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FORECASTING THE AEROGAS STATE OF MINE ATMOSPHERE WITH APPLICATION OF ARTIFICIAL NEURAL NETWORKS

Purpose. Development of a method for forecasting a highly dynamic process of changing the concentration of explosive gases in a mine using artificial neural networks that allow considering external factors. Nowadays, increase in industrial safety in the mining industry is solved at the expense of introduction of modern computer systems of the aerogas control at the enterprises; the systems' work is aimed at the forecast of parameters of the environment condition. In this regard, the introduction of computer systems based on the use of artificial neural networks allows providing valid recommendations for the adoption of optimal technological and management solutions.

Methodology. Forecasting the aerogas state of the mine atmosphere is based on the use of artificial neural networks, autoregressive models and meta-heuristics.

Findings. Nowadays, the main measures for the forecast of methane concentration are aimed at finding the dynamics regularities of gas concentration, which served as the basis for forecasting gas-dynamic phenomena. The main results were obtained in studies of the dynamics of methane concentration using telemetric monitoring devices. This approach is based on the use of linear models. The proposed use of non-linear forecast models based on artificial neural networks provides more accurate forecasts comparing to widely used linear models.

Originality. In the framework of forecasting the air-gas state of the mine atmosphere, artificial neural networks and autoregressive models were further developed. At the same time, the autoregressive forecast model was improved by adding the exogenous factors to its structure, which are the measured dynamic parameters of the aerogas state of mine developments. To adapt the model, the meta-heuristic algorithm is improved.

Practical value. The results of the experiments showed that the proposed artificial neural network proved to be more effective for solving the problem of forecasting the aerogas state of the mine atmosphere in comparison with the existing approach. Numerical studies have shown that the proposed model allows increasing accuracy of the forecast by 10 % in comparison with the widely used gradient methods. The positive economic effect from introduction of the proposed approach is to reduce the likelihood of emergencies, which leads to a reduction in financial costs aimed at eliminating the consequences of accidents.

Keywords: *forecast, neural network, autoregressive model, exogenous factors*

Introduction. Currently one of the most important problems in the mining industry is the increase in production safety. Today this problem is solved by introduction of modern computer systems of aerogas control at enterprises, whose operation is aimed at improving the safety of operations, improving the working conditions of personnel, forecasting the parameters of the environment's state, early detection of the beginning of development of emergency situations, timely submission of instructions on behavior in extreme situations and on the elimination of accidents. The main objective of introducing computer systems is to increase the technical and economic indicators of coal-mining enterprises by analysis and multi-level forecast of the state of all mining developments with the aim of issuing recommendations for the adoption of optimal technological and managerial decisions. Such measures would allow reducing losses from the elimination of the consequences of accidents. However, currently, the systems used in mines, do not provide for the possibility of a comprehensive forecast of the content of explosive gases. This leads to the fact that measures aimed at preventing accidents or mitigating their consequences can be held too late. Due to the lack of effective systems of forecasting explosive situations, accidents at mines continue, which leads to a partial or total stoppage of coal production, which in turn entails serious economic losses, and the lack of funds to eliminate the consequences of accidents leads to complete cessation of the enterprise operations. At the same time, it is becoming obvious that the cost of control systems for aerogas condition of the mine atmosphere is significantly lower than the damage that can result in corresponding accidents.

Thus, the problem of forecasting the aerogas state of mine atmosphere is topical, and its solution using artificial neural networks is based on the application of a modern and effective approach. It is important to have information about the state of a mining facility for further analysis of the data obtained by the information automated control and diagnostic systems.

Analysis of the recent research and publications. Nowadays, the main measures for the forecast of methane concentration are aimed at finding the dynamics regularities of gas concentration, which served as the basis for forecasting gas-dynamic phenomena. The main results were obtained in studies on the dynamics of methane concentration using telemetric monitoring devices [1]. The optoelectronic computerized measuring systems of methane concentration have also been developed and updated [2, 3].

Among the software methods and methods of forecasting, works of foreign scientists should be noted [4], which consider modern methods and methods of forecasting based on linear regression and autoregressive models, integrated autoregressive models of the moving average used for forecasting methane concentrations at coal mining enterprises of foreign countries.

Unsolved aspects of the problem. Despite the wide range of existing computerized automated systems widely implemented at coal-mining enterprises in Ukraine, there is still no possibility of forecasting the concentration of explosive gases taking into account external factors. The performed analysis showed that today there are not enough accurate and reliable methods for forecasting gas-dynamic phenomena, and among the considered works only linear models of the methane concentration forecast are found, and the nonlinear autoregressive model proposed previously [5] does not have sufficient forecast accuracy.

Objectives of the article. The research aims at developing a method for forecasting a highly dynamic process of changing the concentration of explosive gases in a mine with the use of artificial neural networks that allow considering the external factors.

Presentation of the main research and explanation of scientific results. Based on the analysis of sources and publications, to solve the forecast problem, it was decided to use a network of nonlinear autoregression, – the moving average with exogenous (external) factors. Fig. 1 shows the model structure of such a neural network. The NARMAX model is presented as

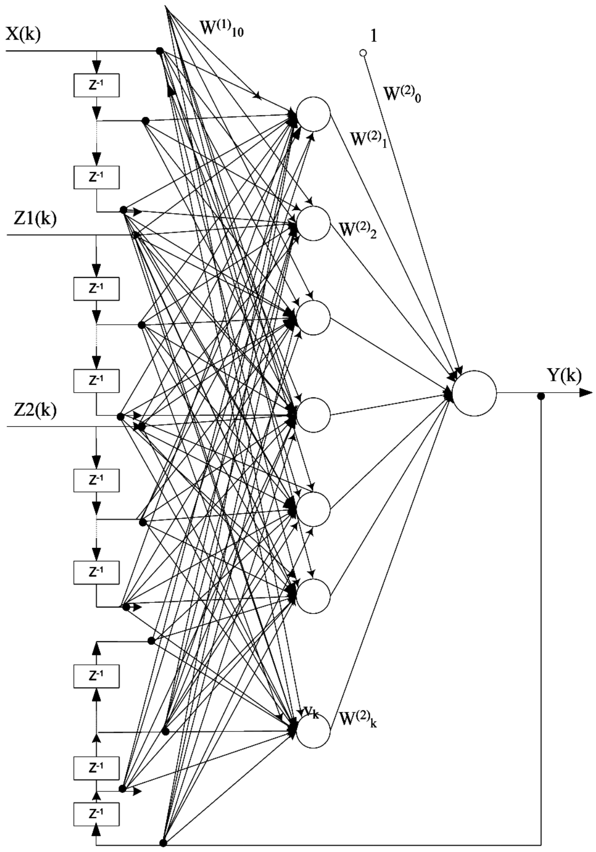

Fig. 1. Network structure of nonlinear autoregression of a moving average (NARMAX)

$$y_j^{(1)}(n) = f^{(1)}(s_j^{(1)}(n));$$

$$s_j^{(1)}(n) = b^{(1)} + \sum_{l=1}^{M^{(0)}} w_{lj}^{(1)} y^{(0)}(n-l) + \sum_{l=1}^{M1^{(0)}} w1_{lj}^{(1)} z1^{(0)}(n-l) +$$

$$+ \sum_{l=1}^{M2^{(0)}} w2_{lj}^{(1)} z2^{(0)}(n-l) + \sum_{l=1}^{M^{(2)}} v_{lj}^{(1)}(y^{(0)}(n-l) - y^{(2)}(n-l));$$

$$y^{(2)}(n) = f^{(2)}(b^{(2)} + \sum_{i=1}^{N^{(1)}} w_i^{(2)} y_i^{(1)}(n)), \qquad (1)$$

where $N^{(k)}$ is the number of neurons in the k^{th} layer, $M^{(k)}$, $M1^{(k)}$, $M2^{(k)}$ is the delay in the k^{th} layer; $w_{lj}^{(1)}(n)$, $w1_{lj}^{(1)}(n)$, $w2_{lj}^{(1)}(n)$, $v_{lj}^{(1)}(n)$ are weighting connection coefficients from input neuron at the instant of time $n - l$ to j^{th} neuron in the first layer at the instant of time n; $w_i^{(2)}(n)$ is the weight communication coefficient from the i^{th} neuron to the neuron in the second layer at the instant of time n; $y_j^{(1)}(n)$ is the output of the j^{th} neuron in the first layer; $y^{(2)}(n)$ is the output of the neuron in the second layer; $f^{(k)}$ is the activation function of neurons of the kth layer (logistic function or hyperbolic tangent).

To select a specific activation function for neurons in the MatLab environment, the following experiments were performed: NARMA was taken as the reference network. For the network, the time taken for a different number of learning epochs with a sample size of 100 values was measured. The results showed that the use of hyperbolic tangent in comparison with the logistic function takes 6 % more time for training. Since the forecasting of the explosive gases concentration is an extremely important problem and the time for obtaining forecasted result is one of the most important factors, it was decided to use the logistic function.

The neurons number of the input (zero) layer is determined by number of forecasted parameters and the exogenous factors that affect them. The number of neurons of the hidden layer is determined experimentally. Numerical experiments were carried out to determine the number of neurons of the hidden layer. Samples of the values of the methane sensors (forecast parameter), temperature and humidity (exogenous factors) obtained at the same time were taken as initial data. The sample size was 15000 values. The experiment results showed that 10 hidden neurons are sufficient for forecasting the methane concentration, since the change in the error value is insignificant with a further increase in the number of neurons.

To study the model, the criterion of model adequacy was chosen, which means the choice of such parameter values $w_{lj}^{(1)}$ $w1_{lj}^{(1)}$, $w2_{lj}^{(1)}$, $v_{lj}^{(1)}$, and $w_i^{(2)}$ that provides a minimum root-mean-square error (the difference between the output obtained with the proposed model and the test output)

$$F=\frac{1}{P}\sum_{p=1}^{P}(y_p-d_p)^2 \to \min_{w_{lj}^{(1)},w1_{lj}^{(1)},w2_{lj}^{(1)},v_{lj}^{(1)},w_i^{(2)}},$$

where P is the number of test implementations; y_p is the forecast obtained with the help of the model; d_p is test forecast.

The neural network model training is subject to criterion (1), where an algorithm for back propagation or a genetic algorithm can be used.

Consider the back propagation algorithm.

1. The first step in the implementation of this algorithm is the initialization of the threshold coefficients $b^{(1)}(n)$, $b^{(2)}(n)$, weight coefficients, $w_{lj}^{(1)}(n)$, $l\in\overline{1,M^{(0)}}$, $w1_{lj}^{(1)}(n)$, $l\in\overline{1,M1^{(0)}}$, $w2_{lj}^{(1)}(n)$, $l\in\overline{1,M2^{(0)}}$, $v_{lj}^{(1)}(n)$, $l\in \overline{1,M^{(2)}}$, $j\in\overline{1,N^{(1)}}$, $w_i^{(2)}(n)$, $i\in\overline{1,N^{(1)}}$, wherein $N^{(1)}$ is the number of neurons in the first layer, $M^{(k)}$, $M1^{(k)}$,$M2^{(k)}$ is the delay in the kth layer.

2. Next we set training-set $\{(x_\mu, z1_\mu, z2_\mu, d_\mu)|x_\mu\in R, z1_\mu\in R, z2_\mu\in R, d_\mu\in R\}$, $\mu\in\overline{1,P}$, wherein – μ^{th} is the input value of the forecast characteristic, $z1_\mu$ – μ^{th} is the value of the first exogenous factor at the input, $z2_\mu$ – μ^{th} is the second exogenous factor value at the input, d_μ – μ^{th} is the output value of the forecast characteristic, P is the power of the training set.

3. Initial computation of the output signal for each layer

$$M=\max\{M^{(0)}, M1^{(0)}, M2^{(0)}, M^{(2)}\};$$

$$y_j^{(1)}(n+v)=f^{(1)}\left(\sum_{l=0}^{M}w_{lj}^{(1)}(n+v)x_l+\right.$$
$$\left.+\sum_{l=1}^{M}w1_{lj}^{(1)}(n+v)z1_l+\sum_{l=1}^{M}w2_{lj}^{(1)}(n+v)z2_l\right);$$

$$y^{(2)}(n+v)=f^{(2)}\left(\sum_{i=0}^{N^{(1)}}w_i^{(2)}(n+v)y_i^{(1)}(n+v)\right),\quad v\in\overline{1,M};$$

$$y^{(0)}(n+v)=x_v;\quad z1^{(0)}(n+v)=z1_v;$$
$$z2^{(0)}(n+v)=z2_v,\quad v\in\overline{1,M};$$

$$n=n+M+1;$$

$$\mu=M+1;$$

$$w_{lj}^{(1)}(n+v)=w_{lj}^{(1)}(n);$$

$$w1_{lj}^{(1)}(n+v)=w1_{lj}^{(1)}(n);$$

$$w2_{lj}^{(1)}(n+v)=w2_{lj}^{(1)}(n);$$

$$v_{lj}^{(1)}(n+v)=v_{lj}^{(1)}(n);$$

$$w_i^{(2)}(n+v)=w_i^{(1)}(n).$$

It is believed that,

$$w_{0j}^{(1)}(n)=b^{(1)}(n),\quad x_0=1,\quad w_0^{(2)}(n)=b^{(2)}(n),\quad y_0^{(1)}(n)=1.$$

4. Computation of the output signal for each layer (direct move)

$$y_j^{(1)}(n)=f^{(1)}(s_j^{(1)}(n));$$

$$s_j^{(1)}(n)=\sum_{l=0}^{M^{(0)}}w_{lj}^{(1)}(n)y^{(0)}(n-l)+\sum_{l=1}^{M1^{(0)}}w1_{lj}^{(1)}(n)z1^{(0)}(n-l)+$$
$$+\sum_{l=1}^{M2^{(0)}}w2_{lj}^{(1)}(n)z2^{(0)}(n-l)+$$
$$+\sum_{l=1}^{M^{(2)}}v_{lj}^{(1)}(n)(y^{(0)}(n-l)-y^{(2)}(n-l));$$

$$y^{(2)}(n)=f^{(2)}(s^{(2)}(n));$$

$$s^{(2)}(n)=\sum_{i=0}^{N^{(1)}}w_i^{(2)}(n)y_i^{(1)}(n);$$

$$y^{(0)}(n)=x_\mu;$$

$$z1^{(0)}(n)=z1_\mu;$$

$$z2^{(0)}(n)=z2_\mu,$$

where $N^{(1)}$ is the number of neurons in the first layer, $w_{lj}^{(1)}(n)$, $w1_{lj}^{(1)}(n)$, $w2_{lj}^{(1)}(n)$ is the coupling weight coefficient from the input neuron at the instant of time $n-l$ to j^{th} neuron in the first layer at the instant of time, n, $v_{lj}^{(1)}(n)$ is the coupling weight from the output neuron at the instant of time $n-l$ to the jth neuron in the first layer at the instant of time, n, $w_i^{(2)}(n)$ is the coupling weight coefficient from i^{th} neuron to the output neuron at the instant of time, n, $y_j^{(1)}(n)$ is the output of the j^{th} neuron in the first layer, $y^{(2)}(n)$ is the output of the neuron in the second layer, $f^{(k)}$ is the activation function of the neurons of the k^{th} full-sphere.

It is believed that

$$w_{0j}^{(1)}(n)=b^{(1)}(n);\quad y_0^{(1)}(n)=1;$$
$$w_0^{(2)}(n)=b^{(2)}(n);\quad y_0^{(1)}(n)=1.$$

5. Computation of the root-mean-square error of the network

$$E(n) = \frac{1}{2} e^2(n);$$

$$e(n) = y^{(2)}(n) - d_\mu.$$

6. Adjustment of synaptic coupling weight factors (return move).

To adjust the coupling weight coefficients, a recursive algorithm is used, which is first applied to the output neurons of the network, and then passes the network in the opposite direction to the first layer. Synaptic coupling weights are adjusted according to the formula

$$w_i^{(2)}(n+1) = w_i^{(2)}(n) - \eta \frac{\partial E(n)}{\partial w_i^{(2)}(n)};$$

$$w_{lj}^{(1)}(n+1) = w_{lj}^{(1)}(n) - \eta \frac{\partial E(n)}{\partial w_{lj}^{(1)}(n)};$$

$$w1_{lj}^{(1)}(n+1) = w1_{lj}^{(1)}(n) - \eta \frac{\partial E(n)}{\partial w1_{lj}^{(1)}(n)};$$

$$w2_{lj}^{(1)}(n+1) = w2_{lj}^{(1)}(n) - \eta \frac{\partial E(n)}{\partial w2_{lj}^{(1)}(n)};$$

$$v_{lj}^{(1)}(n+1) = v_{lj}^{(1)}(n) - \eta \frac{\partial E(n)}{\partial v_{lj}^{(1)}(n)},$$

where η is the parameter that determines the speed of training (with great η value the training is faster, but it increases probability of incorrect solution), $0 < \eta < 1$.

$$\frac{\partial E(n)}{\partial w_i^{(2)}(n)} = y_i^{(1)}(n) g^{(2)}(n);$$

$$\frac{\partial E(n)}{\partial w_{lj}^{(1)}(n)} = y^{(0)}(n-l) g_j^{(1)}(n);$$

$$\frac{\partial E(n)}{\partial w1_{lj}^{(1)}(n)} = z1^{(0)}(n-l) g_j^{(1)}(n);$$

$$\frac{\partial E(n)}{\partial w2_{lj}^{(1)}(n)} = z2^{(0)}(n-l) g_j^{(1)}(n);$$

$$\frac{\partial E(n)}{\partial v_{lj}^{(1)}(n)} = (y^{(0)}(n-l) - y^{(2)}(n-l)) g_j^{(1)}(n);$$

$$g^{(2)}(n) = f'^{(2)}(s^{(2)}(n))(y^{(2)}(n) - d_\mu);$$

$$g_j^{(1)}(n) = f'^{(1)}(s_j^{(1)}(n)) w_j^{(2)}(n) g^{(2)}(n).$$

7. Checking the termination condition.

If n mod $P > 0$, then return to 4.

If n mod $P = 0$ and $\frac{1}{P}\sum_{s=1}^{P} E(n-P+s) > \varepsilon$, then increasing the number of iterations $n = n + 1$, we proceed to the problem of a new training set.

If n mod P = 0 and $\frac{1}{P}\sum_{s=1}^{P} E(n-P+s) < \varepsilon$, , then the model training algorithm is terminated.

To estimate the forecast accuracy of the proposed model, experiments were carried out with sensors sample data of methane, temperature and humidity of 1000 values, taken at the same time and stored in the database of the UTAS system with an interval of 10 seconds. To compare the obtained forecast accuracy with proposed NARMAX model, similar experiments were conducted using INS ARMA, NARX, NARMA. The forecast result is shown in Fig. 2.

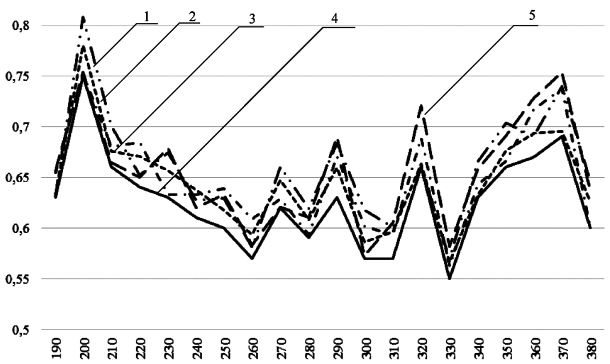

Fig. 2. The forecast results:

1 – ARMA; 2 – NARMAX; 3 – NARMA; 4 – initial data; 5 –NARX

Fig. 2 shows that the proposed INS NARMAX gives a forecast with an error of 5 %, NARMA – 7 %, ARMA – 9 % and NARX – 10 %.

Conclusions. On the basis of numerical research on the INS NARMAX structure, activation functions were chosen, the number of neurons in the hidden layer and the delay value were determined, which allowed accelerating the training procedure.

The results of the experiments showed that the proposed INS proved to be more effective for solving the problem of short-term forecasting in comparison with similar INS.

The proposed INS model can further be used in a multi-agent system for forecasting the mine atmosphere state, where the explosive gases measured by the UTAS system will act as forecast parameters [6]. In real time, the system is designed to recognize the emergency situation of the air-gas state of mines at the time of its incipience. This is explained by the fact that such a system is able to control the dynamics of the changing process of the air-gas state of mines and at the same time to issue appropriate recommendations for elimination of emergency situations.

In addition, the use of non-linear forecast models provides more accurate forecast than the widely used linear models, which shall have a positive economic effect, for instance, decreasing emergencies, which leads to a reduction in financial costs aimed at eliminating the consequences of accidents.

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Прогнозування аерогазового стану рудничної атмосфери із застосуванням штучних нейронних мереж

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Мета. Розробка методу прогнозування високодинамічного процесу зміни концентрації вибухонебезпечних газів у шахті із застосуванням штучних нейронних мереж, що дозволяють ураховувати зовнішні чинники. Підвищення виробничої безпеки на сьогоднішній день у гірничій промисловості вирішується за рахунок впровадження на підприємствах сучасних комп'ютерних систем аерогазового контролю, робота яких спрямована на прогноз параметрів стану навколишнього середовища. У зв'язку з цим, упровадження комп'ютерних систем на основі застосування штучних нейронних мереж дозволяє видати обґрунтовані рекомендації для прийняття оптимальних технологічних і управлінських рішень.

Методика. Прогнозування аерогазового стану рудникової атмосфери засноване на застосуванні штучних нейронних мереж, авторегресійних моделей і метаевристик.

Результати. На сьогоднішній день основні заходи за прогнозом концентрації метану спрямовані на пошук закономірностей динаміки концентрації газу, що послужили основою для прогнозу газодинамічних явищ. Основні результати отримані в галузі досліджень динаміки концентрації метану з використанням приладів телеметричного контролю. Такий підхід заснований на застосуванні лінійних моделей. Запропонований варіант використання нелінійних моделей прогнозування на основі штучних нейронних мереж дає точніші прогнози в порівнянні з широко вживаними на виробництвах лінійними моделями.

Наукова новизна. У рамках прогнозування аерогазового стану рудникової атмосфери отримали подальший розвиток штучні нейронні мережі та авторегресійні моделі. При цьому вдосконалена авторегресійна модель прогнозу за рахунок додавання до її структури екзогенних факторів, в якості яких виступають вимірювані динамічні параметри аерогазового стану шахтних виробок. Для адаптації моделі вдосконалено метаевристичний алгоритм.

Практична значимість. Результати експериментів показали, що запропонована штучна нейронна мережа показала себе більш ефективною для вирішення завдання прогнозування аерогазового стану рудникової атмосфери в порівнянні з існуючим підходом. Проведені чисельні дослідження показали, що запропонована модель дозволяє підвищити точність прогнозу на 10 % в порівнянні з широковживаними градієнтними методами. Позитивний економічний ефект від упровадження запропонованого підходу полягає у зменшенні ймовірності виникнення аварійних ситуацій, що веде до зменшення фінансових витрат, спрямованих на ліквідацію наслідків аварій.

Ключові слова: *прогноз, нейронна мережа, авторегресійна модель, екзогенні фактори*

Прогнозирование аэрогазового состояния рудничной атмосферы с применением искусственных нейронных сетей

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Цель. Разработка метода прогнозирования высокодинамичного процесса изменения концентрации взрывоопасных газов в шахте с применением искусственных нейронных сетей, позволяющих учитывать внешние факторы. Повышение производственной безопасности на сегодняшний день в горной промышленности решается за счет внедрения на предприятиях современных компьютерных систем аэрогазового контроля, работа которых направлена на прогноз параметров состояния окружающей среды. В этой связи, внедрение компьютерных систем на основе применения искусственных нейронных сетей позволяет выдать обоснованные рекомендаций для принятия оптимальных технологических и управленческих решений.

Методика. Прогнозирование аэрогазового состояния рудничной атмосферы основано на применении искусственных нейронных сетей, авторегрессионных моделей и метаэвристик.

Результаты. На сегодняшний день основные меры по прогнозу концентрации метана направлены на поиск закономерностей динамики концентрации газа, которые послужили основой для прогноза газодинамических явлений. Основные результаты получены в области исследований динамики концентрации метана с использованием приборов телеметрического контроля. Такой подход основан на применении линейных моделей. Предложенный вариант использования нелинейных моделей прогнозирования на основе искусственных нейронных сетей дает более точные прогнозы по сравнению с широко применяемыми на производствах линейными моделями.

Научная новизна. В рамках прогнозирования аэрогазового состояния рудничной атмосферы получили дальнейшее развитие искусственные нейронные сети и авторегрессионные модели. При этом усовершенствована авторегрессионная модель прогноза за счет добавления в ее структуру экзогенных факторов, в качестве которых выступают измеряемые динамические параметры аэрогазового состояния шахтных выработок. Для адаптации модели усовершенствован метаэвристический алгоритм.

Практическая значимость. Результаты экспериментов показали, что предложенная искусственная нейронная сеть показала себя более эффективной для решения задачи прогнозирования аэрогазового состояния рудничной атмосферы по сравнению с существующим подходом. Проведенные численные исследования показали, что предлагаемая модель позволяет повысить точность прогноза на 10 % по сравнению с широко применяемыми градиентными методами. Положительный экономический эффект от внедрения предложенного подхода состоит в уменьшении вероятности возникновения аварийных ситуаций, что ведет к уменьшениям финансовых затрат, направленных на ликвидацию последствий аварий.

Ключевые слова: *прогноз, нейронная сеть, авторегрессионная модель, экзогенные факторы*

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