Investigations of Cascade Neo-Fuzzy Neural Networks in the Problem of Forecasting at the Stock Exchange

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Abstract— **The problem of the forecasting stock prices and indexes in the stock market is considered. The application of new class of neural networks - cascade neo-fuzzy neural networks for the forecasting is investigated. For the forecasting data of the company's stock quote NYSE and the RTS index and the Dow Jones over the last year have been used. The comparison of results for the cascade neo-fuzzy neural networks with varying types of membership functions with the classical fuzzy neural networks, Group Method of Data Handling (GMDH) and fuzzy GMDH has been performed. The best results among the fuzzy neural networks showed cascaded NF network with Gaussian membership functions, their error does not exceed 3%.**

Keywords— ***stock indexes forecasting; neo-fuzzy cascade neural networks; fuzzy GMDH***

I. INTRODUCTION

One of the important problems in financial analysis is the problem of stock prices and indexes forecasting. The specific features of financial processes forecasting are the following: nonstationarity of financial processes at stock exchanges and unknown complex dependencies among the input and out processes. This prevents to use classical methods of statistical analysis for forecasting such as regression analysis and dispersion analysis and demands the elaboration of novel predicting methods based on artificial intelligence technologies, e.g. neural networks (NN) and fuzzy neural networks (FNN). One of the new classes of FNN is so-called cascade neo-fuzzy neural networks (NFNN) [1]. The goal of the present paper is the investigation of cascade NFNN for stock prices and stock indexes forecasting's, estimation of their efficiency and comparison with known forecasting methods.

II. ARCHITECTURE OF CASCADE NFNN

Architecture of cascade NFNN is shown at the fig.1. Its input-output mapping has the following form:

– neo-fuzzy neuron of the first cascade

$$\hat{y}^{[1]} = \sum_{i=1}^{n}\sum_{j=1}^{h} w_{ji}^{[1]}\mu_{ji}(x_i), \tag{1}$$

− neo-fuzzy neuron of the m-th cascade

$$\hat{y}^{[m]} = \sum_{i=1}^{n}\sum_{j=1}^{h} w_{ji}^{[m]}\mu_{ji}(x_i) + \sum_{\tau=n+1}^{n+m-1}\sum_{j=1}^{h} w_{j\tau}^{[m]}\mathrm{t}\left(\hat{y}^{[\tau-n]}\right). \tag{2}$$

Training criterion is the standard mean squared error (MSE) which is minimized by the gradient method:

$$E(k) = \frac{1}{2}\left(y(k)-\hat{y}(k)\right)^2 = \frac{1}{2}\left(e(k)\right)^2 = \frac{1}{2}\left(y(k)-\sum_{i=1}^{n}\sum_{j=1}^{h} w_{ji}\mu_{ji}\left(x_i(k)\right)\right)^2. \tag{3}$$

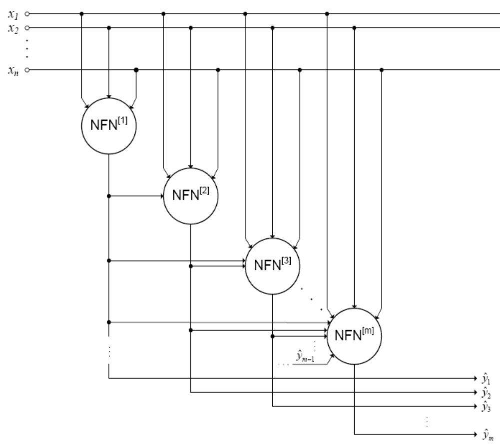

Figure 1.

Therefore a cascade neo-fuzzy neural network [2] contains $h\cdot\left(n+\sum_{l=1}^{m-1} l\right)$ adjustable parameters and all of them are linear which is very important for training.

Let $h(n+m-1)x_1$ – be a vector of membership functions values of the m-th neo-fuzzy neuron $\mu^{[m]}$ and the corresponding synaptic weights vector has the same dimension. Then we can present this expression in the following vector form:

$$\hat{y}^{[m]} = w^{[m]T} \mu^{[m]} . \tag{4}$$

III. Cascade NFNN Training Algorithms

The training of cascade NFNN may be performed in packet mode as well as in on-line mode using recursive algorithms. [2].

Let the case is considered when a learning sample is determined a priori, that is we have the sample of values

$x(1), y(1); x(2), y(2); \ldots; x(k), y(k); \ldots; x(N), y(N)$.

For a neo-fuzzy neuron of the first cascade NFN [1] the sample membership functions values are estimated

$$\mu^{[1]}(1), \mu^{[1]}(2), \ldots, \mu^{[1]}(k), \ldots, \mu^{[1]}(N) \cdot ,$$
$$\cdot (hn \cdot x \cdot 1 \cdot vector)$$

where

$$\mu^{[1]}(k) = \begin{pmatrix} \mu 1 1(x1(k)), \ldots, \mu h1(x1(k)), \mu 12(x2(k)), \ldots \\ \ldots, \mu h2(x2(k)), \ldots, \mu ji(xi(k)), \ldots \mu hn(xn(k)) \end{pmatrix}^T$$

Further, after minimizing training criterion (3) synaptic weights vector may be estimated

$$\begin{aligned} \omega^{[1]}(N) &= \left(\sum_{k=1}^{N} \mu^{[1]}(k) \mu^{[1]T}(k) \right) + \sum_{k=1}^{N} \mu^{[1]}(k) y(k) \\ &= P^{[1]}(N) \sum_{k=1}^{N} \mu^{[1]}(k) y(k). \end{aligned} \tag{5}$$

Where $(\bullet)^+$ means Moore-Penrose pseudo inverse.

In case of sequential data processing the recurrent LSM –method is used.

$$\begin{cases} \omega^{[1]}(k+1) = \omega^{[1]}(k) + \dfrac{p^{[1]}(k) y(k+1) - \omega^{[1]T}(k) \mu^{[1]}(k+1)}{1 + \mu^{[1]T}(k+1) p^{[1]}(k) \mu^{[1]}(k+1)} \mu^{[1]}(k+1) \\ p^{[1]}(k+1) = p^{[1]}(k) + \dfrac{p^{[1]}(k) \mu^{[1]}(k+1) \mu^{[1]T}(k+1) p^{[1]}(k)}{1 + \mu^{[1]T}(k+1) p^{[1]}(k) \mu^{[1]}(k+1)}, \quad p^{[1]}(0) = \beta I. \end{cases} \tag{6}$$

where β is a great positive number I is identity matrix.

The application of training algorithms leads to reducing of computational complexity of learning process and cuts learning time.

After the first cascade learning synaptic weights of neo-fuzzy neuron NFN [1] are "frozen", all output variables are determined and we obtain the second cascades which consist of only one neuron NFN [2]. It has one additional input for output signal of the first cascade. Then the process of training is performed for a neuron of this cascade.

In on-line mode all the neurons are trained sequentially. In case of sequential data processing the recurrent LSM method is used.

The process of neural network growth is repeated until we obtain the desired accuracy of forecasting or the minimum of MSE criterion. For the adaptation of the last cascade the following expression is used.

$$\omega^{[m]}(N) = P^{[m]}(N) \sum_{k=1}^{N} \mu^{[m]}(k) y(k) \cdot \tag{7}$$

IV. Experimental Investigations

In the paper the application of cascade neo-fuzzy neural networks for forecasting of stock prices and indexes was investigated.

The companies' stock prices at the stock exchange New York stock exchange (NYSE), and Dow Jones and Russian trade system (RTS) in the last year were used as input data for forecasting.

As the criteria of forecasting accuracy MSE (mean squared error) и MAPE were used. Some of the obtained results are in table 1.

TABLE 1. Forecasting results for 9-layered cascade NFNN. British Petroleum Shares (BP, NYSE)

Criterion	BP, NYSE
MAPE	5,05228088
MSE	3,9612744

Consider forecasting results of stock indexes. In this paper indexes Dow Jones Industrial and RTS were chosen as the most substantial indexes for stock exchanges in USA (NYSE) and Russia some of the experimental results are presented below (tables 2, 3).

TABLE 2. Forecasting results for 9-layered cascade NFNN. RTS Index

Criterion	RTS Index
MAPE	4,470381366
MSE	1,6754807

TABLE 3. Forecasting results for 10-layered cascade NFNN. Dow Jones Industrial Index

Criterion	Dow Jones Industrial Index
MAPE	3,765981607
MSE	4,5277613

Below the experimental results for considered indexes of Gaussian membership functions are presented in tables 4-6.

TABLE 4. Forecasting results for 6-layered cascade NFNN. Shares BP (NYSE)

Criterion	Shares BP (NYSE)
MAPE	3,759762101
MSE	3,3054605

TABLE 5. Forecasting results for 9-layered cascade NFNN. RTS Index

Criterion	RTS Index
MAPE	3,210853177
MSE	1,7688684

TABLE 6. Forecasting results for 10-layered cascade NFNN. Dow Jones Industrial

Criterion	Results	Dow Jones Industrial
MAPE	2,312873953	3,76598161
MSE	3,8372695	4,527761

The experimental forecasting results obtained by cascade NFNN were compared with results of classical fuzzy neural networks and the results obtained by classical and fuzzy Group Method of Data Handling (GMDH [2,3]. Some of the final results obtained by different methods are presented in tables 7, 8.

TABLE 7. The best results of investigated forecasting methods. BP (NYSE)

Criterion	Cascade NFNN with Gaussian MF	Fuzzy GMDH Linear model	GMDH Linear model
MAPE	3,759762101	1.019151	1.019151
MSE	3,3054605	3,153671	3,153671

TABLE 8. The best results of investigated forecasting methods for Dow Jones Industrial

Criterion	Cascade NFNN with Gaussian MF	Fuzzy GMDH Chebyshev polynomial	GMDH Chebyshev polynomial
MAPE	2,312873953	0.448088	0.550859
MSE	3,8372695	3,9227	4,4157

V. CONCLUSIONS

The investigations of cascade neo-fuzzy neural networks in the problem of stock indexes and share prices forecasting have been carried out. The comparison with alternative forecasting methods was fulfilled. *The best results has showed cascade NFN with Gaussian membership functions.*

Its MAPE didn't exceed 3%. This proves the efficiency of application of the suggested neo-fuzzy neural network for forecasting in the financial sphere. But GMDH and fuzzy GMDH have shown slightly better results: their error had not exceeded 2%.

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