Simulation Modelling of Neural Control System for Coal Mine Ventilation

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Abstract: *In this paper it is developed simple simulation model of a mine section in order to model sequential neural control scheme of the mine airflow. A technique of neural network's training set forming, neural network structure and a training algorithm are described. The results of simulation modeling of control influence recovering are considered in the end of paper.*

***Keywords*:** Neural control system, coal mine ventilation, neural networks.

I. 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. 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 possible unexpected conditions.

Economically desirable for fulfillment of the first task is using multi-parameter sensors based on SnO_2 twin film, for example produced by Figaro Inc [2]. High accuracy of a measurement system could be reached by using neural networks to process 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 control strategies. From the point of view of control theory coal mine ventilation is a multivariable control problem where acting in one branch of MVN can affect the airflow and concentration in the other branches in an unexpected way. Therefore aerogasdynamic processes of MVN should be described by a complicate mathematical model [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 models 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 [8] quite enough reflect real properties of the objects but they are quite complicated and, therefore, practically cannot 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 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 modelling of ventilation process 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 networks. Adaptive neural control is widely using now 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 the method of airflow neural control on the section of mine ventilation network using its simulation model.

II. SIMULATION MODEL OF THE SECTION OF MINE VENTILATION NETWORK

It is expedient to consider simple structure of the section of MVN for development of its simulation model in order to estimate potential possibilities of a neural control system. A fragment of the MVN section is presented on Fig. 1, where the section's parts are numbered by appropriate numbers. Let us suppose that the sensor *S1* is installed in the main ventilation bord *2*, the sensors *S2* and *S3* are installed in the mine galleries and the sensor *S4* is installed in entry *5*. Sensors *S1-S4* measure methane concentrations in the appropriate parts of the section. The numerical parameters of the simulation model (lengths and crosscuts of the galleries) are gathered from [6].

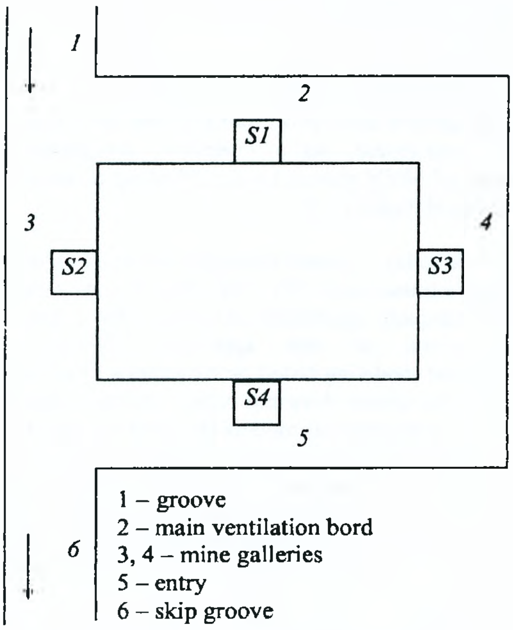

Fig. 1 – A fragment of mine ventilation network section used to design a simulation model.

Thc main task of MVN is to provide ventilation modes of mine sections in condition of high intensity of gas emission according to safety requirements [6]. The ventilation modes are characterized by airflow Q and methane concentration c on the required sections of MVN. Let us consider stable ventilation modes, where parameters Q and c are interrelated by the following equation [6]:

$$c = \frac{Q_m}{Q_m + Q} \cdot 100\%, \tag{2.1}$$

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

Saf concentration of methane c is provided by airflow adjustment ΔQ, which should be considered as control influence in relation to concentration c. The airflow adjustment ΔQ can be estimated by concentration change Δc at two necessary moments of time. Let us consider methane concentrations c_1 and c_2 in first and second moments of time. Then, substituting these variables in (2.1), we can derive an expression for concentration change

$$\Delta c = c_2 - c_1 = \frac{1}{Q_t}\left(\Delta Q_m - \frac{Q_m \cdot \Delta Q}{Q + \Delta Q}\right), \tag{2.2}$$

where $Q_t = Q_m + Q$ is the change of methane and air mixture to form appropriate methane concentration in the section with index t. In a case of simple simulation model it is considered four sections *2, 3, 4, 5* from Fig. 1 with installed sensors *S1-S4* respectively. Now the airflow adjustment in the section with index t can be derived from equation (2.2)

$$\Delta Q = \frac{\Delta c \cdot Q_t^2}{Q_m - \Delta c \cdot Q_t}. \tag{2.3}$$

III. SEQUENTIAL NEURAL CONTROL SCHEME OF THE MINE AIRFLOW

Preliminary analysis shown [15-18], that sequential neural control scheme (Fig. 2) can 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 reference signal r on the input, preliminary trained neural network 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 reference signal r. If under external influence factors the state of control object is changed, then this changing goes to neural network input. Neural network forms new control influence u in order to compensate the change of output signal y. In general case neural network 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. 2, that neural controller transforms input space of control object's states y into output space of control influences u.

Let us suppose for the simulation model from Fig. 1, that methane concentration c can take on values from the set $\{0.6\%, 0.8\%, 1.0\%, 1.2\%, 1.4\%\}$. Let us suppose, that methane concentration c=1.5% is a maximum (after it increasing all people should be evacuated from the mine) and methane concentration c=0.5% is a minimal with no necessity to ventilate. Then concentration change Δc should take on values from the set $\{0.1\%, 0.3\%, 0.5\%, 0.7\%, 0.9\%\}$ respectively. The algorithm for neural network's training set forming for the simulation model from Fig. 1 can be described as following:

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

2. To calculate the value of control influences $\Delta Q_1 .. \Delta Q_4$ using (2.1) and (2.3) 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 training vectors of neural network according to the Table 1.

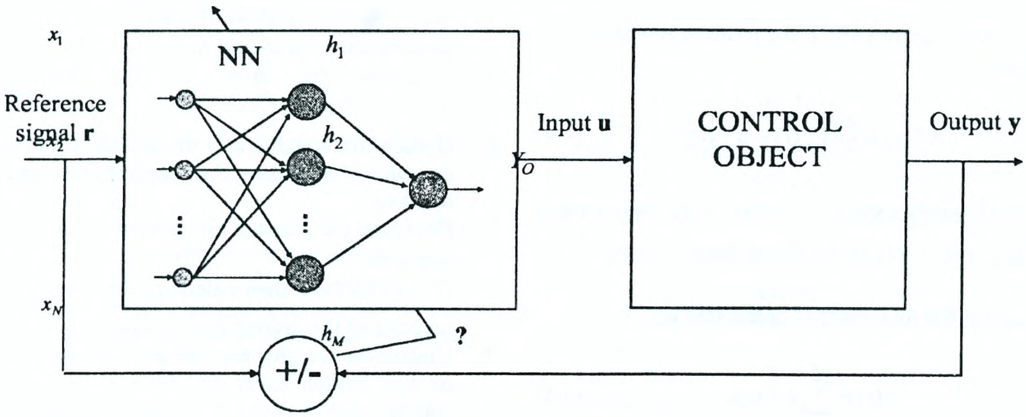

Fig. 2 – Sequential neural control scheme

Table 1. Structure of the training vector of neural network

Input values				Output value ΔQ_Σ, m^3/min
c_1	c_2	c_3	c_4	
0.6	0.6	0.6	0.6	1064
...	...	...	...	...
1.4	1.4	1.4	1.4	9576

IV. NEURAL NETWORK MODEL

It is seen from Table 1 that neural network should have four input and one output neurons. The multi-layer perceptron can be used for this research with nonlinear activation functions because this kind of neural network has the advantage of being simple and widely used for the control problems [26-28].

The output value of three-layer perceptron (Fig. 3) can be formulated as:

$$y = F_3\left(\sum_{i=1}^{N} w_{i3} h_i - T\right), \qquad (4.1)$$

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:

$$h_j = F_2\left(\sum_{i=1}^{M} w_{ij} x_i - T_j\right), \qquad (4.2)$$

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].

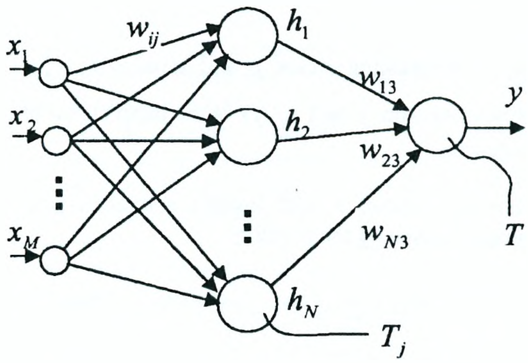

Fig. 3 – Structure of neural network

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:

$$\Delta w_{ij}(t) = -\alpha \frac{\partial E^p(t)}{\partial w_{ij}(t)}, \quad \Delta T_j(t) = -\alpha \frac{\partial E^p(t)}{\partial T_j(t)}, \qquad (4.3)$$

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:

$$E^{p}(t)=\frac{1}{2}\left(y^{p}(t)-d^{p}(t)\right)^{2}, \qquad (4.4)$$

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:

$$E(t)=\sum_{p=1}^{P} E^{p}(t). \qquad (4.5)$$

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:

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

$$\alpha(t)=\frac{1}{\sum_{i=1}^{N}(h_{i}^{p}(t))^{2}+1} \qquad (4.6)$$

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:

$$\gamma_{i}^{p}(t)=\sum_{j=1}^{N}\gamma_{3}^{p}(t)w_{i3}(t)h_{j}^{p}(t)(1-h_{j}^{p}(t)), \qquad (4.7)$$

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 (4.2) 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 (4.3) using the adaptive learning rate given by (4.6);
7. Decrease the number of current layer $LAYERS$ by one unit;
8. If $LAYERS=1$ then calculate the error $\gamma_{i}^{p}(t)$ of the neurons of the hidden layer by (4.7);
9. Update the weights and the thresholds of the neurons of the hidden layer by (4.3) using the adaptive learning rate (4.6) for the logistic activation function;
10. Calculate the SSE for the training iteration t using (4.4);
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 (4.5);
13. If $E(t)$ is still greater than the desired error $E_{\min}$ then go to step 3, otherwise stop the training process.

V. SIMULATION MODELING RESULTS

Simulation modeling should show experimentally the optimal choice of neural network structure and its training parameters from the point of view accuracy of control influences recovering and providing real time operations. During the experiments neural network 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. 4. 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, neural network structure 4-5-1 provides better result, i.e. minimal relative error of control influence recovering and minimal training time.

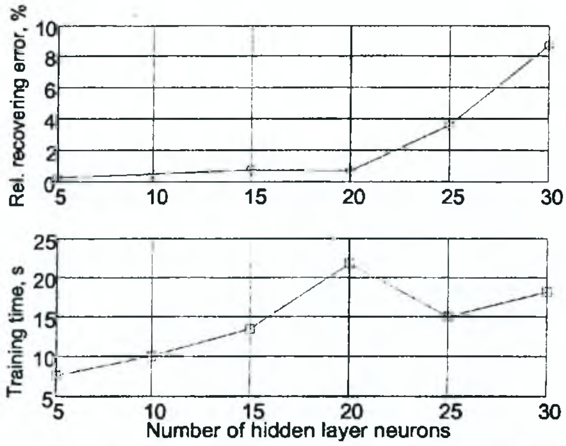

Fig. 4 – Dependencies of relative recovering error and training time from the number of hidden layer neurons

Therefore let us use this model of neural network to investigate the parameters of neural network training. Simulation modeling results with different values of SSE are shown on Fig. 5. 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 rime of model working.

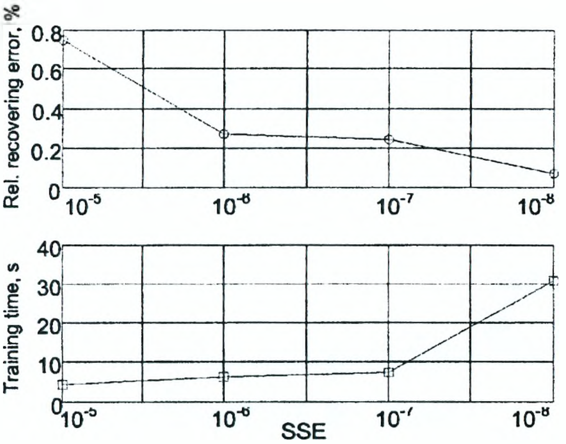

Fig. 5 – Dependencies of relative recovering error and training time from the SSE values

VI. CONCLUSIONS

A simple simulation model of the section of mine ventilation network and a technique of training set creation for neural control of the airflow are developed in this paper. The simulation modeling results have shown good potential capabilities of neural control of mine airflow in the real time. Future researches it is expedient to fulfill using complicated simulation model of the airflow in mine ventilation networks.

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