ELECTRIC ENERGY DEMAND BY THE POPULATION OF THE SIBERIAN FEDERAL DISTRICT: TWO APPROACHES TO FORECASTING

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According to the forecast of Russian Federation long-term socio-economic development up to 2030, the share in the growth of gross regional product (GRP) Siberian Federal District (SFD) will increase from 10.9% to 11.2% [1]. During all forecast period, the growth of final consumption in the SFD will be higher nationwide indicator (for 2012 -. 2030 will make to 235%). It will increase the district share in final consumption (from 10.6% in 2010 to 11,3% in 2030 year), and increase the electrical energy (EE) consumption share of by economic activity and the population [1].The population is the second largest (after industrial) consumers in the SFD. It accounted for the period 2000 - 2014 from 9.3% to 11.7% EE consumption [2].

In this context, it seems appropriate to study in detail the SFD population electricity consumption in the short and long term. Regions planning and strategic development are relevant in the economic crisis. Population electricity consumption forecasting of the (SFD) becomes especially important, considering specificity of the electricity market functioning. In the article has been produced handling and time series analysis using two models for assessing demand for the part SFD population EE (ARIMA, Automated Neural Network [2]) in the statistics program to estimate the demand for EE on the part of the SFD population. [1].

Following problems have been solved to achieve the goal:

- Graphical analysis of energy consumption indicators have been performed;
- Seasonal and regular components have been detected;
- Time series forecast have been executed;
- Forecast quality assessment have been produced.

Baseline data are the EE consumption of population by months in 2000 - 2015. Time series visualization and descriptive analysis are shown below.

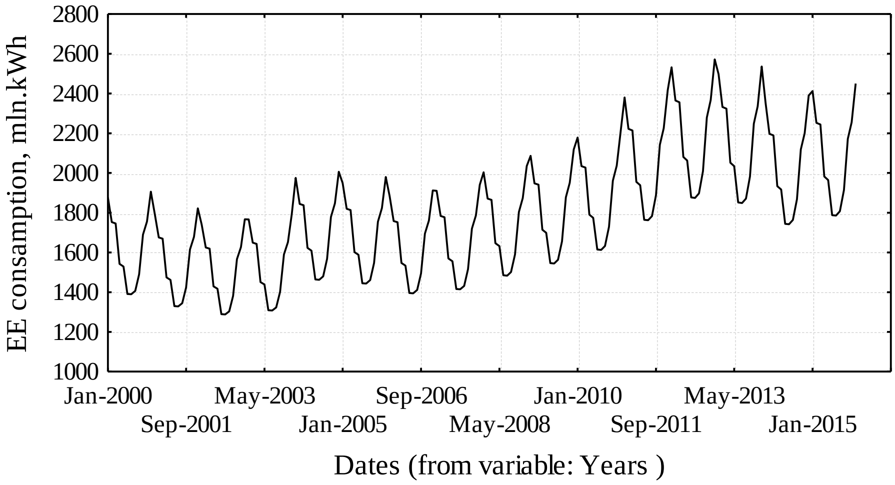

Fig. 1. Plot of population electrical energy consumption, mln.kWh

Study indicators levels must be comparable and uniform to build the quality forecast, data should be stable and full to identify trends, that is the number of observations must be large enough [3].

There are clear peaks in the periodogram in June 2001 for the single series Fourier spectral analysis. EE consumption is changing according to seasonality certain laws within each seasonal cycle. Seasonality can be traced by the smoothed moving average chart of the classical seasonal decomposition (fig.2).

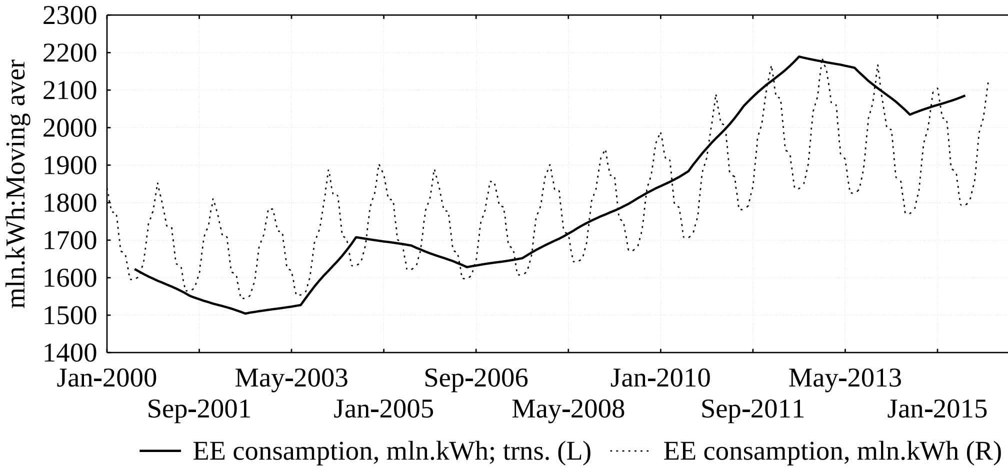

Fig.2. Plot of selected variables (series)

Classic additive model Graph of the moving average has not stationary and shows that are expected the forecast fall of the total consumption.

The next, we have built a short-term forecast (3 years) of the time series by autoregressive model of the integrated moving average (ARIMA), by means of which the data will be given to a stationary form. Necessary to build two functions for rebounds parameters of ARIMA model: autocorrelation and partial autocorrelation functions for the converted data with seasonality order 1, 12, 24. According to the theory model identification converted data corresponds to the converted MA (1) criterion [4]. The relative error of the cross-validation is 4.8%. In this case, the histogram does not fully satisfy the distribution normality.

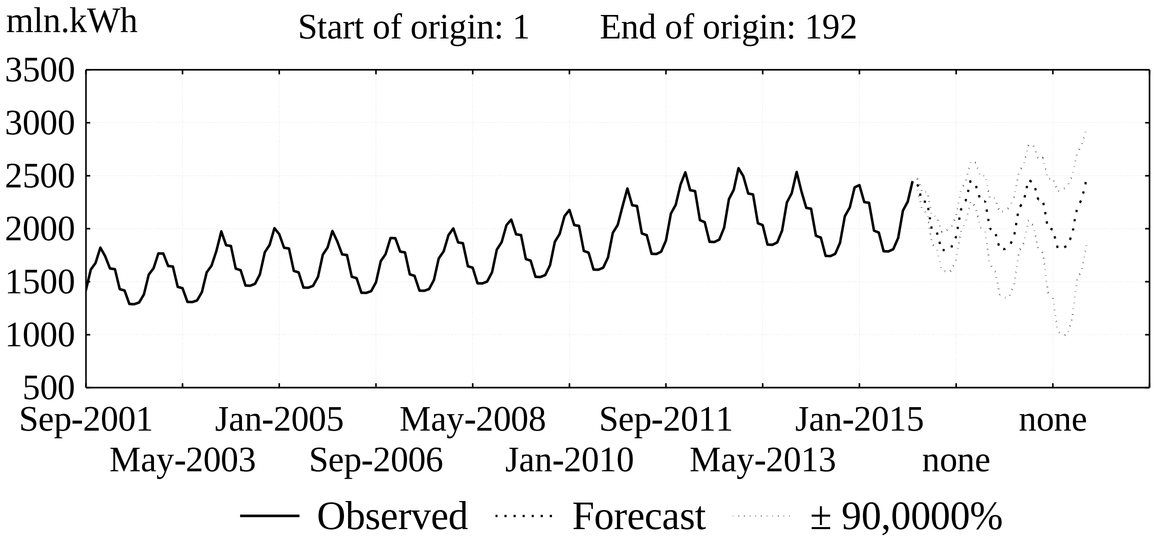

Fig.3. Forecasts from 2015 to 2018, mln.kWh; Model:(0,1,0)(0,1,1) Seasonal lag: 12

On the figure 3, we can see a result of forecast model with the seasonality parameters values Q = 1 and P = 0.

Then, we choose a learning strategy of the data fetch for the following neural networks (NN) method: Training=60%, Testing=20%, Validation=20%.

Have been used the identity (1), logistics (2), and tangential (3) for the input and only the first two for the output.

$$F(x) = A \cdot x \tag{1}$$

where $F(S)$ – identity activation functions, A – function parameter defining the slope, x – function argument.

$$F(x) = \frac{1}{1 + e^{(-Ax)}} \tag{2}$$

$$F(x) = \frac{e^{Ax} - e^{-Ax}}{e^{Ax} + e^{-Ax}} \tag{3}$$

The number of hidden neurons in a hidden layer is used from 2 to 7, error function – sum of squares, we have chosen the best option from 12 iterations – 11 (table 1).

Tab. 1. Summary of active networks

№N	Net. name	Train.perf.	Test perf.	Valid. perf.	Train. error	Test error	Valid. error	Training algorithm	Hidden activation	Outp
11	MLP 2-6-1	0,96	0,97	0,969	0,0017	0,0008	0,002	BFGS147	Logistic	

The coefficients on all three levels of education are close in value in the table of results, training errors within an acceptable range.

Residuals normal distribution and scattering density of an objective function depending on output forecast indicators (fig. 4, b). is an good quality indicator of the constructed models.

a) ***b)***

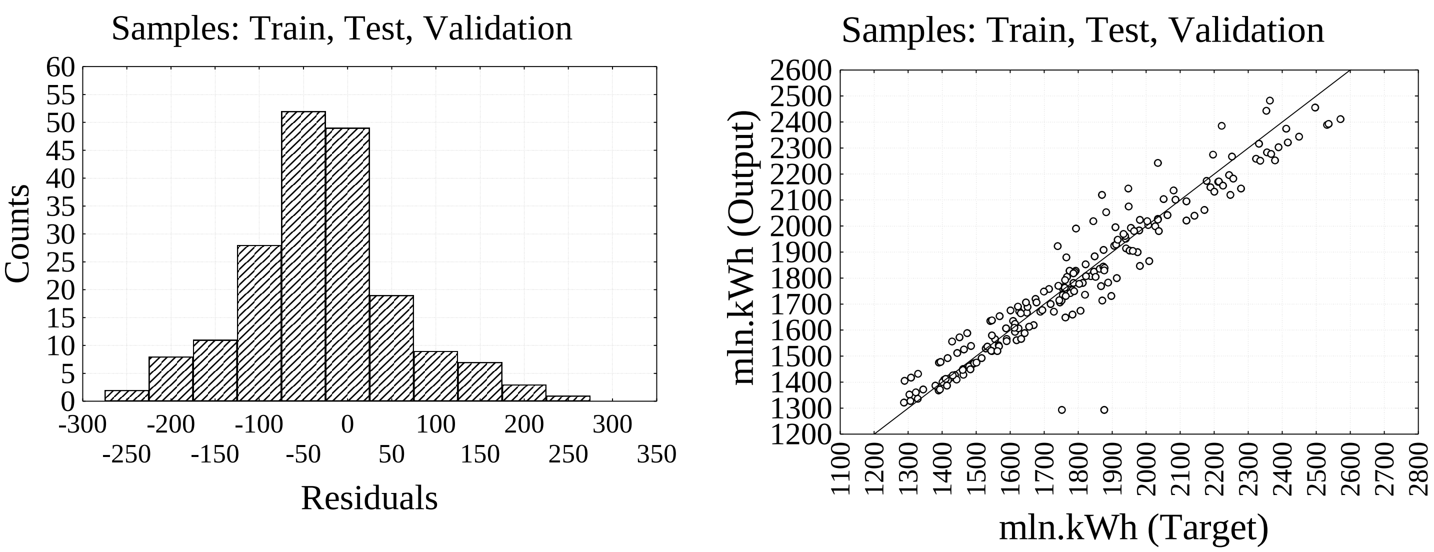

Fig. 4. Histogram of residuals normal distribution (a), graph of the objective function scattering (b)

For 11 iterations residuals are normally distributed and better compared to the previous version (fig. 4, a), points lie more closely to the line on the scatterplot (fig. 4, b).

Also cross-validation results (3,3%) shows us, that forecasting method based on neural networks is the most appropriate, this confirms the forecast on the figure 5.

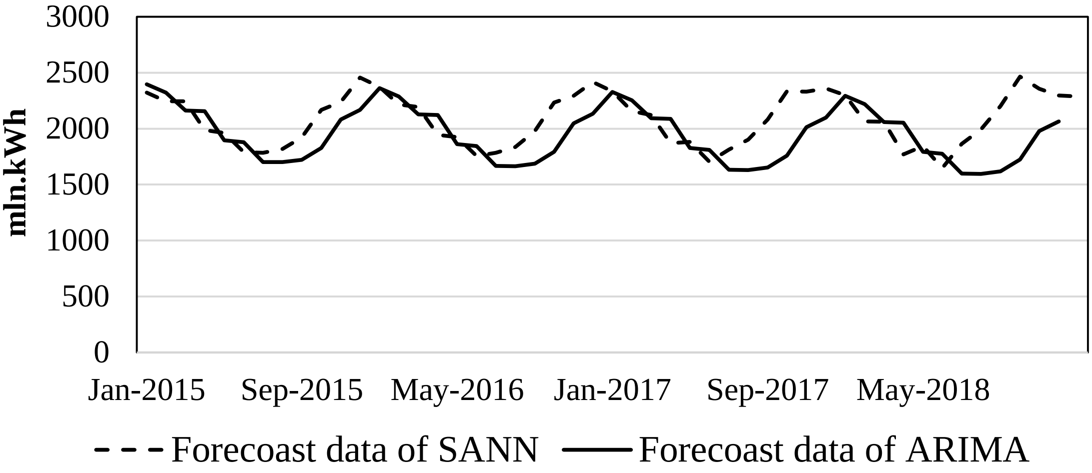

Fig. 5. Comparison of two methods of forecasting variants

Neural networks provide the most reliable results for the data prediction thanks to the complexity and nonlinearity of the data series structure. Classical methods are designed for using the series data with more visible and obvious structural regularities, in contrast to the considered neural networks [7].

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