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NEURAL NETWORK INTERPOLATION PARAMETERS OF A MULTI-MODE DYNAMIC MODEL OF THE AIRCRAFT ENGINE

The foundations of the concept of creation of intelligent aircraft engine control systems based on the decomposition of control processes within the architecture of open information systems are considered. Unlike well-known approaches, the suggested approach allows achieving the management goal based on the principle of minimum entropy by redistributing system resources in conditions of their shortage, as well as adapting system characteristics when changing the management situation based on self-learning and self-organization of intelligent control systems. Based on an analysis of the development trends of aircraft engines, as well as development trends of production and technological systems, including the creation of new composite materials and new technologies for the manufacture and control of parts and components of aircraft engines, the intellectualization of their automatic control systems is discussed. Moreover, the development trends of aircraft engine control systems are considered from the development of their structures, functions, properties, and abilities for new qualitative changes. The article gives the general characteristics and the main directions of the design of intelligent control systems for aircraft engines as complex technical objects. The problem of designing nonlinear dynamic models of aircraft engines using artificial neural networks is discussed. The statement of this problem and possible approaches to its solution are being formed. The results of the neural network identification of an aircraft engine are compared using the least-squares method. Such a technique for designing a model of aircraft engines makes it possible to indirectly calculate engine coordinates inaccessible to measurement - traction, fuel consumption, etc. The suggested approach allows calculation of the design of neural networks simulating aircraft engines at each step using standard procedures, which makes it possible to automate the creation of neural networks. To reduce the computation time, it is suggested using the optimization algorithms taking into account changes in the state entropy. This simplifies the implementation of the neural network model of an aircraft engine in real time as part of an onboard computer complex.

Keywords: aircraft engine; diagnostics; neural network.

Introduction

The development of technical systems can occur due to the development of their structures, as well as individual subsystems and elements. For aircraft engines, as a developing system, the evolution of their structure is reflected, first of all, in the evolution of their basic structural scheme, in particular the control and monitoring systems.

An analysis of the control and monitoring systems of modern aircraft engines shows that their functions are extremely large in volume and diverse in content. These functions are associated with the following tasks:

– ensuring high quality control of aircraft engine operating modes in a wide range of changing operating conditions due to «with full responsibility» onboard adaptive digital electronic systems;

– ensuring the integration of the aircraft engine control system with the air inlet and aircraft control systems;

– ensuring high reliability of the functioning and service life of aircraft engines and their systems due to the built-in digital electronic monitoring and diagnostics system;

– ensuring the required environmental characteristics, high efficiency and durability due to the transition to the operation of aircraft engines and its systems in technical condition;

– ensuring reconfiguration of both the aircraft engine circuit and its control system and its systems according to their technical condition.

Achieving high efficiency of the operation of control and monitoring systems for an aircraft engine under such complex technical requirements for their operating conditions is possible if these systems are designed in the class of intelligent systems, as the most promising systems that function effectively in the face of uncertainty.

Currently, the problem of creating automatic control systems for complex technical systems is characterized by a transition from the paradigms of a program, positional, identification and adaptive control to the paradigms of intelligent control (without automatic goal setting) and intelligent control, i.e. with automatic goal setting [1].

This is due both to the continuous complication of control objects and the conditions of their functioning,

the emergence of new classes of computing tools (in particular distributed computing systems), high-performance telecommunication channels, and a sharp increase in the requirements for reliability and efficiency of control processes in the conditions significant a priori and a posteriori uncertainty. It is becoming generally accepted that the consideration of the above factors is possible only on the basis of the transition from «hard» algorithms of parametric and structural adaptation to the anthropomorphic principle of formation of control.

An intelligent control system for complex technical systems that operate on the basis of a reconfigurable computing environment that has the property of adaptability taking into account the evolving external environment is shown in [2]. The system changes its own behavior in the presence of various kinds of interference in the on-board equipment, active counteraction, a sharp change in the route of movement, etc.

The purpose of this work is to further improve the methodology for creating an effective algorithm for creating a neural network of early indiscriminate diagnostics of aircraft engines.

1. The problem statement

As the main feature of the intelligent aircraft engine control system, the entropy estimation of the amount of information and the capacity information channel can be used. For this, you can use the principle of Increasing Precision with Decreasing Intelligence, which consists in increasing the level of intelligence of the system with precision control as the hierarchy of intelligent control systems increases [3].

With this principle in mind, we can formulate the problem of optimal synthesis of a three-level intelligent aircraft engine control system based on the entropy approach.

It is necessary to find such a way to design an intelligent aircraft engine control system and its levels:

$$\mathbf{\Omega}_{opt} = f(\mathbf{Y}, \mathbf{F}, \mathbf{G}),$$

in other words to determine the composition of control algorithms, the structure of databases and knowledge of the control system, so that the requirement of approximation of the vector of output parameters $\mathbf{Y}$ to the desired result is met under the following condition:

$$H_{\Sigma}(A) \rightarrow \min, \qquad (1)$$

where $H_{\Sigma}(A)$ – is the total entropy of the set of control algorithms ($\mathbf{R}$) for all three levels of control of the intelligent aircraft engine control system, which can be calculated as

$$H_{\Sigma}(A) = H(A)_{el} + H(A)_{cl} + H(A)_{pl},$$

where $H(A)_{el}$, $H(A)_{cl}$, $H(A)_{pl}$ – accordingly, the entropy of the algorithms of the executive level, coordination level and planning level of the intelligent aircraft engine control system.

It is assumed that, in addition to fulfilling condition (1), the following restrictions must be observed:

$$H_{max}(\mathbf{Y}, \Omega_{opt}, \mathbf{F}) \le H_{perm},$$

where $\mathbf{H}$ is the maximum permissible level of entropy of control processes in an intelligent aircraft engine control system.

The task of minimizing the entropy of the state vector of the $\mathbf{X}$ object is equivalent to the task of optimizing control processes based on the integral quality criterion:

$$I(\Omega) = \int_{t_0}^{T_k} L(\mathbf{X}, \Omega, t) dt \rightarrow \min,$$

where $L(\mathbf{X}, \mathbf{\Omega}, t)$ – a positive definite function from $\mathbf{X}$, $\mathbf{\Omega}$, t;

$$t \in T = [t_0, T_k];$$
$$\Omega = \Omega(\mathbf{X}, t);$$
$$\Xi_U \times T \rightarrow \Xi_x.$$

The technique for solving the problem of synthesis of an intelligent aircraft engine control system based on the entropy approach includes the following steps:

Step 1. The control goal ($G = G^*$) and the state of the environment ($F = F^*$) are set.

Step 2. A synthesis of the executive level algorithms of the intelligent control system is carried out from the condition of minimum entropy:

$$H(A)_{ICS} \rightarrow \min$$

and restrictions on the entropy of the output vector:

$$H(\mathbf{Y}/\Omega, \mathbf{F}^*) \le H_{l\,perm};$$
$$\forall \mathbf{X} \in \Xi_{Y_l}; \mathbf{Y} \in \Xi_{Y_l}; \Omega \in \Xi_{\Omega},$$

where $H_{l\,perm}$ – a permissible level of entropy, determined by the requirements for the accuracy of maintaining the operating modes of the object.

Step 3. Fixed $G = G^*$, accepted: $F \in \Xi F$.

Step 4. A synthesis of the algorithms of the coordination level of the intelligent control system is performed from the condition:

$$H(A)_{cl} \rightarrow \min$$

and restrictions on the magnitude of the entropy of the vector of GTE outputs:

$$H(\mathbf{Y}/\Omega, \mathbf{F}^*) \le H_{2\,perm};$$

$$\forall \mathbf{X} \in \Xi_{X_2}; \mathbf{Y} \in \Xi_{Y_2}; \Omega \in \Xi_\Omega,$$

where $H_{2\,perm}$ – a permissible level of entropy of the output vector $\mathbf{Y}$, determined by the requirements for the accuracy of control processes in a given range of the external environment ($G \in \Xi G$).

Step 5. The synthesis of algorithms for the level of organization of the intelligent control system from the conditions:

$$H(A)_{ol} \to \min$$

and limitations of the form:

$$H(\mathbf{Y}/\Omega_{opt}, \mathbf{F}^*) \le H_{3\,perm};$$

$$\forall \mathbf{X} \in \Xi_{X_2}; \mathbf{Y} \in \Xi_{Y_3}; \Omega \in \Xi_\Omega,$$

where $H_{3\,perm}$ – a permissible level of entropy of the output vector Y, taking into account the uncertainty of control objectives ($G \in \Xi G$).

It is assumed that

$$H_{1\,perm} < H_{2\,perm} < H_{3\,perm}.$$

Step 6. The total complexity of the intelligent engine management system is evaluated:

$$H_\Sigma(A) = H(A)_{el} + H(A)_{cl} + H(A)_{pl}.$$

Step 7. Evaluation of the goal achievement.

Since the problem of choosing a design solution for an intelligent aircraft engine control system belongs to the class of inverse problems, the process of solving this problem can be iterative. Moreover, it is necessary to develop a library of standard design solutions with an evaluation of the entropy complexity of control algorithms at various levels of the hierarchy by an intelligent aircraft engine control system.

In order to evaluate the complexity of the neural network model, you can use the estimate of the entropy of the signals at its output [4] under the assumption that the probability density of the $p(E_i)$ propagation at the i-th output of the neural system (y_i) has the following form:

$$p(E_i) = \begin{cases} (q_i - v_i)^{-1}, & \text{if } q_i \le E_i \le v_i, \\ 0, & \text{otherwise,} \end{cases}$$

where $[q_i, v_i]$ – a possible range of variation of E_i error of the learning process of a neural network.

Then we can write the entropy for the deviation of the output vector of the neural network:

$$\mathbf{Y}_{NN} = \left(y_1^{NN}, \ldots, y_n^{NN}\right)^T$$

in relation to the desired exit vector

$$\mathbf{Y} = \left(y_1, \ldots, y_n\right)^T$$

by means of the following formula:

$$H(\mathbf{E}) = -\sum_{i=1}^n p(E_i)\ln(p(E_i)) = \sum_{i=1}^n \ln(v_i - q_i).$$

Obviously, the value of the entropy $H(\mathbf{E})$ during the learning process of the neural network will change, in the direction of decreasing, since the interval of variation of the error $[q_i, v_i]$ will decrease in this case. If you require the condition

$$|E_i| \le E_{i\,perm},$$

where

$$H(\mathbf{E})_{perm} = n \cdot \ln 2 + \sum_{i=1}^n \ln(E_{i\,perm}).$$

Most often, piecewise linear interpolation is used to solve this problem, which is due to the simplicity of its algorithmic and software implementation. The main disadvantage of these models is the following: jumps of derivatives at interpolation nodes and a significant approximation error at points between the nodes. More acceptable from the point of view of ensuring the smoothness of the approximated characteristics is the use of spline interpolation using third-order polynomials [5].

2. The problem solution

Consider the model of a multi-mode double-shaft double-circuit gas turbine engine in the form of a set of piecewise linear dynamic models of the following form:

$$\dot{\mathbf{x}} = \mathbf{A}_i(\mathbf{x} - \mathbf{x}_i^{st}) + \mathbf{B}_i(\omega - \omega_i^{st}),$$

$$\mathbf{y} = \mathbf{y}_i^{st} + \mathbf{C}_i(\mathbf{x} - \mathbf{x}_i^{st}) + \mathbf{D}_i(\omega - \omega_i^{st}),$$

where $\mathbf{A}_i$, $\mathbf{B}_i$, $\mathbf{C}_i$, $\mathbf{D}_i$, $\mathbf{x}$, $\mathbf{y}$, ω, $\mathbf{y}_i^{st}, \mathbf{x}_i^{st}, \omega_i^{st}$ the values of the vectors of variables x, ω, y at steady-state engine operation modes;

$\mathbf{x} = (n_1, n_2)^T$ – is the vector of state variables;

$\omega = (G_T, F_c)$ – is the vector of control actions;

$\mathbf{y} = (p_c, p_T^*, T_T^*)$ – is a vector of controlled variables.

In order to ensure the functioning of the model in a given range of changes in engine operating modes, the problem of interpolating the coefficients of piecewise-linear dynamic models is usually solved.

Considering the fact that the parameter

$$\eta = k_1 \bar{n}_1 + k_2 \bar{n}_2$$

determining the choice of the point of the i-th operating mode is continuous, a multimode engine model can be represented in the form of a system of differential equations:

$$\dot{\mathbf{x}} = \mathbf{A}(\eta)(\mathbf{x} - \mathbf{x}^{st}(\eta)) + \mathbf{B}(\eta)(\omega - \omega^{st}(\eta)) \, ,$$

$$\mathbf{y} = \mathbf{y}^{st}(\eta) + \mathbf{C}(\eta)(\mathbf{x} - \mathbf{x}^{st}(\eta)) + \mathbf{D}(\eta)(\omega - \omega^{st}(\eta)) \, .$$

In the case of piecewise linear interpolation, it is difficult to ensure the required accuracy of the model over the entire operating range. In the case of polynomial approximation, it is necessary to construct interpolation polynomials of the third order, which in some cases makes it difficult to ensure the required accuracy of the model.

When solving the interpolation problem using a three-layer neural network, the nonlinear multimode dynamic model of an aircraft engine will have the following form:

$$\dot{\mathbf{x}} = \left(\sum_{i=1}^{N} W_i^1 f_i(\mathbf{x}) + \mathbf{B}^1 \right)(\mathbf{x} - \mathbf{x}^{st}) + \qquad (2)$$

$$+ \left(\sum_{i=1}^{N} W_i^2 f_i(\mathbf{x}) + \mathbf{B}^2 \right)(\omega - \omega^{st}),$$

$$\mathbf{y} = \left(\sum_{i=1}^{N} W_i^3 f_i(\mathbf{x}) + \mathbf{B}^3 \right)(\mathbf{x} - \mathbf{x}^{st}) + \, ,$$

$$+ \left(\sum_{i=1}^{N} W_i^4 f_i(\mathbf{x}) + \mathbf{B}^4 \right)(\omega - \omega^{st}),$$

$$\mathbf{x}^{st} = \left(\sum_{i=1}^{N} W_i^5 f_i(\mathbf{x}) + \mathbf{B}^5 \right),$$

$$\omega^{st} = \left(\sum_{i=1}^{N} W_i^6 f_i(\mathbf{x}) + \mathbf{B}^6 \right),$$

where $f_i(\cdot)$ –is a neuron activation function;

W_i^j – are customizable weights;

B_j – are displacements in separate layers,

N – is the number of neurons in the hidden layer.

The accuracy of the model in this case will depend on the number of neurons in the hidden layer. The obvious advantage of this approach is a possibility to provide the required accuracy of the interpolation of coefficients and variables by learning the interpolating neural network.

The neural network architecture, which interpolates the required parameters of the dynamic model (2), contains three layers, the parameter η is supplied to its input, and the values of the matrix elements **A, B, C, D** are determined at the output. The accuracy of the calculation of engine parameters depends on the number neurons in the hidden layer N.

Despite the fact that in the recent years the considerable attention has been paid to the identification of gas turbine engines using neural networks, the results obtained in this area are not without certain drawbacks, which are as follows:

– the process of solving the identification problem in a neural network basis, as a rule, is carried out on the basis of trial and error;

– there are no reasonable recommendations on the choice of the structure of the neural network, learning algorithms, etc.;

– there is no formalized engineering methodology for solving such problems.

As studies show, the main stages of the engineering methodology for constructing a neural network model of aircraft engines should include:

– preliminary data analysis at the stage of setting the task;

– data conversion to create an effective network setup procedure;

– selection of neural network architecture;

– selection of the neural network structure;

– the choice of neural network learning algorithm;

– learning and testing the neural network.

We will consider the problem statement of identifying the characteristics of an aircraft engine in steady-state operating modes. In these modes, the engine is described by equations of the form:

$$\mathbf{X} = f_1(\mathbf{A}, \Omega) \, ,$$
$$\mathbf{Y} = f_1(\mathbf{A}, \mathbf{X}) \, ,$$

where **X, Y, Ω** and **A** – are the vectors of state variables, engine outputs (measured thermogasdynamic parameters), and control actions and model parameters, dimensions r, n, m and k, respectively;

f_1 and f_2 are some nonlinear vector functions.

The task of identification is to find such a correspondence

$$\mathbf{Y}^* = f^*(\mathbf{A}, \Omega) \, ,$$

which would satisfy the condition

$$\left\| \mathbf{Y} - \mathbf{Y}^* \right\| < \varepsilon$$

on a given set of values

$$\mathbf{X} \in \Xi_x, \mathbf{Y} \in \Xi_y, \mathbf{\Omega} \in \Xi_\omega,$$

where Ξ_x, Ξ_y, Ξ_ω – determined by the permissible engine operating conditions;

ε – is the specified error.

The solution to the problem of the engine identification is reduced to a neural network learning:

$$E = \sum_{i=1}^{n} \left(Y_i - Y_i^* \right)^2 \to \min,$$

where E is the total quadratic error of the neural network learning.

As an example, let's consider the identification of a dynamic multi-mode aircraft engine model.

An aircraft engine, as a nonlinear dynamic object, is described by a system of differential equations of the form:

$$\dot{\mathbf{X}}(t) = F(\mathbf{X}(t), \mathbf{\Omega}(t), \mathbf{V}(t), \mathbf{A}(t)) ;$$
$$\mathbf{Y}(t) = G(\mathbf{X}(t), \mathbf{\Omega}(t), \mathbf{V}(t)) ;$$

where $X(t)$ – is the vector of state variables;

$\mathbf{\Omega}(t)$ – is the vector of control actions;

$\mathbf{V}(t)$ – is the vector of external disturbing influences;

$\mathbf{Y}(t)$ – is the vector of output coordinates;

$\mathbf{F, G}$ – are nonlinear vector functions.

The task of identifying the engine is to determine an approximating correspondence:

$$\mathbf{Y}^M(k) = f\left(\mathbf{Y}^M(k-1), \mathbf{Y}^M(k-2), \ldots \right.$$
$$\left. \ldots, \mathbf{\Omega}(k), \mathbf{\Omega}(k-1), \ldots \right)$$

between the output vector $\mathbf{Y}_{(k)}$ and the input vectors $\mathbf{\Omega}_{(k)}$ at discrete time instants according to the results of observations of these quantities over a certain interval during the operation of the engine.

In this case, the identification error should not exceed the specified permissible value ε_{perm}:

$$\left\| \mathbf{Y}(k) - \mathbf{Y}^M(k) \right\| < \varepsilon_{perm}$$

with the same input stimulus $\mathbf{\Omega}_{(k)}$.

The initial data for designing the model are recorded on board the aircraft using the on-board data recording device.

In the process of experimental studies, the Elman neural network was selected for identification.

Each hidden neuron has its own analogue in the input layer, forming the input layer together with the

external input α_{eck} of the network. The output layer of the network consists of neurons, at the outputs of which the values of the desired engine parameters n_{lp}, n_{hp}, T_T^*.

The input vector of the Elman network is the value of the variable α_{eck}, as well as the signals at the outputs of the neurons of the hidden layer, delayed by one clock cycle of discrete time.

We denote the state vector of the neurons of the hidden layer as $\mathbf{V}$, and the vector of network outputs as $\mathbf{Y}$. Then the expression for the input network vector:

$$\Omega(k) = \left(\alpha_{eck}(k), \mathbf{V}_1(k-1), \mathbf{V}_2(k-1) \right)^T .$$

We denote the weights of the synaptic connections of the hidden layer of the network as $W_{ij}^{(1)}$, and the weights of the connections of the output layer as $W_{ij}^{(2)}$, then the weighted sum of the inputs of the i-th neuron of the hidden layer γ_i and its output signal V_i are found by the formulas:

$$\gamma_i(k) = \sum_{j=1}^{3} w_{ji}^{(1)} \Omega_j(k),$$
$$V_i = f_1(\gamma_i(k)) .$$

where $f_i(\gamma_i)$ – is an activation function of the i-th neuron of the hidden layer.

The weighted sum of the inputs of the i-th neuron of the output layer φ_i and the i-th output signal of the network Y_i:

$$\varphi_i(k) = \sum_{j=1}^{2} w_{ji}^{(2)} V_i(k),$$
$$y_i(k) = f_2(l_i(k)),$$

where $f_2(\varphi_i(k))$ – the activation function of the i-th neuron of the output layer of the neural network.

The neural network learning function at time k is defined as the sum of the squared differences between the outputs of the network Y_i and their desired values of d_i:

$$E(k) = 0.5 \sum_{i=1}^{3} \left(y_i(k) - d_i(k) \right)^2 .$$

In the process of experimental studies, a comparative analysis of the operation of the neural network and the classical least squares method under flat noise with zero mathematical expectation and mean-square deviations of 0.01, 0.02, 0.04 was carried out.

The accuracy of the dynamic identification of the mathematic engine control system based on the Elman

neural network turned out to be 1.35 times higher compared to the least squares method.

Conclusion

The analysis of the results indicates the advantage of using neural network methods in the presence of noise. The error in dynamic identification of automatic control systems for aviation engines when using the classical method, almost 1.5 times exceeds the error of similar calculations obtained using the Elman neural network, which shows the high robustness of neural networks to external perturbations.

The application of the suggested approach opens up new possibilities in the development of methods for early indiscriminate diagnostics of hard-to-recognize defects in aircraft engine parts using computer data acquisition and processing systems.

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НЕЙРОМЕРЕЖЕВА ІНТЕРПОЛЯЦІЯ ПАРАМЕТРІВ БАГАТОРЕЖИМНОЇ ДИНАМІЧНОЇ МОДЕЛІ АВІАЦІЙНОГО ДВИГУНА

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Розглянуті основи концепції побудови інтелектуальних систем управління авіаційними двигунами, основаних на декомпозиції процесів керування в рамках архітектури відкритих інформаційних систем. На відміну від відомих підходів, підхід, що розглядається, дозволяє забезпечити досягнення мети управління на основі принципу мінімальної ентропії шляхом перерозподілу ресурсів системи в умовах їх дефіциту, а також адаптації характеристик системи при зміні ситуації керування на основі самонавчання й самоорганізації інтелектуальних систем керування. На основі аналізу тенденцій розвитку авіаційних двигунів, а також тенденцій розвитку виробничих і технологічних систем, включаючи створення нових композитних матеріалів і нових технологій виготовлення й контролю деталей і вузлів авіаційних двигунів обговорюються тенденції інтелектуалізації систем їх автоматичного керування. При цьому тенденції розвитку систем керування авіаційними двигунами розглядаються з точки зору розвитку їх структур, функцій, властивостей і здатностей до нових якісних змін, враховуючи загальні характеристики й основні напрямки побудови інтелектуальних систем управління авіаційними двигунами як складними технічними об'єктами. Обговорюється задача побудови нелінійних динамічних моделей авіаційних двигунів з використанням штучних нейронних мереж. Формується постановка цієї задачі й можливі підходи до її розв'язку. Проведено порівняння результатів нейромережевої ідентифікації авіаційного двигуна із застосуванням методу найменших квадратів. Така методика побудови моделі авіаційних двигунів дозволяє побічно обчислювати недоступні виміру координати двигуна – тягу, витрату палива тощо. Запропонований підхід дозволяє при побудові нейронних мереж, що моделюють авіаційні двигуни, на кожному кроці застосовувати стандартні процедури, які дають можливість

автоматизувати створення нейронної мережі. Для скорочення часу обчислень пропонується застосування оптимізаційний алгоритм з урахуванням зміни ентропії стану. Це спрощує реалізацію нейромережевої моделі авіаційного двигуна в реальному часі в складі бортового обчислювального комплексу.

Ключові слова: авіаційний двигун; діагностика; нейрона мережа.

НЕЙРОСЕТЕВАЯ ИНТЕРПОЛЯЦИЯ ПАРАМЕТРОВ МНОГОРЕЖИМНОЙ ДИНАМИЧЕСКОЙ МОДЕЛИ АВИАЦИОННОГО ДВИГАТЕЛЯ

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Рассмотрены основы концепции построения интеллектуальных систем управления авиационными двигателями, основанной на декомпозиции процессов управления в рамках архитектуры открытых информационных систем. В отличие от известных подходов, предлагаемый подход позволяет обеспечить достижение цели управления на основе принципа минимальной энтропии путём перераспределения ресурсов системы в условиях их дефицита, а также адаптации характеристик системы при изменении ситуации управления на основе самообучения и самоорганизации интеллектуальных систем управления. На основе анализа тенденций развития авиационных двигателей, а также тенденций развития производственных и технологических систем, включая создание новых композитных материалов и новых технологий изготовления и контроля деталей и узлов авиационных двигателей обсуждаются тенденции интеллектуализации систем их автоматического управления. При этом тенденции развития систем управления авиационными двигателями рассматриваются с точки зрения развития их структур, функций, свойств и способностей к новым качественным изменениям, учитывая общие характеристики и основные направления построения интеллектуальных систем управления авиационными двигателями как сложными техническими объектами. Обсуждается задача построения нелинейных динамических моделей авиационных двигателей с использованием искусственных нейронных сетей. Формируется постановка этой задачи и возможные подходы к её решению. Произведено сравнение результатов нейросетевой идентификации авиационного двигателя с применением метода наименьших квадратов. Такая методика построения модели авиационных двигателей позволяет косвенно вычислять недоступные измерению координаты двигателя – тягу, расход топлива и др. Предложенный подход позволяет при построении нейронных сетей, моделирующих авиационные двигатели, на каждом шаге применять стандартные процедуры, что даёт возможность автоматизировать создание нейронной сетей. Для сокращения времени вычислений предлагается применение оптимизационных алгоритмов с учётом изменения энтропии состояния. Это упрощает реализацию нейросетевой модели авиационного двигателя в реальном времени в составе бортового вычислительного комплекса.

Ключевые слова: авиационный двигатель; диагностика; нейронная сеть.

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