ONBOARD PARAMETER IDENTIFICATION METHOD OF THE TV3-117 AIRCRAFT ENGINE OF THE NEURAL NETWORK TECHNOLOGIES**S. Vladov, Yu. Shmelov, K. Kotliarov, S. Hrybanova, O. Husarova, I. Derevyanko, L. Chyzhova**

Kremenchuk Flight College of Kharkiv National University of Internal Affairs

vul. Peremogy, 17/6, Kremenchuk, 39605, Ukraine. E-mail: ser26101968@gmail.com

Purpose. The work is devoted to the development of an on-board method for identifying the parameters of TV3-117 aircraft engine based on neural network technology. The solution of the problem of identifying a model of TV3-117 engine in onboard conditions by classical methods, including the method of least squares and approximation by cubic splines, and neural network, by building a neural network according to source data. **Methodology.** The work is based on the methods of probability theory and mathematical statistics, neuroinformatics, information systems theory and data processing. Two neural network architectures were used in the work: a perceptron-type neural network and a radial basis function neural network. **Results.** A method was developed for determining the optimal structure of a neural network, which consists in determining the neural network architecture, choosing the optimal algorithm for finding weights of neurons and teaching a neural network, analyzing the effectiveness of various neural network training algorithms, determining the structure of a neural network, which consists in finding the minimum error of neural network training depending on the number of neurons in the hidden layer, as well as in the analysis of the effectiveness of the results. It has been established that neural networks solve the identification problem more precisely than classical methods, since the error of identification at the output of the perceptron architecture neural network is 1.6 times less than in the regression model developed on the basis of the least square's method for the considered range of engine operating modes. **Originality.** The scientific novelty of the results obtained is as follows: For the first time, a method was developed for determining the optimal structure of a neural network, which made it possible to solve the problem of identifying a model of an aircraft engine, the TV3-117, in onboard conditions with minimal errors. The method of identifying the technical condition of the TV3-117 aircraft engine in onboard conditions, which differs from the existing ones due to the use of neural network technologies, makes it possible to increase the reliability of monitoring and diagnostics of the technical condition of the TV3-117 aircraft engine under its flight conditions. **Practical value.** The developed neural network can be one of the units of the expert system that can automatically make decisions regarding the technical condition of the aviation engine TV3-117 in flight modes and provide information to the crew about the possibility of further safe movement of the aircraft. The task of developing an expert system can be effectively solved using the mathematical apparatus of neural networks, since its use increases the reliability and accuracy of classification of modes, identification, control, diagnostics, time series analysis (forecasting), debugging of engine parameters, etc., which will increase reliability of obtaining the necessary results.

Key words: aircraft engine, identification, neural network, mathematical model, least squares method.

БОРТОВИЙ МЕТОД ІДЕНТИФІКАЦІЇ ПАРАМЕТРІВ АВІАЦІЙНОГО ДВИГУНА ТВ3-117 НА ОСНОВІ ТЕХНОЛОГІЇ НЕЙРОННИХ МЕРЕЖ**С. І. Владов, Ю. М. Шмельов, К. Г. Котляров, С. А. Грибанова, О. В. Гусарова, І. Г. Дерев'янюк, Л. І. Чигова**

Кременчуцький льотний коледж Харківського національного університету внутрішніх справ

вул. Перемоги, 17/6, м. Кременчук, 39605, Україна. E-mail: ser26101968@gmail.com

Розв'язано актуальну науково-практичну задачу ідентифікації параметрів авіаційного двигуна ТВ3-117 у бортових умовах класичним методом – методом найменших квадратів і нейромережевими – шляхом побудови нейронної мережі відповідно до вихідних даних. Розроблено методику визначення оптимальної структури нейронної мережі, що полягає у визначенні архітектури нейронної мережі, виборі оптимального алгоритму пошуку ваг нейронів і навчання нейронної мережі, аналізу ефективності різних алгоритмів навчання нейронної мережі, визначення структури нейронної мережі щодо знаходження мінімальної помилки навчання нейронної мережі залежно від кількості нейронів у прихованому шарі, а також в аналізі ефективності отриманих результатів. У роботі застосовано дві архітектури нейронних мереж: нейронна мережа типу «персептрон» і нейронна мережа на радіально-базисних функціях. Результати тестування обраних архітектур показали, що найменша похибка навчання нейронної мережі типу «персептрон» складає 0,025 % при одному нейроні у вхідному шарі, чотирьох нейронів у прихованому шарі і шести нейронів у вихідному шарі нейронної мережі; нейронної мережі на радіально-базисних функціях складає також 0,025 % при одному нейроні у вхідному шарі, дванадцяти нейронів у прихованому шарі і шести нейронів у вихідному шарі нейронної мережі. Результати досліджень показали, що похибка ідентифікації параметрів авіаційного двигуна ТВ3-117 в умовах дії зазначеного шуму не перевищує 0,818 % при використанні нейронної мережі типу «персептрон», 0,884 % – при використанні нейронної мережі на радіально-базисних функціях і 1,928 % при використанні методу найменших квадратів. Похибка ідентифікації параметрів авіаційного двигуна ТВ3-117 за допомогою методу найменших квадратів в умовах дії білого шуму збільшилася з 0,918 до 1,928 %, а для нейронних мереж в цих умовах вона зросла відповідно з 0,612 до 0,818 % при використанні нейронної мережі типу «персептрон», з 0,726 до 0,884 % при використанні нейронної мережі на радіально-базисних функціях.

Ключові слова: авіаційний двигун, ідентифікація, нейронна мережа, математична модель, метод найменших квадратів.

PROBLEM STATEMENT. Exploitation of aviation equipment, including aircraft and engine TV3-117, occurs when a continuous change of the technical state of assemblies, units and parts due to the inevitable aging process that is characterized by constant change its properties as a whole in the downside. This occurs under the influence of internal and external factors that have either a fairly strict deterministic or unpredictable character of manifestation. Under conditions of increased load on the engine components and assemblies, the increased safety of its operation is achieved through the use of an operational control strategy based on the actual technical condition. Along with classical approaches, this implies the use of new intelligent methods to efficiently and efficiently carry out the process of identifying the parameters of an aircraft engine, taking into account the incompleteness of the measured information, measurement noise, the presence of structural, parametric and expert uncertainties in assessing the parameters of the TB3-117 aircraft engine. The efficiency of identifying the technical condition of an aircraft engine essentially depends on the probability of correctly identifying its parameters, which directly affects the quality of its operation control systems, which ultimately determines the efficiency and safety of flights.

Despite a considerable amount of research in this area [1–3], information technologies for identifying aircraft engine parameters are not perfect for several reasons: on the one hand, weak information “linking”, lack of “intellectual” elements that allow for quick, high-quality and efficient implementation support decision-making [4] and, as a result, reduce the total time spent on maintenance of aircraft engines. On the other hand, the unsteadiness of the physical processes in the aviation engine, the complexity of their mathematical description, the dependence of its performance characteristics from the external working environment, the limited set of measured parameters of technological variation, etc. These factors lead to the need of automate decision-making processes about the technical condition of the engine in conditions of uncertainty.

The main directions determining the efficiency of onboard information technologies for monitoring the state of aircraft engines should be considered intellectualization of information processing processes using neural network methods that can improve the quality of onboard algorithms for monitoring parameters of aircraft engines under the action of the above uncertainties.

Thus, the creation of on-board information technologies for monitoring and diagnosing the technical condition of an aircraft engine involves the development of an appropriate method, method, algorithmic and software that will improve the efficiency and quality of solving problems of monitoring and controlling the operation of the aviation engine TB3-117.

Currently, the problems of information diagnostics of aviation technology are actively involved in scientists of the Moscow State Technical University of Civil Aviation (MSTUCA), among which should be highlighted the work of Professor O. Mashoshin [5–7], in which various methods for determining malfunctions of aviation equipment are applicable, including aircraft engines. Much attention was paid to methods of diagnos-

ing aircraft from the point of view of informativeness and information support of the processes of its diagnosis. Also, it is worth noting the works of Professor S. Gernakov (Ufa State Aviation Technical University) [8–10], dedicated to monitoring and diagnosing the technical state of aviation gas turbine engines based on data mining. But their work is devoted to the development of information systems for managing the state of aircraft engines under conditions of bench testing only. Thus, the development of the onboard control system for the technical condition of the aviation engine TB3-117 (including the identification of parameters) is relevant.

MATERIAL AND RESULTS. Let's consider the problem of identifying the characteristics of aviation engine on steady modes of its operation. In these modes, the engine is described by 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 are nonlinear vector functions; A and U are vectors of engine parameters.

The identification problem reduces to the finding of a function f^* , which, with a given degree of accuracy, would correspond to the dependence:

$$Y^* = f^*(A, X). \quad (3)$$

Procedure identify characteristics of aircraft engine TV3-117 with the help of the neural network shown in fig. 1, where $\varepsilon_1 \dots \varepsilon_n$ the deviation between the measured parameters of individual aircraft and engine parameters calculated using the neural network with the same control effects $U_1 \dots U_m$; E – learning error for the neural network

Figure 1 – Scheme of building a neural network identifier

Thus, the task of identifying the engine TV3-117 is based on the training of the neural network, which is to adjust its weight based on the condition:

$$E = \sum_{i=1}^n (y_i - y_i^*)^2 \rightarrow \min. \quad (4)$$

In this paper, the method of the identification problem solution in the neural network basis is used to identify the multi-mode model of the aircraft engine TV3-117.

It is assumed that the set of stable operating modes of aviation engine TV3-117 is described by a set of functional dependencies with respect to the values of the following engine parameters:

$$\begin{aligned} n_{sp} &= f_1(G_{T_{sp}}); \quad G_{air_{sp}} = f_2(G_{T_{sp}}); \quad P_{2_{sp}}^* = f_3(G_{T_{sp}}); \\ T_{2_{sp}}^* &= f_4(G_{T_{sp}}); \quad T_{3_{sp}}^* = f_5(G_{T_{sp}}); \quad R_{sp} = f_6(G_{T_{sp}}); \end{aligned} \quad (5)$$

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

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:

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

$$T_{2_{sp}}^* = T_2^* \cdot \frac{288}{T_N^*}; T_{3_{sp}}^* = T_3^* \cdot \frac{288}{T_N^*}; R_{sp} = R \cdot \frac{760}{P_N^*}; \quad (6)$$

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

$$T_N^* = T_N \left(1 + \frac{k-1}{2} M^2 \right); \quad (7)$$

$$P_N^* = P_N \sigma_{rec} \left(1 + \frac{k-1}{2} M^2 \right)^{\frac{k}{k-1}}; \quad (8)$$

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} – full recovery rate of full pressure in the air intake.

Figure 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

Let's consider the example of the identification characteristics problem solution of the aircraft engine TV3–117 based on its operation, recorded regarding the standard atmospheric conditions.

The fragment of the training sample for identifying the multi-mode model of the aircraft engine TV3–117 is shown in the table 1. The complete training sample contains 120 lines. One of the main issues solved at the data analysis stage is the evaluation of the sample representativeness, that is, the completeness of its presentation. The solution to this question is based on the application of one of the cluster or discriminant analysis methods [11].

Table 1 – Fragment of educational selection for the automatic model of an aircraft engine TV3–117 identification

$G_{T_{sp}}$	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

Figure 3 – Measurement results of the metric distance in the process of clustering: a – output (experimental) sample; b – training sample; c – test sample

Analysis of fig. 3,a–c shows that in the process of clustering, eight classes have been identified. After the randomization procedure, the training and test samples (in the ratio of 2:1, ie 38 % and 19 %) were selected. The process of clustering the training (fig. 3,b) and the

test (fig. 3,c) samples shows that they, as well as the original sample (table 1), contain eight classes. The distance between clusters almost coincides in each of the selected samples. Consequently, the training and test samples are representative. An important issue solved at the stage of pre-processing of the measurement data is the assessment of the homogeneity of the training and test samples. To do this, we use the Fisher-Snedecor criterion [12] for the values of the rotational speed [12] n_{sp} , the results obtained in this case are given in table 2, the analysis of which shows that the ratio of a larger dispersion $\sigma_{\max}^2$ to less $\sigma_{\min}^2$ 1.246, is less than the critical value of F_{cr} , taken from the standard Fisher-Snedecor table, which in this case is $F_{cr} = 3.128$, hence the samples are homogeneous.

Table 2 – Fragment of educational choice for the automatic model of an aircraft engine TV3–117 identification

Statistical estimates	Training sample	Test sample
Medium	0.614	0.625
Dispersion	0.042	0.057
The ratio of greater dispersion to less	1.246	
F_{cr}	3.128	

For the solution of the problem of identification the multi-model aircraft engine TV3–117 in neural basis as basic architectures were selected and perceptron neural networks radial basis function (RBF). The expediency of using these architectures of neural networks is based on the analysis of the neural network and the classical methods of identification error. At this stage, the optimal structure of the neural network of the perceptron type should be chosen to solve the identification problem of the multi-mode aviation engine model TV3–117 based on the neural network.

In fig. 4 the experimental dependence $E = f(N)$ is constructed, where E – error of training of the neural network; N – the number of neurons in the hidden layer (it is assumed that the number of neurons in the input layer is equal to 1, in the output layer – 6). In the same figure, a similar dependence for a neural network of the RBF type is given.

Figure 4 – The choice of optimal complexity of neural networks structures for solving the direct identification problem: 1 – perceptron; 2 – RBF

As can be seen from fig. 4, the optimal structures of neural networks are:

– for the perceptron – the structure (1–4–6), that is, 1 neuron – in the input layer; 4 neurons – in a hidden layer and 6 neurons – in the original layer of the neural network;

– for RBF – the structure (1–12–6), that is, 1 neuron in the input layer; 12 neurons in the radial (hidden) layer and 6 neurons in the original layer.

These neural network models allow you to calculate the six listed above engine parameters as a function of the indicated fuel consumption $G_{T_{sp}}$. As an activation function of the neural network, the perceptron uses a sigmoid function.

he neural network RBF is a two-layer network (fig. 5), in which the first layer carries a nonlinear transform of the input parameter $G_{T_{sp}}$ without the use of adjustment weights, and the initial layer combines the received outputs of the 1st layer by calculating their linear weighted combination.

Figure 5 – Structure of RBF neural network

Outputs of the neural network RBF described by the equation:

$$Y_i = W_{oi} + \sum_{j=1}^n W_{ij} f_j(U); \quad (8)$$

where $i = 1, 2, \dots, n$; $U = G_{T_{sp}}$ – input signal; W_{ij} – weights of connection ($i = 1, 2, \dots, 6$; $j = 1, 2, \dots, 12$); W_{oi} – offset value at the i -th output of the neural network; $f_j(U)$ – activation functions of the neural network, which are defined in the class of Gaussian functions:

$$f_j(U) = e^{-\frac{(U-C_j)^2}{2\sigma_j^2}}; \quad (9)$$

where C_j – value that determines the position of the center (standard) j -th class; σ_j – the width of the Gaussian function $f_j(U)$.

Adjusted parameters of the neural network RBF in fig. 5 is the weights W_{ij} , W_{oi} ($i = 1, 2, \dots, 6$; $j = 1, 2, \dots, 12$), since they are linearly related to the outputs of the neural network and, therefore, with a learning error, then their values can be found directly using the method of least squares, while minimizing the total square error of the neural network:

$$E = \frac{1}{2} \sum_{r=1}^R \sum_{i=1}^n (Y_i^{(r)} - Y_{io}^{(r)})^2; \quad (10)$$

where $Y_i^{(r)}$ – the output of the neural network in the r -th experiment, that is, upon presentation of the network r -th input image $U^{(r)}$; $Y_{io}^{(r)}$ – i -th desired output of the neural network for the input $U^{(r)}$; R – the number of dif-

ferent experiments (the size of the training sample); $n = 6$. Calculating the value of partial derivatives

$$\frac{\partial E}{\partial W_{io}} = \sum_{r=1}^R (Y_i^{(r)} - Y_{io}^{(r)}); \quad (11)$$

$$\frac{\partial E}{\partial W_{ij}} = \sum_{r=1}^R (Y_i^{(r)} - Y_{io}^{(r)}) f_j(U^{(r)}); \quad (12)$$

$$i = 1, 2, \dots, n; j = 1, 2, \dots, m;$$

and equating them to zero based on the expression:

$$Y_i^{(r)} = W_{io} + \sum_{j=1}^m W_{ij} f_j(U^{(r)}); \quad (13)$$

$$i = 1, 2, \dots, n;$$

we arrive at a system with $n(m+1)$ linear equations for $n(m+1)$ unknown coefficients W_{ij} , W_{oi} ($i = 1, 2, \dots, n$; $j = 1, 2, \dots, m$).

Unlike the frequent situation, when the use of gradient methods for adjusting the parameters of the perceptron leads only to the achievement of local minima, here the finding of the weight of connections is faster and more accurate.

In the process of accuracy comparative analysis of the neural networks (perceptron and RBF) and the classical (LSM) methods for identifying the engine for a particular parameter, namely: rotor frequency of the turbine compressor, on the test sample (fig. 6) it was established that the identification error using neural Perceptron network (curve 2) is 2.6 times less than for a polynomial regression model of the 8th order constructed using LSM (curve 1), and for RBF (curve 3) less than 1.5 times. The perceptron provides the identification error does not exceed 0.342 %; RBF neural network and 0.578 %; LSM – 0.918 %.

Figure 6 – Comparative analysis of errors neural networks and classical methods of identification parameters TV3-117 aircraft engine in the test sample: 1 – least-squares method (LSM); 2 – perceptron; 3 – RBF

The results of the comparative analysis of the identification accuracy of neural network and classical methods for each of the outputs of the aircraft engine model TV3-117 are given in table 3.

Table 3 – Analysis of the error effect and classical methods of identification

Identification methods	Absolute error, %					
	n_{sp}	$G_{air_{sp}}$	$P_{2_{sp}}^*$	$T_{2_{sp}}^*$	$T_{3_{sp}}^*$	R_{sp}
LSM	0.918	0.885	0.796	0.863	0.871	0.884
Perceptron	0.342	0.612	0.562	0.611	0.609	0.538
RBF	0.578	0.726	0.651	0.722	0.723	0.723

Table 3 analysis shows that the value of aircraft engine TV3-117 identification parameters error does not exceed when used: perceptron – 0.612 %; RBF – 0.726 %; LSM – 0.918 %.

In order to analyze the stability of the neural networks to the change in input data (table 1) an additive interference with the current value of each of the parameters in the form of white noise with a zero mathematical expectation $\sigma_i = 0.025$, was added to them, ie 1.8 % in relation to the maximum value.

The results of the comparative analysis of the neural network identification accuracy and classical methods for each individual engine component, under noise conditions are shown in table 4.

Table 4 – Analysis of the error effect and classical methods of identification in the conditions of noise

Identification methods	Absolute error, %					
	n_{sp}	$G_{air_{sp}}$	$P_{2_{sp}}^*$	$T_{2_{sp}}^*$	$T_{3_{sp}}^*$	R_{sp}
LSM	1.875	1.128	1.202	1.403	1.928	1.202
Perceptron	0.635	0.702	0.776	0.708	0.814	0.818
RBF	0.725	0.884	0.812	0.866	0.884	0.792

The graphical interpretation (table 4) for the values of the rotation frequency, rotor of the turbine compressor n_{sp} and the gas temperature behind the compressor turbine $T_{3_{sp}}^*$ is shown, respectively, in fig. 7, 8.

Table 4 analysis, as well as fig. 7, 8, shows that the identification error under the conditions of the indicated noise does not exceed: with the use of perceptron – 0.818 %; RBF – 0.884 %; LSM – 1.928 %.

The error in identifying the parameters of the aviation engine TB3-117 using the method of least squares under the conditions of white noise increased from 0.918 to 1.928 %, and for neural networks (perceptron and RBF) in these conditions it increased, respectively:

- perceptron for the neural network from 0.612 to 0.818 %;
- for the neural network RBF from 0.726 to 0.884 %.

Figure 7 – Comparative analysis of neural network errors and classical methods of identification of TV3-117 aircraft engine parameters in the conditions of noise for the rotor frequency of a turbine compressor n_{sp} : 1 – LSM; 2 – perceptron; 3 – RBF

Figure 8 – Comparative analysis of neural network errors and classical methods of TV3–117 aircraft engine identification parameters in conditions of noise for gas temperature behind a compressor turbine T_{3p}^* : 1 – LSM; 2 – perceptron; 3 – RBF

CONCLUSIONS. Thus, the results analysis of the engine TV3–117 the parameters identifying on the basis of neural network and classical methods makes it possible to draw the following conclusions:

1. It has been established that neural networks solve the problem of identifying more precisely classical methods: the identification error at the output of a neural network of type perceptron is 1.6 times less than in a regression model obtained with the help of MNC for the range of changes in the operating modes of the engine, starting with small gas to the take-off mode.

2. It was shown that the error of the multi-mode model identification of the aircraft engine TV3–117 with the help of a perceptron in calculating individual parameters of the engine did not exceed 0.612 %; for the neural network RBF – 0.726 %, while for the classical method (LSM) it is about 1 % in the range of changes in engine operation modes.

Comparative analysis of neural network and classical methods of identification under noise conditions shows that neural network methods are more robust to external perturbations: for noise level $\sigma = 0.025$ the identification error of engine TV3–117 parameters with the use of perceptron increases from 0.612 to 0.818 %; for the neural network RBF from 0.726 to 0.884 %, and for the least squares method – from 0.918 to 1.928 %.

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БОРТОВОЙ МЕТОД ИДЕНТИФИКАЦИИ ПАРАМЕТРОВ НА ОСНОВЕ ТЕХНОЛОГИИ НЕЙРОННЫХ СЕТЕЙ

С. И. Владов, Ю. Н. Шмелев, К. Г. Котляров, С. А. Грибанова, О. В. Гусарова, И. Г. Деревянко, Л. И. Чиждова
Кременчугский летный колледж Харьковского национального университета внутренних дел
ул. Победы, 17/6, г. Кременчуг, 39605, Украина. E-mail: ser26101968@gmail.com

Решено актуальную научно-практическую задачу идентификации параметров авиационного двигателя ТВ3–117 в бортовых условиях классического метода наименьших квадратов и нейросетевого – путем построения нейронной сети согласно исходных данных. Разработана методика определения оптимальной структуры нейронной сети, состоящей в определении архитектуры нейронной сети, выборе оптимального алгоритма поиска весов нейронов и обучения нейронной сети, анализа эффективности различных алгоритмов обучения нейронной сети, определение структуры нейронной сети по нахождению минимальной ошибки обучения нейронной сети в зависимости от количества нейронов в скрытом слое, а также в анализе эффективности полученных результатов. В работе применены две архитектуры нейронных сетей: нейронная сеть типа «персептрон» и нейронная сеть на радиально-базисных функциях. Результаты тестирования выбранных архитектур показали, что наименьшая погрешность обучения нейронной сети типа «персептрон» составляет 0,025 % при одном нейроне во входном слое, четырех нейронах в скрытом слое и шести нейронах в выходном слое нейронной сети; нейронной сети на радиально-базисных функциях составляет также 0,025 % при одном нейроне во входном слое, двенадцати нейронах в скрытом слое и шести нейронах в выходном слое нейронной сети. Результаты исследований показали, что погрешность идентификации параметров авиационного двигателя ТВ3–117 в условиях действия указанного шума не превышает 0,818 % при использовании нейронной сети типа «персептрон», 0,884 % при использовании нейронной сети на радиально-базисных функциях и 1,928 % при использовании метода наименьших квадратов. Погрешность идентификации параметров авиационного двигателя ТВ3–117 по методу наименьших квадратов в условиях действия белого шума увеличилась с 0,918 до 1,928 %, а для нейронных сетей в этих условиях она возросла соответственно с 0,612 до 0,818 % при использовании нейронной сети типа «персептрон», с 0,726 до 0,884 % – при использовании нейронной сети на радиально-базисных функциях..

Ключевые слова: авиационный двигатель, идентификация, нейронная сеть, математическая модель, метод наименьших квадратов.

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