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РЕШЕНИЕ ПРОБЛЕМЫ НЕПОЛНОТЫ ИНФОРМАЦИИ ОБ ОБЪЕКТЕ АВТОМАТИЧЕСКОГО УПРАВЛЕНИЯ НА ОСНОВЕ ВИРТУАЛЬНЫХ ДАТЧИКОВ РЕАЛЬНОГО ВРЕМЕНИ

Современные системы управления активно используют встроенные математические модели объекта для реализации целевых функций и параметров управления, которые не могут быть получены прямым измерением, в частности эмиссии вредных веществ (окислов азота и углерода). В качестве виртуального сенсора эмиссии оксидов азота малоэмиссионной камеры сгорания, пригодного для встраивания в структуру регулятора, рассматривается два варианта.

Первый вариант – это стохастическая нелинейная математическая модель генерации окислов азота на базе уравнения Зельдовича. Особенностью представленной математической модели является применение принципа суперпозиции генерации окислов азота в диффузионном и гомогенном факелах. Функции распределения плотности вероятности концентрации топливовоздушной смеси в этих факелах учитывают как пространственную неоднородность состава смеси, так и гармоническую составляющую от акустических волн, генерируемых теплоподводом. Представленная концепция математической модели в виде интегральных соотношений сформирована на основе результатов численного моделирования пространственной и временной неоднородностей концентрации топливовоздушной смеси на 4D-метамодели и имеющихся экспериментальных данных.

Второй вариант основан на применении технологии нейронных сетей. Представлен пример разработанной нейронной сети и результаты ее обучения на реальной малоэмиссионной камере сгорания. Показано, что двух- или трехслойная нейронная сеть с количеством нейронов 20–30 обеспечивает достаточную погрешность (не более 10 %) отображения эмиссии оксидов азота и может быть использована как виртуальный сенсор эмиссии в системе управления двигателем.

В качестве целевой функции (критерия) управления малоэмиссионной камерой сгорания авиационного газотурбинного двигателя рассматривается нормируемый уровень эмиссии оксидов азота за цикл взлет–посадка. Для оценки уровня эмиссии NO_x предлагается встроенный виртуальный датчик.

Ключевые слова: система автоматического управления, авиационный двигатель, камера сгорания, диффузионный факел, гомогенный факел, граница бедного срыва, коэффициент избытка воздуха, эмиссия, виртуальный сенсор, стохастическая нелинейная математическая модель, нейронная цепь.

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SOLVING THE PROBLEM OF INCOMPLETE INFORMATION ABOUT AN AUTOMATIC CONTROL OBJECT BASED ON REAL-TIME VIRTUAL SENSORS

Modern automatic control systems use built-in mathematical models for estimation of unmeasured by the direct methods parameters such as NO_X emission in aeroengine low-emission combustion chamber. The two models of NO_X emissions virtual sensor built into the controller are proposed.

A stochastic nonlinear mathematical model is based on the Zeldovich equation. It applies the superposition principle of NO_X production in diffusion and homogeneous flames. Probability density distribution functions of the air-fuel mixture concentration in these flames take into account both of a spatial non-uniformity of the mixture composition and a harmonic component of the acoustic waves generated by the heat release. The concept of integral relations models has been developed with the use of numerical modeling of spatial and temporal non-uniformities of the air-fuel mixture concentration (4D-metamodeling) and available experimental data.

Another virtual sensor model is based on the neural network predicting NO_X emission in gas turbine combustion chamber. The example of a neural network and results of its training on a real combustion chamber is presented. It is shown that the two or three-layer neural network having 20–30 neurons provides an acceptable error (not exceeding 10 %) of the NO_X emission display and can be used as a virtual emission sensor in an engine control system.

The normalized level of NO_X emission per take-off and landing cycle is considered as a target function of the automatic control of low-emission combustion. To estimate the level of NO_X emission a built-in virtual sensor is proposed.

Keywords: automatic control system, aeroengine, combustion chamber, diffusion flame, homogeneous flame, lean blow-out line, air-fuel mixture concentration, emission, virtual sensor, stochastic nonlinear mathematical model, neural network.

Introduction

Built-in mathematical models of an object are actively used in modern control systems to implement target functions and control parameters that cannot be directly measured. This is applied particularly to NO_X and CO emissions (nitrogen and carbon oxides). Meanwhile, emission levels in modern gas turbine engines are no less significant than thrust (power) performance or an engine life.

Low-emission combustion systems have a narrow operating range that on the one hand is restricted by a regulated level of NO_X emission, and on the other hand, by a flame blow-out or high combustion dynamics (thermal acoustic natural vibrations) which are not acceptable in the field operation. Hazardous emission (primarily, NO_X) for the new generation engines becomes an equally important parameter as an engine thrust.

All other requirements are unconditionally met. So it is necessary to arrange both a system for continuous monitoring of emissions according to engine parameters, and the control over the combustor diffusion circuit to ensure a target level of emission (not exceeding the regulations).

1. The Actuality and Scientific Relevance of the Problem

As the peculiarity of the target NO_X emission indication is its integral nature, i.e. the number of emissions per TOL (take-off and landing) cycle within the flight altitude up to 1000 meters. Therefore, it is advisable to choose Climbing as an emission tuning mode based on the following considerations:

– Climbing contributes significantly to emissions thanks to a combination of a high power (85 % of maximum thrust) and the engine runtime (up to 2.2 minutes). Climbing is not critical (compared to Take-Off) in terms of the flight safety.

– During Climbing, compared to Take-Off, the probability of a high combustion dynamics is lower due to less heat release.

Thus, in order to determine the target emission level at Climb up to 1000 meters it is necessary to sum up the emissions in each specific case. These are a combination of ambient conditions and Take-Off and Climb profiles which require continuous monitoring of emission. The task is complicated by the fact that there is no existing on-board emission sensor, and functionally the emission level depends on a large number of variables (at least six to seven). In addition, the low emission combustor stability margin (from lean blow-out to high combustion dynamics) also depends on many parameters, and the extension of the safe envelope (where required) by increasing fuel flow through the diffusion circuit results in higher emission. This should be considered when an integral principle for the control is used. In addition, it is necessary to take into account the fact that, in view of continuous challenges to meet more and more stringent NO_X emission standards for the low emission combustor by means of exclusively design measures, the low emission combustion systems have a limited emission margin against standards. In this regard, the development of a virtual sensor of the emission of nitrogen oxide, built into the diffusion flame tracking automatic control system, becomes relevant [1].

Nowadays, in combustion design practice, methods of virtual reality construction (in particular, gas turbine combustion system) are widely used to allow predicting NO_X emission [2–4]. As an example of this solution, below is the shot-by-shot breakdown of changes in the flame surface during

lean premix down to flame blow-out (while the diffusion flame goes on stable). This visualization is obtained by numerical simulation and is shown in Fig. 1–4. The lean blow-out line is identified based on the test results obtained on the test rig presented in [5]. It should be noted that high-level mathematical models similar to those used above require prohibitively large resources for using them both for teaching (training) neural networks and developing software for control systems, and as a virtual emission sensor. In this regard, it is necessary to develop a specific expert model suitable both for training a neural network and for integrating it in the structure of a control as a virtual NO_X emission sensor.
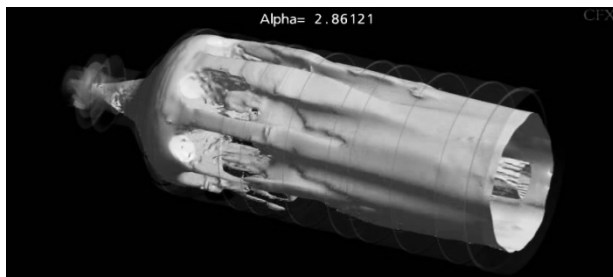

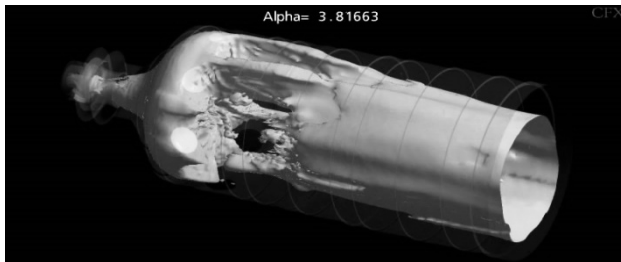Fig. 1. Normal work of DLN (equivalence ratio $\varphi = 0.35$)

Fig. 2. Partial blow-out of homogenuous flame
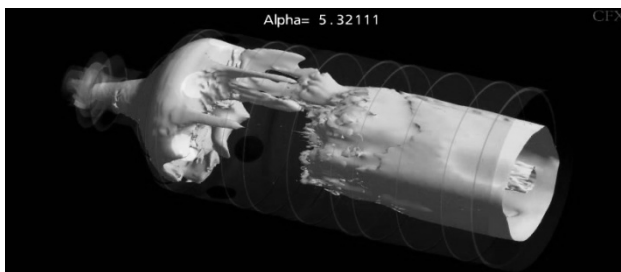(equivalence ratio $\varphi = 0.26$)

Fig. 3. Propagation of blow-out of homogenuous flame
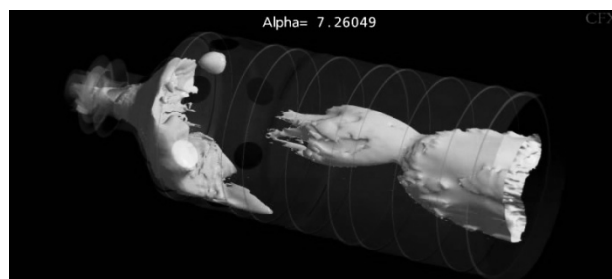(equivalence ratio $\varphi = 0.19$)

Fig. 4. Full blow-out of homogenuous flame
(equivalence ratio $\varphi = 0.14$). Pilot (diffusion) flame is stable

In engineering practice, two methods are known to address it. The first way is to represent the emission value in the form of a polynomial function depending on the determining variables (pressure and air temperature in combustor) [6]. The second method is approximation of multiple (emission) variable function using neural network technology [7]. Typically, these methods are used for industrial gas turbines in monitoring systems.

2. Statement of the Problem

The task of an emission of pollutants control is to minimize the proportion of the fuel consumption through the diffusion circuit, taking into account the stability limitations of the combustion process in a wide range changing of external and internal factors [8]. The minimum emission level of nitrogen and carbon oxides is chosen as the main control objective function. For the generality of the obtained solutions, it is proposed to consider the normalized integral level of emission for the full work cycle of the aeroengine as an additional objective function.

The fulfillment of these criteria can be carried out by a smart regulator – a control system based on a neural network [9, 10] with a built-in mathematical model of the generation of NO_X and CO emissions. The possible implementation of a nonlinear controller is shown in Fig. 5, where Y_s – emission target; y – real emission value; y_m – model emission value; f – disturbances (interference); e – control error; X – input vector of DLN and a model of emission; DLN – dry low NO_X emission combustion chamber.

The choice of the neuro-fuzzy algorithm for the design of the emissions generation mathematical model is explained by its technological simplicity and high speed. It should be noted that high-level mathematical models require significant computing power, the usage of complex software and they are characterized by a relatively low speed.
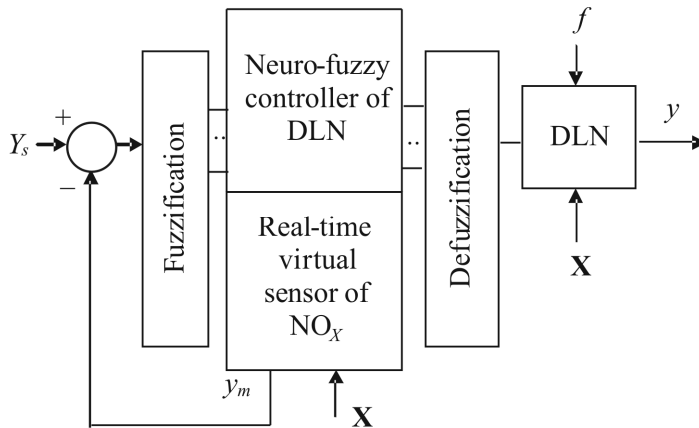
Fig. 5. Neuro-fuzzy controller of DLN

At present, the neural networks technology is widely used for mathematical model design, including for predicting (estimating) an emission of nitrogen and carbon oxides [11].

In general, the experience of using neural network technology for aero-engine control tasks shows that the main problems are incompleteness and inaccuracy of the input information (a limited number of measured parameters supplied to the network input) and a weak correlation of the measured parameters with some states of the system (the state vector has a larger dimension than the input vector).

As a rule, the number of measured parameters on the engine is minimized based on the need to ensure the reliability of the system as a whole. Therefore, to provide the necessary input information to the engine automatic control system, it is advisable to use a virtual sensor, implemented as a built-in mathematical model of an emission generation. As the world experience shows, to solve the problem of an emissions estimation with an error of no more than 15 %, the neural networks having 6 inputs and 12 neurons in a hidden layer with linear activation functions are efficiently used.

If the built-in mathematical model of the combustion chamber based on the Zeldovich mechanism is used for training the neural network, we can obtain a deviation of the measured emission level from the model value, taking into account the boundaries of the lean blow-out (LBO) and the vibrating combustion (thermal acoustic vibrations). Next, to obtain correct training data, parameters of the neural control system of aero engine low-emission combustion chamber (DLN) are optimized.

As it has already been noted, the main feature of the low-emission combustion chamber of new generations of aero engines as a control object

is a significant non-linearity. This is caused by a discrete division into operating zones with specific properties, which make it difficult to identify its characteristics, and, as a consequence, the incompleteness and incorrectness of its mathematical description.

In this work, the identification of DLN is based on a neural network design. The use of neural network significantly improves the quality of solving the problem of identification of multidimensional objects by using of the flexible and simple (from a mathematical point of view) algorithms. The network structure is determined by the mathematical statement of the problem. In this case, the neural network converts the multidimensional input vector $X(x_1, x_2, \ldots)$ into the multidimensional output vector depending on the problem conditions.

The possibility of a mathematical description of such conversion in the form of a sum of polynomials with different weight coefficients at coordinates of the vector $X(x_1, x_2, \ldots)$ is confirmed by the Kolmogorov – Arnold – Hecht – Nielsen theorem (KAHN) [12]. According to this theorem, for any set of mutually consistent pairs of distinct input and output vectors of an arbitrary dimension, there is a two-layer perceptron with sigmoid activation functions and with a finite number of neurons, which for each input vector X forms the corresponding output vector $Y(y_1, y_2, \ldots)$.

Thus obtained model implements the function of several variables $(x_1, x_2, \ldots)$ as the sum of the functions of one variable x_i with different weighting coefficients w_i.

It should be noted, that adaptive control of the emission of nitrogen oxides is an important problem for aero engines primarily. And a control object model (virtual emission sensor) is required to solve the problem of developing control algorithms. An industrial engine has the characteristics similar to an aircraft engine and is more available for experiments. So the industrial engine is used here as an experimental object to test the developed approach.

3. Theoretical Foundation of Mathematical Modeling

a) Mathematical Model of DLN based on Zeldovich Equation

Below, we formulate the main assumptions that will allow us to make-up an expert model suitable for the set goals. As primary, it is assumed that all burners in terms of geometry and gas dynamics are identical and operate under identical boundary conditions including phase relations.

Zeldovich equation is taken as a mathematical model for NO_X generation. It can be written as in [13]

$$S = 2 \cdot 1.8 \cdot 10^8 \cdot e^{-\frac{38\,370}{T}} [O] \cdot [N_2]. \qquad (1)$$

Further on, it is necessary to simulate the interaction of pilot (diffusion) and the main (technically premixed or homogeneous) flames, as well as the process of NO_X formation.

To describe the interaction of diffusion and premix flames we assume the possibility to applying a superposition principle. The superposition of premix and diffusion flames progresses as follows based on the assumption of their independence in a spacial position. Using the probability addition theorem, $\mathbf{P}(\mathbf{A}+\mathbf{B}) = \mathbf{P}(\mathbf{A}) + \mathbf{P}(\mathbf{B})$, we place the characteristics of flames stochastic in terms of a mixture composition on one of the arguments, bearing in mind that the probability distribution function $\mathbf{F}(\mathbf{x}) = \mathbf{P}\{\mathbf{X} < \mathbf{x}\}$ within the mixture composition operating range varies from 0 to 1. Here, it's convenient to choose a fuel-air equivalence ratio φ as an argument. Then the stable combustion range is φ = 0.15…2.0. An increase in the argument corresponds to the increase in the proportion of the fuel flow.

Next, we place the known average values (expected values) of the flame mixture composition. These values are determined based on the known (controlled) fuel flows over the circuits and air flows, proportional to the circuit throat areas. Here, the following to be kept in mind. The diffusion flame has a large dispersion of the mixture concentration and a probability density function close to the normal law. The probability distribution function in φ ∈ [0,2] interval corresponds to the stable combustion envelope. This function of the diffusion flame is assumed unchanged until the average value moves into the lean zone (φ ≤ 1). Physically, this means that at φ ≥ 1 the diffusion flame is fed by excess air oxygen from the premix flame tube cap (dome). When φ ≤ 1 an assumption is made about the independent work of the diffusion flame. In fact, a stoichiometric diffusion flame is maintained in a wide range of the combustor operation by means of the fuel split.

The equation of the fuel flow (m_f) averaged NO_X generation rate for a typical two-zone (diffusion flame with '*d*' index and homogeneous or technically premixed flame, with '*h*' index) for the low emission combustor with 10:90 % fuel split at Maximum can be represented as

$$\overline{S} = \int\limits_{0}^{0.1} S\left(\tilde{\varphi}_d, \tilde{\varphi}_d^{'2}\right) P(\varphi)d\varphi + \int\limits_{0.1}^{1} S\left(\tilde{\varphi}_h, \tilde{\varphi}_h^{'2}\right) P(\varphi)d\varphi, \qquad (2)$$

where $\tilde{\varphi}_d$ is the prediction of the mathematical expectation of an equivalence ratio in diffusion and homogeneous flames; $\tilde{\varphi}_d^{'2}$ is the dispersion of the equivalent mixture ratio in diffusion and homogeneous flames with taking into account heterogeneity in a fuel flow, harmonic longitudinal acoustic pulsation of a flow and background turbulence.

So the thermal acoustics is used to determine the dispersion of the mixture for subsequent use in the statistical determination of the rate of NO_X emission by the Zeldovich mechanism.

At the next stage, it is necessary to determine the dispersion of the concentration of premix and diffusion flames and the probability density distribution function $f(\varphi) = F'(\varphi)$.

The assessment of the concentration dispersion ($\tilde{\varphi}^{'2}$) is formed from several components of the flow parameters with the corresponding probability density distribution functions:

– the initial non-uniformity of the concentration distribution in the flame over its cross section, which also manifests itself in the axial direction in the turbulent flow due to the correlation of the transverse and lateral momentum and the concentration transfer;

– regular flow dynamics induced by the flame tube cap swirler of the frontal device due to the precessing vortex core (PVC) at high Reynolds numbers representative of gas turbine combustion systems;

– thermal acoustic dynamics of a stream of various fluctuation modes of a gas column;

– background isotropic turbulence (Kolmogorov scale).

To build up an adequate model of both NO_X generation and determination of a lean blow-out margin, it is necessary to know the above parameters of the dynamic (fluctuating) flow. These data, for example, the initial non-uniformity of the concentration and the dynamics distribution can be obtained on the 4D meta-model [14, 15], identified based on the test data [16].

Then it is necessary to average the rate of the NO_X generation throughout the length of a combustion chamber (L) using exponential law. As a first approximation, this proposed distribution can be set as

$$S_x = \overline{S} e^{-bx}.$$ (3)

That is a decrease in the reaction rate throughout the length of a combustion chamber according to the exponential law is due to the rapid decrease in the concentration of reacted atomic oxygen.

Then the reaction rate averaged over the length of the chamber (L) $\overline{\overline{S}}$ and, accordingly, the emission index EINO_X, i.e. the ratio of NO_X generation rate in the combustion chamber (flame tube) volume to a fuel flow is

$$\overline{\overline{S}} = \overline{S} \frac{V}{L} \int_0^L e^{-bx} dx = \overline{S} \frac{V}{bL} \left(1 - e^{-bL} \right);$$ (4)

$$\left(\mathrm{EINO}_x \right) = \overline{S} \frac{\mu_{\mathrm{NO}_x}}{bL} \frac{V}{m_f} \left(1 - e^{-bL} \right) \approx \mu_{\mathrm{NO}_x} \overline{S} \frac{V}{L} \frac{a}{m_f}.$$ (5)

b) Mathematical Model of DLN Based on the Neural Network

The considering DLN refers to a counter flow type with twelve remote flame tubes with the organization of combustion of the "poor" premixed mixture. The DLN uses a front-end device of a single-module type with a flame stabilization by a bluff body. The flame tube cooling system is impact-convective. DLN has three fuel manifolds: a diffusion manifold, a homogeneous manifold, an igniter manifold.

Typical for this class of tasks structure of a two-layer perceptron – a fully-connected neural network with direct signaling, was selected to develop the DLN model. Fig. 10 shows the structure of the neural DLN model.

Fully connected networks are artificial neural networks, each neuron of which transmits its output signal to other neurons, including to itself [17].

In the structure under consideration, neurons are regularly organized into layers. The layer contains an ensemble of neurons with the common input signals. The input (zero) sensors layer is used to enter values of input variables. In the general case, a two-layer perceptron consists of 3 layers, numbered from left to right. External input signals are fed to the inputs of the neurons of the first layer (the input layer is numbered as zero), and the output signals of the last layer are the outputs of the network. Each of the hidden and output neurons is connected to all elements of the previous layer.

When constructing a fully-connected two-layer neural network having one hidden layer of neurons, it is necessary to determine the optimal number of elements in the hidden layer. A corollary of the KAHN theorem allows us

to determine the optimal number of neurons in the hidden layer, which provides, on the one hand, the minimum learning error, and on the other, the minimum generalization error. The optimal number of neurons in the hidden layer depends on the number of synaptic weights (connections), which can be estimated [16] using the inequality

$$\frac{N_y Q}{1 + \log_2(Q)} \le N_w \le N_y \left(\frac{Q}{N_y} + 1 \right) \left(N_x + N_y + 1 \right) + N_y, \qquad (6)$$

where N_x – dimensionality of the input signals; N_y – dimensionality of the output signal; Q – number of training sample elements; N_w – the required number of synaptic weights (connections).

Depending on the obtained number of synaptic connections N_w, the number of neurons in the hidden layers is estimated. In particular, for a two-layer perceptron, the number of hidden layer neurons is

$$N = \frac{N_w}{N_x + N_y}. \qquad (7)$$

Since the inequality (6) and the equation (7) are evaluation formulas, in practice the optimal number of hidden layer neurons necessary to achieve the desired model accuracy is determined experimentally. Obviously, by increasing the number of neurons in the hidden layer, the accuracy of the model increases. At the same time, the network training time increases, and the system speed decreases.

It follows from the KAHN theorem that for any function of many variables there is a neural network of fixed dimension that maps it. When training (tuning) this network, the three degrees of freedom can be used:

– the value range of sigmoidal activation functions of neurons of the hidden layer;

– the slope of sigmoidal activation functions of neurons of this layer;

– the view of the activation functions of neurons of the output layer.

4. Practical Importance, the Results of the Implementation, the Results of the Experiments

a) Experimental Object

To test the proposed methodology for a neural network design for predicting the NO_X and CO emission, the real industrial combustion chamber of a gas turbine unit with a power of 16 MW - GTU-16 was considered. Fig. 6

shows the combustor dome. It is represented by a single-module flame tube cap using a high-drag body concept for a flame stabilization.

In our example we assume a reverse-flow combustor made up of twelve external flame tubes with a lean premix system. It is represented by a single-module flame tube cap using a high-drag body concept for a flame stabilization. The combustion system has an impingement and convective cooling. It includes three fuel manifolds: diffusion, premix and igniter (light-off) manifold.
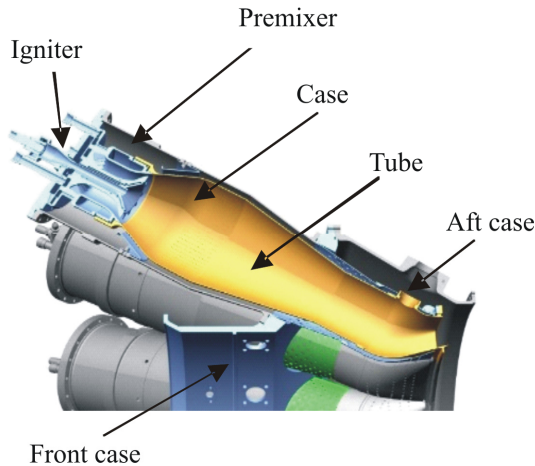
Fig. 6. An industrial low-emission combustion chamber (DLN)
of a gas turbine unit with a power of 16 MW (GTU-16)

This combustor was tested on a dedicated rig with NO_2 and CO emission measurements. Combustor parameter regulation ranges are: pressure is 1.0–1.8 MPa, combustor inlet temperature is 470–730 K, the proportion of a fuel flow through the diffusion (pilot) circuit (PFR) is 0.04–0.20, thermodynamic gas temperature at combustor discharge is 900–1550 K.

b) The Identification of a Mathematical Model

The results of the numeric analysis of non-uniformity and the combustion dynamics distribution for the concentration of the fuel-air mixture over the area of the premix flame were used as inputs. The results are shown in the Fig. 7 as a mixture fraction.

Mixture fraction was obtained on the metamodel using ANSYS CFX.

The standard deviation from the mathematical expectation was 15 %.

Next, taking into account the assumptions made and NO_X emission index test results, the equivalence length of burning zone (parameter "*a*") was determined as a function of thermodynamic gas temperature at combustor discharge. The results are shown in Fig. 8.
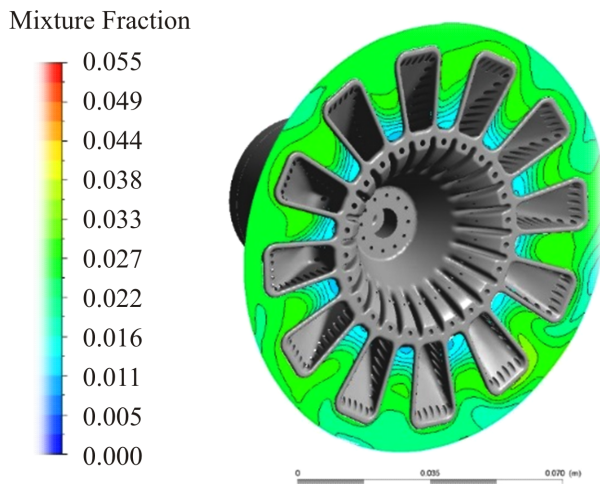
Fig. 7. The distribution of a mixture fraction after premixer
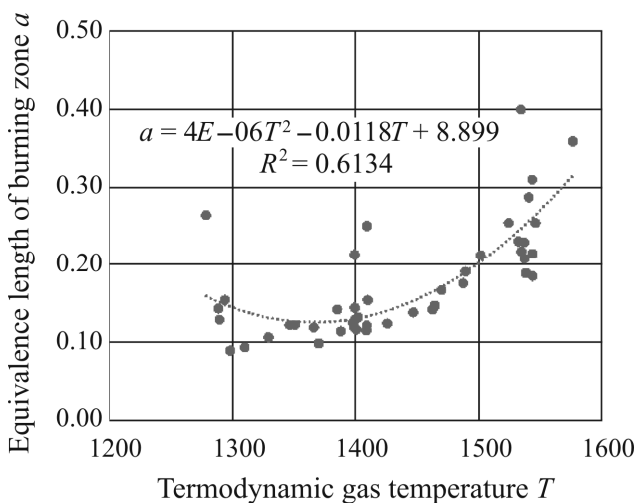(inlet in burning zone)

$$a = 4E{-}06T^2 - 0.0118T + 8.899$$
$$R^2 = 0.6134$$

Fig. 8. The approximation of experimental data using
a presented model

As it can be seen from the presented data, most of the values of NO_X emission index can be predicted using the discussed approach with no exceeding 10–20 % error.

It should be borne in mind that this model operates as a part of an automatic control system of DLN in a real time. And this determining factor requires some compromise with an accuracy. So, the obtained accuracy is sufficient for testing the adaptive software for the emission control channel

at the design stage. The obtained results are the basis for the reasonable confidence that it is possible to achieve an error of not more than 10–20 % with the further use of neural network technology to represent the identification parameter *a* (equivalence length of burning zone) as a function of the superposition of many variables.

It is sufficient to replace the real item with a virtual one during the synthesis of the control system software. The simulation of control processes using the presented mathematical model is provided in real time.

c) The Real-Time Virtual NO$_X$ Sensor Based on Neural Network

The considering DLN refers to a counter flow type with twelve remote flame tubes with the organization of combustion of the "poor" premixed mixture. The DLN uses a front-end device of a single-module type with a flame stabilization by a bluff body. The flame tube cooling system is impact-convective. DLN has three fuel manifolds: a diffusion manifold, a homogeneous manifold, an igniter manifold.

Typical for this class of tasks structure of a two-layer perceptron – a fully-connected neural network with direct signaling, was selected to develop the DLN model. Fig. 9 shows the structure of the neural DLN model.
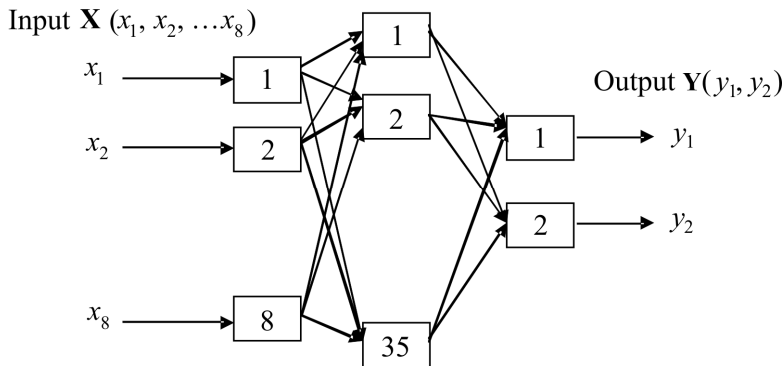

Fig. 9. The neural network structure for DLN modeling

Fully connected networks are artificial neural networks, each neuron of which transmits its output signal to other neurons, including to itself.

In the structure under consideration, neurons are regularly organized into layers. The layer contains an ensemble of neurons with the common input signals. The input (zero) sensors layer is used to enter values of input variables. In the general case, a two-layer perceptron consists of 3 layers, numbered from left to right. External input signals are fed to the inputs of the neurons of the first layer (the input layer is numbered as zero), and the

output signals of the last layer are the outputs of the network. Each of the hidden and output neurons is connected to all elements of the previous layer. As the coordinates of the input vector of virtual sensor X the eight measurable parameters of DLN were selected [10,18]: operating mode; temperature behind the compressor T_C; pressure behind the compressor P_C; air flow m_A; fuel flow m_f; gas temperature T_G; ripple amplitude at frequencies A200–400 Hz; proportion of fuel in the pilot burner-pilot fuel ratio (PFR).

As the coordinates of the output vector of the neural network Y the two output parameters of DLN, characterizing the emission of pollutants, were selected: concentration of NO_X; concentration of CO.

According to the full-scale experiment, 26 training samples, one testing sample and one predictive sample were formed. One test sample (example) and one predictive sample were also formed. The corresponding arrays y_1, y_2 were selected as targets.

The number of hidden layer neurons $N = 35$ was selected.

In the considered practical example, the optimization of hidden layers in the process of the neural network training is based on the algorithm of a back propagation of an error (Fig. 10).
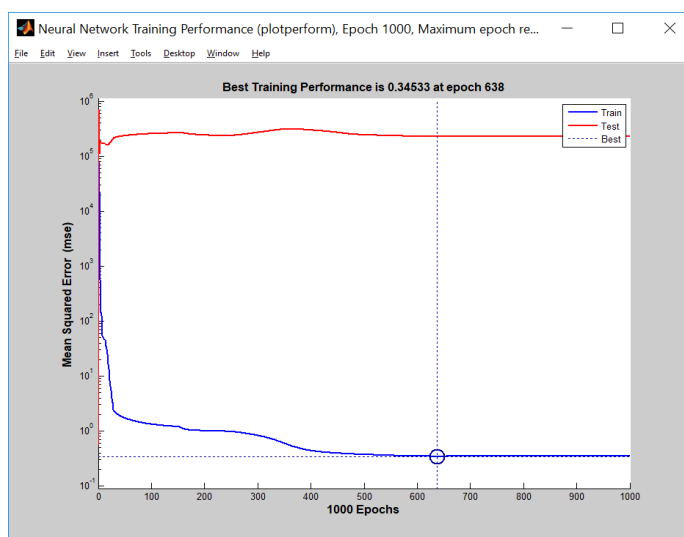

Fig. 10. The mean square error σ during the study's period

The neural network was modeled by the tools of MATLAB. The best result of neural network tunings according to the minimum of the mean square error criterion performed an average relative test error of σ = 10 %, an average relative prediction error of 3 %.

The analysis of the significance of the individual coordinates of the input vector X for the accuracy of the model (Fig. 11), and, therefore, the degree of their influence on the amount of emissions showed, that the most significant parameters affecting the accuracy of the DLN model are the pressure behind the compressor P_C, thegas temperature T_G and the pilot fuel ratio (PFR).
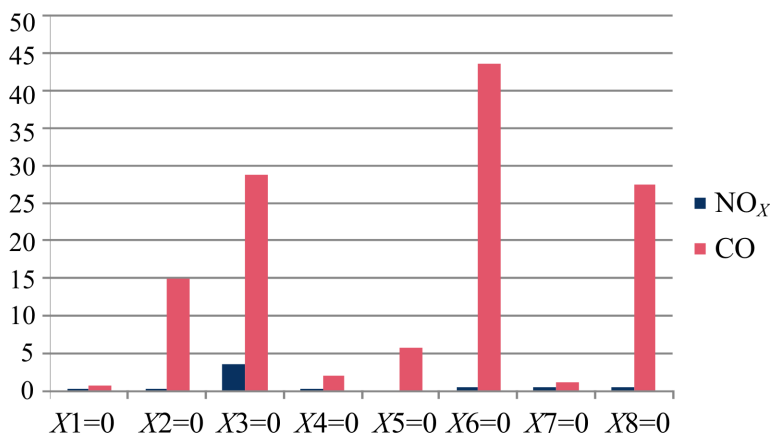

Fig. 11.The analysis of the significance of the individual coordinates of the input vector X for the accuracy of the DLN model

Conclusion

So the results of MATLAB-modeling confirm the hypothesis of the possibility of the robust DLN mathematical models design based on artificial neural networks with taking into account the significance of influence factors.

The developed virtual emission sensor operates in real time and is suitable both for developing software for an adaptive control of emission channel and for embedding it in the on-board controller model.

In general, the obtained results comply with modern international requirements to studies of complex objects and can be used to increase its reliability of fault-tolerant automatic control systems of gas turbine engines.

Список литературы

1. Sensor and actuator needs for more intelligent gas turbine engines / S. Garg, K. Horn, H. Schadow, W. Horn, H. Pfoertner, Io. Stiharu // Proceed. of the ASME Turbo Expo, GT2010-22685, Glasgow, UK, 14–18 June 2010. – Glasgow, UK, 2010. – P. 155–167. DOI: 10.1115/GT2010-22685

2. Avgustinovich V., Kutsenko Yu. Creation andapplication of combined calculation methodology for low emission combustion chamber // Russian Aeronautics. – 2011. – Vol. 54, no. 2. – P. 170–178. DOI: 10.3103/S1068799811020103

3. Tsatiashvili V., Avgustinovich V. Nonequilibrum effect of nitrogen oxides production in diffusion flame // Proceed. of the ASME Turbo Expo, GT2012-68222, Copenhagen, Denmark, 11–15 June 2012. – Copenhagen, Denmark, 2012. – P. 125–132. DOI: 10.1115/GT2012-68222

4. Tsatiashvili V., Avgustinovich V. NO_X reduction in gas turbine combustors with compact non-premixed flame front // Proceed. of the ASME Turbo Expo, GT2014-25598: V04AT04A044, Düsseldorf, Germany, 16–20 June 2014. – Düsseldorf, Germany, 2014. – 12 p. DOI: 10.1115/GT2014-25598

5. Prediction of combustion efficiency NO_X level for diffusion flame combustors in HAT cycles / A. Belokon, K. Khirtov, L. Klyachko, S. Tschepin, V. Zakharov, G. Opdyke // Proceed. of the ASME Turbo Expo, GT2002-30609, Amsterdam, Netherlands, 3–6 June 2002. – Amsterdam, Netherlands, 2002. – P. 791–797. DOI: 10.1115/GT2002-30609

6. Model based prediction of off-design operation condition NO_X emission from DLE gas turbine combustor / M. Lauer, J. Farber, F. Reith, J.El. Masalme // Proceed. of the ASME Turbo Expo, GT2017-63063: V04AT04A003, Charlotte, North Carolina, USA, 26–30 June 2017. – Charlotte, North Carolina, USA, 2017. – 11 p. DOI: 10.1115/GT2017-63063

7. Predictive emissions monitoring using a continuously updating neural network / E. Vanderhaegen, M. Deneve, H. Laget, N. Faniel, J. Mertens // Proceed. of the ASME Turbo Expo, GT2010-22899, Glasgow, UK, 14–18 June 2010. – Glasgow, UK, 2010. – P. 769–775. DOI: 10.1115/GT2010-22899

8. Bhagwan R., Habisreuther P. Experimental investigation on lean blow out of piloted aero-engine burner // Proceed. of the ASME Turbo Expo, GT2014-25199: V04AT04A011, Düsseldorf, Germany, 16–20 June 2014. – Düsseldorf, Germany, 2014. – 9 p. DOI: 10.1115/GT2014-25199

9. Reddy D.R., Lee C.M. An overview of low-emission combustion research at NASA glenn // Proceed. of ASME Conference Turbo-Expo, V04AT04A003, Seoul, South Korea, 13–17 June 2016. – Seoul, South Korea, 2016. – 9 p. DOI: 10.1115/GT2016-56100

10. Kuznetsova T., Avgustinovich V. Automatic control system of low-emission combustion chamber based on neural network emission mode // Proceed. of the IEEE RusAutoCon-2018, Paper 18168390, Sochi, Russia, 8–14 September 2018. – Sochi, Russia, 2018. – 6 p. DOI: 10.1109/RUSAUTOCON.2018.8501681

11. Lamont W., Roa M., Lucht R. Application of artificial neural networks for the prediction of pollutant emissions and outlet temperature in fuel staged gas turbine combustion rigin // Proceed. of the ASME Turbo Expo, GT2014-25030:

V04AT04A002, Düsseldorf, Germany, 16–20 June 2014. – Düsseldorf, Germany, 2014. – 10 p. DOI: 10.1115/GT2014-25030

12. Hassoun M.H. Fundamentals of artificial neural networks. – Cambridge, MA, USA: MIT Press, 1995. – 511 p. – URL: https://dl.acm.org/doi/book/10.5555/526717 (accessed 25 Junary 2020).

13. Peters N. Turbulent combustion. – Cambridge: University Press, 2000. – 304 p.

14. Nazukin V., Avgustinovich V. Analysis of swirling flows in premixers // Proceed. of the ASME Turbo Expo. GT2014-25785: V04AT04A051, Düsseldorf, Germany, 16–20 June 2014. – Düsseldorf, Germany, 2014. – 10 p. DOI: 10.1115/ GT2014-25785

15. Nazukin V., Avgustinovich V. Development of requirements for numerical modeling of the premixer aerodynamics // Proceed. of the ASME Turbo Expo, GT2016-57529: V04BT04A027, Seoul, South Korea, 13–17 June 2016. – Seoul, South Korea, 2016. – 10 p. DOI: 10.1115/GT2016-57529

16. Turbulent transport measurements in a cold model of GT-burner at realistic flow rate / O. Gobuzov, L. Chikishev, A. Lobasov, D. Sharaborin, V. Dulin, A. Bilsky, V. Tsatiashvili, V. Avgustinovich, D. Markovich // Proceed. of the Conference Experimental Fluid Mechanics "EFM-2015 WEB Conference", 28 March 2016. – Vol. 114. – Paper 02032. – P. 195–205. DOI: 10.1051/epjconf/201611402032

17. Artificial neural networks / K. Makisara, O. Simula, J. Kangas, T. Kohonen. – North Holland, Netherland: Elsevier, 1991. – 836 p.

18. Avgustinovich V., Kuznetsova T., Nugumanov A. Development of neural systems for monitoring and controlling emission of gas8transmission and power gas turbine units // Bulletin of the Tomsk Polytechnic University: Geo Assets Engineering. – 2019. – Vol. 330, no. 8. – P. 7–17. DOI: 10.18799/24131830/2019/8/2207

References

1. Garg S., Horn K., Schadow H., Horn W., Pfoertner H., Stiharu Io. Sensor and actuator needs for more intelligent gas turbine engines. Proceedings of the ASME Turbo Expo, GT2010-22685:, 2010, June 14–18 [Glasgow, UK], pp. 155–167. DOI: 10.1115/GT2010-22685.

2. Avgustinovich V., Kutsenko Yu. Creation andapplication of combined calculation methodology for low emission combustion chamber. *Russian Aeronautics*, 2011, vol. 54, no. 2, pp. 170–178.DOI: 10.3103/S1068799811020103.

3. TsatiashviliV., Avgustinovich V. Nonequilibrum Effect of Nitrogen Oxides Production in Diffusion Flame. Proceedings of the ASME Turbo Expo, GT2012-68222, 2012, June 11–15, [Copenhagen, Denmark], pp. 125–132. DOI: 10.1115/GT2012-68222.

4. Tsatiashvili V., Avgustinovich V. NO_X Reduction in Gas Turbine Combustors with Compact Non-premixed Flame Front / Proceedings of the ASME Turbo Expo, GT2014-25598: V04AT04A044, 2014, June 16–20 [Düsseldorf, Germany], 12 p. DOI: 10.1115/GT2014-25598.

5. Belokon A., Khirtov K., Klyachko L., Tschepin S., Zakharov V., Opdyke G. Prediction of Combustion Efficiency NO_X Level for Diffusion Flame Combustors in HAT Cycles. Proceedings of the ASME Turbo Expo, GT2002-30609, 2002, June 3–6, [Amsterdam, Netherlands], pp. 791–797. DOI: 10.1115/GT2002-30609.

6. Lauer M., J. Farber, F. Reith and Jaman El. Masalme, "Model Based Prediction of Off-Design Operation Condition NO_X Emission from DLE Gas Turbine Combustor," in Proceedings of the ASME Turbo Expo, GT2017-63063: V04AT04A003, 2017, June 26–30 [Charlotte, North Carolina, USA], 11 p. DOI: 10.1115/GT2017-63063.

7. Vanderhaegen E., Deneve M., Laget H., Faniel N., Mertens J. Predictive Emissions Monitoring Using a Continuously Updating Neural Network, proceedings of the ASME Turbo Expo, GT2010-22899,2010, June 14–18 [Glasgow, UK], pp. 769–775. DOI: 10.1115/GT2010-22899

8. Bhagwan R., Habisreuther P. Experimental Investigation on Lean Blow Out of Piloted Aero-Engine Burner /Proceedings of the ASME Turbo Expo, GT2014-25199: V04AT04A011, 2014, June 16–20[Düsseldorf, Germany], 9 p. DOI: 10.1115/GT2014-25199.

9. Reddy D.R., Lee C.M. An Overview of Low-Emission Combustion Research at NASA Glenn / Proceedings of ASME Conference Turbo-Expo, V04AT04A003, 2016, June 13-17[Seoul, South Korea], 9 p. DOI: 10.1115/GT2016-56100.

10. Kuznetsova T., Avgustinovich V. Automatic control system of low-emission combustion chamber based on neural network emission mode, Proceedings of the IEEE RusAutoCon-2018, Paper 18168390, 2018, September 8–14 [Sochi, Russia], 6 p. DOI: 10.1109/RUSAUTOCON.2018.8501681.

11. Lamont W., RoaM., Lucht R. Application of Artificial Neural Networks for the Prediction of Pollutant Emissions and Outlet Temperature in Fuel Staged Gas TurbineCombustion Rigin, Proceedings of the ASME Turbo Expo, GT2014-25030: V04AT04A002, 2014, June 16–20[Düsseldorf, Germany],10 p. DOI: 10.1115/GT2014-25030.

12. Hassoun M.H. Fundamentals of Artificial Neural Networks. Cambridge, MA, USA, MIT Press, 1995, 511 p. Available at https://dl.acm.org/doi/book/10.5555/526717 (accessed 25.01.20)

13. Peters N. Turbulent Combustion. Cambridge, University Press, 2000, 304 p.

14. Nazukin V., Avgustinovich V. Analysis of Swirling Flows in Premixers / Proceedings of the ASME Turbo Expo. GT2014-25785: V04AT04A051, 2014, June 16–20 [Düsseldorf, Germany], 10 p. DOI: 10.1115/GT2014-25785.

15. Nazukin V., Avgustinovich V. Development of requirements for numerical modeling of the premixer aerodynamics / Proceedings of the ASME Turbo Expo, GT2016-57529: V04BT04A027, 2016, June 13–17[Seoul, South Korea], 10 p. DOI: 10.1115/GT2016-57529

16. Gobuzov O., Chikishev L., Lobasov A., Sharaborin D., Dulin V., Bilsky A., Tsatiashvili V., AvgustinovichV., Markovich D. Turbulent transport measurements in a cold model of GT-burner at realistic flow rate.Proceedings of the Conference Experimental Fluid Mechanics "EFM-2015 WEB Conference", Paper 02032: vol. 114, 2016, March 28, pp. 195–205.DOI: 10.1051/epjconf/201611402032.

17. Makisara K., Simula O., Kangas J., Kohonen T. Artificial Neural Networks. Netherland, Elsevier, 1991, 836 p.

18. Avgustinovich V., Kuznetsova T., Nugumanov A. Development of neural systems for monitoring and controlling emission of gas8transmission and power gas turbine units. *Bulletin of the Tomsk Polytechnic University: Geo Assets Engineering,* 2019, vol. 330, no. 8, pp. 7–17.DOI: 10.18799/24131830/2019/8/2207

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Библиографическое описание статьи согласно ГОСТ Р 7.0.100–2018:

Kuznetsova, T.A. Solving the problem of incomplete information about an automatic control object based on real-time virtual sensors = Решение проблемы неполноты информации об объекте автоматического управления на основе виртуальных датчиков реального времени / T. A. Kuznetsova, V. G. Avgustinovich. – DOI 10.15593/2499-9873/2020.2.05. – Текст : непосредственный // Прикладная математика и вопросы управления = Applied Mathematics and Control Sciences. – 2020. – № 2. – С. 75–95. – Ст. на англ. языке.

Цитирование статьи в изданиях РИНЦ:

Kuznetsova T.A., Avgustinovich V.G. Solving the problem of incomplete information about an automatic control object based on real-time virtual sensors // Прикладная математика и вопросы управления. – 2020. – № 2. – С. 75–95. DOI: 10.15593/2499-9873/2020.2.05

Цитирование статьи в references и международных изданиях:

Cite this article as:

Kuznetsova T.A., Avgustinovish V.G. Solving the problem of incomplete information about an automatic control object based on real-time virtual sensors. *Applied Mathematics and Control Sciences*, 2020, no. 2, pp. 75–95. DOI: 10.15593/2499-9873/2020.2.05