Virtual NOx-emission sensors for robust aero engine automatic control system

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Abstract. Modern robust control systems use built-in mathematical models for estimation of unmeasured by the direct methods parameters such as NOx emission. The two models of NOx emissions virtual sensor built into the smart controller of an aero engine low-emission combustion chamber are proposed in this study. A stochastic nonlinear mathematical model is based on the Zeldovich equation. It applies the superposition principle of NOx 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 NOx generation rate is averaged over the fuel flow through diffusion and homogeneous flames based on the probability density distribution function. An exponentiality of a decrease in the generation rate along the length of the combustor space is proposed. 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. A well-known approach of NOx emissions prediction used in monitoring systems of gas turbine power plants is applied. 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 NOx emission display and can be used as a virtual emission sensor in an engine control system. The normalized level of NOx emission per take-off and landing cycle is considered as a target function of the automatic control of low-emission combustion. The estimation of the level of NOx emission by a built-in virtual sensor is proposed for robust aero engine automatic control.

1. Introduction
Built-in mathematical models of an object are actively used in modern robust control systems to implement target functions and control parameters that cannot be directly measured. This is applied particularly to NOx 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 NOx 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, NOx) 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).

As the peculiarity of the target NOx 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.
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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 NOx 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].

2. Materials and methods

Nowadays, in combustion design practice, methods of virtual reality construction (in particular, gas turbine combustion system) are widely used to allow robust predicting NOx emission [2,3,4]. 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 figures 1-4. The lean blow-out line is identified based on the test results obtained on the test rig presented in [5].

![Figure 1. Normal work of DLN (ϕ = 0.35).](image-url)
Figure 2. Partial blow-out of homogenous flame (ϕ = 0.26).

Figure 3. Propagation of blow-out of homogenous flame (ϕ = 0.19).

Figure 4. Full blow-out of homogenous flame (ϕ = 0.14). Pilot (diffusion) flame is stable (ϕ = 0.19).

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 NOx emission sensor.

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.

2.1. Mathematical model 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 NOx generation. It can be written as in [8]:

\[ S = 2 \cdot 1.8 \cdot 10^8 \cdot e^{-38370/T} \cdot [O] \cdot [N_2] \]  \hspace{1cm} (1)

where \( S \) - the speed (rate) of the NOx generation \([\text{mol}/(\text{m}^3\text{s})]\), \( T \) - temperature of flame [K], \([O]\) - oxygen concentration, \([N_2]\) - nitrogen concentration.

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 NOx 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, \( P(A + B) = P(A) + P(B) \), 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 \( F(x) = P[X < x] \) within the mixture composition operating range varies from 0 to 1. Here, it’s convenient to choose a fuel-air equivalence ratio \( \phi \) as an argument. Then the stable combustion range is \( \phi = 0.15 \ldots 2.0 \). 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 \( \phi \in [0.2] \) 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 (\( \phi \leq 1 \)). Physically, this means that at \( \phi \geq 1 \) the diffusion flame is fed by excess air oxygen from the premix flame tube cap (dome). When \( \phi \leq 1 \) 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 NOx 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:

\[ \bar{S} = \int_{0}^{\phi} S\left(\bar{\phi}_d, \bar{\phi}_d^2\right) P(\phi)d\phi + \int_{\phi}^{1} S\left(\bar{\phi}_h, \bar{\phi}_h^2\right) P(\phi)d\phi \]  \hspace{1cm} (2)

where: \( S \) - the rate of the NOx generation, \( P \) - probability, \( \phi \) - equivalence ratio, \( \bar{\phi}_d(h) \) is the prediction of the mathematical expectation of an equivalence ratio in diffusion and homogeneous flames; \( \bar{\phi}_d(h) \) 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 NOx 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 \( f(\phi) = P(\phi) \).

The assessment of the concentration dispersion \((\bar{\phi}_d^2))\) 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 NOx 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 [9,10], identified based on the test data [11].

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

\[ S_x = \bar{S} e^{-bx} \]  

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) \( \bar{S} \) and, accordingly, the emission index \( EINO_x \), i.e. the ratio of NOx generation rate in the combustion chamber (flame tube) volume to a fuel flow is:

\[ \bar{S} = \frac{S}{L} \int_0^L e^{-bx} dx = \frac{S}{b L} (1 - e^{-bL}) \]  

and:

\[ (EINOx) = \bar{S} \frac{\mu_{NOx}}{b L m_f} \left(1 - e^{-bL}\right) \approx \mu_{NOx} \bar{S} \frac{V}{L m_f} \frac{a}{(1 - e^{-bL})} \]  

where: \( EINOx \) - NOx emission index [g/kg], \( a \) - equivalence length of burning zone [m], \( L \) - combustor length [m], \( m_f \) - mass fuel flow [kg/s], \( \mu \) - molar mass [g/mol], \( V \) - combustor volume [m³].

2.2. Mathematical model based on the neural network

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 [12]. 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 [13, 14] with a built-in mathematical model of the generation of NOx and CO emissions. The possible implementation of a nonlinear controller is shown in figure 5, where: \( Y \) - 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 NOx 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.

At present, the neural networks technology is widely used for mathematical model design, including for predicting (estimating) an emission of nitrogen and carbon oxides [15].

In general, the experience of using neural network technology for aeroengine 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 aeroengine 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) [16]. 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 $w_i$.

The identification algorithm based on the method of a synthesis of multilayer artificial neural

![Figure 5. Neuro-fuzzy controller of DLN.](image-url)
networks includes the steps [17]:

- The full-scale testing of the identifiable object for the training data obtaining;
- The definition of an input signals (parameters) vector of a neural network \( \mathbf{X}(x_1, x_2, \ldots) \);
- The definition of an output signals (parameters) vector of a neural network \( \mathbf{Y}(y_1, y_2, \ldots) \);
- The definition of an error vector of a neural network \( \mathbf{E}(e_1, e_2, \ldots) \);
- The forming of the target function of the primary optimization of the neural network \( F_1 \);
- The forming of the target function of the secondary optimization of the neural network \( F_2 \) through the signals, operating in the system;
- The choice of the hill-climbing method for the secondary optimization target function \( F_2 \);
- The analytical definition of the conversion implemented by the neural network, and the choice of the specific structure of the neural network;
- The definition of an analytical form for determining the gradient of the target function of the secondary optimization \( \text{grad} F_2 \) by the tuning parameters;
- The design of the neural network tuning algorithm;
- The definition of initial conditions for tuning of the neural network;
- The selection of typical input signals for testing the neural network.

The implementation of the algorithm of a model experiment for neural network optimization is shown in figure 6, where: \( F_1, F_2 \) are functionals of the primary and the secondary optimization of the neural network; \( \mathbf{X}(x_1, x_2, \ldots), \mathbf{Y}(y_1, y_2, \ldots), \mathbf{E}(e_1, e_2, \ldots) \) are input, output and error vectors of a neural network.

\[ F_1 \]
\[ \mathbf{X}(x_1, x_2, \ldots) \rightarrow \text{Neural network model of DLN} \rightarrow \mathbf{Y}(y_1, y_2, \ldots) \rightarrow \text{Forming of } F_2 \rightarrow \text{Calculating of errors } \mathbf{E}(e_1, e_2, \ldots) \rightarrow \text{Calculating of } \text{grad } F_2 \rightarrow \text{Forming of an extremum search procedure} \]

Figure 6. The algorithm of a neural network synthesis for the identification of low-emission combustion chamber parameters.

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.
To test the proposed methodology for a neural network design for predicting the NOx and CO emission, the real industrial combustion chamber of a gas turbine unit with a power of 16 MW - GTU-16 (figure 7) was considered.

3. Results and Discussion

3.1. Experimental object
In our example we assume a reverse-flow combustor made up of twelve external flame tubes with a lean premix system. Figure 7 shows the combustor dome. 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.

![Figure 7. An industrial low-emission combustion chamber (dln) of a gas turbine unit with a power of 16 MW (GTU-16).](image)

This combustor was tested on a dedicated rig with NO2 and CO emission measurements. Combustor parameter regulation ranges are: pressure is 1.0 ... 1.8 MPa, combustor inlet temperature is 470 ... 730K, the proportion of a fuel flow through the diffusion (pilot) circuit (PFR - pilot fuel ratio) is 0.04 ... 0.20, thermodynamic gas temperature at combustor discharge is 900 ... 1550K.

3.2. 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 figure 8 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 NOx 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 figure 9.

As it can be seen from the presented data, most of the values of NOx 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.

3.3. The development of a nitrogen and carbon oxides emission control 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.

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.

Figure 10 shows the structure of the neural DLN model.

As the coordinates of the input vector $X \{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\}$ the eight input parameters of DLN were selected [18]:
- $x_1$ – operating mode;
- $x_2$ – temperature behind the compressor $T_C$;
- $x_3$ – pressure behind the compressor $P_C$;
- $x_4$ – air flow $m_A$;
- $x_5$ – fuel flow $m_f$;
• $x_6$—gas temperature $T_G$;
• $x_7$—ripple amplitude at frequencies A200-400 Hz;
• $x_8$—proportion of fuel in the pilot burner - pilot fuel ratio (PFR).

As the coordinates of the output vector of the neural network $\mathbf{Y}(y_1,y_2)$ the two output parameters of DLN, characterizing the emission of pollutants, were selected:

• $y_1$—concentration of NOx;
• $y_2$—concentration of CO.

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:

$$\frac{N_y Q}{1 + \log_2(Q)} \leq N_w \leq N_y \left( \frac{Q}{N_y} + 1 \right) (N_x + N_y + 1) + N_y$$

(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:

$$N = \frac{N_w}{N_x+N_y}$$

(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.

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.

The neural network, the structural diagram of which is shown in figure 10, was modeled by the tools of MATLAB.

The obtained mean square error curve over the entire training period is shown in the figure 11.
Figure 11. Evolution of the root-mean-square error $\sigma$ during training period (1000 epochs).

The best result of neural network tunings according to the minimum of the mean square error criterion performed an average relative test error of 10%, an average relative prediction error of 3%.

The analysis of the significance of the individual coordinates of the input vector $\{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\}$ for the accuracy of the model, and, therefore, the degree of their influence on the amount of emissions of NOx and CO into the atmosphere is illustrated by figure 12.

Figure 12. The results of studies of the effect of dln input parameters on the emission of pollutants into the atmosphere.
As the analysis showed, the increasing of NOx emissions is most influenced by \( x_3 \) – the pressure \( P_K \). A significant effect on the model error for this output parameter is also exerted by \( x_6 \) – the gas temperature \( T_G \), \( x_7 \) – the pulsation frequency A200-400 Hz, \( x_8 \) – the pilot fuel ratio (PFR). But the influence of these parameters is almost 6.5 times less.

The most significant for increasing of CO emission is \( x_6 \) – the gas temperature \( T_G \). A significant effect on the model error for this output parameter is also exerted by \( x_3 \) – the pressure \( P_K \) and \( x_8 \) – the pilot fuel ratio (PFR).

But the influence of these parameters is almost 1.5 times less than the gas temperature \( T_G \). Also it should be pointed out the influence of \( x_2 \) – the temperature behind the compressor \( T_C \), which is almost 3 times less than the effect of \( T_G \).

In addition, it should be noted that the CO emission is much more sensitive to the completeness of the set of input parameters. In particular, the most significant parameters differ in influence by 12.5 times.

Thus, by the data of a model experiment, the most significant parameters affecting the accuracy of the DLN model are the pressure behind the compressor \( P_C \), the gas temperature \( T_G \) and the pilot fuel ratio (PFR).

4. 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 robust automatic control systems of gas turbine engines.

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