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Application of MLP and stochastic simulations for electricity load forecasting in Russia

E. Savelieva, A. Kravetski, S. Chernov, V.Demyanov,
V. Timonin, R. Arutyunyan, L. Bolshov[1], M. Kanevski[1,2]

[1] Nuclear Safety Institute RAS, 113191, Moscow, B.Tulskaya, 52, esav@ibrae.ac.ru,
http:\\www.ibrae.ac.ru/~m_kanevski/
[2] IDIAP Research Institute, Martigny, Switzerland, kanevski@idiap.ch

Abstract. The work is devoted to an application of artificial neural network (multilayer perceptron) and conditional stochastic simulations to electricity load forecasting in Russia. One of the problems is missing data and some important weather parameters (wind, cloudiness, precipitation, historical information). This gives rise to rather large forecasting errors with complex statistical structure. Another problem deals with economic trends in the country during the last decade and its influence (sometimes contradictory) on electricity consumption. The methodological innovative aspect of the study is a use of geostatistical tools (variography) and simulations to characterise the expected variability of the results.

1. Introduction

Nowadays artificial neural networks became a frequently used tool using for electricity load forecasting. They are powerful universal non-linear models able to include a great amount of information concerning and depending on the value of electricity load. It is known that electricity load is dependent on season, type of a day, weather parameters and economic activities of the region. The dependencies appeared to be different for different countries and even regions of one country [1]. So even having some preliminary knowledge about investigations performed in some other countries, detailed analysis of historical data for the region of presumed forecasting have to be done.

An interest how to use adaptive methods for electricity load forecasting appeared in Russia too. It was forced by several strong failures made by traditional methods. But there is a strong limitation with historical information. Only historical data on load and temperature are available. It is well-known that temperature is one of the most important parameters depending on the electricity consumption. But it was shown [2] that knowledge of other weather parameters (cloudiness, fallout, temperature in adjacent regions, wind speed and direction) can significantly improve the forecast.

The basic idea of the present study is to apply artificial neural network (multilayer perceptron) for electricity load forecasting and then detailed analysis of ANN residuals by using geostatistical conditional simulations. Simulations reproduce the correlation structure (if there is any) of ANN residuals. The mean and standard deviation of the residuals for each forecasted time were estimated on the base of simulations. These means were used to improve the ANN load predictions. Standard

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deviations were used to indicate the expected ranges of electrical consumption. Obtained results were compared with real data.

2. Description of forecasting method

The problem under study is to make short term hourly load forecasts for a following week. Weather forecast for the whole week (minimal and maximal, night and day temperatures) and historical load and temperature data for 2 years are available.

Three multilayer perceptrons were used as basic models for the load forecasting. Each one was devoted to a special season – summer, winter and transitional seasons (spring and autumn). Architecture of all ANNs and the set of input parameters were the same for all seasons. The difference was in the set of data used for the ANN training.

Input parameters were selected based on simple common sense – to insert in training all kinds of periodicity (daily and weekly) and similarities (adjacent hours).

Several experiments were performed for choosing the architecture of ANN. It appeared that the simple (1 hidden layer with 7 neurons) shows the best results while training in a reasonable time.

All available data for a season were split into 2 parts – training and validation. Training part was in its turn split into 3 parts – training (to adjust synaptic weights), testing (for early stopping of training) and a part to model residuals. Validation part (1 week) was used for forecasting and analysis of the obtained results.

Conjugate gradient method with random initialisation of the weights was used for ANN multilayer perceptron training. The early stopping was used to prevent overfitting.

Recursive forecasting was selected as a forecasting technique. It means that the following forecast (L_{t+1}) is made using forecast obtained at the previous step (L_t). It can be written as

$$L_{t+1}=F(L_t,P)=F(F(L_{t-1},P),P),$$

where P represents other parameters used for the estimation, and F is the forecasting function.

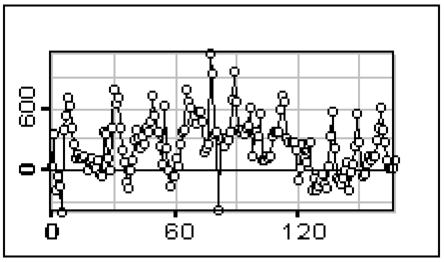
It can be thought that using such technique we will overgrow the forecasting error, which will be present in all following estimations once appeared. But the practice disproves it. For example, winter ANN residuals and their correlation structure (in form of variogram) are presented in Figure 1. Residuals don't grow and radius of correlation is rather small (6 hours). It means that residuals separated by more than 6 hours don't affect at each other (short memory correlation).

Correlation structure of the residuals was analysed using a variogram model. It can be determined as follows:

$$2\gamma(\tau)=Var\{L_t-L_{t+\tau}\},$$

where L_t is a value of some variable at time t and E means averaging for all pairs of variable separated by time delay τ. Working with incriments we needn't to be anxoius about the stationarity of a variable under study.

Correlation structure of ANN residuals opens the possibility to model/simulate them [3]. A simple linear model can be developed with taking into account correlation structure. It is supposed that multilayer perceptron have already took out all nonlinearity. Corresponding linear methods (ARMA, geostatistical - kriging) lead again to sequential estimation procedure because of a small correlation radius.



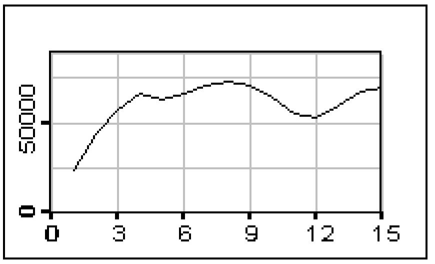


Figure 1. Winter ANN residuals (left) and winter ANN residuals' correlation structure (right)

Stochastic simulation approach provides several equally probable realisations with the same correlation structure. It allows to estimate for each time point a mean (estimation of a residual) and variance (range of residual's distribution).
Approach of general constrained randomisation was used to generate simulations [4]. This approach is as follows: all constraints which have to be reproduced in simulations are presented in the form:

$$F_i(\{\hat{s}_n\}) = 0, i = 1,...., L,$$

where $\{\hat{s}_n\}$ denotes a simulated time series, L – a number of constraints. Cost function is constructed to include constraints in simulation process:

$$C(\{\hat{s}_n\}) = \left(\sum \left| w_i F_i(\{\hat{s}_n\}) \right|^q \right)^{1/q}.$$

Here q denotes order of averaging (usually $q=2$ – least squares average). The constraints are fulfilled when cost function has got its global minimum.
In our case autocorrelation function was used as constraint for generation of simulations. Minimisation of the cost function was made by permutations of original time series (residuals) using method of simulated annealing [5]. Pairs in simulating time series were inverted and annealing scheme have choose which changes to accept and which to reject.

3. Multilayer perceptron forecasting

Multilayer perceptrons described above were used for the preliminary electricity load forecasting for 2 weeks – the last 2 weeks of each season of 1997 year (2 last weeks of August, 2 last weeks of February, 2 last weeks of November). We made forecasting with ANN for 2 weeks: 1 week for analysis and modelling of residuals and the second for validation. Results of forecasting are presented in Figure 2.
It can be seen, that relative errors never overcome the value of 15%, and the main part of them are within the range of 5%.

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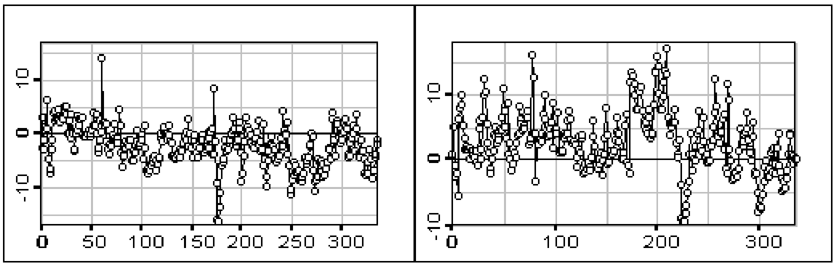

Figure 2. Relative errors (in %) of ANN forecasts. November (left), February (right)

4. Analysis of the residuals

ANN was used for 2 weeks forecasting. Residuals of the first one were used for constructing of a geostatistical model. On the base of this geostatistical model residuals of the second week are going to be constructed. But correlation structures of residuals of these weeks are different (see Figure 3). It can be explained by the consequence of recursive forecasting method.

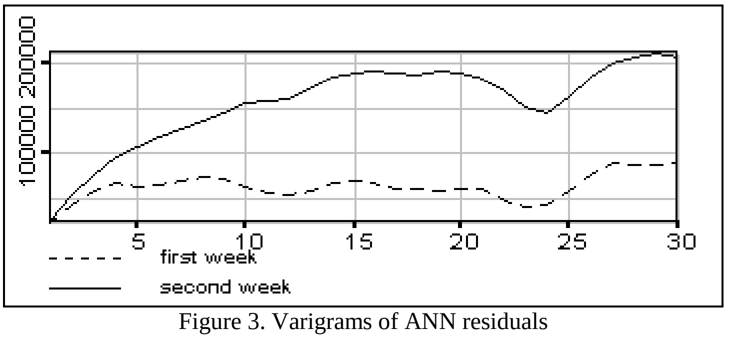

Figure 3. Varigrams of ANN residuals

To overcome this problem we made special ANN forecasting only for the second week. So we expected to get the residuals with the same correlation structure as one has been modelled.

Calculation and modelling of correlation structure was the first part of the analysis of the residuals. It was used as a constraint for the following conditional simulations. 30 realisations were simulated with the limit of cost function difference 0.002. In Figure 4 one can see the reproduction of variogram by some of the realisations. It seems to be perfect. Constraint is satisfied.

The same analysis has been performed for all other seasons' residuals. They present the same correspondence.

Means of simulations present strong smoothing of the residuals (see Figure 5). They are wavering around the mean value of the residuals. It can't be considered as very good result for we didn't get the variability of residuals. Maybe it can be improved by developing another constraint in cost function.

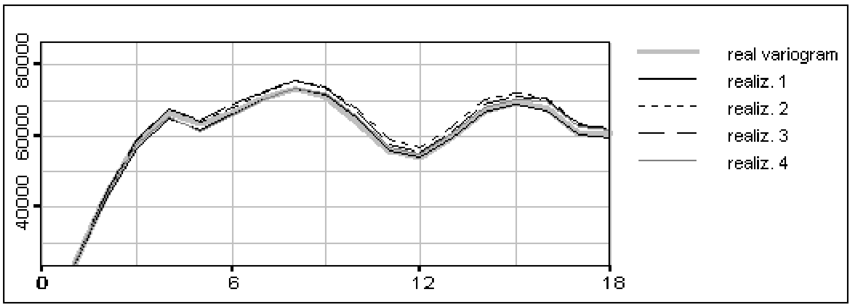

Figure 4. Correlation structure of ANN residuals' simulations (Winter)

Standard deviation shows the expected range of the residuals (see Figure 5). It can be seen that the largest residuals have not been caught in the range of lower and upper bounds. The poorest results were obtained for negative residuals – there was few of them, that's why they didn't give sufficient influence on modelling.

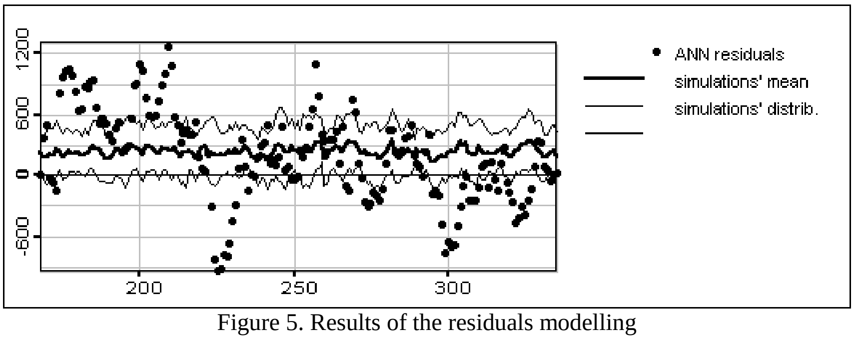

Figure 5. Results of the residuals modelling

5. Conclusions

In this work an attempt to forecast the electricity load with one hour ahead. Poor data set of available weather parameters complicates the situation. ANN model could be more stable while using important, but absent parameters. In their absence ANN treated all electricity load fluctuations caused by them as stochastic. In spite of these problems sufficient forecasting results by ANN have been obtained.

Detailed analysis of ANN residuals has been taken with the help of geostatistical tools. It was shown that the residuals are correlated and can be modelled by constrained conditional stochastic simulations. The mean of a set of simulations was added to electricity load forecasted by ANN and was considered as a final forecast. It is accompanied by variation of final result.

The final obtained result is that for the most part of time points some improvement has been achieved. It is due to a great number of points where ANN gave underestimation. The positive addition of simulated mean improves the final result. The deviation of simulated mean allows to estimate the ranges of load prediction.

The problem deals with ANN overestimations and how to overcome them. There are few of them and so they lower affect the result of residuals modelling. It can be expected to find any better constraint to model residuals so to improve this situation.

Also the situation can be improved itself by including additional weather parameters in ANN.
Finally, it seems that application of the geostatistical tools (variography) and conditional stochastic simulations can improve both predictions and description of the associated uncertainties.

6. Acknowledgements

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