VIRTUAL NOX-EMISSION SENSORS FOR ROBUST AEROENGINE AUTOMATIC CONTROL SYSTEM

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The relevance and purpose of the study

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).

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 1000meters. 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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The problems and purpose of the study

Problems:

- there is no existing on-board emission sensor;
- functionally the emission level depends on a large number of variables (at least six to seven);
- the low emission combustor stability margin (from lean blow-out to high combustion dynamics) 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;
- it is necessary to take into account the NOx emission standards for the low emission combustor

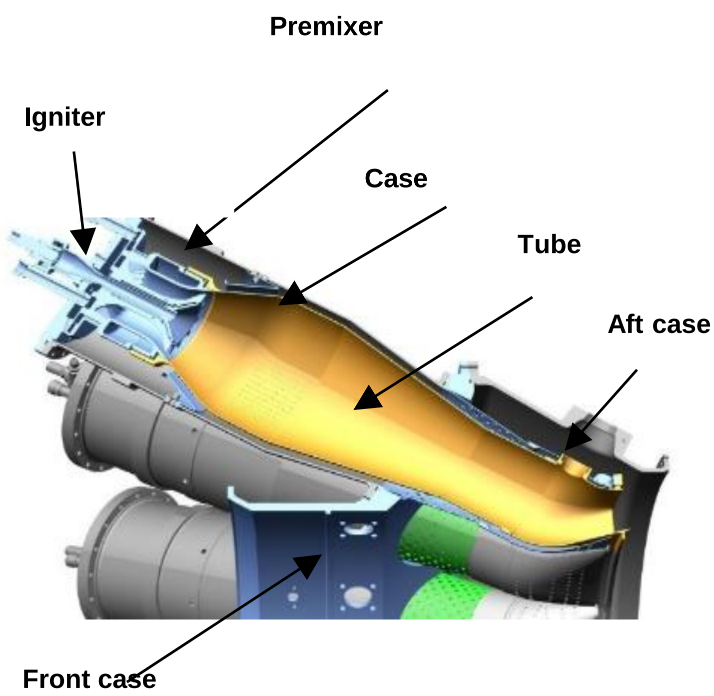
Purpose :

The development of a virtual sensor of the emission of nitrogen oxide, built into the diffusion flame tracking automatic control system.

RESEARCH OBJECT:
THE LOW EMISSION COMBUSTION CHAMBER

Structure:

- Front-mounted device with a blade swirl and nozzle and four fuel metering devices (diffusion and homogeneous), which function are injection, evaporation and uniform mixing of the air-fuel mixture due to transverse concentration pulsations (homogeneous collectors) and flame stability (diffusion circuit with flow rate up to 30% of total fuel consumption).
- The combustion space where the combustion process is carried out. The length of the furnace space is determined by the residence time of the mixture required to complete the combustion.



MATHEMATICAL MODEL OF EMISSION BASED ON ZELDOVICH EQUATION

Zeldovich equation is taken as a mathematical model for NOx generation:

$$S = 2 \cdot 1.8 \cdot 10^8 \cdot e^{-38370/T} \cdot [O] \cdot [N_2]$$

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

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, we place the characteristics of flames stochastic in terms of a mixture composition on one of the. 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.

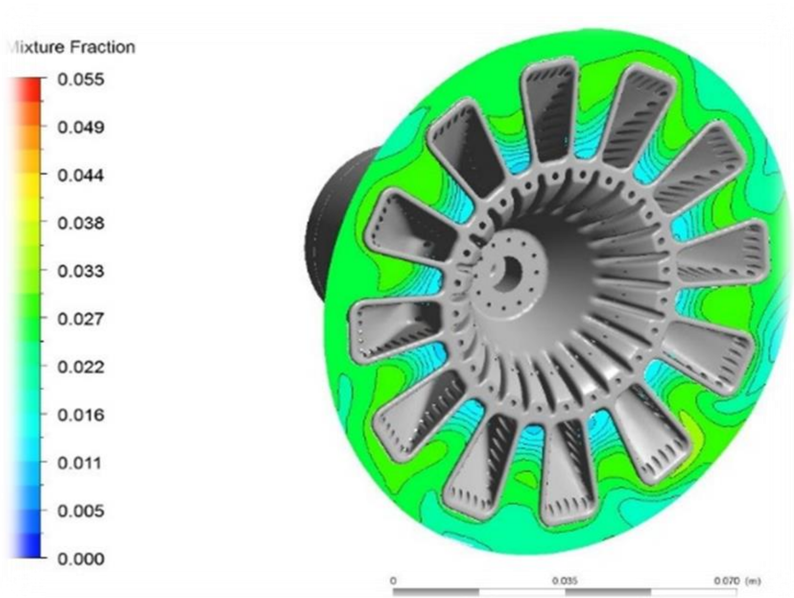
The equation of the fuel flow (m_f) averaged NOx generation rate for a typical two-zone (diffusion flame with 'd' index and homogeneous or technically premixed flame, with 'h' index) for the low emission combustor with 10:90 %% fuel split at Maximum can be represented as:

$$\bar{S} = \int_0^{0.1} S\left(\widetilde{\phi_d}, \widetilde{\phi_d'^2}\right) P(\phi) d\phi + \int_{0.1}^{1} S\left(\widetilde{\phi_h}, \widetilde{\phi_h'^2}\right) P(\phi) d\phi$$

where S -the rate of the NOx generation, P- probability, ϕ -equivalence ratio, is the prediction of the mathematical expectation of an equivalence ratio in diffusion and homogeneous flames; 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.

THE RESULTS OF THE NUMERIC ANALYSIS OF NON-UNIFORMITY AND THE COMBUSTION DYNAMICS DISTRIBUTION

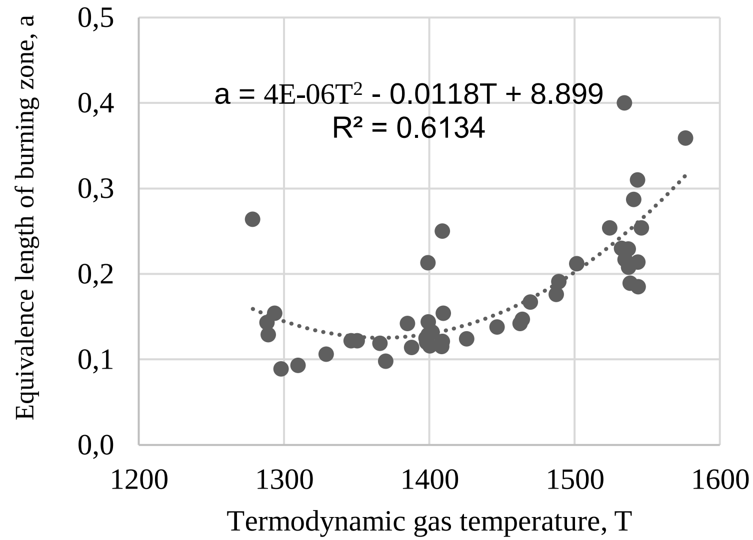
The distribution of a mixture fraction after premixer (inlet in burning zone)



Mixture fraction was obtained on the metamodel using ANSYS CFX . For the concentration of the fuel-air mixture over the area of the premix flame were used as inputs. The standard deviation from the mathematical expectation was 15%.

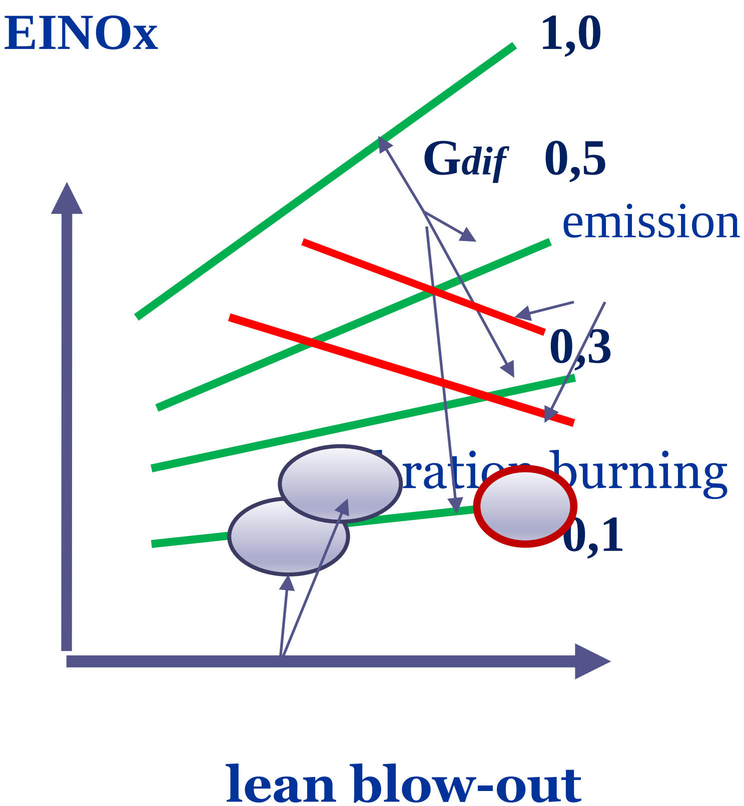
The approximation of experimental data using a presented model

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 values of NOx emission index can be predicted using the discussed approach with no exceeding 10…20% error.



STATEMENT OF THE CONTROL PROBLEM

The characteristic of low-emission combustion chamber (DLN)



The objective function

$$\int_0^t EINOx\, m_f dt < [NOx]$$

$$EINOx \approx \mu_{NOx}\bar{S}\frac{V}{L}\frac{a}{m_f}$$

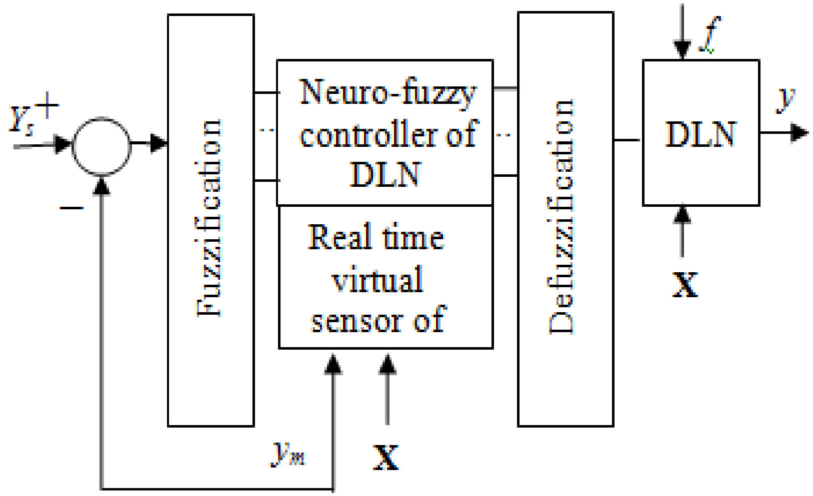
where:
EINOx - NOx emission index [g/kg],
$[NOx]$ – NOx concentration,
a - equivalence length of burning zone [m],
L - combustor length [m],
m_f - mass fuel flow [kg/s],
μ - molar mass [g/mol],
V - combustor volume [m^3]

The task of an emission 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

THE NONLINEAR CONTROLLER WITH MATHEMATICAL MODEL BASED ON THE NEURAL NETWORK

The main control objective function is the minimum emission level of nitrogen and carbon oxides.

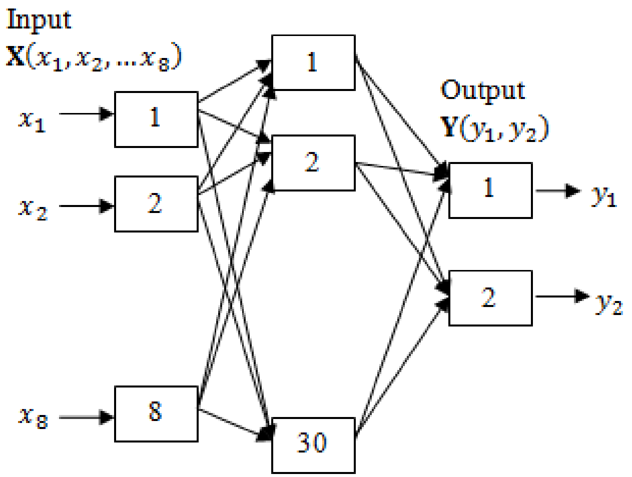
The possible implementation of a nonlinear controller with built-in mathematical model of the generation of NOx and CO emissions



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 NOx emission combustion chamber

MATHEMATICAL MODEL BASED ON THE NEURAL NETWORK

The neural network structure for DLN modelling



As the coordinates of the input vector $\mathbf{X}\{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\}$ the eight input parameters of DLN were selected:

- 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).

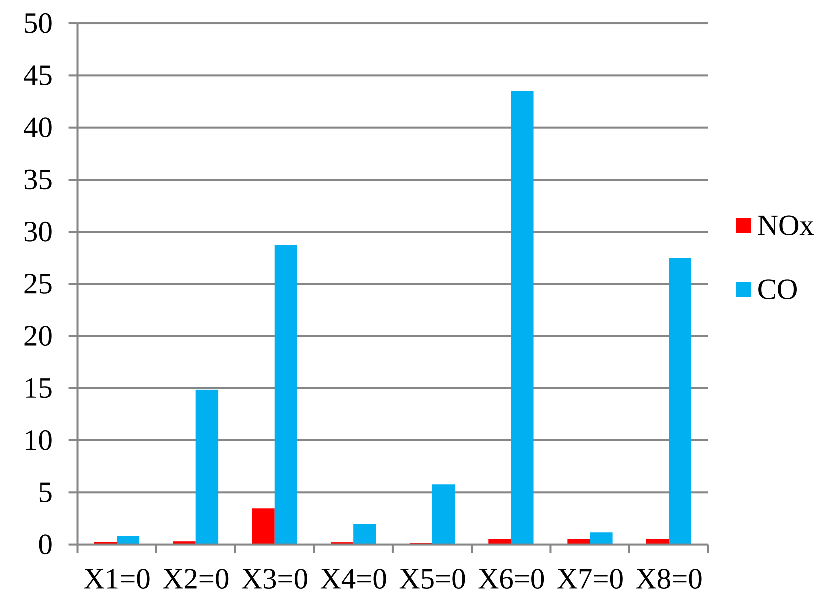
As the coordinates of the output vector of the neural network $\mathbf{Y}(y_1, y_2)$ the two output parameters of DLN, characterizing the emission were selected:

- y_1 – concentration of NOx;
- y_2 – concentration of CO.

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%.

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

The results of studies of the effect of DLN input parameters on the emission of pollutants into the atmosphere



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