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*Published in:*

Proceedings of the 2005 International Conference on Computational Intelligence for Modelling, Control and Automation, and International Conference on Intelligent Agents, Web Technologies and Internet Commerce (CIMCA-IAWTIC'05)

*DOI (link to publication from Publisher):*

[10.1109/CIMCA.2005.1631248](https://doi.org/10.1109/CIMCA.2005.1631248)

*Publication date:*

2007

*Document Version*

Early version, also known as pre-print

[Link to publication from Aalborg University](#)

*Citation for published version (APA):*

Ortiz-Arroyo, D., Skov, M. K., & Huynh, Q. (2007). Accurate Electricity Load Forecasting with Artificial Neural Networks. In Proceedings of the 2005 International Conference on Computational Intelligence for Modelling, Control and Automation, and International Conference on Intelligent Agents, Web Technologies and Internet Commerce (CIMCA-IAWTIC'05) (pp. 94-99). IEEE Press. DOI: 10.1109/CIMCA.2005.1631248

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# Accurate Electricity Load Forecasting with Artificial Neural Networks

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## Abstract

*In this paper we present a simple yet accurate model to forecast electricity load with Artificial Neural Networks (ANNs). We analyze the problem domain and choose the most adequate set of attributes in our model. To obtain the best performance in prediction, we follow an experimental approach analyzing the entire ANN design space and applying different training strategies. We found that when little data is available, applying this approach is critical to obtain the best results. Our experiments also show that a simple ANN-based prediction model appropriately tuned can outperform other more complex models. Our feed-forward ANN-based model obtained 29% improvement in prediction accuracy when compared to the best results presented in the 2001 EUNITE competition.*

## 1. Introduction

Time series analysis is a very effective method to create mathematical models for solving a broad variety of complex problems. These models are used to identify or predict the behavior of a phenomenon represented by a sequence of observations. However, creating an accurate model for a time series that represents nonlinear processes or processes that have a very wide variance is very difficult.

Artificial Neural Networks (ANNs) have been successfully used to solve a broad variety of systems, entailing linear and non-linear processes. The application of ANNs in time series prediction is presented in [1],[2]. The success in the application of ANNs lies in the fact that when these networks are properly trained and configured they are capable of accurately approximating any measurable function. The neurons learn the patterns hidden in data and make generalizations of these patterns even in the presence of noise or missing information. Predictions are performed by the ANN based on the observed data. An

example of a time series prediction problem that can be solved with ANNs is *electricity load forecasting*. Accurate methods of electricity load forecasting are required to increase the efficiency in the supply of electrical energy. Furthermore, accurate predictions may save important operating costs for the supplier companies. In electricity load forecasting, the prediction accuracy is generally evaluated using the *mean average percentage error (MAPE)* and the *maximal error (ME)*. The equations describing these errors are:

$$MAPE = 100 \cdot \frac{\sum_{i=1}^n \left| \frac{VR_i - VP_i}{VR_i} \right|}{n} \quad (1)$$

$$ME = \max (|VR_i - VP_i|) \text{ where } i = 1, \dots, n \quad (2)$$

where  $n$  is the number of days in a month,  $i$  is a specific day of a month, and  $VR_i$  and  $VP_i$  are the real and predicted values respectively, of the maximum daily electrical load.

Load forecasting may be applied in the long, medium, short, and very short term time scale. Electricity demand accumulated on different time scales exhibits different characteristics, e.g. daily detailed variations are lost when demand is accumulated at weekly level [5]. Hence, forecasting models must be appropriately adapted to the time scale of interest. Electricity usage may be predicted using data from previous history of load, temperature, humidity, luminosity, and wind speed among other factors. However, accurate models of load forecasting that use all these factors increase modeling complexity.

In year 2001 EUNITE – the *European Network of Excellence on Intelligent Technologies for Smart Adaptive Systems* - organized a world wide competition on methods to accurately predict electricity load [10]. In the contest, the average temperature and load data - on a half hourly basis - for years 1997 and 1998 were provided. The objective of the contest was to predict daily peak demands of electricity for January 1999 based on the data from these previous years.

In this paper we present a simple yet accurate model to forecast electricity load using Artificial Neural Networks (ANN). Using data from the EUNITE contest, we evaluated our model comparing our prediction results with those obtained by the participants in the contest. This paper is organized as follows. Next section briefly describes previous related work on electricity load forecasting. Our proposed model is described in detail in section 3. Section 4 presents experimental results and provides an evaluation of our model. Finally, section 5 presents the conclusions.

## 2. Related Work

During last decade numerous researchers have proposed diverse methods to forecast electricity load. A comprehensive review of methods based on ANNs is presented in [11]. In the rest of this section we provide a brief summary of some of the methods employed by the participants in the EUNITE contest, jointly with some more recent research work in this area.

W. Brockmann and S. Kuthe proposed several models to forecast electricity usage, from simple statistical models up to hybrid crisp-fuzzy, neuro-fuzzy models based on rules and learning [6]. Their simplest model describes load as an average for the two years 1997 and 1998. This model is later improved by shifting the days of the week. However, it was still unable to account for holidays that do not occur on same date each year. Another model proposed in [6], considers load as having a base value with oscillating variations superimposed. Additionally, an offset was included in the nominal load by means of a holiday indicator. Fuzziness is introduced because the load and the oscillation of various holidays differ in amplitude and time. The effect of temperature on load variation was ignored as it was considered noise. The best model presented in [6] scored as the third place in the EUNITE competition in terms of MAPE.

D. Esp proposed the use of an *Adaptive Logic Network* (ALN) to model electric load prediction [7]. ALN is a form of non-parametric, non-linear modeling technique broadly similar to ANNs. In his approach, D. Esp used additional data such as maximum illumination (taken from England's records) and load/temperature records from 1996 (requested separately to the organizers), to fine tune the model. As is described in [7], the model assumed that the average temperatures from 1997 and 1998 were an approximation to the temperature on January 1999; as such data were not available. The performance of the model was evaluated by predicting the load for January 1996. This model

obtained the second place in the EUNITE competition in terms of MAPE.

In [8], Chang, Chen, and Lin used support vector machines to predict electricity load. In support vector regression, time series prediction is considered an optimization problem subjected to some constraints. In their experiments, Chang et al. used local modeling to generate predictions, finding segments in the time series that closely resembled the segment at the points immediately preceding the point to be predicted. Conversely, global modeling was also employed by training the model to predict the load of a particular day. Attributes such as maximum loads of past seven days, whether a day was a holiday or not, which day of the week was a particular day etc., were used in the global modeling. Temperature data were discarded. Moreover, all days in January 1999 were treated as non-holidays to simplify the prediction. In spite of these simplifications, the model of Chang et al. obtained the first place in the EUNITE competition in terms of MAPE.

There were some similarities among the approaches used by the participants in the EUNITE contest. Some of them used time series analysis or polynomial regression; others fuzzy logic or fuzzy time series prediction; auto-associative ANN, feed forward ANN or Kohonen maps were also employed. Additionally, most approaches discarded temperature data since it is difficult to predict. The prediction methods that obtained the highest marks in the contest ([7][8]) were not based on the application of feed forward ANNs, but instead on ALN and support vector machines. One motivation for the work described in this paper was to determine if we could improve the prediction results reported in the EUNITE contest by using a simple feed forward ANN model.

More recently, outside the EUNITE competition, Taylor and Buizza [4] proposed a method to forecast electrical load using weather ensemble predictions. In their experiments they employed a feed-forward neural network with 10 nodes in the input layer, 10 nodes in the single hidden layer, and 1 node in the output layer. The input layer nodes were the 7 different days of a week and 3 weather variables. From the 7 nodes, 6 were used to represent different days in the week, and the last one was used for the second week of the industrial closure in the summer. The 3 weather variables employed were the effective temperature, cooling power of the wind, and effective illumination. Four different methods were modeled and tested to determine what influence the weather had on forecasting accuracy. The three methods based on neural networks, which used weather data showed

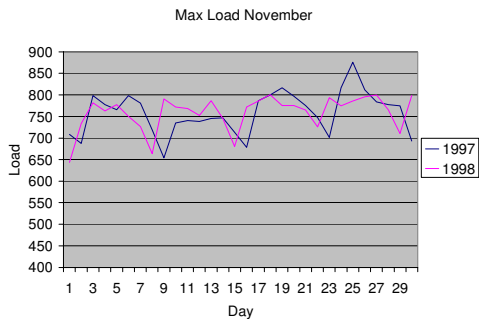


Figure 2 – Load pattern for November

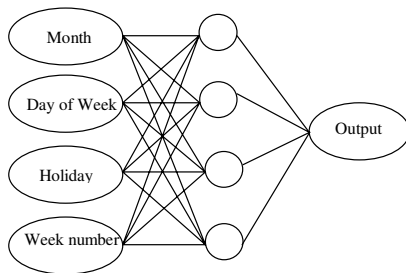


Figure 3 – ANN in the final model

better prediction results when compared to the one that did not use weather data. Moreover, the method that did the best forecast used actual weather data.

In [5], Ringwood et al. modeled electricity load forecasting using neural networks at three different time scales: hourly, weekly and yearly. Using data from the national electricity demand in Ireland, ANN-based models were supplied with parameters obtained from previous experiences with linear modeling techniques and from manual forecasting methods. The last two approaches described in [4] and [5] show that including data from other sources may improve prediction accuracy considerably. However, accuracy is obtained at the cost of making the models more complex.

### 3. Electricity Load Modeling

Data analysis from the EUNITE contest [10] clearly shows that the usage of electricity is relatively constant during week days and drops in the weekend. Figure 1 shows an example of this pattern for the weeks in January 1997 and 1998. To model this behavior the following 2 inputs are needed:

1. *Date in a year.*
2. *Maximum load for that day.*

Additionally, we noticed that the seasonal load pattern is practically the same for both years. The

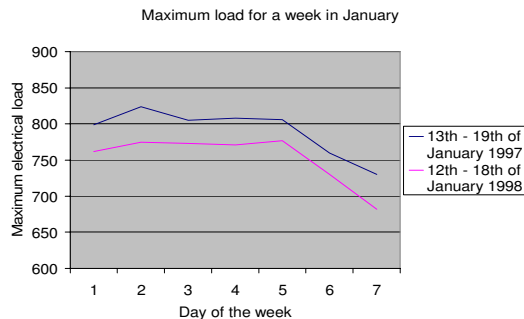


Figure 1 – Load pattern during a week

curves shown in Figure 2 for the example month of November also illustrate that the load follows a repetitive pattern. Contrarily, as Figure 1 indicates, there is no repetitive pattern in a week. Based on this analysis, the “year” and the “day of the month” parts were removed from the original attribute “date in a year”, leaving just the “month” information for such attribute. The *month* attribute is used to represent the seasonal fluctuations in a year. Additionally, (as most EUNITE competition participants did) we added an input value to represent the “day of the week” attribute. This is done to distinguish weekdays from Saturday/Sundays where normally few people work. This causes load to be nearly constant during the week but drop during weekend. The pattern exhibited by this attribute is repetitive for all weeks in a year, except for the weeks that include one or more holidays. However, since these special weeks are very few, comparatively to the weeks without holidays in a year, the “week with holiday” attribute was not included in our modeling. Instead, to account for the effect that holidays have on a lower electricity usage, the attribute “holiday” was used with values 0-1. Finally, to treat special weeks differently, the attribute “week number” in a month was added. This last attribute enables the ANN to differentiate among the weeks in a month and still preserve the weekly pattern. This is an important feature in our model since its prediction accuracy will be compared with the results presented in the EUNITE contest specifically for the month of January 1999.

Based on the aforementioned discussion, our simple ANN-based model employs the following input attributes:

1. *Month of the year*
2. *Day of the week*
3. *Holiday*
4. *Week number*

Each of these attributes was encoded as a binary number. The model is depicted in Figure 3. It must be noticed that the binary encoding of the attributes causes

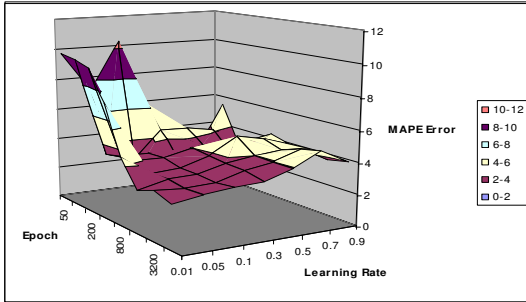


Figure 4 – Results from experiment 1

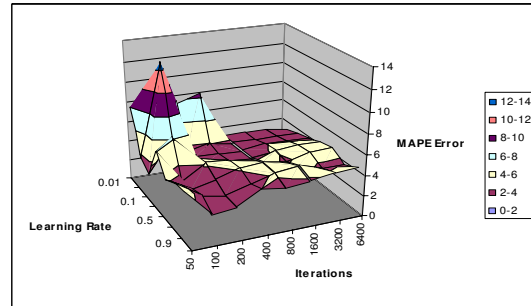


Figure 5 - Results from experiment 3

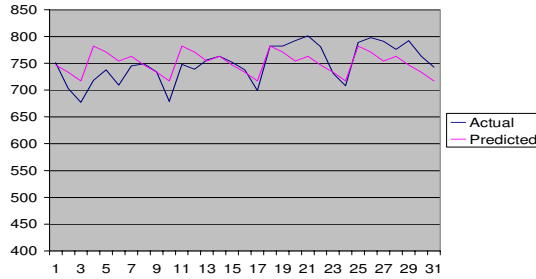


Figure 6 – Forecasting results for January 1999

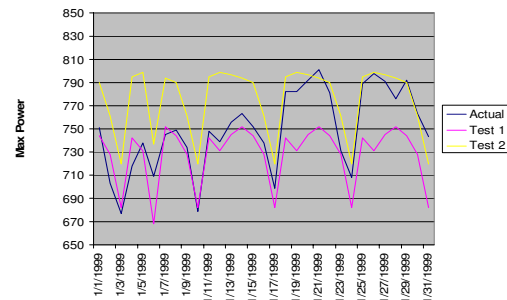


Figure 7 – Two training runs with same data

“Month of year” attribute to consist of 4 input nodes, “Day of the week” of 3, “Holiday” of 1, and “Week number” of 3 nodes, giving a total of 11 inputs nodes for the ANN. The “Week number” attribute is set to zero each time a new month is presented to the ANN. The hidden layer employs activation levels in all nodes that are limited by the use of a sigmoid function ( $y = 1 / (1 + e^{-x})$ ).

#### 4. Experimental Results

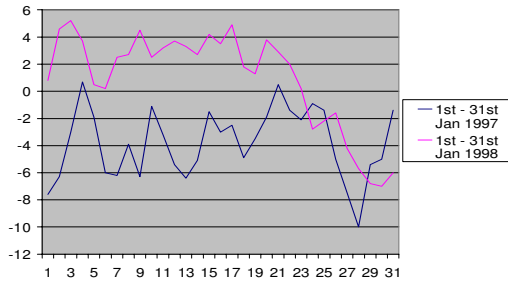
Determining the learning rate, number of hidden nodes in the ANN, and the number of epochs necessary to obtain optimal prediction results is difficult. Many approaches solve this problem by using heuristics or simple rules of thumb. Contrarily, we employed an experimental approach similar to the one described in [2] to find the optimal ANN configuration. For this purpose we created a flexible testbed in C#. The testbed allowed us to experiment with the ANN varying the number of nodes in the hidden layer, the number of training epochs, the learning rate  $\lambda$  etc., observing their effect on prediction accuracy. EUNITE contest’s data was stored and accessed in a MySQL database using SQL command queries. The predicted output of our model ( $POut(i)$ ) was calculated as:

$$POut(i) = (HiL(i) - LowL(i)) * ANNout(i) + LowL(i) \quad (3)$$

where  $ANNout(i)$  is the  $i^{th}$  output of the ANN and

$HiL(i)$  and  $LowL(i)$  are the  $i^{th}$  values of the highest and lowest load values in the EUNITE data set. Using half-hourly daily load data we obtained the average daily values for the load in Equation (3). In each test we calculated the MAPE obtained by our model using data from 1999. In the first experiment the ANNs were configured with 5 nodes in the hidden layer. All training data for both 1997 and 1998 were used concurrently during each epoch. Figure 5 shows that several local minimums exists in the MAPE error curve. In this experiment the MAPEs obtained varied in the range 2.59-9.91. Subsequently, we increased the number of hidden units to 10, obtaining in this case MAPEs in the range of 2.94-9.0.

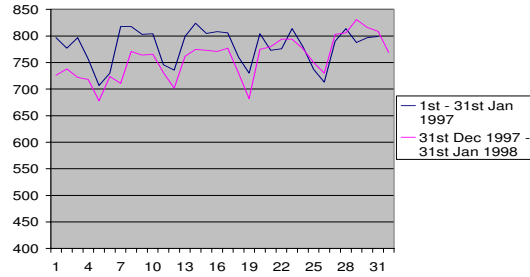
In a third experiment the ANN was configured with 15 nodes in the hidden layer. As it was done in the first and second experiments, all training data for both years 1997 and 1998 were used concurrently during each epoch. This configuration was tested by running up to 6400 iterations. Results from this experiment are shown in Figure 6. Finally, the ANN was trained for up to 12,800 epochs; however the overall improvement in results was less than 2%. The MAPEs obtained in this last case varied over a range of 2.52-12.68. The surface in Figure 5 shows that good prediction results occur at a high learning rate using a few iterations, but also at a low learning rate, when more iterations are used. These experiments show that the learning rate, the number of



**Figure 8 – Temperature graphs for January**

hidden units and number of epochs used for training, have a severe impact on the prediction accuracy of our model. The MAPE obtained by our best model was 2.52. This value may have scored as the 4<sup>th</sup> best in the EUNITE competition in terms of MAPE. This result was obtained training the ANN using the back propagation algorithm with data from both years 1997 and 1998 in the same training set. The following parameters were used: learning rate of 0.9, 15 nodes in the hidden layer and 100 training epochs. Figure 6 shows the prediction results of this model.

Figure 7 shows our model's forecasting for January 1999 in two identical training runs. The two different predictions (Test1 and Test2) have almost identical patterns, but the alignment along the Y-axis is off. Since there were only two data sets available in the EUNITE contest (January 1997 and 1998) and they differ widely in amplitude, they can be interpreted as the upper and lower boundaries for load prediction. When the network begins to learn from these patterns, it might easily get confused as to which one is the correct one. One possible explanation for this "alignment error" along the Y-axis may be the fact that the training data is very different and too little. As Figure 8 shows, January 1997 was generally colder compared to 1998. This behavior suggests that giving the neural network some input attribute about the temperature may compensate for the difference. However, predicting temperature accurately is difficult. Figure 9 shows that the electricity load for 1997 is consistently higher than in 1998 until around the 21<sup>st</sup> of January. Additionally, Figure 8 shows that the temperature graph for January 1997 is consistently lower before the same date. This suggests that the first weeks of January must be treated differently, an issue that was taken into account in the early design of our model by using the "Week number" attribute. By looking at the EUNITE contest data for 1999, it is also noticed that the electricity usage patterns for January 1998 and 1999 are more alike, comparatively with those of year 1997. This fact indicates that the ANN



**Figure 9 – Electricity load curves for January**

training strategy employed might have an effect on prediction accuracy. In all the previous experiments the ANN was trained using data from both years 1997 and 1998 included in the same training set. However, since data is significantly different for these years, training the ANN with the data for 1997 first, and then with the data for 1998 may help the ANN to learn the tendency of load to change slightly from year to year. We call this training method the *alternative training strategy* (ATS). Using this training method we performed a new series of experiments with the ANN using 5, 10 and 15 nodes in the hidden layer and varying the learning rate. Table 1 show the prediction results obtained by our best model with 10 nodes in the ANN's hidden layer and varying the learning rate  $\lambda$ , and number of training epochs. As Table 1 shows the best prediction results in terms of MAPE obtained by our model are roughly 13% better than the best presented in the EUNITE competition ([8]) using  $\lambda=.5$  and 3200 epochs for training. The ME obtained with the same parameters was 36.9, a value slightly better that the best result obtained in the contest ([7]). We performed a new series of experiments varying the number of hidden nodes (HN) in the ANN, using data from both years and from a single year, and using the two training strategies described previously. We also experimented adding a second ANN to our model to predict accurately the holiday that occurs the 6<sup>th</sup> of January, 1999. However, the overall prediction accuracy obtained was not improved significantly and the new ANN made training and evaluation more difficult.

Finally, to evaluate the effect of temperature data in our model we adjusted load data with the simple linear mechanism described in [9] (showed as *Adjusted Data* in Table 2). Table 2 shows a summary of the best results we obtained in some of the experiments performed. These results show a 29% improvement over EUNITE competitors. The best result was obtained with an ANN with 5 hidden nodes,  $\lambda=0.1$ , using ATS, training the ANN first with '97 data in 600 epochs and then with '98 data in 1200 epochs. Figure

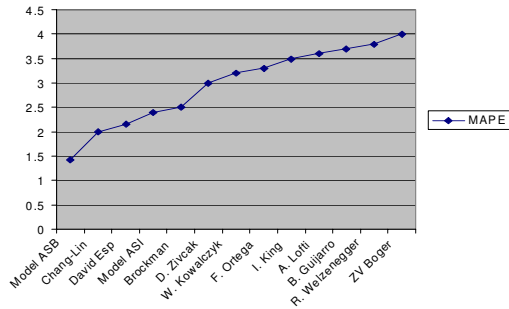


Figure -10 Comparison of prediction results

10 shows an overall comparison of our model in performance prediction with the results obtained by the participants in the EUNITE competition. Our best model – identified as *Model ASB* in the graph - employs binary encoding in the attributes. These attributes were also encoded as integers – shown as *Model ASI* in the graph - obtaining lower performance.

## 5. Conclusions

In this paper we presented a simple model based on ANNs to forecast electricity load. In spite of its simplicity, our first model could have scored as the 4<sup>th</sup> best in the 2001 EUNITE competition. Further analysis showed that the ANN was very sensitive to the training strategy and design parameters used. We created a testbed program in C# to explore the entire ANN's design space and find the optimal parameters and the best training strategy. Our model obtained prediction results that are 29% better - in terms of MAPE - than the best results presented in the EUNITE competition. The model was fine tuned using electricity load data from year 1999. Such data were not available at the time of the original competition. However, the same methodology could have been applied to predict January 1998 from 1996 and 1997 data. A similar strategy was used by D. Esp in [7], who requested and obtained extra data from year 1996 from the EUNITE competition organizers. Our experimental results show that a simple ANN-based prediction model appropriately tuned can outperform other more complex models. Finally, the drawbacks of our model are its ad-hoc applicability to the EUNITE contest data and sensitivity to small changes in ANN design.

## 6. References

[1] K. Chakraborty, K. Mehrota, C. K. Mohan and S. Ranka. Forecasting the Behavior of Multivariate Time Series

Table 1 MAPE results from the model

Epoch/A	0.05	0.1	0.3	0.5
400	2.55	2.47	2.26	2.26
800	2.43	2.47	1.92	1.91
1600	1.87	1.85	1.98	2.09
3200	1.83	1.92	1.85	1.74

Table 2 Other experimental results

Experiment	MAPE	ME
1. Model ASB - 10HN - ATS	1.58	32.85
2. Model ASB - 10HN - 1998	1.76	52.71
3. Model ASB - 10HN - Adjusted Data & 1998	1.66	48.28
4. Model ASB - 5HN - ATS	1.42	39.41
5. Model ASB - 15HN - ATS	1.53	35.45

Using Neural Networks. *Neural Networks*, 5:961-970, 1992.

[2] T. Kolarik and G. Rudorfer. Time Series Forecasting Using Neural networks. *Proceedings of the international conference on APL*. Antwerp, Belgium Pages 86 – 94, 1994.

[3] R. J. Frank, N. Davey, S. P. Hunt, Time Series Prediction and Neural Networks, *Journal of Intelligent and Robotic Systems*, Volume 31, Issue 1 - 3, May 2001, Page 91.

[4] J. W. Taylor, and R. Buizza, “Neural Network Load Forecasting With Weather Ensemble Predictions”, *IEEE Transactions on Power Systems*, vol. 17, no. 3, pp. 626–632, August 2002.

[5] J. V. Ringwood, D. Bofelli, F. T. Murray, Forecasting Electricity Demand on Short, Medium and Long Time Scales Using Neural Networks, *Journal of Intelligent and Robotic Systems*, Volume 31, Issue 1 - 3, May 2001, Pages 129 – 147.

[6] W. Brockmann, and S. Kuthe, “Different Models to Forecast Electricity Loads”, *EUNITE competition*. Available: <http://neuron.tuke.sk/competition/index.php>.

[7] D. Esp, “Adaptive Logic Networks for East Slovakian Electrical Load Forecasting”, *EUNITE competition*. Available: <http://neuron.tuke.sk/competition/index.php>.

[8] M.-Wei Chang, B.-Juen Chen, and C.-Jen Lin, “EUNITE Network Competition: Electricity Load Forecasting”, *EUNITE competition*. Available: <http://neuron.tuke.sk/competition/index.php>.

[9] A. Lewandowski, F. Sandner, and P. Protzel, “Prediction of Electricity Load by Modeling the Temperature Dependencies”, *EUNITE competition*. Available: <http://neuron.tuke.sk/competition/index.php>.

[10] EUNITE – World wide competition within the EUNITE network. <http://neuron.tuke.sk/competition/>

[11] H. S. Hippert, C. E. Pedreira, and R. C. Souza, “Neural networks for short term load forecasting: A review and evaluation”, *IEEE Trans. Power-Syst.*, vol. 16, pp44-55, 2001.