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IDENTIFICATION OF REAR MODEL OF TV3-117 AIRCRAFT ENGINE BASED ON THE BASIS OF NEURO-MULTI-FUNCTIONAL TECHNOLOGIES

The **subject** matter in the article is TV3-117 aircraft engine and methods of identification of its technical condition. The **goal** of the work is to develop methods for identifying the technical state of the aircraft engine TV3-117 on the basis of real-time neural network technologies. The following tasks were solved in the **article**: the task of identifying the reverse multi-mode model of the aircraft engine TV3-117 using neural networks. The following **methods** used are – methods of probability theory and mathematical statistics, methods of neuroinformatics, methods of the theory of information systems and data processing. The following **results** were obtained – The application of the neural network apparatus is effective in solving a large range of tasks: identifying the mathematical model of the aircraft engine TV3-117, diagnosing the condition, analyzing the trends, forecasting the parameters, etc., despite the fact that these tasks usually relate to the class difficultly formalized (poorly structured), neural networks are adequate and effective in the process of their solution. In the process of solving the task of identifying the mathematical model of the aircraft engine TV3-117 on the basis of neural networks, it was established that neural networks solve the problem of identification more precisely classical methods. **Conclusions**: It was established that the error of identification of the aircraft engine TV3-117 with the help of a neural network of type perceptron did not exceed 1.8 %; For the neural network of radial-basic function (RBF) – 4.6 %, whereas for the classical method (LSM) it makes about 5.7 % in the considered range of changes in engine operation modes. It was found that neural network methods are more robust to external perturbations: for noise level $\sigma = 0.01$, the error of identification of aircraft engine TV3-117 with the use of perceptron has increased from 1.8 to 3.8 %; for the neural network RBF – from 4.6 to 5.7 %, and for the least squares method – from 5.7 to 13.93 %. In the process of solving the task of identifying the inverse multi-mode model of the aviation engine TV3-117 on its parameters on the basis of neural networks (perceptron and RBF) it was shown that their use allows for indirect measurement of the parameters of the flowing part of the engine at different modes of its operation: in the absence of noise – with an error of not more than 1,8 and 4,6 % respectively; in the presence of noise ($\sigma = 0{,}01$) – with an error of not more than 3,8 and 5,7 % respectively. Application in these conditions of the least squares method (polynomial regression model of the 8th order) allows us to obtain the error value: in the absence of noise – no more than 5,7 %; in the presence of noise – no more than 13,93 %.

Keywords: aircraft engine; neural network; perceptron; radial-basic function, identification.

Introduction

The aircraft engine TV3-117 as a recoverable object during its lifetime requires continuous monitoring and diagnostics of its technical condition, the complexity of which depends on the level of automation of the processes of receiving, processing, storing, documenting information on the current state of the aircraft engine, as well as monitoring, diagnosis, forecasting of its the technical state, the sequence and methods of execution of which determine the information system of control and diagnostics.

The means of their implementation are distributed monitoring and diagnostics systems, which are tasked with determining the degree of conformity of the research object with the requirements, that is, control of its technical condition.

Distributed monitoring and diagnostics system is a logical addition to the information monitoring and diagnostic system, since it together with the latter carries out an analysis of the actual technical state of the engine: forecasting the residual resource, monitoring the degradation of the performance of the aircraft engine, determines the program of repair and restoration works, etc.

At the same time, despite the considerable amount of research in these areas, the information systems for monitoring and diagnosing the technical state of aviation engines are not perfect for a number of reasons, the main ones being, on the one hand, the dissociation of the databases of testing, control and diagnostics, the lack of intelligent components, which allow qualitatively and efficiently to support decision-making [1] and, as a consequence, reduce the total time spent on engine maintenance; on the other hand, the unsteadiness of physical processes in an aircraft engine, the complexity of its mathematical description, the dependence of engine technical characteristics on external operating conditions, the limited composition of the measured thermogasdynamic parameters of the engine, their technological spread, etc. These factors lead to the need to make decisions about the technical state engine in conditions of significant uncertainty.

Analysis of works in the field of control and diagnostics of the state of aviation engines on the basis of neural networks [2–6] shows that at present, such works are being conducted, however, due to a number of reasons (secrecy, narrow specialization of the tasks to be solved), in most publications there are no engineering methods, as well as theoretical and practical recommendations for solving similar problems. The task of the problem and possible algorithms for choosing the architecture of neural networks, their algorithms, evaluation of their work efficiency, etc. are studied, as well as the engineering methodology for solving the problem of classification of operating modes of aircraft engine TV3-117 using neural network technologies.

Analysis of existing methods for identifying the technical condition of aviation engines

Professor Zhernakov S.V. is currently actively engaged in the task of identifying the technical state of aviation gas turbine engines (GTE) using neural network technologies. (Ufa State Aviation Technical University), in whose work the necessary techniques have been

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developed and the following tasks are successfully solved: identification of characteristics of the GTE; identification of the inverse multimode model of the GTE according to the parameters of its oil system; identification of the multi-mode dynamic model of the GTE [7–10]. The solution to these problems was obtained both in bench test conditions and in the flight operation of the aircraft. However, the results obtained are applicable only to turbojet engines installed on aircraft.

It is known that helicopters in most of their cases use turboshaft engines, the number of which includes the engine TV3-117, the structure and running processes, which differ from the structure and processes occurring inside turbojet engines. Therefore, it is necessary to modify (refine) previously developed methods for solving the tasks of identifying the technical state of aviation engines using neural network technologies, which will allow them to be used for monitoring and diagnostics of turbocharged engines, including the engine TV3-117. Therefore, the scientific and practical tasks solved in this work are relevant.

Problem formulation

It is assumed that aircraft engine TV3-117 as a nonlinear control object on steady operating modes is described using the equations of the form:

$$f_1(A,U)=0; \quad (1)$$

$$Y=f_2(A,X); \quad (2)$$

where f_1 and f_2 – nonlinear vector-function; A and U – vectors of engine parameters; X – vector of engine state variable [11].

In practice, the task of indirect measurements is relevant: by observing the vector of the output thermogasdynamic parameters of the engine, determine the values of its control influences (that is, components of the vector U). For example, according to the measured value of parameters n, T_3^*, P_2^* it is necessary to calculate the value of fuel consumption in the combustion chamber G_T. Analytical statement of this problem is reduced to the definition of inverse nonlinear dependence f^{-1} in the expression:

$$U=f^{-1}(A,Y); \quad (3)$$

where Y – vector of engine output coordinates [11].

Thus, the goal of the work is to develop methods for identifying the technical state of the aircraft engine TV3-117 on the basis of real-time neural network technologies, while it is necessary to determine its structure and parameters, which ensures a minimum error of learning E based on the procedure presented in fig. 1, where $\varepsilon=(\varepsilon_1,\varepsilon_2,...,\varepsilon_k)^T$ – the vector of inconsistencies between the actual and estimated by means of the neural network of the values of control influences, that is $\varepsilon=U-U^*$, and $E=\sum_i \varepsilon_i^2$. After training, the neural network reproduces the characteristics of the reverse multi-mode aircraft engine model TV3-117.

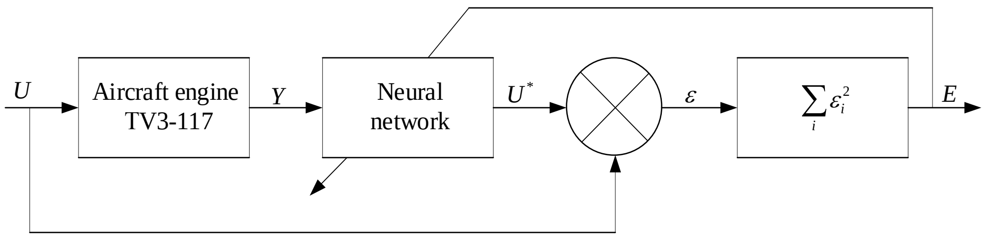

Fig. 1. Scheme of the solution of the problem of identification of the return multi-mode model of the aircraft engine TV3-117

The solution of the identification problem of the reverse multi-mode model of the aircraft engine TV3-117 on the basis of neural network technologies will be based on the following steps of the proposed method:

1. Data analysis;
2. Pre-processing of data;
3. Selection of the architecture of the neural network;
4. Selection of the neural network structure;
5. Choosing the algorithm for training the neural network;
6. Evaluating effectiveness.

Development of the neural network: the choice of architecture, structure, learning algorithm

The inverse problem of identifying a multi-mode aircraft engine model TV3-117 is as follows: the values of the following engine parameters are reduced to standard atmospheric conditions (table 1). It is necessary to construct a multi-mode neural network mathematical model for the calculation (indirect measurement) of the value of the reduced fuel consumption.

Data for table 1 entered in accordance with the provisions [7] that the set of steady-state operating modes of the aircraft engine TV3-117 is described by a combination of functional dependencies on the values of the following engine parameters:

$$n_{sp}=n\sqrt{\frac{288}{T_N^*}};\ G_{airsp}=\frac{G_{air}\cdot 760}{P_N^*}\sqrt{\frac{288}{T_N^*}};\ P_{2sp}^*=P_2^*\cdot\frac{760}{P_N^*};$$

$$T_{2sp}^*=T_2^*\cdot\frac{288}{T_N^*};\ T_{3sp}^*=T_3^*\cdot\frac{288}{T_N^*};\ R_{sp}=R\cdot\frac{760}{P_N^*}; \quad (4)$$

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where $G_{T sp}$ – specific value of fuel consumption (kg/s); n_{sp} – specific value of the rotor frequency of the turbine compressor (%); G_{airsp} – specific value of the air consumption (kg/s); P^*_{2sp} and T^*_{2sp} – respectively, the pressure (kPa) and temperature (K) are calculated for the turbine compressor; T^*_{3sp} – specific value of the gases temperature behind the compressor turbine (K); R_{sp} – specific value of the engine thrust is shown.

Table 1. *Fragment of the training sample for identification of multi-mode model of aircraft engine TV3-117*

$G_{T_{sp}}$	n_{sp}	$G_{air_{sp}}$	$P^*_{2_{sp}}$	$T^*_{2_{sp}}$	$T^*_{3_{sp}}$	R_{sp}
0.188	0.533	0.413	0.323	0.439	0.513	0.148
0.126	0.343	0.247	0.199	0.249	0.471	0.051
0.198	0.543	0.422	0.331	0.446	0.519	0.156
0.475	0.793	0.752	0.638	0.804	0.753	0.495
0.145	0.403	0.299	0.238	0.294	0.463	0.076
0.348	0.707	0.614	0.501	0.663	0.667	0.331
0.239	0.582	0.464	0.366	0.475	0.547	0.189
0.728	0.901	0.923	0.849	0.925	0.854	0.769
1.011	1.009	1.031	1.038	1.050	1.014	1.051
0.136	0.374	0.274	0.219	0.271	0.465	0.065
0.148	0.409	0.306	0.243	0.299	0.465	0.084
0.557	0.832	0.821	0.714	0.866	0.788	0.590
0.188	0.533	0.413	0.323	0.439	0.513	0.148

The process of transition from the physical parameters of the engine to the given values (and back), carried out using the neural network model of the aircraft engine TV3-117, shown in fig. 2, where the conversion of the measured (physical) parameters of the engine to the reduced, which correspond to the standard atmospheric conditions T^*_N = 288,15 K, P^*_N = 760 mm Hg is carried out with the help of the operator $F(\bullet)$, which is described by the expressions (1) and (2), and the inverse transition – using the operator $F_1(\bullet)$ by the formulas of the gas-dynamic similarity:

$$n_{sp} = n\sqrt{\frac{288}{T^*_N}};\ G_{airsp} = \frac{G_{air}\cdot 760}{P^*_N}\sqrt{\frac{288}{T^*_N}};\ P^*_{2sp} = P^*_2\cdot\frac{760}{P^*_N};$$

$$T^*_{2sp} = T^*_2\cdot\frac{288}{T^*_N};\ T^*_{3sp} = T^*_3\cdot\frac{288}{T^*_N};\ R_{sp} = R\cdot\frac{760}{P^*_N}; \quad (5)$$

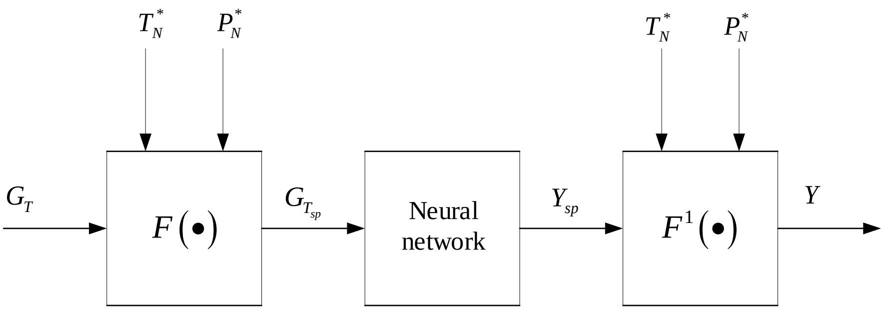

Fig. 2. The scheme of transition from the neural network model of the aircraft engine TB3-117 in the given parameters to the model in physical quantities

and the influence of flight conditions on the parameters of the air entering the engine is thus considered as:

$$T^*_N = T_N\left(1+\frac{k-1}{2}M^2\right);\ P^*_N = P_N\sigma_{rec}\left(1+\frac{k-1}{2}M^2\right)^{\frac{k}{k-1}};(6)$$

where T_N and P_N – respectively, the temperature (K) and pressure (mm Hg) air at a given flight altitude; T^*_N and P^*_N – are inhibited values of these parameters at a given altitude; k – adiabatic index; M – the number of flaps the flight; σ_{rec} – recovery rate of full pressure in the air intake.

The analysis of the initial data (training sample) and the process of their pre-processing is carried out in the same way as it was done in solving the problem of identifying a direct multi-mode model of the aircraft engine TV3-117. In the process of experimental research as the main architectures of neural networks, for the solution of this problem, perceptron and RBF were investigated [12, 13].

The architecture of the neural network RBF for solving the problem of identifying the reverse multi-mode model of the aircraft engine TV3-117 is shown in fig. 3.

Experimental studies on the selection of optimal structures of neural networks RBF and perceptron showed that the optimal complexity of neural networks should have respectively 12 and 16 neurons in the hidden layer (fig. 4, curve 1) and (fig. 4, curve 2).

Thus, the structure of 8–12–1 is optimal for the complexity of the structure of the neural network RBF for solving the inverse problem of identification of the multimode model of the aircraft engine TV3-117; and for the perceptron – the structure 8–16–1. Activation functions of neurons were taken sigmoid, i.e. $f\left(s\right)=\frac{s}{a+\left|s\right|}$. The analysis of the effectiveness of various algorithms for training the neural network, described in detail in [14, 15], where the choice of the most optimal – additive step of training the neural network, which is realized in the form of a gradient method, is substantiated.

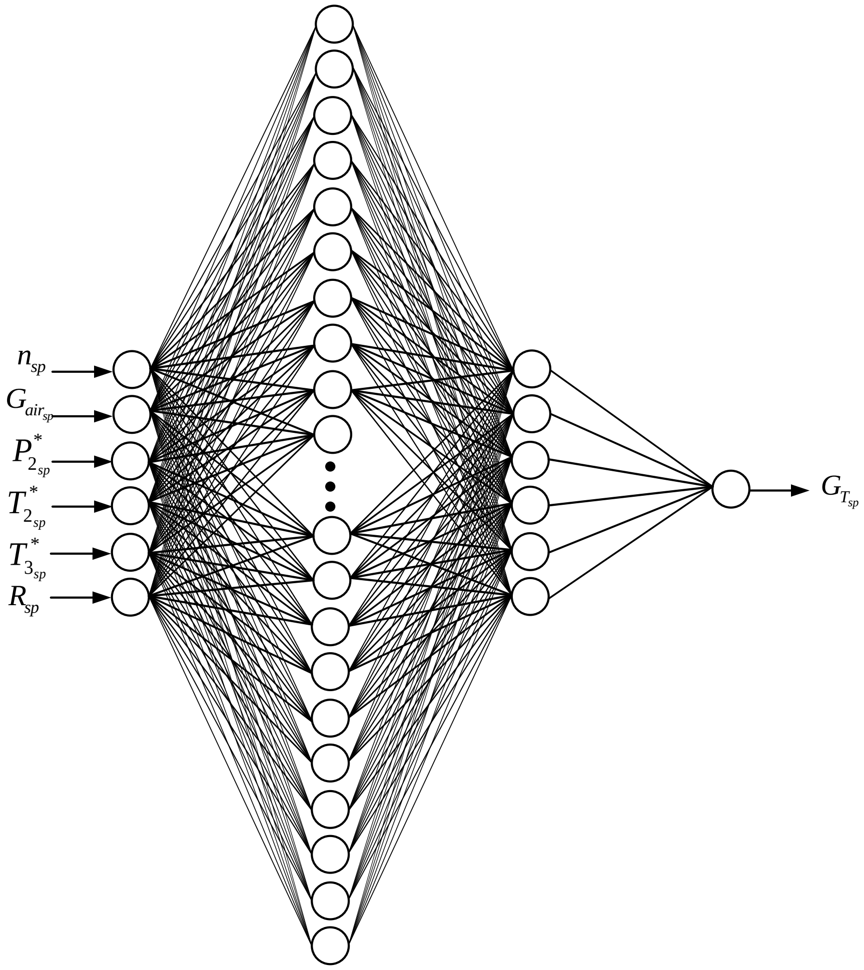

Fig. 3. Reverse multi-mode model of aviation engine TV3-117 based on neural network RBF

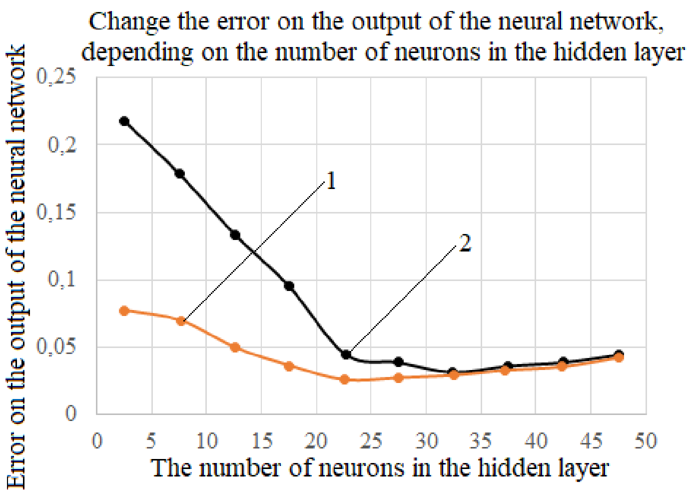

Fig. 4. The choice of the optimal complexity of neural network structures for solving the inverse identification problem: 1 – perceptron; 2 – RBF

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Results of the task solution

In the framework of the developed method, a comparative analysis of the accuracy of the neural networks (perceptron and RBF) and the classical (LSM) methods of identifying the inverse multi-mode model of the aviation engine TV3-117 on the test sample (fig. 5) and on the same sample in the conditions of the additive component of the obstacle (white noise with zero mathematical expectation M = 0 and σ = 0.01, fig. 6). Curves on fig. 5 and 6 correspond to the errors of calculation of the reduced fuel consumption for the two classes of neural network models (perceptron and RBF), as well as for the polynomial regression model of the 8th order received by the LSM.

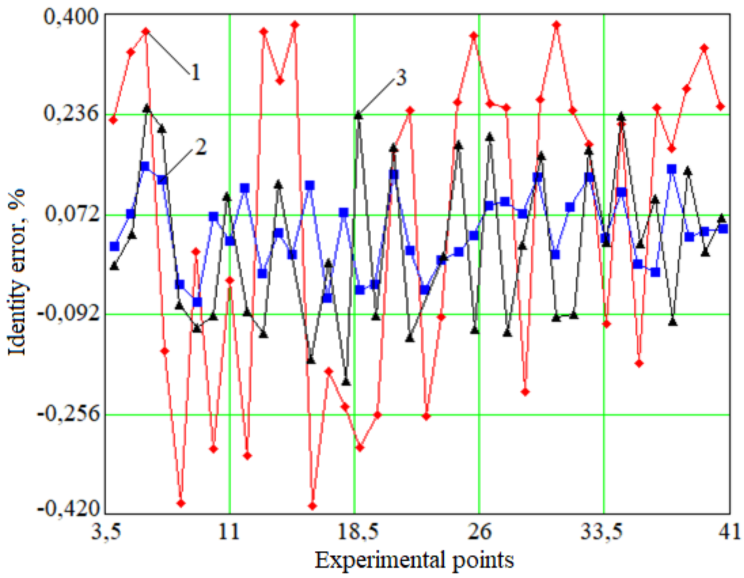

Fig. 5. Results of research of neural network and classical methods of identification of the return multi-mode model of aircraft engine TV3-117: 1 – least squares method; 2 – perceptron; 3 – RBF

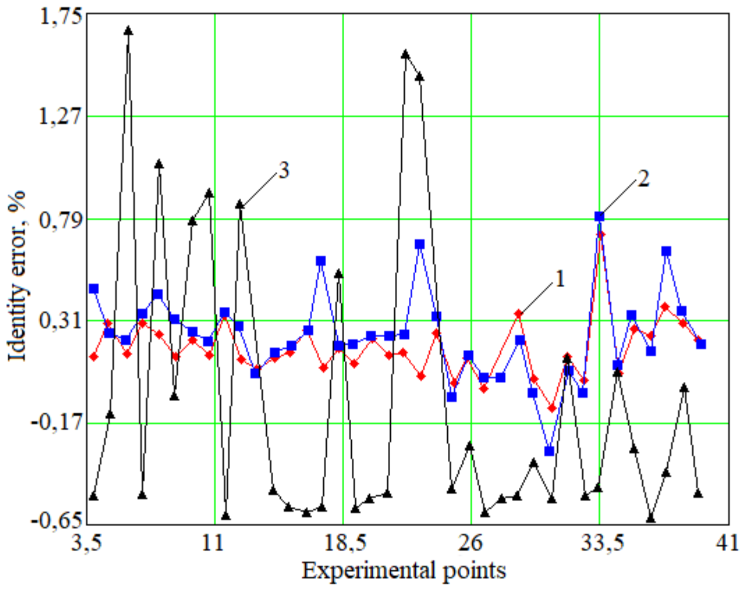

Fig. 6. Results of research of neural network and classical methods of identification of the reverse multi-mode model of aircraft engine TV3-117 on a test sample in conditions of additive noise (white noise): 1 – least squares method; 2 – perceptron; 3 – RBF

Table 2. *Comparative analysis of the accuracy of neural networks and classical methods of identification of the reverse multi-mode model of aircraft engine TV3-117 (indirect measurement of fuel consumption)*

Identification method	Mean square error (no noise)	Absolute error (no noise), %	Mean square error (with noise)	Absolute error (with noise), %
Least squares method	0.057	0.508	1.393	1.742
Perceptron	0.018	0.128	0.038	0.607
Radial-basic function	0.046	0.275	0.057	0.754

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The analysis of the obtained results shows that the best performance is the perceptron neural network, which allows for indirect measurements of fuel consumption over a wide range of engine operation:

- without noise – with an error of not more than 0.128 %;
- with the presence of noise (σ = 0,01) – with an error of not more than 0.607 %.

Applying the least squares method in these conditions allows you to get the error value:

- no noise – no more than 0.508 %;
- with the presence of noise – no more than 1.742 %.

Consequently, in solving the inverse problem of identifying a multi-mode aircraft engine model TV3-117, neural networks are more prone to disturbances of the initial data than the classical methods, which in the conditions of the obstacles give a great error of identification.

Conclusions

Obviously, the application of neural network technologies in solving the problems of control, diagnostics and forecasting of the parameters of the technical condition of the aircraft engine TV3-117 is not an end in itself. The use of neural networks should be considered economically viable (that is, giving real economic effect) only in those cases where existing methods can not provide the desired quality of the solution, that is, when there is evidence in favor of higher efficiency of neural networks. Summarizing the above, we can draw the following conclusions.

1. Application of the device of neural networks turns out to be effective in solving a large range of tasks: the identification of the mathematical model of the aircraft engine TV3-117, diagnostics of the state, analysis of trends, forecasting of parameters, etc. Although these tasks usually belong to the class of difficultly formalizable (poorly structured), neural networks are adequate and effective in their solution.

2. In the process of solving the problem of identifying the mathematical model of the aircraft engine TV3-117 on the basis of neural networks, it was established that neural networks solve the problem of identification more precisely than classical methods: the identification error at the output of the neural network type perceptron in 3.16 times, the neural network of the RBF type – 1.24 times less than the regression model obtained with the help of LSM for the range of changes in engine operation.

3. The error of identification of the aircraft engine TV3-117 with the help of perceptron did not exceed 1.8 %; for the neural network RBF – 4.6 %, while for the classical method (LSM) it makes about 5.7 % in the considered range of changes in engine operation modes.

4. Neural network methods are more robust to external perturbations: for the noise level σ = 0.01, the error of identification of the aircraft engine TB3-117 with the use of the perceptron has increased from 1.8 to 3.8 %; for the neural network RBF – from 4.6 to 5.7 %, and for the method of least squares – from 5.7 to 13.93 %.

5. In the process of solving the problem of identifying the inverse multi-mode model of the aircraft engine TV3-117 on its parameters on the basis of neural networks (perceptron and RBF) it was shown that their use allows for indirect measurement of the parameters of the flow part of the engine at different modes of its operation: in the absence of noise – with an error of not more than 1.8 and 4.6 % respectively; in the presence of noise (σ = 0.01) – with an error of not more than 3.8 and 5.7 %, respectively. Using in these conditions the method of least squares (polynomial regression model of the 8th order) allows us to obtain the value of the error: in the absence of noise – no more than 5.7 %; in the presence of noise – no more than 13.93 %. Thus, when solving the problem of identifying the inverse multi-mode model of the aircraft engine TV3-117, neural networks are more robust to perturbations of the original data than the classical methods which in the conditions of interference give a big error of identification.

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