Control and Diagnostics of TV3-117 Aircraft Engine Technical State in Flight Modes Using the Matrix Method for Calculating Dynamic Recurrent Neural Networks

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Abstract

In this paper, one of the methods of using dynamic recurrent neural networks for solving applied problems of control and diagnosing of aircraft engines technical state, including TV3-117, is considered. A method for coding neural networks into signal graphs is proposed, and it is shown that their adjacency matrices can be used as associative memory in step matrix algorithms for solving dynamic recurrent neural networks. It is shown that in fully connected recurrent neural networks, any neuron can be input or output, and one neuron can simultaneously be input and output. Examples of teaching by the evolutionary optimization algorithm for multiextremal problems of recurrent dynamic neural networks intended for control and diagnosing of TV3-117 aircraft engine technical state are given. The functions of activation blocks of neurons in dynamic recurrent neural networks in this work are used difference expressions of simulation models of linear dynamic links. It is shown that for identification in the time domain of transient processes in dynamic systems of the third order, satisfactory accuracy is achieved at the output of any neuron of a recurrent dynamic neural network with four neurons, while it was found that useful information about the dynamic properties of the dynamic system under study can be simultaneously obtained from the output of any neuron network.

Keywords 1

Aircraft engine, neural network, signal graph adjacency matrices, synaptic weights, associative memory.

1. Introduction

Flight safety of aircraft, including helicopters, is one of the key problems of aviation, largely depends on the reliability of the operation of their power plants. In turn, the reliable operation of power plants and, in particular, a gas turbine engine (GTE) (for example, TV3-117, which is part of the power plant of the Mi-8MTV helicopter and its modifications) is ensured by a whole range of measures, among which an important place is given to its diagnostics technical state. At present, the technical diagnostics of a GTE, in the broad sense of this concept, is carried out only on the ground by an engineering and technical staff, who have at their disposal the appropriate tools and methodological apparatus. But most of the failures that affect the safety of a helicopter operation arise and manifest themselves in flight, which requires an effective on-board diagnostic system that determines the technical condition of the gas turbine engine in real time directly on board the helicopter. The difficulty of carrying out diagnostics of the power plant in automatic mode in flight is associated with the high complexity of aircraft GTE, due to the multiparametry, multi-connectivity, nonlinearity of the processes occurring in them, the multi-mode application, which requires significant machine and time resources [1].

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Today engines of the 4th generation have on-board parameter control systems, which solve a wide range of tasks related to the assessment of the residual life of aircraft engines and control of their parameters. In the process of performing the task of engine life development, the problem of forecasting (short-term) the current state of the engine and trend analysis of its parameters is solved. In modern on-board system for control and diagnosing the following tasks of control of a large number of parameters of the engine [1] are solved: temperature and pressure of gases behind and in front of the turbine; rotational speed of the compressor rotor of low and high pressure; the efficiency of the oil system and engine prompting on the limit values of the parameters of the engine oil system; oil consumption to change the level in the engine oil tank; efficiency of the engine fuel system; vibration level; temperature in the engine cavities; bearing temperature; mass fuel consumption; temperature and air pressure behind the compressor; technical state of the flowing part of the engine according to its thermogas-dynamic parameters [2, 3].

However, with a wide variety of tasks, there are some difficulties: limited computing resources (amount of RAM, speed, accuracy of the results); difficulties in formalizing classical control and diagnostic algorithms and, as a consequence, their practical implementation; the need to implement the above algorithms in low-level language (assembler); difficulties in recovering information when sensors fail.

Taking into account the specific features of the diagnostic object (aircraft GTE), as a complex technical system with essential nonlinear characteristics, the above difficulties can be effectively eliminated by using the mathematical apparatus of artificial neural networks, which have a number of advantages given in [4].

2. Mathematical model of the change of aircraft engine TV3-117 technical state

To study the possible of TV3-117 aircraft engine technical states according to [5, 6], it is assumed that the engine in the helicopter flight mode can be in four states: S_0 – engine idling (here we mean idling), S_1 – engine works in the nominal mode (here we mean takeoff, nominal, cruising I, cruising II), S_2 – the engine is working properly, readjustment is in progress, S_3 – the engine is faulty (emergency mode of the engine). According to these data, it is possible to obtain a discrete Markov network based on the following possible transition states: $S_0 - S_1$, $S_1 - S_0$, $S_0 - S_3$, $S_1 - S_3$, $S_2 - S_0$, $S_2 - S_1$, $S_2 - S_3$, $S_3 - S_2$, the probability of the engine being in each of the above states must be taken into account (fig. 1) [5, 6].

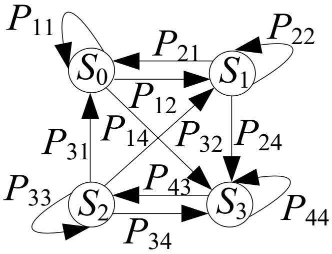


Figure 1: Markov discrete network showing all kinds of changes of TV3-117 aircraft engine technical state as a part of a helicopter power plant during flight tests [5, 6]

According to fig. 1, transition probabilities matrix has the form:

$$P = \begin{pmatrix} P_{11} & P_{12} & 0 & P_{14} \\ P_{21} & P_{22} & 0 & P_{24} \\ P_{31} & P_{32} & P_{33} & P_{34} \\ 0 & 0 & P_{43} & P_{44} \end{pmatrix}. \quad (1)$$

To find the probabilities of the stay of Markov chain in certain states as $n \to \infty$ (final probabilities) in [5, 6] an equations system of the form is solved:

$$\begin{cases} P_{11}\pi_1 + P_{21}\pi_2 + P_{31}\pi_3 = \pi_1; \\ P_{12}\pi_1 + P_{22}\pi_2 + P_{32}\pi_3 = \pi_2; \\ P_{33}\pi_3 + P_{43}\pi_4 = \pi_3; \\ P_{14}\pi_1 + P_{24}\pi_2 + P_{34}\pi_3 + P_{44}\pi_4 = \pi_4. \end{cases} \quad (2)$$

According to [5, 6], in matrix form, system (2) has the form $\pi = P^T\pi$ and $(P^T - E)\pi = 0$, where $P^T = \begin{pmatrix} P_{11} & P_{21} & P_{31} & 0 \\ P_{12} & P_{22} & P_{32} & 0 \\ 0 & 0 & P_{33} & P_{43} \\ P_{14} & P_{24} & P_{34} & P_{44} \end{pmatrix}$ – transposed matrix; $E = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$ – identity matrix.

According to [5, 6], adding to this equation the normalization condition of the form:

$$\pi_1 + \pi_2 + \pi_3 + \pi_4 = 1; \quad (3)$$

the final matrix is obtained, $P^T - E = \begin{pmatrix} P_{11}-1 & P_{21} & P_{31} & 0 \\ P_{12} & P_{22}-1 & P_{32} & 0 \\ 0 & 0 & P_{33}-1 & P_{43} \\ P_{14} & P_{24} & P_{34} & P_{44}-1 \end{pmatrix}$.

Replacing the fourth row of the matrix $(P^T - E)$ with a single row, that is, $P^T - E = \begin{pmatrix} P_{11}-1 & P_{21} & P_{31} & 0 \\ P_{12} & P_{22}-1 & P_{32} & 0 \\ 0 & 0 & P_{33}-1 & P_{43} \\ 1 & 1 & 1 & 1 \end{pmatrix}$, a final system of linear algebraic equations is obtained:

$$\begin{cases} (P_{11}-1)\pi_1 + P_{21}\pi_2 + P_{31}\pi_3 = 0; \\ P_{12}\pi_1 + (P_{22}-1)\pi_2 + P_{32}\pi_3 = 0; \\ (P_{33}-1)\pi_3 + P_{43}\pi_4 = 0; \\ \pi_1 + \pi_2 + \pi_3 + \pi_4 = 1. \end{cases} \quad (4)$$

As a result of solving (4), expressions were obtained for determining the elements of the vector of state probabilities $\pi(\pi_1, \pi_2, \pi_3, \pi_4)$ (shows the probability that the engine will be in the i-th state), which will allow in the presence of values of the transition probabilities $P_{11}\ldots P_{33}$ to obtain prognostic indicators of changes of TV3-117 aircraft engine technical state. As can be seen from system (4), to determine the probability of engine failure π_4, it is enough to know the transition probabilities for the other three states, as well as the transition probabilities P_{34}, P_{43}, which can be obtained as a result of technical diagnostics of the helicopter.

The adequacy of the developed method is confirmed in [5] by definition. The paper proposes an implementation of this method using dynamic recurrent artificial neural networks.

3. Matrix method for determining dynamic recurrent artificial neural networks

In this paper, the topology (internal connections) of the neural network is proposed to be encoded by signal graphs [7, 8]. A model of a neuron of a neural network is proposed to be represented by a node in the signal graph with the assignment of a serial number 1, 2, ..., $N - 1$, N. The nodes are connected by directed arcs. The arcs are identified by synaptic weights w_{ij}, where i – number of the donor neuron, j – number of the acceptor neuron.

A convenient descriptor of a neural network is the adjacency matrix of the signal graph W. Elements of the adjacency matrices are the storage of the associative memory of neural network for various purposes. The fig. 2 shows the signal graphs and the corresponding adjacency matrices: for the forward-directed and recurrent neural network. From the theory of graphs it follows that if the column of the adjacency matrix is zero (fig. 2, *a*), then the vertex of the signal graph is a sink, and in a neural network this neuron is an input one. The zero-line points to the top of the source of the signal graph, and in the neural network this neuron is the output. In a recurrent neural network (fig. 2, *b*) there is no formal concept of layers. Any neuron can be both input and output.

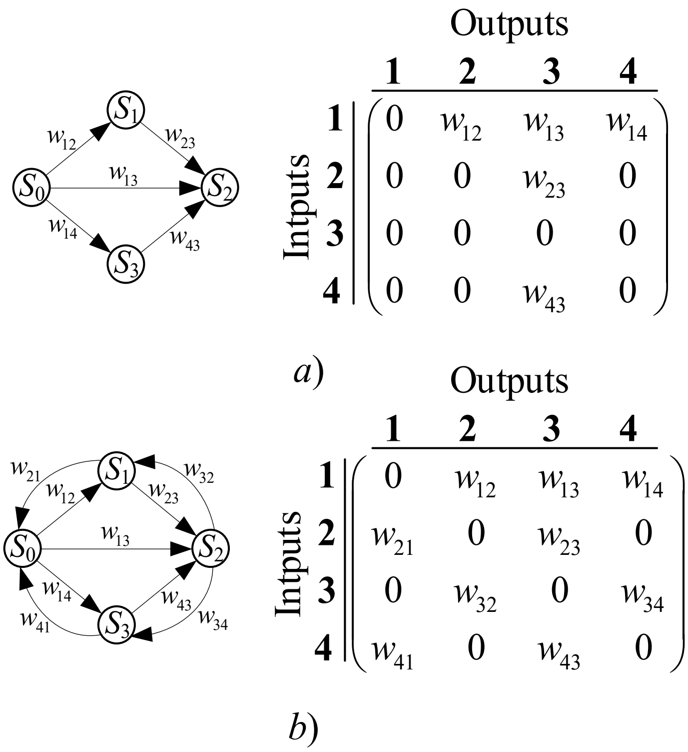


Figure 2: Signal graphs and adjacency matrices: *a* – direct neural network; *b* – recurrent neural network

The most widespread at present are direct-directional neural networks – perceptron's [9–12], which are currently widely used in technology to solve problems of classifying the state of equipment and diagnosing events. For training forward-directed neural networks with a large number of neurons, there is a layer-by-layer backpropagation method [9–12]. For modeling and synthesis of control systems, dynamic recurrent neural networks are more attractive (fig. 2, *b*).

Due to intranet feedbacks, to calculate each neuron in a recurrent neural network, signal values are required not only from the associated outputs of the neurons of previous layers, as in forward-directed neural networks, but also the values of signals received on this neuron itself, and others associated with him neurons. Layer-by-layer calculation of recurrent neural networks becomes impossible, in which each neuron can be both input and output at the same time. Currently, there are no formalized algorithms for calculating recurrent neural networks, including those designed to simulate dynamic systems.

The known algorithms aim at adapting the backpropagation algorithm for calculating forward-directed neural networks with feedback [13, 14]. Dynamic properties (associative memory) in forward-directed neural networks are achieved by applying input signals to various layers of the neural network and increasing the total number of neurons.

An analogy is seen with neural networks of existing structures of aggregate and controller control algorithms, and in the control algorithms there are real nonlinear elements (analogs of activation blocks). But they have a very small number of neurons (functional blocks). This necessitates, in contrast to multi-neural networks of scanners-classifiers, the study of dynamic neural networks from below, from a small number of neurons. And their complexity, topology and the number of neurons, must meet the requirements of the assigned tasks – high-quality implementation of various types of classical, adaptive, single-channel and hybrid multichannel, linear with switching and non-linear algorithms for regulation and logic control.

Studies have shown that the listed tasks can be implemented by dynamic recurrent neural networks, for which there are currently no formalized calculation algorithms. In this article, we propose a matrix algorithm for the numerical step-by-step calculation of recurrent neural networks. In the proposed algorithm, the models of neural network neurons are represented by static equations of linear adders [15]:

$$s_{jk} = \sum_{i=1}^{N} x_{ik} \cdot w_{ij};\ j = 1, 2, \ldots, N \tag{5}$$

and activation block

$$\gamma_n = \varphi(s_{nk}); \tag{6}$$

where x_{1n}, x_{2n}, …, x_{Nn} – signal values at the input of the n-th neuron; w_{1n}, w_{2n}, …, w_{Nn} – synaptic weights of channels at the input of the n-th neuron; (s_{nk}) – value of the signal at the output of the adder at the k-th step of the neural network calculation.

In the processes of training or operation of a neural network, the proposed matrix algorithm requires [15]:

1) adjacency matrix of the signal graph of the neural network W filled with the values of synaptic weights;

2) vector of functions of activation blocks $\Phi(S)$:

$$\Phi(S) = \{\varphi_1(s_1), \varphi_2(s_2), \ldots, \varphi_{N-1}(s_{N-1}), \varphi_N(s_N)\}; \tag{7}$$

3) vector of values supplied to the inputs of all neurons of the neural network of external signals X_0^{in}:

$$X_0^{in} = \{x_{10}^{in}, x_{20}^{in}, \ldots, x_{N-10}^{in}, x_{N0}^{in}\}; \tag{8}$$

4) vector of signal values at the outputs of the activation blocks:

$$\Gamma_0 = \{\gamma_{10}, \gamma_{20}, \ldots, \gamma_{N-10}, \gamma_{N0}\}. \tag{9}$$

In the process of calculating neural networks, the elements of vectors X^{in} and Γ change from step to step. Suppose at the k-th step they have values X_{k-1}^{in} and Γ_{k-1}. Then the signals that at the kth step must be fed to the inputs of all neurons are summed up from vectors X_{k-1}^{in} and Γ_{k-1} [15]:

$$X_k = X_k^{in} + \Gamma_{k-1}. \tag{10}$$

The procedure for calculating the signal at the output of the adder of the j-th neuron of the neural network in accordance with (5) consists in multiplying the elements of the columns of the adjacency matrix W by the elements of the vector X_k, followed by summing the multiplication results with the elements of the j-th column of this matrix.

It follows from the above that at the kth step, the neural network calculation procedure is reduced to three computation stages. At the first stage, using the values of the input signals X_{k-1}^{in} and the results of calculating the neural network at the $(k-1)$-th step Γ_{k-1}, from expression (10), the elements of the vector of actual inputs of the neurons of the neural network for the k-th step X_k are calculated: $X_k = X_k^{in} + \Gamma_{k-1}$.

At the second stage, the transposed adjacency matrix W^T is multiplied by the vector X_k:

$$S_k = W^T \cdot X_k. \tag{11}$$

At the third stage, after the transformation of the vector elements by the functions of activation blocks:

$$S_k = \{s_{1k}, s_{2k}, \ldots, s_{N-1k}, s_{Nk}\}; \tag{12}$$

where for the k-th step the elements of the signal vector at the outputs of the neurons of the neural network are calculated:

$$\Gamma_k = \{\gamma_{1k}, \gamma_{2k}, \ldots, \gamma_{N-1k}, \gamma_{Nk}\}. \tag{13}$$

Then the algorithm returns to the first stage to calculate the values of signals at the outputs of neurons at the $(k+1)$-th step of the neural network.

The fig. 3 shows graphs of four fully connected recurrent neural networks as test results of the proposed matrix algorithm for calculating a fully connected dynamic recurrent neural network. The arrows in fig. 3 indicate the contacts between the variables (in this case, the possible TV3-117 aircraft engine technical states), while the signal passes only in the direction of the graph arrows.

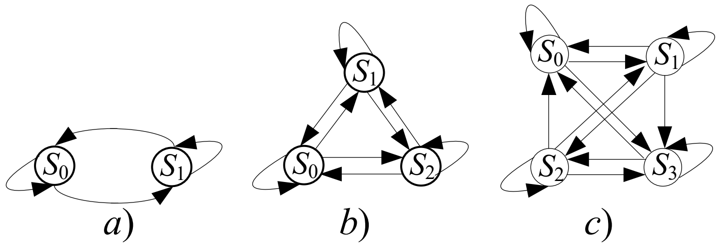


Figure 3: Signal graphs of three fully connected recurrent neural networks

4. Training a neural network with an evolutionary algorithm based on the matrix method

The topology of fully connected neural networks is interesting for maximum intelligence when learning. It is well formalized and convenient for the algorithmization of matrix transformation operations of expressions (10) – (13).

In matrix form [15], these calculations are convenient because in a fully connected recurrent neural network, the number of synaptic weights is equal to the square of the number of neurons, and in the network any neuron, including the input one, can be used as an output one.

For dynamic neural networks, oriented to work in regulation and control systems, an important property is their inertia. In the proposed stepwise algorithm, to calculate the elements of the vector Γ at the current k-th step, the values at the outputs of all neurons at the previous (k – 1)-th step are required. Then, if the increment of the signal value at the output of the n-th neuron from step to step [15]:

$$\Delta\gamma_{kn} = \gamma_{kn} - \gamma_{(k-1)n} \tag{14}$$

multiply by the accepted time interval between calculation steps

$$\Delta t = t_k - t_{k-1} \tag{15}$$

then the operation of integrating the primitive of the simulation dynamic model of the neuron with N inputs will be reproduced in the neuron:

$$\gamma_{kn} = \gamma_{(k-1)n} + \Delta t \cdot \sum_{z=1}^{N} \gamma_{(k-1)z}; \; n = 1, 2, \ldots, N-1, N. \tag{16}$$

In this case, the step size (the time interval between calculations Δt) will determine the accuracy of the transient simulation. Then the elements of the vector Γ will be the stack storage of the associative memory of the dynamic neural network.

As activation blocks in the proposed algorithm, we tested simplified primitives of recurrent expressions with unit parameters of one-dimensional simulation models of a linear integral link:

$$\gamma_k = \gamma_{k-1} - \Delta t \cdot s_{k-1}; \tag{17}$$

and linear inertial (aperiodic) link

$$\gamma_k = (1 - \Delta t) \cdot \gamma_{k-1} - \Delta t \cdot s_{k-1}. \tag{18}$$

For comparison, the algorithm was tested with the sigmoid function as an activation block:

$$\gamma_k = \frac{e^{s\cdot(k-1)} - e^{-s\cdot(k-1)}}{e^{s\cdot(k-1)} + e^{-s\cdot(k-1)}}. \tag{19}$$

It was found that expressions (17) and (18) have almost the same positive effect on the dynamic properties of the trained neural network, and with expression (19) it was not possible to train the neural network for a dynamic mode of operation. Obviously, the sigmoid is applicable only for neural network classifiers.

The neural network was trained in the identifier mode using test graphs of the object's response to a step effect and to harmonic oscillations of the same amplitude at three frequencies. Test signals were generated by a circuit from recurrent expressions of sequential connection of simulation models of aperiodic links (A-links) with parameters: T_a = 10 s and k_a = 3 units out / units in:

$$\begin{cases} y_{k1} = \left(1 - \frac{\Delta t}{T_a}\right) \cdot y_{(k-1)1} + k_a \cdot \frac{\Delta t}{T_a} \cdot x_{k-1} \\ y_{k2} = \left(1 - \frac{\Delta t}{T_a}\right) \cdot y_{(k-1)2} + k_a \cdot \frac{\Delta t}{T_a} \cdot y_{k1} \\ y_{k3} = \left(1 - \frac{\Delta t}{T_a}\right) \cdot y_{(k-1)3} + k_a \cdot \frac{\Delta t}{T_a} \cdot y_{k2} \end{cases} \quad (20)$$

and a circuit of recurrent expressions of the serial connection of the *A*-link and the integrating (*I*-link) with negative feedback

$$\begin{cases} y_{k1} = y_{(k-1)2} + k_a \cdot \frac{\Delta t}{T_u} \cdot \left(x_{k-1} - y_{(k-1)2}\right) \\ y_{k2} = \left(1 - \frac{\Delta t}{T_a}\right) \cdot y_{(k-1)2} + k_a \cdot \frac{\Delta t}{T_a} \end{cases} \quad (21)$$

In system (21), the parameters of the *A*-link are T_a = 10 s and k_a = 3 units out / units in, and for the *I*-link the neural network is trained for two options: T_i = 50 s, when the transient process is monotonic, and T_i = 3 s, when the transient is oscillatory.

A probabilistic evolutionary algorithm for optimizing multiextremal problems is used as a tool for tuning a neural network. The algorithm consists of a probabilistic Monte Carlo procedure for creating a set (population) of starting points for finding an optimal solution $R\{r_1, r_2, ..., r_{z-1}, r_z\}$ [16], where Z – given number, a genetic procedure for eliminating (removing) 10 % of unpromising points from a set *R*, an operation of replenishing a set *R* with new, randomly selected points and their distribution by a regular optimization algorithm over the coordinates of local extrema [17–19].

5. Description of input data

The input data for control and diagnostics of TV3-117 aircraft engine technical state are the results of modeling the transient process in it. The papers [20, 21] describe in detail the general approaches to modeling aviation gas turbine engines together with their automation in the simulator DVIG_OTLADKA. The TV3-117 aircraft engine automatic control system operates as follows: depending on the engine control joystick (ECJ) installation angle, the rotor speed is maintained with a temperature correction at the engine inlet (i.e., the following control laws are implemented ($n = f(\alpha_{ECJ}, T_H)$, $G_T = f(n)$), the limiting values of the rotor speed n_{max} and the gas temperature in front of the compressor turbine T_G^* are limited.

According to [22], the dynamic characteristics of an aircraft engine are determined by the moment of inertia of the compressor rotor. With the help of the structural element «Pump-regulator», the set rotor speed is maintained by changing the fuel consumption in the combustion chamber. For the simulated TV3-117 aircraft engine, the rotor moment of inertia is taken equal to 0.00045 kg · m^2. As described in [23], the dynamic characteristics of various automation elements are unified in the form of coefficients of a second-order nonlinear differential equation:

$$kx(t) = T_K^2 y''(t) + T_D y'(t) + y(t); \quad (22)$$

where k – gain; T_K – oscillatory time constant, s; T_D – differentiating time constant, s; $x(t)$ – value of the function (for the structural element «Pump-regulator» – the value of the fuel consumption); $y(t)$ – value of the controlled parameter (for the structural element «Pump-regulator» – the reduced or physical rotor speed); $y''(t)$ and $y'(t)$ – respectively the second and first time derivatives of the value of the controlled parameter.

According to [20], the schedule of the transient process in the TV3-117 aircraft engine has the form shown in fig. 4.

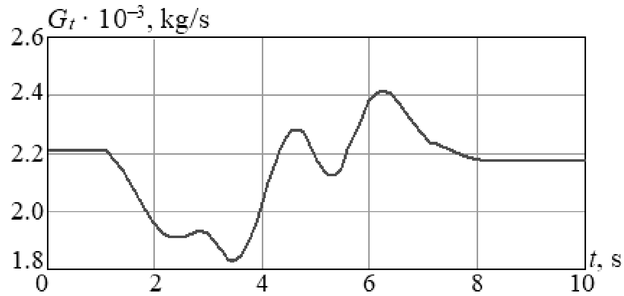


Figure 4: Fuel consumption graph in the transient process with the settings of the structural element "Pump-regulator" T_D = 0.15 s, T_K = 0.25 s.

6. Results and discussion

The above-considered evolutionary algorithm trained fully connected recurrent neural networks with two, three, and four neurons, which set the possible operating modes of the TV3-117 aircraft engine. For all options, the same cardinality of the set of initial points was set μ = 800, and the criterion for exiting the solution was the admissible difference between the minimum and maximum values of the optimized function $\varepsilon = 10^{-3}$.

The fig. 5 shows the results of the optimization program; adjacency matrices with optimal values of synaptic weights for a neural network: with two (fig. 5, *a*), with three (fig. 5, *b*) and with four neurons (fig. 5, *c*).

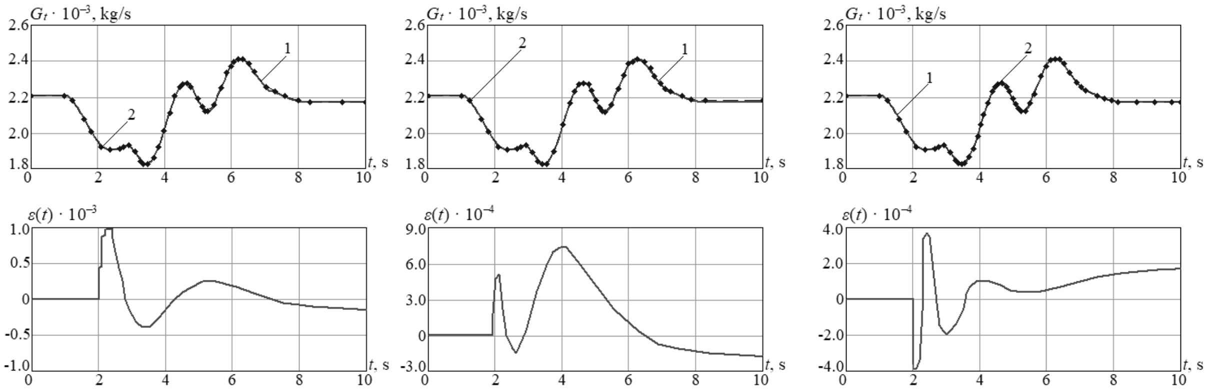
$$\begin{pmatrix} 0.356 & 0.158 \\ -0.832 & 1.093 \end{pmatrix} \qquad \begin{pmatrix} 1.089 & -0.235 & 0.031 \\ 0.426 & 0.633 & -1.225 \\ -0.144 & 0.282 & -0.399 \end{pmatrix} \qquad \begin{pmatrix} -0.171 & -0.188 & 0.375 & 0.031 \\ -0.127 & 0.554 & 0.193 & 0.623 \\ 0.833 & 1.119 & 0.745 & 1.251 \\ 1.613 & 0.674 & -0.841 & -0.113 \end{pmatrix}$$

a) *b*) *c*)

Figure 5: Adjacency matrices of synaptic weights for recurrent neural networks: *a* – with two neurons; *b* – with three neurons; *c* – with four neurons

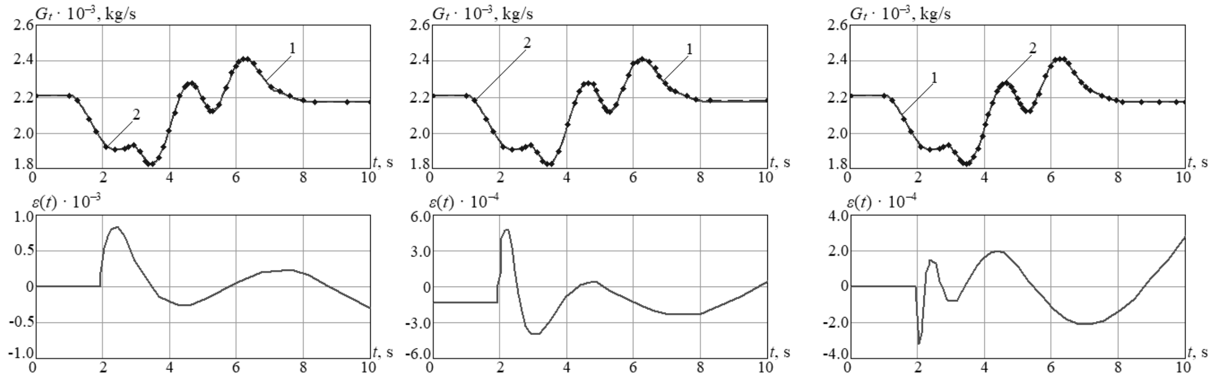
To train a neural network with four neurons (search for 16 values of synaptic weights for the matrix according to fig. 5, *c*), the program takes from 10 to 20 seconds.

The fig. 6, 7 and 8 show graphs of the results of studying the learning processes of a neural network: with two neurons (*a*), with three neurons (*b*) and with four neurons (*c*). It can be seen that the identification accuracy depends on the number of neurons, and the dynamic error of the neural network depends on the rate of change of the modeled process. The dynamic error of modeling transient processes is no more than 10^{-4} attained by a neural network with four neurons.



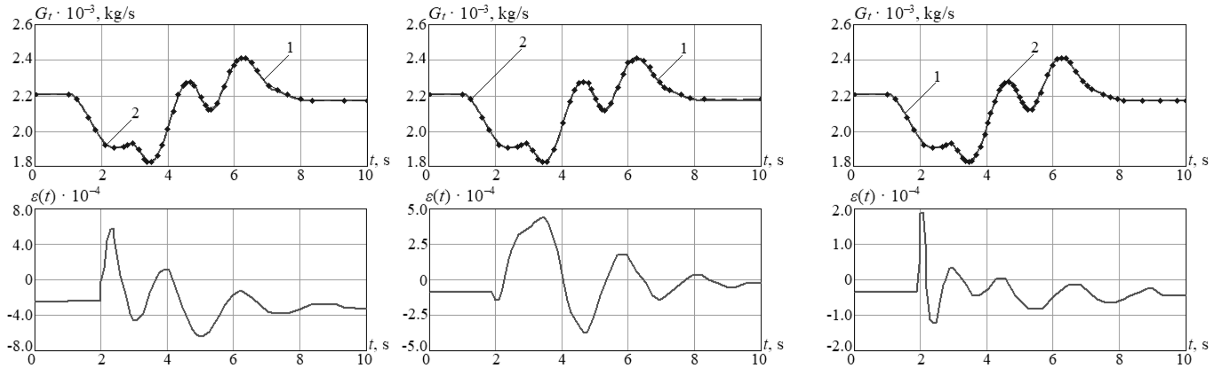
a) *b*) *c*)

Figure 6: Graphs of learning outcomes of dynamic recurrent neural networks for system identification (20): 1 – neural network; 2 – analytical calculation



a) *b*) *c*)

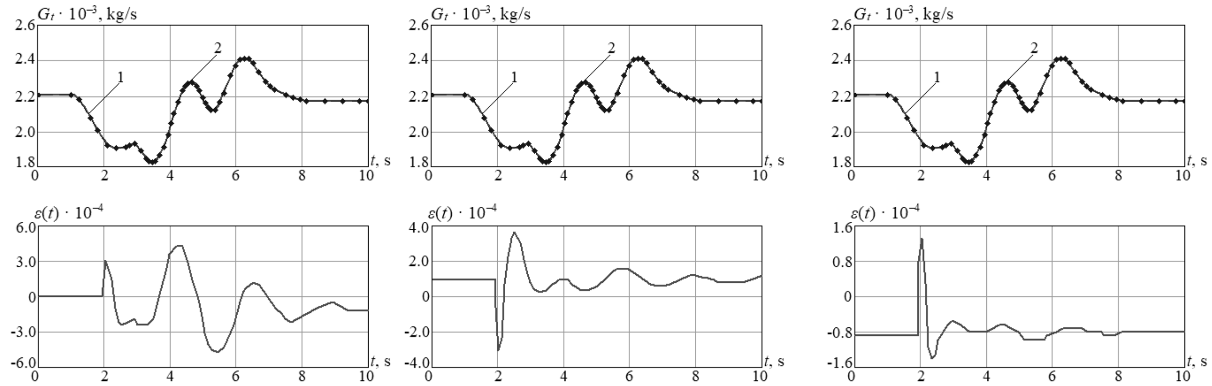
Figure 7: Graphs of learning outcomes of dynamic recurrent neural networks for the identification of system (21) with *A*-link parameters T_a = 10 s and k_a = 3 units out / units in and *I*-link: T_i = 50 s: 1 – neural network; 2 – analytical calculation



a) *b*) *c*)

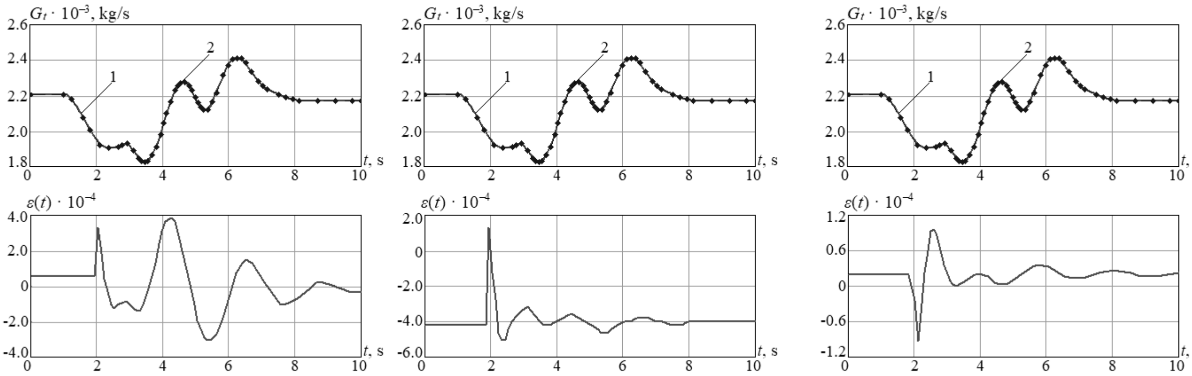
Figure 8: Graphs of learning outcomes of dynamic recurrent neural networks for system identification (21) with A-link parameters T_a = 10 s and k_a = 3 units out / units in and *I*-link: T_i = 3 s: 1 – neural network; 2 – analytical calculation

The fig. 9 and 10 show graphs of the results of studying the learning processes of dynamic recurrent neural networks with four neurons to identify the transient process (fig. 4) at the output: *a* – first neuron, *b* – second neuron, *c* – third neuron.



a) *b*) *c*)

Figure 9: Graphs of the results of studying the learning processes of a dynamic recurrent network with four neurons to identify the transient process at the output: *a* – first neuron, *b* – second neuron, *c* – third neuron for transient processes in system (21) with parameters T_a = 10 s and k_a = 3 units out / units in and *I*-link: T_i = 50 s: 1 – neural network; 2 – analytical calculation



a) *b*) *c*)

Figure 10: Graphs of the results of studying the learning processes of a dynamic recurrent network with four neurons to identify the transient process at the output: *a* – first neuron, *b* – second neuron, *c* – third neuron for transient processes in system (21) with parameters T_a = 10 s and k_a = 3 units out / units in and *I*-link: T_i = 3 s: 1 – neural network; 2 – analytical calculation

In the work, a neural network with four neurons is tested for the identification of graphs under various stepwise disturbances. The fig. 11 shows the test results under disturbances: *a* – 0.5; *b* – 1.0; *c* – 2.0 units. Good agreement of the neural network with analytical calculations with a satisfactory error is seen.

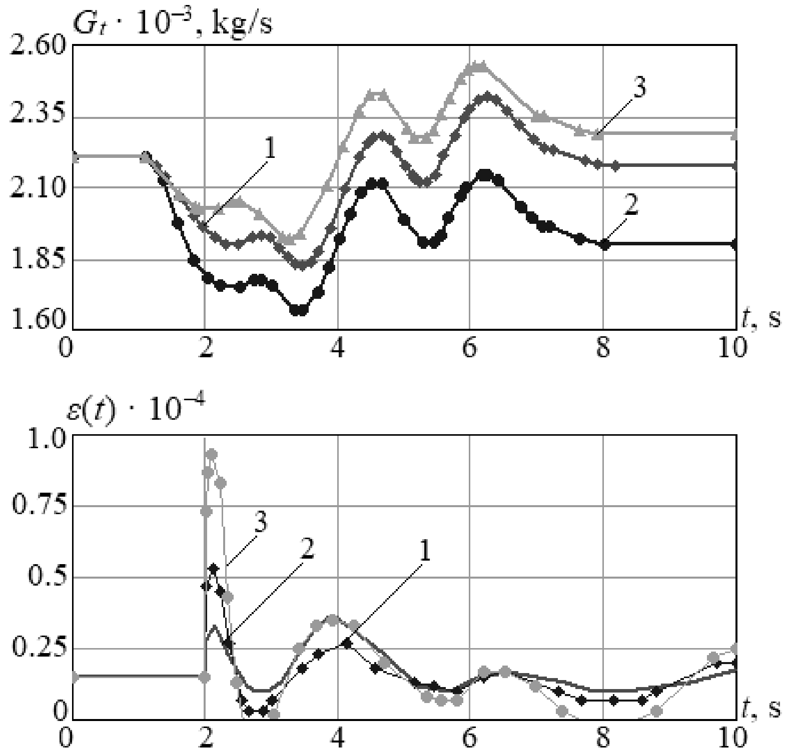


Figure 11: Graphs of transient processes and dynamic errors of identification of a dynamic system (21) of a recurrent neural network under stepwise disturbances, where "——" – neural network; "•" – analytical calculation: 1 – original signal; 2, 3 – modified signal (0.5 and 2.0 units, respectively)

The fig. 12 shows neural networks and graphs of transient processes obtained at the outputs of all neurons, obtained after training the neural network to identify transient processes at the output of the second neuron: 1 – output from a neuron characterizing the operating mode of the engine S_i; 2 – output from neuron 2, characterizing the normal operation of the engine S_1 (nominal, I cruising, II cruising)

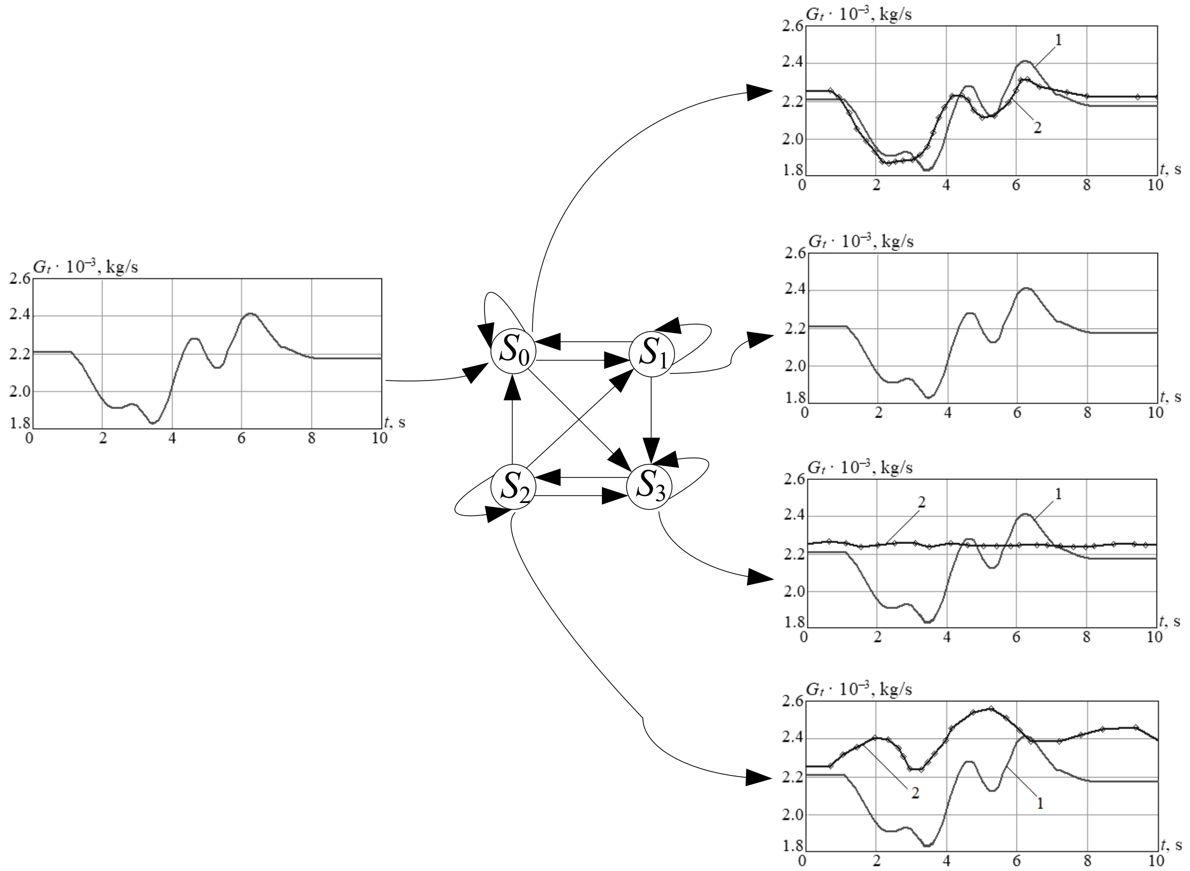


Figure 12: Signal graph of a recurrent neural network trained to identify the transient process at the output of the second neuron, signaling the normal operation of aircraft engine TV3-117, and graphs of the corresponding transient processes at the outputs of the remaining neurons

7. Conclusions

This work is devoted to the implementation of Markov discrete network showing all kinds of changes of TV3-117 aircraft engine technical state as a part of a helicopter power plant during flight tests using neural network technologies, which allows using, along with quantitative mathematical models of the TV3-117 aircraft engine, qualitative and experimental information obtained during flight tests.

For modeling and implementation Markov discrete network showing all kinds of changes of TV3-117 aircraft engine technical state as a part of a helicopter power plant during flight tests as dynamic systems in control algorithms, a dynamic recurrent neural network, encoded by signal graphs, is proposed.

To calculate dynamic recurrent neural networks, a step-by-step matrix method is proposed that uses the signal graph adjacency matrix as an associative memory storage, which made it possible to obtain sufficient accuracy in approximating the thermogas-dynamic parameter signal, for example, fuel consumption in the transient process with the settings of the structural element «Pump-regulator».

It was found that to identify a third-order dynamic system, it is sufficient to train a fully connected recurrent neural network with four neurons, symbolizing the vector of probabilities of TV3-117 aircraft engine technical states, in which the number of synaptic weights is equal to the square of the number of neurons, and any neuron in the network, including the input one, can be used as an output.

Studies have shown that in a neural network trained for the selected (second) output neuron, active signals dynamically connected with the signal on the second neuron are observed at the outputs of its other neurons.

Research prospects are the use of the obtained properties of recurrent neural networks as virtual intermediate signals in the control and diagnostics system of aircraft GTEs technical state, including TV3-117, as dynamic systems.

The results of this work can be introduced into an intelligent on-board system for control and diagnosing of aircraft GTEs technical state, including TV3-117 [24].

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