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METHODOLOGY FOR MINING PREDICTION PARAMETERS BASED ON NETWORK OF NONLINEAR AUTOREGRESSIVE MOVING AVERAGE WITH EXOGENOUS FACTORS

The paper offers a methodology for forecasting the aerogas state of mining atmosphere with the use of artificial neural networks, autoregressive models and metaheuristics. It also suggests an improved AR model for forecasting the state of mine atmosphere by adding exogenous factors to its structure, which are measureable dynamic parameters of the gaseous state of mine workings. The metaheuristic algorithm is used to adapt the model. Numerical studies have shown that the proposed model can improve forecast accuracy by 10% as compared with the existing gradient methods.

Keywords: *forecast; neural network; autoregressive model; exogenous factors.*
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МЕТОДОЛОГІЯ ПРОГНОЗУ ПАРАМЕТРІВ ГІРНИЧИХ ВИРОБОК НА БАЗІ МЕРЕЖІ НЕЛІНІЙНОЇ АВТОРЕГРЕСІЇ КОВЗНОГО СЕРЕДНЬОГО З ЕКЗОГЕННИМИ ФАКТОРАМИ

У статті запропоновано методологію прогнозування аерогазового стану рудничної атмосфери із застосуванням штучних нейронних мереж, авторегресійних моделей і метаевристик. Розглянуто вдосконалену авторегресійну модель прогнозу за рахунок додавання до її структури екзогенних факторів, якими виступають вимірювані динамічні параметри аерогазового стану шахтних виробок. Для адаптації моделі використано метаевристичний алгоритм. Проведені чисельні дослідження показали, що пропонована модель дозволяє підвищити точність прогнозу на 10% в порівнянні з існуючими градієнтними методами.

Ключові слова: *прогноз; нейронна мережа; авторегресійна модель; екзогенні фактори.*
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МЕТОДОЛОГИЯ ПРОГНОЗА ПАРАМЕТРОВ ГОРНЫХ ВЫРАБОТОК НА БАЗЕ СЕТИ НЕЛИНЕЙНОЙ АВТОРЕГРЕССИИ СКОЛЬЗЯЩЕГО СРЕДНЕГО С ЭКЗОГЕННЫМИ ФАКТОРАМИ

В статье предложена методология прогнозирования аэрогазового состояния рудничной атмосферы с применением искусственных нейронных сетей, авторегрессионных моделей и метаэвристик. Рассмотрена усовершенствованная 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 использован метаэвристический алгоритм. Проведенные численные исследования показали, что предлагаемая модель позволяет повысить точность прогноза на 10% по сравнению с существующими градиентными методами.

Ключевые слова: *прогноз; нейронная сеть; авторегрессионная модель; экзогенные факторы.*

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Introduction. One of the major problems existing in mining industry today is increasing production safety. At present this problem is solved through implementation of computer systems for aerogas monitoring at enterprises so that to provide increase in safety of operations, improving working conditions for staff, forecast the parameters of environment, early detection of alert conditions, timely instructions on behavior in extremal situations and accidents. The main objective of such computer systems implementation is to increase technical and economic indices of coal-mining enterprises at the expense of carrying out the analysis and multilevel forecast of a status of all excavations for the purpose of timely adoption of measures to prevent any emergency. Such measures would allow lowering losses from accidents consequences. However, the systems used in mines today, don't provide a possibility for complex forecast of contents of explosion-dangerous gases. Thus, the actions aimed at prevention of accidents or lowering their consequences can be too late. Due to the lack of effective systems for prediction of explosion-dangerous situations and accidents in mines continue, leading to partial or complete termination of operations of coal mining, and also to serious economic losses. This shows that economic damages from accidents can be many times higher, than the costs of the control system over mine atmosphere.

Therefore, the research problem and development of methods and algorithms for operational and long-term forecast of gas separation, and also monitoring of gas status of mine atmosphere by most advanced methods and technical means becomes more and more urgent. It is important to have information on a status of a mining object for further data analysis, received via the implemented information automated control and diagnostics.

Recent research and publications analysis. Today the main measures in forecasting the concentration of methane are used to search for regularities in the dynamics of gas concentration which forms the basis for forecasts of gas dynamics. The main results are received in the field of research of the dynamics of methane concentration with use of telemetric monitoring (Ulitenko, 2007). Also, optoelectronic computerized measuring systems for methane concentration gained development and enhancement (Vovna and Zori, 2014, 2015).

Among program methods and forecasting methods it is necessary to mention the works (Dixon, 1992; Kozielski et al., 2015), which consider the methods of prediction on the basis of linear regression and autoregression models, integrated autoregression models of sliding average (Bodyanskiy and Rudenko, 2004; Osovskiy, 2002; Haykin, 1999) applied those too to forecast the concentration of methane at coal-mining enterprises in foreign countries.

Unresolved issues. Despite a wide range of the existing computerized automated systems widely implemented at coal-mining enterprises in Ukraine still there is no possibility for prediction of concentration of explosion-dangerous gases taking into account numerous external factors. Our own analysis shows that there are not present enough exact and authentic methods to forecast the gas dynamic phenomena today, and only linear forecast models of methane concentration are used in such operations, one study offered earlier a non-linear autoregression model (Fedorov and Dikova, 2016) but it has not adequate accuracy of the forecast.

The purpose of the study is development of a forecasting method for highly dynamic process of change in concentration of explosion-dangerous gases in mines using artificial neural networks allowing to consider external factors.

Key research findings. On the basis of analysis of sources and publications on the related solutions and forecasts we have made the decision to use the network nonlinear autoregression-moving average with exogenous (external) factors. Figure 1 shows the structure of this neural network model. Model NARMAX is represented as:

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

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

$$y^{(2)}(n) = f^{(2)}(b^{(2)} + \sum_{i=1}^{N^{(1)}} w_i^{(2)} y_i^{(1)}(n)), \tag{3}$$

where $j \in \overline{1,N^{(1)}}$; $N^{(k)}$ – the number of neurons in k layer; $M^{(k)}$, $M1^{(k)}$, $M2^{(k)}$ – delay in k layer; $w_{lj}^{(1)}(n)$, $w1_{lj}^{(1)}(n)$, $w2_{lj}^{(1)}(n)$, $v1_{lj}^{(1)}(n)$ – connection weights from the input neuron at time $n - l$ to neuron j in the first layer at time n; $w_i^{(2)}(n)$ – connection weights from neuron i to neuron in the second layer at time n; $y_j^{(1)}(n)$ – output of neuron j in the first layer; $y^{(2)}(n)$ – output of neuron in the second layer; $f^{(k)}$ – activation function of neurons of a k-layer (logistic function or hyperbolic tangent).

For the choice of a specific function of neurons' activation in the environment of MatLab the next experiments were made, as a standard network NARMA was taken. The results show that the use of a hyperbolic tangent takes 6% more time for training in comparison with a logistic function. Since prediction of concentration of explosion-dangerous gases – the task extremely important and time of obtaining the predicted result is one of the major factors, the decision to use a logistic function was made.

The amount of neurons of an input (zero) layer is defined by the number of predicted parameters and exogenous factors influencing them. The amount of neurons in the buried layer is defined experimentally. For determination of amount of neurons in the buried layer numerical experiments were carried out. As basic data selections for the values indications sensors of methane (the predicted parameter), temperatures and humidity (exogenous factors) in a same timepoint were taken. The volume of selection is 15000 values. The results of the experiment (Figure 2) show that for the forecast of methane concentration it is enough to use 10 hidden neurons as in the case of further increase in the amount of neurons change in the value of an error is insignificant.

Model criterion of adequacy was chosen, which means the choice of parameters that provide a minimum mean square error (the difference between the obtained output with a model and a test output):

$$F = \frac{1}{P}\sum_{p=1}^{P}(y_p - d_p)^2 \to \min_{w_{ij}^{(1)}, w1_{ij}^{(1)}, w2_{ij}^{(1)}, v_{ij}^{(1)}, w_i^{(2)}}, \quad (4)$$

where P – the number of a test realizations; y_p – the forecast received by means of a model; d_p – test forecast.

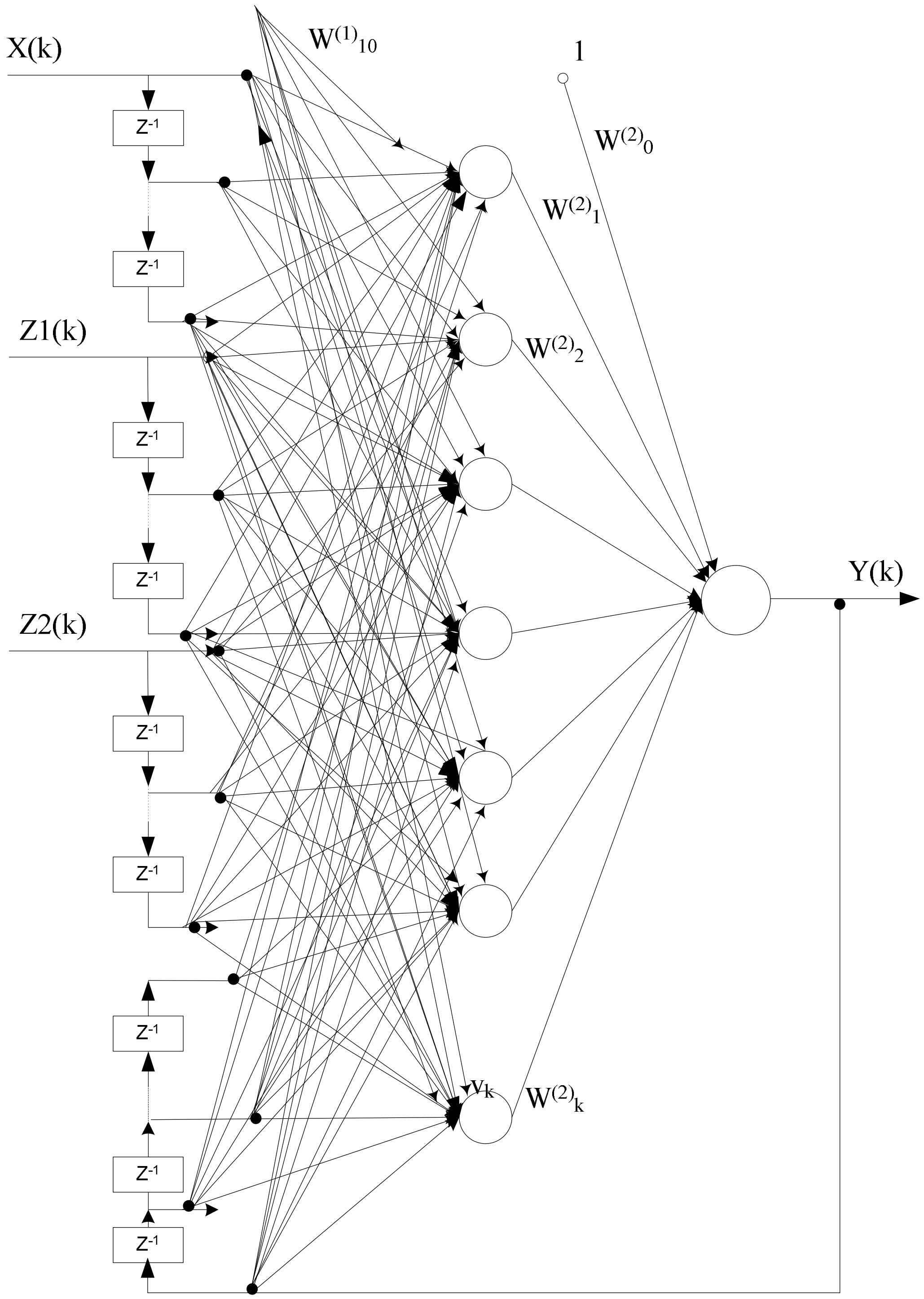

Figure 1. **Structure of network non-linear autoregression moving average (NARMAX),** *authors' development*

Training of model of a neural network is subordinate to criterion (4) for what the back propagation algorithm or the genetic algorithm can be used. In operation the back propagation algorithm is offered to use distribution, therefore, we will consider it in more detail.

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

2. Further, given the training set $\{(x_\mu, z1_\mu, z2_\mu, d_\mu) \mid x_\mu \in R, z1_\mu \in R, z2_\mu \in R, d_\mu \in R\}$ $\mu \in \overline{1,P}$, where x_μ – μ-e input value of feature, that predicted; $z1_\mu$ – μ-e the first exogenous factor's value at the input; $z2_\mu$ – μ-e the second exogenous factor's value at the input; d_μ – μ-e output value of feature that predicted; P – power of training set.

3. The initial calculation of output for each layer

$$M = \max\{M^{(0)}, M1^{(0)}, M2^{(0)}, M^{(2)}\}; \tag{5}$$

$$y_j^{(1)}(n+v) = f^{(1)}\left(\sum_{l=0}^{M} w_{lj}^{(1)}(n+v)x_l + \sum_{l=1}^{M} w1_{lj}^{(1)}(n+v)z1_l + \sum_{l=1}^{M} w2_{lj}^{(1)}(n+v)z2_l\right); \tag{6}$$

$$y^{(2)}(n+v) = f^{(2)}\left(\sum_{i=0}^{N^{(1)}} w_i^{(2)}(n+v)y_i^{(1)}(n+v)\right),\quad v \in \overline{1,M}; \tag{7}$$

$$y^{(0)}(n+v) = x_v,\quad z1^{(0)}(n+v) = z1_v,\quad z2^{(0)}(n+v) = z2_v,\quad v \in \overline{1,M}; \tag{8}$$

$$n = n + M + 1; \tag{9}$$

$$\mu = M + 1; \tag{10}$$

$$w_{lj}^{(1)}(n+v) = w_{lj}^{(1)}(n); \tag{11}$$

$$w1_{lj}^{(1)}(n+v) = w1_{lj}^{(1)}(n)' \tag{12}$$

$$w2_{lj}^{(1)}(n+v) = w2_{lj}^{(1)}(n); \tag{13}$$

$$v_{lj}^{(1)}(n+v) = v_{lj}^{(1)}(n); \tag{14}$$

$$w_i^{(2)}(n+v) = w_i^{(1)}(n), \tag{15}$$

where $j \in \overline{1,N^{(1)}}$, $v \in \overline{1,M}$. It is considered that $w_{0j}^{(1)}(n) = b^{(1)}(n)$, $x_0 = 1$, $w_0^{(2)}(n) = b^{(2)}(n)$, $y_0^{(1)}(n) = 1$.

4. Calculation of output for each layer (forward stroke)

$$y_j^{(1)}(n) = f^{(1)}(s_j^{(1)}(n)); \tag{16}$$

$$\begin{aligned} s_j^{(1)}(n) = &\sum_{l=0}^{M^{(0)}} w_{lj}^{(1)}(n)y^{(0)}(n-l) + \sum_{l=1}^{M1^{(0)}} w1_{lj}^{(1)}(n)z1^{(0)}(n-l) + \\ &+ \sum_{l=1}^{M2^{(0)}} w2_{lj}^{(1)}(n)z2^{(0)}(n-l) + \sum_{l=1}^{M^{(2)}} v_{lj}^{(1)}(n)(y^{(0)}(n-l) - y^{(2)}(n-l)); \end{aligned} \tag{17}$$

$$y^{(2)}(n) = f^{(2)}(s^{(2)}(n)); \tag{18}$$

$$s^{(2)}(n) = \sum_{i=0}^{N^{(1)}} w_i^{(2)}(n) y_i^{(1)}(n); \tag{19}$$

$$y^{(0)}(n) = x_\mu; \tag{20}$$

$$z1^{(0)}(n) = z1_\mu; \tag{21}$$

$$z2^{(0)}(n) = z2_\mu, \tag{22}$$

where $N^{(1)}$ – the number of neurons in the first layer; $w_{lj}^{(1)}(n)$, $w1_{lj}^{(1)}(n)$, $w2_{lj}^{(1)}(n)$ – weight coefficient of communication from input neuron in timepoint $n - l$ to neuron j in the first layer in timepoint n; $v_{lj}^{(1)}(n)$ – weight coefficient of communication from input neuron in timepoint $n - l$ to neuron j in the first layer in timepoint n; $w_i^{(2)}(n)$ – weight coefficient of communication from neuron i to output neuron in timepoint n; $y_j^{(1)}(n)$ – output of neuron j in the first layer; $y^{(2)}(n)$ – output of neuron in the second layer; $f^{(k)}$ – activation function of neurons of k-layer.

It is considered that $w_{0j}^{(1)}(n) = b^{(1)}(n), y_0^{(1)}(n) = 1, w_0^{(2)}(n) = b^{(2)}(n), y_0^{(1)}(n) = 1$.

5. Calculation of the mean square error:

$$E(n) = \frac{1}{2} e^2(n); \tag{23}$$

$$e(n) = y^{(2)}(n) - d_\mu. \tag{24}$$

6. Then we ajust the synaptic connection weight coefficients (reverse).

To adjust the weighting coefficients used a communication recursive algorithm is first applied to the output neurons of the network, the network then passes in the reverse direction of the first layer. Synaptic weights coupling coefficients are adjusted in accordance with the formula:

$$w_i^{(2)}(n+1) = w_i^{(2)}(n) - \eta \frac{\partial E(n)}{\partial w_i^{(2)}(n)}; \tag{25}$$

$$w_{lj}^{(1)}(n+1) = w_{lj}^{(1)}(n) - \eta \frac{\partial E(n)}{\partial w_{lj}^{(1)}(n)}; \tag{26}$$

$$w1_{lj}^{(1)}(n+1) = w1_{lj}^{(1)}(n) - \eta \frac{\partial E(n)}{\partial w1_{lj}^{(1)}(n)}; \tag{27}$$

$$w2_{lj}^{(1)}(n+1) = w2_{lj}^{(1)}(n) - \eta \frac{\partial E(n)}{\partial w2_{lj}^{(1)}(n)}; \tag{28}$$

$$v_{lj}^{(1)}(n+1) = v_{lj}^{(1)}(n) - \eta \frac{\partial E(n)}{\partial v_{lj}^{(1)}(n)}, \tag{29}$$

where η – the parameter that determines the rate of learning (learning at large η is faster but more likely to receive the wrong decision), $0 < \eta < 1$.

$$\frac{\partial E(n)}{\partial w_i^{(2)}(n)} = y_i^{(1)}(n) g^{(2)}(n); \tag{30}$$

$$\frac{\partial E(n)}{\partial w_{lj}^{(1)}(n)} = y^{(0)}(n-l) g_j^{(1)}(n); \tag{31}$$

$$\frac{\partial E(n)}{\partial w1_{lj}^{(1)}(n)} = z1^{(0)}(n-l) g_j^{(1)}(n); \tag{32}$$

$$\frac{\partial E(n)}{\partial w2_{lj}^{(1)}(n)} = z2^{(0)}(n-l) g_j^{(1)}(n); \tag{33}$$

$$\frac{\partial E(n)}{\partial v_{lj}^{(1)}(n)} = (y^{(0)}(n-l) - y^{(2)}(n-l)) g_j^{(1)}(n); \tag{34}$$

$$g^{(2)}(n) = f'^{(2)}(s^{(2)}(n))(y^{(2)}(n) - d_\mu); \tag{35}$$

$$g_j^{(1)}(n) = f'^{(1)}(s_j^{(1)}(n)) w_j^{(2)}(n) g^{(2)}(n). \tag{36}$$

7. Check the termination condition.

If n mod $P > 0$ than we proceed to item 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 assignment 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 of the learning algorithm is completed.

For assessment of forecast accuracy of the offered model experiments for which as basic data selection of indications of sensors of methane, temperature and humidity of 1000 values removed at the same time and saved in the database of the UTAS system at the interval of 10 sec were taken. For comparing forecast accuracy received by means of the offered here NARMAX model, similar experiments were made using ANN ARMA, NARX, NARMA. The results of forecasts are given in Figure 2.

In Figure 2 it is visible that the offered ANN NARMAX gives the forecast with the margin error of 5%, NARMA – 7%, ARMA – 9% and NARX – 10%.

Conclusions and prospects for future research. On the basis of a numerical research of the structure of ANN NARMAX activation functions were selected, the amount of neurons in the buried layer and the delay factor are defined that allowed accelerating the procedure of training.

The results of the experiments showed that the offered ANN proved to be the task of short-term prediction, more effective for the decision, in comparison with the similar ANN.

The offered ANN model can be used further in the multiagent system of prediction of a status of the miner atmosphere where as predicted parameters all explosion-dangerous gases measured by the UTAS (Sistemyi kompleksnoy bezopasnosti) will appear. Such a system allows recognizing an alert condition from the moment of its beginning and submission of the expected diagram in real time; it also gives messages on the character and dynamics of processes of the abnormal state change of the mine atmosphere; and gives recommendations on possible actions for elimination of an alert condition in combination with the operating plan of accident elimination.

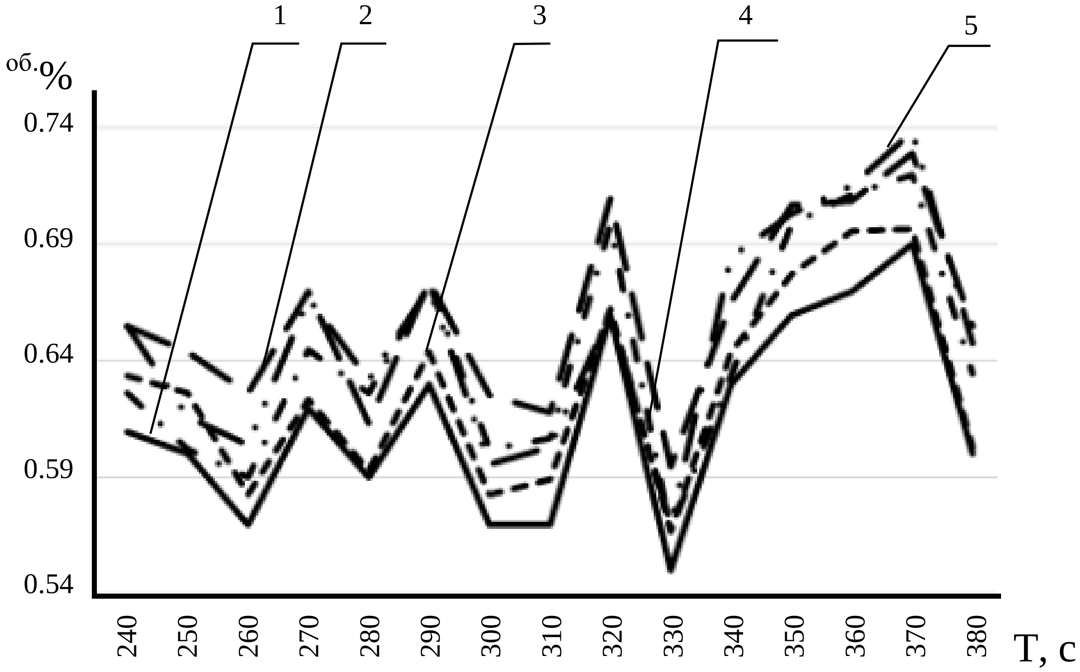

Figure 2. **Forecast results for 1 – ARMA, 2 – NARMAX, 3 – NARMA, 4 – initial data, 5 – NARX,** *author's development*

Besides, the use of non-linear forecasting models provides more exact forecasts in comparison with linear models which are widely applied on productions. This may have a positive economic effect, for example, reduction of probability of alert conditions emergence, this in turn will lower financial expenses related to mitigation of accidents' consequences.

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