

Short Term Electricity Load Forecasting: A Case Study of Electric Utility Market in Turkey

Muhammed Yasin
Ishik University
Erbil, KRG, Iraq
muhammed.yasin@ishik.edu.iq

Tolga Göze
İhsan Özcan
Alcatel Lucent Teletaş
İstanbul, Turkey
tolga.goze@alcatel-lucent.com
ihsan.ozcan@alcatel-lucent.com

Vehbi Çağrı Güngör
Zafer Aydın
Computer Engineering Dept.
Abdullah Gul University
Kayseri, Turkey
cagri.gungor@agu.edu.tr
zafer.aydin@agu.edu.tr

Abstract— With the recent developments in energy sector, the pricing of electricity is now governed by the spot market where a variety of market mechanisms are effective. After the new legislation of market liberalization in Turkey, competition-based on hourly price has received a growing interest in the energy market, which necessitated generators and electric utility companies to add new dimensions to their scope of operation: short-term load and price forecasting. The field has several opportunities though not free from challenges. The dynamic behavior of the market price has caused the electric load to become variable and non-stationary. Furthermore, the number of nodes, in which the load must be predicted, is not constant anymore and can no longer be estimated by experts alone. In this competitive scenario, statistical forecasting methods that can automatically and accurately process thousands of data samples are essential. The purpose of this study is to demonstrate the importance of short-term load forecasting, how it has received a growing interest in Turkey and to propose an artificial neural network that can forecast the short term electricity load. Through detailed performance evaluations, we demonstrate that our forecasting method is capable of predicting the hourly load accurately.

Index Terms-- Demand forecasting, Neural networks, Short-term electricity load forecasting

I. INTRODUCTION

Energy is one of the most important factors in enhancing the quality of life and promoting the economic and social well-being of a society. However, rising energy prices, climate change and global warming has led to an increase in energy demand throughout the world. On the other side, the rapid consumption of fossil fuel and insufficient investment for developing new technologies to meet the growing demand for commercial energy made countries worry about the security of energy supply. To overcome these challenges and to avoid the risk of being incapable of supply, a new power grid infrastructure, called smart grid, has been proposed recently.

The integration of the current electric power grid with novel information technologies is one of the most challenging

and exciting issues of the 21st century. The smart grid aims to utilize modern information and communication technologies to monitor and control the power grid environments, which ultimately require intelligent monitoring techniques to be adapted to the dynamics of the power grid. In addition, with the new reformation of the power grid, more sophisticated trading settings have arisen and practices for human resource management have emerged.

The new business model of smart grid contains electricity demand and price forecasts, load control, hydro thermal generation scheduling, demand response programs, power fraud detection, pricing and trading processes and management. However, the realization of these envisioned business models and smart grid applications depends on effective monitoring capabilities and forecasting techniques in the power grid.

In the smart grid, the electric load can be defined as the power supplied by an electrical utility to its customers [1]. The inability to store electric energy effectively necessitates the utilities to forecast the future electricity consumption of their customers. Estimating the electricity demand in advance enables a power system to operate efficiently by implementing effective planning, marketing, risk assessment, and billing practices. It also improves the reliability of a network by increasing the security and by reducing the occurrence of equipment failures.

Importantly, load and price forecasting techniques are used in demand response and load management applications in smart grid. In general, demand response applications aim at accomplishing an acceptable balance between electrical energy supply and demand by the efficient control of electric load during critical peak hours and electric energy demand. Utilizing demand response programs, such as price-based and incentive-based programs, the electric utilities try to achieve more reliable and cost-effective operation of the power grid [2].

Depending on the lead times required by the power supply industry load forecasting techniques can be classified into

three main categories: short, medium and long-term forecasting. In short-term load forecasting, the future electricity demand is estimated within a short time interval (a few minutes, hours or days) whereas in long-term forecasting, the time span rises up to 20 years. With the competitive electric utility market, short-term demand forecasting has become increasingly critical. Many countries have privatized their power generation, transmission and distribution systems and electricity has been turned into a service traded at market prices. In this particular setting, the pricing of electricity mainly depends on short-term load forecasting, which is used to plan the buying and selling of energy in a daily market [3]. Short-term load forecasting is also used in planning and controlling the start-up and shut-down scheduling of power generation units. On the other hand, medium and long-term forecasting is performed for several days to several years ahead. These are useful in system planning, such as building new power generators and transmission lines [4].

Several statistical and artificial intelligence methods have been developed for electricity load forecasting including regression models, time series models, fuzzy logic, neural networks, expert systems, support vector machines, grey prediction, and hybrid approaches [3], [5]-[12]. In this paper, we implemented a feed-forward neural network for short term electricity load forecasting (STELF) in Turkey. Our network employs daily electricity consumption and ambient temperature data as the input features and can predict the next-day hourly load (i.e., within a time window of 24 hours) for the electricity spot market of Turkey. After training a single network on all weekdays of a given year, we have also investigated the effect of training separate networks each specialized for a given season of the year. In addition, we have compared seasonal forecasting accuracy of the artificial neural network with a support vector machine.

II. MATERIALS AND METHODS

A. Market Mechanism in Turkey

The need of new legislation in electric market has turned electricity into a traded good recently; it is sold and bought at market prices. This brought liberalization in pricing mechanism and forced electric companies and new investors to analyze and predict the market's future behavior both in the short and the long run. As in any other liberal market, the long run marginal price always depends on the long term demand. This knowledge led us to focus on demand forecasting since pricing might not be matched directly to a specific function or a model. Moreover, the fuel resource in power plants is not constant and the pricing is not always related to the cost of generation.

In Turkey, the massive need for short term demand forecasting has first emerged when the value of price forecasting has become very high in the electric market after the market development regulation was published in 2001. Since then short term forecasting has maintained its importance. One reason for this behavior is the way electricity is sold and purchased in the market. There are two different trading strategies in a deregulation market: the pool and bilateral contracts trading. In pool trading, the producers and

consumers submit their bids on a digital market environment for selling and buying country's electricity on an hourly basis. Finally, a market operator EMRA (Energy Market Regulatory Authority) clears the market by approving the fittest offer and demand on which the selling and buying are performed. Companies that follow pool trading or power generator companies who offer bids in the market, need hourly demand to decide whether to bid their generation capacity on a day ahead spot market or power market.

B. Short Term Electricity Load Forecasting (STELF) by Artificial Neural Networks

Neural networks are powerful and flexible tools for forecasting. A neural network functions similarly to the human brain in certain ways [13]. They are among the artificial intelligence (AI) techniques, which learn the mapping between a set of input and output variables [14]. One advantage of AI approaches is that they do not require any complex mathematical modeling between inputs and outputs. The most attractive side of a neural network is its ability to estimate any nonlinear function and solve problems in which the relation between inputs and outputs is not well defined or easily computable. Since they have the ability to fit on nonlinear statistical data, they can be used to model complex problems, and may learn the relation between input and output or finding the patterns in data [15]. This is particularly useful for electricity demand forecasting because holiday activities and unusual weather conditions generate a highly nonlinear relationship with the daily power load. Furthermore, compared to other machine learning solutions, neural networks are relatively easy to implement due to its low complexity and have good performance with less computation time.

An artificial neuron is the simplest unit of a neural network that can manage complex behaviors by the connections between the processing neurons and weight parameters of those connections (Fig. 1).

In the terminology of machine learning, a network refers to the connections between the neurons in different layers of the system. Therefore, the arrangement of units defines the network architecture. In feed-forward networks, there is an input layer, one or more hidden layers and an output layer with units arranged in layers. In an input layer, the same input could be shared with all neuron units. The input layer units, without any processing, serve only for delivering data from input layer to the rest of the network. In a fully connected neural network, every neuron in an input or hidden layer is connected to all of the neurons in the following layer. The network in Fig. 2 consists of four layers with two hidden layers. In a neural network, there could be more than two hidden layers and many input as well as output neurons in input and output layers, respectively. Weights between each connection are the coefficients that are used to define the relation (i.e., the function) between the input and the output variables.

The three major aspects of a neural network are: (1) the connection pattern between neurons, (2) weights of the connections, (3) the activation functions in each neuron. The

weights are typically estimated using efficient algorithms on a training set of known input and output values. These algorithms progressively minimize a cost function and stop when the error satisfies a convergence criterion [15].

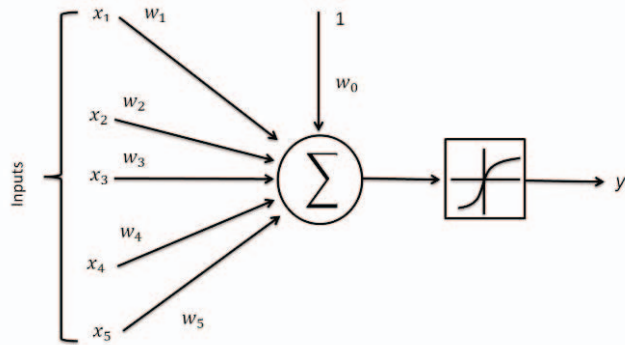


Fig. 1. A simple neuron architecture

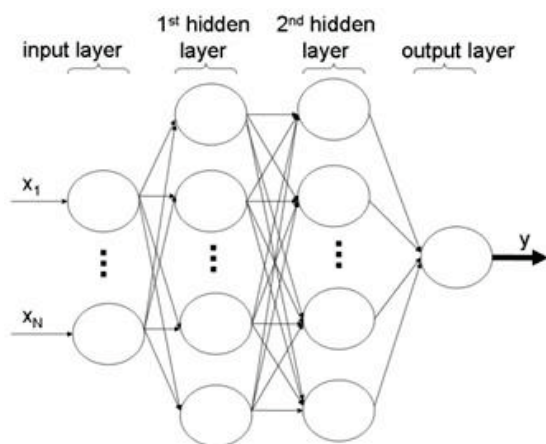


Fig. 2. A neural network with two hidden layers

In this work, we trained a feed-forward neural network to predict the next-day load in the electricity market of Turkey. We used hyperbolic tangent sigmoid functions in the hidden layers and linear functions in the output layer. The hyperbolic tangent sigmoid transfer function which is used in hidden layers as an activation function is defined as

$$f(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \quad (1)$$

We trained the network by the Levenberg-Marquardt algorithm, which is known to be more robust than Gauss-Newton algorithm by finding a solution even if the weights are initialized far from their optimums [16]-[17].

C. Dataset

Our original dataset contains 12168 data samples. In this dataset, we obtained the hour and date information from EMRA's website (<https://dgpys.pmum.gov.tr/dgpys/>). Each

row of this data file contains the following information: hour, day of week, month, year, temperature of Ankara, temperature of Istanbul, temperature of Izmir, and the electricity load. The hour is represented by integers from 0 to 23, the day of week is coded as integers from 1 to 7 such that 1 denotes Monday and 7 denotes Sunday. The month column includes integers from 1 to 12 and the year contains the year information expressed as an integer. Following the hour and date information, we used the airport temperatures of Ankara, Istanbul and Izmir, which are the three major cities of Turkey constituting approximately 28% of the total population (<http://www.wunderground.com/history/>). Fig. 3 shows the hourly electricity load of Turkey during a one week period which has an oscillatory behavior, a characteristic of the weekly power consumption.

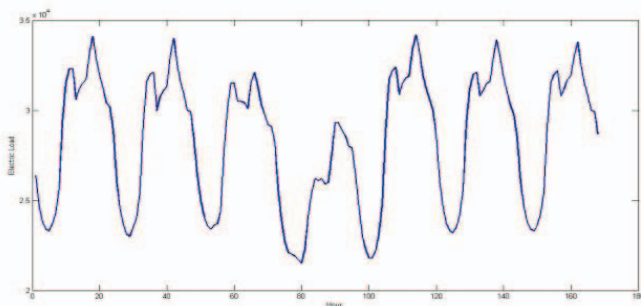


Fig. 3. Weekly electricity load of Turkey

D. Accuracy Measures

We considered two accuracy measures to assess the prediction performance of the neural network: the mean absolute percentage error (MAPE), and the mean absolute error (MAE). The mean absolute percentage error is defined as

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{f(x)_i - y_i}{f(x)_i} \right| \quad (2)$$

and the mean absolute error (MAE) is defined as

$$MAE = \frac{1}{n} \sum_{i=1}^n |f(x)_i - y_i| \quad (3)$$

where $f(x)_i$ and y_i are the i^{th} actual and predicted load values respectively, and n is the total number of predictions.

III. RESULTS AND DISCUSSION

We implemented a feed-forward neural network using MATLAB's Neural Network Toolbox (<http://www.mathworks.com/products/neural-network/>). Our feature set contains the following variables: hour, day of week, month, temperature of Ankara, temperature of Istanbul, and temperature of Izmir. Therefore, the input layer of the network has 6 units. Our output variable is the electricity load of a given hour, which is represented by a single unit in the output layer. We set the number of hidden layers to two where each layer contains the same number of hidden units. For

simplicity, we performed model training and evaluation on data that belongs to 2012 only. For this purpose, we randomly divided the data samples coming from weekdays of 2012 into three parts such that 70% of the samples formed the training set, 15% formed the validation set, and the remaining 15% became the test set. We then optimized the number of iterations by maximizing the accuracy on the validation set and estimated the final accuracy of the network on the test set.

A. Performance of the Weekday Network

In this section, we evaluated the accuracy of the feed-forward neural network on the test set. For this purpose, we set the number of hidden layers to 2 and the number of hidden units in each layer to 50. To prevent over-fitting, we first optimized the number of iterations using the early stopping procedure of MATLAB's Neural Network Toolbox. This procedure monitors the mean square error (MSE) on the validation set and checks the number of iterations the MSE error increases after reaching its minimum. When the validation error increases for a specified number of iterations, the training is stopped. Fig. 4 shows the MSE with respect to the number of iterations for the training, validation and test sets. Note that the test set error behaves similarly to the validation set error, which shows that the division of the dataset into test and validation sets is satisfactory. At the end of this experiment, we found the optimum number of epochs as 103.

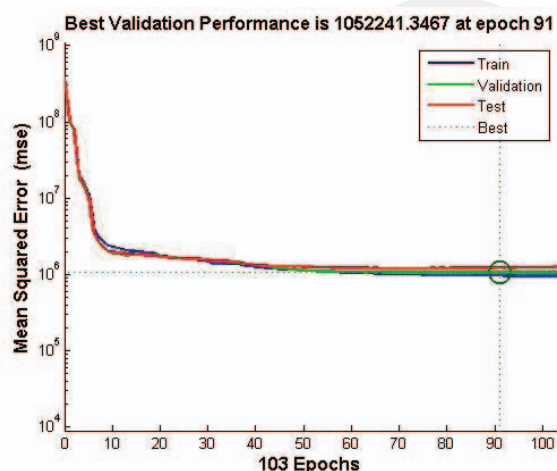


Fig. 4. Mean square error with respect to the number of iterations made during model training. The optimum number of iterations is found by the early stopping procedure of the Neural Network Toolbox.

In the next step, we set the number of epochs to 103 and computed the predictions on the test set. Comparing the predicted load values to the true values, we obtained a MAE of 600 MWh and a MAPE of 2.3%. This shows that we are able to get fairly accurate predictions even if we do not optimize the network architecture. Fig. 5 shows the scatter plots of the predicted load values with respect to the true values for the samples in training, validation, test, and the combined datasets. Based on these plots, we can say that the predictions are highly correlated with the true values, which

is also manifested by the high R-values on the test and validation sets. Furthermore, the network is free from over-fitting as the R-value obtained for the test set is high and close to the R-value on the validation set. The latter also shows that the partitioning of the dataset into train, test, and validation sets is good.

B. Performance of the Seasonal Networks

We investigated the effect of training separate networks for each season of the year. For the Turkish market the winter is from December to February, the spring from March to May, the summer from June to August and the fall from September to November. We set the number of hidden layers to 2 and the number of hidden units in each layer to 40. For comparison, we also trained support vector machines (SVM) for each season of the year where we chose the Puk kernel and set the C parameter to 1. All the SVMs in this paper are implemented in WEKA (<http://www.cs.waikato.ac.nz/ml/weka/>).

Table I shows the MAPE and MAE values of the neural networks and the SVMs for each season of the year. Based on this table, the accuracy of the neural network is similar to that of the SVM. Neural network performs better on the winter and spring data, whereas the SVM predictions are more accurate on summer and fall data.

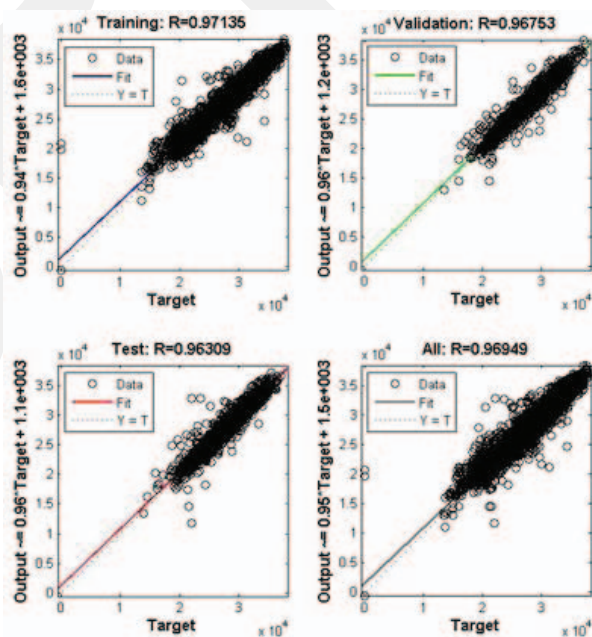


Fig. 5. Scatter plots showing the predictions of the neural network (y-axis) and the true values (x-axis) for data samples in training (top-left), validation (top-right), test (bottom-left), and the combined (bottom-right) datasets. A high R-value demonstrates strong correlation between predicted and true values.

C. Performance for Different Periods in a Day

For trade companies the forecasting accuracy computed on different periods of the day is important. Therefore we separated the test set into the following three subsets: (1)

daytime set, (2) evening set, (3) nighttime set where the daytime set contains samples from 06:00 to 17:00, evening set has data from 17:00 to 22:00 and the nighttime set consist of samples from 22:00 to 06:00. Similar to Section III.A, we trained a single neural network and evaluated the accuracy on each period. Table II shows the accuracy result of the network with two hidden layers and 40 neurons in each layer.

TABLE I
SEASONAL FORECASTING ACCURACY OF NEURAL NETWORK AND SUPPORT VECTOR MACHINE.

Season	ANN	SVM
winter	(MAE): = 743	(MAE): = 820
	(MAPE): = 2.7	(MAPE): = 3.1
spring	(MAE): = 543	(MAE): = 687
	(MAPE): = 2.0	(MAPE): = 2.5
summer	(MAE): = 1018	(MAE): = 1015
	(MAPE): = 3.55	(MAPE): = 3.48
Fall	(MAE): = 983	(MAE): = 928
	(MAPE): = 3.7	(MAPE): = 3.4

TABLE II
ERROR METRICS FOR THE THREE PERIODS OF A DAY.

Time period	MAE (MWh)	MAPE
Daytime	958	3.5 %
Evening	879	3.0 %
Nighttime	768	3.2 %

IV. CONCLUSIONS

Turkey's electricity sector has been changing fundamentally since 1994. In this new era, the importance of future demand forecasting has increased rapidly. There is no doubt that the short term price and load prediction has become the most important matter for Turkish market players who strive for a bigger bite in the spot market.

In this paper, we developed artificial neural networks, which aim to forecast Turkey's short term electricity demand. We used a year-long historical and hourly energy consumption and temperature data as a time series to train the networks. Upon request, the complete experimental data set will be made available. It is expected that this valuable data set will help the research community to develop novel forecasting techniques for demand response applications in smart grid.

As a future work, we are planning to optimize the architecture of the neural network (i.e., the number of hidden layers and number of hidden units). It is also possible to compare different types of neural networks such as RBF and

recurrent networks or even implement hybrid approaches. Further decrease in the prediction error will substantially contribute to the economy reducing the costs caused by losses.

ACKNOWLEDGMENT

This research was supported by Alcatel Lucent Teletaş, İstanbul, Turkey and TUBITAK TEYDEB with Project No: 3120959. We also would like to thank Erdinç ARISOY, who works in Ankara for Energy Market Regulatory Authority, for his helpful comments and suggestions.

REFERENCES AND FOOTNOTES

- [1] P. Siano, "Demand response and smart grids - A survey," *Renewable and Sustainable Energy Reviews*, vol. 30, pp. 461–478, February 2014.
- [2] Q. Zhang, et al, "Demand response in electricity markets: A review," in *Proc. of IEEE International Conference on the European Energy Market*, 2012.
- [3] H. S. Hippert, C. E. Pedreira, and R. C. Souza. (2001). Neural networks for short-term load forecasting: a review and evaluation. *IEEE Trans. Power Syst.* 16, pp. 44-55.
- [4] S. Kuusisto, M. Lehtokangas, J. Saarinen, and K. Kaski. (1997). Short term electric load forecasting using a neural network with fuzzy hidden neurons. *Neural Comput. and Applic.* 6, pp. 42-56.
- [5] E. Kyriakides and M. Polycarpou, (2007). "Short term electric load forecasting: a tutorial," in *Trends in Neural Computation, Studies in Computational Intelligence*, K. Chen and L. Wang, Eds. Springer, 2007, pp. 391–418.
- [6] S. Kucukali and K. Baris. (2010). Turkey's short term gross annual electricity demand forecast by fuzzy logic approach. *Energ. Policy* 38, pp. 2438–2445.
- [7] S. Rahman and R. Bhatnagar. (1998). An expert system based algorithm for short term load forecast. *IEEE Trans. Power Syst.* 3, pp. 392–399.
- [8] G. Ogcı, O. F. Demirel, and S. Zaim. (2012). Forecasting electricity consumption with neural networks and support vector regression. *Procedia Soc. Behav. Sci.* 58, pp. 1576–1585.
- [9] D. Akay and M. Atak. (2007). Grey prediction with rolling mechanism for electricity demand forecasting of Turkey. *Energ. Policy* 32, pp. 1670–1675.
- [10] C. Chiu, L. Kao, and D. Cook. (1997). Combining a neural network with a rule-based expert system approach for short-term power load forecasting in Taiwan. *Expert Syst. Applicat.* 13, pp. 299–305.
- [11] M. Tamimi and R. Egbert. (2000). Short term electric load forecasting via fuzzy neural collaboration. *Electric Power Syst. Res.* 56, pp. 243–248.
- [12] K. Metaxiotis, A. Kagiannas, D. Askounis, and J. Psarras. (2003). Artificial intelligence in short term electric load forecasting: a state-of-the-art survey for the researcher. *Energ. Convers. Manage.* 44, pp. 1525–1534.
- [13] W. S. McCulloch and W. Pitts. (1943). A logical calculus of ideas immanent in nervous activity. *B. Math. Biophys.* 5, pp. 115-133.
- [14] S. Haykin, *Neural Networks: A Comprehensive Foundation*. New Jersey, NJ, USA: Prentice-Hall, 1997.
- [15] C. M. Bishop. *Neural Networks for Pattern Recognition*, Oxford, UK: Oxford University Press, 1996.
- [16] K. Levenberg. (1944). A method for the solution of certain nonlinear problems in least squares. *Q. Appl. Math.* 2, pp. 164–168.
- [17] D. Marquardt. (1963). An algorithm for least-squares estimation of nonlinear parameters. *J. Soc. Indust. Appl. Math.* 11, pp. 431–441.