ПРОБЛЕМИ ПРИЙНЯТТЯ РІШЕНЬ ТА УПРАВЛІННЯ В ЕКОНОМІЧНИХ, ТЕХНІЧНИХ, ЕКОЛОГІЧНИХ І СОЦІАЛЬНИХ СИСТЕМАХ

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INVESTIGATION OF COMPUTATIONAL INTELLIGENCE METHODS IN FORECASTING AT FINANCIAL MARKETS

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Abstract. The work considers intelligent methods for solving the problem of short- and middle-term forecasting in the financial sphere. LSTM DL networks, GMDH, and hybrid GMDH-neo-fuzzy networks were studied. Neo-fuzzy neurons were chosen as nodes of the hybrid network, which allows to reduce computational costs. The optimal network parameters were found. The synthesis of the optimal structure of hybrid networks was performed. Experimental studies of LSTM, GMDH, and hybrid GMDH-neo-fuzzy networks with optimal parameters for short- and middle-term forecasting have been conducted. The accuracy of the obtained experimental predictions is compared. The forecasting intervals for which the application of the researched artificial intelligence methods is the most expedient have been determined.

Keywords: optimization, GMDH, hybrid GMDH-neo-fuzzy network, LSTM, short- and middle-term forecasting.

INTRODUCTION

Problems of forecasting share prices and market indexes at stock exchanges pay great attention of investors and various money funds. For its solution were developed and for a long time applied powerful statistical methods, first of all ARIMA [1; 2]. Last years different intelligent methods and technologies were also suggested and widely used for forecasting in financial sphere, in particular among them neural networks and fuzzy logic systems.

The efficient tool of modelling and forecasting of non-stationary time series is Group method of data Handling (GMDH) suggested and developed by acad. Alexey Ivakhnenko [3; 4]. This method is based on self-organization and enables to construct optimal structure of forecasting model automatically in the process of algorithm run. Methods GMDH and fuzzy GMDH were successfully applied for forecasting at stock exchanges for long time.

As alternative approach for forecasting in finance is application of various types of neural network: MLP [5], fuzzy neural networks [6; 7], neo-fuzzy networks [8] and Deep learning (DL) networks [9].

New trend in sphere DL networks is a new class of neural networks – hybrid DL networks based on GMDH method [10]. The application of self-organization in these networks enables to train not only neuron weights but to construct optimal structure of a network. Due to a method of training in these networks weights are adjusted not simultaneously but layer after layer. That prevents the phenomenon of vanishing or explosion of gradient. It's very important for networks with many layers.

The first works in this field used as nodes of the hybrid network Wang-Mendel neurons with two inputs [10]. But drawback of such neurons is the necessity to train not only neural weights but the parameters of fuzzy sets in antecedents of rules as well. That needs a lot of calculation expenses and large training time as well. Therefore, later DL neo-fuzzy networks were developed in which as nodes were used neo-fuzzy neurons by Yamakawa [8; 11; 12]. The main property of such neurons is that it's necessary to train only neuron weights but not fuzzy sets. That demands less computation in comparison to Wang-Mendel neurons and significantly cuts training time as a whole. The investigation of both classes of hybrid DL networks was performed and their efficiency at forecasting in financial sphere was compared in [13].

At the same time for long term forecasting LSTM networks were developed [14–16] and successfully applied for forecasting in economy and financial sphere. LSTM networks have long memory where the information about preceding values of forecasted time series is stored and they are enabled to forecast at middle term and long term forecasting intervals. Therefore, it presents great interest to compare the efficiency of hybrid DL networks, GMDH and LSTM at the problems of short-term and middle-term forecasting at financial sphere.

The goal of this paper is to investigate the accuracy of intelligent methods – hybrid DL networks, GMDH and LSTM at the problem of forecasting market indices at the stock exchange at the different forecasting intervals (short-term and middle-term), compare their efficiency and to determine the classes of forecasting problems for which the application of corresponding computational intelligence methods is the most perspective.

THE DESCRIPTION OF THE EVOLVING HYBRID GMDH-NEO-FUZZY NETWORK

The evolving hybrid DL-network architecture is presented in Fig. 1. To the system's input layer a $n \times 1$-dimensional vector of input signals is fed. After that

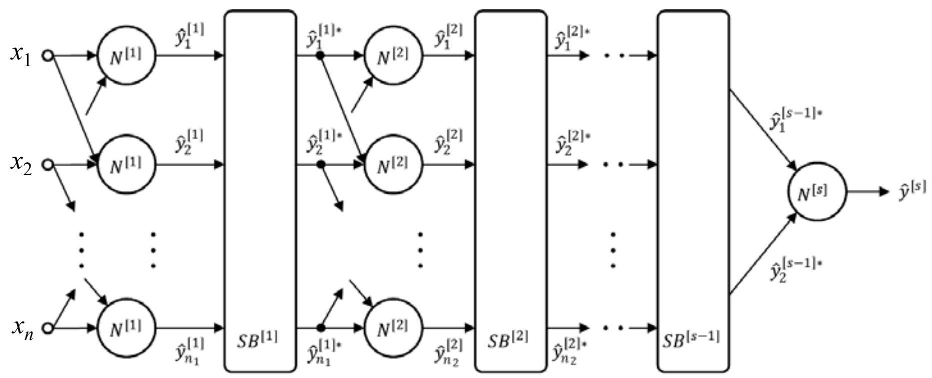

Fig. 1. Evolving GMDH-network

this signal is transferred to the first hidden layer. This layer contains $n_1 = c_n^2$ nodes, and each of these neurons has only two inputs.

At the outputs $N^{[1]}$ of the first hidden layer the output signals are formed. Then these signals are fed to the selection block of the first hidden layer.

It selects among the output signals $\hat{y}_l^{[1]} n_1 *$ (where $n_1 * = F$ is so-called freedom of choice) most precise signals by some chosen criterion (mostly by the mean squared error $\sigma^2_{y_l^{[1]}}$). Among these $n_1 *$ best outputs of the first hidden layer $\hat{y}_l^{[1]} * n_2$ pairwise combinations $\hat{y}_l^{[1]} *, \hat{y}_p^{[1]} *$ are formed. These signals are fed to the second hidden layer, that is formed by neurons $N^{[2]}$. After training these neurons output signals of this layer $\hat{y}_l^{[2]}$ are transferred to the selection block $SB^{[2]}$ which choses F best neurons by accuracy (e.g. by the value of $\sigma^2_{y_l^{[2]}}$) if the best signal of the second layer is better than the best signal of the first hidden layer $\hat{y}_1^{[1]} *$. Other hidden layers work similarly. The system evolution process continues until the best signal of the selection block $SB^{[s+1]}$ appears to be worse than the best signal of the previous *s-h* layer. Then it's necessary to return to the previous layer and choose its best node neuron $N^{[s]}$ with output signal $\hat{y}^{[s]}$. And moving from this neuron (node) along its connections backwards and sequentially passing all previous layers the final structure of the GMDH-neo-fuzzy network is constructed.

It should be noted that in such a way not only the optimal structure of the network may be constructed but also well-trained network due to the GMDH algorithm. Besides, since the training is performed sequentially layer by layer the problems of high dimensionality as well as vanishing or exploding gradient are avoided.

NEO-FUZZY NEURON AS A NODE OF HYBRID GMDH-SYSTEM

Let's consider the architecture of the node that is presented in Fig. 2 and is suggested as a neuron of the proposed GMDH-system. As a node of this structure a neo-fuzzy neuron (NFN) developed by Takeshi Yamakawa and co-authors in [9] is used. The neo-fuzzy neuron is a nonlinear multi-input single-output system shown in Fig. 2. The main difference of this node from the general neo-fuzzy neuron structure is that each node uses only two inputs.

It realizes the following mapping:

$$\hat{y} = \sum_{i=1}^{2} f_i(x_i),$$

where x_i is the input i $(i = 1, 2, \ldots, n)$, $\hat{y}$ is a system output. Structural blocks of neo- fuzzy neuron are nonlinear synapses NS_i which perform transformation of input signal in the form

$$f_i(x_i) = \sum_{j=1}^{h} w_{ji}\mu_{ji}(x_i)$$

and realize fuzzy inference: *if* x_i *is* x_{ji} *then the output is* w_{ji} ,where x_{ji} is a fuzzy set which membership function is μ_{ji} , w_{ji} is a synaptic weight in consequent [11].

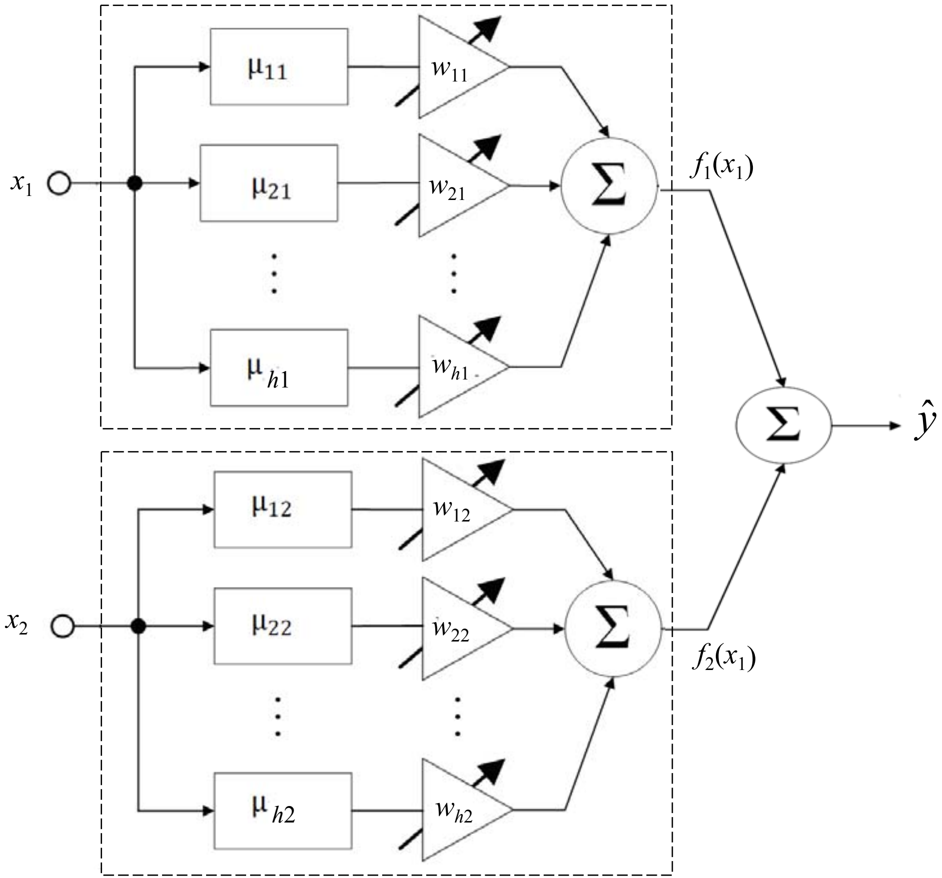

Fig. 2. Architecture of neo-fuzzy neuron with two inputs

THE NEO-FUZZY NEURON LEARNING ALGORITHM

The learning criterion (goal function) is the standard local quadratic error function:

$$E(k) = \frac{1}{2}(y(k) - \hat{y}(k))^2 = \frac{1}{2}e(k)^2 = \frac{1}{2}\left(y(k) - \sum_{i=1}^{2}\sum_{j=1}^{h} w_{ji}\mu_{ji}(x_i(k)) \right)^2 .$$

It is minimized via the conventional stochastic gradient descent algorithm.

In case we have a priori defined data set the training process can be performed in a batch mode at one epoch using conventional least squares method [12]

$$w^{[1]}(N) = \left(\sum_{k=1}^{N} \mu^{[1]}(k)\mu^{[1]T}(k) \right)^{+} \sum_{k=1}^{N} \mu^{[1]}(k)y(k) = P^{[1]}(N)\sum_{k=1}^{N} \mu^{[1]}(k)y(k) ,$$

where $(\bullet)^+$ means pseudo inverse of Moore–Penrose (here $y(k)$ denotes external reference signal (real value).

If training observations are fed sequentially in on-line mode, the recurrent form of the LSM can be used in the form:

$$\begin{cases} w_l^{ij}(k) = w_l^{ij}(k-1) + \dfrac{P^{ij}(k-1)(y(k) - (w_l^{ij}(k-1))^{\mathrm{T}} \varphi^{ij}(x(k)))\varphi^{ij}(x(k))}{1 + (\varphi^{ij}(x(k)))^{\mathrm{T}} P^{ij}(k-1)\varphi^{ij}(x(k))}, \\ P^{ij}(k) = P^{ij}(k-1) - \dfrac{P^{ij}(k-1)\varphi^{ij}(x(k))(\varphi^{ij}(x(k)))^{\mathrm{T}} P^{ij}(k-1)}{1 + (\varphi^{ij}(x(k)))^{\mathrm{T}} P^{ij}(k-1)\varphi^{ij}(x(k))}. \end{cases}$$

DATASET

As the data set for forecasting were taken close values of market index NASDAQ Composite in the period since 01.01.22 till 01.01.23. The whole sample consisted of 251 instances included Open values, minimal, maximal and Close values and volume in each day. The sample was divided into training and test subsamples. The dynamics of NASDAQ Close values is shown in the Fig. 3.

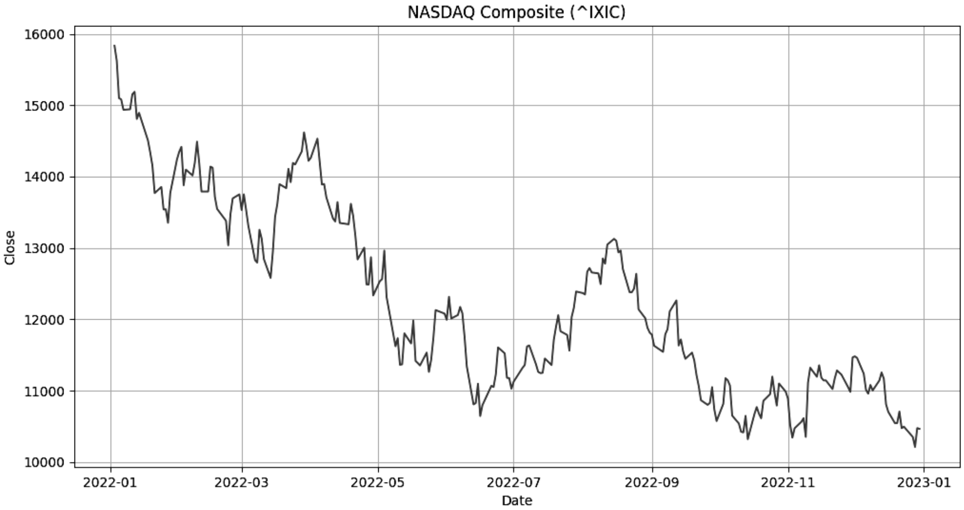

Fig. 3. Dynamics of the index Close

The correlogram of NASDAQ index is presented in the Fig. 4.

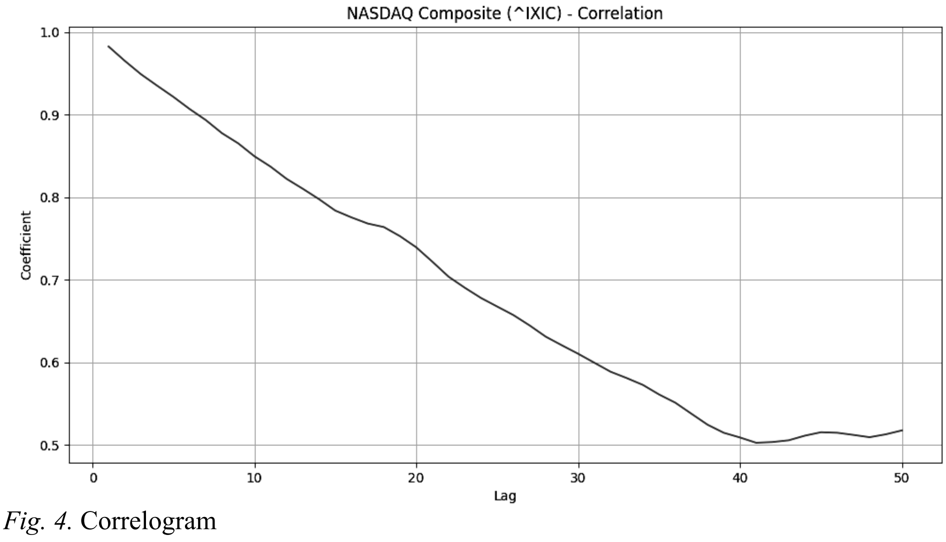

Fig. 4. Correlogram

Analyzing the presented curve, one may conclude that there is strong correlation between preceding and conceding values and even for lag 50 days the correlation is more than 0.5.

EXPERIMENTAL INVESTIGATIONS

In the investigations was explored the forecasting accuracy of hybrid DL neo-fuzzy networks at various forecasting intervals: short-term forecasting with intervals 1, 3, 5 and 7 days and middle-term forecasting with intervals 20 and 30 days. At the first step the variable experimental parameters of hybrid network were chosen which are presented in the Table 1.

Table 1. Experimental parameters

Parameter	Value
Membership functions	Gaussian
Number of inputs	3; 4; 5
Number of linguistic variables	3; 4; 5
Ratio (percentage of the training sample)	0.6 (60%); 0.7 (70%); 0.8 (80%)
Criterion	MSE; MAPE
Forecast interval	1; 3; 5; 7; 20; 30

The optimization of these parameters was performed in result the following optimal values were determined inputs: 3; linguistic variables: 3; ratio: 0.7.

After that the structure optimization of hybrid DL neo-fuzzy network was performed using GMDH method. The process of structure generation is presented in the Table 2.

Table 2. Structure generation (inputs: 3; variables: 3; ratio: 0.7)

Nodes	SB1	SB2	SB3
(0, 1)	2.6152319		
(0, 2)	5.6112545		
(1, 2)	3.8828252		
((0, 1), (0, 2))		0.03519317	
((0, 1), (1, 2))		0.0357832	
((0, 2), (1, 2))		0.05844182	
(((0, 1), (0, 2)), ((0, 1), (1, 2)))			0.09281185
(((0, 1), (0, 2)), ((0, 2), (1, 2)))			0.11276198
(((0, 1), (1, 2)), ((0, 2), (1, 2)))			0.08893768

In result the optimal structure of three layers: at the first layer 3 inputs, second layer – two neurons, third layer – one output neuron.

Further the training of the best hybrid network was carried out using method SGD (stochastic gradient descent) with variable step. Flow chart of forecasting results for interval 20 in presented in the Fig. 5. The values of MSE and MAPE for this experiment are shown in the Table 3.

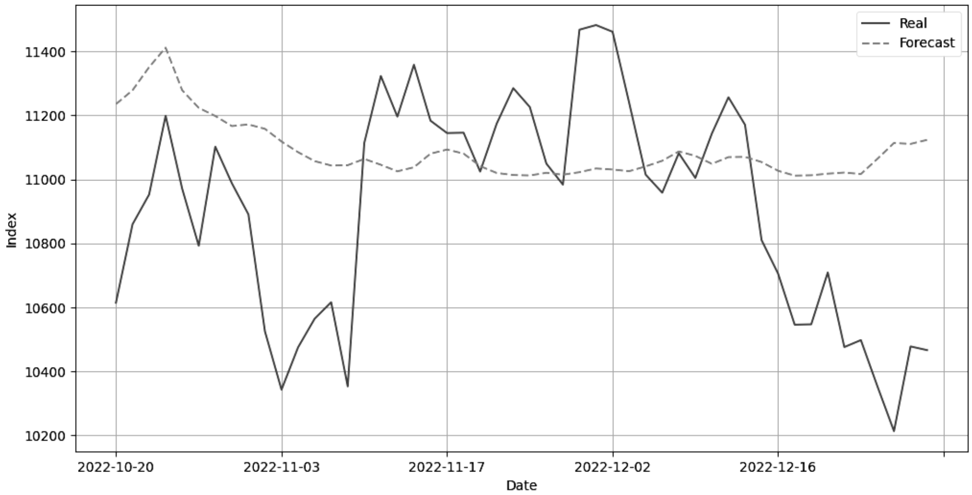

Fig. 5. The best forecast (inputs: 3; variables: 3; ratio: 0.7)

Table 3. Forecasting accuracy of hybrid neo-fuzzy network at forecasting interval 20 days

Criterion	MSE	MAPE
min	30.68518	0.049986
average	158515.7	3.024738
maximal	811272.4	8.818966

In the Fig. 6. flow chart of MAPE values for the best model of hybrid network is shown.

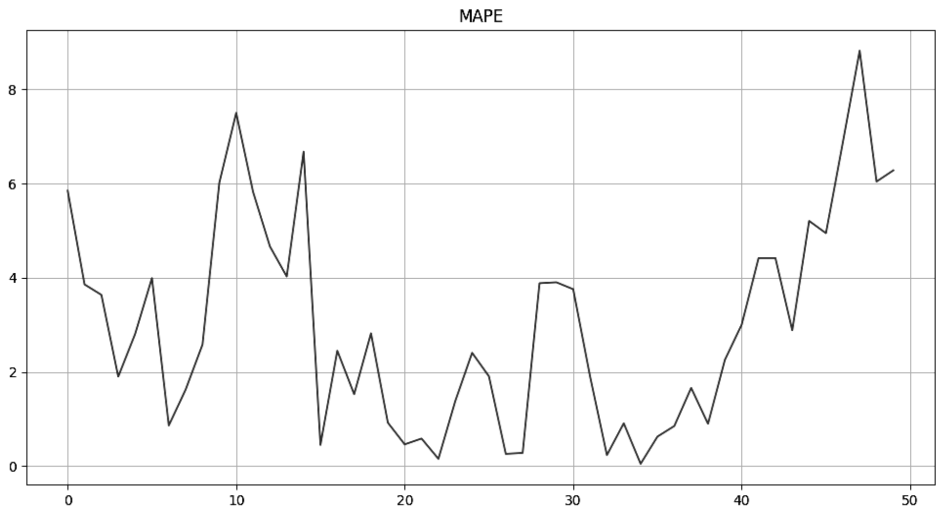

Fig. 6. MAPE for the best forecast (inputs: 3; variables: 3; ratio: 0.7)

Further the similar experiments of hybrid network were performed with forecasting interval 30 days. After optimization the parameters and structure of hybrid network it was trained using training subsample. The forecasting accuracy y at the test sample is presented at the Table 4.

Table 4. Forecasting accuracy of hybrid neo-fuzzy network at interval 30 days

Criterion	MSE	MAPE
min	177.865	0.120699
average	164611	3.07087
maximal	840641.8	8.977178

For estimating forecasting accuracy of hybrid DL network, it was compared with alternative methods: GMDH and LSTM. For GMDH algorithm the following parameters values were set after preliminary explorations: linear partial descriptions, number of inputs 5, ratio training/test 0.6. Flow chart of the best forecast is shown in the Fig. 7 and Fig. 8.

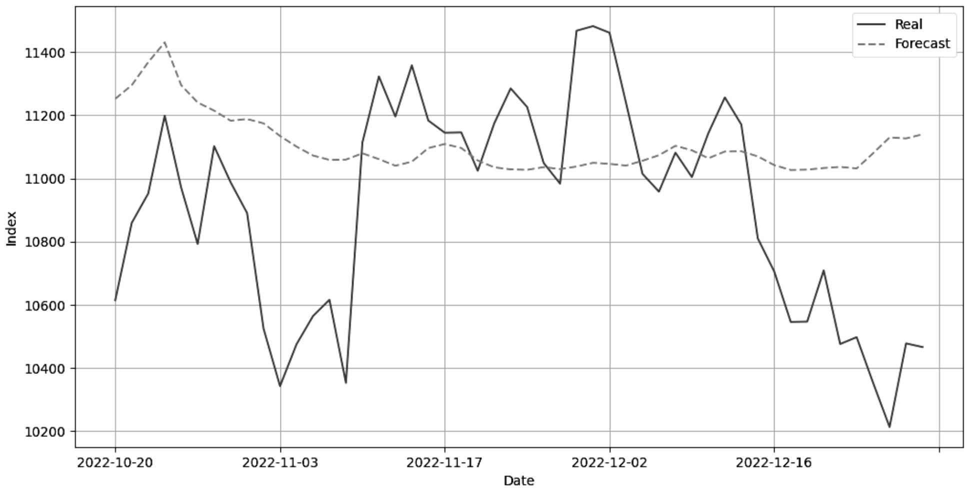

Fig. 7. The best forecast (inputs: 3; variables: 3; ratio: 0.8) for interval 30 days

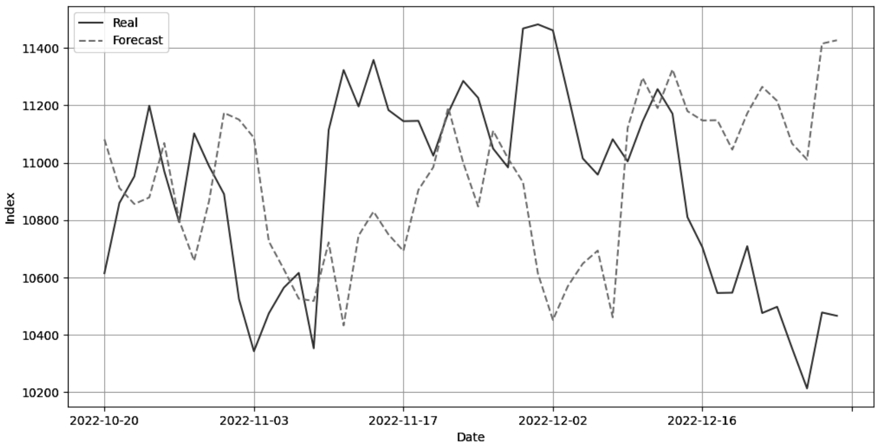

Fig. 8. The best forecast by GMDH (function: linear; inputs: 5; ratio: 0.6) 20 days

After that the experiments were performed with LSTM network. LSTM was trained and tested at the different forecasting intervals 1, 3, 5, 7, 20 and 30 days. The goal of experiments was to find the optimal parameters. The following parameters varied: number of inputs 3-5, ratio training/test 0.6, 0.7, 0.8. After that the LSTM with optimal parameters was applied for forecasting.

In the Table 5 forecasting accuracy of LSTM network at interval 3 days and in the Fig. 9 forecasting results are presented. The optimal parameters values were found number of inputs 5, ratio training/test 0.6.

Table 5. Forecasting accuracy of LSTM network at forecasting interval 3 days

Criterion	MSE	MAPE
min	113.4100292	0.098063438
average	117981.36	2.652192244
maximal	517650.7403	6.953914724

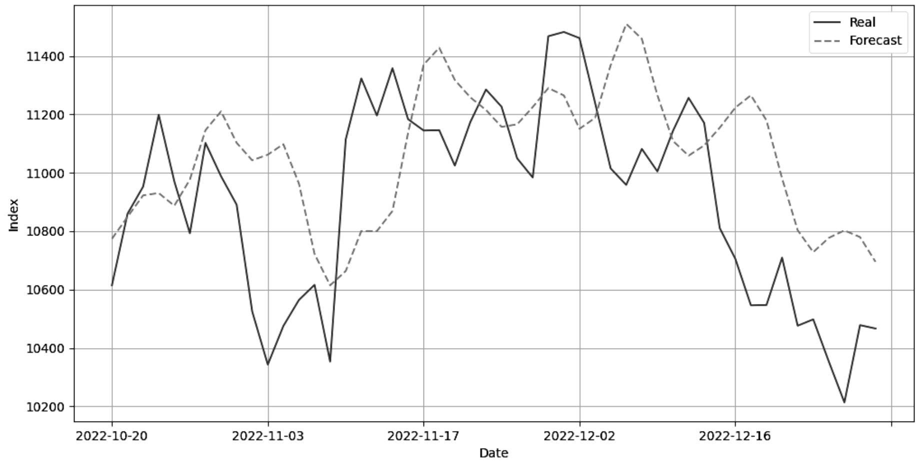

Fig. 9. The best forecast by LSTM (inputs: 5; ratio: 0.6) 3 days

The values of MSE and MAPE for forecasting with an interval of 20 days are shown in Table 6. The forecasting results are presented in Fig. 10.

Table 6. Forecasting accuracy of LSTM network at forecasting interval 20 days

Criterion	MSE	MAPE
min	49.56215352	0.06300144
average	327754.696	4.11679646
maximal	1545745.838	12.17316133

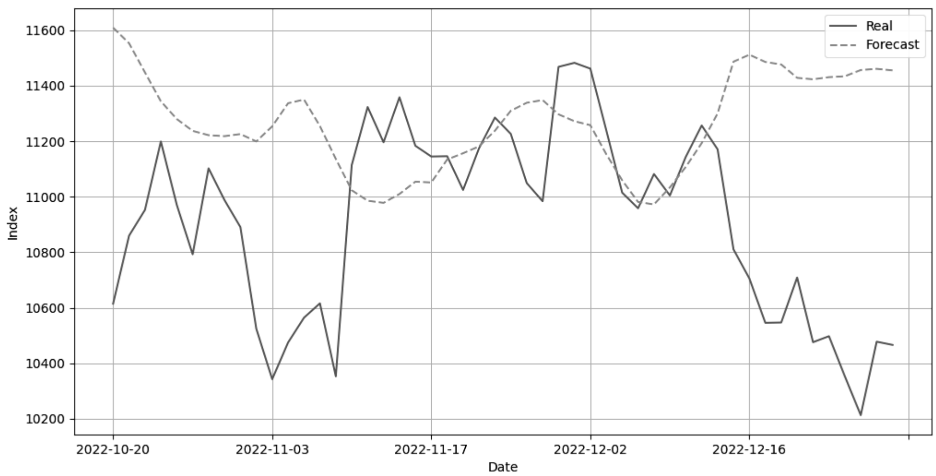

Fig. 10. The best forecast by LSTM (inputs: 5; ratio: 0.6) 20 days

The comparative experiments were performed in which the accuracy of forecasting by hybrid DL network, GMDH and LSTM at the different forecasting intervals was estimated and compared. The corresponding results are presented in the Tables 7, 8 and Fig. 11, 12.

Table 7. Average MSE values of the best models for different intervals

Interval	GMDH-neo-fuzzy	GMDH	LSTM
interval 1	97865.41363	44462.69	55461.3459
interval 3	104012.245	122615	117981.36
interval 5	155308.7139	151131.5	220850.108
interval 7	156023.0308	191982.4	241535.576
interval 20	158515.6721	243991.7	327754.7
interval 30	164610.9742	245615.6	327216.9

Table 8. Average MAPE values of the best models for different intervals

Interval	GMDH-neo-fuzzy	GMDH	LSTM
interval 1	2.483877618	1.557535	1.76242389
interval 3	2.544556353	2.623422	2.65219224
interval 5	2.889892779	3.035898	3.56067021
interval 7	2.867433998	3.428108	3.73361624
interval 20	3.02473808	3.710976	4.116796
interval 30	3.070870375	3.870127	4.25219

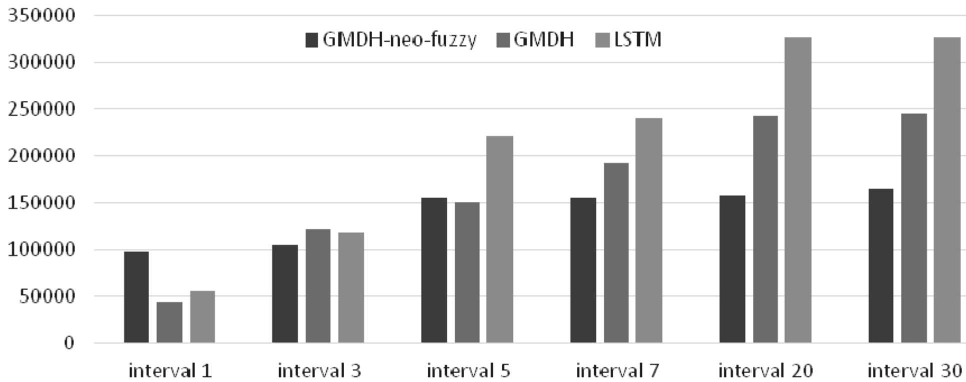

Fig. 11. Average MSE values of the best models for different intervals

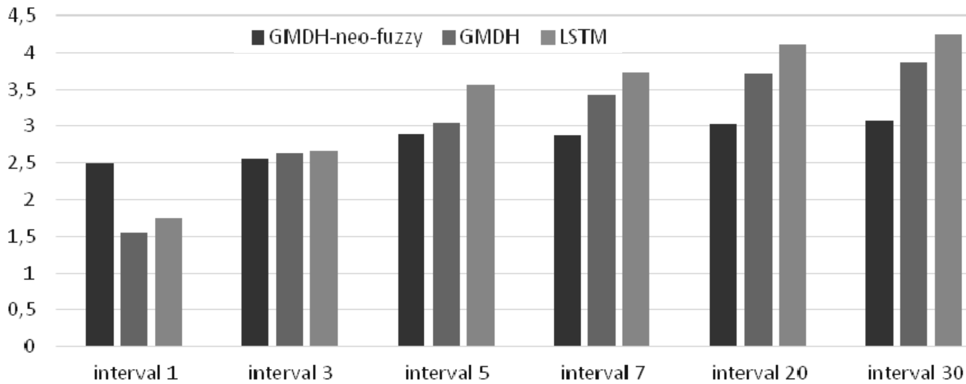

Fig. 12. Average MAPE values of the best models for different intervals

Analyzing the presented results in the Fig. 11 one may conclude that GMDH method appears to be the best at short term forecasting 1, 3 days which complies the theory.

Hybrid deep learning neo-fuzzy networks are the best at middle-term forecasting 7, 20, 30 days. LSTM networks appeared to be the worst by accuracy as compared with intelligent methods – hybrid DL networks and GMDH.

CONCLUSION

In this paper the investigations of artificial intelligence methods: hybrid Deep learning networks and GMDH were carried out in the problem of forecasting NASDAQ close prices.

During the experiments the optimal structure and optimal parameters: number of inputs, number of linguistic values, ratio training/test samples of hybrid neo-fuzzy networks were determined.

After optimization of hybrid neo-fuzzy networks and parameters of GMDH method the experiments on forecasting NASDAQ Close were performed at different intervals: 1, 3, 5, 7 (short-term forecast) and 20, 30 days (middle-term forecast).

The accuracy of forecasting by Hybrid DL networks and GMDH was compared with alternative method – LSTM networks.

The analysis of obtained results have shown that GMDH method is the best at short term forecasting 1, 3 days while hybrid deep learning neo-fuzzy networks are the best at middle-term forecasting 7, 20, 30 days. LSTM networks appeared to be the worst by accuracy as compared with intelligent methods – hybrid DL networks and GMDH.

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INFORMATION ON THE ARTICLE

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ДОСЛІДЖЕННЯ МЕТОДІВ ОБЧИСЛЮВАЛЬНОГО ІНТЕЛЕКТУ У ПРОГНОЗУВАННІ НА ФІНАНСОВИХ РИНКАХ / Ю.П. Зайченко, О.Ю. Зайченко, О.В. Кузьменко

Анотація. Розглянуто інтелектуальні методи для короткострокового та середньострокового прогнозування у фінансовій сфері. Досліджувалися DL мережі LSTM, МГУА та гібридні МГУА неофаззі мережі. Як вузли гібридної мережі обрано неофаззі нейрони, що дозволяє зменшити обчислювальні витрати. Знайдено оптимальні параметри мереж. Виконано синтез оптимальної структури гібридних мереж. Проведено експериментальні дослідження мереж LSTM, МГУА та МГУА неофаззі з оптимальними параметрами для короткострокового та середньострокового прогнозування. Порівняно точність отриманих експериментальних прогнозів. Визначено інтервали прогнозування, для яких застосування досліджених методів штучного інтелекту є найбільш доцільним.

Ключові слова: оптимізація, МГУА, гібридна мережа МГУА-неофаззі, LSTM, короткострокове та середньострокове прогнозування.