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SIMULATION MODELING OF NEURAL CONTROL SYSTEM FOR SECTION OF MINE VENTILATION NETWORK

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Abstract: *Static and dynamic simulation models of a section of a mine ventilation network in order to research a sequential neural control scheme of mine airflow are developed in this paper. The techniques of neural network training set creation for both simulation models, a structure of neural network and its training algorithm are described. The simulation modeling results using static and dynamic models have showed good potential capabilities of neural control approach.*

Keywords: *Mine ventilation network, airflow control, neural network.*

1. INTRODUCTION

A problem of allowable concentration control of dangerous gases CH_4 and CO is very urgent in coal mines and other closed environments due to safety of the people working in such areas. For instance, coal mining industry is a tough industry in every country. For example, in 2001 there were 6.63 fatalities per million tons of coal equivalent (mtce) produced in China's mines, 0.02 fatalities per mtce in Australia, 0.83 in Russia, and 0.48 in India [1]. Therefore development of an Automated Control Systems for coal-mine ventilation in order to prevent fatalities is a crucial issue today. It is obvious, that recent advances in science and technology should be used to fulfill this task. Thus we should account two properties of such automatic ventilation control system at least: (i) the sensors must supply the system by accurate information in order to provide precise ventilation control and (ii) the system should provide adaptive ventilation control in normal and unexpected exploitation conditions.

Usage of multi-parameter sensors based on SnO_2 twin film, for example produced by Figaro Inc [2], is economically desirable for fulfillment of the first task. A high accuracy of a measurement system could be reached by using neural networks to recognize the output signal of the multi-parameter sensor [3-4].

A complexity of the second task is caused by (i) stochastic character of aerogasdynamic processes in mine ventilation networks (MVN), (ii) changing the MVN topology and parameters, (iii) huge distribution of the control system and large number of measurement sensors [5, 6]. The MVN aerogasdynamic processes are characterized as objects with distributed parameters where airflow dynamics is described by a system of differential equations with partial derivatives [6]. A solution of such a system for real objects requires high qualification of the mathematician and considerable computing power. It is expedient to note, than nonlinear characteristics make worse MVN modeling, in particularly airflow speed and foil gases concentration. Moreover additional factors such as noise, handicaps and plurality of feedbacks have complicated the control strategies. From the point of view of control theory coal mine ventilation is a multivariable control problem where acting in one MVN branch affects the airflow and concentration in the other branches in an unexpected way [7,8].

Most of the today's control strategies are based on an idea of system's linearization [9]. First of all it is necessary to develop adequate mathematical model for a practical implementation of this approach. However the mathematical modeling based on hypothesis of a linearity of the control object does not reflect its true properties. Non-linear mathematical models [6, 8] quite enough reflect real properties of the object, but they are quite complicated and, therefore, practically could not be used effectively for a control. Statistical models [10] can be classified as good models, but their assumptions often do not provide enough accuracy of the control system. Nowadays there are several well-known approaches to mine ventilation control such as prediction on methane emission by mathematical methods [11-12], analysis of ventilation control systems by operational research [13] and modeling of ventilation processes by correlation approach [14].

Against the mentioned above methods, adaptive control approaches [15-18] provides better control at reducing of complexity of mathematical model describing control object in terms of artificial neural network. A neural network-based approach can provide better results in comparison with other approaches due to high generalized properties, self-training and self-adaptation of neural network. Adaptive neural control is widely used in different areas, for example in aircraft industry [19], nonlinear [20] and robotic systems [21], chemistry [22], energy management [23], chaotic processes [24], medical science [25] etc.

The goal of this paper is to estimate neural-based method of airflow control for the section of mine ventilation network using two simulation models which describe a behavior of aero-gas processes in static and dynamic modes.

2. A SEQUENTIAL NEURAL CONTROL SCHEME

Preliminary analysis shown [15-18], that sequential neural control scheme (Fig. 1) could provide enough control efficiency due to absence of additional control branches such as additional controllers. The control is provided by the following way [18]: getting the reference signal r on the input, preliminary trained neural network (NN) recovers it to the control influence u for the control object. According to this control influence the control object changes own state and its output signal y which might be close to the reference signal r. If the state of control object is changed under external influence factors, then this changing goes to NN input. NN forms new control influence u in order to compensate the change of output signal y. In general case NN might have several inputs and outputs, therefore the variables described above might be considered as sets

$$r = \{r_1 \dots r_k\}, y = \{y_1 \dots y_l\}, \Delta = \{\Delta_1 \dots \Delta_n\}, u = \{u_1 \dots u_m\}.$$

It is seen from Fig. 1, the NN transforms input space of control object's states y into output space of control influences u.

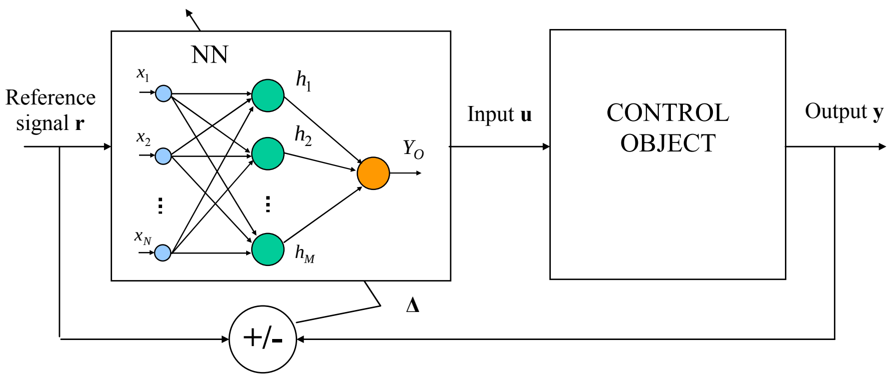

Fig. 1 – Sequential neural control scheme

3. NEURAL NETWORK MODEL

The multi-layer perceptron can be used for this research with nonlinear activation functions because this kind of NN has the advantage of being simple and widely used for the control problems [26-28].

The output value of three-layer perceptron (Fig. 2) can be formulated as:

$$y = F_3\left(\sum_{i=1}^{N} w_{i3} h_i - T\right), \qquad (3.1)$$

where N is the number of neurons in the hidden layer, w_{i3} is the weight of the synapse from neuron i in the hidden layer to the output neuron, h_i is the output of neuron i, T is the threshold of the output neuron and F_3 is the activation function of the output neuron.

The output value of neuron j in the hidden layer is given by:

$$h_j = F_2\left(\sum_{i=1}^{M} w_{ij} x_i - T_j\right), \qquad (3.2)$$

where w_{ij} are the weights from the input neurons to neuron j in the hidden layer, x_i are the input values and T_j is the threshold of neuron j. The logistic activation function is used for the neurons of the hidden layer and the linear activation function, having a coefficient k, is used for the output neuron [29].

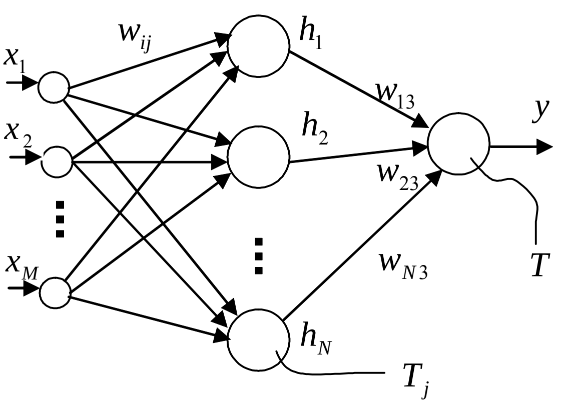

Fig. 2 – Structure of neural network

The back propagation error algorithm [30] is used for the training algorithm. It is based on the gradient descent method and provides an iterative procedure for the weights and thresholds updating for each training vector p of the training sample:

$$\Delta w_{ij}(t) = -\alpha \frac{\partial E^p(t)}{\partial w_{ij}(t)}, \ \Delta T_j(t) = -\alpha \frac{\partial E^p(t)}{\partial T_j(t)}, \quad (3.3)$$

where α is the learning rate, $\frac{\partial E^p(t)}{\partial w_{ij}(t)}$ and $\frac{\partial E^p(t)}{\partial T_j(t)}$ are the gradients of the error function on each iteration t for the training vector p with $p \in \{1,...,P\}$, where P is the size of the training set.

The Sum-Squared Error (SSE), for training iteration t, is calculated as:

$$E^p(t) = \frac{1}{2}\left(y^p(t) - d^p(t)\right)^2, \quad (3.4)$$

where for the training vector p, $y^p(t)$ is the output value on iteration t and $d^p(t)$ is the target output value.

During training, the total error is calculated as:

$$E(t) = \sum_{p=1}^{P} E^p(t). \quad (3.5)$$

The steepest descent method for calculating the learning rate [29] is used for removing the classical disadvantages of the back propagation error algorithm. Thus, the adaptive learning rate for the logistic and linear activation functions are given, respectively, by:

$$\alpha(t) = \frac{4}{\left(1+(x_i^p(t))^2\right)} \times \frac{\sum_{j=1}^{N} (\gamma_j^p(t))^2 h_j^p(t)(1-h_j^p(t))}{\left(\sum_{i=1}^{N} (\gamma_j^p(t))^2 (h_j^p(t))^2 (1-h_j^p(t))^2\right)},$$

$$\alpha(t) = \frac{1}{\sum_{i=1}^{N} (h_i^p(t))^2 + 1} \quad (3.6)$$

where, for the training vector p and iteration t, $\gamma_j^p(t)$ is the error of neuron j and $h_i^p(t)$ is the input signal of the linear neuron.

The error of neuron i with logistic activation function can be determined by the relation:

$$\gamma_i^p(t) = \sum_{j=1}^{N} \gamma_3^p(t) w_{i3}(t) h_j^p(t)(1-h_j^p(t)), \quad (3.7)$$

where $\gamma_3^p(t) = y^p(t) - d^p(t)$ is the error of the output neuron, $w_{i3}(t)$ is the weight of the synapses between the neurons of the hidden layer and the output neuron.

A slight modification of the back propagation error algorithm, called multiple propagation error, has been implemented in order to stabilize the training process [31]. This approach consists in modifying the weights of only one layer of the neural network during a single training iteration. This algorithm includes thus the following steps:

1. Set the desired value of SSE to $E_{\min}$;
2. Initialize the weights and the thresholds of the neurons by values in the range (0-0.5);
3. Set a counter for the number of neural network layers, $LAYERS$;
4. If $LAYERS = 2$ then calculate the output value $y^p(t)$ using expression (3.2) for the training vector p and perform the steps 5 and 6;
5. Calculate the error of the output neuron: $\gamma_3^p(t) = y^p(t) - d^p(t)$;
6. Update the weights and the thresholds of the output neuron by (3.3) using the adaptive learning rate given by (3.6);
7. Decrease the number of current layer $LAYERS$ by one unit;
8. If $LAYERS = 1$ then calculate the error $\gamma_j^p(t)$ of the neurons of the hidden layer by (3.7);
9. Update the weights and the thresholds of the neurons of the hidden layer by (3.3) using the adaptive learning rate (3.6) for the logistic activation function;
10. Calculate the SSE for the training iteration t using (3.4);
11. Repeat the steps from 3 to 10 for all the other vectors in the training set;

12. Calculate the total SSE, $E(t)$ of the neural network using (3.5);
13. If $E(t)$ is still greater than the desired error $E_{\min}$ then go to step 3, otherwise stop the training process.

4. AIRFLOW CONTROL MODEL OF MINE VENTILATION NETWORK IN STATIC MODE

4.1 SIMULATION MODEL OF MVN SECTION

The main task of MVN is to provide ventilation modes of mine sections taking into account high intensity of gas emission according to safety requirements [7]. The ventilation modes are characterized by airflow Q and methane concentration c within required MVN section. Safe concentration of methane c is provided by airflow adjustment ΔQ, which should be considered as a control influence in relation to the concentration c.

In static ventilation mode parameters Q and c are related by the following equation [6]:

$$c = \frac{Q_m}{Q_m + Q} \cdot 100\% , \qquad (4.1)$$

where Q_m is a methane emission to section's atmosphere.

The airflow adjustment $\Delta Q = Q_{t2} - Q_{t1}$ can be estimated by a concentration change $\Delta c = c_{t2} - c_{t1}$ at two sequential moments of time $t2$ and $t1$. Then the mine section can be divided on several parts which should be indexed by index s. Substituting the variables c_{t2} and c_{t1} in (4.1), we can derive an expression for concentration change

$$\Delta c = c_{t2} - c_{t1} = \frac{1}{Q_s}\left(\Delta Q_m - \frac{Q_m \cdot \Delta Q}{Q + \Delta Q}\right), \qquad (4.2)$$

where $Q_s = Q_m + Q$ is the change of methane and air mixture which form appropriate methane concentration in the MVN section with index s.

For example, the fragment of MVN section, where indexes *2*, *3*, *4*, *5* are numbering the parts of MVN, is presented on Fig. 3. Let us suppose that sensor *S1* is installed in main ventilation drift *2*, sensors *S2* and *S3* are installed in longwall *3*, *4*, sensor *S4* is installed in main entry *5*. Sensors *S1*-*S4* measure methane concentrations on the mentioned parts of MVN section. The numerical parameters of the simulation model are based on the real data of MVN sections gathered from work [6]. Thus the airflow adjustment for s-part of MVN section can be defined from equation (4.2)

$$\Delta Q = \frac{\Delta c \cdot Q_s^2}{Q_m - \Delta c \cdot Q_s} . \qquad (4.3)$$

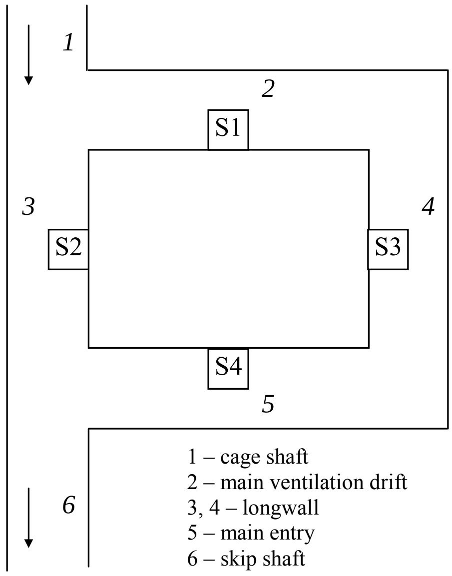

Fig. 3 – A fragment of mine ventilation network section used to design a simulation model

4.2 AIRFLOW NEURAL CONTROL MODEL

Let us suppose for the simulation model on Fig. 3, that methane concentration c can take the values from the set $\{0.6\%,\ 0.8\%,\ 1.0\%,\ 1.2\%,\ 1.4\%\}$. The methane concentration c=1.5% is a maximum allowable value (all people should be evacuated from the coal mine at $c \geq 1.5\%$) and methane concentration c=0.5% is a minimal with no necessity to ventilate. Then concentration change Δc will take the values from the set $\{0.1\%,\ 0.3\%,\ 0.5\%,\ 0.7\%,\ 0.9\%\}$ respectively. According to the sequential neural control scheme described in section 2, the concentrations $\Delta c_1 ... \Delta c_4$ from each of s-parts of MVN section should be the input data of NN, necessary airflow $\Delta Q_\Sigma = \sum_{i=1}^{4} Q_i$ (Fig. 4) should be the output value of NN (control sequence).

The algorithm for NN training set forming for the simulation model in Fig. 3 can be described as following:

1. To define all possible combinations of concentrations change $\Delta c_1 ... \Delta c_4$ according to possible values from the set above ;

2. To calculate the value of control influences $\Delta Q_1 ... \Delta Q_4$ using (4.1) and (4.3) for each s-part of MVN section and to calculate $\Delta Q_\Sigma = \sum_{i=1}^{4} Q_i$ for all possible combinations $\Delta c_1 ... \Delta c_4$ from point 1 above;
3. To save obtained NN training vectors according to the Table 1.

Table 1. Structure of the NN training vector within static simulation model

Input values				Output
c_1	c_2	c_3	c_4	
0.6	0.6	0.6	0.6	106.4
…	…	…	…	…
1.4	1.4	1.4	1.4	957.6

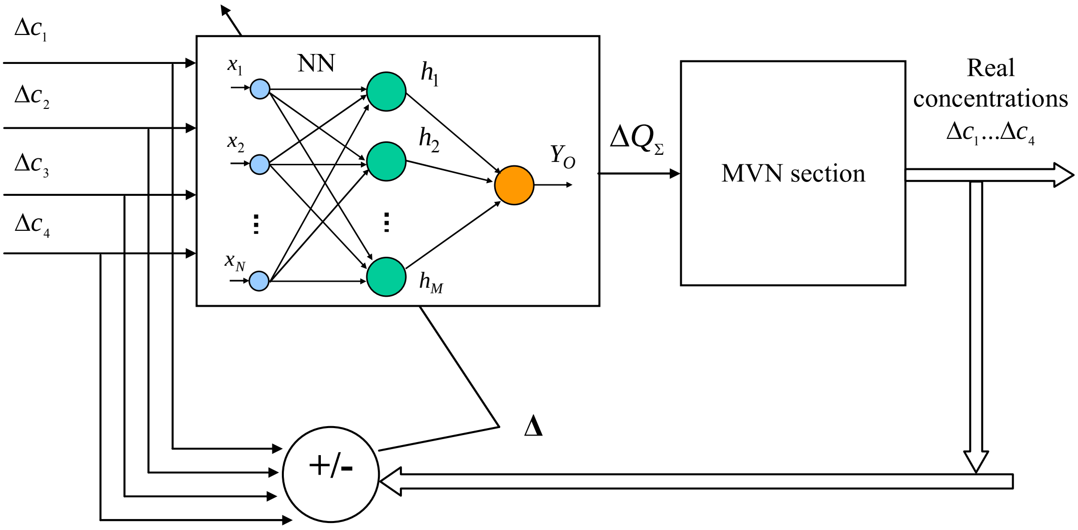

Fig. 4 - Airflow neural control model in static mode

4.3 SIMULATION MODELING RESULTS

Simulation modeling should show experimentally the optimal choice of NN structure and its training parameters from the point of view of accuracy of control influences recovering and real time operation [32].

During the experiments the NN is trained on 400 vectors. It tested on 225 testing vectors which did not included in the training set. Simulation modeling results with different number of the hidden layer neurons are shown on Fig. 5. The relative error of control influences recovering is increasing from 0.1% to 8% at increasing the number of hidden layer neurons from 5 to 30. Also the training time is increased from 8 to 15-20 seconds. Therefore, NN structure 4-5-1 provides better result, i.e. minimal relative error of control influence recovering and minimal training time.

Therefore let us use this NN model further to investigate the training parameters. Simulation modeling results with different values of SSE are shown on Fig. 6. The relative error of control influences recovering does not exceed 1% and decreases till 0.07% at increasing of SSE till 10^{-8}, the training time is increasing from 5 to 30 seconds respectively. The relative error of control influences recovering is allowable for all values of SSE according to the safety rules of mine ventilation. Therefore necessary SSE values for the training should be chosen to provide needed real working time of mine ventilation system.

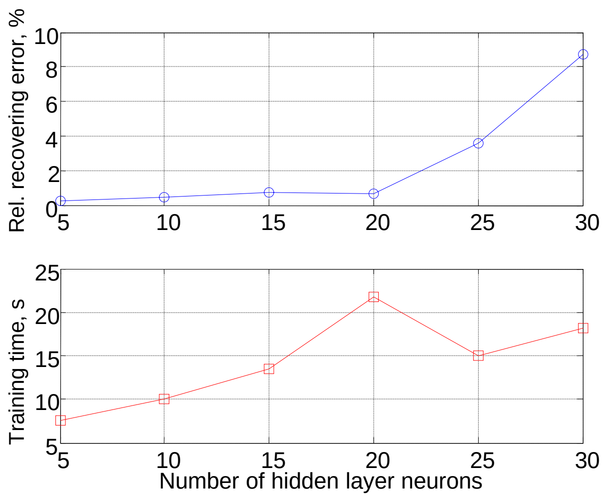

Fig. 5 – Dependencies of relative recovering error and training time from the number of hidden layer neurons

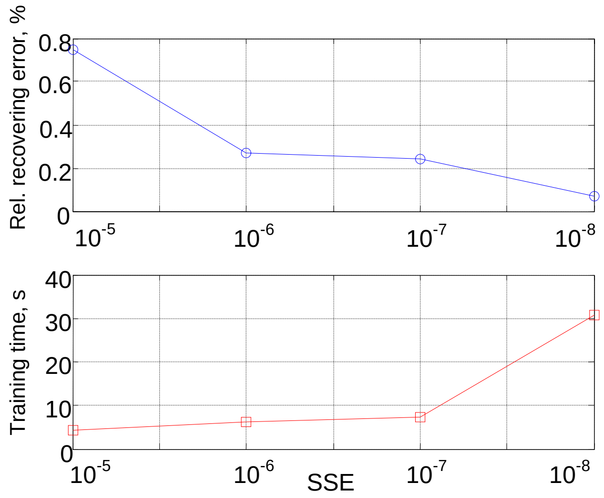

Fig. 6 – Dependencies of relative recovering error and training time from the SSE values

5. AIRFLOW CONTROL MODEL OF MINE VENTILATION NETWORK IN DYNAMIC MODE

5.1 SIMULATION MODEL OF MVN SECTION

In order to build a simulation model of MVN section in dynamic mode it is necessary to consider one of the most distributed ventilation scheme of coal-mine section [7] with trilateral fitting of mined-out space (forward way) to entry, longwall and ventilation drift (Fig. 7).

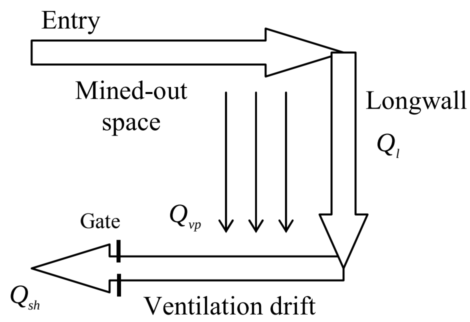

Fig. 7 - Ventilation scheme of coal-mine section with trilateral fitting of mined-out space

The coal-mine section as a control object in general is described by differential equation [6] of transient aerodynamic process of airflow Q forming in the entry caused by a depression H provided by main ventilation fans and aerodynamic resistances of the section R and the gate RR, which adjusts outgoing airflow from ventilation drift (see Fig. 7).

$$\frac{dQ}{dt} = \frac{1}{k}\left(H - R\cdot Q\cdot|Q| - RR\cdot Q\cdot|Q|\right), \qquad (5.1)$$

where $k = \frac{\rho \cdot l}{S}$ is inertia coefficient, which can be defined by air density ρ, section length l and equivalent cross-section S of the coal-mine section.

Danger methane concentration in coal-mine section is caused by methane debits of the following components: mined-out space, longwall and ventilation drift. However the ventilation process changes the values of methane concentrations in these components. Therefore it is necessary to create the simulation models, which describe the debits and charges of each component in order to develop the simulation model of whole MVN section.

A model of aerogas environment of mined-out space should describe transient aerodynamic processes in the open area, which remains after mining the coal banks, and therefore it should be considered as filtration space. Airflow filtration in this case is caused by distributed difference of pressures among the shafts and non-linear aerodynamic resistance of mined-out space. Dynamics of methane debit Q_m from mined-out space is described by model [6]

$$T_m \frac{dQ_m}{dt} + Q_m = Q_{0m} + \beta \frac{dQ^2}{dt}, \qquad (5.2)$$

where T_m is a time constant, Q_{0m} is initial methane volume in mined-out space, β is specific aerodynamic resistance of mined-out space.

However the expression (5.2) is not convenient for creation of simulation software because of $\frac{dQ^2}{dt}$ part of the expression. Therefore it is necessary to integrate both left and right parts of the expression and remove the differential at Q^2

$$Q_m = \frac{1}{T_m}\int (Q_{0m} - Q_m)dt + \frac{\beta}{T_m}Q^2. \qquad (5.3)$$

The methane, which gets out from the sources in the mined-out space, is mixed with the airflow that creates the debit of air-methane mixture Q_{vp} on the all length of ventilation drift with methane concentration C_{vp}. The dynamics of this process is described by expression [6]

$$\frac{dC_{vp}}{dt} = \frac{1}{V_{vp}}\left(Q_m - (Q_m + Q_{vp})\cdot C_{vp}\right), \qquad (5.4)$$

where V_{vp} is a volume of mined-out space.

The longwall is the place of direct coal mining. The slope angle of the longwall is equal of the occurrence angle of the coal banks. A model of aerogas environment of longwall should account transient process of longwall atmosphere saturation by the methane. It can be described by the following differential equation [6]

$$\frac{dC_l}{dt} = \frac{1}{V_l}\left(Q_{ml} - (Q_l + Q_{ml}) \cdot C_l\right), \qquad (5.5)$$

where V_l is a volume of longwall, Q_{ml} is a volume of the methane in longwall, Q_l is a volume of the air in the mixture, C_l is a methane concentration in the longwall.

The debit of air-methane mixtures from mined-out space Q_{vp} and longwall $Q_l + Q_{ml}$ forms the resulting flow of air-methane mixture Q_{sh} in the ventilation drift with methane concentration C_{sh}. A model of aerogas environment of ventilation drift is described by the following differential equation [6]

$$\frac{dC_{sh}}{dt} = \frac{1}{V_{sh}}\left(Q_{md} + Q_{mld} - (Q + Q_{mld} + Q_{md}) \cdot C_{sh}\right), \qquad (5.6)$$

where Q_{md} is a volume of methane gets out from the mined-out space, Q_{mld} is a volume of methane gets out from the longwall, V_{sh} is a volume of ventilation drift.

Let us use this simulation model for neural-control system described in the following section.

5.2 AIRFLOW NEURAL CONTROL MODEL

The main difference of a control system based on dynamic simulation model against previous static model is usage of a simulated time on the NN input (Fig. 8). Because NN training and NN-based control is fulfilled on the simulation model developed in the section 5.1. It is obvious, that real time will be used on the NN input in real exploitation conditions of the control system.

During training the training set, consisting from several curves, which describe the dynamics of aero-gas environment of coal-mine section, is putted on NN input. These curves are obtained during simulation modeling of models (5.1)-(5.6) in MATLAB/Simulink tool. The structure of NN input training vector is presented in Table 2.

The goal of training is decreasing of appropriate concentrations C_{vp}, C_l, C_{sh} to safe level without methane outbursts in the parts of coal-mine section by changing airflow $Q(t)$. These outbursts are caused by airflow $Q(t)$ jumps during the control and they outperform allowable limit concentrations. The NN training process, characterized by iterative modifications of NN synapses and thresholds, is depicted by stroke line in Fig. 8.

In the control mode NN recovers desirable curve of airflow $Q(t)$ for appropriate values of input concentrations C_{vp}, C_l, C_{sh} and their absolute errors $\Delta C_{vp}, \Delta C_l, \Delta C_{sh}$. In the control mode the synapses and thresholds of NN do not change, the stroke line on Fig. 8 does not work.

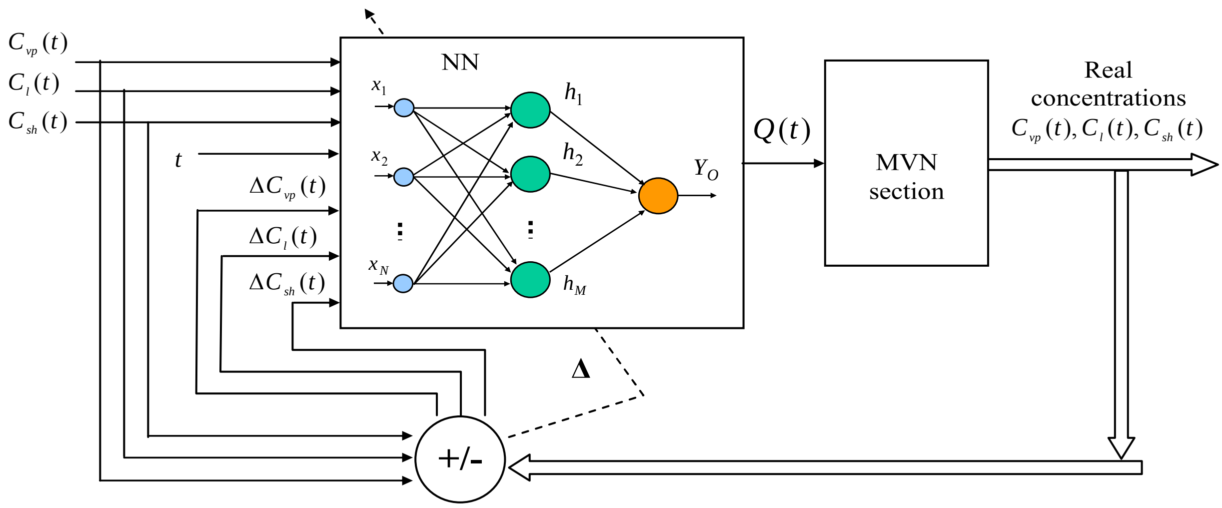

Fig. 8 - Airflow neural control system in dynamic mode

Table 2. Structure of NN training vector within dynamic simulation model

Input NN values							Output NN value
$C_{vp}(t)$	$C_l(t)$	$C_{sh}(t)$	$\Delta C_{vp}(t)$	$\Delta C_l(t)$	$\Delta C_{sh}(t)$	t	$Q(t)$
%	%	%	%	%	%	seconds	m^3/seconds

5.3 SIMULATION MODELING RESULTS

The response of the system (changing methane concentrations C_{vp}, C_l, C_{sh}), caused by step junction of the airflow at point-to-point control is showed on Fig. 9. As it is shown the point-to-point control approach does not provide necessary allowable limitations of the control object. We can see huge methane outbursts (up to 11% concentration in the mined-out space and up to 3.5% concentration in the ventilation drift) at airflow jump. These outbursts are caused by accumulation of the methane in places with low quantity of air circulation and methane blowing at jumped changing of the section's airflow [6].

The response of the system does not have methane concentration outbursts (Fig. 10) at usage of neural control system. It is caused by non-linear airflow changing that is provided by non-linear internal synapses and thresholds of NN. Usage of NN provides necessary airflow dynamics at different values of methane concentrations C_{vp}, C_l, C_{sh} and its absolute errors $\Delta C_{vp}, \Delta C_l, \Delta C_{sh}$.

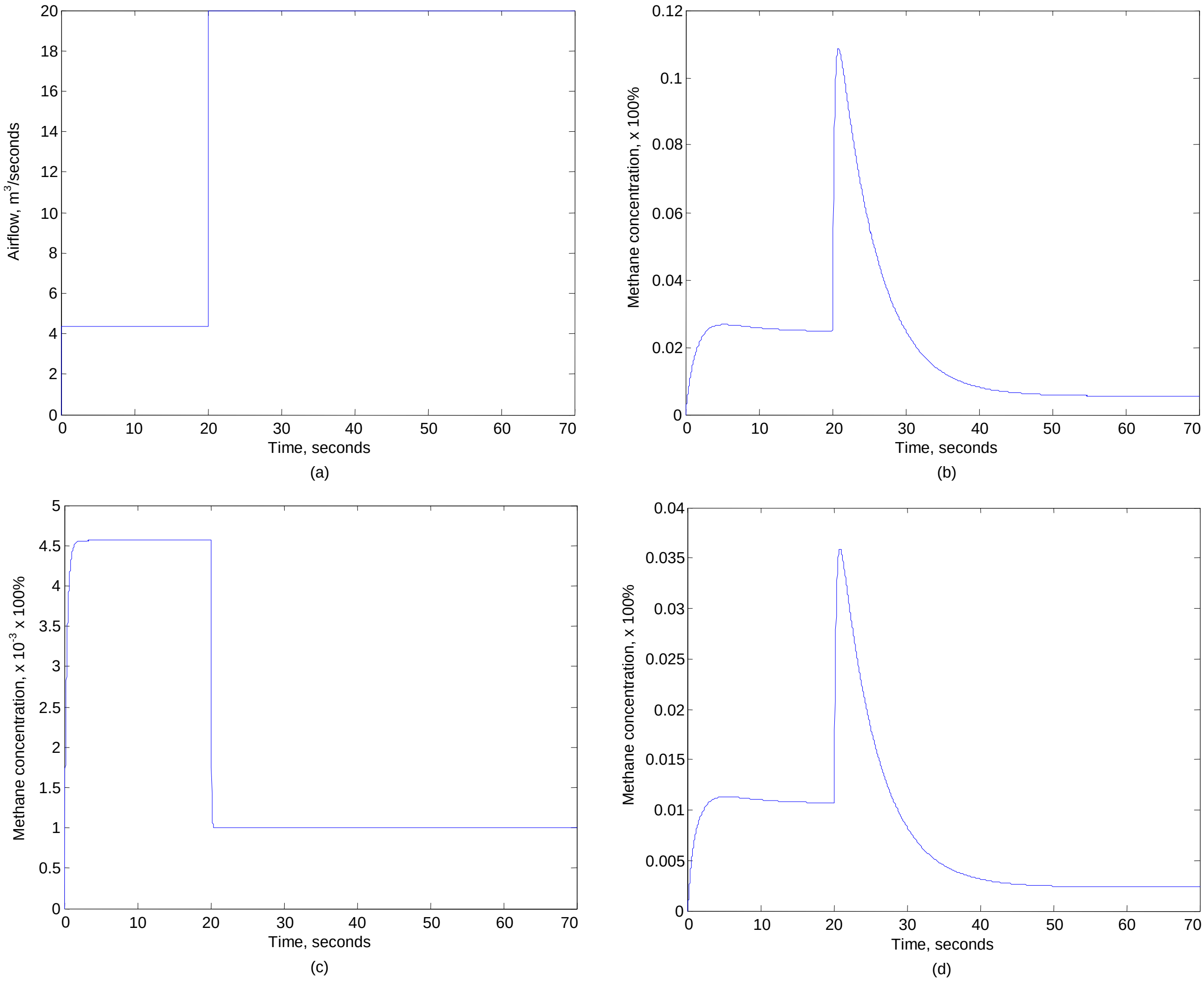

Fig. 9. Changing methane concentrations in mined-out space (b), longwall (c) and ventilation drift (d) at point-to-point airflow control (a)

6. CONCLUSIONS

The simulation models of coal-mine section in static and dynamic modes are developed in this paper. The simulation model in static mode allows just estimate the potential capabilities of artificial neural networks for airflow control in mine ventilation networks. The dynamic simulation model adequately represents the dynamics of aerogas processes in the sections of mine ventilation networks [6]. Simulation modeling results gathered on dynamic model is showed better control quality in comparison with widely used point-to-point approach. However neural control method is considerably increased the transient process time of airflow control. For future research it is necessary to optimize the neural network method towards decreasing the transient process time.

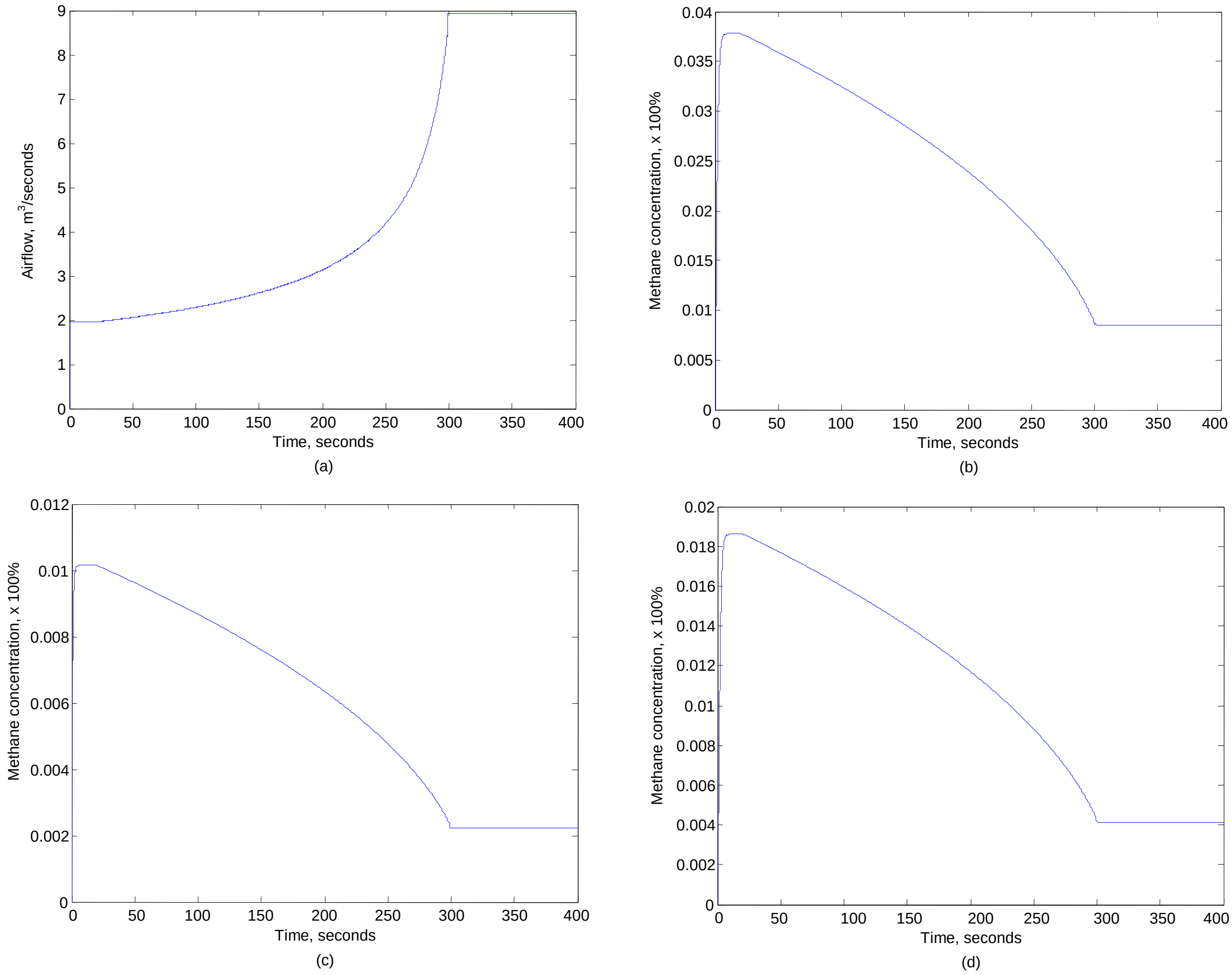

Fig. 10. Changing methane concentrations in mined-out space (b), longwall (c) and ventilation drift (d) at neural airflow control (a)

7. REFERENCES

[1] http://www.sinomedia.net/eurobiz/v200402/regional0402.html

[2] http://www.figarosensor.com/gaslist.html

[3] I. Turchenko. Simulation Modeling of Multi-Parameter Sensor Signal Identification Using Neural Networks. *Proceedings of the "Second IEEE International Conference on Intelligent Systems"*, Varna, Bulgaria, 2004, vol. 3, pp. 48-53.

[4] I. Turchenko, V. Kochan, A. Sachenko. Neural-Based Recognition of Multi-Parameter Sensor Signal Described by Mathematical Model, *International Scientific Journal of Computing* 3 (2) (2004). p. 140-147.

[5] L.A. Puchkov, L.A. Bahvalov. *Methods and algorithms of automatic control of coal mine ventilations*. Nedra. Moscow, 1992. p. 399 (in Russian).

[6] F.A. Abramov, L.P. Feldman, V.A. Svjatnyj. *Modelling of dymanic processes in mine aerology*. Naukova dumka. Kiev, 1981. p. 284 (in Russian).

[7] V.A. Svjatnyj, S.S. Efremov. Development of the structure and operating algorithms of a microprocessor-based safe control system for mine ventilation, *Mekh. Avtomat. Upravleniya* (4) (1983). p. 31–34 (in Russian).

[8] Hu Y., O. Koroleva, M. Krstic. Nonlinear control of mine ventilation networks, *Systems and Control Letters* 49 (4) (2003). p. 239-254.

[9] B. Kosko. *Neural Networks for Signal Processing*. New Jersey: Prentice Hall, Englewood Cliffs, 1992.

[10] G. Box, G. Jenkins. *Time Series analysis: Forecasting and Control*. Holden-Day. San Francisco, 1976.

[11] L. Lunarzewski. Gas emission prediction and recovery in underground coal mines, *International Journal of Coal Geology* 35 (1-4) (1998). p. 117-145.

[12] K. Noack. Control of gas emissions in underground coal mines, *International Journal of Coal Geology* 35 (1-4) (1998). p. 57-82.
[13] X. Wu, E. Topuz. Analysis of mine ventilation systems using operations research methods, *International Transactions in Operational Research* 5 (4) (1998). p. 245-254.
[14] I. Lowndes, A. Crossley, Z. Yang. The ventilation and climate modelling of rapid development tunnel drivages, *Tunneling and Underground Space Technology* 19 (2) (2004). p. 139-150.
[15] P.J. Werbos. *Overview of Design and Capabilities in Neural Networks for Control*. MIT Press, Cambridge (MA), 1990. p. 59-65.
[16] K. Astrom. Towards Intelligent Control, *IEEE Control Systems Magazine* 9 (1989). p. 60-69.
[17] D. White, D. Sofge. *Handbook of Intelligent Control*. Van Nostrand Reinhold. New York, 1992.
[18] S. Omatu, M. Halid, R. Yusof. *Neuro-control and its applications*. Editors A. I. Galushkin, V. A. Ptichkin. IPRZHR. Moscow, 2000. p. 272 (in Russian).
[19] P. Melin, O. Castillo. Adaptive intelligent control of aircraft systems with a hybrid approach combining neural networks, fuzzy logic and fractal theory, *Applied Soft Computing Journal* 3 (4) (2003). p. 353-362.
[20] A. Calise, N. Hovakimyan, M. Idan. Adaptive output feedback control of nonlinear systems using neural networks, *Automatica* 37 (8) (2001). p. 1201-1211.
[21] S. Yildirim. Adaptive robust neural controller for robots, *Robotics and Autonomous Systems* 46 (3) (2004). p. 175-184.
[22] C. Ng, M. Hussain. Hybrid neural network – prior knowledge model in temperature control of a semi-batch polymerization process, *Chemical Engineering and Processing* 43 (4) (2004). p. 559-570.
[23] Y. Oysal. A comparative study of adaptive load frequency controller designs in a power system with dynamic neural network models, *Energy Conversion and Management* 46 (15-16) (2005). p. 2656-2668.
[24] E. Sanchez, L. Ricalde. Chaos control and synchronization, with input saturation, via recurrent neural networks, *Neural Networks* 16 (5-6) (2003). p. 711-717.
[25] K. Kashihara, T. Kawada, K. Uemura, M. Sugimachi, K. Sunagawa. Adaptive Predictive Control of Arterial Blood Pressure Based on a Neural Network During Acute Hypotension, *Annals of Biomedical Engineering* 32 (10) (2004). p. 1365-1383.
[26] K. Hornik, M. Stinchcombe, H. White. Multilayer Feedforward Networks are Universal Approximators, *Neural Networks* 2 (1989). p. 359-366.
[27] M. Saerens, A. Soquet. A Neural Controller Based on Backpropagation Algorithm, *Proceedings of "First IEE International Conference on Artificial Neural Networks"*, London, UK, 1989. pp. 211-215.
[28] Y. Iiguni, H. Sakai, H. Tokumaru. A Non-linear Regulator Design in the Presence of System Uncertainties Using Multi-layered Neural Networks, *IEEE Transactions on Neural Networks* 2 (1991). p. 410-417.
[29] V. Golovko. *Neural Networks: training, models and applications,* Radiotechnika, Moscow, 2001, p. 256 (in Russian).
[30] D. Rumelhart, G. Hinton, R. Williams. Learning representation by back-propagation errors, *Nature* (323) (1986). p. 533-536.
[31] V. Golovko, Y. Savitsky, T. Laopoulos, A. Sachenko, L. Grandinetti. Technique of Learning Rate Estimation for Efficient Training of MLP, *Proceedings of the "IEEE-INNS-ENNS International Joint Conference on Neural Networks (IJCNN'2000)",* Como, Italy, 2000, vol. 1, pp. 323-328.
[32] I. Turchenko, V. Kochan, A. Sachenko. Simulation Modeling of Neural Control System for Coal Mine Ventilation, *Proceedings of the Fourth International Conference on Neural Networks and Artificial Intelligence (ICNNAI`2006)*, 2006, Brest (Belarus), pp. 93-98.

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