Neural Network Modeling of Helicopters Turboshaft Engines at Flight Modes Using an Approach Based on "Black Box" Models

Serhii Vladov, Ruslan Yakovliev, Oleksandr Hubachov, Juliia Rud and Yurii Stushchanskyi

Kremenchuk Flight College of Kharkiv National University of Internal Affairs, Peremohy street 17/6, Kremenchuk, 39605, Ukraine

Abstract

The work is devoted to further research in the field of creation and modernization of an on-board monitoring system for helicopters turboshaft engines. In this work, neural network modeling of helicopters turboshaft engines at flight modes was carried out using an approach based on "black box" models, and the main approaches to modeling complex dynamic systems are described. It is shown that the developed universal diagram for training a neural network model of helicopters turboshaft engines, as well as a universal mathematical model of helicopters turboshaft engines (gas turbine engines with a free turbine), which establishes the relation between all thermogas-dynamic parameters, are fully implemented in the described approaches to modeling complex dynamic systems. Having introduced the previously developed mathematical model of helicopters turboshaft engines (gas turbine engines with a free turbine) in the Matlab/Simulink program into a neural network of the NARX type (nonlinear autoregression model with exogenous inputs), its performance of the neural network model was assessed in relation to the TV3-117 turboshaft engine, which is part of the power installation of the Mi-8MTV helicopter. The work involved a computational experiment, the results of which were to obtain values degree of increase in the total pressure in the compressor, compressor turbine shaft power, compressor turbine operation, fuel consumption in the combustion chamber in dynamics. It is shown that the implementation error of the method for helicopters turboshaft engines working process thermogas-dynamic parameters identification using a neural network – NARX model, did not exceed 0.43 % when calculating individual engine parameters, while for the classical method (helicopters TE thermogas-dynamic model) it is about 1.96 % for considered engine parameters.

Keywords [1]

neural network, helicopters turboshaft engines, "black box", training, thermogas-dynamic parameters, NARX model, error

1. Introduction

Presently, neural network technology stands out as one of the most rapidly advancing domains within artificial intelligence [1, 2]. It finds successful applications across diverse fields of science and technology, including pattern recognition, diagnostic systems for complex technical objects, ecology and environmental science (encompassing weather forecasts and disaster predictions), the formulation of mathematical models describing climatic characteristics, biomedical applications, and more [3, 4]. In the realm of aircraft engine engineering, there is a pertinent need to establish a unified methodology for developing algorithms that construct and train various types of neural networks to address issues related to the parametric diagnostics of gas turbine engines (GTE). This encompasses the development of algorithms and software for a neural network-based parametric diagnostics method, aiming to enhance the probability of detecting defects in GTE compared to existing methods. Additionally, there

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EMAIL: ser2610196@gmail.com (S. Vladov); director.klk.hnuvs@gmail.com (R. Yakovliev); oleksandrgubachov@gmail.com (O. Hubachov); juliarud25@gmail.com (J. Rud); skety@ukr.net (Yu. Stushchanskyi)
ORCID: 0000-0001-8009-5254 (S. Vladov); 0000-0002-3788-2583 (R. Yakovliev); 0000-0002-1826-259X (O. Hubachov); 0000-0002-0328-5895 (J. Rud); 0000-0002-3021-6756 (Yu. Stushchanskyi)

is a focus on evaluating the effectiveness of the neural network method using specific GTE examples and identifying neural network architectures that prove most efficacious for the parametric diagnostics of GTE operational status [5, 6].

The evaluation of the operational state of helicopter turboshaft engines (TE) in real-world conditions typically relies on a restricted set of information, primarily because of the limited number of standards monitored parameters. This limitation considerably hampers the effectiveness of parametric identification, control, and diagnostic methods that are built upon the identification of mathematical models of engine operating processes. Hence, there is a need for research aimed at enhancing the efficiency of identification, control, and diagnostic methods, encompassing approaches such as the neural network method [7, 8].

2. Related works

Monitoring and controlling the operation of helicopter TE is recognized to be imperative, especially amid considerable and diverse uncertainties in the values of their parameters, characteristics, helicopter flight modes, and environmental influences. Furthermore, during flight, various emergency situations may occur, including failures of engine components and structural damage, such as the destruction of compressor blades or burnout of the combustion chamber. Addressing these challenges necessitates the reconfiguration of the control system and engine controls.

The implication is that the situation in which the helicopter operates can undergo significant and unpredictable changes at any given moment. The automatic control system for helicopter turboshaft engines (TE) [9, 10] needs to adeptly adjust to these changes by promptly modifying the parameters and/or structure of the control laws applied. The principles of adaptive control theory offer a means to meet this requirement effectively [11, 12]. Among the most potent approaches to realizing adaptability concepts is the methodology grounded in the methods and tools of neural network modeling and control [13, 14]. A pivotal aspect of implementing this approach is the acquisition of a neural network model for the control object.

Conventionally, models for nonlinear dynamic systems, such as helicopter TE, rely on differential equations (for continuous-time systems) or difference equations (for discrete-time systems). However, as mentioned earlier, in certain instances, these models may fall short of meeting specific requirements, notably the need for adaptability essential for incorporating the model into on-board systems for controlling the behavior of helicopter turboshaft engines. An alternative approach involves employing neural network models, which offer the advantage of adaptive implementation.

In this work, neural network models of the traditional empirical type are considered for dynamic systems, that is, "black box" models (fig. 1, where $u_1(t)\ldots u_N(t)$ – coordinates of the N-dimensional vector $u(t)=\left\|u_i(t)\right\|_{N\times 1}$ – controlling influences; $y_1(t)\ldots y_M(t)$ – coordinates of the M-dimensional vector $y(t)=\left\|y_i(t)\right\|_{M\times 1}$ of control coordinates; $w_1(t)\ldots w_\kappa(t)$ – coordinates of the k-dimensional vector $w(t)=\left\|w_i(t)\right\|_{\kappa\times 1}$ of external influences) [7] with the possibility of subsequent expansion to semi-empirical ones by introducing into them theoretical knowledge about the object of modeling – helicopters TE.

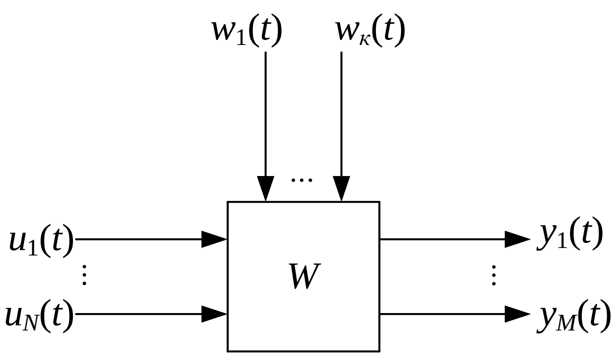

Figure 1: Image of the helicopter's turboshaft engines in the form of a "black box" [7]

According to fig. 1 values $y_i(t)$, $i \in \{\overline{1,M}\}$, $u_i(t)$, $i \in \{\overline{1,N}\}$, $w_i(t)$, $i \in \{\overline{1,K}\}$, taking into account the dynamics of processes in the helicopters TE can change in real time t. When the set of values of these quantities is denoted by $Y_i(t)$, $i \in \{\overline{1,M}\}$, $U_i(t)$, $i \in \{\overline{1,N}\}$, $\Omega_i(t)$, $i \in \{\overline{1,K}\}$, the set is considered [15]

$$\begin{gathered} Y = Y_1 \times Y_2 \times \ldots \times Y_M; \\ U = U_1 \times U_2 \times \ldots \times U_N; \\ \Omega = \Omega_1 \times \Omega_2 \times \ldots \times \Omega_K; \end{gathered} \tag{1}$$

where the symbol "×" means the Cartesian product, and taking into account these sets, the helicopter TE, as an object of observation, can be described as

$$W : T \times T \times U \times \Omega \to Y; \tag{2}$$

which generally defines the helicopters TE operational status at the moment of time $t \in T$, where T – set of time intervals $t \geq 0$, when the engine is simultaneously affected by both control and disturbance influences at the moment $0 \leq \tau \leq t$.

If we consider some subset $Y^{(0)} \subseteq Y$ as some area of identification of the parameters of helicopters TE operational status, then the goal of the coordinating part of the system is the formation of such values $u_1(t) \ldots u_N(t)$, for which the set $(y_1(t), ..., y_M(t)) \in Y^{(0)}$. This task can be considered as a general area of helicopters TE operational status monitoring in relation to the entire system. To solve such problems, it is important to take into account information about the behavior of the control coordinates, the setting and disturbing influences. The process of obtaining this information in a generalized form can be described by the expression [16]:

$$M : T \times T \times Q \times Y \times \Omega \to D; \tag{3}$$

where Q and D – Cartesian products of the set of values of the corresponding influences and the input coordinates of the control part of the system.

Many schemes of adaptive control require the presence of a control object model [17]. Obtaining such a model is the content of the classic task of identifying dynamic systems [18, 19]. One of the most effective approaches to solving this problem in relation to nonlinear systems is, as experience shows [20, 21], the use of methods and tools of artificial neural networks. Neural network modeling makes it possible to build sufficiently accurate and computationally efficient neural network models.

3. Materials and methods used

In the dissertation by Yurii Tiumentsev titled "Neural Network Modeling of Adaptive Dynamic Systems" [22], the general neural network modeling of complex dynamic objects, illustrated through the example of aircraft movement, is elucidated using an approach grounded in "black box" models. Extracting some key concepts from this work, there are two primary approaches for representing (describing) nonlinear dynamic systems [23]: representation in the state space of nonlinear dynamic systems and representation in terms of inputs and outputs of nonlinear dynamic systems (input-output representation). For the sake of simplifying the discussion on modeling helicopter turboshaft engines (TE) as nonlinear dynamic systems, we assume that the system in question has a single output, signifying that the process it undergoes is characterized by a singular value. It is presumed that the model of helicopter TE as a nonlinear dynamic system corresponds to a representation in state space if this model takes the form [22]:

$$\begin{gathered} x(k) = f\left(x(k-1), u(k-1)\xi_1(k-1)\right); \\ y(k) = g\left(x(k), \xi_2(k)\right); \end{gathered} \tag{4}$$

In the provided expression, the vector $x(k)$ represents the state vector (or phase vector) of the helicopter TE model as a nonlinear dynamic system. Its components are variable quantities that characterize the state of the object at the time t_k. The vector $x(u)$ encompasses components serving as input control quantities for the engine, specifically thermogas-dynamic parameters [22, 24]. The vectors $\xi_1(k)$ and

$\xi_2(k)$ are descriptive of disturbances impacting the engine, while the scalar quantity $y(k)$ denotes the output. The functions $f(\bullet)$ and $g(\bullet)$ represent a nonlinear vector function and a scalar function, respectively. The dimension of the state vector, signifying the number of state variables included in this vector as its components, is commonly referred to as the order of the model [22, 25]. State variables within the vector can be either observable, with their values measurable, or unobservable. In a specific scenario, any of the engine state variables can be utilized as an output value. Disturbances $\xi_1(k)$ and $\xi_2(k)$ have the potential to influence the values of motor outputs and/or its states. Unlike input control actions, disturbing influences remain unobservable.

Constructing a model of the helicopter TE in the state space involves obtaining approximations for the functions $f(\bullet)$ and $g(\bullet)$ based on the accessible data on the dynamic system. In the scenario where a "black box" model is created (fig. 1), implying the absence of any knowledge about the nature and operational characteristics of the engine, the pertinent data would be sequences of values for the input and output quantities of the engine. Additionally, it includes those state variables whose values can be acquired through measurements.

It is conventional to describe the model of the helicopter TE as a nonlinear dynamic system through an input-output representation (representing the system in terms of its inputs and outputs) when this model takes the form [22]:

$$y(k)=h\big(y(k-1),...y(k-n),u(k-1),...u(k-m),...,\xi(k-1),...\xi(k-p)\big); \qquad (5)$$

where $h(\bullet)$ denotes a nonlinear function, n is the order of the model, m and p are positive integer constants, $x(u)$ represents the vector of engine input control signals, and $\xi(k)$ is the vector of disturbances. This input-output representation can be regarded as a specific instance of a state-space representation, wherein the components of the state vector are observable and are considered as engine output signals.

It is established that in modeling linear systems, the state-space representation and the input-output representation are interchangeable [25, 26]. Hence, one can opt for the representation that is more convenient and efficient for the specific problem at hand. In contrast, in nonlinear modeling, the state-space representation is more comprehensive and simultaneously more economical (compact) than the input-output representation. However, the implementation of a state-space model generally requires more effort than an input-output model due to the necessity of obtaining approximate representations for two maps, $f(\bullet)$ and $g(\bullet)$ in (4), as opposed to a single map $h(\bullet)$ in (5) [22].

Determining the model type (in state space or input-output) is not the sole consideration when modeling a nonlinear dynamic system. Another crucial aspect is the method of incorporating disturbances into the formulated model. Two possible options exist in this regard: disturbances impacting the state of the engine, disturbances influencing motor outputs, or disturbances affecting both the states and outputs of the engine.

As demonstrated in [22, 27], the manner in which disturbances influence the engine has a notable impact on the structure of the resultant model, the algorithm necessary for its training, and the operational characteristics of the generated model.

Let's initially explore the scenario in which disturbances affect the operational status of helicopter TE. Suppose the desired representation of the engine takes the following form [22]:

$$y_p(k)=\psi\big(y_p(k-1),...,y_p(k-n),u(k-1),...,u(k-m)\big)+\xi(k); \qquad (6)$$

where $y_p(k)$ – observed (measured) output of the process implemented by the engine.

Let's presume that the engine output experiences the influence of additive noise, and the summation point of the output signal and noise precedes the point from which the feedback signal emerges. Consequently, at time k, the system's output will be influenced by this noise directly and through its effect on the preceding n outputs. In the realm of nonlinear modeling, this structural configuration aligns with an NARX type model, as proposed in [22], specifically, a nonlinear autoregression with external inputs in its series-parallel version (fig. 2, b).

The additive noise affecting the motor output in the considered embodiment has an influence not only directly at time t, but also through the outputs at the previous n steps, when such an influence also took place. The need to take into account previous outputs is due to the fact that, ideally, the modeling error at step k should be equal to the noise value at the same time. Accordingly, when forming a motor model, it is necessary to take into account the outputs of the system at past times in order to compensate for the noise effects that have taken place. The corresponding ideal model can take the form of a feed-forward network that implements a mapping of the form [22]:

$$g(k) = \varphi_{NN}\left(y_p(k-1),...,y_p(k-n),u(k-1),...,u(k-m),\omega\right); \tag{7}$$

where ω – vector of parameters, $\varphi_{NN}(\bullet)$ – function implemented by the feedforward network.

Let the parameter vector ω of the network be chosen during its training in such a way that $\varphi_{NN}(\bullet) = \varphi(\bullet)$, that is, this network accurately reproduces the outputs of the engine model. In this case, for all instants of time k the relation $y_p(k) - g(k) = \xi(k)$, $\forall k \in \{0, N\}$, will be satisfied, that is, the modeling error is equal to the noise affecting the engine output. This model can be termed "ideal" in the sense that it accurately captures the deterministic components of the engine's functioning process and does not replicate the noise that distorts the system's output signal. The inputs of this model encompass the values of the control variables, as well as the measured outputs of the process executed by the engine. In this scenario, the ideal model, functioning as a one-step predictor, undergoes training as a feedforward network rather than a recurrent network. Consequently, for establishing an ideal model in this context, it is recommended to employ supervised learning methods designed for static neural network models. Since the inputs of the predictor network include both control variables and measured (observed) values of the outputs of the process implemented by the engine, the model's output of this type can only be calculated one time step ahead. Consequently, models of this nature are commonly referred to as single-step predictors. If the generated model is required to reflect the engine's behavior over a time horizon exceeding one time step, the predictor's input will need to be supplied with its own outputs from the previous time. In such instances, the predictor will no longer possess the characteristics of an ideal model due to the accumulation of prediction errors [22, 28].

The second category of noise impact on the system that necessitates examination occurs when noise influences the motor output. In this instance, the pertinent description of the process carried out by the engine takes the following form [22]:

$$\begin{gathered} x_p(k) = \varphi\left(x_p(k-1),...,x_p(k-n),u(k-1),...,u(k-m)\right); \\ y_p(k) = x_p(k) + \xi(k). \end{gathered} \tag{8}$$

In this structural arrangement of the model, additive noise is directly introduced to the output signal of the engine (constituting a parallel architecture for models of this kind, as depicted in fig. 2, a). Consequently, noise exclusively influences the ongoing step of the engine's operational process. As the model's output at time k is solely contingent on the noise at the same moment in time, the model does not necessitate the values of the outputs realized by the engine at preceding time intervals; estimates generated by the model itself prove sufficient. Therefore, analogous to the "ideal model" discussed earlier for the series-parallel version, we can consider a recurrent neural network [28] that embodies a representation in the form of:

$$g(k) = \varphi_{NN}\left(g(k-1),...,g(k-n),u(k-1),...,u(k-m),\omega\right); \tag{9}$$

where, similar to (7), ω – vector of parameters, $\varphi_{NN}(\bullet)$ – function implemented by the feed-forward network.

Let, as in the previous case, the vector of parameters ω of the network is chosen during its training in such a way that $\varphi_{NN}(\bullet) = \varphi(\bullet)$. Let us also assume that for the first n moments of time the prediction error is equal in magnitude to the noise affecting the engine. In this case, for all moments of time k ($k = 0, ..., n-1$) the relation $y_p(k) - g(k) = \xi(k)$, $\forall k \in \{0, n-1\}$ will be satisfied. Hence, the modeling error will be precisely equal to the noise impacting the engine output. In essence, this model can be deemed ideal as it faithfully represents the deterministic components of the engine's operational process and abstains from replicating the noise that distorts the system's output signal. In instances where the initial conditions of the simulation are not met (the model exhibits "imperfection" at the initial time), but the condition $\varphi_{NN}(\bullet) = \varphi(\bullet)$ holds true, and the model remains stable in the face of changes in initial conditions, the modeling error will diminish with an increasing value of k [22].

As evident from the aforementioned equations, the ideal model in the parallel version manifests as a dynamic recurrent network. This is in contrast to the series-parallel version, where the ideal model was represented by a static feed-forward network.

Consequently, to effectively train a parallel-type model, it is generally essential to employ methods tailored for dynamic networks, which, naturally, pose greater challenges compared to methods used for static networks. Nonetheless, for models of the specified type, training methods can be proposed that leverage the unique characteristics of these models and are less labor-intensive than conventional methods designed for dynamic networks [29]. Given the nature of noise impact on the operational process of parallel models, they can be utilized not only as single-step predictors, as observed with series-parallel models, but also as comprehensive models enabling the analysis of these systems' behavior over a desired time interval, rather than merely one time step forward. Another scenario for the influence of noise on the simulated system involves the simultaneous introduction of noise effects on both the outputs and states of the engine. This scenario aligns with a model of the form [22]:

$$x_p(k)=\varphi\left(x_p(k-1),...,x_p(k-n),u(k-1),...,u(k-m),\xi(k-1),...,\xi(k-p)\right);$$
$$y_p(k)=x_p(k)+\xi(k). \tag{10}$$

As indicated in [22], these models fall within the NARMAX class (Nonlinear Auto-Regressive with Moving Average and eXogenous inputs), signifying nonlinear autoregression with a moving average and external inputs [30]. In this particular scenario, the generated model considers both the preceding values of the engine outputs and the previous values of the outputs of the model itself – essentially estimates of the engine outputs. Since such a model amalgamates aspects of the two previously discussed models, it is limited to functioning as a one-step predictor, akin to a model with noise affecting states.

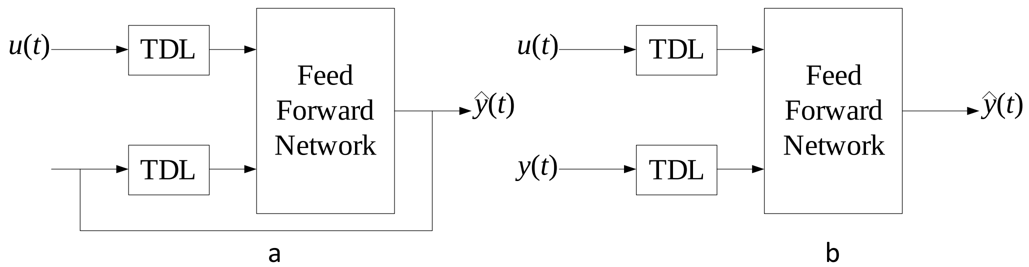

Figure 2: General structure of the neural network NARX model: a – model with parallel architecture; b – model with serial-parallel architecture [22, 30]

Now, let's delve into the depiction of the engine in state space, which, in the context of nonlinear modeling, possesses greater versatility compared to the input-output representation. Initially, we will explore the scenario where noise influences the engine's output. We can assume that the requisite representation of the engine takes the following form, as outlined in: [22]:

$$x(k)=\varphi\left(x(k-1),u(k-1)\right);$$
$$y(k)=\psi\left(x(k)+\xi(k)\right). \tag{11}$$

Given that in this version, noise is exclusively present in the observation equation, its presence doesn't impact the dynamics of the modeled object. Drawing parallels with the rationale provided for the case of input-output representation, the ideal model in this context will possess a recurrent structure defined by the relations:

$$x(k)=\varphi_{NN}\left(x(k-1),u(k-1)\right);$$
$$y(k)=\psi_{NN}\left(x(k)\right). \tag{12}$$

where $\varphi_{NN}(\bullet)$ – exact representation of the function $\varphi(\bullet)$; $\psi_{NN}(\bullet)$ – exact representation of the function $\psi(\bullet)$.

Another scenario for noise impact on the system involves noise affecting the operational status of the engine. In this case, the corresponding representation of the process implemented by the engine is formulated as per [22]:

$$x(k)=\varphi\left(x(k-1),u(k-1),\xi(k-1)\right); \tag{13}$$
$$y(k)=\psi\left(x(k)\right).$$

Given the same considerations as for the input-output representation of the engine, we can deduce that in this scenario, the ideal model's inputs, besides controls u, should also encompass state variables of the process implemented by the engine. Two situations arise:

– if state variables are observable, they can be construed as system outputs, reducing the problem to the previously discussed input-output representation case. The ideal model in this scenario would be a feed-forward network, applicable as a one-step predictor;

– if state variables are unobservable, an ideal model cannot be constructed. In such cases, one should resort to the input-output representation (with some loss of model generality) or devise a recurrent model, albeit suboptimal in this context.

Another potential scenario for the impact of noise on the simulated system is the simultaneous introduction of noise effects on both the outputs and the operational status of the engine. This scenario aligns with the model delineated by the relations according to [22]:

$$\begin{gathered} x(k)=\varphi\left(x(k-1),u(k-1),\xi_1(k-1)\right); \\ y(k)=\psi\left(x(k),\xi_2(k)\right). \end{gathered} \tag{14}$$

Similarly, to the previous scenario, two situations arise once again:

– if the state variables are observable, they can be construed as outputs of the engine, and the problem is akin to what was previously considered in the case of an input-output representation;

– if the state variables are not observable, an ideal model should encompass both the states and the observable output of the system.

The utilization of neural networks in developing models for helicopters TE offers several undeniable advantages, as outlined in [31]:

– classical methods for approximating functions of multiple variables do not facilitate the implementation of straightforward mechanisms for selecting the structure of mathematical models. In contrast, the development of neural network models is founded on employing standard procedures for selecting the structure of a neural network and their training methods;

– implementing classical interpolation methods based on spline functions demands significant computing resources, often posing challenges for real-time calculations. The layered architecture of neural networks enables parallel computations (when the neural network is hardware-implemented), addressing the issue of real-time approximation;

– neural networks make the construction of inverse models for helicopters TE, employed in compensating regulators, relatively straightforward.

Fig. 3 depicts a generalized structural diagram illustrating the process of adjusting the parameters of the neural network model for helicopters TE.

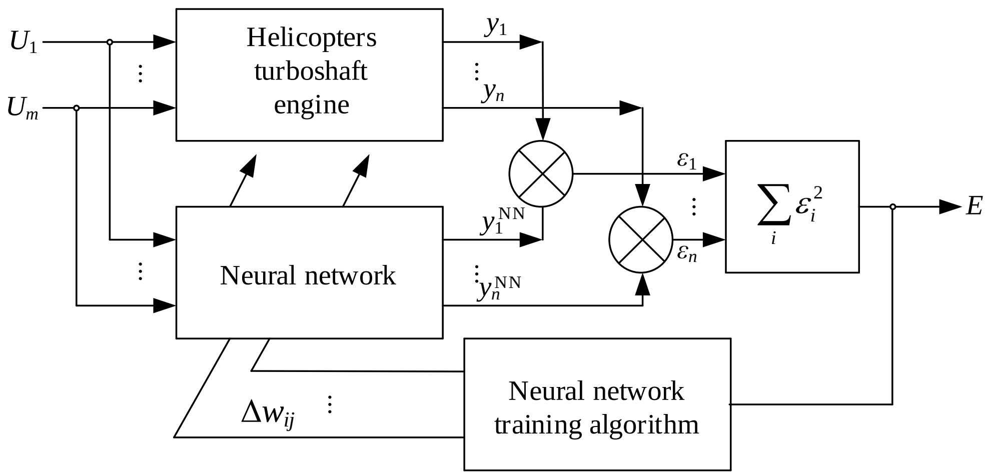

Figure 3: Training diagram of helicopters turboshaft engines neural network model: **U** = $(u_1, u_2, ..., u_m)^T$ – vector of input (control) influences; **Y** = $(y_1, y_2 ..., y_m)^T$ – vector of engine output parameters; $\mathbf{Y^{NN}}=\left(y_1^{NN},y_2^{NN},...,y_n^{NN}\right)^T$ – vector of neural network outputs; ΔW_{ij} – increase in the weights of the synaptic connections of the neural network [31]

The conversion of a vector of control influences into a vector of initial parameters is elucidated by the operator **F** (which, in general, can portray a static or dynamic model):

$$\mathbf{Y} = \mathbf{F}(\mathbf{U}). \tag{15}$$

The objective of identifying helicopters TE using a neural network can be formulated as follows. Leveraging the outcomes of the proposed neural network during the training process, which forms the "training sample" of vectors ($\mathbf{U}_i$; $\mathbf{Y}_i$) acquired experimentally for an individual instance of the engine, the goal is to find the $\mathbf{F}^{\mathrm{NN}}$ operator within the class of neural network architectures. This operator should best represent (approximate) the operator **F**.

The approximation of the operator **F** by the operator $\mathbf{F}^{\mathrm{NN}}$ is deemed optimal if a specified functional from the difference ($\mathbf{Y} - \mathbf{Y}^{\mathrm{NN}}$) does not surpass a given small value ε_{add}, defining the accuracy of the operator **F** approximation

$$E = \left\| \mathbf{Y} - \mathbf{Y}^{\mathrm{NN}} \right\| = \sum_{i}^{n} \varepsilon_i^2 \le \varepsilon_{add}; \tag{16}$$

The satisfaction of condition (16) is guaranteed by training the neural network, i.e., adjusting its parameters based on the training sample {(**U**, **Y**)}, and is verified on a meticulously organized "test sample".

The direct construction of a neural network follows the subsequent sequence of actions [31, 32]:

1. Definition of the goals and tasks of ensuring the fault tolerance of the automatic control system of helicopters TE.
2. Selection of the structure and inclusion location of the neural network.
3. Selection of the neural network training algorithm.
4. Formation of the training sample based on experiments (utilizing a digital model with flight data results).
5. Training of the neural network.
6. Contrasting the neural network (reduction, simplification).
7. Modeling and debugging (testing) of control algorithms of the automatic control system with a neural network.
8. Software or hardware implementation of the neural network.

Virtual changes in the state of helicopters TE can be provisionally classified as follows [31, 32]:

1. Deterministic changes, a priori known changes influenced by controlled factors (flight conditions, resource utilization, air sampling values, etc.).
2. Stochastic changes caused by different initial thermal conditions of rotors and stators, changes in radial clearances, etc.), uncontrolled air and power withdrawals, etc.
3. Accidental changes resulting from an uncontrolled modification in the engine configuration (damage to turbocharger blades, contamination of the engine's flow part, changes in fan characteristics in the case of strong side wind, etc.).

In [33], a universal mathematical model of helicopters TE (GTE with a free turbine) was developed based on the block diagram (fig. 4), establishing correlations among all thermo-gas-dynamic parameters. The universal mathematical model encompasses a system of equations describing processes in all engine components: in the air inlet section, in the compressor, in the combustion chamber, in the compressor turbine, in the free turbine, and in the exhaust unit.

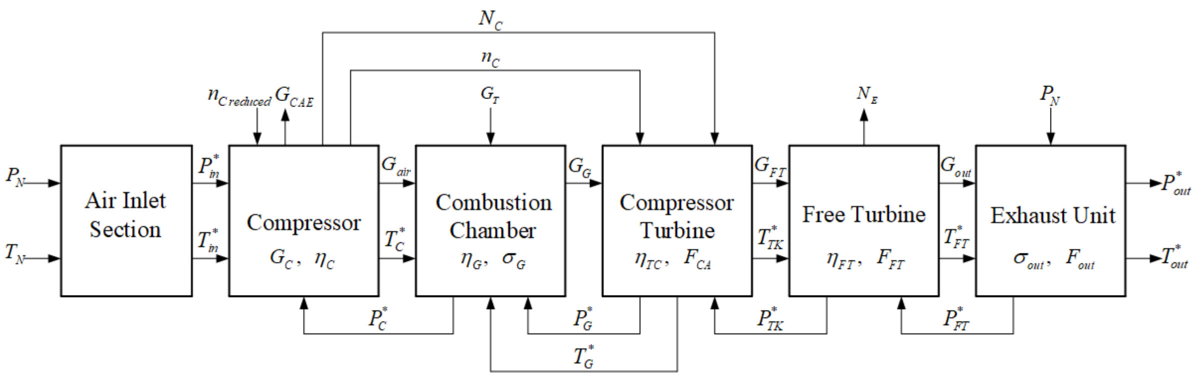

Figure 4: Helicopters turboshaft engines (GTE with a free turbine) mathematical model block diagram [33]

Fig. 5 illustrates a segment of the mathematical model for helicopter TE (GTE with a free turbine), implemented in the Matlab/Simulink program. This model was developed based on the universal mathematical model for helicopter turboshaft engines [34, 35].

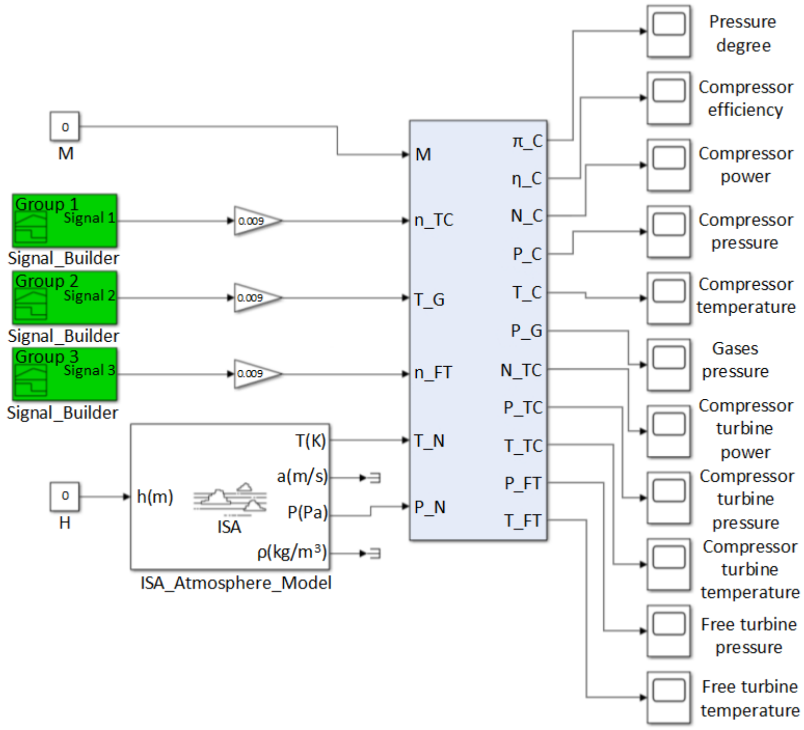

Figure 5: Overall depiction of a segment of the mathematical model for helicopter turboshaft engines (GTE with a free turbine) within the Matlab/Simulink program, involving the calculation of 11 thermogas-dynamic parameters throughout the engine's operational processes [34, 35]

In [34, 35], the proposed implementation of the discussed system involves utilizing a three-layer perceptron. This approach allows for the precise identification of the thermogas-dynamic parameters of helicopter turboshaft engines, achieving an accuracy surpassing 99.362 %. The computational efficiency of neural network models is rooted in the fact that an artificial neural network serves as an algorithmically universal mathematical model [36, 37]. This implies that it can represent any nonlinear mapping with any predetermined accuracy $\varphi : \Re^n \rightarrow \Re^m$, capturing the intricate relationships between an *n*-dimensional vector of input data and an *m*-dimensional vector of output data

The development of a nonlinear neural network model for helicopters TE is conceptualized as deriving a neural network approximation of the original mathematical model governing helicopter motion. Typically expressed as a system of differential equations, this mathematical model serves as a reference. The training process of the neural network model involves minimizing the error signal ε, representing the squared discrepancy between the output of the control object y_p and the neural network model y_m, both influenced by the control signal u. The trained neural network model operates through a recurrent computation scheme, utilizing the values of and u at time t_i to compute the output value for time t_{i+1}.

4. Proposed neural network approach

Unlike [22], where it was proposed to use standard neural network architectures of the NARX type (fig. 2) (training was carried out in batch mode and in real time) to simulate the aircraft movement, in this work it is proposed to use a modified gaussian NARX architecture with a choice input regressor based on the modified gradient algorithm [38]. Modification of the standard NARX architecture is justified by the relatively outdated NARX models that use old machine learning models [39].

The structure of the proposed neural network consists of two parts: nonlinear and linear block (fig. 6). The nonlinear block only accepts input regressors selected by the modified gradient algorithm [38]. A linear block is a single neuron that accepts all input and output regressors.

As in [22], a neural network model implements a dynamic mapping described by a difference equation of the following form:

$$y(t)=\psi\left(y(t-1),y(t-2),...,y\left(t-N_y\right),u(t-1),u(t-2),...,u\left(t-N_u\right)\right); \quad (17)$$

where the value of the output signal $y(t)$ for a given time t is calculated based on the values $y(t-1),y(t-2),...,y\left(t-N_y\right)$ of this signal for the sequence of previous time points, as well as the values of the input (control) signal $u(t-1),u(t-2),...,u\left(t-N_u\right)$ external to the NARX model. In the general case, the length of the history for outputs and controls may not coincide, that is, $N_y \neq N_u$.

Unlike [39], in this work it is proposed to use the Gaussian architecture of NARX instead of the sigmoidal architecture of NARX, since in the problem of identifying helicopters TE parameters, the neuron response should be maximum for some specific input value.

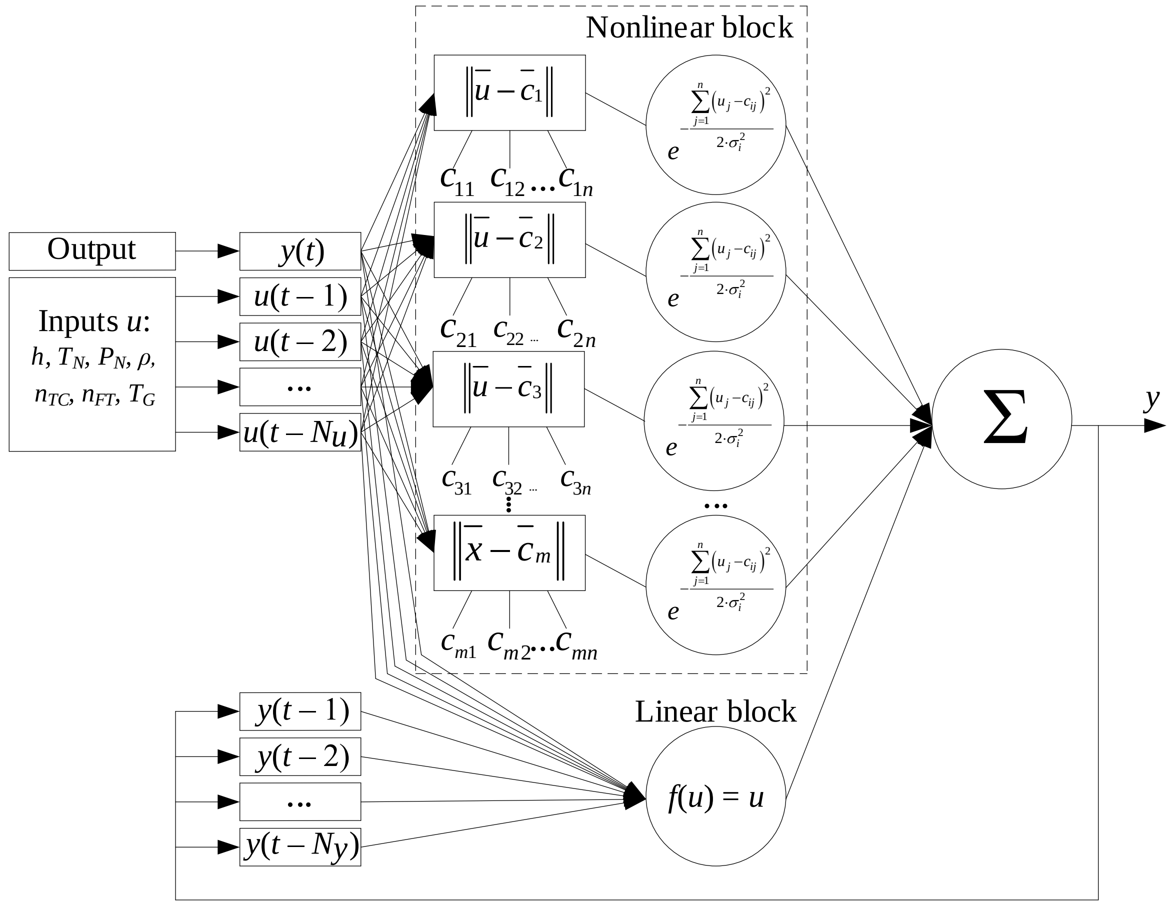

Figure 6: Block diagram of helicopters turboshaft engines neural network modified – proposed gaussian NARX architecture (author's development)

Fig. 6 are shows: u_1, u_2, ..., u_n – input signals; c_{i1}, c_{i2}, ..., c_{in} – coordinates of the center of the i-th element; σ_i – width of the radial function of the i-th element [38].

Removing output regressors from the nonlinear block increases the reliability of the neural network model of helicopter TE and allows the use of more than one output regressor in models. Reducing the number of unnecessary inputs regressors and obtaining parsimonious models improves robustness and reduces sensitivity to parameter changes [39]. In addition, the implementation of these models on equipment such as modified closed onboard helicopters turboshaft engines automatic control system [5, 8] are much more feasible due to the smaller number of parameters to be estimated. The total number of parameters evaluated in the proposed architecture is

$$N_Y = \left(N_{NLreg} + 1\right) \cdot \left(N_{unit} + 1\right); \tag{18}$$

where N_{NLreg} – number of regressors used in the nonlinear block, N_{Lreg} – number of regressors used in the linear block, N_{unit} – number of neurons used in the nonlinear block.

Representing the helicopter TE with the proposed neural network allows us to reduce the identification task to training the network, which consists of adjusting its weight parameters. In this case, the quadratic error functional is usually chosen as a training criterion (the functional to be minimized)

$$J = \varepsilon^2 = M\left(y(t) - y(t)\right) \tag{19}$$

minimization of which is carried out using a modern nonlinear optimization method – the Levenberg–Marquardt algorithm [40].

5. Experiment

The authors' team, led by Serhii Vladov, has extensively documented the description of input data and its preliminary processing, as evident in numerous works, such as [7, 8]. The input parameters for the mathematical model of helicopters TE encompass atmospheric conditions (h – flight altitude, T_N – temperature, P_N – pressure, ρ – air density). These parameters, acquired onboard the helicopter (n_{TC} – gas generator rotor r.p.m., n_{FT} – free turbine rotor speed, T_G – gas temperature in front of the compressor turbine), are normalized to absolute values following Professor Valery Avgustinovich's gas-dynamic similarity theory (see table 1). The work assumes constancy in atmospheric parameters (h – flight altitude, T_N – temperature, P_N – pressure, ρ – air density) [7, 8].

Table 1
Part of training set (on the example of TV3-117 TE, author's development, described in [7, 8])

Number	T_G	n_{TC}	n_{FT}
1	0.932	0.929	0.943
2	0.964	0.933	0.982
3	0.917	0.952	0.962
4	0.908	0.988	0.987
5	0.899	0.991	0.972
6	0.915	0.997	0.963
7	0.922	0.968	0.962
8	0.989	0.962	0.969
9	0.954	0.954	0.947
10	0.977	0.961	0.953
…	…	…	…
256	0.953	0.973	0.981

Assessing the homogeneity of the training and test samples is a crucial consideration. To address this, the Fisher-Pearson criterion χ^2 with $r - k - 1$ degrees of freedom is employed [7, 8]:

$$\chi^2 = \min_{\theta} \sum_{i=1}^{r} \left(\frac{m_i - np_i(\theta)}{np_i(\theta)} \right); \tag{21}$$

where θ – maximum likelihood estimate determined based on the frequencies m_1 through m_r, where n represents the total number of elements in the sample. The probabilities of individual outcomes, denoted as $p_i(\theta)$, are associated with a certain indeterminate k-dimensional parameter θ.

The concluding step in the statistical data processing involves normalizing the data, a process that can be carried out in accordance with the given expression:

$$y_i = \frac{y_i - y_{i\min}}{y_{i\max} - y_{i\min}}; \quad (22)$$

where y_i – dimensionless quantity in the range [0; 1]; $y_{i\min}$ and $y_{i\max}$ – minimum and maximum values of the y_i variable.

The mentioned χ^2 statistics, under the stated assumptions, allow for testing the hypothesis regarding the representativeness of sample variances and covariance of factors within the statistical model. The range of hypothesis acceptance is denoted by $\chi^2 \leq \chi_{n-m,\alpha}$, where α represents the significance level of the criterion. The computed results based on equation (21) are presented in table 7 [7, 8].

Table 2

Part of the training sample during the operation of helicopters TE (on the example of TV3-117 TE) (author's development, author's development, described in [7, 8])

Number	$P(T_G)$	$P(n_{TC})$	$P(n_{FT})$
1	0.561	0.109	0.652
2	0.588	0.155	0.574
3	0.542	0.128	0.515
4	0.612	0.147	0.655
5	0.644	0.121	0.612
…	…	…	…
256	0.537	0.098	0.651

To assess the representativeness of both the training and test samples, an initial data cluster analysis was conducted (see table 2), revealing the identification of eight classes (see fig. 7, *a*). Subsequently, through a randomization procedure, the specific training (control) and test samples were chosen in a 2:1 ratio, i.e., 67 % and 33 %, respectively. The clustering process applied to both the training (see fig. 7, *b*) and test samples indicated the presence of eight classes in each, mirroring the original sample. Notably, the distances between the clusters closely align in all considered samples, affirming the representativeness of both the training and test samples [7, 8].

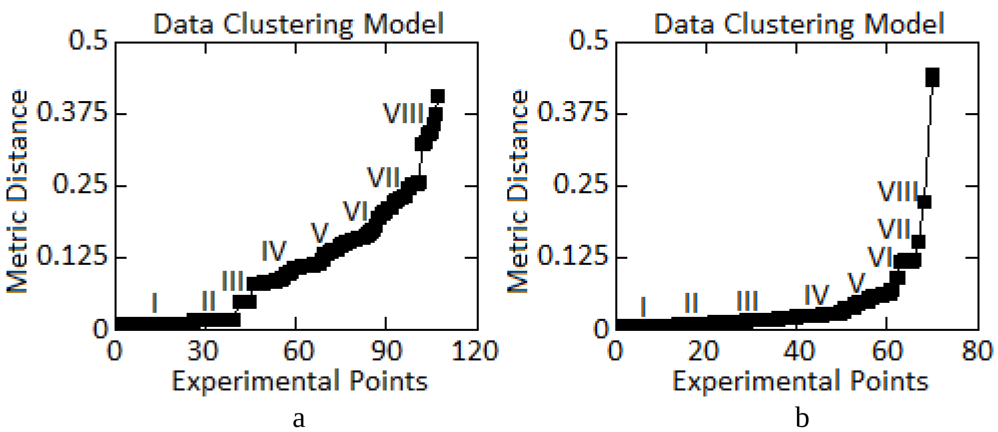

Figure 7: Clustering results: a – initial experimental sample (I…VIII – classes); b – training sample (author's development, described in [7, 8])

6. Results

The assessment of the neural network model's performance was conducted concerning the TV3-117 TE, a component of the power system in the Mi-8MTV helicopter. The evaluation employed conventional mathematical models relevant to the operation of the power system during helicopter flight [33, 41]. This study involved a computational experiment designed to provide insights into the characteristics of the specific class of neural network models under investigation. The outcomes of the conducted experiments are illustrated in fig. 8 – 12.

Figure 8 displays instances of input training samples utilized in the training of neural network models. It is evident from these examples that the generation of each sample involves the computation of the primary thermogas-dynamic parameters of the TV3-117 TE (see fig. 5). The purpose behind employing this method for forming the training set is to ensure the inclusion of a diverse range of states within the modeled system, aiming to cover the entire state space of the system as uniformly and comprehensively as possible. Additionally, the method seeks to capture a broad spectrum of differences in states that are temporally adjacent, enhancing the neural network model's ability to accurately reflect the dynamics of the simulated system. As the primary objective of control in the given problem is the precise tracking of the prescribed values for the thermogas-dynamic parameters of the TV3-117 turboshaft engine, the evaluation of the model's accuracy revolves around a comparison of the behavior of this parameter between the actual control object (helicopter TE) described by a system of differential equations and the generated neural network model. Model accuracy is determined by assessing the error, computed as the disparity between the obtained values of the engine’s thermogas-dynamic parameters for the control object and the neural network model at the corresponding time point.

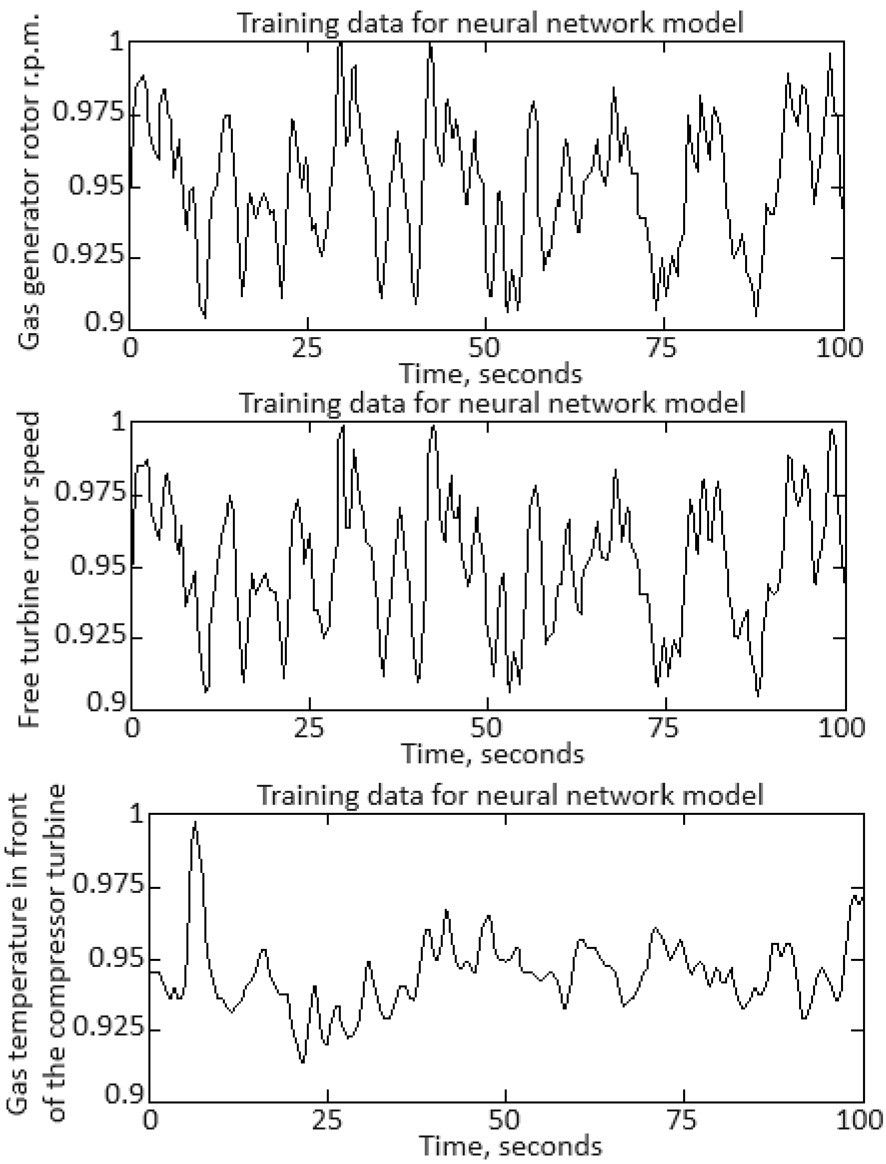

Figure 8: Formation of a neural network model for TV3-117 turboshaft engine input data (author's development)

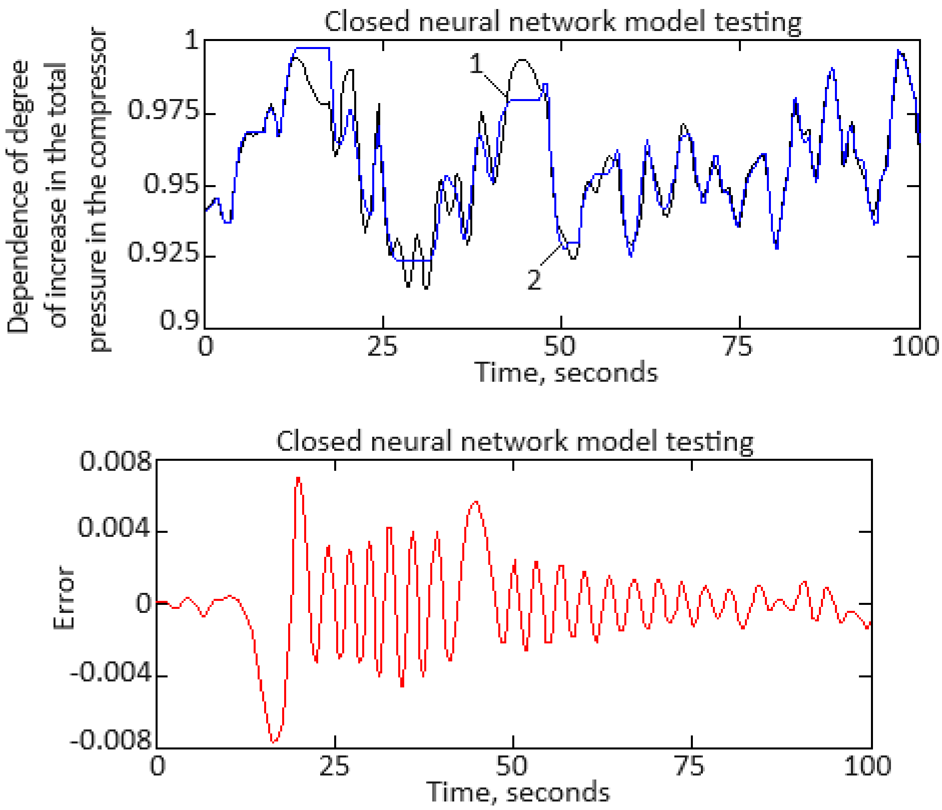

Figure 9: Formation of a neural network model for TV3-117 turboshaft engine dependence of degree of increase in the total pressure in the compressor (1 – neural network model output, 2 – target) (author's development)

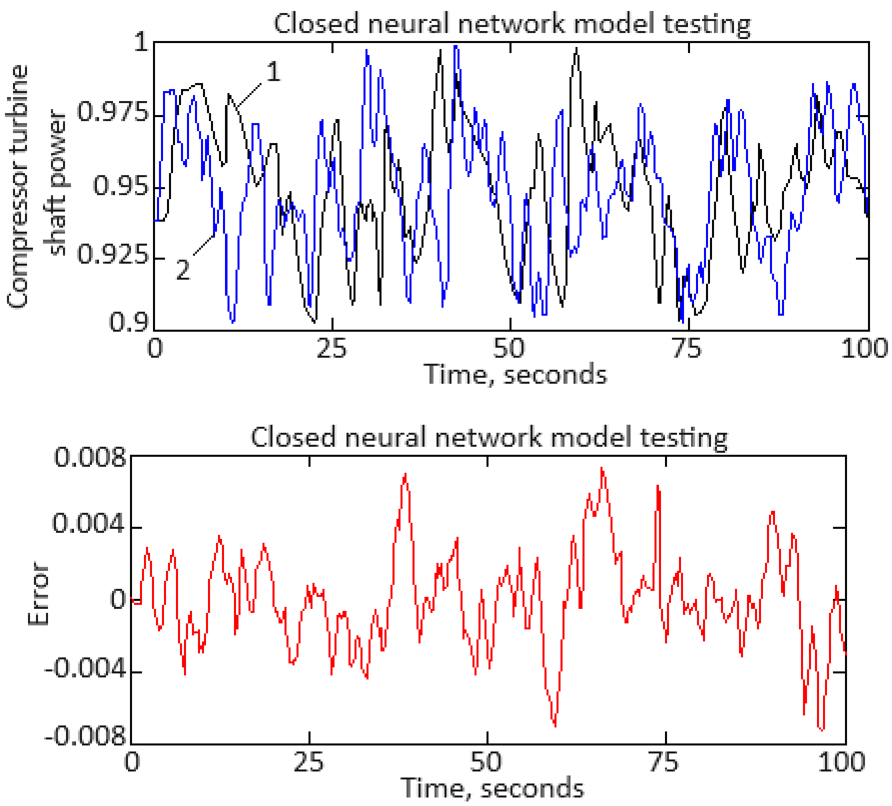

Figure 10: Formation of a neural network model for TV3-117 turboshaft engine compressor turbine shaft power (1 – neural network model output, 2 – target) (author's development)

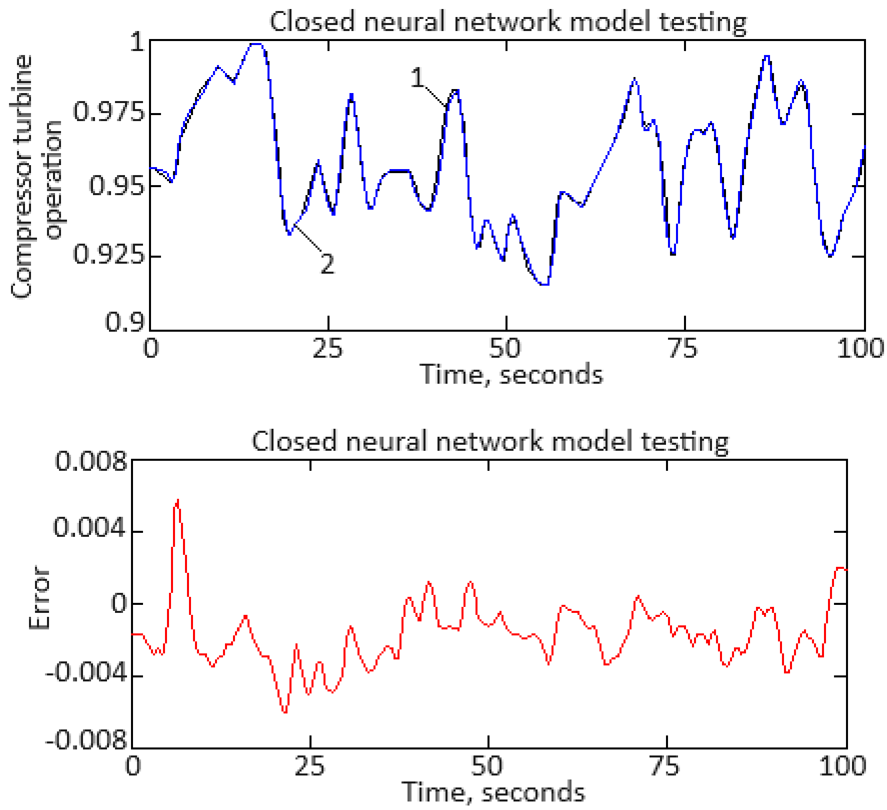

Figure 11: Formation of a neural network model for TV3-117 turboshaft engine compressor turbine operation (1 – neural network model output, 2 – target) (author's development)

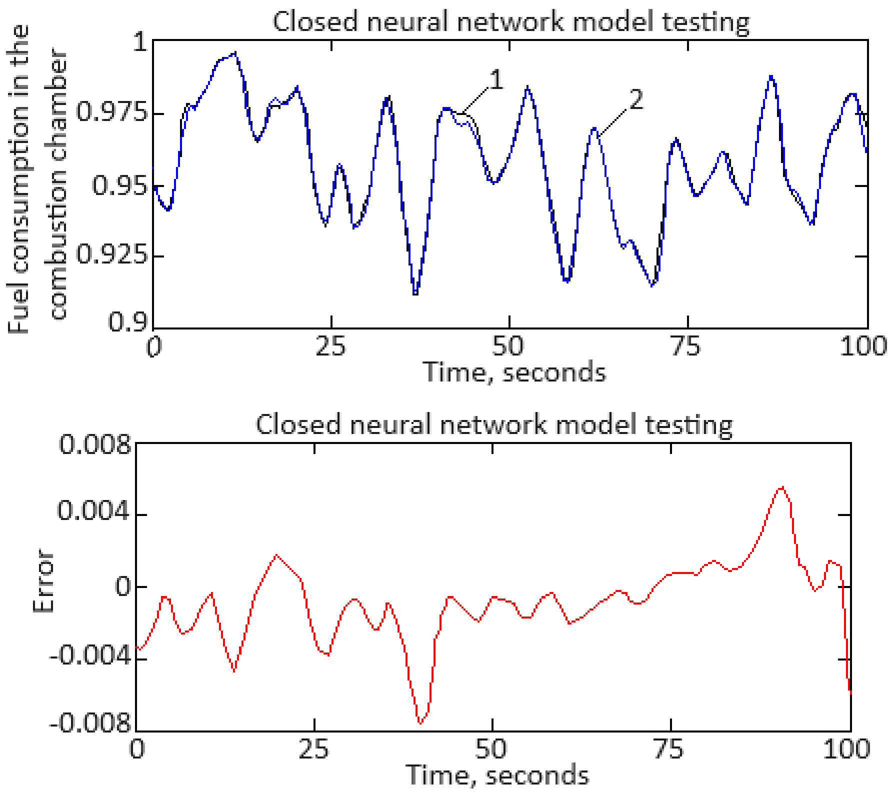

Figure 12: Formation of a neural network model for TV3-117 turboshaft engine fuel consumption in the combustion chamber (1 – neural network model output, 2 – target) (author's development)

As evident from fig. 9 – 12, the training error of the neural network, as determined by the identified parameter reflecting the increase in total pressure in the compressor, remains below 0.8 % for both the training and test sets. Throughout the experimental investigations, it was observed that, similarly, the neural network training error for the remaining 35 thermogas-dynamic parameters of the engine working process did not exceed 0.8 % at both the training and test sets. The provided examples illustrate that the proposed approach enables the construction of relatively accurate neural network models. However, it is acknowledged that there exists a potential for accuracy degradation, leading to unsatisfactory adaptive properties of the synthesized neural network. Strategies to address these challenges will be explored in subsequent research.

7. Discussions

The results of a comparative analysis of the accuracy of the implementation of the neural network method for engine working process thermogas-dynamic parameters identification of neural network and classical methods for each of engine model parameters are given in table 3.

Table 3

Comparative analysis of the accuracy of neural network and classical implementation methods (author's development)

Model	Absolute error, %			
	Dependence of degree of increase in the total pressure in the compressor	Compressor turbine shaft power	Compressor turbine operation	Fuel consumption in the combustion chamber
Classical	1.95	1.96	1.95	1.95
Neural network:				
three-layer perceptron [34, 35]	0.66	0.64	0.68	0.65
Gaussian NARX-model (proposed)	0.42	0.41	0.43	0.41

To assess the stability of neural networks to variations in input data (refer to table 1), additive noise was introduced to the data. This noise was applied to each parameter by incorporating white noise with a zero mean and $\sigma_i = 0.025$, equivalent to 2.5 % of the maximum value for each parameter. Table 4 presents the results of a comparative analysis of the accuracy in implementing the method for identifying thermogas-dynamic parameters of the helicopter TE working process using neural network and classical methods. The analysis is conducted for each parameter of the engine model under conditions of added noise.

Table 4

Comparative analysis of the accuracy of neural network and classical implementation methods (author's development)

Model	Absolute error, %			
	Dependence of degree of increase in the total pressure in the compressor	Compressor turbine shaft power	Compressor turbine operation	Fuel consumption in the combustion chamber
Classical	3.11	3.15	3.14	3.15
Neural network:				
three-layer perceptron [34, 35]	1.13	1.09	1.17	1.11
Gaussian NARX model (proposed)	0.74	0.72	0.73	0.71

The analysis of table 4 reveals that the identification error, considering the specified noise conditions, remains below certain thresholds: for the gaussian NARX model – 0.71%, for the three-layer perceptron with an architecture of 7–53–36 – 1.09 % [34, 35], and for the thermogas-dynamic model of helicopters TE – 3.15 %.

Under the influence of white noise, the maximum absolute error in implementing the identification method for the thermogas-dynamic parameters of the helicopter TE working process using the least squares method increased from 1.96 % to 3.15 %. For the three-layer perceptron with an architecture of 7–53–36, this error increased from 0.64 % to 1.09 %, and for the gaussian NARX model, it increased from 0.43% to 0.74%.

To assess the reliability of the neural network method for identifying the thermogas-dynamic parameters of the helicopter TE working process, the following expressions can be utilized [42, 43]:

$$K_{error} = \frac{T_{error}}{T_0} \cdot 100\%; \tag{23}$$

$$K_{quality} = \left(1 - \frac{T_{error}}{T_0}\right) \cdot 100\%; \tag{24}$$

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

Table 5 shows the results of calculating the coefficients of erroneous and qualitative identification of parameters: dependence of degree of increase in the total pressure in the compressor, compressor turbine shaft power, compressor turbine operation, fuel consumption in the combustion chamber.

Table 5

Results of calculating the coefficients of erroneous and qualitative (author's development)

Parameter	Coefficient of erroneous, K_{error}	Coefficient of qualitative, $K_{quality}$
Degree of increase in the total pressure in the compressor	0.521	99.872
Compressor turbine shaft power	0.523	99.871
Compressor turbine operation	0.528	99.873
Fuel consumption in the combustion chamber	0.526	99.872

As can be seen from table 5, the coefficients of erroneous identification rate do not exceed 0.528 %, and the minimum coefficients of qualitative identification rate is 99.873 %.

8. Conclusions

1. The technique of a unified structural description of neural network models of complex dynamic objects has been further developed, providing a uniform representation of all types of static and dynamic networks, allowing to automate the process of synthesis of neural network models.

2. In relation to helicopters turboshaft engines, the available results in the field of modeling complex dynamic systems using traditional neural networks ("black box" models) are systematized, and the limitations and area of possible use of these tools are identified, which makes it possible to optimally use the apparatus of neural networks to solve the problem helicopters turboshaft engines working process parameters identification at flight modes

3. A neural network method for helicopters turboshaft engines working process thermogas-dynamic parameters identification has been developed, which is based on the use of a gaussian NARX model, the use of which allows, with an accuracy higher than 99.873 %, to helicopters turboshaft engines working process thermo-gas-dynamic parameters identification.

4. It has been established that the neural network – gaussian NARX model, solves the problem for helicopters turboshaft engines working process thermogas-dynamic parameters identification more accurately than classical methods: the identification error at the output of the gaussian NARX model is at least squares method 4.78 times less than that of the regression model obtained with using the helicopters turboshaft engines thermogas-dynamic model.

5. It is shown that the implementation error of the method for helicopters turboshaft engines working process thermogas-dynamic parameters identification using a neural network – gaussian NARX model, did not exceed 0.43 % when calculating individual engine parameters, while for the classical method (helicopters TE thermogas-dynamic model) it is about 1.96 % for considered engine parameters.

6. A comparative analysis of neural network (gaussian NARX model) and classical methods (helicopters turboshaft engines thermogas-dynamic model) for helicopters turboshaft engines working process thermogas-dynamic parameters identification implementing under noise conditions shows that neural network methods are more robust to external disturbances. The noise level σ_i = 0.025 (2.5 %), the maximum absolute error when using a neural network (gaussian NARX model) increases from 0.43 to 0.74 %, and the helicopters turboshaft engines thermogas-dynamic model increases from 1.96 to 3.15 %.

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