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Application of Neural Network Technologies for Price Forecasting in the Liberalized Electricity Market*

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***Abstract*--The paper presents the results of experimental studies concerning calculation of electricity prices in different price zones in Russia and Europe. The calculations are based on the intelligent software "ANAPRO" that implements the approaches based on the modern methods of data analysis and artificial intelligence technologies.**

INTRODUCTION

Today one of the key conditions for a successful activity of electricity market participants in the free trade sector is consideration for the price situation in the market while preparing the bids for electricity purchase and/or sale [2]. It should be noted that before 2008 electricity and capacity had been supplied to the market in Russia at regulated prices. And in the second half of 2008 the share of liberalized electricity market segment made up only 15%. The dynamics of change in the liberalized average monthly price[1] was favorable for generation companies of European Russia and Urals since it was much higher than the average regulated electricity tariff (Fig.1). However, in the Siberian price zone the dynamics of change in the spot price during this period was negative due to abnormally warm winter in this region in 2006-2007 and available large volumes of accessible water resources.

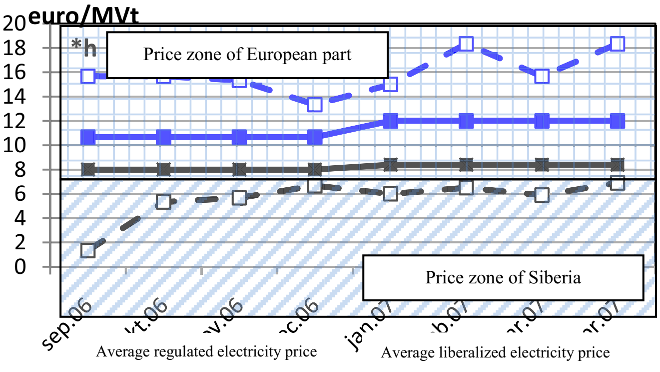

Fig. 1. Average monthly spot prices for different zones in Russia

Based on the current trends an essential increase in electricity and capacity supply at unregulated prices is expected in the years to come (Fig. 2). Total liberalization of the Russian electricity market is planned for 2011.

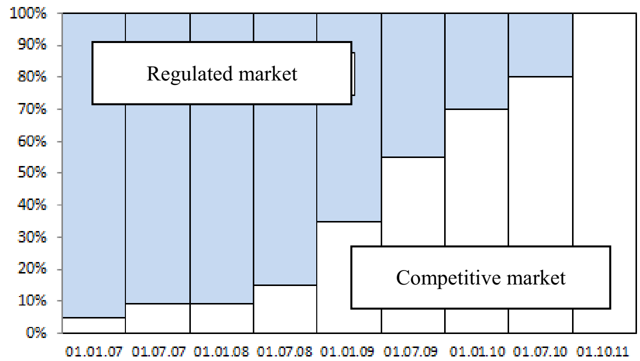

Fig. 2. A diagram of Russia's electricity market liberalization

Analysis of competitive market operation indicates to the fact that electricity prices are subject to large seasonal, daily and diurnal fluctuations depending on electricity consumption. In particular seasonal temperature fluctuations explain essentially the fluctuations in electricity consumption and as a result – fluctuations of prices. The tendency of electricity price change in time can be characterized using such a statistical index as volatility[2], σ [3], determined from the following expression

$$\sigma = \sqrt{\frac{1}{n}\left[\ln {P_I}/{P_{i-1}} - \frac{\sum_{i=1}^{N} \ln {P_I}/{P_{i-1}}}{n-1}\right]^2} \cdot \sqrt{m} \qquad (1)$$

where m is the number of periods of certain duration for the workdays of a year; n – quantity of days; P_i, P_{i-1} - price values during current and previous time instants, respectively.

The volatility is characterized by the so called clusterization, i.e. the presence of a large number of price peaks in some time intervals and rather calm price behavior in the other ones. Table 1 presents the results of volatility analysis for competitive electricity markets in Europe and Russia before May 2007.

It is necessary to underline that currently the susceptibility of Russian generation companies to the volatility of spot prices[3] is limited (Table 1) since only 35 % of the wholesale market is liberalized. But the probability of change in the spot prices

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[1] Hereinafter mean values of hourly prices for a certain time interval (day, week, month) are taken for prices.

[2] Historical volatility is used in the paper

[3] Spot price – a day ahead hourly price

will increase as the wholesale market is liberalized and by 2011 the level of susceptibility to the risk of spot price changes will reach 100%.

TABLE I
DATA ON VOLATILITY OF COMPETITIVE ELECTRICITY MARKETS IN EUROPEAN COUNTRIES AND IN RUSSIA

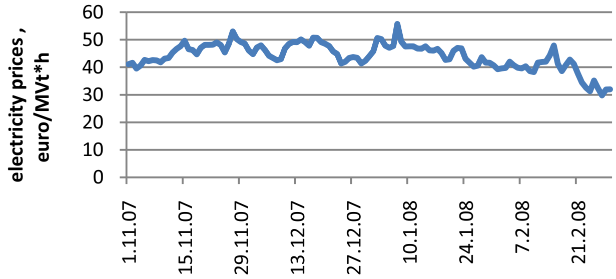
Competitive market		Weighted average monthly price, Euro/MW*h	Volatility, %
European countries	Nord Pool	37,8	77
	GME	68,2	42
	EEX	33,9	94
	OMEL	49,4	78
	Powernext	32,1	90
	APX NL	41,7	91
Russia	ATS – European part	17,0	2
	ATS – Siberia	14,3	6

After the total liberalization of the wholesale electricity market the dynamic of change in the spot price will be determined by their trade strategy, experience and qualification in the field of management of risks and acceptable level of risks as well as by how the generation company will balance the potentially profitable but volatile possibilities of selling at spot prices and a desire to hedge the risk and retain the profit at a stable level of profitability. It should be noted that all other conditions being equal a large share of electricity sales in the forward market at fixed prices supposes a lower level of business risk. This provides generation companies with an acceptable level of profitability to maintain credit capacity of the company provided the generation costs remain fixed. Currently generation companies can hedge the risk of price volatility by unregulated forward contracts at fixed price. Further to expand the possibilities of hedging power industry the exchanges can involve other financial instruments, for example, futures.

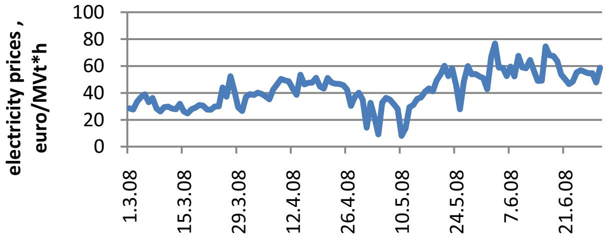
Fast creation of competitive electricity market in Russia has considerably complicated interrelations among the participants of the market that have to act under uncertainty. Therefore, the use of an efficient price forecasting system becomes a competitive advantage for the market participants.

I. MODELS OF ELECTRICITY PRICE FORECASTING

Very many mathematical models have been developed lately. They are based both on traditional statistic methods (Autoregressive Integrated Moving Average, ARIMA; Generalized Autoregressive Conditional Heteroscedasticity, GARCH; Fourier Spectral Analysis) and on the neural network approaches (Radial basis function, RBF; Support vector machine, SVM; Multilayer perceptron, MLP) [1] (Fig.3). Analysis of the works dedicated to this subject shows that the techniques of day-ahead hourly[4] price forecasting [4, 5] and price peak forecasting [6, 7] are best worked through.



a) price zone A



b) price zone B

Fig. 3. Time series average daily electricity price for different price zone

The models from the family of ARIMA and GARCH were successfully tested on the Spanish and Norwegian electricity markets [8, 9]. The models based on the artificial neural networks were applied to the electricity markets in Brazil [10], Canada [11], Australia and Wales [12, 13].

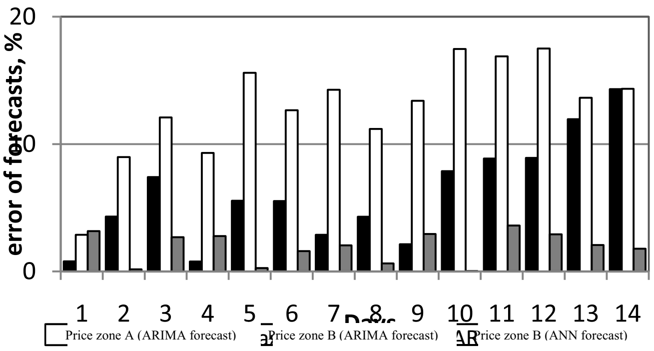


Fig. 4. A block diagram of errors of the day-ahead electricity price forecast on the basis of ARIMA model

It should be noted that a common disadvantage of the ARIMA and GARCH models is the fact that disregarding the computing techniques applied they use only retrospective data. And if the conditions in the electricity markets, for example, market volatility or autocorrelations between values of analyzed time series change sharply these changes will be taken into account only in some time interval. While till that moment the forecasts will be incorrect. For example, the calculations made using ARIMA for two price zones A and B

[4] The price for a certain hour of the period at issue

(Fig. 3) show that the average electricity price forecast error on a two-week interval for the price zone A, which is characterized by weak non-stationarity of price change, made up nearly 6% (Fig.4). Whereas for the price zone B which is characterized by a considerable degree of non-stationarity (in particular, by high volatility) the average forecast error for similar forecasting interval exceeded 13%.

Most of the works emphasize that the highest accuracy of the price forecast, including its peak values, can be obtained on the basis of neural network models. According to [4], for example, the RBF model involving fuzzy logic turned out to be rather efficient for the day-ahead half-hourly forecast of prices. This was proved by the forecasts for the Chinese electricity market. Besides, to make a reliable forecast of peak prices which are in a general case random events in the electricity market the SVM-based neural network models are successfully applied [7]. In these cases the traditional models ARIMA and GARCH did not give the required forecast accuracy comparable with the forecasts on the basis of artificial neural networks (ANN).

The advantages of applying ANN for the price forecasting problem are:

- The possibility to use a great number of input variables that affect the price (for example, preliminary consumption schedule, maintenances of unique and large energy units, generation, ambient air temperature, inflow, operating reserves, precipitation, etc.)
- Low errors of forecasts under high volatility of the considered time series which is typical of the competitive electricity market.

For example ANN application for a day-ahead price forecast for the price zone B (Fig.4) shows that the error of the neural network forecast in this case is essentially lower than the error of the ARIMA model for the same price zone, and does not exceed 2.2%.

II. EXPERIMENTAL CALCULATION

The paper suggests an intelligent[5] approach based on the neural network technologies to forecast electricity prices for different lead time intervals. This approach allows an efficient solving of forecasting problems under strict requirements for accuracy of such calculations and under considerable non-stationarity of the parameters studied. The suggested approach is implemented in the subsystem of forecasting (Fig.5, blocks 7-10) within the intelligent software ANAPRO. The general structure of the ANAPRO software, functions and interactions of individual blocks are presented in [14, 15].

Application of the SA algorithm makes it possible to analyze the properties of the initial sampling and organize a competition-based system among different neural network forecast models when during the process of nonlinear optimization the best forecasting model is selected. In the neural network forecasting the ANN structures themselves are the forecasting models.

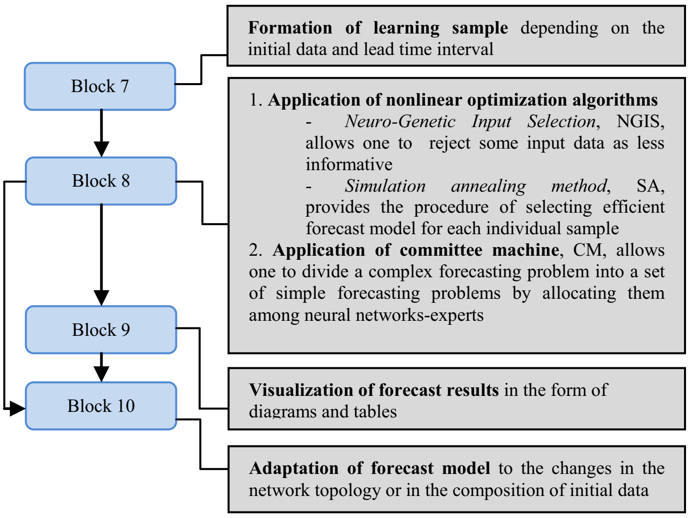


Fig. 5. Forecasting subsystem of the ANAPRO software

Each iteration of the SA algorithm represents an ANN variant of a certain type and architecture. The ANN type can be repeated but network architecture will always be different. According to the chosen criterion the iteration algorithm makes a search for the optimal ANN structure. With changes in the network topology or input data, including also the factors that affect the forecasted parameters the algorithm envisages adaptation of the forecasting model. Normally 10-20 iterations is enough to find the optimal type and architecture of ANN.

In the work the suggested intelligent approach was used to forecast nodal and spot electricity prices for two price zones for different time intervals

- Average daily "a day ahead"
- Average weekly "4 weeks ahead"
- Hourly "a fortnight ahead"

Along with the retrospective values of electricity prices the following parameters and characteristics were used in calculations:

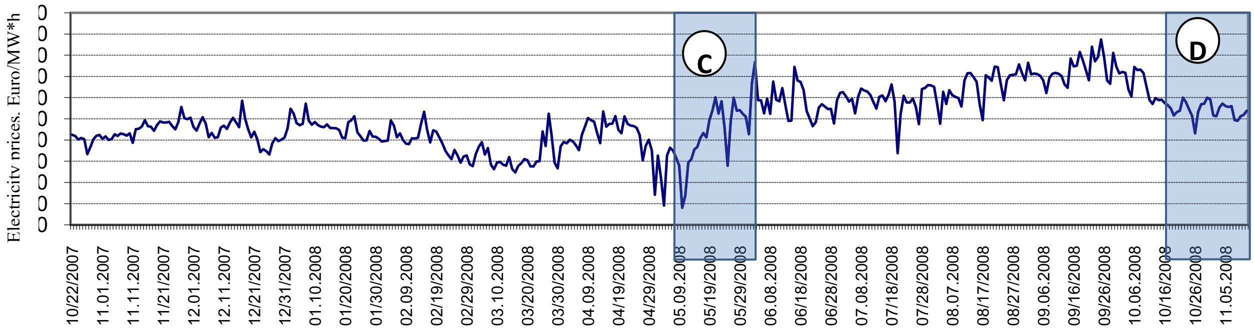
- Power flows;
- Basic and peak electricity values in the adjacent zones;
- Inflow;
- Precipitation;
- Air temperature

A. A day-ahead electricity price forecast

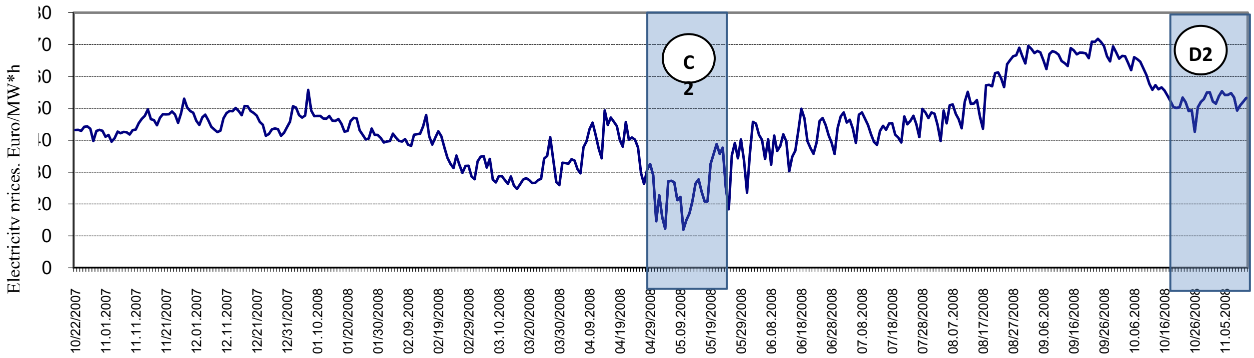
Initial time series were represented by the arrays of average daily electricity price values for Price zone 1 and Price zone 2 (Fig.6) over the period 22.10.2007 – 05.11.2008.

The studies show that the price zones, though differ geographically, are strongly statistically interrelated (correlation coefficient is 0.89).

[5] The term "intelligent" is used in reference to the approaches, methods, systems and complexes using artificial intelligence technologies



a) Price zone 1



b) Price zone 2

Fig. 6. Initial time series of electricity price for Price zone 1 and Price zone 2 over the period 22.10.2007-05.11.2008

The forecast was made for two time zones with different volatility values that were calculated for identical periods, namely:

- «Price zone 1» - C1 zone (the period 12.05.08 ÷ 31.05.08 (σ_M=43 %), D1 zone - the period 29.10.08 ÷ 11.11.08(σ_M=7 %) (Fig. 6a);
- «Price zone 2» - C2 zone (the period 12.05.08 ÷ 31.05.08 (σ_M=28 %), D2 zone – the period 29.10.08 ÷ 11.11.08(σ_M=4 %) (Fig. 6b).

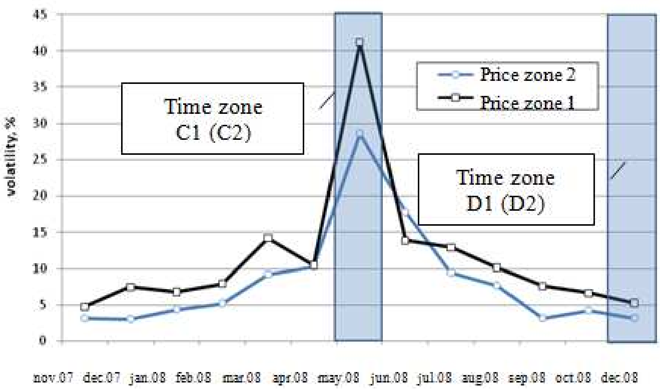


Fig. 7. Diagrams of change in the monthly volatility for two price zones

The calculations carried out in block 8 using a competition principle of the SA algorithm have shown that the best results of the day-ahead electricity price forecasting are achieved with the help of the neural network model MLP.
Here the model includes all the initial parameters except for the parameter "Precipitation" that was excluded by the NGIS algorithm as the least important for the forecast.

The results of the electricity price forecast for Price zone 1 and Price zone 2 for time zones with different volatility (Figs. 8 and 9, Table 2) show that the maximum errors in electricity price forecast are observed for the zone of C1(C2), which is characterized by high value of monthly volatility.

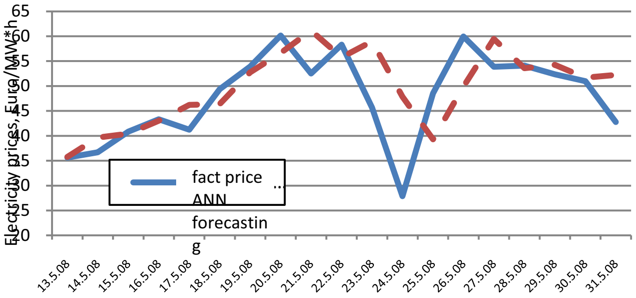
B. Fortnight-ahead average weekly electricity price forecasts

To solve this problem the initial array of data on "Price zone 1" and "Price zone 2" (Fig. 6) was averaged by week. The best results were obtained with the neural network model MLP. Its architecture was chosen by the SA algorithm. Here the model included all the initial parameters except for the parameters of base and peak price values in the adjacent zones, inflow and precipitation, that were excluded by the NGIS procedure as the least important for the forecast.

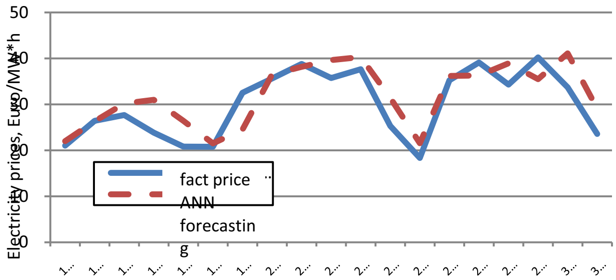
The results of the price forecasting four weeks ahead for Price zone 1 are presented in Table 3.

C. Fortnight-ahead average hourly electricity price forecasts

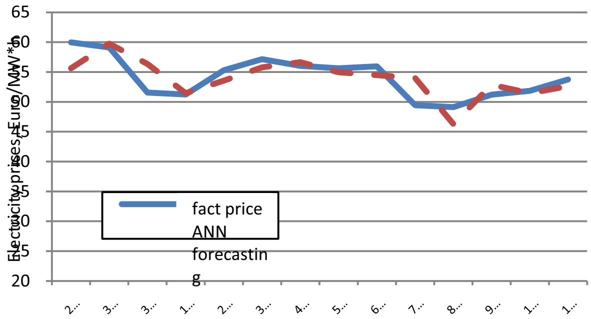
Initial data were represented by average hourly electricity price values for Price zone 1 and Price zone 2 over the period 05.11.2007 ÷ 24.11.2008.



a) Region C1

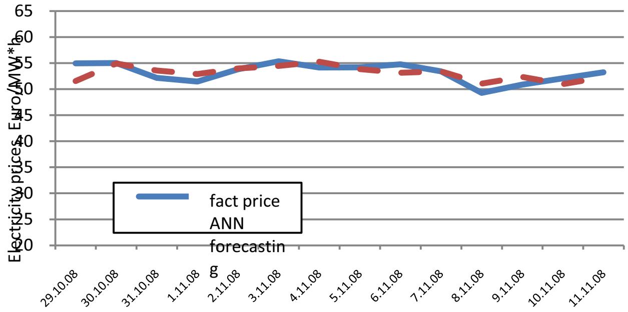


a) Region D1



b) Region D1

Fig. 8. A day-ahead electricity price forecast for Price zone 1



b) Region D2

Fig. 9. A day-ahead electricity price forecast for Price zone 2

TABLE 2
ERROR OF ELECTRICITY PRICE FORECASTING FOR THE TWO PRICES ZONE WITH DIFFERENT VOLATILITY VALUES

Price zone 1	Region C1	days	13.05	14.05	15.05	16.05	17.05	18.05	19.05	20.05	21.05	22.05	23.05	25.05	26.05	27.05
		error, %	0.31	8.08	1.09	0.66	12.09	6.06	2.17	5.83	16.42	4.33	29.1	18.99	16.75	10.42
	Region D1	days	29.10	30.10	31.10	1.11	2.11.	3.11	4.11	5.11	6.11	7.11	8.11	9.11	10.11	11.11
		error, %	5.24	1.10	9.27	0.43	3.12	2.37	1.13	1.20	2.61	9.22	5.80	3.27	0.78	2.09
Price zone 2	Region C2	days	13.05	14.05	15.05	106.05	17.05	18.05	19.05	20.05	21.05	22.05	23.05	25.05	26.05	27.05
		error, %	4.71	0.43	9.04	30.01	26.94	3.56	24.68	2.45	1.56	10.87	7.02	17.42	2.69	7.21
	Region D2	days	29.10	30.10	31.10	1.11	2.11.	3.11	4.11	5.11	6.11	7.11	8.11	9.11	10.11	11.11
		error, %	6.17	0.16	2.69	2.78	0.27	1.60	2.05	0.63	2.94	0.02	3.61	2.91	2.07	1.78

TABLE 3
A FOUR WEEK-AHEAD AVERAGE WEEKLY PRICE FORECAST FOR PRICE ZONE 1 ON THE BASIS OF ANN

Number of week	Real price, Euro/MW	Forecast, Euro/MW	Forecast error, δ, %
52	56.87	61.87	8.80
53	53.42	55.80	4.45
54	55.59	54.84	1.33
55	54.08	49.73	8.04
Average error, MAPE			**5.66**

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|x_i - \bar{x}_i\right|}{x_i}\cdot 100\% \qquad (2)$$

where: $\bar{x}_i$ - a forecast value of parameter; x_i - an actual value of parameter; n – a lead time interval

Based on the SA algorithm in the block 8 the best neural network model of RBF type was selected for Price zone 1 and neural network model of GRNN[6] type for Price zone 2. It should be emphasized that while the RBF model was formed for Price zone 1 the NGIS algorithm excluded the data on the prices at 10 a.m. and 11a.m. from the initial sampling as those not affecting further hourly price forecast. Therefore only 22 of 24 hours were used as the initial values of the ANN for Price zone 1.

The results of price forecasts for Price zone1 on the basis of RBF and GRNN models are presented in Table 4 and illustrated in Fig. 10.

The results of forecasting show that the largest forecast errors of the ANN model have been obtained for 24.11.2008. On this day in the intervals 8:00÷12:00 and 16:00÷20:00 the actual hourly prices changed considerably which resulted in

[6] Generalized Regression Neural Network

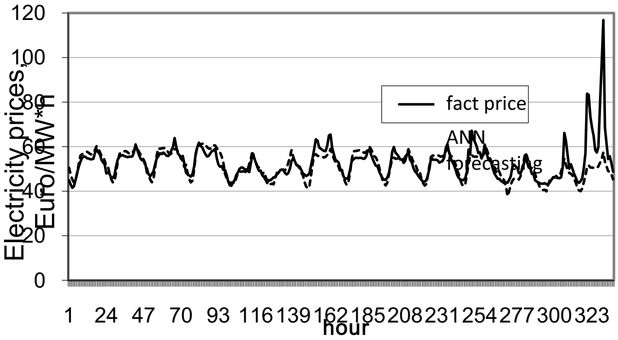
TABLE 4
A ERROR OF A FORTNIGHT-AHEAD HOURLY ELECTRICITY PRICE FORECAST FOR PRICE ZONE 1 (2008)

Days	11.11*	12.11	13.11	14.11	15.11	16.11	17.11	18.11	19.11	20.11	21.11	22.11	23.11	24.11
Forecast error , MAPE, %	4,39	2,82	3,62	5,09	2,30	3,22	6,55	4,30	3,44	3,05	5,13	6,31	5,07	19,73

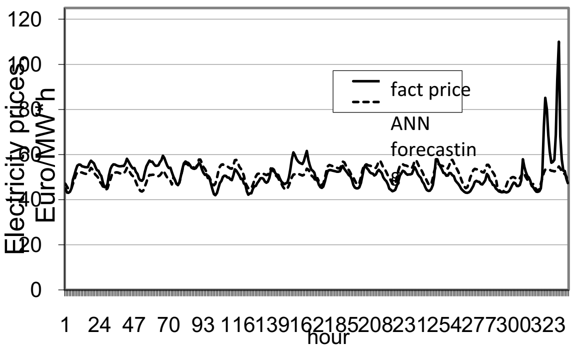
* For simplification the Table presents mean values of hourly price error for a certain day

the largest forecasting error of hourly price values for Price zone 1.

The obtained results of calculations show that the most efficient ANN architectures for electricity price forecasting are RBF, MLP and GRNN models.



a) «Prices zone 1»



b) «Prices zone 2»

Fig.10. Fortnight-ahead hourly electricity price forecasts for two prices zone

CONCLUSION

The paper presents some specific features of the competitive electricity market formation in Russia. A considerable volatility of electricity prices in the liberalized sector is shown by the example of electricity (power) market in Russia, and electricity price volatility should be expected to rise further as the sector increases.

The results of experimental electricity price calculations on the basis of intelligent ANAPRO software:

- Average daily "a day ahead"
- Average weekly "4 weeks ahead"
- Hourly "a fortnight ahead"

show relatively low errors in the electricity price forecasts under high level of volatility in the studied competitive electricity markets.

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