Modified Neural Network Method for Trend Analysis of Helicopter Turboshaft Engine Parameters at Flight Modes

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Abstract

The article discusses the use of expert systems with neural network knowledge bases for the process of helicopters turboshaft engine parameters at flight modes information monitoring. The method for determining the trend of aircraft gas turbine engine parameters based on neural networks, adapted to helicopters turboshaft engines that implement the dynamic knowledge base of an expert system during engine operation, has been further developed. A modified Jordan neural network with dynamic stack memory has been developed, which, through the use of dynamic stack memory, makes it possible to detect the appearance of a trend in the parameters of helicopters turboshaft engines at flight modes, increase the accuracy to 0.999 and reduce the trend recognition error to 0.056. A hybrid algorithm consisting of adaptive and genetic training of recurrent neural networks has been improved, adapted to Jordan modified neural network with dynamic stack memory, which made it possible to optimize its training process in relation to the problem of helicopters turboshaft engines at flight modes parameters trend recognizing. The modified method for determining the trend of parameters has been tested in the onboard neural network expert system for the integrated monitoring of helicopters turboshaft engines operational status.

Keywords [1]

Aircraft engine, expert system, neural network, operational status, modified Jordan neural network, trend analysis

1. Introduction

The process of monitoring and aircraft gas turbine engines (GTE) operation control is carried out by expert systems (ES) [1, 2]. The use of it allows taking into account a number of factors that contribute to the qualitative improvement of their functioning [3, 4]. The presence of close information interaction of the control system (aircraft GTE) with the environment using specially organized information communication channels; fundamental openness of the system in order to increase its intelligence and improve its own behavior. The presence of mechanisms for predicting changes in the environment and the behavior of the system; development a control system based on a multi-level hierarchical structure. It satisfies the following rule: as the rank of the hierarchy increases, the intelligence of the system increases and the requirements for its accuracy decrease, and vice versa; persistence of functioning in case of partial rupture of links or loss of control actions from higher levels of the hierarchy of the control system. Despite the weighty evidence base of the relevance of the use of ES in aircraft GTE on-board monitoring systems [5, 6], there are currently no such ES in relation to helicopters turboshaft engines (TE).

Thus, an urgent scientific and practical task is the development of an on-board ES for monitoring helicopters TE operational status, which, in the process of monitoring and their operation control, is able to fully control the parameters, analyze (simulate) the current situation with a predict of its development in the engine (information from sensors).

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One of the classic tasks of monitoring the parameters of helicopters TE is the disorder (determining the trend of controlled data). In the general case, trend analysis allows you to control the time series formed by the sequence of values of controlled indicators, and determine the presence of a trend: changes (disorder) in this series. The value of trend analysis in modern active ES is very high, as it allows you to identify defects at an early stage of their development (even if the values of the controlled parameters are within acceptable limits).

In connection with the foregoing, the purpose of this work is to develop and modify methods for determining the trend of controlled data (trend analysis) of helicopters TE, which will be part of monitoring helicopters TE operational status onboard ES.

2. Literature review

Under the current conditions, along with the traditional classification of ES: static and dynamic, recently, in domestic and foreign periodicals, a class has been distinguished – active ES [7, 8]. From dynamic ES (real-time ES – RT ES), active ES differ in the participation of the human factor in the control loop. So, if in RT ES the share of a human operator in the decision-making process can be 30... 50 %, then in active ES this percentage of participation is reduced to a minimum of 5...10 % or completely eliminated [9].

It is quite obvious that with such an approach to the organization of active ES and its implementation in the management process, it is necessary to take into account a number of factors that contribute to the qualitative improvement of its functioning [10, 11]:

– presence of close information interaction of the control system with the environment using specially organized information communication channels;

– fundamental openness of the system in order to increase its intelligence and improve its own behavior;

– presence of mechanisms for predicting changes in the environment and the behavior of the system;

– construction of a control system based on a multilevel hierarchical structure that satisfies the following rule: as the rank of the hierarchy increases, the intelligence of the system increases and the requirements for its accuracy decrease, and vice versa;

– persistence of functioning in case of partial breakage of connections or loss of control actions from the highest levels of the hierarchy of the control system.

Thus, the developed ES should be easily reconfigurable (adaptable) to external changes, for which it requires the presence of the following subordinate levels [12]: training, self-organization (restructuring), predicting (recognition) of events (situations), working with event databases (databases) (DB) and knowledge bases (KB), decision making (DM); planning operations for the implementation of the formed solution, adaptation.

The listed levels form the strategic level of the active ES (fig. 1), the rest perform its tactical functions. The solver (logical output machine) of an active ES is complex. It is with known methods and knowledge (logic of predicates, semantic networks, frames, production output). The methods based on soft computing (fuzzy logic (FL), genetic algorithms (GA), neural networks (NN), cognitive networks (CN), probabilistic output (PO) – heuristics). The combination of methods and their extension with elements of soft computing increases the mobility of the computational process by the active ES solver and as a result, the quality of the decisions making with the connection to the planning of banks of algorithms and models. Having a powerful solver, the active ES is relatively easy to adapt to an external dynamic model, allowing you to set and solve direct, inverse and mixed problems. In the process of monitoring and operation control of helicopters turboshaft engines at flight modes, the ES is able to fully control the parameters, analyze (simulate) the current situation with a predict of its development in the engine (information from sensors).

Active ES knowledge bases store declarative and procedural knowledge. Procedural ones include conceptual knowledge bases (CKB): concepts in the form of formulas, dependencies, tables, procedures, etc. Declarative ones include expert knowledge bases (EKB) that are descriptive (qualitative) in nature. At the same time, CKB and EKB closely interact with each other, constantly checking for consistency (redundancy) of knowledge. In the process of interaction with the object and its own heterogeneous KB, the active ES performs training and self-training. Real-time scanning tests facts and knowledge. The new situation "forms" a precedent and is stored in the knowledge base. Elements of traditional modeling tools in the active ES carry out mathematical (simulation) modeling of the engine, as well as storage of a priori and a posteriori data in the active ES database (initial information and test results). Additional "flexibility" and mobility of the knowledge base in the active ES is achieved by pairing the artificial intelligence models and the mathematical model (MM) of the engine [11, 12].

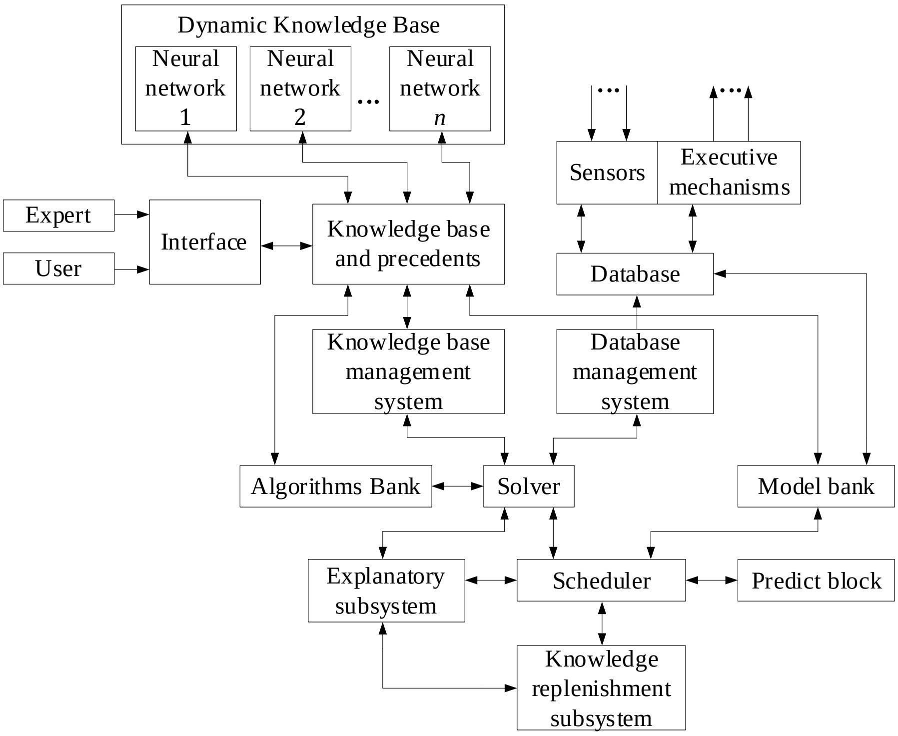


Figure 1: Generalized functional diagram of an active ES

During the operation of helicopter TE, the active ES connected to it allows real-time modeling, forecasting and evaluation of the efficiency of helicopter power plant.

3. Formulation of the problem

It is assumed that $x(t)$, $t = 1\ldots N$ is a sequence of discrete observations $x(t) = f(t) + \xi(t)$ in the background of interference $\xi(t)$ with zero mean and variance σ^2. A set of polynomials are used as trend models according to [13]

$$f(t) = \sum_{s=0}^{j-1} c_{sj} t^s, \; j = 1\ldots N; \tag{1}$$

with unknown coefficients c_{sj}, where j – model type index.

With the current estimation, model (1) according to [13] is represented as

$$f_j(t+\Delta t) = \sum_{s=0}^{j-1} f_j^{(s)}(t) \cdot \frac{\Delta t^s}{s!}; \tag{2}$$

where Δt – time counted from the present moment of time. $f_j^{(s)}(t)$ – s-th derivative of the function $f_j(t)$, the values of which are determined by the sliding $x(t - N + 1)$, $x(t - N + 2)$, ..., $x(t)$ observations sample of a constant volume N, which makes it possible to track the change in the coefficients c_{sj} of the model (1). Regular data correspond to the presence of a certain regularity, the violation of which occurs when the coefficients change c_{sj} in (1).

The task of this work research is to construct a neural network detector (dynamic knowledge base of an active ES), which allows, as a result of the observations $x(t)$ processing, to establish the facts of violation of the regularity and the time of these violations (trends) appearance.

At the same time, the KB of the active ES stores the following information:

– assessment of the randomness of the discrepancy between the given mathematical expectation and the sampling mean (parametric methods that require knowledge of a priori information about the helicopter TE), usually the standard deviation of the parameter under study);

– assessment of the belonging of two samples to the same general population (non-parametric methods that do not require a priori information, classical criteria: Hald-Abbe and its modifications [14]);

– trend analysis of controlled parameters based on neural networks.

An important task in the process of analyzing experimental data, which reflects the recognition of the “appearance” of helicopters TE, is to determine the discord in the measured parameters of the time series, i.e. analysis of statistical characteristics of the results of registration of controlled parameters in order to determine their stationarity. The main task of trend analysis is to identify regularity in a sequence of data. The most complete description of trend detection methods is given at [14], among which the most common "classical" methods of trend analysis are: parametric, non-parametric and mixed methods. Of the parametric methods, according to [13], an integral criterion is used, which consists in the following sequence of operations:

– preliminary processing of the numerical series (measurement data) $\{Y_1, ..., Y_N\}$ is carried out in order to convert it to a form convenient for subsequent evaluation;

– logic and physics of the process is analyzed, which has a significant impact on both the choice of the type of approximating function and the determination of the limits of its parameters.

Preliminary processing of the initial number series within the time interval $T \in [t_1,...,t_N]$ is aimed at reducing the influence of the random component $\varepsilon(t)$ in the initial number series $\{Y_1, ..., Y_N\}$ (i.e., bringing it closer to the trend). The presentation of the information contained in the numerical series in such a way as to significantly reduce the difficulties of the analytical description of the trend.

The main methods for solving these problems are the procedures for smoothing and leveling the statistical series. In this case, the smoothing procedure is aimed at minimizing random deviations of points from some smooth curve of the assumed process trend. Smoothing is performed using polynomials that approximate groups of points measured during the experiment using the least squares method (LSM). Even in a simple linear version, the smoothing procedure is very effective in identifying a trend when superimposed on an empirical numerical series of random interference and measurement errors. If smoothing is aimed at the primary processing of a number series to eliminate random fluctuations and identify a trend, then alignment serves the purpose of a more convenient presentation of the original series while maintaining its values. In the simplest case, this procedure can be carried out by approximating the initial series of processed experimental points.

The choice as the criterion of optimality of the measure of the deviation of the points of the empirical series from the approximating function is carried out according to the expression (LSM):

$$\sum_{j=1}^{N}\left(Y_j - \eta\left(t_j, \alpha_1, ..., \alpha_N\right)\right)^2 \to \min; \tag{3}$$

where Y_j – points of the empirical series (measured values); η – approximating function; t_j – time component; $\alpha_1 \ldots \alpha_N$ – approximated points.

According to [13], the following functionals are used as one of the integral criteria for evaluating the trend:

$$\delta = \sum_{j=1}^{N}\frac{Y_j - Y_n(j)}{Y_n(j)}; \tag{4}$$

Where Y_j – experimental data, $j = \overline{1, N}$; $Y_n(j)$ – data calculated by the model; N – number of points measured during the experiment; δ – trend estimate.

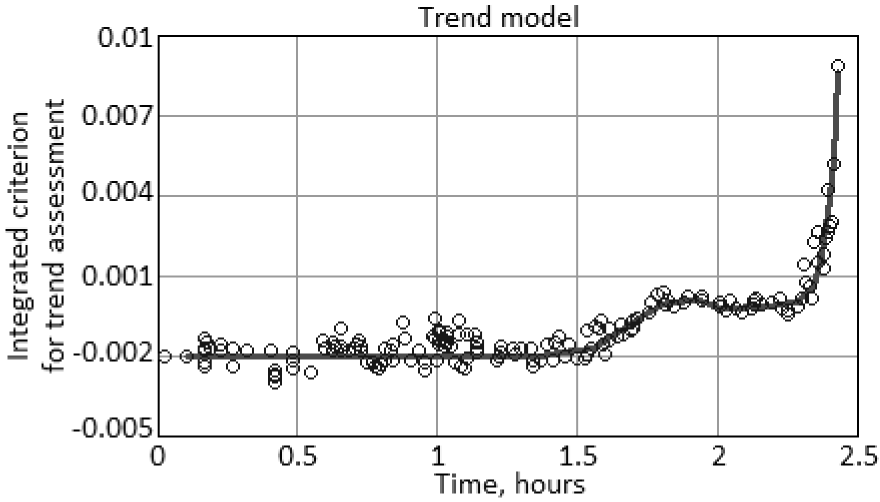
The application of this criterion (4) in the process of evaluating experimental data is shown in fig. 2*a*. In fig. 2*a* four characteristic sections can be distinguished: I – from 0 to 1.5 hours; II – from 1.5 to 1.75 hours; III – from 1.75 to 2.25 hours; IV – from 2.25 to 2.5 hours of engine operation. The trend is absent in sections I and III, but is evident in sections II and IV. In fig. 2*a* four characteristic sections can also be observed: I – from 0 to 1.5 hours; II – from 1.5 to 2.05 hours; III – from 2.05 to 2.25 hours; IV – from

2.25 to 2.5 hours of engine operation. It is obvious that the trend is absent only in the first run-in section, and in the other three there is a noticeable tendency to change the gas temperature in front of the compressor turbine, that is, the presence of a trend. At the same time, if only in the second section the temperature rises slowly, then in the third and fourth its change has a clearly expressed character.

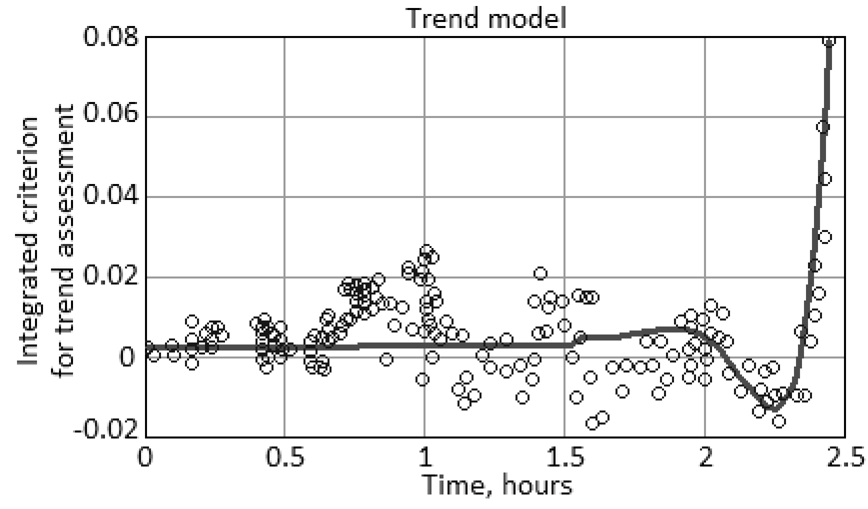
Another integral criterion for evaluating the trend is a functional of the form [13]:

$$\delta = \sum_{j=1}^{N} \left(\frac{Y_j - Y_n(j)}{Y_n(j)} \right)^2. \tag{5}$$

The application of criterion (5) in the process of analyzing the gas generator rotor r.p.m. is shown in fig. 2*b*, where four characteristic sections are also visible: I – from 0 to 0.35 h; II – from 0.35 to 1.75 hours; III – from 1.75 to 2.25 hours; IV – from 2.25 to 2.5 hours of operation of the helicopter control systems (HCS). The first area of work is characterized as part-time work; the second area of the normal period of operation; the third and fourth are areas of intensive wear and aging.



a



b

Figure 2: Trend analysis: *a* – gas temperature in front of the compressor turbine; *b* – gas generator rotor r.p.m.

In the process of studying the trend by classical methods, it can be concluded that the "classic" integral criteria are very effective in express analysis, have accuracy, clarity and are able to determine with a high degree of certainty the moment the trend begins to appear. However, in order to apply these criteria in the onboard (expert) system for monitoring helicopters TE, it is necessary to develop an appropriate method.

4. Neural network development

Among the numerous methods of trend analysis, the following are noted [14, 15]: the linear filtering method, the Kalman filter, extrapolation methods, which are most simply implemented in a neural network basis, since they are based on smoothing and equalizing statistical series procedures.

Smoothing and equalization procedures can be implemented on the basis of neural networks in the form of two series-connected filters – low frequency (LF) and high frequency (HF), while in [13] their implementation based on recurrent neural networks was proposed. In this case, the low-pass filter "passes" the constant component $f_j(t)$ and filters the noise $\xi(t)$, and the high-pass filter passes $f_j^{(s)}(t)$ and filters $f_j(t)$ and the noise $\xi(t)$. Implementation of low-pass and high-pass filters based on recurrent neural networks is shown in fig. 3. These options differ in that they are implemented by the corresponding external filters. The structure of the external filter is shown in fig. 4.

It is known from the theory of neural networks [16, 17] those static architectures of neural networks are capable of approximating multidimensional, non-linear static functions. The identification of dynamic systems, on the other hand, requires a model with appropriate storage elements. Therefore, static full-sized neural networks should be extended with dynamic structures. One of the possibilities of dynamic extension is the addition of external filters that implement a dynamic model outside the network. Such neural networks with external dynamics include [18, 19]:

– non-linear models with output feedback;
– non-linear models with finite impulse response;
– non-linear orthogonal models of basic functions.

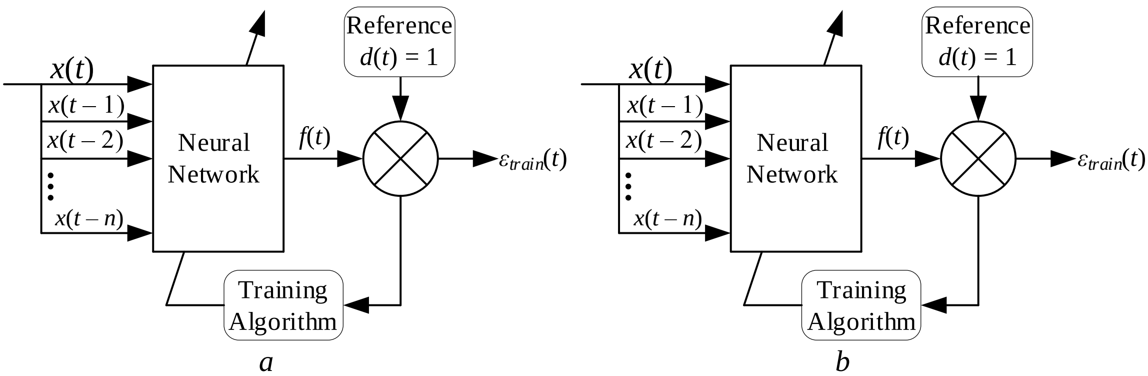


Figure 3: Implementation of filters based on recurrent neural networks: a – low frequency filter; b – high frequency filter [13]

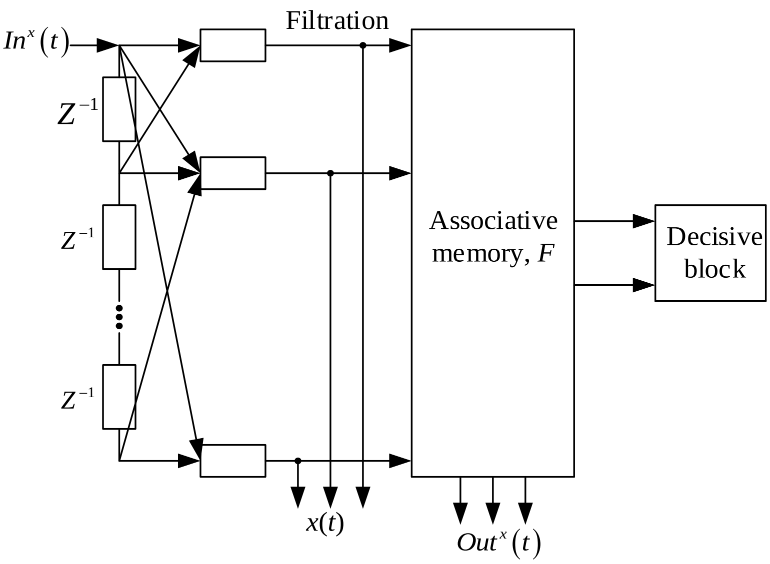


Figure 4: External filter diagram [13]

During preprocessing, it is considered that the functions $f(t)$ and $\xi(t)$ are not correlated. It is required that the vector $Out^x(t)$ of the output values of the filter $Out_l^x(t)$, $l=\overline{1,N}$, which is a response to an external influence, approaches the desired function of the useful signal:

$$Out^x(t) \approx Ff(t); \tag{6}$$

where $F = (F_l)$ is some vector operator that describes the mapping of the set of useful signals into the output signals of the filter [20, 21].

As a measure of approximation $Out^x(t)$ to $Ff(t)$ in the general case, one can choose the functional:

$$J = J\left\{\varphi\left(Ff(t) - Out^x(t)\right)\right\}; \tag{7}$$

where $\varphi[\bullet]$ – some measure of a vector function.

In the simplest case [20, 21] (fig. 2), the input signal is applied to a set of serially connected functional elements with a delay Z^{-1} (in synapses). Their input values are represented as signals $In^x(t - kZ^{-1})$, $k = 1, N$ with weights W_{jk}, forming a vector of estimates of useful signals $(x_j(t))$, on the basis of which, with the help of a network that implements the matrix of operators (F_{lj}), a vector of output signals is formed:

$$Out_l^x(t) = F_{lj}\left(\sum_k W_{jk} In^x\left(t - kZ^{-1}\right)\right). \tag{8}$$

The task of filtering is to reproduce the useful signal against the background of noise and perform the required transformation. To solve this problem, it is necessary to minimize the standard deviation of the estimate of the useful signal $x_j(t)$ from the expected j – useful signal $f_j(t)$, characterizing the corresponding useful result of the neural network filter, i.e. find:

$$\min_{W_{jk}} M\left\{\sum_j\left(f_j(t) - \sum_k W_{jk} In^x\left(t - kZ^{-1}\right)\right)^2\right\}; \tag{9}$$

where M – mathematical expectation.

According to this criterion, classical filter adaptation algorithms can be implemented using a priori information about the useful signal and noise.

To solve the given problem, Professor Serhii Zhernakov [22] proposed to use a perceptron as a dynamic (recurrent) neural network that implements a low frequency filter; for high frequency filter – RBF (radial basis function) neural network. Ensemble neural network learning algorithm – complex back propagation.

A signal having N samples $x = (x_1, \ldots, x_n)$ can be approximated by a neural network with G neurons in the hidden layer by the following equations:

– for perceptron:

$$f(t) = \sum_{i=0}^{G} W_i^0 q\left(\overline{W_i^{(h)}}^T \bar{t}\right); \tag{10}$$

– for RBF:

$$f(t) = \sum_{i=0}^{G} W_i^0 R_i\left(\bar{t}, \overline{W_i^{(h)}}\right); \tag{11}$$

where $q(\bullet)$ – different types of multilayer perceptron basis functions that have a scalar argument (the original N-dimensional approximation problem is decomposed by weight superposition into simple scalar basis functions. The compression of the N-dimensional input space to a one-dimensional input $f(\bullet)$ is carried out by means of a scalar products $\overline{W_i^{(h)}}^T \bar{t}$); $R(\bullet)$ – weighted basis functions of the RBF (each basis function is implemented by a separate neuron).

In order to carry out helicopters TE parameters trend analysis at flight modes, that is, in real time, it is proposed to use a recurrent neural network with a dynamic stack memory, built on the basis of the Jordan neural network, the basis of which is a multilayer perceptron. Feedback is implemented by supplying to the input layer not only output data, but also network output signals with a delay of one or more cycles, which allows you to take into account the background history of the observed processes and accumulate information to develop the correct control strategy. Jordan's modified neural network is obtained by adding a delay to the feedback signals of the hidden layer by several cycles, that is, by adding a dynamic stack memory to the layer [23, 24].

The outputs of the hidden layer c_1, c_2, …, c_k are fed to the input neurons with weighting coefficients $\{w_{ij}\}^{-t}$, where i – index of the neuron to which the signal is given (i = 1, 2, …, n); j – index of the output signal of the hidden layer neuron (j = 1, 2, ..., k); t – time delay index (t = 1, 2, ..., m). We will change the number of time delays from 1 to m. Thus, the Elman network is obtained at m = 1, and the multilayer perceptron is obtained at m = 0. A detailed examination of the architecture of the neural network (fig. 5) shows that the inverse of the hidden layer or the output of the network can be excluded by adding signals to the training sample feedback.

Jordan modified neural network is described by a system of recurrent equations:

$$v_j(n+1)=\sum_{i=1}^{p} w_{ji}^{(1)} u_i(n)+\sum_{i=1}^{N} w_{ji}^{c} y_i(n)+\alpha y_i(n-1)+b_j^{(1)}; \tag{12}$$

$$x_j(n+1)=F_1\left(v_j(n+1)\right);\ j=1,2,\ldots,N; \tag{13}$$

$$y_j(n+1)=F_2\left(\sum_{i=1}^{N} w_{ji}^{(2)} x_i(n+1)+b_j^{(2)}\right);\ j=1,2,\ldots,M; \tag{14}$$

or in matrix form:

$$\mathbf{X}(n+1)=\mathbf{F}_1\left(\mathbf{W}^{(1)}\mathbf{U}(n)+\mathbf{W}^{c}\left(\mathbf{Y}(n)-\alpha\mathbf{Y}(n-1)\right)+\mathbf{B}^{(1)}\right); \tag{15}$$

$$Y(n+1)=\mathbf{F}_2\left(\mathbf{W}^{(2)}\mathbf{X}(n+1)+\mathbf{B}^{(2)}\right); \tag{16}$$

where $\mathbf{U}(n)$ – vector of external input signals at time n; p – number of external network inputs; $\mathbf{X}(n+1)$ – vector of the output signals of the hidden layer at the moment of time $(n+1)$; N – number of signals in the context layer. $\mathbf{W}^{(1)}$, $\mathbf{W}^{c}$, $\mathbf{W}^{(2)}$ – matrices of synaptic weights of external input signals, context and output layer signals, respectively. $\mathbf{B}^{(1)}$, $\mathbf{B}^{(2)}$ – vectors of shift weights in neurons of the hidden and output layers, respectively; $\mathbf{F}_1$, $\mathbf{F}_2$ – vectors of activation functions in the hidden and output layers, respectively; $\mathbf{Y}(n+1)$ – vector of output signals of the network at the moment of time $(n+1)$; M – number of network outputs.

The decision rule for a modified Jordan neural network with dynamic stack memory implementing low-pass and high-pass filters is as follows [13, 22]:

$$\alpha=\frac{\sum_{j=1}^{N} f\left(_{j+1}(t)-f_j(t)\right)^2}{t}\geq C; \tag{17}$$

where the numerator of expression (17) means the accumulation of the sum of deviations of the controlled parameters (C – activation threshold (sensitivity) of the neural network; when C = 0 (normal operation mode), when $\alpha \geq C$ (trend)).

5. Experiment

Consider the process of transformation of the training sample to solve the problem of trend analysis of the time series of the gas temperature parameter in front of the compressor turbine (fig. 2*a*) using a modified Jordan neural network with a dynamic stack memory (table 1).

It is assumed that in modified Jordan neural network, the hidden layer contains three neurons, the output contains one neuron, the dynamic memory stack contains feedback signals of the hidden layer with a delay of two cycles. Since the number of neurons of the hidden layer with feedback to the input layer is three, the size of the input vector when training the modified Jordan neural network by remembering the previous output signal one step back will increase by three, by remembering two previous output signals – by six. We denote the input signals of the training sample that change during the transformation as x_1, x_2, x_3, and the feedback signals as x_4, x_5, x_6, x_7, x_8, x_9. We transform the time series (for example, the values of the integral criterion, which are in the range from 1.375 h to 2.0 h) using the sliding window method (table 2).

Inputs x_4, x_5, x_6 – fed output signals of the hidden layer with a delay of one cycle $c_{1\text{-}1}$, $c_{2\text{-}1}$, $c_{3\text{-}1}$, inputs x_7, x_8, x_9 – output signals of the hidden layer with a delay of two cycles $c_{1\text{-}2}$, $c_{2\text{-}2}$, $c_{3\text{-}2}$. In fig. 6, the layer memory is represented as a stack of layer output signals y^1, y^2, …, y^n, where n – size of the stack.

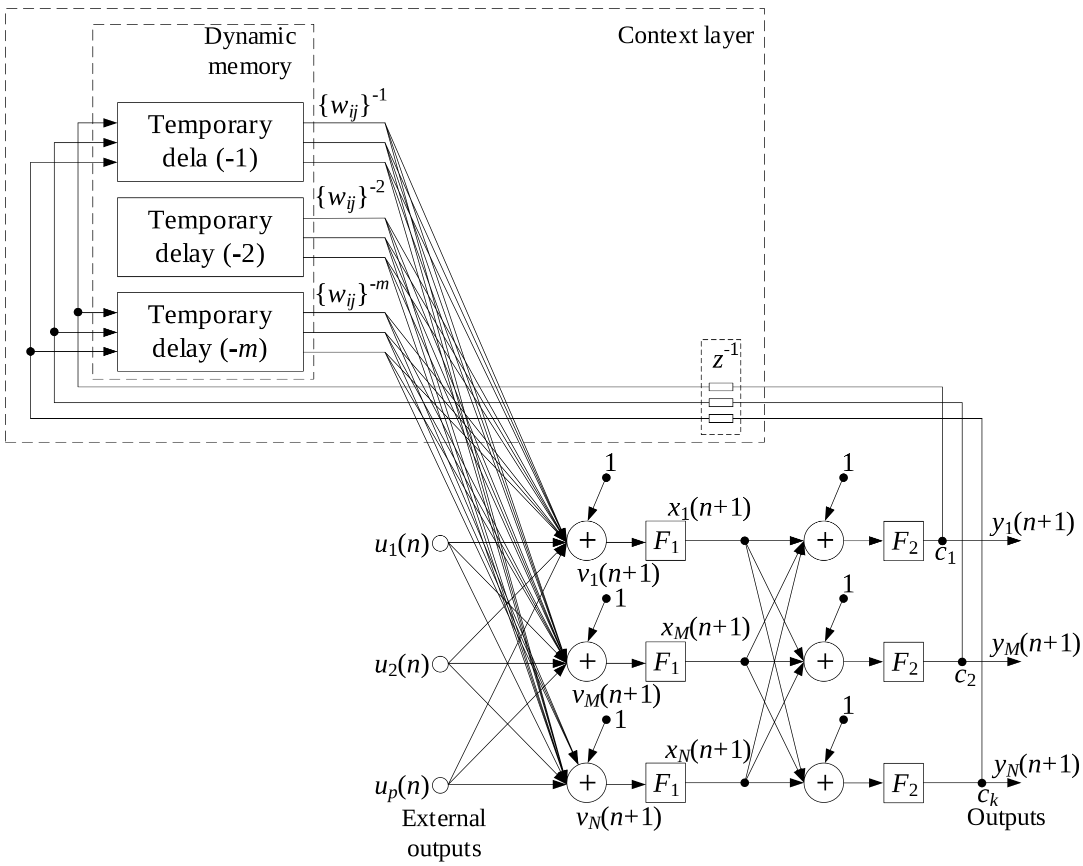


Figure 5: Modified Jordan neural network with dynamic stack memory

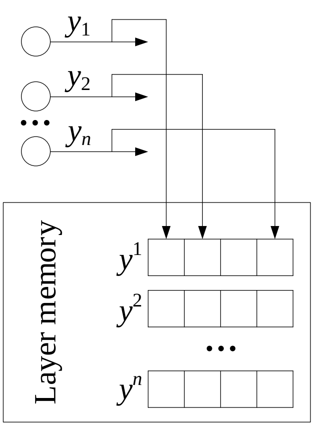


Figure 6: Implementation diagram of the memory layer for a modified Jordan neural network with dynamic stack memory [24]

Each cell of the stack y^i consists of an array of outputs of the neurons of the layer y_1, y_2, …, y_n. The stack is organized so that when the memory overflows, the last cell y_n is removed, the entire queue is shifted by one position, so that $y^i = y^{i-1}$.

Training a modified Jordan neural network with a dynamic stack memory by error backpropagation method [16] can be reduced to training a multilayer perceptron by transforming the training sample (table 2).

Table 1
Fragment of the training sample

Number	Time, hours	Integral criterion value
1	0	–0.002
2	0.125	–0.002
3	0.25	–0.002
4	0.375	–0.002
5	0.5	–0.002
6	0.625	–0.002
7	0.75	–0.002
8	0.875	–0.002
9	1.0	–0.002
10	1.125	–0.002
11	1.25	–0.002
12	1.375	–0.002
13	1.5	–0.0017
14	1.625	–0.0004
15	1.75	0.0003
16	1.875	0.0007
17	2.0	0.0003
18	2.125	0.0003
19	2.25	0.0004
20	2.375	0.0015
21	2.5	0.01

Table 2
Training sample of a neural network for solving the problem of trend analysis of the time series of the gas temperature parameter in front of the compressor turbine, obtained as a result of the transformation of the time series using the sliding window method

Number	Neural Network Inputs, x_i			Neural Network Output, y_1
	x_1	x_2	x_3	
1	–0.002	–0.0017	–0.0004	0.0003
2	–0.0017	–0.0004	0.0003	0.0007
3	–0.0004	0.0003	0.0007	0.0003

The algorithm and software implementation of the hybrid training method for recurrent neural networks were developed by the authors Hryhorii Bieliavskyi, Volodymyr Lila, Yevhenii Puchkov [25]. The result of their work is to obtain a parametric training model for recurrent neural networks that contains a wide range of known training algorithms (adaptive and genetic algorithms) and allows you to adjust the parameters for the best solution to the problem of time series analysis. In this work, a modification of the developed algorithm was carried out, which consists in clarifying the choice of the best individuals from the population, as well as introducing a correction factor into the crossing procedure, which takes into account the probability of a stochastic change in engine parameters under current operating conditions (table 3). To conduct an experiment, namely, training a neural network, committees of 10 modified Jordan neural networks were built using each algorithm. The number of neurons in the hidden layer is 9 (according to the Kolmogorov-Arnold-Hecht-Nielsen theorem). The criterion for stopping training of the modified Jordan neural network is the root mean square error with a value of 0.001, the step size η_k = 0.05, training epoch threshold – 1000. Examples from the training sample, which was formed according to fig. 2, a, were submitted by chance. Sigmoidal functions of the form $f(x)=\frac{1-e^{-x}}{1+e^{-x}}$ were used as the neuron activation function.

Table 3

Modified hybrid method for neural network training of the "adaptive + genetic" variant

Step	Specification
1	Neural network creation with initial initialization of weight coefficients
2	Training the neural network with an adaptive algorithm (table 4) until the transition criterion to the genetic training method is reached
3	Creation of a population of *N*–1 individuals. A neural network trained by an adaptive algorithm is added to the first population
4	Individuals are crossed with the probability of choosing a pair P_c, while each pair produces *S* offspring. Determination of the genes of the descendant is made according to the expression: $$G_i = D + Random?0.5?G_i^a : G_i^b;$$ where G_i – gene of the new chromosome; G_a and G_b – genes of parental chromosomes; *i* – serial number of the gene in the chromosome; *Random* – function that generates a uniform random value on the segment of real numbers [0; 1]; *D* – correction factor for introducing randomness into the value of the gene, the introduction of which is a modification of the existing algorithm, which makes it possible to take into account the "instant" change at helicopter flight engine parameter
5	Selection of the best *N* individuals from the new population, giving the smallest recognition error, determined according to the expression: $$\varepsilon_i = 1 - \frac{y}{y_0};$$ where y_0 – output signal reference value; *y* – output signal value when recognizing the reference value of the thermos-gas-dynamic parameter of the engine from the training sample with a given set of weight coefficients (output signal reference value in this problem is the value of engine thermos-gas-dynamic parameter in the absence of defects under normal operating conditions).
6	If the best representative of the individual corresponds to the given quality of training, the transition to step 9 is performed.
7	A mutation is carried out for individuals selected with a probability P_m. For each gene of the selected individual with probability P_g, the gene is mutated according to the expression: $$G_i = G_i + \lvert G_i \rvert \cdot K_m \cdot (2 \cdot Random - 1);$$ where G_i – chromosome gene; *i* – serial number of the gene in the chromosome; *Random* – function that generates a uniform random value on the segment of real numbers [0; 1]; K_m – mutation coefficient (as a rule, $K_m \in [0; 1]$).
8	If the best representative of the individual corresponds to the specified training quality, go to step 9, if not, return to step 4.
9	Finish

Fig. 7 shows the diagram of the dependence of the training error on the number of epochs for the adaptive algorithm. The average training time of the modified Jordan neural network using the adaptive algorithm was 200 epochs, which is 3 times less than the average training time of the genetic algorithm. The convergence of the algorithm to the local minimum occurred in 50...60 epochs.

The results of applying the genetic algorithm are shown in fig. 8. The genetic algorithm coped with the task, but the intensity of the change in the training error decreased sharply after 380 epochs. The average training time for Jordan modified neural network was 600 epochs.

Fig. 9 shows the dependence of the training error on the number of epochs for the improved hybrid method (table 3), based on the sequential application of the adaptive and genetic algorithms. When switching to a genetic algorithm, a chromosome is added to the population – modified Jordan neural network trained by an adaptive algorithm. As a transition criterion, the value of the training error is used – 0.001. The results of the analysis of training algorithms for the modified Jordan neural network (gradient descent, adaptive algorithm, genetic algorithm, "adaptive + genetic", "improved adaptive + genetic") are given in table 5 and 6.

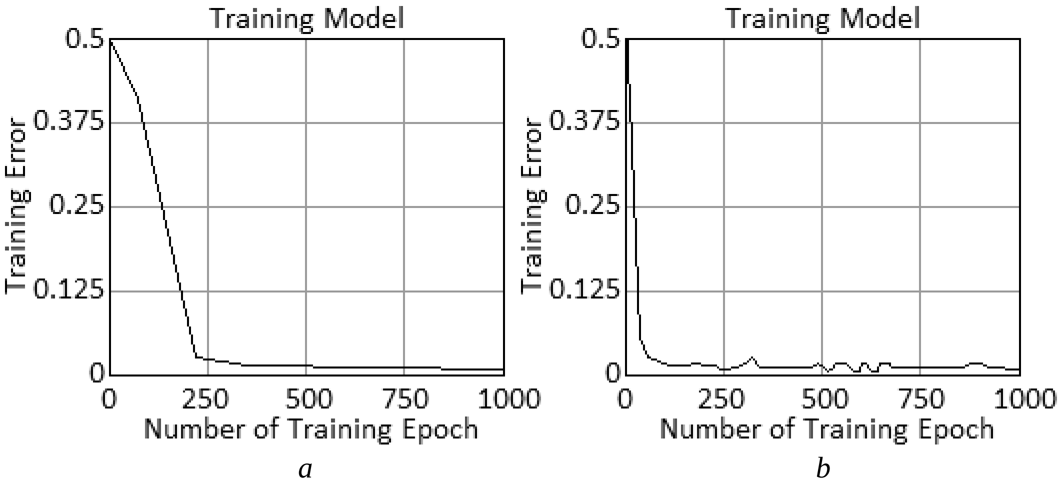


Figure 7: Diagram of training error versus number of epochs for an adaptive algorithm: *a* – best result; *b* – worst result

Table 4
Algorithm for training a multilayer perceptron by the backpropagation method with an adaptive algorithm for minimizing the error function (in description by Hryhorii Bieliavskyi, Volodymyr Lila, Yevhenii Puchkov [25])

Step	Specification
1	Finding the initial values of the parameters: w_0 – starting point, p_0 – initial direction of movement, η_0 – step
2	Choosing the next vector from the training set and feeding it to the input of the neural network
3	Determining the direction of movement $\vec{p}_k$ according to the expression: $$\vec{p}_k = \vec{g}_k + \sum_{i=1}^{\min(k-1,m)} \beta_i \cdot \vec{g}_{k-i};$$ where $\vec{p}_k$ – direction of movement; $\vec{g}_j$ – direction of the anti-gradient at the *j*-th iteration; β_i – coefficient that determines the weight of the *i*-th gradient; *m* – number of memorized gradients; *k* – serial number of the current iteration.
4	Stop criteria computation – root mean square error
5	If the stop condition is met, go to step 6, if not, go to step 2
6	Finish

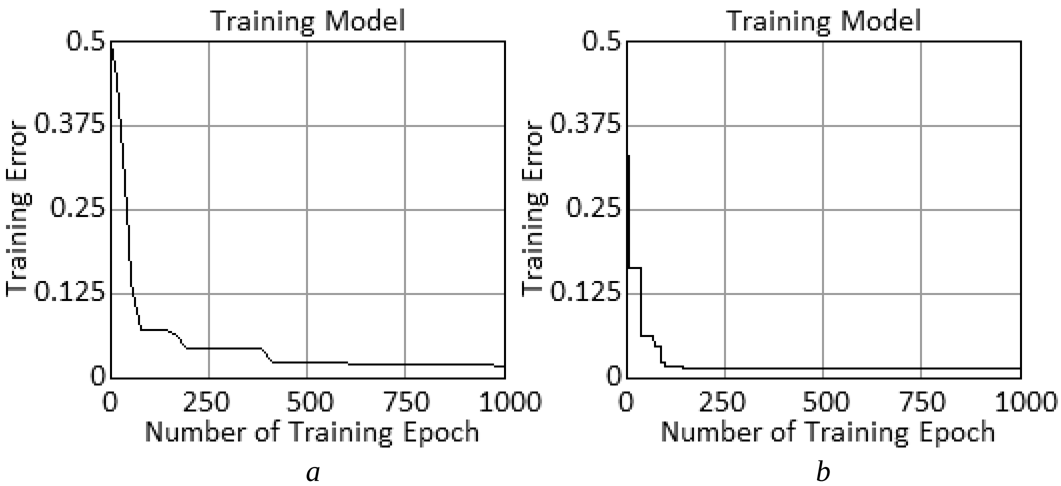
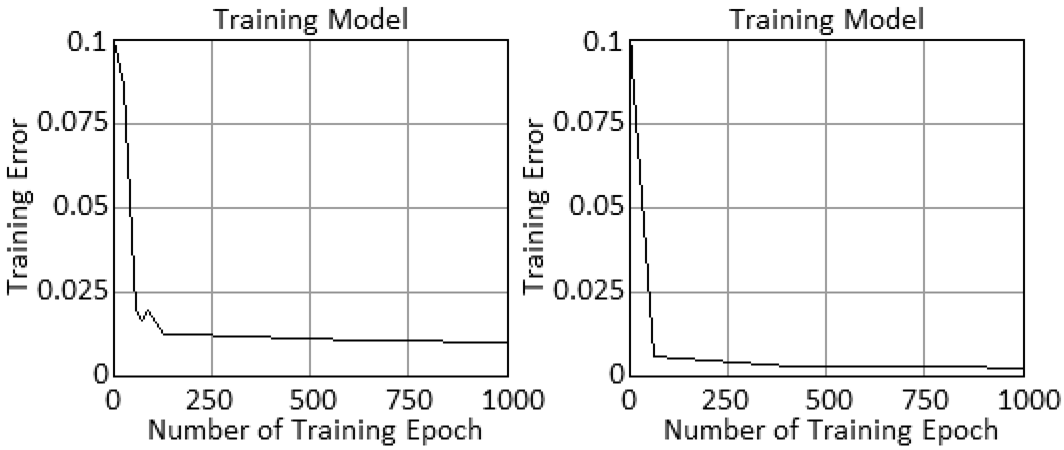


Figure 8: Diagram of training error versus number of epochs for genetic algorithm: *a* – best result; *b* – worst result



a *b*

Figure 9: Diagram of training error versus number of epochs for hybrid algorithm: *a* – best result; *b* – worst result

Table 5
Training algorithms study results for Jordan modified neural network

№	Modified Jordan neural network training algorithms									
	Gradient descent		Adaptive algorithm		Genetic algorithm		"Adaptive + genetic"		"Improved adaptive + genetic"	
	Error	Number of epochs	Error	Number of epochs	Error	Number of epochs	Error	Number of epochs	Error	Number of epochs
1	0.003126	1000	0.002415	1000	0.000999	750	0.000889	550	0.000844	550
2	0.002219	1000	0.002388	1000	0.000995	500	0.000973	640	0.000928	640
3	0.001795	1000	0.002769	1000	0.001014	1000	0.000965	400	0.000920	400
4	0.001912	1000	0.002825	1000	0.000998	730	0.001004	1000	0.000997	1000
5	0.001638	1000	0.002792	1000	0.001005	620	0.000971	580	0.000926	580
6	0.001611	1000	0.002638	1000	0.000986	800	0.000988	930	0.000943	930
7	0.001609	1000	0.002706	1000	0.000992	580	0.000961	960	0.000916	960
8	0.001605	1000	0.002701	1000	0.000984	600	0.001038	1000	0.000993	1000
9	0.001605	1000	0.002718	1000	0.000993	700	0.000996	980	0.000951	980
10	0.001813	1000	0.003002	1000	0.001029	1000	0.001009	1000	0.000964	1000

Table 6
Comparative characteristics of the training process of Jordan's modified neural network training algorithms

Modified Jordan neural network training algorithms	Time of one epoch (in milliseconds)	Best result		Worst result	
		Error	Number of epochs	Error	Number of epochs
Gradient descent	60	0.001605	1000	0.003126	1000
Adaptive algorithm	120	0.002701	1000	0.003002	1000
Genetic algorithm	200	0.000984	600	0.001029	1000
"Adaptive + genetic"	140	0.000971	580	0.001009	1000
"Improved adaptive + genetic"	140	0.000844	550	0.000997	1000

According to the results of the comparison, the adaptive algorithm converges faster than the genetic and hybrid ones. The threshold of 0.001 for 1000 epochs has not been overcome by any gradient method. From this it follows that it is most expedient to use an adaptive method at the beginning of training, which quickly finds a solution with a root-mean-square error of 0.003, and then apply the genetic algorithm. In terms of the number of epochs, the genetic algorithm is in some cases faster than the hybrid one. But for this task, the time of one epoch of the genetic algorithm is much higher (200 milliseconds) than the average time of one epoch of the improved hybrid one (140 milliseconds). Therefore, we can conclude that the hybrid algorithm of the “improved adaptive + genetic” option is best suited for this task. Fig. 10 shows the diagram of the change in the mean square error function according to the number of training epochs for "improved adaptive + genetic" algorithm.

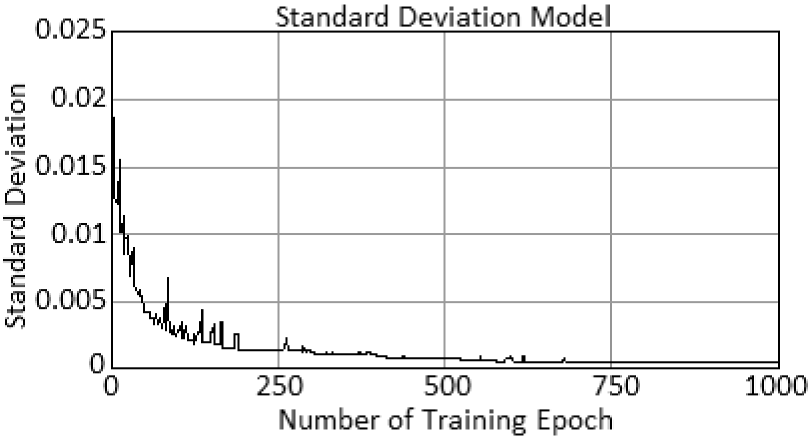


Figure 10: Diagram of the rms error function of a modified Jordan neural network with dynamic stack memory during training

The statistics of the approximation of the result to the reference value by the improved hybrid algorithm in the problem of trend recognition is shown in fig. 11, which shows the values of the output signal of the best chromosome in the current epoch. Experiments have shown that in order to achieve the best recognition result with the resulting set of weights, the crossover probability is P_c = 0.64, P_m = 0.01.

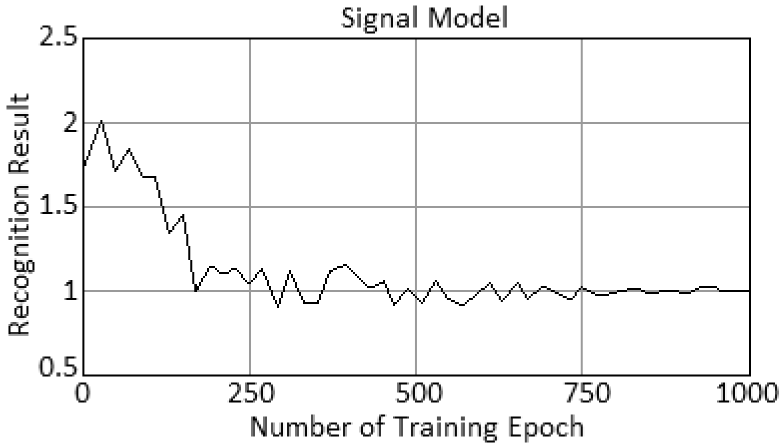
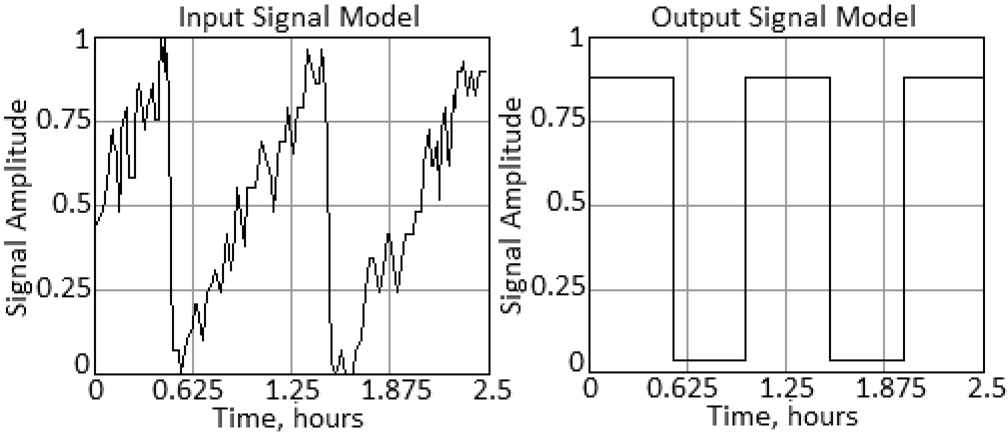


Figure 11: Statistics of the approximation of the result to the reference value

6. Results and discussion

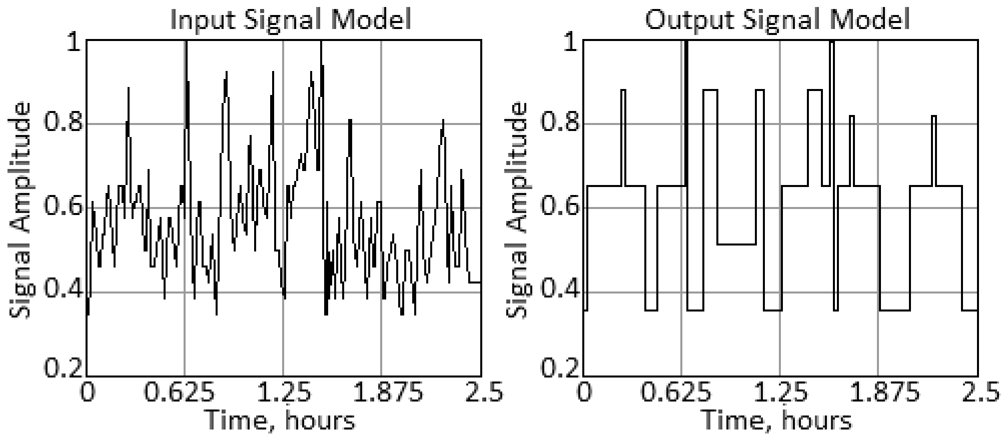
We will analyze the presence of a trend (fig. 2, *a*) in sections I and II using the neural network apparatus. The implementation of low-pass and high-pass filters based on a modified Jordan neural network with dynamic stack memory is shown in fig. 8. Analysis of the trend in the first section is shown in fig. 9. The determination of the trend of the neural network on the second characteristic area is shown in fig. 10. At the same time, one cell corresponds to half an hour of operation of the helicopter's control system. It can be seen that the emergence of a trend is noticed by the neural network after the sixth cell. To complicate the process of trend recognition and to get as close to the real situation as possible, an obstacle is "superimposed" on the input signal identified by the neural network.

In the process of mathematical modeling on a modified Jordan neural network with a dynamic stack memory that implements recurrent filters, in comparison with the classic criteria for detecting the trend of parameters. For example, of the TV3-117 engine, the results shown in fig. 11, where 1 – neural network criterion (using a modified Jordan neural network with dynamic stack memory); 2 – neural network criterion (using an ensemble of neural networks consisting of a perceptron and an RBF network); 3 – *s*-criterion; 4 – *S*'-criterion; 5 – Halden-Abbe *r*-criterion; 6 – modified r-criterion; 7 – *u*-criterion [14].



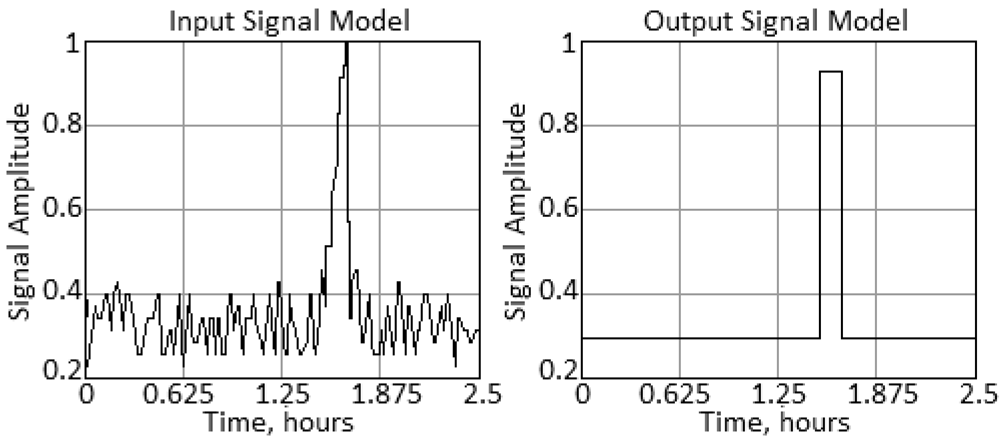
a *b*

Figure 8: The training process of a modified Jordan neural network with a dynamic stack memory for trend recognition: *a* – signal at the filter input; *b* – signal at the filter output



a *b*

Figure 9: The process of testing a modified Jordan neural network (there is no trend): a – signal at the filter input; b – signal at the filter output



a *b*

Figure 10: Determination of the trend using a modified Jordan neural network knowledge base: *a* – signal at the filter input; *b* – signal at the filter output

In the work, a comparative assessment of the effectiveness of trend analysis of neural network and classical criteria was carried out. A comparative study of the criteria was carried out on the basis of simulation modeling, which made it possible to check a wide range of changes in measurement errors and the intensity of trend manifestation. The value of the controlled parameter is equal to the sum of the deterministic basis and random normally distributed interference with variance ξ. The deterministic component is constant in the interval [0, t_0], and then changes linearly with the rate a = tg(α) (1/s) (where α – intensity of the trend). During the simulation, the value of a varied in the range [0.01; 1]; and the value of ξ is in the range [0.001; 1]. During modeling, a sample variance calculated on the stationarity interval [0, t_0] was used to adjust the mathematical model of the helicopter TE. Starting from the moment t_0, the values of the criteria were calculated and the presence of a trend was checked. The effectiveness of the criteria was evaluated by the time of activation of the criteria from the beginning of the trend τ_0 to the moment of time corresponding to the detection of the trend τ_{late} [13, 22].

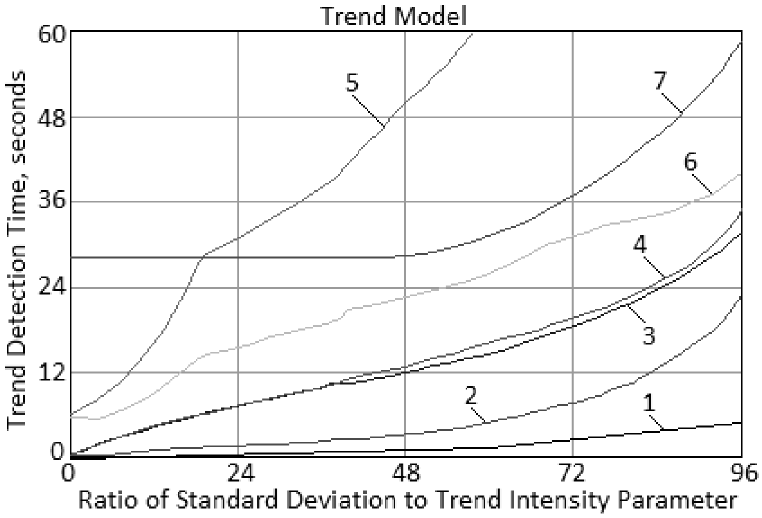


Figure 11: Characteristics of trend criteria for the 5% significance level in dimensionless coordinates

The results of numerical modeling (table 7) indicate the possibility of solving the problems of information monitoring of helicopter aircraft engines operational status, which allow, along with the classical criteria for detecting the trend of parameters, to apply qualitatively new neural network criteria that expand and complement the classical criteria. That increases the reliability of information at helicopters TE operational status monitoring and at the stages of decision-making.

Table 7

Algorithm for training a multilayer perceptron by the backpropagation method with an adaptive

Methods	Measurement sample	Trend emergence time (measurement)	Recognition quality, %	Quality of trend recognition when changing		
				α, %	τ_0, %	σ_y (sensibility)
Classical	50	7…8	95	70…95	90…95	10…25 measurements
Neural networks	50	4…5	100	95…100	95…100	3…5 measurements

Similar research was conducted using other architectures of neural recurrent networks as implementing low-pass and high-pass filters (table 8). From the table 8, it can be seen that Jordan's modified neural network with dynamic stack memory is appropriate for use as an implementation of low-pass and high-pass filters for the purpose of solving the task of helicopters TE parameters trend analysis at flight modes, i.e., in real time.

The technique of helicopters TE parameters complex monitoring at flight modes in a neural network basis:

1. Obtaining a training sample in N modes of a normally operating engine at a real-time rate under normal operating conditions.
2. Obtaining a training sample in N engine modes with a parameter trend in real time at the current operating conditions.
3. Choice of neural network architecture.

4. Choice of training algorithms.

5. Training, testing and real-time trend recognition of engine parameters under current operating conditions.

6. Monitoring of helicopters TE parameters at flight modes by neural networks.

7. Adaptation of neural networks in the environment of an active expert system [27, 28].

Table 8

Comparison of the results of solving the problem of trend analysis of the parameters of helicopters turboshaft engines at flight modes

Neural network architecture	Maximum root means square error		Trend recognition accuracy	
	No trend	Trend	No trend	Trend
Modified Jordan neural network with dynamic stack memory	0.025	0.056	0.999	0.995
Ensemble of neural networks: perceptron + RBF network (proposed by professor Serhii Zhernakov)	0.087	0.117	0.932	0.916
Jordan neural network	0.093	0.128	0.901	0.887
Elman neural network	0.118	0.175	0.863	0.831
Modified LSTM network [26]	0.134	0.204	0.814	0.798
LSTM-network	0.159	0.261	0.776	0.732
Hopfield neural network	0.232	0.327	0.711	0.689
Hamming neural network	0.261	0.401	0.688	0.613
Cosco neural network	0.298	0.437	0.652	0.606
Real time recurrent network RTRN	0.311	0.487	0.613	0.574

Under the conditions of on-board implementation of the developed neural network method for trend analysis of helicopter turboshaft engine parameters, the expediency of using the 64-bit Intel Neural Compute Stick 2 neuro processor using a Python programming language (using the Keras open-source library) was proved in [29] (fig. 12).

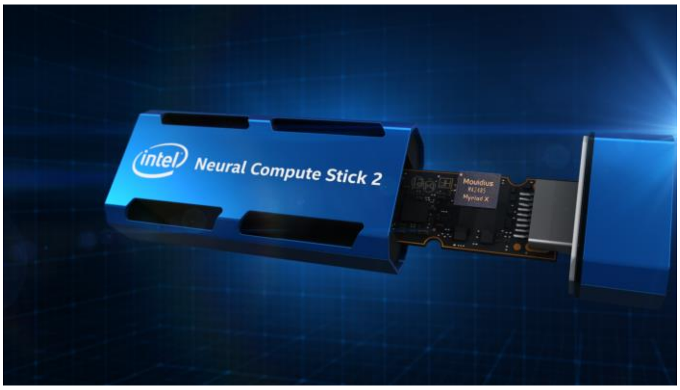


Figure 12: Intel Neural Compute Stick 2 neuroprocessor general view

Neuro processors of this series are widely used in modern digital automatic control systems, including in aviation. The presence of a multiplier-accumulator module in the core of this microprocessor makes it possible to increase the speed of calculating the algorithm by combining multiplication and addition operations with weighted summation in the neuron adder.

7. Conclusions

1. The neural network method for analyzing aircraft engine parameters trend has been further developed, which, through the use of a modified Jordan neural network with dynamic stack memory, makes it possible to detect the appearance of helicopters turboshaft engines parameters trend at flight modes, improve accuracy to 0.995 and reduce the trend recognition error to 0.056.

2. The hybrid algorithm (adaptive + genetic) for training recurrent neural networks, in particular, the Jordan neural network, has been improved, which, by refining the criterion for choosing the best individuals from the population, as well as introducing a correction factor into the crossing procedure. It takes into account the probability of a stochastic change in engine parameters in the current conditions, allowed to optimize the training of the modified Jordan neural network with dynamic stack memory to solve the task of helicopters turboshaft engines at flight modes parameters trend recognizing.

3. The results of numerical simulation indicate the possibility of solving the problems of integrated monitoring of helicopters turboshaft engines operational status at flight modes based on active expert systems [27, 28], which allow, along with the classical criteria for identification of parameters trend, to apply qualitatively new neural network criteria that expand and supplement the classical criteria. It increases the reliability of information up to 100 % in the control and diagnostics of helicopters turboshaft engines parameters and at the decision-making stages.

4. The technique developed and described in this work has been tested in the environment of active expert systems [27], has shown high efficiency in solving the problems of integrated monitoring of the operational status and operation management (parameters control, diagnostics, debugging and predicting) of helicopters turboshaft engines in flight modes.

5. The operation of aircraft gas turbine engines of the 5th–6th generations, including helicopters turboshaft engines, the complication of their technical systems and subsystems, as well as the increased requirements for flight safety, have led to the need to create intelligent systems capable of performing certain functions of a human expert. To assist in the search of the optimal solution, to issue advice and recommendations in real time in the process of integrated monitoring and operation management of helicopters turboshaft engines.

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