ESTIMATION OF UNBALANCE COST DUE TO DEMAND PREDICTION ERRORS USING ARTIFICIAL NEURAL NETWORK

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Abstract

Estimation of energy demand is used as an important tool for decision makers determining company strategies and policies. Apart from this, the fact that the actual consumption differs from the forecast is harmful for the economy of the company and even for the economy of the big scale. In this study, it is aimed to estimate the imbalance aberration caused by demand forecast deviation with Artificial Neural Networks and to evaluate its results.

Keywords: Artificial Neural Network, Demand Prediction, Unbalance cost, prediction, Energy Demand

1. Introduction

Accurate estimation of the amount of energy needed by countries is important for decision makers that determine energy strategies and policies. Particularly, in energy-driven outsourcing countries and in developing countries where demand for electricity is rising relatively fast, the demand forecasts become even more important. On the basis of this precept lies both economic and political reasons. It is economically important; energy consumption has affected many economic parameters such as current account deficit, inflation and growth. Furthermore, the liberalization of energy markets, which are becoming increasingly widespread throughout the world, has led to the energy prices being

determined by supply and demand to a large extent. For this reason, imbalances are generally punished in other examples of energy markets in the world and in Turkey.

Electricity is an energy that must be consumed when it is produced because it cannot be stored, or rather it is very costly to store. Therefore, demand forecasts in electricity markets are indispensable. In order to meet the electricity need, TETAŞ (Türkiye Elektrik Ticaret ve Taahhüt A.Ş.- Turkey Electricity Trade and Contracting Co.) receives energy with bilateral agreement depending on the estimations that it has sent from 1 year ago. However, estimates made a year ago do not adequately reflect the needs of the present day, and companies are aiming to get the energy they need by estimating demand in the Day Ahead Market (DAM). However, if the amount of energy received by TETAŞ cannot meet the amount of energy in the day, or if it is in excess of the amount of energy, companies have to provide the supply demand balance by selling the excess electricity on

their hands or by purchasing the missing part from this market. This situation causes the imbalance costs. This loss must be able to be controlled / predicted.

Recently, studies have been carried out on electricity energy consumption and load forecasting, distribution and planning analysis in electricity generation. In the paper entitled "Grey prediction with rolling mechanism for electricity demand forecasting of Turkey" are proposed in the estimation of electricity demand. The study shows that the GPRM approach can be used as a useful tool for short-term load estimation for Turkey [1].

For Niğde in Turkey, load estimation was performed by two different methods. These methods are artificial neural network backpropagation algorithm and nonlinear trend analysis moving average methods. It has been shown that the most appropriate method is artificial neural network. The estimates obtained by both methods of 2001 were compared with the actual values and it was found that the estimation results are very close to the real values [2].

Turkey's electricity consumption is modeled using the Support Vector Regression. According to the model result, Turkey's electricity consumption in the next 20 years will reach 284.9 TWh, which is estimated to be about twice the 2006 value. They stated that the

relevant institutions should plan a significant increase in the future power plant capacity [3].

In order to estimate China's energy demand from the countries with the highest energy consumption and to examine the dynamic nature of electricity consumption, a statistical power consumption model from 1980 to 2012 was developed. It was developed using the model Intelligent Swarm Firefly algorithm [4].

Many other similar works have been proposed either in the past [5–9] or more recently [10–14].

In this study, models were developed to predict demand for electricity in the DAM using artificial neural networks (ANN). Different architectures have been tried to achieve the most optimal prediction in the developed models.

2. Materials and Methods

2.1. Artificial Neural Networks

Artificial neural networks can collect information about samples, make generalizations, and then decide on those samples using information they have learned in comparison with samples they have never seen before. The goal of an ANN is to compute between output and input values with some internal calculations [15]. The first computational model of artificial neural networks was based on 1943 by W.S. McCulloch ve W.A. Pitts [16]. ANN is widely used in various fields such as prediction [17], control systems [18], classification [19], optimization [20] and decision making [21]. ANNs are a parallel distribution processing method in which neurons and weights linked to neurons are put together. The relationship between the input and output can be learned, simply based on the basic principle of operation. A multilayer sensor (MLP) is one of the best-known types of ANNs consisting of an input layer, an output layer, and one or more hidden layers [22].

There are activation functions defined between layers. The most common ones are given in Table 1.

Table 1: Transfer functions common used in algorithms

Transfer function	Algorithm
Tansig	tansig(n) = 2(1 + exp (-2n)) – 1
Purelin	purelin(n) = n, for all n
Logsig	logsig(n) = 1(1 + exp (-n))

Also there are many different types of training algorithms. One of the most common training algorithms is Feed Forward Back Propagation algorithm (FFBP) [23].

2.2. Data Collection

The data were obtained from TETAS web page [24]. TETAŞ, which was established as the first and only public wholesale company of Turkey with the split of Turkish Electricity Generation and Transmission Company (TEAS) in 2001 as part of the liberalization activities in the energy sector, is an Economic State Entity limited to the responsibility of the State and is in compliance with the general energy and economy policy of the State electricity trading and contracting activities. 120 data were taken from the TETAŞ web page.

DAM (Day Ahead Market), MCP (Market Clearing Price), DBA (Distribution Bilateral Agreement) and RBA (Retail Bilateral Agreement) were used as input data. The owning cost is considered as output data for each model. The statistics belong the data are given table 2.

Table 2. The ranges of data set and their statistic

Parameters	Data Statistic		
	Ranges	Mean ± S.D.	Unit
Input Layer			
MCP	10,1 - 227,2	149,6 ± 52,53	Lira
DAM	302,8 - 647,8	450,6 ± 77,01	
DBA	4,0 - 248,0	116,5 ± 41,13	MWh
RBA	150,0 – 386,0	271,3 ± 54,20	MWh
Output Layer			
O. Cost	-12636,9-52258,2	13051,7 ± 14421,7	Lira

This data was used as 100 training data and the remaining 20 pieces were used for testing purposes. RBA, the amount of energy received from the TETAŞ for the retail

company, DBA, the amount of energy received from the TETAŞ is estimated, and the estimate of the DAM is the estimate for the day. Depending on the structure of the energy market, companies can buy from the market in several different ways. As stated earlier, the prices in the liberalizing market and the electricity market are determined by hourly supply and demand amounts. The MCP shown in our data set shows the actual hourly prices, which are based on the supply and demand balance.

And in order to obtain convergence within a reasonable number of cycles, the input and output data should be usually normalized. Normalization method as follows:

$$x' = 0.8 * \frac{x_i - x_{min}}{x_{max} - x_{min}} + 0.1$$

[1]

where x' is the normalized value, x is the original data, xmax and xmin, respectively, is the maximum and minimum values, thus the scaled data ranging between 0,1 and 0,9.

2.3. Network Properties

Neural network based modeling were performed using MATLAB. 24 different models were developed to find the architect who made the most optimal prediction. The network properties used in these models are as follows:

- Network type: Feed-Forward Back-Propagation.
- Training function: TRAINLM.
- Adaption learning function: LEARNGDM.
- Performance function: MSE.
- Number of hidden layers: 1,2.
- Number of Neurons: 1-14
- Input Layer Transfer function: logsig, purelin and tansig
- Output Layer Transfer function: purelin
- Iterations numbers : 1000

The mean square error (MSE) was applied as the error function calculated from the following equation [25]:

$$RMSE = \sqrt{\frac{1}{n}\sum_1^n (X_e - X_p)^2} \qquad [2]$$

$$R^2 = 1 - \frac{\sum_1^n (x_p - x_e)^2 \sum_1^n (x_p - x_e)^2}{\sum_1^n (x_e - \bar{x})^2} \qquad [3]$$

$$MAE = \frac{1}{n}\sum_{j=1}^n |y_j - \hat{y}_j| \qquad [4]$$

where n is the number of data points, $q_{i,pre}$ is the network prediction,

$q_{i,exp}$ is the experimental response and i is an index of the data.

y_i is the measurement,

$\hat{y}_i$ is the true value.

3. Result and Discussion

In this study, ANN models were developed to estimate the imbalance loss caused by the electricity demand forecast deviation of energy market suppliers. Levenberg-Marquardt (TrainLM) backpropagation algorithm, Hyperbolic tangent sigmoid (TansiG), Log sigmoid (sigmoid) and Linear (Purelin) functions are used as transfer functions in hidden layer and output layer in ANN models. In addition, 1 or 2 hidden layers were used in each model and the training process of the model was performed using 1000 iterations. The number of neurons in the hidden layer was varied from 1-14, and the predictive value of each model was measured by MSE. The most optimal number of neurons is 14, the number of hidden layers is 1, and the learning function is trainlm. The regression values for the most optimal ANN model are shown in Fig 1.

Statistical information showing the performance of the developed ANN model is summarized in Table 2. The correlation coefficient values obtained from the ANN model for the training and test data set were found to be 0.96 and 0.78, respectively.
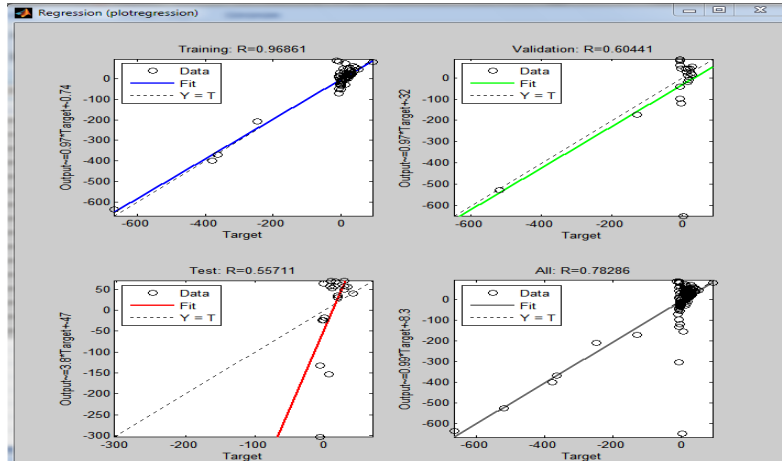
Figure 1. Optimum Network Regression

Table 2: Statistical information of optimum ANN model

Optimum	Statistic Value					
Structure	Train			Test		
4-1(14)-	RMSE	MAE	R	RMSE	MAE	R
1	0,080	0,032	0,976	0,105	0,079	0,952

The accuracy of the improved ANN model is proved by the low low RMSE and high correlation coefficient values for the test data set.

The results show that the ANN algorithm identifies the relation between input and output variables in a meaningful way and that the output variable can be estimated with high accuracy.
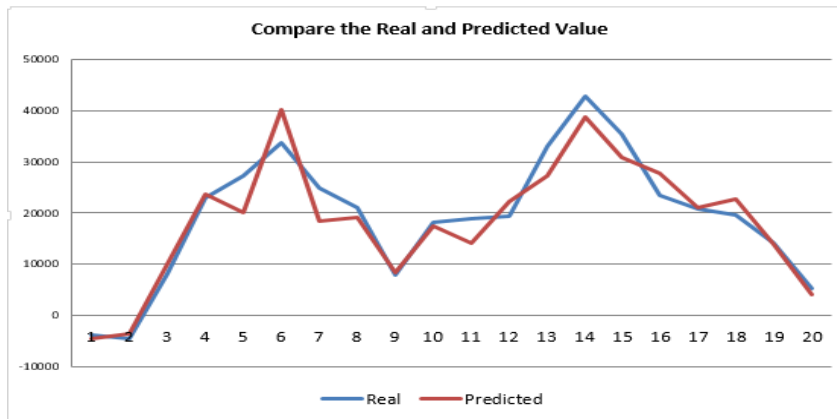
Figure 2. Compare the real and predicted value

4. Conclusion

Artificial Neural Networks (ANN) are used successfully in modeling the problem by learning the complex relationship between input and output data in the best way. In this study, ANN models were developed to estimate the imbalance loss caused by the electricity demand forecast deviation of energy market suppliers. For this purpose, 120 different data sets obtained from the TETAŞ web page were used in the development of the ANN model. Levenberg-Marquardt backpropagation algorithm is used as a learning algorithm in the ANN models developed to estimate the imbalance loss caused by demand forecast deviation, and tansig, sigmoid, purelin function is used as an activation function in the hidden layer and output layer.

In addition, it was determined that the statistical comparison of the estimated values obtained from the established ANN models with the measurement results is the structure of the network architecture (4-1(14)-1) that best predicts the resultant R%, RMSE and MAE both traing and test study.

In the results obtained from the developed model, it was seen that the best ANN model defined the relationship between the input and output variables in the data set very well and predicted the output variables at high accuracy. This has shown that ANN can be used as a successful tool in predicting the imbalance loss caused by energy market suppliers' deviation of electricity demand forecasts.

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