ = const, $F(t)$ = const; H_4 – class of transient operating modes for which $U(t)$ = var, $A(t)$ = var, $F(t)$ = var.

In addition to the listed (serviceable) states, a class of faulty (failure) states is distinguished, characterized by a change in the class of operators F and G in (1), (2). In this case, the classification of TE states is theoretically possible in the state space if state variables are used as classification parameters. However, components of the vector $Y(t)$, including additive random measurement noises, are available for observation. Consequently, there is a problem of determining a working set of features for constructing decision rules that are invariant to random noise of observations. Another problem of improving the quality of recognition is increasing the accuracy of determining the boundaries of classes of states of an aircraft engine. This problem is due to the fact that they significantly depend on the relationships between the dynamic parameters of the gas turbine engine (and the spectral characteristics of all types of impacts and disturbances that are random in nature and, therefore, are conditional). The main method on the basis of which the process of classifying the ratings of TE is carried out is the Bayesian approach [7]. In this case, the conditional probability is estimated

$$P\left(r_j/k\right)=\frac{P\left(r_j\right)P\left(k/r_j\right)}{\sum_{i=1}^{n}P\left(r_i\right)P\left(k/r_i\right)};\qquad(3)$$

where $P\left(r_j/k\right)$ – probability of the *j*-th diagnosis, that is, the considered dynamic regime belongs to the subset m_{rj}. Value $P\left(r_j/k\right)$ is the posterior probability, that is, it is determined after receiving information on the complex of features $k = (k_1, k_2, \ldots, k_n)$. Element $P\left(k/r_j\right)$ determines the probability of occurrence of the realized complex of features *y* of the subset m_{rj}.

The shortcoming of this method include: the need to take into account large volumes of a priori and a posteriori information about the power and spectral density of impacts, measurement errors in all ratings of TE operation; the classification is carried out only in the steady-state ratings of the TE operation; low quality of classification due to errors in the estimates of the distribution scale, caused by both unreliable a priori information about the probabilistic characteristics of classes, and errors in calculations and the proximity of the centers of recognized classes.

In [8], the quality of the classification of the operating ratings of aircraft TE is improved by increasing the compactness of the analyzed signals of each class relative to the grouping centers by choosing the type of nonlinear transformation of the space of the classified parameters. In this case, the distance between the classes changes such that the measures of the proximity of the classes in the chosen metric increase. Currently, the process of classifying the operating ratings of TE, as a rule, is carried out manually, with the participation of a highly qualified specialist, whose long and monotonous work, on the one hand, can lead to classification errors, and on the other hand, to significant time costs. To eliminate the above disadvantages, an algorithm is proposed for solving the problem of classifying the operating ratings of TE based on neural networks. It should be noted that the neural network classifier of the operation ratings of TE was developed in [5, 6], based on the reconstructed oscillogram of thermogasdynamic indicators. However, this method is limited in applicability to helicopter TE (TE with a free turbine) due to the design features of these engines. Therefore, the modernization of the method of neural network classification of operating modes of aviation TE [5, 6] is an urgent scientific and practical task.

III. Problem Statement

According to [5, 6], there is a time series formed by data sets of engines thermogasdynamic parameters $y_1(t)$, $y_2(t)$, …, $y_N(t)$, at some monitoring interval $t\in\left[t_1,t_2\right]$. It is required to select the characteristic areas of the time series corresponding to certain classes S_1, S_2, …, S_k states of helicopters aircraft GTE: $\bigcup_{\alpha=1}^{k}S_\alpha=S_0$, where S_0 – class of possible modes (serviceable states) of aircraft TE (fig. 2).

The procedure for solving this problem using a neural network is shown in fig. 2 [5, 6], where $F\left(t\right)=\left\{F_1\left(t\right),F_2\left(t\right),...,F_M\left(t\right)\right\}$ – vector of the desired output reactions of the neural network; ξ_1, …, ξ_M – neural network outputs; $\varepsilon_1(t)$, …, $\varepsilon_M(t)$ – values of the error vector at the output of the neural network. Neural network training is as follows. The "segments" of the time series are fed to the inputs of the neural network $y_1(t)$, …, $y_N(t)$, $t\in\left[t_i,t_{i+1}\right]$, belonging to known classes (operating modes) of the engine S_α, (α = 1, 2, …, *k*). The desired reactions of the neural network in each case will be the binary representation of the number of the recognized class α. For example, the code (0, 0) at the output of the neural network corresponds to the class of steady-state TE ratings, the code (0, 1) to the class of transient modes, the code (1, 0), to the class of transient modes, etc.

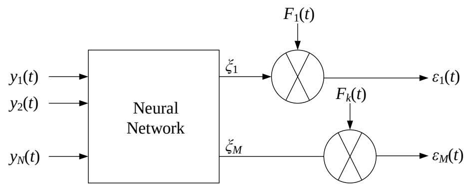


Fig. 2. Diagram of aircraft TE operating modes neural network classifier [5, 6].

The neural network training error is determined according to expression:

$$E=\sum_{i=1}^{m}\varepsilon_i^2\left(t\right)\to\min.\qquad(4)$$

The trained network, which solves the problem of recognition (classification) of the TE operating ratings, corresponds to the minimum error (4).

IV. Development of a Neural Network Classifier of Operating Modes for Helicopters TE

The main thermogasdynamic parameters of aircraft TE recorded on helicopter board are the gas generator r.p.m. n_{TC} and the temperature of the gases in front of compressor turbine T_G. According to [5, 6], the neural network classifier has the form shown in fig. 3, where Δ – time delay, Δt = 1 s. According to fig. 3, the neural network must have $2\times L$ inputs of *L* for each of the parameters: n_{TC} and T_G. The *L* parameters indicated are the measured n_{TC} and T_G parameters as well as the delayed values. The signals ξ_1 and ξ_2 are the outputs of the neural network. For the trained network, the outputs should take values F_1 and F_2 (table 1).

TABLE I. Desired Values of the Outputs of the Neural Network Classifier

Recognized Modes	Neural Network Output Signals	
	F_1	**F_2**
Constant	0	0
Racing	1	0
Throttling	0	1

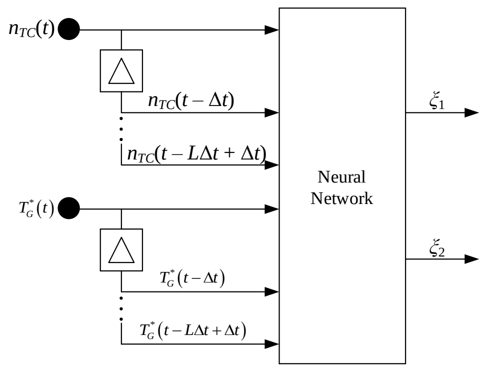


Fig. 3. Neural network classifier architecture.

To create a high-speed neural network classifier, a hybrid network has been developed, which is based on the architecture of the ART-1 neural network (adaptive resonance neural network) [9]. A distinctive feature of the new neural network classifier is that the layers of comparison and recognition, inherent in neural networks of adaptive resonance, are replaced by a two-layer network of bidirectional associative memory (BAM).

To preserve the characteristic features of the selected neural networks, the proposed hybrid network was initially limited by the following requirements:

1. For the implementation of stable-plastic memory based on the ART-1 network, it is necessary to preserve the order of the phases of search, comparison and output of the result.

2. The last phase consists either in deciding whether to belong to one of the existing classes, or in creating a new one.

3. To implement associative memory and use the advantages of the BAM network, it is necessary: presence of two layers of neural elements; interaction by means of a matrix of weights of neurons of one layer with all neurons of the second layer; limiting the duration of the process of restoring associations upon reaching either the relaxation point of the network, or a predetermined number of iterations.

From fig. 4 that the hybrid neural network classifier contains proposed architecture the characteristic features of the ART-1 and BAM networks. It consists of F_1 comparison layers and F_2 recognition layers, identical neural elements, therefore, the performance of the recognition or comparison functions is determined not by their internal structure, but only by their structural purpose.

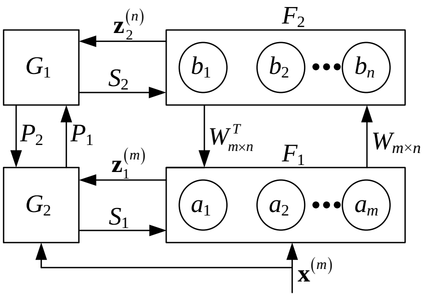


Fig. 4. Diagram of the proposed hybrid network.

It should be noted that the neurons in the layers function F_1 and F_2, as in other neural network paradigms, first finding the sum of the weighted inputs, and then calculating the value of the activation function:

$$\begin{aligned} \mathbf{a}^{(m)} &= f\left(\mathbf{b}^{(n)} W_{m\times n}\right) \\ \mathbf{b}^{(n)} &= f\left(\mathbf{a}^{(m)} W_{m\times n}^T\right) \end{aligned} \quad (5)$$

where $\mathbf{a}^{(m)}$ – vector of input neurons of the F_1 layer; $\mathbf{b}^{(n)}$ – vector of output neurons of layer F_2; $W_{m\times n}$ – matrix of weights of connections between layers F_1 and F_2; $W_{m\times n}^T$ – transposed weight matrix; $f(x)$ – neuron activation function.

The coefficients of the total weight matrix $W_{m\times n}$, which are the synaptic weights of both layers of neurons F_1 and F_2, contain long-term memory. However, at the outputs of the neurons of the F_1 layer in the values of the vector $\mathbf{a}^{(m)}$, short-term memory is realized, which is the associated images of the input vector $\mathbf{x}^{(m)}$, where m is the dimension of the input vector. Therefore, the F_1 layer is an input layer and performs a recognition function.

The second, the output layer of neurons F_2 performs the function of comparison. After a short-term supply of the values of the investigated vector $\mathbf{x}^{(m)}$ to the input of the first layer F_1, at the outputs of the neurons of the second layer F_2 in the vector $\mathbf{b}^{(n)}$, the values of the classifier vector are generated, on the basis of which a conclusion is made about the belonging of the input vector $\mathbf{x}^{(m)}$ to one or another class, where n – dimension of the output vector.

The process of restoring associations contained in memory is as follows. Long-term memory (or associations) are implemented in the weight matrices $W_{m\times n}$ and $W_{m\times n}^T$, and each image consists of two vectors: the vector $\mathbf{a}^{(m)}$, which is the output of the F_1 layer, and the vector $\mathbf{b}^{(n)}$, the associated image, which is the output of the F_2 layer. To restore the associated image, the vector $\mathbf{a}^{(m)}$ or a part of it are briefly set at the outputs of the F_1 layer. Then the vector $\mathbf{a}^{(m)}$ is removed and the network is brought to a stable state, generating the associated vector $\mathbf{b}^{(n)}$ at the output of layer F_2. Further, the resulting vector acts on the transposed matrix $W_{m\times n}^T$, as a result of which the original input vector $\mathbf{a}^{(m)}$ is reproduced at the output of the F_1 layer.

The implementation of the BAM network makes it possible to associate a large number of input multidimensional vectors with a finite number of small-sized identifier vectors. Consequently, the proposed hybrid network compares not the (most often noisy) images themselves, but their associated identifier vectors.

If the previous and actual values of the comparison layer F_2 are the same, then the block G_1 from the block G_2 receives a positive single signal P_2, otherwise it is equal to zero. If a similar situation, when the image reproduces itself, also arises with the values of the recognition layer F_1, or the limit of a predetermined number of iterations is reached, then a positive signal S_1 will be sent to the recognition layer, and a positive signal P_1 to the block G_2. Thus, with the help of positive stop signals P_1 and P_2, the pattern recognition process will be stopped and the values at the outputs of the F_1 and F_2 layers will be fixed.

Each cycle described above causes refinement of the output vectors of layers F_1 and F_2 until a point of stability in the state space of the network is reached. Therefore, in the phase space of states of the input vector, after the fifth iteration, the wandering point will become stationary. After a positive signal P_1 arrives at block G_2, the number of ones in the output vector $\mathbf{b}^{(n)}$ is counted. To simplify and automate the modes of operation and training of the hybrid network, the following encoding of the identifier vectors was used. If we make the assumption that the number of images stored in long-term memory does not exceed the number of neurons in the comparison layer F_2, then the ordinal number of the image recorded in memory will be equal to the number of the only nonzero element of the corresponding identifier vector.

If at the end of the iteration there is only one unit in the values of the vector $\mathbf{b}^{(n)}$, and all other values of the elements are equal to zero, then we will assume that the network has classified this image correctly. Otherwise, with the help of synaptic feedback $W_{m\times n}^T$, the values of the obtained vector will be fed to the inputs of the recognition layer F_1, at the outputs of which changes in short-term memory will be observed.

In turn, the resulting image through direct connections $W_{m\times n}$ will affect the inputs of the comparison layer F_2. After defining a new vector-identifier in block G_1, control will be made again for the presence and position of units in the vector. If the number of iterations exceeds the predetermined number, then a positive signal S_2 will be sent to the comparison layer F_2, which will allow the addition of new data.

In the course of the experiments carried out aimed at improving the performance of the BAM network, a number of proposals were put forward and implemented, concerning both the presentation of the output values of neurons and the modification of the training process.

1. In the expression for the activation function of BAM neurons $f\left(x_{t+1}\right)=\begin{cases}1 & \text{, if } x_{t+1}>0\\ f\left(x_t\right) & \text{, if } x_{t+1}=0\\ -1 & \text{, if } x_{t+1}<0\end{cases}$ [9], which proved itself well in the course of experiments, the static activation threshold, equal to zero, was replaced by the dynamic T_t, which is calculated for each iteration separately:

$$T_{t+1}=\frac{\max\left(x_t\right)+\min\left(x_t\right)}{2}; \tag{6}$$

where $\max(x_t)$ и $\min(x_t)$ – maximum and minimum values of the short-term memory stored in the values of the elements of the vectors $\mathbf{a}^{(m)}$ and $\mathbf{b}^{(n)}$ after the t-th iteration.

2. Also in the process of work, good results were obtained by using bipolar encoding of vectors $\mathbf{a}^{(m)}$ and $\mathbf{b}^{(n)}$ not only for training, but also for pattern recognition, that is, vectors take values only "+1" or "–1" ... Taking into account the previous point, the above expression of the activation function of BAM neurons [9] takes the following form:

$$f\left(x_{t+1}\right)=\begin{cases}+1, \text{ if } x_{t+1}\ge T_{t+1}\\ -1, \text{ if } x_{t+1}<T_{t+1}\end{cases} \tag{7}$$

3. After calculating the output signal of layer F_1 in (5), two-dimensional filtering was added in the plane of the input data. The filtering consisted in averaging the values of the outputs of neurons among their four neighbors (except for the outermost neurons). This avoids an abnormal increase in the values of the activity of individual neurons. Fig. 5 shows a graphical interpretation of the influence of connections of neighboring neurons on each other. If we convolve the vector $\mathbf{a}^{(m)}$ into a two-dimensional matrix $A_{a\times b}$ with dimensions a and b corresponding to the input images, then the value of an individual neuron $A_{i,j}$ will be determined by the expression:

$$A_{i,j}^{t+1}=A_{i,j}^{t}+A_{i+1,j}^{t}+A_{i,j+1}^{t}+A_{i-1,j}^{t}+A_{i,j-1}^{t}. \tag{8}$$

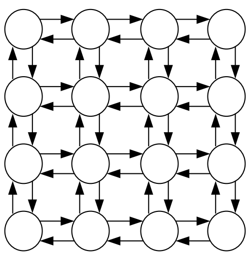


Fig. 5. Diagram of directions of influence of neighboring neurons on each other.

As a result, if among neurons with negative values there is a neuron with an abnormal positive value, its value, i.e., its own influence on neighboring neurons, decreases.

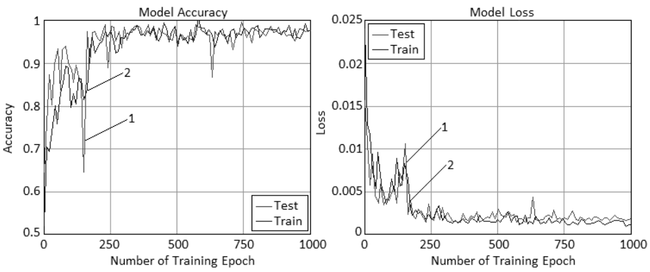
4. An attempt was also made in this work to give the BAM network adaptive properties. The adaptive network must change its weights in the course of its operation in order to more flexible recognition. This means that feeding a training set of input vectors to the input of the network makes it change the energy state until a resonance is obtained. Gradually, short-term memory in the process of network functioning by adjusting the coefficients of the weight matrix should turn into long-term memory.

5. In computational experiments, to correct the weight matrix, Hubb's rule was used [10], in which the change in weight is proportional to the level of activation of its source neuron and the level of activation of the receiver neuron:

$$\Delta\omega_{ij}=\eta a_i b_j; \tag{9}$$

where $\Delta\omega_{ij}$ – changing the connection of the i-th neuron of the vector $\mathbf{a}^{(m)}$ with the j-th neuron of the vector $\mathbf{b}^{(n)}$ in matrices $W_{m\times n}$ and $W_{m\times n}^{T}$; η – positive normalizing learning factor less than one.

This method allows adapting the network without adding a new class and training (fig. 6) it to recognize already existing classes, when the incoming data only slightly differs from those recorded in the long-term memory. Thanks to the new architecture and the listed modifications, the recognition process of the neural network classifier has become more adaptive. By adaptability we mean not only resistance to noise and the choice of a similarity criterion for determining characteristic features, but also the presence of supervised training. The latter allows non-identical data to be associated with one identifier vector, which makes it possible, when using the classifier in the control system of helicopters TE, to correctly respond to the presented data.



a b

Fig. 6. Neural network classifier training results (1 – test; 2 – train): a – *Accuracy* indicator; b – *Loss* indicator

Obviously, the small size of the "window" width will not allow to correctly recognize the ratings of helicopters TE, and the large size of the "window" width L will cover neighboring classes, which will reduce the probability of recognition of modes. The dependence of neural network training error at the output on the size of the time window is shown in fig. 7, *a*. In this case, function (7) was used as the activation function, and the number of neurons in the comparison layer F_1 was taken equal to 35. Similar studies were carried out in order to select the optimal number of neurons in the hidden layer. At the same time, it was taken into account that a small number of them leads to poor-quality training of the neural network, and a large number leads to the effect of retraining of the neural network [11]. In fig. 7, *b* shows the dependence of the training error of the hybrid neural network on the number of neurons in the comparison layer F_1.

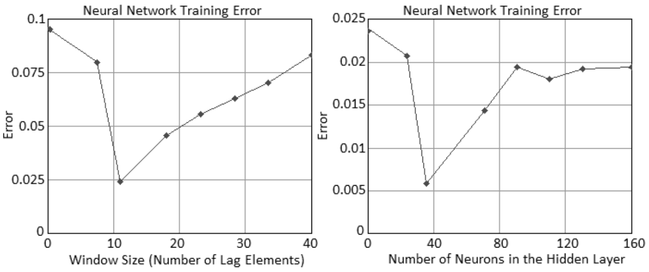


Fig. 7. Dependence of the neural network training error: *a* – on the width of the time window; *b* – on the complexity of the neural network.

When hybrid neural network training, the value of the "window" width L = 10 was taken, which corresponds to 2 × L = 20 inputs of the neural network. Analysis of fig. 7 shows that when solving the problem of classifying (recognizing) the ratings of helicopters TE, it is sufficient to take the width of the time window equal to 8...12, and the number of neurons in the hidden layer 35...45.

V. Results and Discussion

Let us consider an algorithm for solving this problem using the example of data recorded on board a Mi-8MTV helicopter for the TV3-117 TE. A fragment of the reconstructed oscillogram of the thermogasdynamic processes of the gas turbine engine is shown in fig. 8, where a six-minute flight interval of a helicopter with a twin-engine power plant is highlighted. It is assumed that the following are the recognized operating modes of the engine: I – constant mode; II – acceleration mode; III – throttling mode.

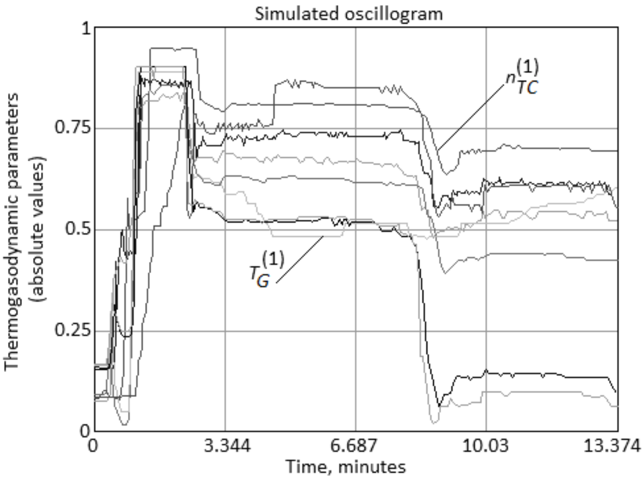


Fig. 8. Fragment of the digitized oscillogram of the thermogasdynamic indicators of TV3-117 aircraft TE, recorded on board the Mi-8MTV helicopter.

The main feature by which the selection of "reference" sections of the time series is made when constructing a training sample of a neural network is the position of the engine separate throttle control lever (*ESPL*). In what follows, from the general group of thermogasdynamic parameters shown on the oscillogram, we will consider those of them that relate to the first TE (N = 1): gas generator r.p.m. $n_{TC}^{(1)}$ and temperature of the gases in front of the compressor turbine $T_G^{(1)}$. These data, together with the time coordinate t, form the input vector $y(t) = \left\{n_{TC}^{(1)}, T_G^{(1)}\right\}$, where $t \in [7.268;\, 13.374]$.

In the process of working with the oscillogram (fig. 8), a training interval $T_{train} \in [7.268\,\text{min}; 13.374\,\text{min}]$ corresponding to two minutes was allocated, within which there are the following modes: overclocking mode: t_1 = 7.268 min; t_2 = 7.318 min; constant (0.8 nominal) mode: t_2 = 7.318 min; t_3 = 8.268 min; throttling mode: t_3 = 8.268 min; t_4 = 8.308 min. The data was taken every second, so the training sample contained 120 time samples. At the same time, the acceleration and throttling modes accounted for only five readings. The total observation interval was six minutes (360 time counts).

When solving the problem of classifying TE rating using a neural network, the classification process is carried out in a time window. For a qualitative classification, the width of the time window must be at least five counts in order to recognize the classes of TE technical states.

According to [5, 6], the preliminary processing of the input data includes the normalization of each of the above engine parameters $y_i(t)$ according to the expression:

$$y_i = \frac{y_i - y_{i\min}}{y_{i\max} - y_{i\min}}; \tag{10}$$

where y_i – dimensionless quantity, which is in the range [0; 1]; $y_{i\min}$ and $y_{i\max}$ – minimum and maximum value y_i.

To recognize of TE ratings (classes of states) of the neural network, it is necessary to select from the values of the time series of observations the readings that, within the time window $\Delta y_i(t)$, correspond to the steady-state rating of TE. This is done by subtracting the average value (moving average), within the time window, over the entire interval $t \in [t_1;\, t_2]$, since $\Delta y_i(t)$ in the constant operating mode it is identically equal to zero, and in other ratings of TE operation it is different from zero:

$$\Delta y_i(t) = y_i - \frac{\sum_{i=0}^{L-1} y_i}{L}; \tag{11}$$

where L – width of the "window", while the optimal size of the time window is in the process of experimental research.

After the neural network training process on the training interval (33 % of the sample), it is necessary to check the efficiency of its work on the test sample, which is 67 % of the entire sample size. From fig. 9 can be seen, the reference values of the outputs of the neural network take on the values 0 or 1, and the actual signals at the output of the neural network (due to the inertia of the process of moving the time ("window") can take continuous values in the interval [0; 1]. Therefore, it is necessary to round off the calculated values ξ_1 and ξ_2 to the nearest integer:

$$\overline{\xi_i} = \begin{cases} 0, \text{ if } \xi_i \le 0.5; \\ 1, \text{ if } \xi_i > 0.5. \end{cases} \tag{12}$$

In this case, errors of the I and II kind may occur, that is, the assignment of the state S_i to the class S_j. To determine the reliability of the classification, you can use the following expressions:

$$K_{error} = \frac{T_{error}}{T_0} \cdot 100\%; \tag{13}$$

$$K_{quality} = \left(1 - \frac{T_{error}}{T_0}\right) \cdot 100\%; \qquad (14)$$

where K_{error}, $K_{quality}$ – misclassification and quality factors; T_{error} – cumulative time of areas corresponding to misclassification; T_0 – duration of the test sample (in this case T_0 = 4.0 min).

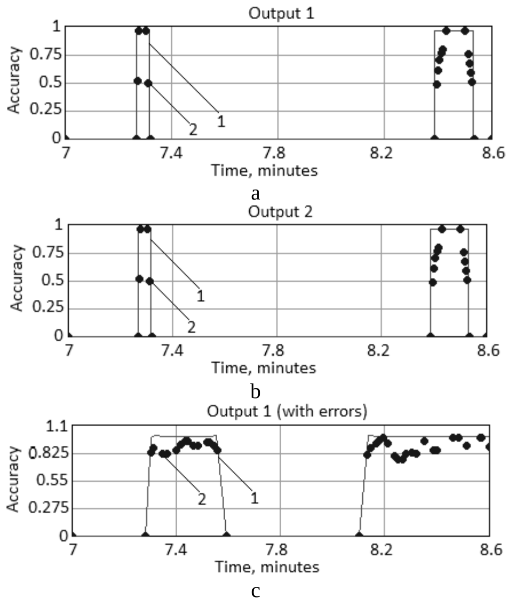


Fig. 9. Classification diagram of the operating ratings of TV3-117 aircraft TE (1 – etalon; 2 – proposed hybrid network): a – 1st exit (n_{TC}); b – 2nd exit (T_G); c – 1st exit (n_{TC}) taking into account errors

Tables 2 and 3 show the results of a comparative analysis of classification errors and the quality of classification of TE ratings for different classes of neural network architectures.

TABLE II. MODE CLASSIFICATION ERRORS FOR DIFFERENT NEURAL NETWORK ARCHITECTURES, %

Neural Network Architecture	**Output 1 classification error n_{TC} (ε_1)**	**Output 2 classification error T_G (ε_2)**
Proposed hybrid network	0.1812	0.0733
Multilayer perceptron	0.4131	0.1322
Elman network	0.3611	0.1681
Hamming network	0.4133	0.2988
Radial-Basic Functions network	0.4772	0.7891
Hopfield network	0.4258	0.2654
Kohonen self-organized map	0.4683	0.2913
Adaptive resonance network	0.5117	0.8409
Vector signal quantization networks	0.5532	0.9176

TABLE III. QUALITY COEFFICIENT OF CLASSIFICATION OF MODES FOR DIFFERENT ARCHITECTURES OF NEURAL NETWORKS, %

Neural Network Architecture	**Output 1 n_{TC} (ε_1)**	**Output 2 T_G (ε_2)**
Proposed hybrid network	99.99	99.99
Multilayer perceptron	99.96	99.99
Elman network	99.96	99.98
Hamming network	99.95	99.97
Radial-Basic Functions network	99.95	99.92
Hopfield network	99.95	99.94
Kohonen self-organized map	99.96	99.92
Adaptive resonance network	99.94	99.87
Vector signal quantization networks	99.95	99.96

CONCLUSIONS

Solving the problem of classifying the helicopters turboshaft engines ratings at flight modes in the neural network basis allows to solve this problem more efficiently and operatively with less time and computing resources. To solve this problem, it is proposed to use a hybrid neural network based on the ART-1 and BAM networks, which makes it possible to add new data classes to long-term memory without deleting those already stored. Analysis of the quality of classifying the helicopters turboshaft engines ratings using a neural network based on data obtained in flight modes shows that the quality of recognition of their operating modes is almost 100 %, and the recognition error in this example did not exceed 0.18 % in the test sample.

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