ТЕОРЕТИЧНІ ТА ПРИКЛАДНІ ПРОБЛЕМИ ІНТЕЛЕКТУАЛЬНИХ СИСТЕМ ПІДТРИМАННЯ ПРИЙНЯТТЯ РІШЕНЬ

UDC 519.925.51
DOI: 10.20535/SRIT.2308-8893.2022.1.06

HYBRID GMDH DEEP LEARNING NETWORKS – ANALYSIS, OPTIMIZATION AND APPLICATIONS IN FORECASTING AT FINANCIAL SPHERE

Yu. ZAYCHENKO, He. ZAICHENKO, G. HAMIDOV

Abstract. In this paper, the new class of deep learning (DL) neural networks is considered and investigated — so-called hybrid DL networks based on self-organization method Group Method of Data Handling (GDMH). The application of GMDH enables not only to train neural weights, but also to construct the network structure as well. Different elementary neurons with two inputs may be used as nodes of this structure. So the advantage of such a structure is the small number of tuning parameters. In this paper, the optimization of parameters and the structure of hybrid neo-fuzzy networks was performed. The application of hybrid Dl networks for forecasting market indices was considered with various forecasting intervals: one day, one week, and one month. The experimental investigations of hybrid GMDH neo-fuzzy networks were carried out and comparison of its efficiency with FNN ANFIS in the forecasting problem was performed which enabled to estimate their efficiency and advantages.

Keywords: hybrid deep learning networks, self-organization, parameters and structure optimization, forecasting.

INTRODUCTION

Nowadays deep learning (DL) networks are widely used in different problems of artificial intelligence: forecasting, pattern recognition, medical diagnostics, etc.[1–4]. For its training various algorithms were developed usually based on Back propagation method. Presence of many layers when using gradient algorithm usually leads to occurrence drawbacks as vanishing or explosion of gradient. Therefore, the approach was suggested how to exclude this drawback to perform layer after layer training using stacked encoder-decoder or stacked restricted Boltzmann machines [1, 2]. However, the problem is left how to choose the number of layers in DL network. The existing DL methods don't enable to generate structure of DL networks. But the training process will be more efficient if to adapt not only neuron weights but the structure of network as well. For this goal the application of GMDH method seems very promising. GMDH is based on principle of self- organization and enables to construct network structure automatically in the process of algorithm run [5–7]. In the previous years GMDH-neural networks having active neurons [5–7], R-neurons [19], Q-neurons [3] as nodes were developed; in the area integrating fuzzy GMDH and neural networks the GMDH neuro-fuzzy and GMDH neo-fuzzy systems [13] were developed.

The very important property of GMDH is that as building blocks for construction of a structure of DL networks elementary models with only two inputs, so-called partial descriptions, are used. This allows to cut substantially training time for hybrid Dl network as compared with conventional DL networks.

Therefore, new generation of deep learning — GMDH-hybrid neuro-fuzzy networks were developed in [16] that combine advantages of the traditional GMDH and DL fuzzy networks and may be trained with simple learning procedures. The nodes of this network are Wang-Mendel elementary neural networks with only two inputs. The experimental investigations of this class of hybrid DL networks have shown their efficiency and preference over conventional DL networks. But the drawbacks of application of Wang-Mendel networks as nodes of hybrid DL networks lies herein that it's necessary to train not only neural weights but membership functions as well.

Later another class of hybrid DL networks — GMDH neo-fuzzy networks were developed wherein as nodes of network neo-fuzzy neurons with two inputs are used [17]. For their training its necessary to adapt only neuron weights that demands less computational resources and cuts training time. That's very important for DL networks with a large number of hidden layers. The experimental investigations of hybrid neo-fuzzy networks and comparison with conventional DL network have shown their efficiency and less computational calculations for training. But the problem is left to find the optimal parameters and structure of hybrid neo- fuzzy networks and investigate them in practical applications.

The goal of this paper is to find optimal parameters and structure of hybrid deep learning networks and investigate their efficiency in forecasting problem at financial markets.

HYBRID NETWORK STRUCTURE OPTIMIZATION BASED ON GMDH METHOD

The GMDH method was used to synthesize the structure of the hybrid network based on the principle of self-organization. The principal idea of generation optimal structure is the successive increase in the number of layers until the value of the external criterion of optimality MSE begins to increase for the best model of the current layer. In this case it is necessary to return to the previous layer, to find there the best model with the minimum value of criterion. Then moving backward, go through its connections, find the corresponding neurons of the previous layer. This process continues until we reach the first layer and the corresponding structure is automatically determined.

The process of synthesis of the network structure in the forward direction is shown in Fig. 1 where in grey color the outputs which passed through selection block (SB)are shown while in black color -outputs which were dropped (excluded) by SB.

The process of restoring the desired structure in the backward direction is shown in Fig. 2. In the grey color nodes and their connections selected by this process are indicated.

The corresponding optimal constructed structure of the hybrid network for this forecasting problem is shown in Fig. 3.

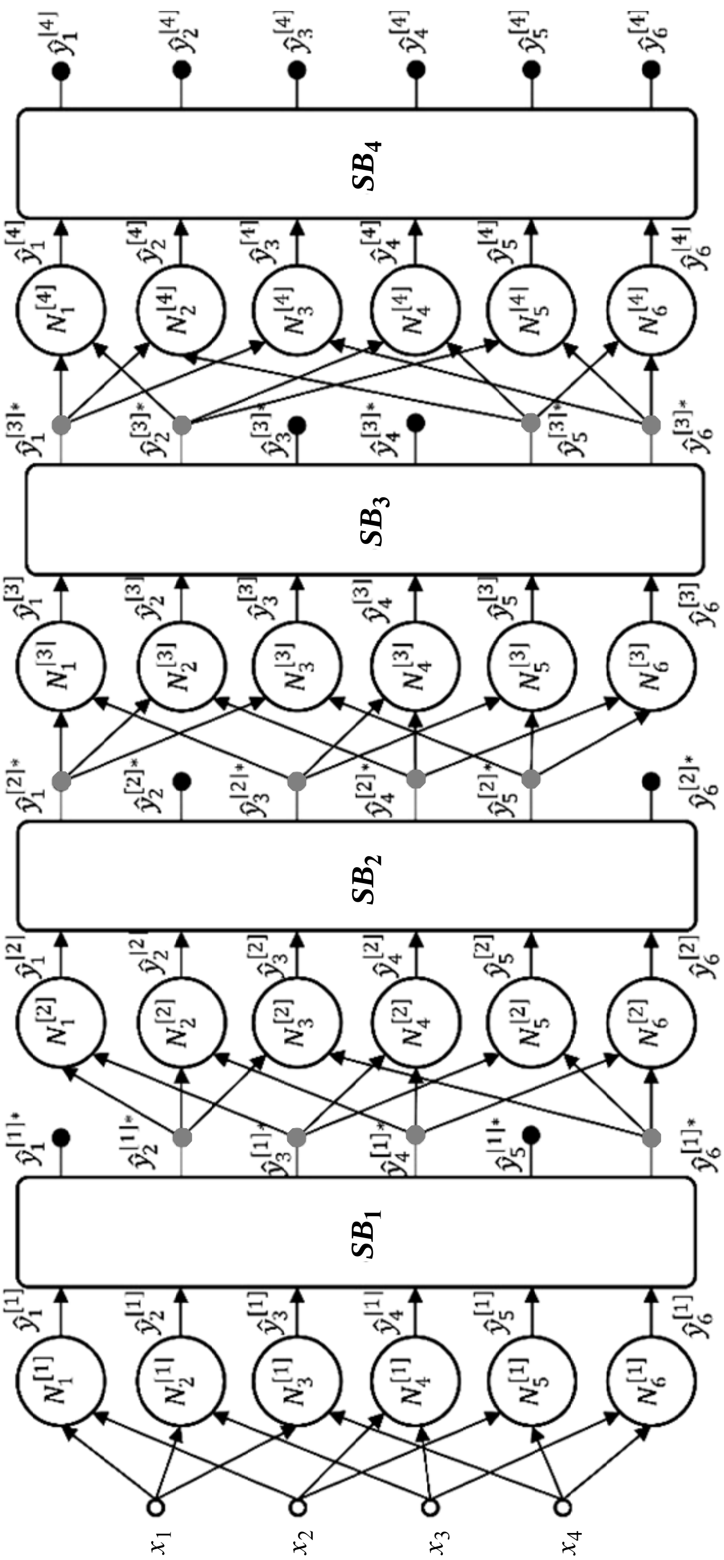

Fig. 1. Hybrid network structure construction using GMDH method

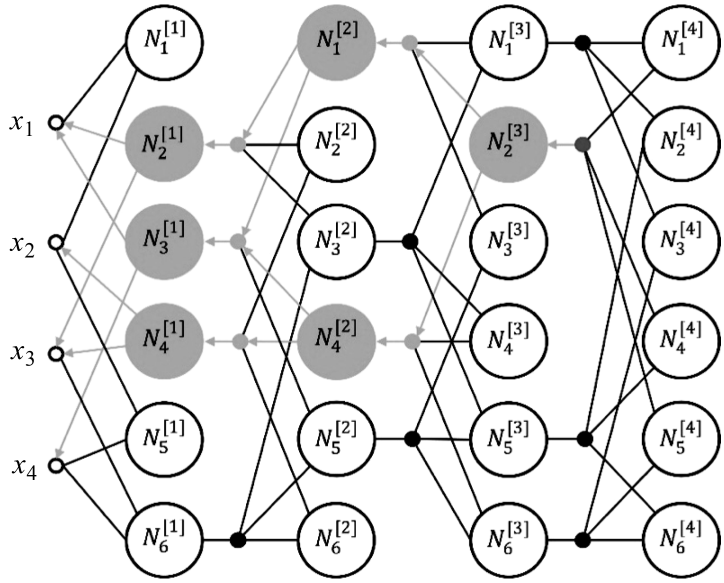

Fig. 2. Process of restoring found optimal structure in backward direction

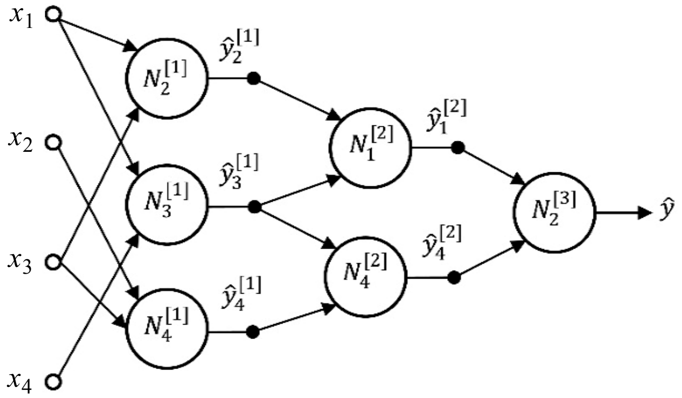

Fig. 3. Optimal Structure of hybrid network for covid forecast constructed by GMDH

It consists of 3 layers: first layer has 3 neo-fuzzy neurons, second layer- two neurons and the last- one neuron.

EXPERIMENTAL INVESTIGATIONS FOR SEARCH OPTIMAL PARAMETERS OF HYBRID GMDH NEO-FUZZY NETWORK

The experimental investigations of hybrid GMDH neo-fuzzy network were performed in the problem of Dow Jones and Nasdaq Index forecasting and compared with FNN ANFIS. In the process of experiments optimal parameters and structure of hybrid GMDH networks were found. The experiments were performed with different forecasting intervals: one day, one week and one month. For each forecasting interval optimal parameters of hybrid neo-fuzzy networks were found and investigated.

The Dow Jones is the stock index of the 30 largest American companies, which was founded in 1896. The initial data was taken from Yahoo, a leading financial information provider owned by Yahoo!

To prepare the initial data, data were uploaded at various intervals, namely the value of the stock index by days, weeks and months. Each of the sets contains the following data:

- Date — data period;
- Open — opening price;
- High — the highest price for the period;
- Low — the lowest price for the period;
- Close — the price at the end of the period;
- Adj Close — average closing price;
- Volume — sales for the period.

The data set for the interval of one day contains 4867 records, of which non-zero records are 4788 ones. The data set for the interval one month contains 1001 records, of which 1000 records are non-zero. The data set for the interval of one month contains 195 records, of which 195 are non-zero.

Data normalizing. Reduction to a single scale is provided by normalization of each variable to the range of its values. In the simplest case, it is a linear transformation

$$m\overline{x_i} = \frac{x - x_{i\,\min}}{x_{i\,\max} - x_{i\,\min}}, \text{ in the interval } x_i \in [0,1].$$

To find the most informative features as an input vector the network was alternately trained on data sets that transmit only the following features subsets:

('Open', 'High', 'Low', 'Volume', 'Close'); ('Open', 'High', 'Low', 'Volume');

('Open', 'High', 'Low', 'Close'); ('Open', 'High', 'Low'); ('Open', 'High', 'Close');

('Open', 'High', 'Volume'); ('Open', 'Close', 'Low'); ('Open', 'Volume', 'Low');

('High', 'Low', 'Close'); ('Open', 'High'); ('High', 'Close'); ('Low', 'Close'); ('Open', 'Volume').

The main network parameters that can be configured and are to be optimized include the size of the input vector, the number of rules, and the function that sets them, the number of parameters that are transferred to the next layer.

The size of the input vector is determined by the number of informative features that are transmitted for training, and the number of days on the basis of which the network gives the predicted value. Also, the number of network functions that can be set includes the number of membership functions and their appearance, as well as the degree of freedom of choice of the system.

To select these parameters, it is necessary to conduct an experiment, training the system, setting these parameters in the interval, and keeping those that give the best results in the test sample.

The following parameters were investigated:

- n — number of preceding days, based on which the forecasting is performed (sliding window size) $N \in [1;6]$;

- h — number of membership functions in each node, $N \in [2;9]$;
- s — membership function parameter, where $\sigma = \frac{(b-a)}{h}(sh-1)$;
- b — an interval end;
- a — an interval beginning;
- h — membership functions number, which cover the interval;
- $s \in [0{,}01; 1{,}5]$;
- f — number of parameters which are transferred to the network next layer (freedom of choice).

The set of initial data was divided into a training sample and test sample in the ratio of 70% and 30%, respectively.

Having launched GMDH neo-fuzzy system for training, values of MAE and MAPE criteria were obtained with different combinations of these parameters.

For the Dow Jones stock index with different forecast intervals, the best parameters for the different set of informative features were obtained as a result of training and testing, which are shown in Table 1.

Table 1. The results of the selection of the optimal parameters of GMDH-neo-fuzzy system for Dow Jones index with different prediction intervals

Sets of informative features	**1 month**						**1 week**					
	n	h	f	s	MAE	MAPE	n	h	f	s	MAE	MAPE
'Open', 'High', 'Low', 'Volume', 'Close'	1	2	2	1,0	**0,0147**	**0,0452**	2	4	2	0,7	**0,0077**	**0,0295**
'Open', 'High', 'Low', 'Volume'	1	2	3	1,3	0,0156	0,0476	2	4	3	0,9	0,0086	0,0332
'Open', 'High', 'Low', 'Close'	1	2	2	1,0	**0,0147**	**0,0453**	2	4	2	0,7	**0,0077**	**0,0295**
'Open', 'High', 'Low'	1	2	3	1,3	0,0156	0,0476	2	4	3	0,9	0,0086	0,0332
'Open', 'High', ' Close'	1	2	3	1,2	0,0153	0,0467	2	4	3	0,9	0,0079	0,0309
'Open', 'High', ' Volume'	5	2	5	0,1	0,0177	0,0654	2	4	3	1,0	0,0098	0,0380
'Open', 'Low', 'Close'	1	2	3	1,2	0,0147	0,0456	2	4	3	0,7	0,0081	0,0308
'Open', 'Volume', ' Low'	5	3	7	0,1	0,0171	0,0644	4	2	6	0,1	0,0095	0,0348
'High', 'Low', 'Close'	1	2	2	1,0	**0,0147**	**0,0453**	2	4	2	0,7	**0,0077**	**0,0295**
'Open', 'High'	5	2	5	0,1	0,0177	0,0654	2	4	3	1,0	0,0098	0,0380
'Open', 'Close'	1	2	2	1,3	0,0165	0,0498	2	4	3	0,6	0,0085	0,0331
'High', 'Close'	1	2	2	1,2	**0,0154**	**0,0467**	2	4	3	0,9	0,0079	0,0309
'Low', 'Close'	1	2	2	1,2	**0,0147**	**0,0456**	2	4	2	0,7	0,0081	0,0306
'Open', 'Volume'	5	2	2	0,8	0,0189	0,0689	3	4	2	0,1	0,0112	0,0445

Thus, analyzing presented results one may conclude that the most informative for GMDH neo-fuzzy system are the following sets of features: ['Open', 'High', 'Close'], ['Open', 'Low', 'Close'], ['High', 'Low', 'Close'], ['High', 'Close'], ['Low', 'Close'].

For the Dow Jones stock index for one month forecast period, the following optimal configurations of GMDH neo-fuzzy network were obtained:

- the number of informative features — 3;
- the number of periods on the basis of which the forecast is made — 1;
- the number of membership functions in each of the nodes — 2;
- the number of layers — 2;
- the number of nodes in the first layer — 3;
- number of nodes on the second layer — 1.

For the Dow Jones stock index for the one week forecast period, the following optimal configurations of the GMDH neo-fuzzy system were obtained:

- the number of informative features — 3;
- the number of periods on the basis of which the forecast is made — 2;
- the number of membership functions in each of the nodes — 4;
- the number of layers — 2;
- the number of nodes on the first layer — 24;
- the number of nodes on the second layer — 1.

The form of the membership function for forecasting interval of one week is shown in the Fig. 4.

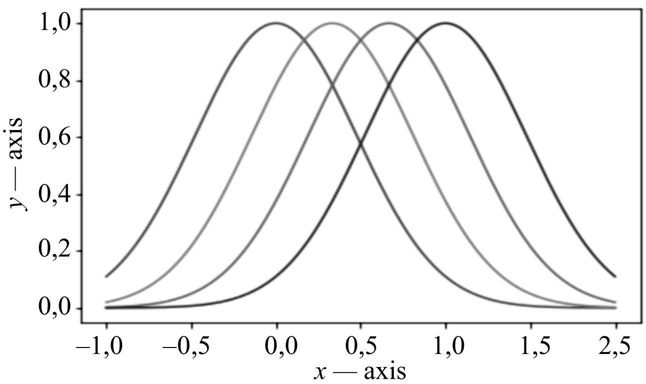

Fig. 4. Forms of the membership function of Dow Jones index for the forecast period of 1 week

For the Dow Jones stock index for one day forecast period, the following optimal configurations of GMDH neo-fuzzy network were obtained:

- number of informative features — 3;
- the number of periods on the basis of which the forecast is made — 5;
- the number of membership functions in each of the nodes — 2;
- the number of layers — 2;
- the number of nodes in the first layer — 30;
- the number of nodes in the second layer — 1.

In the next series of experiments the optimal parameters of hybrid GMDH neo-fuzzy network were searched for the problem of Nasdaq index forecast with different forecasting intervals. The optimal parameters and sets of informative features for interval one month and one week are presented in the Table 2, while for the interval one day — in the Table 3.

Table 2. The results of the selection of the optimal parameters of GMDH neo-fuzzy system for Nasdaq index with different prediction intervals

Sets of informative features	1 month						1 week					
	n	*h*	*f*	*s*	MAE	MAPE	*n*	*h*	*f*	*s*	MAE	MAPE
'Open', 'High', 'Low', 'Volume', 'Close'	1	3	2	0,58	**0,0090**	**0,0796**	3	3	2	0,1	**0,0043**	**0,0400**
'Open', 'High', 'Low', 'Volume'	1	3	3	0,78	0,0088	0,0812	5	2	3	0,7	0,0048	0,0445
'Open', 'High', 'Low', 'Close'	1	3	3	0,58	**0,090**	**0,0796**	3	3	2	0,1	**0,0044**	**0,0400**
'Open', 'High', 'Low'	1	3	3	0,78	0,0088	0,0812	5	2	3	0,7	0,0048	0,0445
'Open', 'High', 'Close'	1	3	3	0,68	0,0095	0,0824	3	3	2	0,1	0,0045	0,0427
'Open', 'High', 'Volume'	2	3	3	0,18	0,0109	0,1124	4	8	3	0,9	0,0054	0,0520
'Open', 'Low', 'Close'	1	3	3	0,88	0,0085	0,0850	3	5	2	0,5	**0,0044**	**0,0414**
'Open', 'Volume', 'Low'	2	3	3	0,48	0,0095	0,0941	5	2	4	0,1	0,0051	0,0472
'High', 'Low', 'Close'	2	5	3	0,08	**0,0089**	**0,0796**	3	3	2	0,1	**0,0043**	**0,0400**
'Open', 'High'	2	3	3	0,18	0,0109	0,1128	4	8	3	0,9	0,0054	0,0520
'Open', 'Close'	2	2	3	0,18	0,0093	0,1011	4	6	2	0,5	0,0046	0,0421
'High', 'Close'	1	3	2	0,68	0,0095	0,1066	3	3	2	0,1	0,0045	0,0427
'Low', 'Close'	1	3	2	0,88	0,0085	0,085	3	5	2	0,5	**0,0044**	**0,0414**
'Open', Volume'	2	5	4	1,38	0,0121	0,1503	4	7	3	0,9	0,0064	0,0597

Table 3. The results of the selection of the optimal parameters of GMDH neo-fuzzy system for Nasdaq index with one day prediction interval

Sets of informative features	1 day					
	n	*h*	*f*	*s*	MAE	MAPE
'Open', 'High', 'Low', 'Volume', 'Close'	6	8	2	0,1	**0,0023**	**0,0193**
'Open', 'High', 'Low', 'Volume'	6	7	3	0,7	0,0026	0,0232
'Open', 'High', 'Low', 'Close'	6	8	2	0,1	**0,0023**	**0,0193**
'Open', 'High', 'Low'	6	7	3	0,7	0,0026	0,0232
'Open', 'High', 'Close'	6	7	2	0,1	0,0024	0,0204
'Open', 'High', 'Volume'	6	10	3	0,1	0,0030	0,0262
'Open', 'Low', 'Close'	6	7	5	0,1	**0,0024**	**0,0200**
'Open', 'Volume', 'Low'	6	9	5	0,1	0,0028	0,0242
'High', 'Low', 'Close'	6	8	2	0,1	**0,0023**	**0,0193**
'Open', 'High'	1	7	2	0,1	0,0029	0,0241
'Open', 'Close'	6	8	6	0,1	0,0025	0,0213
'High', 'Close'	6	7	2	0,1	0,0024	0,0205
'Low', 'Close'	6	9	6	0,1	**0,0024**	**0,0202**
'Open', 'Volume'	6	7	2	0,1	0,0034	0,0288

For Nasdaq stock index for one month forecast period, the following optimal configurations of GMDH-neo-fuzzy network were obtained:

- the number of informative features — 4;
- the number of periods on the basis of which the forecast is made — 1;

- the number of membership functions in each of the nodes — 3;
- the number of layers — 2;
- the number of nodes in the first layer — 12;
- number of nodes on the second layer — 1.

For Nasdaq stock index for the one week forecast period, the following optimal configurations of the GMDH-neo-fuzzy system were obtained:

- the number of informative features — 4;
- the number of periods on the basis of which the forecast is made — 3;
- the number of membership functions in each of the nodes — 3;
- the number of layers — 2;
- the number of nodes on the first layer — 36;
- the number of nodes on the second layer — 1.

In the Fig. 5 forms of membership functions of Nasdaq index for one month forecast are presented.

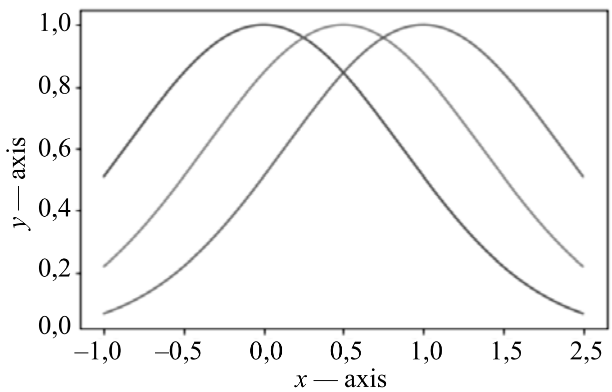

Fig. 5. Forms of the membership function of Nasdaq index for the forecast period of 1 month

For Nasdaq index with forecasting interval 1 month the following results were obtained:

- MAE — 0,02812;
- MAPE — 0,03165;
- Forecasting time — 0,0005815 *s*.

For Nasdaq index with forecasting interval 1 week the following results were obtained:

- MAE — 0,0099397;
- MAPE — 0,0109336;
- Forecasting time — 0,0003004 *s*.

For Nasdaq index with forecasting interval 1 day the following results were obtained

- MAE — 0,005740;
- MAPE — 0,0063267;
- Forecasting time — 0,000287 *s*.

Next, experiments were performed to find the optimal values of the parameters of FNN ANFIS. The size of the input vector is determined by the number of informative features that are transmitted for training, and the number of days of prehistory, on the basis of which the forecasting is performed.

To select these parameters, an experiment was performed, including training of the network, setting these parameters in the interval, and choosing those that give the best results at the test sample.

The set of initial data was divided into a training sample and test data in the proportion of 70% and 30%, respectively. By launching the ANFIS network with different combinations of these parameters, data on MAE and MAPE criteria were obtained.

For the Dow Jones stock index one month forecast period, the following optimal ANFIS network configurations were obtained:

- number of informative features — 3;
- number of nodes — 6;
- the number of periods on the basis of which the forecast is made — 2;
- the number of membership functions in each of the nodes — 6.

The optimal parameters of FNN ANFIS for Dow Jones index forecast are shown in Table 4.

Table 4. The results of the selection of the optimal characteristics of ANFIS network for Dow Jones index with different forecast intervals

Sets of informative features	**1 month**				**1 week**				**1 day**			
	n	*h*	MAE	MAPE	*n*	*h*	MAE	MAPE	*n*	*h*	MAE	MAPE
'Open', 'High', 'Low'	2	6	0,222	0,0710	1	9	0,0091	0,0334	1	10	0,0037	0,0142
'Open', 'High', 'Close'	2	3	0,0223	0,0727	2	8	0,0080	0,0303	1	11	**0,0034**	**0,0129**
'Open', 'Low', 'Close'	2	6	**0,0192**	**0,0680**	2	10	0,0804	0,0307	1	5	0,0045	0,0154
'High', 'Low', 'Close'	2	8	0,0209	0,0720	2	9	0,0903	0,0325	2	10	0,0036	0,0134
'High', 'Close'	2	9	0,0223	0,0750	1	3	**0,0077**	**0,0282**	1	7	0,0035	0,0135
'Low', 'Close'	2	7	0,0201	0,0691	1	5	0,0094	0,0338	1	5	0,0035	0,0136

After finding all the optimal parameters of GMDH neo-fuzzy system and training parameters, the system was trained, and then the data for prediction was provided. Training and testing of the system took place on data for the period up to 01.01.2021 for monthly periods, and until 01.06.2021 for weekly and day periods. Forecasting was based on data for the period after 01.01.2021 for monthly periods and after 01.06.2021 for day and week periods. For Dow Jones index with a forecast period of one month, the following forecasting data were obtained: MAE — 0,02952; MAPE — 0,0335; forecasting time — 0,00025

Learning and forecasting results are shown in Fig. 6.

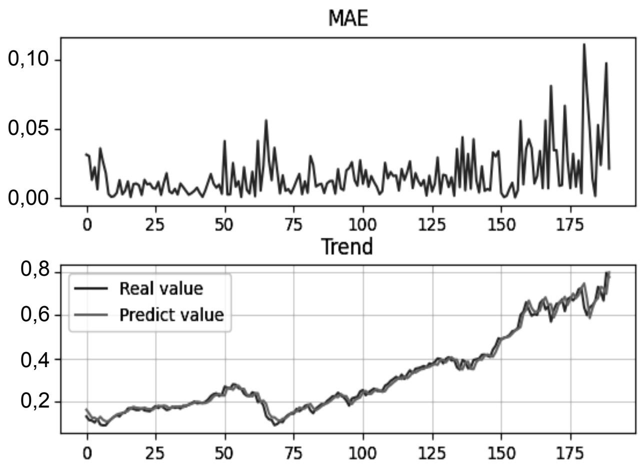

Fig. 6. Results of training and forecasting Dow Jones Index with interval one month by hybrid GMDH neo-fuzzy system

COMPARISON OF FORECASTING RESULTS OF GMDH NEO-FUZZY SYSTEM AND ANFIS NETWORK

Experimental investigations of the accuracy of market indexes Dow Jones and Nasdaq forecasting with forecasting intervals of one month, one week and one day were performed, using a hybrid GMDH neo-fuzzy network. For each prediction interval the optimal parameters found in previous experiments were selected. A comparative analysis with the forecasting results obtained by FNN ANFIS was performed.

According to the results of forecasting, values of MAE, MAPE and training time for each type of neural network were obtained. All comparison results are summarized in Tables 5–7 for Dow Jones index and in Tables 8–10 for Nasdaq index.

Table 5. Comparison of the forecasting results of GMDH neo-fuzzy neural network and FNN ANFIS for Dow Jones Index with forecasting interval 1 month

Criterion	GMDH neo-fuzzy neural network	FNN ANFIS	Difference
MAE at training sample	0,016938	0,016135	4,70%
MAPE at training sample	0,061866	0,052607	14,97%
MAE at test sample	0,02952	0,096734	-227,68%
MAPE at test sample	0,03350	0,107397	-220,59%
Training time (sec)	0,0023246	75,258	32375*x*
Forecasting time (sec)	0,0003123	0,02652	84,92*x*

Table 6. Comparison of the forecasting results of GMDH neo-fuzzy neural network and FNN ANFIS for Dow Jones Index with forecasting interval 1 week

Criterion	GMDH neo-fuzzy neural network	FNN ANFIS	Difference
MAE at training sample	0,007949	0,008564	-7,74%
MAPE at training sample	0,029890	0,029291	2,00%
MAE at test sample	0,011476	0,019279	-67,99%
MAPE at test sample	0,012468	0,020923	-67,82%
Training time (sec)	0,012840	194,3520	14980*x*
Forecasting time (sec)	0,00027132	0,028604	105,42*x*

Table 7. Comparison of the forecasting results of GMDH neo-fuzzy neural network and FNN ANFIS for Dow Jones Index with forecasting interval 1 day

Criterion	GMDH neo-fuzzy neural network	FNN ANFIS	Difference
MAE at training sample	0,003618	0,004234	-17,03%
MAPE at training sample	0,013981	0,014067	-0,615%
MAE at test sample	0,005348	0,005822	-8,86%
MAPE at test sample	0,005812	0,005822	-0,172%
Training time (sec)	0,19944	876,3658	4394,13*x*
Forecasting time (sec)	0,00040317	0,038055	94,39*x*

Table 8. Comparison of the forecasting results of GMDH neo-fuzzy neural network and FNN ANFIS for Nasdaq Index with forecasting interval 1 month

Criterion	GMDH neo-fuzzy neural network	FNN ANFIS	Difference
MAE at training sample	0,011264	0,011140	1,10%
MAPE at training sample	0,098307	0,088272	10,21%
MAE at test sample	0,006635	0,008617	-59,87%
MAPE at test sample	0,060995	0,097332	-59,57%
Training time (sec)	0,0065255	34,5328	5291,9*x*
Forecasting time (sec)	0,0005815	0,024286	41,76*x*

Table 9. Comparison of the forecasting results of GMDH neo-fuzzy neural network and FNN ANFIS for Nasdaq Index with forecasting interval 1 week

Criterion	GMDH neo-fuzzy neural network	FNN ANFIS	Difference
MAE at training sample	0,0052929	0,0055274	-4,43%
MAPE at training sample	0,041831	0,052723	-26,04%
MAE at test sample	0,009940	0,012973	-30,51%
MAPE at test sample	0,010933	0,014203	-29,91%
Training time (sec)	0,0411811	175,5418	4262,7*x*
Forecasting time (sec)	0,00030041	0,02489	82,85*x*

Table 10. Comparison of the forecasting results of GMDH neo-fuzzy neural network and FNN ANFIS for Nasdaq Index with forecasting interval 1 day

Criterion	GMDH neo-fuzzy neural network	FNN ANFIS	Difference
MAE at training sample	0,002349	0,002798	-19,11%
MAPE at training sample	0,019121	0,025317	-32,40%
MAE at test sample	0,005740	0,007161	-24,76%
MAPE at test sample	0,0063267	0,0079001	-24,87%
Training time (sec)	3,8612	823,90	213,39*x*
Forecasting time (sec)	0,0004616	0,085263	184,72*x*

Analyzing the presented results one may conclude, the best forecasting results for all forecasting intervals were obtained for hybrid GMDH neo-fuzzy system for both indexes Dow Jones and Nasdaq. The worst forecasting result for ANFIS network was obtained for one month forecasting period. The largest difference in the accuracy of forecasting by both criteria was obtained for the forecasting period of one month (over 200%). As the forecasting period decreases, the gap between the networks accuracy also decreases.

In addition, training and direct prediction times were also significantly less for hybrid GMDH neo-fuzzy system as compared with ANFIS.

CONCLUSION

In the paper new generation of Deep learning networks-hybrid GMDH neo-fuzzy networks are considered, optimized and investigated.

The algorithm of hybrid network structure synthesis is presented and demonstrated at the problem of forecasting.

The experimental investigations of the hybrid networks were carried out and compared with conventional DL networks. The problem of forecasting Dow Jones and Nasdaq Index with application of hybrid neo-fuzzy networks was considered, investigated and compared with FNN ANFIS at the different forecasting intervals: one month, one week and day.

The optimal parameters of hybrid neo-fuzzy networks and sets of informative features for forecasting problems were found. The experimental results have shown the forecasting accuracy of hybrid neo-fuzzy networks is much better than for FNN ANFIS.

The training time is the least for hybrid neo-fuzzy network as compared with alternative ANFIS network.

In a whole the hybrid DL networks based on GMDH are free from drawbacks of conventional DL networks- decay or explosion of gradient. Besides, they enable to construct optimal network structure automatically in the process of algorithm GMDH run and additionally they demand less computational costs for training due to small number of tunable parameters (only two) in every hidden node as compared with DL networks of general structure. That's is especially significant for DL networks with large number of layers.

REFERENCES

1. I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016.
2. G. Hinton, S. Osindero, and Y.-W. Teh, "A fast learning algorithm for deep belief nets", *Neural Computation*, vol. 18, no. 7, pp. 1527–1554, May 2006.
3. Y. Bengio, Y. LeCun, and G. Hinton, "Deep learning", *Nature*, no. 521, pp. 436–444, May 2015.
4. J. Schmidhuber, "Deep learning in neural networks: an overview", Neural Networks, no. 61, pp. 85–117, 2015.
5. A.G. Ivakhnenko, G.A. Ivakhnenko, and J.A. Mueller, "Self-organization of the neural networks with active neurons", *Pattern Recognition and Image Analysis*, 4, 2, pp. 177–188, 1994.
6. A.G. Ivakhnenko, D. Wuensch, and G.A. Ivakhnenko, "Inductive sorting-out GMDH algorithms with polynomial complexity for active neurons of neural networks", *Neural Networks*, 2, pp. 1169–1173, 1999.
7. G.A. Ivakhnenko, "Self-organization of neuronet with active neurons for effects of nuclear test explosions forecasting", *System Analysis Modeling Simulation*, 20, pp. 107–116, 1995.
8. M. Zgurovsky and Yu. Zaychenko, *Fundamentals of computational intelligence: System approach*. Springer, 2016.
9. L.-X. Wang and J.M. Mendel, "Fuzzy basis functions, universal approximation, and orthogonal least-squares learning", *IEEE Trans. on Neural Networks*, vol. 3, no. 5, pp. 807–814, 1992.
10. J.-S. Jang, "ANFIS: Adaptive-network-based fuzzy inference systems", *IEEE Trans. on Systems, Man, and Cybernetics*, 23, pp. 665–685, 1993.
11. T. Yamakawa, E. Uchino, T. Miki, and H. Kusanagi, "A neo-fuzzy neuron and its applications to system identification and prediction of the system behavior", in *Proc. 2nd Intern. Conf. Fuzzy Logic and Neural Networks «LIZUKA-92», Lizuka, 1992*, pp. 477–483.
12. Ye. Bodyanskiy, N. Teslenko, and P. Grimm, "Hybrid evolving neural network using kernel activation functions", in *Proc. 17th Zittau East-West Fuzzy Colloquium, Zittau/Goerlitz, HS, 2010*, pp. 39–46.
13. Ye. Bodyanskiy, Yu. Zaychenko, E. Pavlikovskaya, M. Samarina, and Ye. Viktorov, "The neo-fuzzy neural network structure optimization using the GMDH for the solving forecasting and classification problems", *Proc. Int. Workshop on Inductive Modeling, Krynica, Poland, 2009*, pp. 77–89.
14. Ye. Bodyanskiy, O. Vynokurova, A. Dolotov, and O. Kharchenko, "Wavelet-neuro-fuzzy network structure optimization using GMDH for the solving forecasting tasks", in *Proc. 4th Int. Conf. on Inductive Modelling ICIM 2013, Kyiv, 2013*, pp. 61–67.
15. Ye. Bodyanskiy, O. Vynokurova, and N. Teslenko, "Cascade GMDH-wavelet-neuro-fuzzy network", in *Proc. 4th Int. Workshop on Inductive Modeling "IWIM 2011", Kyiv, Ukraine, 2011*, pp. 22–30.

16. Ye. Bodyanskiy, O. Boiko Yu. Zaychenko, and G. Hamidov, “Evolving Hybrid GMDH-Neuro-Fuzzy Network and Its Applications”, in *Proceedings of the International conference SAIC 2018, Kiev, Ukraine, 2018*.
17. Evgeniy Bodyanskiy, Yuriy Zaychenko, Olena Boiko, Galib Hamidov, and Anna Zelikman, “The hybrid GMDH-neo-fuzzy neural network in forecasting problems in financial sphere”, in *Proceedings of the International conference IEEE SAIC 2020, Kiev, Ukraine, 2020*.
18. T. Ohtani, “Automatic variable selection in RBF network and its application to neuro-fuzzy GMDH”, *Proc. Fourth Int. Conf. on Knowledge-Based Intelligent Engineering Systems and Allied Technologies, 2000,* vol. 2, pp. 840–843.

Received 17.01.2022

INFORMATION ON THE ARTICLE

Yuriy P. Zaychenko, ORCID: 0000-0001-9662-3269, Institute for Applied System Analysis of the National Technical University of Ukraine “Igor Sikorsky Kyiv Polytechnic Institute”, Ukraine, e-mail: zaychenkoyuri@ukr.net

Helen Yu. Zaychenko, ORCID: 0000-0002-4546-0428, Institute for Applied System Analysis of the National Technical University of Ukraine “Igor Sikorsky Kyiv Polytechnic Institute”, Ukraine, e-mail: syncmaster@bigmir.net

Galib Hamidov, “Azerishiq”, Azerbaijan, e-mail: galib.hamidov@gmail.com

ГИБРИДНІ МГУА-МЕРЕЖІ ГЛИБОКОГО НАВЧАННЯ — АНАЛІЗ, ОПТИМІЗАЦИЯ ТА ЗАСТОСУВАННЯ ДЛЯ ПРОГНОЗУВАННЯ У ФІНАНСОВІЙ СФЕРІ / Ю.П. Зайченко, О.Ю. Зайченко, Г. Гамідов

Анотація. Розглянуто та досліджено новий клас мереж глибокого навчання — гібридні мережі глибокого навчання на основі методу самоорганізації МГУА. Застосування МГУА дозволяє навчати не тільки ваги зв’язків, але і конструювати структуру мережі. Як вузли мережі можуть бути використані елементарні нейрони з двома входами. Перевага такої структури — мала кількість налаштовуваних параметрів. Виконано оптимізацію параметрів та структури гібридних неофаззі мереж. Розглянуто застосування гібридних мереж глибокого навчання з оптимізованими параметрами для прогнозування біржових індексів з різними інтервалами упередження — один день, тиждень та місяць. Проведено експериментальні дослідження гібридних МГУА неофаззі мереж та порівняння їх з нечіткою нейронною мережею ANFIS, що дозволило оцінити ефективність та переваги гібридних мереж порівняно звичайними мережами глибокого навчання.

Ключові слова: гібридні мережі глибокого навчання, самоорганізація, оптимізація параметрів і структури, прогнозування.

ГИБРИДНЫЕ МГУА-СЕТИ ГЛУБОКОГО ОБУЧЕНИЯ — АНАЛИЗ, ОПТИМИЗАЦИЯ И ПРИМЕНЕНИЯ ДЛЯ ПРОГНОЗИРОВАНИЯ В ФИНАНСОВОЙ СФЕРЕ / Ю.П. Зайченко, Е.Ю. Зайченко, Г. Гамидов

Аннотация. Рассмотрен и исследован новый класс сетей глубокого обучения — гибридные сети глубокого обучения на основе метода самоорганизации МГУА. Применение МГУА позволяет обучать не только веса связей, но и конструировать структуру сети. В качестве узлов сети могут быть использованы элементарные нейроны с двумя входами. Преимущество такой структуры — малое количество настраиваемых параметров. Выполнена оптимизация параметров и структуры гибридных неофаззи сетей. Рассмотрено применение гибридных сетей глубокого обучения с оптимизированными параметрами для прогнозирования биржевых индексов с различными интервалами упреждения — один день, неделя и месяц. Проведены экспериментальные исследования гибридных МГУА неофаззи сетей и сравнение их с нечеткой нейронной сетью ANFIS, что позволило оценить эффективность и преимущества гибридных сетей по сравнению обычными сетями глубокого обучения.

Ключевые слова: гибридные сети глубокого обучения, самоорганизация, оптимизация параметров и структуры, прогнозирование.