American Scientific Research Journal for Engineering, Technology, and Sciences (ASRJETS)
ISSN (Print) 2313-4410, ISSN (Online) 2313-4402

http://asrjetsjournal.org/

Modeling and Forecasting Turkey's Electricity Consumption by using Artificial Neural Network

Şule Birim[a], Ayça Tümtürk[b]*

[a,b]*Business Administration, Faculty of Economical and Administrative Sciences, Celal Bayar University, IIBF Uncubozkoy Campus, Manisa, Turkey*
[a]*Email: sule.ozturk@cbu.edu.tr*
[b]*Email: aycademirbilek@hotmail.com*

Abstract

The article describes the future projections of electricity demand in Turkey by using multiple linear regression (MLR) and artificial neural Networks (ANN). For this purpose six independent variables which are GDP, population, import, export, employment and natural gas are identified as the possible predictors of electricity consumption. We used MLR to determine which independent variables will be selected to forecast future electricity consumption with ANN. These variables are used in stepwise regression in order to identify which variables predict the dependent variable best by using 1992 - 2014 data. Four different models were identified as the result of MLR including various combinations of selected four variables that are population, import, natural gas and employment. In model 1 population, in model 2 population, import, in model 3 population, import and natural gas, in model 4 population, import, natural gas and employment are used as independent variables in ANN. In this study to model the proposed problem of forecasting Turkey's electricity consumption in the years 2015-2023, a feed forward multilayer perceptron neural network has been used. According to the forecasted results of four models Turkey's electricity consumption is projected to vary between 337087.4 and 385006.6 Gwh by 2023. Forecasted results were compared with Turkish Electricity Transmission Company (TEIAS) projections. Except Model 2 our forecast results showed lower values than TEIAS estimates.

Keywords: Electricity consumption; artificial neural networks; Turkey; Multiple regression analysis.

----

* Corresponding author.

1. Introduction

Turkey experiences rapid economic and demographic growth for the recent years. Indicator of the economic growth can be seen in rapid increase of GDP with growth rate of 3 percent on average since 2013[1]. As of December 2015 78.7 million people live in Turkey and population is increasing with a growth rate of 1.3% [2]. As the prediction shows Turkey's economy and population are expected to continue to increase in the future years [1, 3]. As the result of economic and demographic growth in Turkey, Turkey's energy demand has also risen rapidly in the last decades. As of 2013 Turkey is the 14th most energy consuming country in the world. Among the energy resources electricity plays a vital role by being used in various tools and equipment in residential and industrial sector. Electricity is widely used in almost every aspect of human lives such as heating, lightening, agriculture, transportation, manufacturing and usage of small and big appliances in both residence and industry. According to Energy Information Agency (EIA) [4], electricity consumption in Turkey has more than double between the years 2001 and 2012. When the last 23 years considered Turkey's electricity consumption raised from 46820 Gwh to 198045 Gwh from 1990 to 2013. Considering ongoing increase in population and GDP, increase in electricity consumption seems to continue in the following years. According to the forecast of TEIAS (Turkish Electricity Transmission Company) [5] on behalf of Ministry of Energy and Natural Resources, energy consumption will be 392 TwH according to the highly probable scenario.

In Turkey electricity generation stems from fossil fuel-fired power plants that considerably depend on natural gas for energy generation [4]. Since Turkey do not have enough fuel and natural gas resources, it is obliged to depend on imports [6]. This dependency to imports of other energy sources affects electricity generation directly. In order to plan electricity generation, prediction of future electricity consumption is a substantial problem in Turkey. ıncorrect estimation of electricity consumption will lead to power shortage or excess electricity generation. Power shortage will result in dissatisfaction and disharmony in both residential and industrial sector. Due to the disharmony in the industrial sector economy will be affected negatively. Excess electricity generation will also be costly for the country because of producing more than what is needed.

Official forecasts of electricity consumption in Turkey are implemented by the MENR. The MENR uses the Model for Analysis of Energy Demand (MAED) technique for electricity consumption prediction. MAED forecasts energy consumption by considering several different types of factors which are about economical, technological, social and demographical aspects of the country [7]. The MAED technique is regarded as not producing reliable results for predicting Turkey's electricity consumption [8]. Since assumption used in the predictions with MAED reflects the objectives of the MENR, forecasted values are usually higher than the realized energy consumption [9]. For this reason, offering new electricity consumption forecasts for Turkey remains as an important topic as the years passed. In order to contribute Turkey's electricity consumption literature, this study aims to propose an artificial neural network (ANN) model to predict future electricity consumption. Six independent variables (population, import, export, natural gas, employment and GDP) are used to predict electricity consumption in Turkey. These six variables are tested in regression as the predictors of electricity consumption. Four of the variables are found as significant regressors which are population, GDP, natural gas and employment. This study contributes to literature by indicating natural gas as a significant predictor of Turkey's electricity consumption. To the best of our knowledge natural gas consumption in Turkey has not been used to forecast electricity consumption in the literature. By using four selected independent variables four models were generated. Four models were used in ANN analysis to predict future electricity consumption in Turkey.

Remaining of this paper is organized as follows. In the second section literature review about energy consumption of Turkey and some other countries are presented. In the third section regression analysis used for determining which variables should be used in ANN modeling is demonstrated. In section 4 ANN approach used in this study is explained. In section 5 results of the ANN modeling and forecasting are presented. In section 6 conclusions about this study is discussed.

2. Literature Review

Energy plays a fundamental role in a country’s economy since it is a need for the industrial functionality. To point this importance, in the literature researchers intensively investigated the relationship between energy and other factors. Future situation in energy need is also a very attractive topic of interest in the literature. In this study finding the factors that predicts energy demand is the main focus and the future energy demand of Turkey is forecasted using ANN and/or MLR.

Reference [10] predicted future energy demand of USA for 2011-2030. In their study, they used multiple linear regression (MLR) technique and artificial neural network (ANN) technique to predict future electricity consumption. Before applying MLR, they choose 7 independent variables which are Gross domestic product (GDP), house hold size, median household income, cost of residential electricity, cost of residential natural gas and cost of residential heating oil to predict energy demand between years (2011-2030). First, proposed models were evaluated using the multiple linear regression method. Using 7 independent variables and the dependent variable, they tested all possible combinations meaning 2^7 equations. Three models were selected as the best and these three models were used in ANN for future energy demand estimation. In ANN method, they used a feed-forward multilayer perceptron neural network with back-propagation technique for training.

Referring to the IMF data for 2016, Turkey has the world's 17th largest purchasing power parity. Financial experts and analysts classify Turkey as a newly industrialized country. For this reason, energy consumption seems to be a hot topic in Turkey. For this reason, in the literature there is also a focus on electricity consumption of Turkey. In their research, Reference [11] found that the energy consumption (EC) is fully associated with the Industrial Production Index (IPI), population and GDP for the time between 1980-2004. Researchers used an exponential function to identify the relation between population-EC and GDP-EC. They used a logarithmic function for IPI-EC relationship. They suggested that instead of multi linear regression, ANN based model can give a good estimate for the electricity consumption.

Some of the researchers used same methods and same variables in their studies. For example, while [12] used GDP, population, import, export and employment variables to estimate future energy demand, Reference [13] used all of the variables but employment. Reference [14] just used two of them; GDP and population. Despite the similar variables, there are significant differences in these three researches. In the study of [12] authors tested 4 models with MLR, PRA (Power Regression Analysis) and ANN consisting variates of 5 indicators which are previously stated. They found the best model is Model 2 which contains GDP, population, import and export amounts. Using the Model 2 with ANN approach, this study used five scenarios to forecast the energy consumption of Turkey in the years 2008-2014 including a crisis scenario.

In [13], ANN model is applied with the teaching-learning based optimization algorithm to forecast energy demand in Turkey. For this purpose, proposed model and classical back propagation-trained ANN model compared by looking error values. Proposed model gave better results than classical ANN for energy demand forecasting. Both in [12] and [13] all of the scenarios revealed lower forecasts of energy consumption than the MENR (Ministry of Energy and Natural Resources) projections.

In another study, [14] estimated the future primary energy consumption (PEC) in Turkey. Primary energy referred to an energy form which has not been processed any conversion process. Examples could be natural gas or coal. Aydın [14] forecasted a model using logarithmic regression and verified his model with coefficient of determination, residual analysis, t-test and F-test too. Furthermore, he used three scenarios, which include different growth rates for CP and GDP, for estimating Turkey's PEC in the years 2010–2025.

Electricity has an important amount of proportion in energy consumption with covering nearly %23. There are also some articles about forecasting electricity consumption in Turkey. In short-term forecasting, there is an interaction between weather conditions and electricity demand. In [15], an approach for Turkey’s long-term electricity demand forecasting is offered by using two different structures, a recurrent neural network (RNN) and a three-layered feed-forward back-propagation (BP). In conclusion, best results produced by RNN structure. Authors predicted electricity demand of Turkey for 2008–2014 years. Furthermore, the forecast results obtained from ANNs are compared with official results of the MENR. MENR uses the model analysis of energy demand (MAED) simulation technique for Turkey’s energy demand forecast since 1984. [15] showed that both BP and RNN models produced better results compared to MAED results.

In 2012, [16] estimated electricity consumption of Turkey’s residential and industrial sectors using ANN, LR and NLR in the years 2008-2015. They chose installed capacity, gross electricity generation, population and total subscribership as independent variables. They suggested two scenarios which named are poor and powerful for forecasting of the future electricity demand. According to their poor scenario, with ANN forecasting Turkey’s residential and industrial sector electricity consumptions will increase to value of 140.64 TWh and 124.85 TWh by 2015, respectively. According to powerful scenario residential and industrial sector electricity consumptions will be 163.32 and 142.73 TWh in 2015.

3. Multiple Linear Regression Analysis

The first analysis in this study is multiple linear regression (MLR) analysis. The aim of MLR is to determine which independent variables will be selected to forecast future electricity consumption with ANN. MLR is applied after logarithmically transforming both independent variables and the dependent variable. By using logarithmic transformation in the MLR, relationship between the independent variables and the dependent variable stays nonlinear while linear model is still preserved [17]. Natural logarithms were used while making transformations. The independent variables used in this study are GDP, export, import, employment, population and natural gas consumption. The dependent variable is electricity consumption. Table 1 shows the values of these variables for 1992-2014, the period used for regression analysis. The data were obtained from different sources. The data for GDP, export, import, employment and population were obtained from the database of the Turkish Statistical Institute. Natural gas consumption and electricity consumption data are taken from Minister of Energy and Natural Sources.

In this study, to predict the value of the dependent variable, independent variables whose values are known are used in MLR method. To build an appropriate regression model, various independent variable selection methods can be used. The most widely used method is Enter. In enter method, all variables in a block are entered into the regression analysis in a single step. Another widely used variable choosing method is stepwise. Stepwise elimination method is a process in which independent variables outside the equation are examined and then the variables having the smallest f probability are stepped in the equation. Variables having the biggest f probability in regression equation are stepped out. Process is over when there is no variable which provides suitable condition.

Table 1: Electricity Consumption and Independent Variables Data (1992-2014)

Year	**Population (person) (X_1)**	**GDP (X_2)**	**Export (X_3)**	**Import (X_4)**	**Employment (person) (X_5)**	**Natural Gas Consumption (X_6)**	**Electricity Consumption (Y)**
1992	55811134	158459130434,8	14714629	22871056	19561	163,6	53984,7
1993	56707454	180169736363,6	15345067	29428370	18679	181,9	59237,0
1994	57608769	130690172297,3	18105872	23270020	20026	192,3	61400,9
1995	58522320	169485941048,0	21637040	35709012	20912	248,2	67393,9
1996	59451488	181475555282,6	23224464	43626644	21548	290,1	74156,6
1997	60394104	189834649111,3	26261072	48558720	21082	346,1	81884,9
1998	61344874	269287100882,2	26973952	45921392	22334	365,5	87704,6
1999	62295617	249751469675,3	26587224	40671272	21507	442,4	91201,9
2000	63240157	266567532789,5	27774906	54502820	21581	523,9	98295,7
2001	64182694	196005289735,6	31334216	41399084	21524	563,1	97070,0
2002	65125766	232534560443,2	36059088	51553796	21354	621,1	102947,9
2003	66060121	303005303084,8	47252836	69339696	21147	748,0	111766,1
2004	66973561	392166275622,6	63167152	97539768	19632	792,6	121141,9
2005	67860617	482979839089,0	73476408	116774152	20067	966,7	130262,8
2006	68704721	530900094644,7	85534676	139576174	20423	1101,2	143070,5
2007	69515492	647155131936,4	107271752	170062720	20738	1292,5	155135,3
2008	70344357	730337495735,7	132027192	201963568	21194	1294,1	161947,5
2009	71261307	614553921806,5	102142616	140928416	21277	1240,1	156894,1

2010	72310416	731168051903,1	113883216	185544336	22594	1346,5	172050,6
2011	73199372	774754155283,6	134906864	240841680	24110	1578,1	186099,6
2012	74099255	788863301670,4	152461744	236545136	24821	1598,1	194923,3
2013	75010202	823242587404,1	151802640	251661248	25524	1611,8	198045,2
2014	75932348	798429233036,3	157610160	242177120	25933	1711,2	207375,0

In backward elimination method, firstly all independent variables step in the regression equation as enter method. Then, variables which don't provide suitable condition are stepped out the equation sequentially. The independent variable which owns smallest positive or negative partial correlation is stepped out first. Process is over when all independent variables in the regression equation have enough partial correlation with dependent variable. In forward elimination method, every independent variable which provides suitable condition is included the equation step by step. After the first variable is included the equation, the variable which owns biggest partial correlation among the others is being considered. This process is the reverse of the backward method. Similarly with other methods, process is being over when there is no variable which satisfies the criterion.

In this study electricity consumption variable defined as dependent variable and other variables defined as independent variables as shown in the first equation:

$$\ln Y = \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_3 \ln X_3 + \beta_4 \ln X_4 + \beta_5 \ln X_5 + \beta_6 \ln X_6 \qquad (1)$$

Table 2: Statistical results of the stepwise regression

Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**F**	**R Square**	**Adjusted R Square**	**Std. Error of the estimate**
		B	Std. Error	Beta					
1	(Constant)	-68,483	1,240		-55,223	4166,756	,995	,994	,03527
	LNpop	4,451	,069	,997	64,550				
2	(Constant)	-55,528	3,631		-15,292	3246,147	,997	,996	,02829
	LNpop	3,628	,229	,813	15,860				
	LNimport	,102	,028	,190	3,710				
3	(Constant)	-36,847	7,115		-5,178	2909,674	,998	,997	,02441
	LNpop	2,549	,418	,571	6,095				
	LNimport	,092	,024	,171	3,825				

	LNnaturalgas	,142	,048	,262	2,924				
4	(Constant)	-22,534	7,741		-2,911	3002,541	,998	,998	,02082
	LNpop	1,559	,488	,349	3,196				
	LNimport	,099	,021	,184	4,794				
	LNnaturalgas	,234	,052	,434	4,531				
	LNemployment	,279	,094	,052	2,979				

Firstly, enter method is used to test the equation 1. Results showed that not all of the t test results for the independent variables are significant. Secondly backward elimination method has been used. In backward elimination method, F test and all the t tests results are statistically significant. The method selected population, GDP, employment and natural gas variables as significant independent variables for predicting the dependent variable. Then stepwise and forward methods have been tested with all the independent variables. Results of stepwise and forward methods also indicate population, GDP, employment and natural gas as significant predictors and they all proposed four models to be used in predicting the dependent variable. The selected four models can be seen in equations 2 to 5. Statistical results of the stepwise regression are given in Table 2.

$$\text{Model 1: } lnY = \beta_{01} + \beta_{11} \ln X_1 \quad (2)$$

$$\text{Model 2: } lnY = \beta_{02} + \beta_{12} \ln X_1 + \beta_{22} \ln X_4 \quad (3)$$

$$\text{Model 3: } lnY = \beta_{03} + \beta_{13} \ln X_1 + \beta_{23} \ln X_4 + \beta_{63} \ln X_6 \quad (4)$$

$$\text{Model 4: } lnY = \beta_{04} + \beta_{14} \ln X_1 + \beta_{24} \ln X_4 + \beta_{64} \ln X_6 + \beta_{54} \ln X_5 \quad (5)$$

where β01, β02, β03 and β04 are the constants, β11, β12 ,β13, β14, β22 ,β23, β24, β63 ,β64 and β54 are the regression coefficients, X1, X4, X5 and X6 are the four selected independent variables stands for population, import, employment and natural gas respectively. Y resembles the dependent variable namely electricity consumption. The selected four models represented in equations 2 to 5 are used in ANN analysis in order to predict electricity consumption between years 2015 and 2023.

4. Artificial neural network approach

ANN is an information processing model that works by resembling the functioning principles of human brain. ANN contains artificial neurons which are resemblances of natural neurons in the brain. Computational processes necessary for ANN are executed in the artificial neurons placed in the layers of ANN [18]. The layers in ANN are connected to each other to process information between input and output. ANNs are similar to human brain in mainly two aspects. Firstly, generation of knowledge in the network is acquired through a learning process. Secondly, obtained knowledge is stored in the interneuron weights that are resemblances of synaptic connections in human brain [10].

ANN models the process by identifying high level nonlinear relationships between the variables [19]. To accomplish this, a multilayer perceptron ANN has three kinds of layers that are input, hidden and output layers. The input layer is the first layer and comprises values for independent variables. Hidden layers contain hidden nodes that have the function of information processing. Output layer is the last layer that contains values for dependent /target variables [20].

As the working principle of ANN, the interneuron weights are calculated by detecting the contribution performance of the neuron to the target value [19]. The weights of the neurons are restructured until the output is as close as it can be to the target value. This process is called training in ANN. Neural networks are trained and weights of neurons are adjusted so that the given input reveals the desired output [10]. Figure 1 can be observed to see how a multilayer perceptron ANN including three layers work.

Neural networks are appealing tool for forecasting since they are non-linear and flexible. Traditional time series tools have restraining functional forms that can result poor fits due to basic assumptions of data generating processes. Neural networks protect flexibility without using underlying assumptions and they learn data generating process from the given data itself [21].

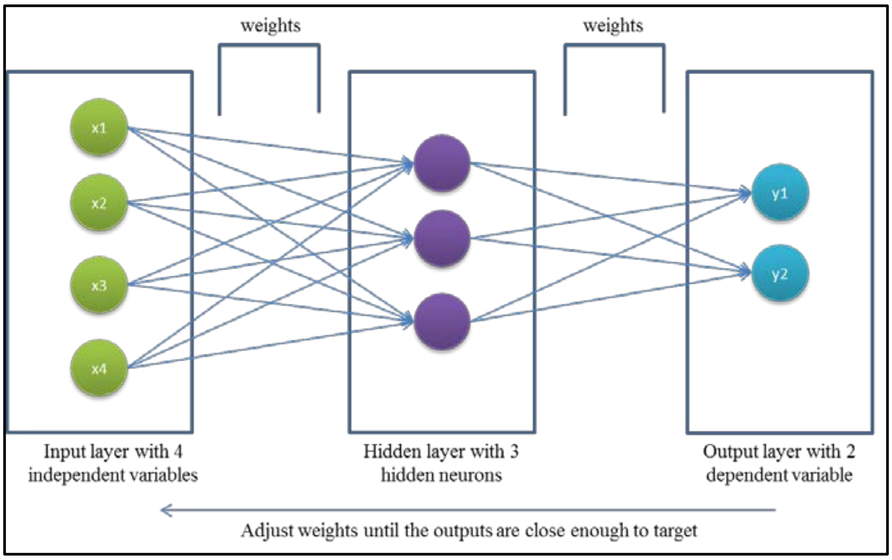

Figure 1: An example of an ANN architecture including 4 independent variables, one hidden layer with 3 hidden neurons and 2 dependent variables

Performance of neural networks depend on some design parameters such as number of hidden layers, number of hidden neurons, transfer functions, and the training algorithm. To determine the values of design parameters there is no well-established method and in the literature trial and error process following specific purposes is mostly used [19, 22].

4.1. ANN modeling

In this study to model the proposed problem of forecasting electricity consumption in Turkey, a feed forward multilayer perceptron neural network has been used. In multilayer perceptron neural networks neurons and layers are organized in a feed forward manner meaning the input layer obtains information from the outside of the system and the output layer calculates values based on the data in the input [23].

As the training technique, back propagation with gradient descent is used in this study. This technique is called backpropagation since it compares output with target values and goes back to input and change neuron weights in the network to reduce error meaning the difference between output and target values. As the gradient based algorithm in the back propagation, Levenberg-Marquard algorithm is utilized. This training algorithm is used since it performs better with function fitting problems [24].

In the back propagation technique, solution is found when the weight combination which minimizes the error function is obtained. In this method, in order to guarantee continuity and differentiability of the error function transfer function between neurons is used [25]. Sigmoid logistic transfer function in hidden layer neurons and linear transfer function in output neurons are often used in feed forward multilayer networks [24]. In consistency with the general use, in this study as transfer functions in hidden layer log-sigmoid, in output layer linear functions are applied.

Each neuron connects to a neuron in the next layer with weights. Each neuron except in the input layer, gets weighted sum of all the neuron values in the previous layer. Then an output value is calculated by putting the weighted sum in the transfer function [26]. How a neuron process information is shown in Fig.2. To mathematically demonstrate the situation output of a neuron is calculated with the equations 6 and 7:

$$a_j = \sum_{i=0}^{n} w_{ji} x_i \tag{6}$$

$$y_i = f(a_i) \tag{7}$$

where j is the neuron number, i is the input number, w is the weight, a is the weighted sum of the inputs, f represents the transfer function, y resembles the output value.

The sigmoid transfer function is defined with the equation 8:

$$f(a_j) = y_j = \frac{1}{1+e^{-a_j}} \tag{8}$$

In this study to forecast electricity consumption four models which are chosen as the selected models from the stepwise regression analysis are used. Input variables for the models are same as the way they are used in regression models meaning their logarithmically transformed versions are used in ANN. In all of the models electricity consumption is used as the dependent variable. In model 1 population, in model 2 population and import, in model 3 population, import and natural gas, in model 4 population, import, natural gas and employment are used as independent variables.

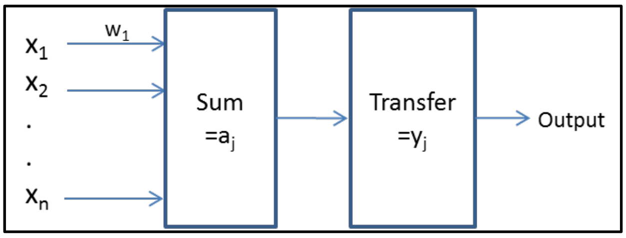

Figure 2: A representation of how a neuron process information

In ANN analysis the available data is allocated as belong to training, validation and the testing sets. In total we have data for independent variables and the dependent variable from 1992-2014. The data of the first 15 years (1992-2006) are used for training. Data in the preceding 4 years (2007-2010) are used for the validation and the last 4 years data (2011-2014) are used for testing.

One input layer, one hidden layer and one output layer is utilized in the ANN architecture. Generally, one hidden layer is adequate to model various continuous functions given that a proper number of hidden neurons are identified [22]. In this study to decide the optimal number of hidden neurons that makes the network bring the desired outputs trial and error method is used. Network is tested for hidden neuron numbers varying between 2 to 20. Based on testing with different architectures it was decided for hidden layer to contain 13 hidden neurons. Corresponding outputs from the selected network architecture are obtained. Comparing corresponding outputs with the target values network error which is the mean squared error (MSE) is computed with the equation 9:

$$MSE = \frac{\sum_{j=1}^{n} (y_i - t_i)^2}{n} \qquad (9)$$

where y_j are the network produced output values and t_j represents actual values of the dependent variable.

In order to see the ANN model is acceptable normalized MSE (NMSE) is estimated. NMSE is calculated as the ratio of MSE to target variance [27] as shown in equation 10. ANN models having NMSE value of 0.05 or below are accepted in this study.

$$NMSE = \frac{MSE}{\operatorname{var}(t_i)} \qquad (10)$$

To summarize, accepted ANN architecture has the following features:

- one input layer with 4 neurons representing 4 independent variables

- one hidden layer with 13 neurons
- one output layer with 1 neuron representing 1 dependent variable
- the maximum epoch's number is set to 100000
- MSE goal is set to 5×10^{-20}

5. Results and forecasting

To obtain the forecasting equations, the identified ANN architecture is trained, validated and tested with actual data using MATLAB 2015b software. To assess how the ANN models working NMSE values are observed. Each of the accepted models has NMSE values below 0.05. NMSE values of four models are 0.0039, 0.0126, 0.0018 and 0.0195 respectively. To evaluate the performance of the ANN visually, actual data of the electricity consumption in Turkey are graphically compared with the output values of four ANN models in Fig.3, Fig.4, Fig.5 and Fig.6 for models 1 to 4 respectively. For all of the models comparisons showed a similar trend meaning a good agreement between output and target values.

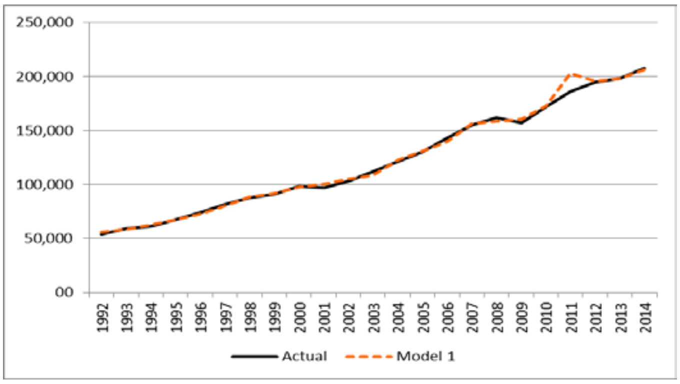

Figure 3: ANN results of model 1 and actual data

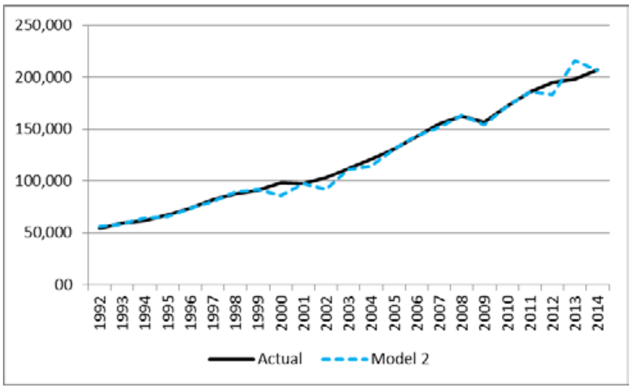

Figure 4: ANN results of model 2 and actual data

Forecasted electricity consumption between the years 2015 to 2023 can be obtained only if the forecasted values of the independent variables are identified. Individual forecasts of independent variables (population, import, natural gas and employment) should be portrayed and then these forecasted values should be run into ANN to forecast future energy consumption. The independent variables are forecasted until 2023 starting from 2015 by linear regression based on the previous data between 1992 and 2014. Forecasted results for all the independent variables are represented in Table 3. The ANN models that have been trained and tested with actual data of 1992-2014 are now applies to produce future electricity consumption values for the next 16 years. The forecasted values of independent variables for the following 9 years are used as the inputs in the previously trained ANN networks. The results for electricity consumption projections for four models can be seen in Table 4.

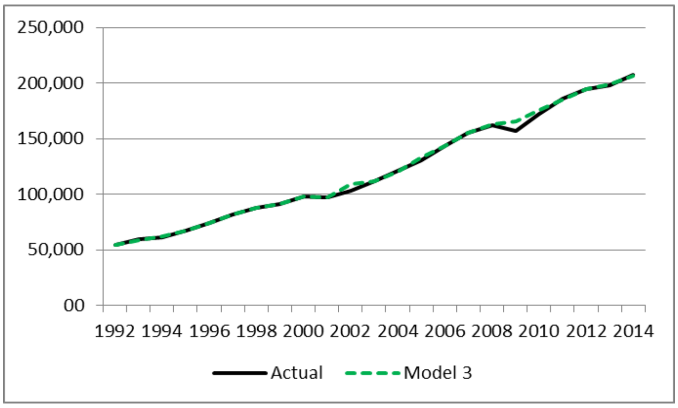

Figure 5: ANN results of model 3 and actual data

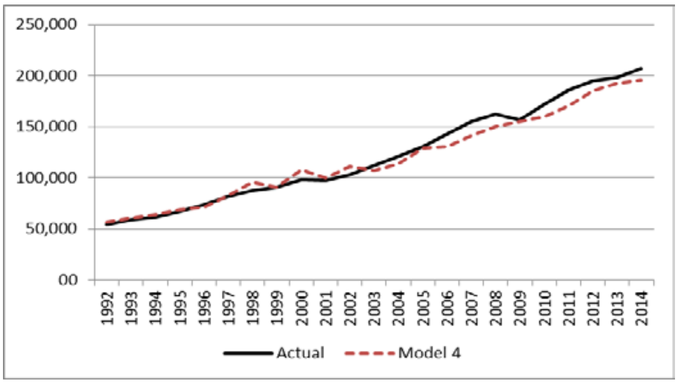

Figure 6: ANN results of model 4 and actual data

According to forecasting results total electricity consumption in Turkey is predicted to be 366005.8 GWh by 2023. Forecasting results of 2023 with using the other three models are 385006.6, 337087.4 and 375536.3 respectively. According to predictions of model 1 and model 4 electricity consumption in Turkey has been steady or slightly decreased a few years after 2015. This result seem quite interesting since the overall electricity consumption in Turkey has raised for the years between 1992 and 2014 which is the period used for modeling. Although the general trend of actual electricity consumption shows an increasing pattern in the examined period, in 2009 there is a sharp decrease. The reason for this decrease is the global economic crisis which had serious impacts on many fields of economies of the world's countries. Turkey's electricity consumption had also been influenced by the global crisis and the consumption values had been decreased. This sharp decrease in actual data showed itself in

Table 3: Forecasted values of independent variables

Year	Population	Import	Employment	Natural gas Consumption
2015	75820.9	238191926.3	24000.2	1722.0
2016	76566.0	248594950.3	24197.8	1794.4
2017	77311.1	258997974.4	24395.3	1866.9
2018	78056.2	269400998.4	24592.8	1939.4
2019	78801.3	279804022.5	24790.4	2011.9
2020	79546.4	290207046.5	24987.9	2084.4
2021	80291.5	300610070.6	25185.5	2156.9
2022	81036.6	311013094.7	25383.0	2229.3
2023	81781.7	321416118.7	25580.5	2301.8

The predicted values. In the predictions of model 2 and model 4 the reason for a slightly decreasing pattern in the first few years of the forecasting period can be explained by the decrease in the electricity consumption in 2009.

Table 4: Forecasted values for electricity consumption in Turkey

Year	Model 1	Model 2	Model 3	Model 4
2015	252958.5	243053.8	224512.1	207857.4
2016	266294.6	253249	259299	205607.3
2017	256474.4	277515.9	269346.9	237021.3
2018	289139	314309.5	276502.8	263250.9
2019	314467.3	340463.8	294144.8	290328.6
2020	317484.8	346482.2	302936.6	315484.1
2021	336652.9	351655.1	314335.1	338264.6
2022	357884.2	367050.5	326708.9	358254.3
2023	366005.8	385006.6	337087.4	375536.2

In order to assess how our forecasting results behave as opposed to official predicted values, forecasting results in this study is compared with the forecasts of TEIAS as reported in Turkey’s electricity production capacity projection report [5]. Forecasting values of TEIAS for the years between 2015 and 2023 and forecasting values of four models in this study can be seen in Fig.7. TEIAS has 3 assumptions while making forecasts. The first and second assumption is based on the assumption that the demand of electricity as being high and low. The third assumption is named the reference demand meaning demand will be moderate. Forecasted values of

TEIAS in high demand assumption demonstrate higher values than all the four proposed models in this study. This result is parallel with some studies showing official forecasts has higher values that the estimated forecasts [12, 16]. Projected values of TEIAS in reference demand assumption exhibit slightly high estimates than the results of model 1, 3 and 4. Results of model 2 show similar values with reference demand assumption of TEIAS around years 2018 and 2019. Low demand assumption forecasts of TEIAS shows closer values to the results of model 1, 3 and 4 when compared to reference demand assumption. However, results of model 1, 3 and 4 are still slightly lower than the forecasts of low demand assumption. When compared to forecasted values of model 2, low demand assumption of TEIAS demonstrate lower estimates after 2017. Before 2017 results of model 2 are lower than the projection results of low demand assumption.

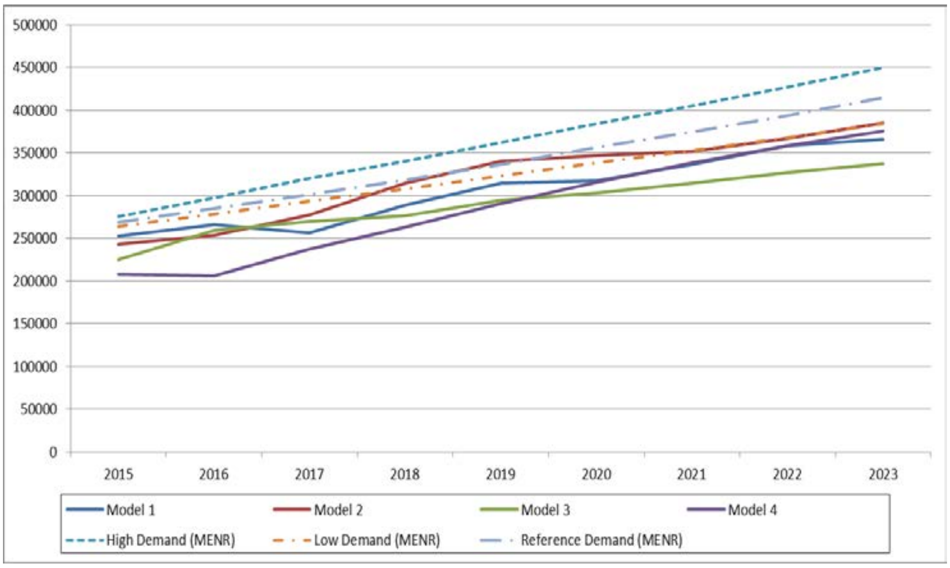

Figure 7: Forecasted results for electricity consumption in Turkey

6. Conclusion

Forecasting of electricity demand is an essential issue since electricity generation is based on capacity planning. Electricity generation in Turkey depends on materials (ie: fuel oil, natural gas) which are imported from abroad. Import amounts of products necessary for electricity generation are planned based on electricity consumption forecasts. Therefore, in Turkey forecasting has a very important role in capacity planning. To obtain successful projections alternate methods should always be evaluated by policy makers to determine which method will be the most beneficial one.

In this study four different ANN models are proposed to forecast electricity consumption in Turkey. Firstly, six independent variables which are GDP, population, import, export, employment and natural gas are identified as the possible predictors of electricity consumption. These variables are used in stepwise regression in order to identify which variables predict the dependent variable best. Four different models were identified as the result of regression analysis including various combinations of selected four variables that are population, import, natural gas and employment. In model 1 population is the independent variable. In model 2 population and import, in model 3 population, import and natural gas, in model 4 population, import, natural gas and employment were independent variables. Four models from the regression analysis are used in ANN to make projections of future electricity consumption. According to the forecasted results of four models Turkey's electricity consumption is projected to vary between 337087.4 and 385006.6 Gwh by 2023. Forecasted results were compared with TEIAS projections. Except model 2 our forecast results showed lower values than TEIAS estimates.

Our research has some limitations. The first limitation of the study is in the part of data collection phase. In data collection phase, we searched about six independent variables and one dependent variable data. And some data can only be available to collect until 1992. So this study used only the data of 1992-2014. The second limitation of the study is in the application phase. In application phase we used only regression analysis and ANN methods for forecasting. Different forecasting tools can also be used and compared.

For future research avenue, different scenarios for the models may be considered and the forecast of the scenarios should be evaluated. We also recommend that future electricity consumption forecasts can be made for a later time after 2023. Moreover, according to our study, ANN is a proper method for making predictions about electricity consumption forecasts.

References

[1] World Bank, Turkey Regular Economic Note, October 2015.

[2] Turkish Statistical Institute (TurkStat), The Results of Address Based Population Registration System, January 2016

[3] World Population Review, Turkey Population 2015, Retrieved from:

http://worldpopulationreview.com/countries/turkey-population/, 2015

[4] Energy Information Administration (EIA), Turkey International Energy Data and analysis, Overview, 2015

[5] Turkish Electricity Transmission Company (TEIAS). Türkiye elektrik enerjisi 5 yillik üretim kapasite projeksiyonu (2015 – 2019), 2015.

[6] Seta Perspektif, Enerji Görünümü: Türkiye, vol. 16, 2013.

[7] C. Hamzaçebi. "Forecasting of Turkey's net electricity energy consumption on sectoral bases." Energy Policy, vol. 35 (3), pp. 2009–2016, 2007.

[8] K. Kavaklioglu. "Modeling and prediction of Turkey's electricity consumption using Support Vector Regression." Applied Energy, vol. 88 (1), pp. 368–375, 2011.

[9] H. Hotunoglu and E. Karakaya "Forecasting Turkey's Energy Demand Using Artificial Neural

Networks: Three Scenario Applications.” Ege Academic Review, vol. 11, pp. 87–94, 2011.

[10] A. Kialashaki and J.R. Reisel. “Modeling of the energy demand of the residential sector in the United States using regression models and artificial neural networks.” Applied Energy, vol. 108, pp. 271–280, 2013.

[11] H.S. Kuyuk, R. Kayikci, O. Özkan, and S. Bayraktaroğlu “Modelling Turkey’s Energy Consumption Based on Artificial Neural Network.” 2010 Ninth International Conference on Machine Learning and Applications, pp. 681–685, 2010.

[12] M. Kankal, A. Akpınar, M.İ. Kömürcü, and T.Ş. Özşahin. “Modeling and forecasting of Turkey’s energy consumption using socio-economic and demographic variables.” Applied Energy, vol. 88 (5), pp. 1927–1939, 2011.

[13] E. Uzlu, M. Kankal, A. Akpınar, and T. Dede. “Estimates of energy consumption in Turkey using neural networks with the teaching–learning-based optimization algorithm.” Energy, vol. 75 (0), pp. 295–303, 2014.

[14] G. Aydin “Modeling of energy consumption based on economic and demographic factors: The case of Turkey with projections.” Renewable and Sustainable Energy Reviews, vol. 35, pp. 382–389, 2014.

[15] M. Çunkaş, and A.A. Altun. “Long Term Electricity Demand Forecasting in Turkey Using Artificial Neural Networks.” Energy Sources, Part B: Economics, Planning, and Policy, vol. 5 (3), pp. 279–289, 2010.

[16] M. Bilgili, B. Sahin, A. Yasar, and E. Simsek. “Electric energy demands of Turkey in residential and industrial sectors.” Renewable and Sustainable Energy Reviews, vol. 16 (1), pp. 404–414, 2012.

[17] K. Benoit. Linear Regression Models with Logarithmic Transformations. ReCALL, 2011. pp 1–8.

[18] J. Szoplik. “Forecasting of natural gas consumption with artificial neural networks.” Energy, vol. 85, pp. 208–220, 2015.

[19] B. Verlinden, J.R. Duflou, P. Collin, and D. Cattrysse. “Cost estimation for sheet metal parts using multiple regression and artificial neural networks: A case study.” International Journal of Production Economics, 111 (2), 484–492, 2008.

[20] D. Golmohammadi. “Neural network application for fuzzy multi-criteria decision making problems.” International Journal of Production Economics, vol. 131 (2), pp. 490–504, 2011.

[21] N. Kourentzes. “Intermittent demand forecasts with neural networks.” International Journal of Production Economics, vol. 143 (1), pp. 198–206, 2013.

[22] J. Ciurana, G. Quintana, and M.L. Garcia-Romeu. “Estimating the cost of vertical high-speed machining centres, a comparison between multiple regression analysis and the neural networks approach.” International Journal of Production Economics, vol. 115, pp. 171–178, 2008.

[23] O. Kaynar, I. Yilmaz, and F. Demirkoparan. “Forecasting of natural gas consumption with neural network and neuro fuzzy system.” Energy Education Science and Technology Part A: Energy Science and Research, vol. 26 (2), pp. 221–238, 2011.

[24] M.H. Beale, M.T. Hagan, H.B. Demuth, Neural Network Toolbox User’ s Guide How to Contact MathWorks, MathWorks pp 1.5 – 1.15.

[25] R. Rojas. The backpropagation algorithm. Springer-Verlag, Berlin, 1996, ch. 7 (Book Section)

[26] M.T. Hagan, H.B. Demuth, and M.H. Beale. Neural Network Design. Boston: PWS Publishing Company, 2014, pp. 2.7-2.19.

[27] K.-Y. Huang. Seismic principal components analysis using neural networks. In: W. Sandham and M. Legget, eds. Geophysical Applications of Artificial Neural Networks and Fuzzy Logic. Springer, 2003. pp. 103–124.