VOL. 16, NO. 22, N0VEMBER 2021 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences


www.arpnjournals.com

# SIMULATING THE COAL DUST COMBUSTION PROCESS WITH THE USE OF THE REAL PROCESS PARAMETERS

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## ABSTRACT

The purpose of the study is to simulate the combustion of coal dust in real combustion using artificial neural networks. The article discusses optical methods of flame diagnostics. The focus is on the secondary air supply. For unknown reasons, the pulverized coal in the boiler is not completely combusted. Incomplete combustion of coal impairs the efficiency of the boiler, that is, it worsens the combustion efficiency and leads to significant costs. The scientific novelty consists in the use of artificial neural networks in control algorithms, making it possible to simulate efficiently complex processes, in particular the process of burning coal dust. In the Matlab software environment, the results of the data collection with the separation output with different amplitudes are shown. The considered scheme takes into account the multi-input and multi-output nature of the combustion process. Using additional information, vector-based optical signals for the flame surface area and the loop length have proven the system tracking properties. As a result of the use of fast optical signals, the control speed of the object increases and stabilization of the output signals of the combustion process is achieved.

**Keywords:** coal dust, combustion process, diagnostics, controller, control, neural networks.

## INTRODUCTION

Combustion of fossil fuels is currently the most important source of energy used by humanity. Coal remains the key energy resource and is expected to continue dominating the horizon for about 50 years. Unfortunately, this method of generating electricity is associated with progressive environmental pollution, such as emission of large amounts of waste gases and dust into the atmosphere [1].

The coal dust combustion process takes place in power boilers. The combustion process is optimized for the entire boiler, with the desired temperature distribution and the correct air-fuel ratio. It is often impossible to control each burner individually. The mixture of dust and air between different burners is not evenly distributed and often changes over time, which leads to decreasing the efficiency of the combustion process and increasing emissions of harmful combustion products. Practical experience shows that if one burner does not work properly, it can lead to a significant increasing the $NO_x$ and CO emissions in several burner systems.

Greenhouse gas emission standards call for changing the current control system that must be complemented with effective diagnostic systems. The need to meet these stringent requirements has led to the development of a number of research programs carried out mainly in the European Union. Currently, when developing an efficient method of the combustion process, one should take into account not only the cost of the process but also the costs associated with the emission of pollutants. This requires the use of modern technical solutions that would allow the combustion processes being maintained under optimal conditions. For this, in particular, artificial intelligence algorithms are used. Expert systems are mainly used not only for modeling but also for diagnostics [2]. Classical neural networks have been used to monitor emissions from small boilers as well as to predict the greenhouse gases of the grate boiler. The fuzzy network is used to evaluate the system of minimizing the $NO_x$ emissions in sprayed coal. All these systems have one significant drawback: the measurement processes are averaged over the entire boiler. In power boilers operating with several dozen burners, the measuring chemical compositions of gases are most often determined using gas analyzers located on the rotary air heater. Depending on the size of the boiler and the working conditions, the information can be delayed up to several minutes, which often makes diagnostics and monitoring not very effective. Even the most sophisticated systems do not allow one burner being controlled separately, redundant air control and the amount of $NO_x$ generated in the coal of the boiler. Diagnostics can detect a malfunction but the location of the damage cannot be determined. The fault analysis indicates that there are no methods available for direct measurement of parameters indicative of the combustion process quality occurring within a single burner. Therefore, it is necessary to use indirect methods, which could include primarily acoustic or optical methods. These methods are non-invasive and allow obtaining additional spatially selective information about the combustion process practically without delay. The flame is used as a source of information of the combustion process. Flame radiation that consists of the combustion chemicals emission and a continuous spectrum, the source of a particulate matter (soot, coal dust, ash, etc.), uses radiation in the ultraviolet to near infrared range of the spectrum.

The main problem that arises in the course of the optical sensors operation is contamination of the optical system. It is necessary to adjust the design of the device

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for receiving the optical signal originating from the flame in such a way as to minimize the possibility of contamination.

In addition to the main problems, such as contamination of the optical system and decreasing the power, there are interference from neighboring burners and the hot state of the chamber walls. Most up-to-date solutions use the information related to the pulsation of the flame, which includes the analysis of the variable component of the output signal from the photodetector. For this, frequency and time-frequency methods of the signal analysis (Fourier transform), short-term Fourier transform, wavelet transform for forecasting time series and the analysis using artificial intelligence algorithms are used [3].

The advanced photodetector signal analysis allows flame scanners being used for combustion diagnostics. They are not limited only to the detection of insufficient flame but also allow detecting changes in the combustion process within a single burner, in particular due to $NO_X$ emissions. Thanks to the intelligent optical system, multi scanners allow measuring the parameters of the flame simultaneously in several of its zones. This expands the diagnostic capabilities of the device, for example, with the ability to track the movement of the burner flame. The flame is used for combustion diagnostics and image processing. Observation of the dust-like flame in different spectral ranges is used to diagnose the state of the fuel being burned as an alternative to microwave radiometric methods [4].

Methods of diagnosing industrial processes, the task of which is to identify early signs of the emergency formation, acquire particular importance for processes of a complex and large scale. Such processes include the process of generating electricity. Energy production processes can be considered, on the one hand, in terms of economics, and on the other hand, in terms of environmental pollution. For requirements and constraints that meet various criteria (for example, economic, environmental and technological), it is important to obtain a compromise in implementing the process without the risk of damage or destruction of the process plant parts.

In the industrial environment, the quality of the pulverized coal combustion process is subjectively assessed by the operator based on the visible image of the flame. Monitoring systems are designed to detect the condition of the flame that leads to an uncontrolled explosion of coal dust. It should be emphasized that the speed of the fuel mixture leaving the burner is high enough for combustion to take place in the turbulent flame. At the moment, there are no measures that allow assessing the turbulent flame occurring in the course of the coal dust combustion on the basis of which it would be possible to evaluate clearly and objectively the quality of the combustion process. Therefore, it seems necessary to determine diagnostic signals that would allow objective controlling the process.

In almost all the countries, harmful emissions into the environment are of particular concern. The pulverized coal combustion technology effectively reduces $NO_X$ emissions into the environment. However, it reduces the efficiency of using coal dust for power generation by several percent. Therefore, it is necessary to use the information from the flame to control the combustion process.

The combustion process of solid natural fuel is a complex of physical-and-chemical phenomena: heat exchange of particles with the medium, release and combustion of volatile substances, combustion of the coke residue.

It is generally accepted that the combustion process can be divided into relatively independent stages:

a) warming up the particle until the volatile substances release or ignition;

b) combustion of volatile substances near the particle, which promotes rapid heating of the particle;

c) burning the coke residue consisting almost exclusively of carbon and ash.

Combustion of volatile substances, as well as heating particles, is a relatively fast process in comparison with combustion of the coke residue. Combustion of the coke residue takes up to 90 % of the total combustion time of the coal particle.

Combustion of carbon is a heterogeneous process determined both by the kinetics of combustion of the carbon mass of a particle and by the diffusion transfer of oxygen and combustion products at the surface of the burning particle.

Experimental studies show that the interaction of oxygen with a carbon particle leads to the formation of both carbon oxide and carbon dioxide. The mechanism of the primary oxides formation is as follows: oxygen is adsorbed from the gas volume on the carbon surface. On the surface, oxygen atoms enter into the chemical compound with carbon forming complex carbon-oxygen compounds $C_xO_y$. The compounds decompose with the formation of $CO_2$ and CO. The decay rate increases greatly with increasing the temperature. In addition to primary reactions, secondary reactions have a significant effect on the combustion rate: the interaction of carbon with carbon dioxide and the combustion reaction of carbon monoxide.
In their pure form, heterogeneous reactions are manifested in extremely limited temperature ranges, when the rates of these reactions are low. Distortion of the reaction law is caused by the appearance of diffusion inhibition: diffusion of oxygen and combustion products in the volume surrounding the burning particle and diffusion inside the mass of coke.

The physical picture is as follows: oxygen is supplied to the outer surface of the piece, in the areas of this surface where there are no cracks, a part of the oxygen enters into the combination with carbon and a certain amount of carbon oxide and carbon dioxide is released.

During the combustion of a carbon particle, two main processes can be distinguished that determine the rate of burnout: the diffusion of oxygen to the surface of the carbon particle and the actual rate of chemical reaction of oxygen with carbon.

When burning a solid fuel in a dense or fluidized bed, combustion of large particles usually takes place in the diffusion region. In pulverized combustion, the relative velocity between the gas and the fuel particle is small, while the Sherwood number tends to two: $\mathrm{Sh} = \alpha_D \delta / D = 2$ . In this expression, the coefficient of molecular diffusion is calculated as the coefficient of interdiffusion of oxygen in nitrogen [4]:

$$D = 0{,}16 \cdot 10^{-4} (T/273)^{1{,}9}. \quad (1)$$

In this region the flow is almost proportional to the temperature: $j = \alpha_D c_0 \sim Dc_0 \sim T^{1,9} \cdot T^{-1} \sim T^{0,9}$. With decreasing the particle diameter there decreases the diffusion resistance: $1/\alpha_D = \delta/2D$, i.e. decreasing the dust particles diameters allow increasing their combustion rate.

For many problems in the practice of combustion, the most interesting quantity is the duration of combustion of a fuel particle. In particular, in the case of pulverized coal combustion, when a solid fuel moves with air, it is the combustion time of the fuel that is important for calculating the dimensions of the furnace.

The total burning time of a particle is described by the dependence representing the sum of the "kinetic" and "diffusion" burning times. In pulverized coal combustion, $Sh \rightarrow 2$, and then the total combustion time of a single carbon particle can be calculated as [4]:

$$\tau = \frac{\rho r_0}{\nu k c_0} + \frac{\rho r_0^2}{2\nu D c_0}. \quad (2)$$

The studies have shown that combustion of particles that are larger than 100 microns occurs in the diffusion region. In the kinetic region, combustion of anthracite particles that are smaller than 100 microns in size takes place. The burnout time for particles from 100 μm to 1 mm can be calculated using the empirical formula [4]:

$$\tau_{\text{г.к}} = k_{\text{г.к}} \cdot 2{,}21 \cdot 10^8 \frac{\rho \delta^2}{T_{\text{г}}^{0,9} O_2}, \quad (3)$$

where $k_{\text{г.к}}$ is the coefficient accounting for the coal properties; ρ is the fuel density, kg/m$^3$; δ is the diameter of the fuel particles, μm; $T$ is the temperature, K; $O_2$ is the oxygen concentration, %.

Let's compare the empirical formula with analytical expression (4.12) for the diffusion mode of a single particle burnout:

$$\tau = \frac{\rho r_0^2}{2\nu D c_0}. \quad (4)$$

The required bed height should be proportional to the diameter of the fuel particles. Increasing the velocity does not change the excess air at the exit from the layer of a given height. This is explained by the fact that increasing the velocity leads to decreasing the residence time of the gas in the layer, but at this, the mass transfer is intensified. Thus, changing the velocity does not lead to deterioration in the combustion conditions, which makes it easy to adjust the furnace load.

The pulverized method of burning solid fuels in a torch has certain advantages over other combustion methods: it allows burning high-ash and high-moisture fuels, increasing the heat flux density, complete mechanizing and automating the supply and combustion of fuel, removing slag and ash.

The torch burns particles which sizes differ by one or two orders of magnitude, i.e. they burn multi-fraction dust. Grinding ensures a good contact of the fuel and oxidizer and fast fuel burnout.

Due to their small size, the dust grains move practically together with the gas flow, the velocities of their flow around them are small. And even for large particles (200-300 microns), we can assume that the Sherwood criterion tends to the minimum value equal to two.

The presence of a volatile part fundamentally distinguishes the process of burning out a natural fuel from the process of burning out pure carbon. Volatile substances make ignition much easier. Volatiles released by small particles (up to 200 microns) saturate the gas volume forming a combustible gas-air mixture, which begins to burn. For large particles (larger than 500 microns), the ignition of volatiles begins at the surface of the particle.

At the beginning of the combustion process, volatiles and coke can be burned out simultaneously. However, combustion of the coke residue is the longest stage (up to 90 % of the total combustion time of a particle).

It should be borne in mind that the particles do not burn separately from each other but in interaction. Co-combustion of particles determines changing the oxygen concentration along the length of the flame. At the beginning of the torch, in the zone of high oxygen concentrations, a large number of small dust grains will burn out, and combustion of medium and large dust grains will occur in the zone with a low oxygen concentration. Therefore, for complete burnout, it is necessary to either stretch the torch or to reduce the particle size. With the help of sieves, it is possible to disperse only dust with the grain size of larger than 40 microns. The analysis of the fractional composition of finer dust is carried out by the air classification method.

For clarity and ease of use, the sieving results are shown graphically in the form of the grain characteristic, where the sieve size is plotted on the abscissa, and the total residue on the sieve of a given size is plotted on the ordinate. The analysis of numerous grain characteristics of grinding various types of fuels shows that all the curves are described by the Rosin-Rammler equation (Figure-1).

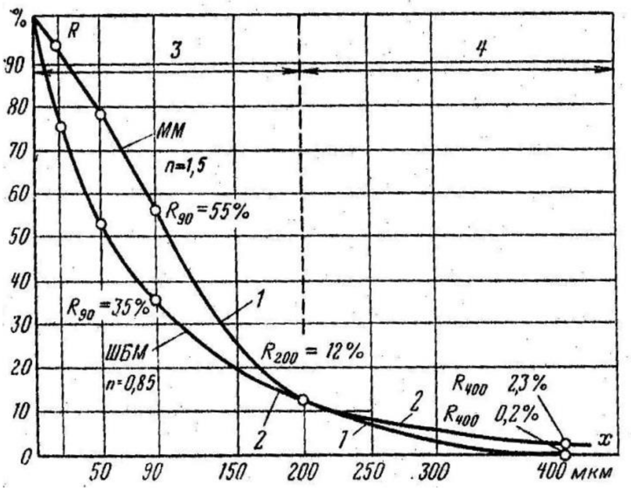


**Figure-1.** Full grain characteristics of the brown coal dust obtained in two types of mills: 1 - grinding in a hammer mill; 2 - grinding in a ball drum mill; 3 - region of the fine dust fractions; 4 - region of the coarse dust fractions [4].

$$R_x = 1 - \exp\left(-b\delta^n\right), \tag{5}$$

where δ is the current coal dust size; *b* and *n* are constants for the given fuel and the given method of grinding, *b* characterizes the fineness of grinding, the larger b, the finer dust. The numerical values are as follows: $b=4\cdot10^{-3}$ for coarse dust, $b=40\cdot10^{-3}$ for fine dust; *n* is the coefficient of the dust polydispersion that characterizes the dust structure from the point of view of the grinding homogeneity. The higher *n*, the less are distinguished the particle sizes. For the industrial conditions the coefficient n is equal to 0.75-1.5.

Tthe Rosin-Rammler equation can be presented in the following form:

$$R_\delta = 100 \cdot \exp\left(-\left(\frac{\delta}{\delta_0}\right)^n\right), \tag{6}$$

where $\delta_0$ is the characteristic particle size in the weight equal to $\delta_0 = 1/\sqrt[n]{\delta}$ .

At δ=0 the sieve residue $R_\delta$=100 %, at $\delta\to\infty$ $R_\delta$=0, i.e. there little large particles. In physical meaning, $\delta_0$ is the size at which the average specific surface area of particles with the size $\delta_0$ is equal to the average specific surface area of the considered polydisperse particles.

In the presence of experimental data of the sieve residues, the coefficients in the Rosin-Rammler equation are found by doubling the logarithm of expression (6):

$$\ln\left[-\ln(R_\delta/100)\right] = \ln(\delta/\delta_0)^n = n\ln\delta - n\ln\delta_0 \tag{7}$$

and by processing the data in the $\ln\delta = \ln(-\ln R_\delta)$ coordinates, in which equation (7) presents an equation of a straight line with the unknown values *n* and $\delta_0$.

Flame radiation reflects the combustion process that occurs in chemical reactions and physical processes. Optical diagnostic methods, in addition to acoustic ones, are some of the most important methods that provide the additional information of the current combustion process in a non-invasive way. In the spectrum of the flame, it is possible to determine the content of the air-fuel ratio, the amount of heat release and the temperature. Among the optical methods, the image processing method is especially important. The flame is the result of a dynamic balance between the local velocity of flame propagation and the velocity of the incoming fuel mixture. Changes in the position of the flame front in the chamber are regarded as fluctuations in the flame and interfere with the balance results. This suggests that the shape of the flame can be an indicator of combustion occurring under certain conditions [5].

The analysis shows the relationship between the parameters that describe changing the flame and the temperature in the chamber or the volume of air flow in the secondary refrigerant. Thus, if the temperature changes slowly, then synthesis can be used to control the velocity (the ratio of an actual parameter or a group of image parameters).

The primary air is mainly used to provide carbide powder to the burner nozzle, while the secondary air is used for control purposes. The input parameters, such as the coal mixture, the biomass and the air flows were changed several times during testing and under different combustion conditions.

Due to the incomplete study of the control object, the use of adaptive control is required. In turn, the study of the object is achieved by artificial modeling of the neuron network.

Conditions and methods of the study. The complexity of the combustion and co-combustion process requires unconventional control methods. This is dictated by non-linearity and the possibility of rapid changes in the number of quality and safety requirements. In such systems, it is better to use neuron adaptive control, which is an interesting approach in present day complex industrial systems. Compared with conventional methods in the field of control theory and automatic control, these systems have the advantage of being applied to multidimensional systems. The problem statement plays an important role because each controller is optimally designed.

The efficiency of pulverized fuels depends on several parameters. Commonly applied low-emission methods of burning pulverized coal use recirculating vortices that lengthen the path of the coal grains passing through the flame to minimize the formation of thermal nitrogen oxides ($NO_x$). To make the combustion of

VOL. 16, NO. 22, N0VEMBER 2021 ISSN 1819-6608
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pulverized coal more efficient and cleaner, it is necessary to measure its basic parameters. The information received at the output (exhaust manifold) is delayed and averaged. Although in [5] some direct methods of combustion diagnostics are given, most of them cannot be used in industrial conditions due to their high cost. Fast and minimally invasive optical techniques make it possible to use the image-based information in the process control system.

Nonlinear autoregression of external input networks (NARX) is a recurrent networked dynamic feedback connection involving multiple network layers. The NARX model is based on the linear ARX model, which is widely used in time series modeling. The definition of the NARX equation for the model is as follows:

$$y(t)=f\left(y(t\text{-}1),\, y(t\text{-}2),...,y(t\text{-}n_y),\, u(t\text{-}1),\, u(t\text{-}2),...,u(t\text{-}n_u)\right), \quad (8)$$

The NARX model can be implemented using a neuron network to approximate the function. The resulting network diagram is shown in Figure 5.3a, where two-layer networks are used. This implementation also allows for the ARX the vector model characterized in that the input and output can be multidimensional.

The NARX output networks can be thought of as a model for evaluating the output of a nonlinear dynamic system. The output is fed back to the input of the neuron network as a part of the standard NARX architecture. With regard to the fact that the real output is available during the training network, it is possible to create a serial-parallel architecture [6]), which is used to evaluate the real output.

We used the neuron $NO_x$ estimation using the NNFIR (Neural Network Finite Impulse Response) model, which is described by the following expression:

$$y(t) = g[\varphi(t), \theta] + e(t) \quad (9)$$

where $t$ is the time; $y(t)$ is the output of the model, a vector that contains θ of the mat weight; $g$ is the nonlinear function that is realized by the neuron network; $e(t)$ is white noise. The regression vector φ($t$) of the NNFIR model is described by the relationship:

$$\varphi(t) = [u(t-n_k), \ldots, u(t-n_b-n_k+1)] \quad (10)$$

where $u$ is the input model; $n_b$ and $n_k$ are its parameters.

This model was implemented as a perceptron of a three-layer network (Figure-2).

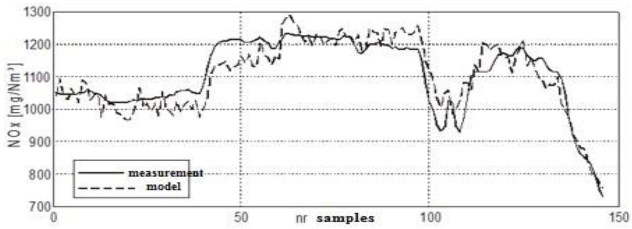


**Figure-2.** Comparison of the $NO_x$ emission measurement (solid line) with the estimate based on measuring of the optical probe (dash line).

The control system for stabilizing nitrogen oxide emissions from one burner, where neural estimation is used, is shown in Figure-3.

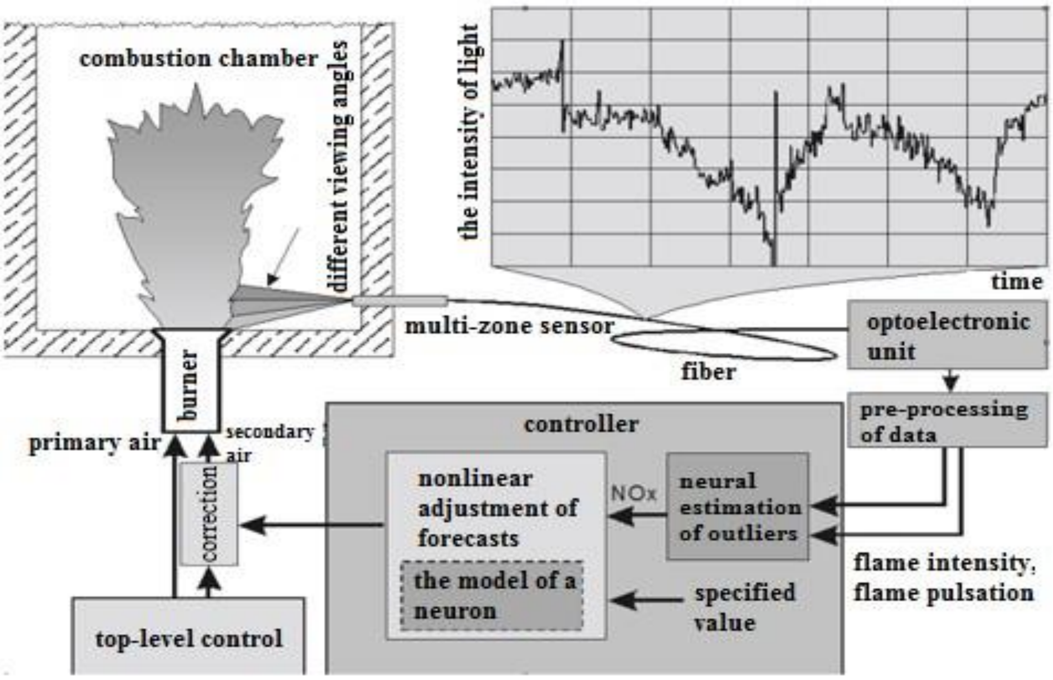


**Figure-3.** Control system of the vortex burner.

To estimate the control quality there is accepted the square control coefficient that take the following form:

$$J(t,U(t)) = \sum_{i=N_1}^{N_2}\left[r(t+i) - \hat{y}(t+i)\right]^2 + \\ + \rho\sum_{i=1}^{N_u}\left[\Delta u(t+i-1)\right]^2, \quad (11)$$

where $U(t)$ is the control vector; $r$ is the set control value; $N_1$ and $N_2$ are respectively the start and the end of the forecast horizon; $N_u$ is the horizon length control; $\hat{y}$ is the model output value; ρ is the change of the weight of the damping controls depending on the deviation; $\Delta u$ is the control signal increment.

The output of the NARX network can be viewed as an estimate of the simulated nonlinear dynamic system output. The output is returned to the input of the feed-forward neuron network as a part of the standard NARX architecture. This has two advantages: firstly, the feed-forward network entry is more accurate; secondly, the resulting network has a purely forward-looking architecture and static back propagation can be used.

The custom architecture used for further analyzes presents the Model Reference Adaptive Control (MRAC). This reference control model has two subnets. One subnet is a controlled installation model. The other subnet is the controller. By purchasing a prepared NARX installation model, it is possible to develop a generic MRAC system and to insert the NARX model inside, and then to add feedback loops to the feed-forward network.

For the closed loop MRAC system to react in the same way as the reference model (used to generate the data), the model installation networks must be inserted at the appropriate place in the MRAC system. The controller outputs must then be set to zero to achieve the initial input of zero. The final MRAC network is shown in Figure-4, where level 3 and level 4 (output) are a subnet of the installation model. Levels 1 and 2 make up the controller.

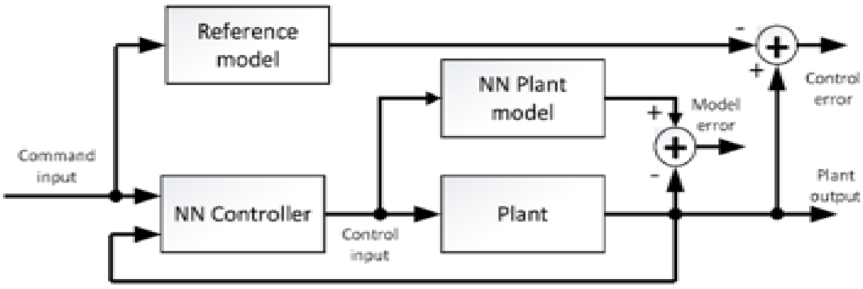


**Figure-4.** The MRAC network.

Training the MRAC system took much longer than training the NARX object model, due to the fact that the network uses periodic and dynamic back propagation. After the network was trained, it was tested with the test input to the MRAC network.

Two MRAC systems were developed and compared. In the first of them, a non-optical measurement-based set of input vectors is used, the secondary air flow, fuel consumption and vectors describing, the temperature of the exhaust gases in the chamber, recorded at the first measurement point, respectively, are quantitatively described. The second scheme uses the secondary airflow control signal and selected flame image descriptors.

Figure-5 shows the response of the system to the system reference input in both cases: with classical measurements (a) and in the case of the vector of the contour length of the flame image descriptor (b).

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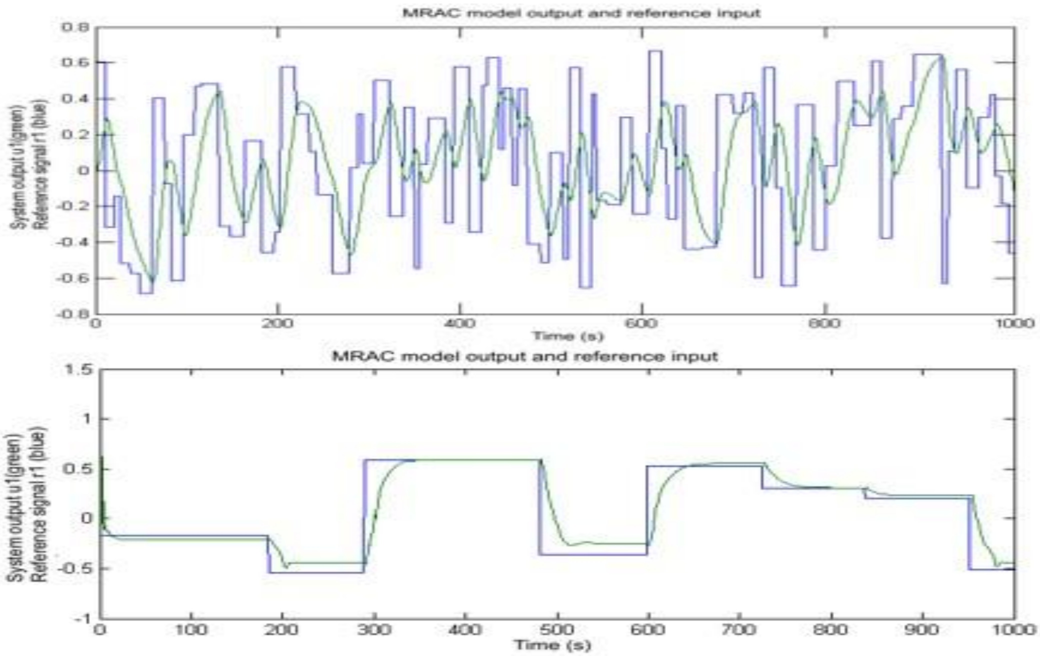


**Figure-5.** The MRAC system response to the input signal: (a) without additional information from the optical signals; (b) with the vector of the loop of the flame image descriptor.

Figure-5 shows that the output of the station model corresponds to the reference input with the correct critically damped response, although the input sequence is not the same as the input sequence in the training data. The steady state response is not ideal for every step, but this can be improved with more training and possibly more hidden neurons. From the obtained results of the proposed neural adaptive control, it can be concluded that control signals are limited, abrupt changes in the system parameters are associated with sudden changes in the amplitudes of command laws and outputs of the controlled system.

Testing for the combustion of a mixture of coal and biomass was carried out in the laboratory facility of 0.5 MW. This unit simulates the reduced (10:1) combustion conditions of a full scale vortex burner that operates on biomass pulverized coal. The laboratory unit contains a horizontal arrangement consisting of a cylindrical combustion chamber with the diameter of 0.7 m and the length of 2.5 m, as shown in Figure 6.

The model of a low $NO_x$ vortex burner with the diameter of about 0.1 m is mounted on the front wall. The laboratory unit is equipped with all the needed power systems; primary and secondary air, coal and oil. The mixture of pulverized coal and biomass is prepared in advance and discharged into the hopper of the coal distributor.

The combustion test consisted of the following steps. Firstly, the combustion chamber was heated by burning oil. When the temperature rose enough, the feeder was started and the air/fuel mixture was delivered to the burner at the same time as the oil. After reaching the correct temperature level, the oil supply was cut off [5].

Radiation emitted by the flame is a reflection of the combustion process that occurs in chemical reactions and physical processes. Optical diagnostic methods, in addition to acoustics, are among the most important methods that make it possible to obtain non-delayed and spatially selective additional information of the ongoing combustion process in a non-invasive way. With regard to the spectrum of the flame in visible light, determining the content of the air-fuel ratio, the amount of heat generation and the temperature can be included. Among optical methods, the image processing approach seems to be especially important. The flame of a stationary and visible position is the result of the dynamic equilibrium between the local speed of flame propagation and the speed of the incoming fuel mixture. Changes in the position of the flame front in space are seen as fluctuations in the shape of the flame upset these balance results. This suggests that the shape of the flame can be an indicator of the combustion process occurring under certain conditions [5].

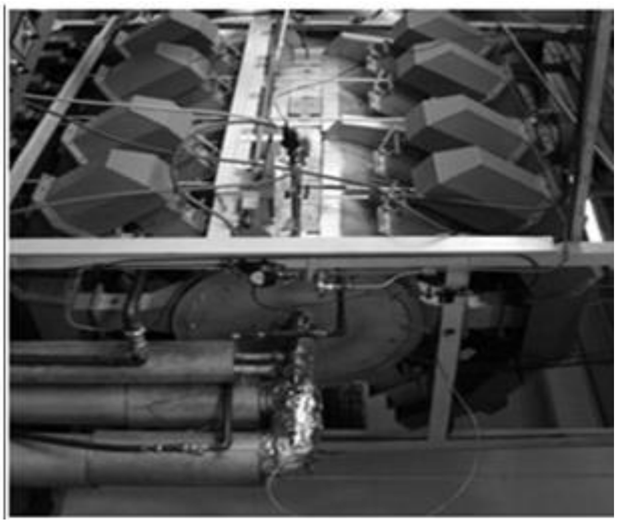

**Figure-6.** The laboratory combustion set with a mounted camera.

The potential problem for complex control systems, such as the combustion process, is difficult (and therefore not complete) for measuring physical-and-chemical quantities. In the proposed solution, the classical approach is supplemented by the information of the flame parameters recorded by a fast CCD camera.

As a result of the experiment, the relationship was revealed between the parameters describing the change in the flame and the temperature of the exhaust gas in the chamber, or the amount of air flow in the secondary factor. Thus, if the temperature changes slowly having an inert nature, then the synthesis of the controller can be used by a parameter or a group of image parameters.

The primary air is mainly used to supply pulverized coal to the burner nozzle, while the secondary air is used for regulation. Input parameters such as the coal/biomass mixture and air flows were changed several times during the tests for developing different combustion states.

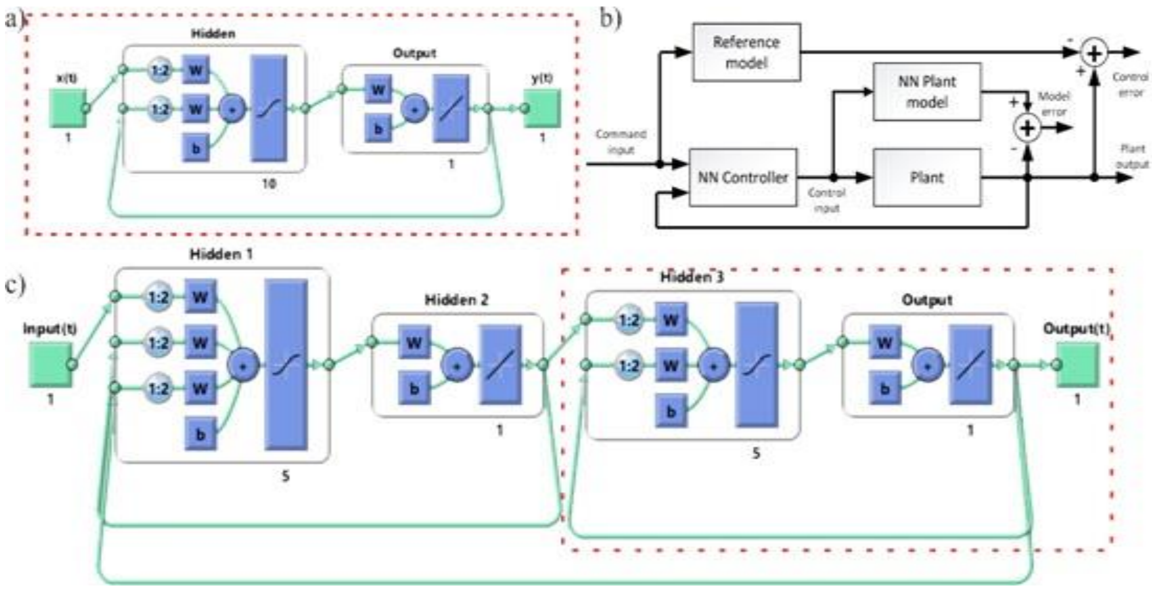


**Figure-7.** The neuron network structure that is used at the stage of the equipment identification (a), the MRAC network structure (b) and the MRAC control scheme (c).

Due to insufficient studies of the control object, the performance of the system with fixed parameters is insufficient and requires the use of adaptive control. In turn, the required knowledge of the object is achieved by modeling an artificial neural network.

## RESULTS

An artificial neuron network is modeled as a computer program. Most programs are limited only by the ability to build Takagi-Sugeno models. An example of this is the ANFIS (Adaptive Neuro Fuzzy Inferencje System) module attached to the Fuzzy Logic Toolbox in the Matlab software.

Figure-8 shows an example data from the Simulink Toll Chart program.

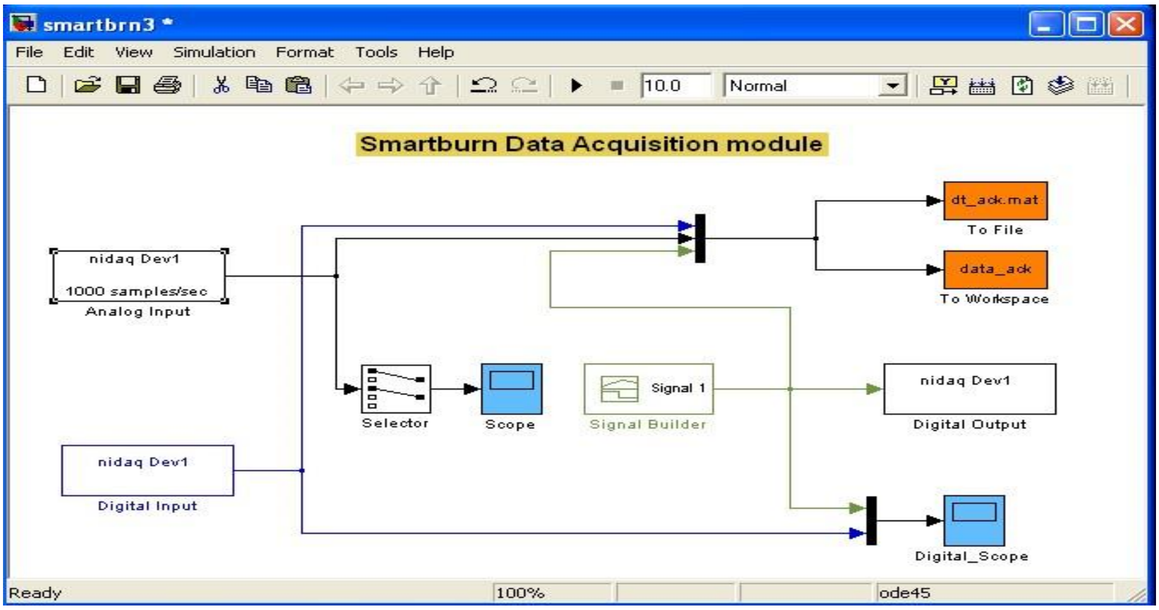


**Figure-8.** The window of the diagram with the application of registering the data in the Simulink software.

To communicate with devices and with analog and digital inputs there are used the nidaq dev1 and nidaq dev1 blocks.

All the signals are saved to the dt_ack.mat file and a variable table in the data_ack workspace in the form of a structure with time.

Figure-9 shows the production of files of the Matlab program with the developed artificial neural network model.

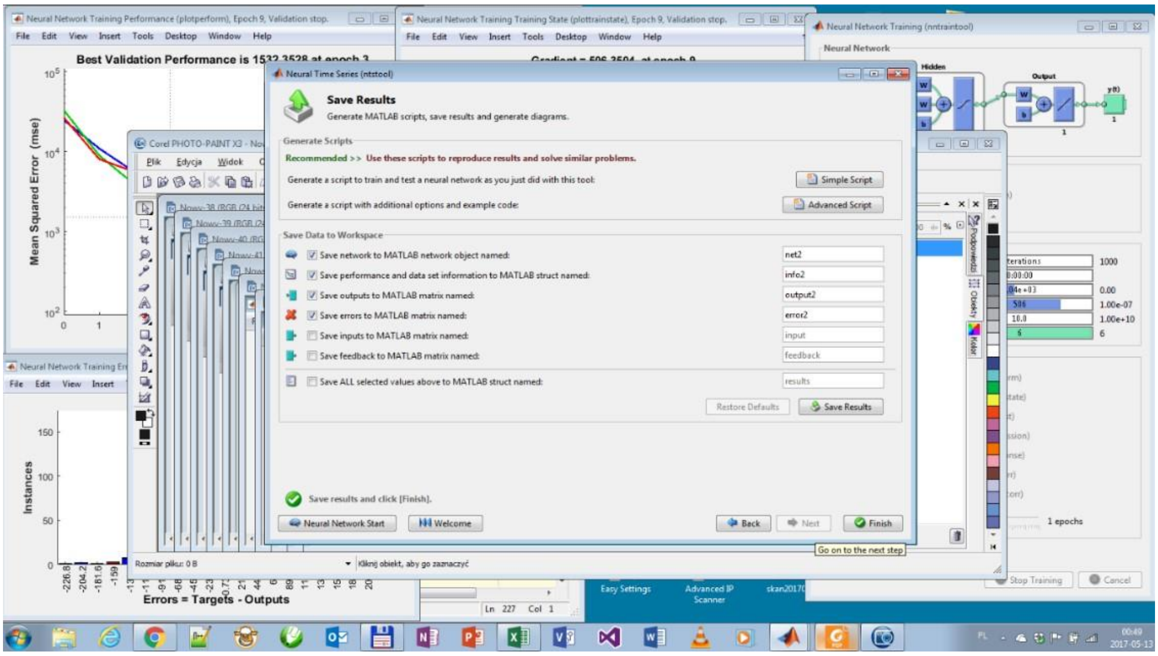


**Figure-9.** Producing files in the Matlab software with the developed artificial model of the neuron network.

The illustration is dealt with by oscilloscopes showing the individual values of analog and digital signals. In order to simplify selecting certain signals in the analog circuit, a block selector is used. A digital output block is used to control the actuators.

Figure 10 shows the results of data collection with separation yields at different amplitudes.

In the main window of Simulink diagrams, there can be set the sampling range, and depending on the use of the block, they are saved in the workspace or written to a .mat file. Collecting is done using the start button (▶), the key combination is Ctrl + T. By the stop button (■) the data collection ends.

The development of smart energy networks opens up new opportunities for innovative approaches to control based on up-to-date diagnostic and control methods.

The flame is a reflection of the combustion process that occurs in chemical reactions and physical processes. Optical diagnostic methods allow obtaining fast, spatially selective additional information of the current combustion process in a non-invasive way. It is quite possible to determine the content of the air-fuel ratio, the amount of heat release and the temperature in relation to the spectrum of the flame in the visible range of radiation. The flame means the result of dynamic equilibrium between the local speed of flame propagation and the speed of the incoming fuel mixture [6]. Changes in the flame position of the front in space are considered as fluctuations in the shape of the flame and provide an imbalance in the results. This suggests that the shape of the flame can be an indicator of the combustion process occurring under certain conditions.

Discussing the scientific results. Real combustion test results from the coal dust and biomass were used to simulate the development of the model. Thus, the stoichiometric combustion conditions were corrected during the tests, to the secondary adjustment of the air flow. This caused changing the dust-air mixture rate of the fuel yield resulting in the near extinction flame state.

The flame area was isolated from the grayscale images in terms of the amplitude of each pixel. It was assumed that the corresponding pixel of the image belongs to the flame if its amplitude is greater than or equal to 64. The surface area of the flame was considered as the sum of all pixels belonging to the flame region and the length of the designated area outline.

For the purposes of modeling, an easy case of the MPC algorithm based on the CAC scheme is selected. The control algorithm is based on the state space model with the structure:

$$x(k+1) = A\,x(k) + B_m u_m(k) + B_w w_m(k) + B_z z(k) \quad \wedge \quad y(k) = C\,x(k) \tag{12}$$

where x is the state vector; y is the output vector; $u_m$ is the input (or control) vector, the matrix of the A states; B is the input matrix; C is the output matrix.

The optimal controller is a solution to the optimization problem with the following minimization of the cost function:

$$J = \sum_{i=1}^{n} \left[r(k+i) - y'(k+i \mid k)\right]' \mu_y(k) \left[r(k+i) - y'(k+i \mid k)\right] + \sum_{i=1}^{c} \Delta u_m(k+i \mid k)' \mu_m(k) \Delta u_m(k+i \mid k), \tag{13}$$

where r (k) is the control value; y'(k+ i | k) is the predictor based on the y(k) and v(k) observations.

The cost function is the weighted sum of the error between the reference and predicted output values up to n steps (forecast horizon) and the control effort with a step forward (control horizon) expressed in terms of the control increment $\Delta u_m$. The controller tuning was developed by selecting the forecast horizons n and c and weights $\mu_y$ and $\mu_u$.

The control system was evaluated by simulating a sudden change in the load request step. This experiment replicates the critical situation that occurs with the unexpected change in $NO_x$ radicals and power occurs (Figure-11).

Conclusion. The ability of artificial neural networks to scale a function using a one-way network with one hidden layer has produced accurate results on the approximation of certain classes of functions [6].

The interest in this area is growing for solving problems of the nonlinear system [7]. They possess the property of nonlinear approximations of any given accuracy of representation using a suitable structure and weighted network. A feature of artificial neural networks is the ability to adapt, that is, this means that it is possible to make the system features a priori.

The correction signals introduced into the optimization algorithm are really small. The introduced simulation of the MIMO controller results in higher performance. Evaluation of the control signals indicates a slight change in the magnitude of the input signals.

The application of multiparameter optimal control methods for coal-fired power plants was considered. In operation, the multi-SISO configuration is replaced by the optimal MIMO approach. In the performed simulation experiment, the following results were achieved:

- increasing the forecast horizon *n* allows increasing the productivity, since a more accurate prediction of the future error is possible;

VOL. 16, NO. 22, N0VEMBER 2021 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences



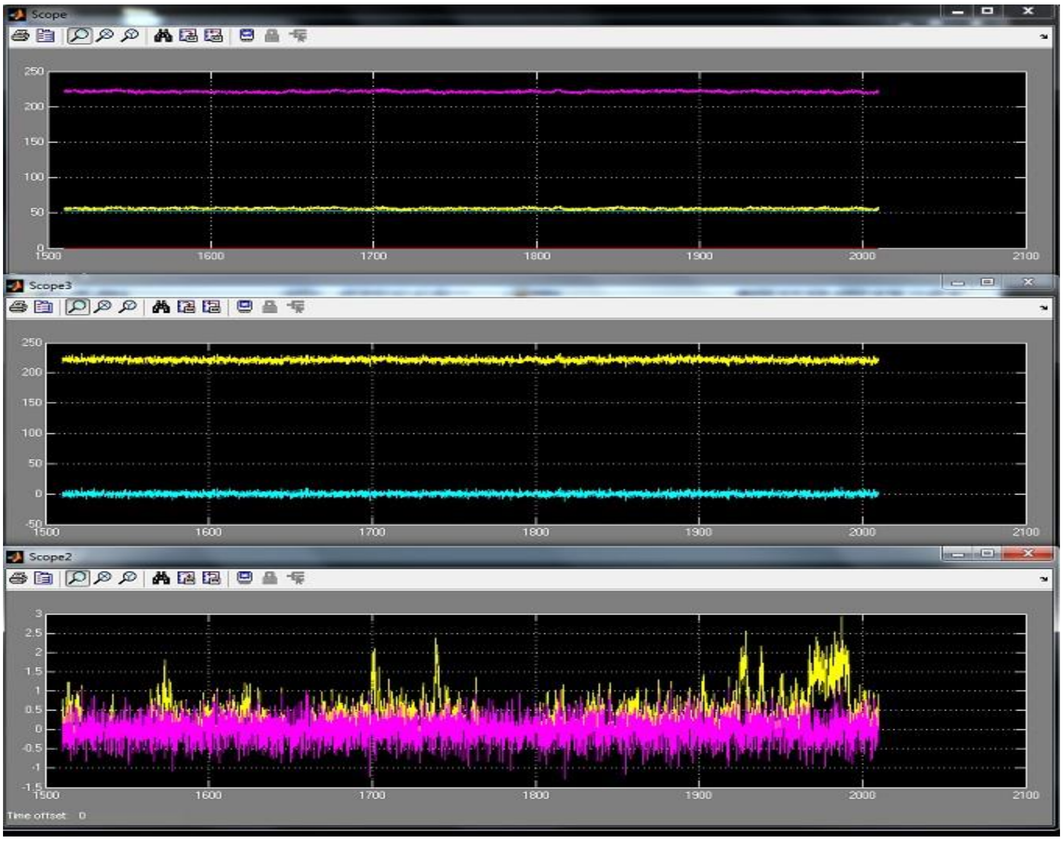


**Figure-10.** Examples of input and output signals in the course of the data collection.

- when using the temperature values, the error weight should be high due to the fact that the classic temperature control is slow and is responsible for the overall performance;
- the $\mu_u$ value should not be too large to avoid a radical change of the control action;
- the values of the upper control horizon return unwanted fluctuations.

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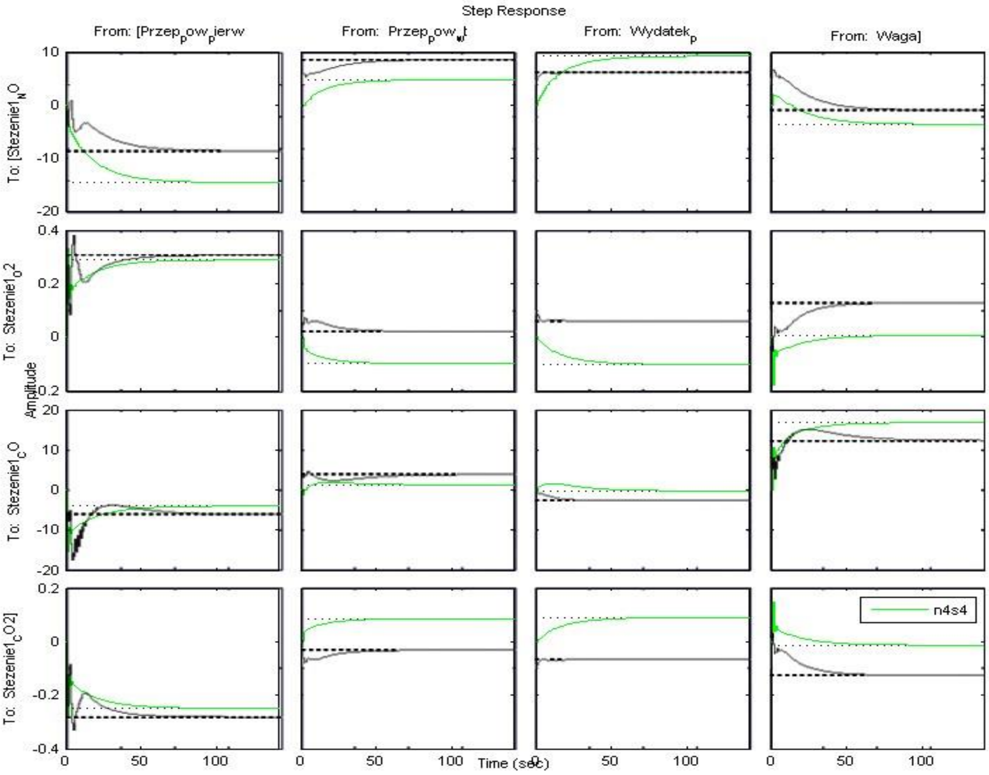


**Figure-11.** Controller response to a sudden change of the power load relative to the interaction between the $NO_x$, CO concentrations, the fume gases temperature in the combustion chamber.

## REFERENCES


[1] Yesmakhanova L. N. 2019. Controlling the combustion of pulverized coal using advanced technologies [Text]: monograph / L.N. Yesmakhanova. - Taraz: Taraz University. p. 100.

[2] Brudka M. 2000. Sieci neuronowe w sterowaniu robotem na podstawie obrazów ultradźwiękowych, praca doktorska, Politechnika Warszawska.

[3] Wójcik W., Smolarz A., Ballester J., Kotyra A., Kalita M., Sanz A., Hernández R. Neural methods of interpretation of data obtained from optical sensor for flame monitoring, Optical Fibers: Applications. Proceedings of SPIE vol. 5952, ISSN-0277-786X, ISBN 0-8194-5959-3.

[4] Wójcik W., Smolarz A. 2007. Stabilizacja emisji NOx z pojedynczego palnika pyłowego z wykorzystaniem NPC i neuronowej metody estymacji parametrów spalania, Pomiary Automatyka Kontrola, vol. 53, nr 11/, str. 20-23, ISSN 0032-4140.

[5] Wójcik W., Smolarz A. Wykorzystanie neuronowej metody estymacji parametrów spalania do regulacji pracy palnika pyłowego, Pomiary Automatyka Kontrola, nr 3/2005, s. 30-33, ISSN 0032-4110.

[6] Wójcik W., Kalita M., Smolarz A., Pilek B. 2005. Controlling combustion process in power boiler by genetic algorithm and neural network, Photonics Applications in Astronomy, Communications, Industry and High-Energy Physics Experiments III, Proceedings of SPIE. 5775: 348-353, ISSN 0277-786X, ISBN 0-8194-5756-6.

[7] Askarova A. S. 2010. Three-dimensional modeling of the processes of formation of harmful substances during the combustion of low-grade coals in combustion chambers [Text] / A.S. Askarova, S.A. Bolegenova, V.Yu. Maximov. Bulletin of the National Academy of Sciences of the Republic of Kazakhstan. (6): 15-18.

[8] Askarova A. S. 2012. Effect of the computational grid size on the results of computer modeling of heat and mass transfer processes in combustion chambers [Text] / A.S. Askarova, Bolegenova S.A., Maksimov V.Yu., Bekmukhamet A. Materials of the 18th All-Russian Scientific Conference of Young Scientists (VNKSF-18). - Krasnoyarsk: Publishing house of Russia. pp. 701-702.

[9] Novikov O. N. 2000. Energy-ecological optimization of fuel combustion in boilers and furnaces by regulating the fuel-air ratio [Text] / ON. Novikov, D.G. Artamonov, A.L. Shkarovsky, M.A. Kochergin, A.N. Okatiev. - M.: Industrial Energy. p. 288.

[10] Boryson A. E., Denham W., Dreyfus S. 1963. Optimal programing problem with inequality Constraints. Part I: Necessary Conditions for Extremal Solutions AiAA Jour. 1, pp. 2544-2550.

[11] Broomhead S. Lowe D. 1988. Multivariable functional interpolation and adaptive network - Complex Systems. 2: 321-323.

[12] Jaroszewski K. 2007. System diagnostyczny instalacji oczyszczania spalin elektrowni węglowej wykorzystujący sztuczne sieci neuronowe, praca doktorska, Politechnika Szczecińska.