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THE PROBLEM OF THE IDENTIFICATION OF TV3-117 AIRCRAFT ENGINE DYNAMIC MULTI-MODE MODEL IN FLIGHT ENVELOPE

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Purpose. Construction of a mathematical model of the aircraft engine TV3-117 based on the results of observations of its reaction to environmental disturbances. The solution of the problem of identifying a dynamic 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. In this paper, the Elman recurrent network with one hidden layer with a sigmoid neuron activation function with feedback was applied. **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. The ability of the developed neural network to smooth out white noise was proved by determining the identification error of the rotational speed of the turbocharger's rotor, which was 0,005 % and did not exceed the limit-permissible value of 0,5 %. **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 dynamic 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. References 10, table 1, figure 4.

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

ЗАДАЧА ІДЕНТИФІКАЦІЇ ДИНАМІЧНОЇ БАГАТОРЕЖИМНОЇ МОДЕЛІ АВІАЦІЙНОГО ДВИГУНА ТВ3-117 У ПОЛЬОТНИХ РЕЖИМАХ

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Розв'язано актуальну науково-практичну задачу ідентифікації динамічної моделі авіаційного двигуна ТВ3-117 у бортових умовах класичними методами, до яких належать метод найменших квадратів і апроксимації кубічними сплайнами і нейромережевими, – шляхом побудови нейронної мережі згідно з вихідними даними. Розроблено методику визначення оптимальної структури нейронної мережі, яка 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 рекурентну мережу Елмана з одним прихованим шаром із сигмоїдною функцією активації нейрона зі зворотним зв'язком, що обумовлено складною формою часових рядів динаміки зміни параметрів авіаційного двигуна ТВ3-117. Спосіб організації роботи рекурентної мережі Елмана обрано «один у багато» (one-to-many) – прихований шар ініціалізується одним входом, з ланцюжка його наступних станів генеруються виходи мережі. Результати тестування застосованої нейронної мережі показали, що найменша помилка навчання нейронної мережі з одним входом і двома виходами (згідно з поставленою задачею) склала 0,006 % за наявності двох нейронів у прихованому шарі. Тестування застосованої нейронної мережі на здатність згладжувати білий шум показало, що похибка ідентифікації частоти обертання ротора турбокомпресора склала 0,005 % і не перевищила гранично допустимого значення 0,5 %. Розроблена нейронна мережа може бути одним з блоків нейромережевої експертної системи, здатної автоматично приймати рішення щодо технічного стану авіаційного двигуна ТВ3–117 у режимах польоту і надавати інформацію екіпажу про можливість подальшого безпечного руху повітряного судна.

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

PROBLEM STATEMENT**.** The need to solve the problem of controlling the parameters of an aircraft engine TV3-117 in onboard conditions is caused by the need to improve the quality of engine control in conditions of uncertainty. Such uncertainty conditions, or «non-factors», include sensor failures, communication link failures with sensors, false failures, and measurement errors (noise). A control system that relies on inadequate data can make an incorrect decision, which, in the future, will reduce the quality of engine control [1]. Thus, in these conditions, the main requirements for the engine management system are: ensuring operational and quality control and diagnostics of its parameters in the conditions of «non-factors».

Reserving full-time sensors aboard the flight apparatus only partially solves the problem and is often fraught with hardware and time costs. At present, the most promising approach is to use the mathematical model of the TV3–117 aircraft engine (individual or average) as an additional measurement channel. Due to the high sensitivity of the mathematical model, which adequately describes the physical processes occurring in aircraft engines, to external disturbances, with an increase in the integration step leads to a significant increase in the calculation error and is more than two percent [2]. For a mathematical model serving as an additional measurement channel, taking into account other problems solved on board the aircraft, approximately 10 % of processor time is allocated, i.e. 2 ms. This means that the minimum time for a single measurement of the onboard computer is 80 s, which is not possible under the board conditions [2].

Therefore, the use of the «complete» mathematical model in the conditions of on-board implementation is not effective and the latter requires significant reductions. In practice, a compromise between the completeness of the mathematical model description and its accuracy is achieved based on the requirements of the technical specifications for a specific type of aircraft engine and practical recommendations of previous implementations of a specific engine on board an aircraft.

In solving the problem of identifying the mathematical model of the TV3-117 aircraft engine, the «classical» approach is used in the work, which assumes that the physical theory of the object is missing, or cannot be used for one reason or another. The identification object is a so-called «black box» with a number of inputs and one or several outputs. Thus, the task of identification is the construction of a mathematical model of the aircraft engine TV3-117, which identifies the main modes of its operation.

MATERIAL AND RESULTS. For the mathematical model of the aviation engine TV3-117, the input parameters are: G_T – fuel consumption (kg/s); T_N – ambient temperature (K); P_N – pressure (mm. mercury); and at its output: n – rotational speed of the rotor of the turbo compressor (min^{-1}), T_3 – gas temperature behind the turbine (K). In the general case, the parameters measured on a real engine were obtained in the process of simulation modeling on its adequate element-wise mathematical model and represent a sequence consisting of 8000 points for the 5 parameters listed above. The first 4000 points obtained during the computational experiment are determined from the condition: T_N = 288,15 K, P_N = 760 mm. Hg; and the following 4000 points were calculated taking into account: H = 2000 m. Using the available data, it is necessary to build an approximating function based on the requirements for the mathematical model of the TV3-117 aircraft engine: providing identification errors of no more than 1 % with a minimum memory size and maximum speed, which is most important in real-time on-board implementation.

We formulate the problem of identification in a generalized formulation for a neural network implementation. Let the TV3-117 aircraft engine as a nonlinear dynamic object be described by a system of differential equations of the form:

$$\dot{X}(t) = F\big(X(t), U(t), V(t), A(t)\big), \qquad (1)$$

$$Y(t) = G\big(X(t), U(t), V(t)\big), \qquad (2)$$

where $X(t)$ – vector of engine state variables; $U(t)$ – vector of control actions; $V(t)$ – vector-torus of external disturbing influences; $Y(t)$ – vector of the observed coordinates; F, G – nonlinear vector functions. Then the main reasons for the change in the states of the engine system are the change in the vectors $U(t)$ and $V(t)$, the parameters of the engine $A(t)$, and the change in the operators F and G as it functions.

The solution of the problem of identification of the TV3-117 aircraft engine is reduced to the definition of an approximate dependence:

$$Y^M(k) = f\big(Y^M(k-1), Y^M(k-2), \ldots, U(k), U(k-1), \ldots\big) \qquad (3)$$

between the output vector $Y(k)$ and the input vector $U(k)$ at discrete instants of time k = 0, 1, 2,… according to the results of observations of these quantities at a certain interval in the course of engine operation. In this case, the identification error, i.e. the difference between the engine outputs (measured values of the thermogas-dynamic parameters of the engine) and the outputs of the dynamic model should not exceed the specified allowable value ε_{add}:

$$\left\| Y(k) - Y^M(k) \right\| \le \varepsilon_{add} \qquad (4)$$

with the same input effects $U(k)$.

The input vector represents the values of the variable $G_T(\alpha_{joy})$ (where α_{joy} is the position of the control knob), as well as the signals at the output of the neurons of the hidden layer that are delayed by one clock cycle of discrete time, and at the moment of time k implements the display:

$$U(k) = \big[G_T\big(\alpha_{joy}(k)\big), V_1(k-1), V_2(k-1)\big], \qquad (5)$$

where V is the state vector of the neurons of the hidden layer.

The vector of the outputs $Y_1(t)$ and $Y_2(t)$ includes the components $Y_1(t) = n(t)$; $Y_2(t) = T_3(t)$.

The construction of an identification model begins with the choice of the model form, i.e. type of dependence (3). In practice, two cases are possible [3]:

1) The form of the mathematical model is known in advance, and the task of identification is reduced to determining the coefficients of this model. Sometimes a model can be defined as a criterion dependency, and the task of identification in this case is reduced to the determination of power indicators of the criteria.

2) The form of the mathematical model is unknown in advance. In this case, to build an identification model, segments of infinite series are used, and the task is to determine the number of members of the series and the coefficients for them.

To identify the form of mathematical model of the TV3-117 aircraft engine, this paper discusses the use of cubic splines (CS), polynomials obtained by the least squares method (LSM), and neural networks.

The assessment of the possibility of using neural networks to build models of identification of the TV3-117 aircraft engine was carried out according to the following procedure:

1) Definition of neural network architecture. The following architectures were considered for building an approximate mathematical model of the TV3-117 aircraft engine:

– a network of direct signal propagation with one hidden layer (activation functions: linear, sigmoid, and hyperbolic tangent) with common feedback;

– the Elman recurrent network with one hidden layer (activation functions: sigmoid and hyperbolic tangent) with and without common feedback.

2) Determination of the activation functions of neurons of the neural network, in which the following functions were considered: sigmoidal, hyperbolic tangent and linear.

3) Analysis of the effectiveness of various neural network learning algorithms, which are described in detail in [4, 5], where the choice of the most optimal one is justified – an additive step of learning a neural network, which is implemented as a gradient method.

4) Determination of the structure of the neural network, which was carried out in 2 stages:

– at the first stage, preliminary training of several neural networks, differing in the number of neurons in hidden layers, is carried out;

– at the second stage, the process of pre-learning the optimal set of non-core networks and determining the best structure from this set is carried out.

5) Analysis of the effectiveness of the solution.

The task of identifying the mathematical model of the TV3-117 aircraft engine in the neural network basis is reduced to the parametric problem of finding the synaptic weights of neurons. The algorithms for searching for weights of neurons or learning neural networks are reflected in many papers [6, 7]. To implement the learning algorithms, a training sample is necessary, assigning the calculated output values to the input effects of the mathematical model of the engine. After training, the resulting weights and displacements of the neural network are used for the onboard neural network, which is a real-time model of the TV3-117 aircraft engine.

The initial data for the training of the model were recorded during the flight tests of the TV3-117 aircraft engine onboard the Mi-8MTV helicopter using an onboard data recording system, which were recorded for 320 seconds of real flight with a sampling period of 1 s. The obtained dynamics of changes in the parameters of the aircraft engine TV3-117 indicates the complexity of the shape of the time series of these parameters (fig. 1). The appearance of the curves indicates the need to take into account the values of the parameters and the accumulation of information in the model's memory, which is impossible without the use of recurrent neural networks. In this case, it is Elman's neural network.

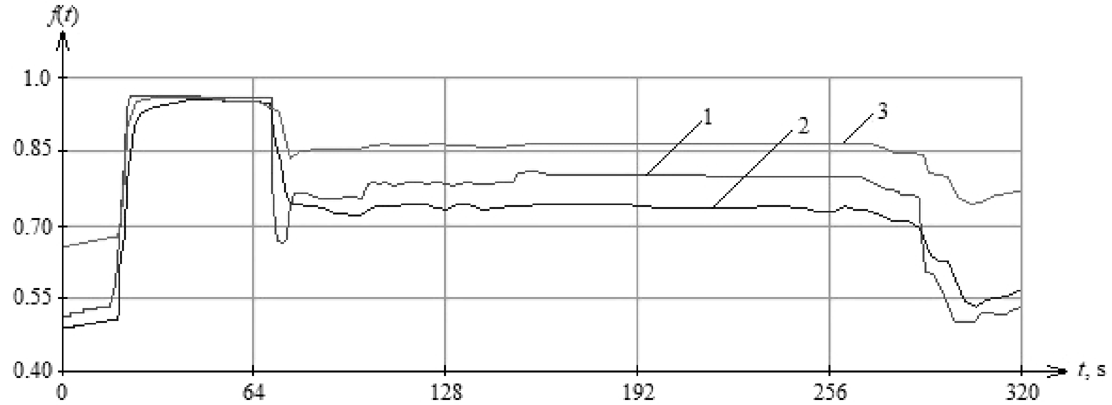

Figure 1 – Chart of dynamics of parameters changes of aircraft engine TV3-117 in time: 1 – α_{joy}; 2 – T_3^* ; 3 – n

In fig. 1 in the time range from 21 to 75 s, there is a sharp surge in all three parameters, which is explained by the transient mode of operation of the engine. Since it is known that most of the time (about 85 %), the TV3-117 aircraft engine is operated at steady state conditions and only about 15 % at unsteady and transient operating conditions. Since the neural network models of the TV3-117 aircraft engine, implemented using a perceptron, cover only the steady state operation of the aircraft engine, to expand the range of the monitoring and diagnostics process of its technical condition, a dynamic multimode model of the aircraft engine TV3-117 is being developed, taking into account unsteady and transient modes of its operation, the implementation of which is possible with the use of recurrent neural networks, including Elman networks. The way of organizing the work of the recurrent network of Elman is chosen one-to-many – the hidden layer is initialized with one input, the network outputs are generated from the chain of its subsequent states.

As a result of testing the previously reviewed architectures, it was found that a neural network with a linear transfer function in a hidden layer poorly solves the In the process of additional training of the neural network, it was established that the Elman recurrent network (fig. 2) is optimal, having 2 neurons in the hidden layer (fig. 3), as well as a logistic sigmoid as a function of neuron activation. In this case, the maximum learning error was no more than 0,35 % (of the interval of variation of the parameter). Testing of this neural network showed that it is robust to external disturbances, which have, for example, the additive component of white noise (M = 0, σ = 0,01), and the maximum error in this case did not exceed 0,5 %.

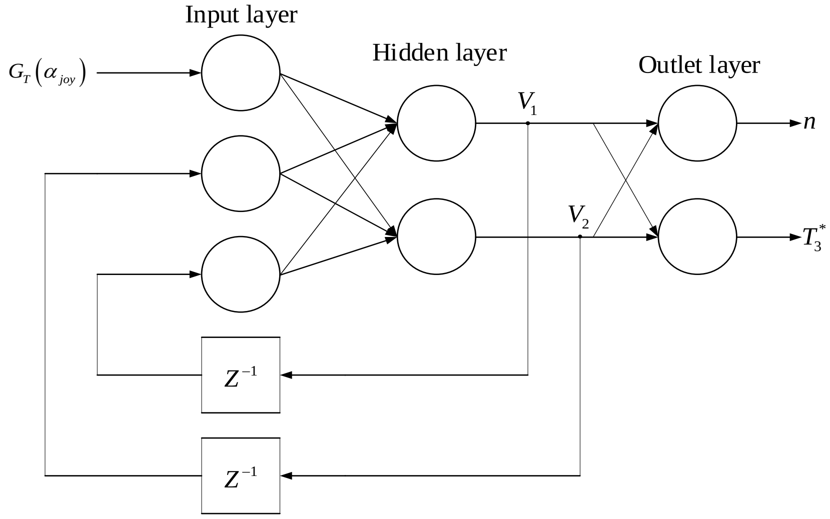

Figure 2 – The structure of the neural network dynamic model of the TV3-117 aircraft engine

For training the Elman network, the same gradient methods [4, 5] are used as for conventional direct propagation networks, but with certain modifications, to correctly calculate the error function gradient. It is calculated using a modified back-propagation method – Back propagation through time (back-propagation method with network expansion in time, BPTT) [8], which expands the sequence, turning the recurrent network into a “normal” one. As in the method of back propagation for networks of direct distribution, the process of calculating the gradient (changing weights) occurs in the following three stages.

– direct pass – calculation of the state of the layers,

– backward pass – calculation of layer error,

– calculation of changes in weights, based on the data obtained in the first and second stages.

Having found a method for calculating the gradient of the error function, one can apply one of the modifications of the gradient descent method [4, 5].

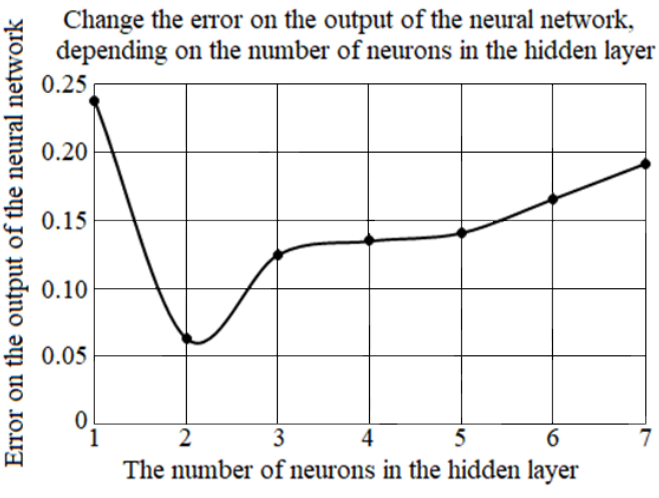

Figure 3 – Neural network error depending on the number of neurons in the hidden layer

The graphs of changes in the neural network learning error as a function of the number of iterations (1 – with 2 neurons in the hidden layer, 2 – with 3 neurons in the hidden layer; 3 – with 4 neurons in the hidden layer; 4 – with 5 neurons in the hidden layer) (fig. 4) indicate the minimal error of learning of the neural network with the presence of two neurons in the hidden layer.

Fig. 5 shows the dependence of the identification error measurement for the rotor speed of a turbocompressor n depending on the time T, s, where 1 – real value of the parameter, 2 – value of the parameter from the neural network in the absence of noise, 3 – data from the neural network with an additive noise of 1 % at the entrance.

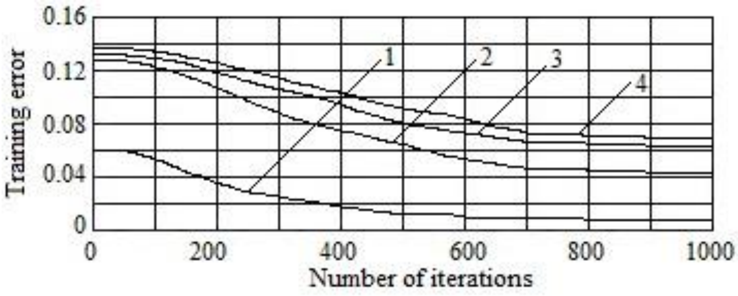

Figure 4 – Graphs of changes in learning errors depending on the number of iterations:
1 – with 2 neurons in the hidden layer; 2 – with 3 neurons in the hidden layer; 3 – with 4 neurons in the hidden layer;
4 – with 5 neurons in the hidden layer

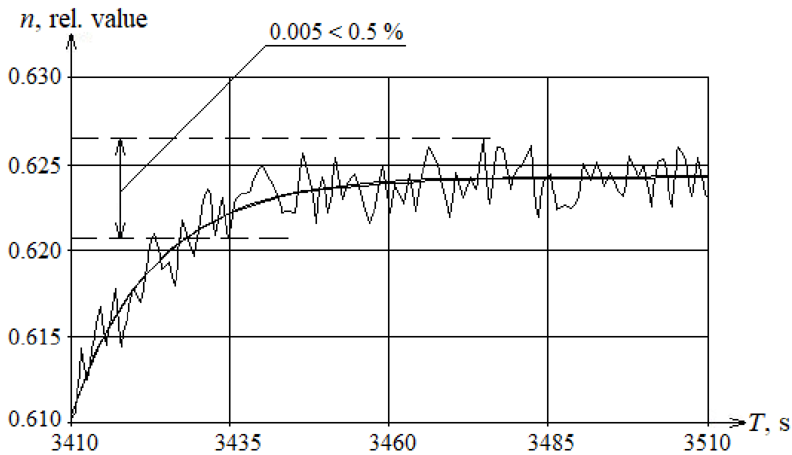

Figure 5 – Fragment of neural network testing for the ability to smooth noise

The use of LSM for the identification of a mathematical model of the TV3-117 aircraft engine is thoroughly considered in [2, 9].

The method of CS approximation [10] also belongs to the «classical» methods for identifying mathematical models. The analysis of these methods shows that, as applied to the solution of this problem, compared with the LSM, the CS provide an accurate approximation of the engine characteristics, but require large amounts of memory to store the coefficients.

So with an increase in the number of control points 50 times, the CS reach an approximation error close to the machine 0. But this number of control points requires 320 times more RAM than the LSM. Therefore, the number of reference points is selected from the conditions of sufficient accuracy (1 % of the parameter variation interval) of the approximation. So for a CS, this accuracy is achieved when 152 reference points are selected from the entire set of available points (8000 points). An increase in the degree of the polynomial LSM does not lead to an improvement in the quality of identification, but on the contrary leads to its deterioration. In this paper we considered polynomials up to the 8th degree. As a result of comparing polynomials of varying degrees, it was found that polynomials of the 5th and 6th degree provide minimal error, while polynomials of the 7th and 8th degree provide a steady increase in the approximation error.

Table 1 shows the characteristics of the mathematical model of the aviation engine TV3-117, obtained using the methods of least squares and a neural network.

Table 1 – Comparative analysis of identification methods

Identification methods	Absolute error (σ = 0,01), %		Absolute error (σ = 0,03), %		Absolute error (σ = 0,05), %	
	n	T_3^*	n	T_3^*	n	T_3^*
Least squares method	0,75	0,86	0,69	0,79	0,68	0,78
Elman neural network	0,54	0,43	0,57	0,46	0,61	0,49

Table 1 follows the advantage of neural network methods in terms of noise. In some cases, the error of dynamic identification using the classical method is almost 2 times higher than similar calculations obtained using the Elman neural network, which shows the high robustness of neural networks to external disturbances.

CONCLUSIONS. According to the results of the research:

1. The possibility of using neural networks to build models for the identification of complex objects, such as the TV3-117 aircraft engine, is shown.

2. It has been established that the optimal architecture of the neural network is the Elman recurrent network with general feedback.

3. The possible activation functions of neurons of the hidden layer are determined: hyperbolic tangent and logistic sigmoid.

4. The optimal algorithm for learning the neural network – the gradient method.

5. It is shown that neural networks have a high robustness to the additive component of white noise (M = 0, σ = 0,01). The identification error did not exceed 0,5 %.

6. A method has been developed for determining the optimal structure of a neural network.

7. A comparison is made with the classical methods of identifying the mathematical model of the TV3-117 aircraft engine.

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ЗАДАЧА ИДЕНТИФИКАЦИИ ДИНАМИЧЕСКОЙ МНОГОРЕЖИМНОЙ МОДЕЛИ АВИАЦИОННОГО ДВИГАТЕЛЯ ТВ3-117 В ПОЛЕТНЫХ РЕЖИМАХ

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Решена актуальная научно-практическая задача идентификации динамической модели авиационного двигателя ТВ3-117 в бортовых условиях классическими методами, включающие метод наименьших квадратов и аппроксимации кубическими сплайнами, и нейросетевыми – путем построения нейронной сети в соответствии с исходными данными. Разработана методика определения оптимальной структуры нейронной сети, заключающаяся в определении архитектуры нейронной сети, выборе оптимального алгоритма поиска весов нейронов и обучения нейронной сети, анализа эффективности различных алгоритмов обучения нейронной сети, определения структуры нейронной сети, заключающаяся в нахождении минимальной ошибки обучения нейронной сети в зависимости от количества нейронов в скрытом слое, а также в анализе эффективности полученных результатов. В работе применена рекуррентная сеть Элмана с одним скрытым слоем с сигмоидной функцией активации нейрона с обратной связью, что обусловлено сложной формой временных рядов динамики изменения параметров авиационного двигателя ТВ3-117. Способ организации работы рекуррентной сети Элмана выбран «один во много» (one-to-many) – скрытый слой инициализируется одним входом, из цепочки его последующих состояний генерируются выходы сети. Результаты тестирования примененной нейронной сети показали, что наименьшая ошибка обучения нейронной сети с одним входом и двумя выходами (согласно поставленной задаче) составила 0,006 % при наличии двух нейронов в скрытом слое. Тестирование примененной нейронной сети на способность сглаживать белый шум показало, что погрешность идентификации частоты вращения ротора турбокомпрессора составила 0,005 % и не превысила гранично допустимое значение 0,5 %. Разработанная нейронная сеть может являться одним из блоков нейросетевой экспертной системы, способной автоматически принимать решения относительно технического состояния авиационного двигателя ТВ3-117 в режимах полета и предоставлять информацию экипажу о возможности дальнейшего безопасного движения воздушного судна.

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

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