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Araştırma Makalesi/Research Article

Prediction of Electricity Consumption in Turkey with Time Series

Zeydin PALA

Muş Alparslan University, Faculty of Engineering and Architecture,
Department of Software Engineering, Muş/Turkey. ORCID: 0000-0002-2642-7788

Corresponding Author: z.pala@alparslan.edu.tr

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Abstract

Today, electrical energy is the cornerstone of modern life and plays a large role in many industries, activities and areas of life. It facilitates and improves many aspects of life and enables the functioning of modern society. The widespread use of electrical energy in Turkey, in a sense, is an indicator of its progress towards a modern society. In this study, annual estimations of the electrical energy consumed per capita in Turkey between 1965-2022 were made with the help of deep learning and statistics-based models and the results were evaluated with the MAPE metric. In addition, the positive and negative aspects of electricity consumption for Turkey were discussed.

Keywords: Electrical Energy Consumption, Time Series, Deep Learning Models, Statistical Based Models, Time-Series

1. INTRODUCTION

Like many other countries, electricity usage in Turkey was limited in the early 20th century, with electricity primarily used in urban areas and industries. Turkey experienced significant growth in electricity consumption as industrialization and urbanization progressed. The 1970s and 1980s marked a period of increased demand for electricity due to economic development and urban expansion.

Turkey's electricity consumption has continued to rise due to factors such as population growth, urbanization, economic development, and increased use of electronic devices [1,2]. Here's an overview of recent trends: Turkey witnessed a steady increase in electricity consumption during this decade due to rapid economic growth and industrialization. The government introduced various policies to meet the growing energy demand. Electricity consumption continued to rise, and Turkey embarked on efforts to diversify its energy sources to ensure a more sustainable energy supply. The country invested in renewable energy projects, such as wind, solar, and hydroelectric power. It has been actively promoting renewable energy sources to reduce its dependence on fossil fuels. The country has set targets for renewable energy capacity and has been conducting auctions for renewable energy projects. Efforts have been made to improve energy efficiency in various sectors, including industry, transportation, and residential buildings. Energy efficiency measures help curb the growth in electricity consumption. It has been exploring the use of smart grids and digital technologies to enhance the efficiency and reliability of its electricity distribution system. It is a net energy importer, and its electricity demand has led to energy import dependency. This has spurred discussions about the need for energy security and diversification. It's energy consumption is influenced by its geopolitical location and relationships with neighboring energy-producing countries.

It's important to note that specific consumption figures can vary from year to year and are influenced by economic fluctuations, policy changes, and technological advancements.

Time series analysis is often used to predict the future based on past data because time series refers to a data set in which data collected over a specific time period is recorded in an orderly manner. These datasets show trends, seasonal variations, and other time-related changes. Therefore, time series analysis can be used to predict when a particular event or events may occur in the future. The usage area of time series is quite wide. Some of these areas can be expressed as: price/sales forecasts [3], stock market forecast [4], economic growth forecasts [5,6] engineering [7], energy demand [8] and forecast [9], environmental science [10], sunspot prediction [11], meteorology [12], weather and climate modeling [13], transportation [14], health predictions [15-19], medical signal analysis and monitoring [20], ionospheric foF2 parameter estimation [21], radiation estimates [15], [22-25], traffic flow modeling and forecasting [26], hybrid and non-hybrid short-term forecasts [27] .

In general, two different basic approaches are used for the estimation of time series in the literature: the statistical-based approach [28-30] and the machine learning-based approach [31-34]. There are also hybrid applications where these two methods are used together [35,36]. These two approaches used in time series estimation have both strengths and weaknesses [37,38]. In conclusion, time series analysis is a powerful tool for predicting a future event using historical data. Therefore, time series models are widely used in many fields.

In this study, future estimations of electrical energy consumed on a per capita basis were made using a data set containing 58-year data between 1965-2022 in Turkey. While deep learning models and statistical-based models are used for the prediction processes performed with two different approaches, on the other hand, the performances of the models are evaluated by using MAPE metrics. This study tries to contribute to the literature in this respect.

2. MATERIALS AND METHOD

In this study, a windows-based computer was used for time series analysis. All of the data on the electricity consumed per capita in Turkey between 1965-2022, used in this study, were obtained from the https://ourworldindata.org/energy website. The purpose of the site where the data is sourced is stated as “to make information about big problems accessible and understandable and to publish research and data that will make progress against the world's biggest problems”. Within the current site, it is possible to access the consumed energy data of the world countries and compare them on the basis of countries.

In this study, both deep learning-based models and statistical-based models are used together for future predictions. These models used are briefly explained:

Neural network time series forecasts (NNETAR) function in the forecast package for R trains a neural network model of a time series with delayed values of the time series as inputs and possibly some other external input. Thus, it is a nonlinear autogressive model and it is not possible to derive prediction intervals analytically. The network is trained for one-step prediction [39].

Multilayer Perceptrons (MLP) consists of vertical stacks of neurons forming a layer and the connections between them. Networks with several layers are called multilayer perceptrons [4,5].

Extreme Learning Machine (ELM), hidden nodes are randomly initialized and then fixed without being set iteratively. In fact, the hidden nodes in the extreme learning machine need not even be the same neuron. The only free parameters to learn are the links between the hidden layer and the output layer. In this way, in the extreme learning machine, it is formulated as a linear model in the parameter that is reduced to solving a linear system [40].

ARIMA (p,d,q) is a very powerful model for estimating time series data, data preparation and parameter tuning processes are really time consuming. Here, p is the order of automatic regression, d is the degree of trend difference, and q is the moving average [41].

Exponential Smoothing (ETS) is a time series estimation method for univariate data [42].

The TBATS model is the Trigonometric Seasonal + Exponential Smoothing Method + Box-Cox Transform + ARMA model for residuals [43]. The mean absolute percentage error (MAPE) metric was used to evaluate the models.

$$MAPE = \frac{100}{n} \sum_{i}^{n} \frac{|y_i - \hat{y}_i|}{|y_i|} \tag{1}$$

MAPE is frequently used in time series models to measure and evaluate the accuracy of forecasts. If there is a zero value among the actual values collected, MAPE cannot be calculated because there will be division by zero and it contains uncertainty. The error rate due to missing, incorrect or low data cannot be 100%, but there is no upper limit to the prediction rate [44]. Here, $\hat{y}_i$ denotes estimates while y_i denotes actual values.

2.1. The Time Series Used for Electrical Energy Consumption

Since the data downloaded from Our World in Data site includes the data belonging to the countries of the world collectively, the data of the consumed electrical energy was first pre-processed and only the data belonging to Turkey were separated and then turned into a time series in the next step. The graph in Figure 1 shows the time series of electricity consumed per capita in Turkey between 1965 and 2022.

When the time series is examined, it is seen that there is a regular upward trend between 1965 and 1975, and decreases from time to time with the rise in the following periods. In the following periods, similarly, decreases are observed along with the upward trend. Especially in the 2000s, sharp decreases were experienced and these decreases were repeated in 2020 with the effect of the pandemic.

It is important to consider several factors when assessing the increase in electricity consumption per capita in Turkey. These factors may include the positive and negative aspects of the increase in energy demand, its environmental effects and the impact of energy policies. Here are some points to consider in this regard:

Positive aspects of electricity consumption: Per capita electricity consumption is generally associated with economic growth. This may indicate an increase in activities in the manufacturing and service sectors. Increasing electricity consumption may mean that people can use more electrical devices and technologies, and their living standards increase. Growth and developments in the industrial sector may cause an increase in energy demand. This can be a positive sign for job opportunities and economic development.

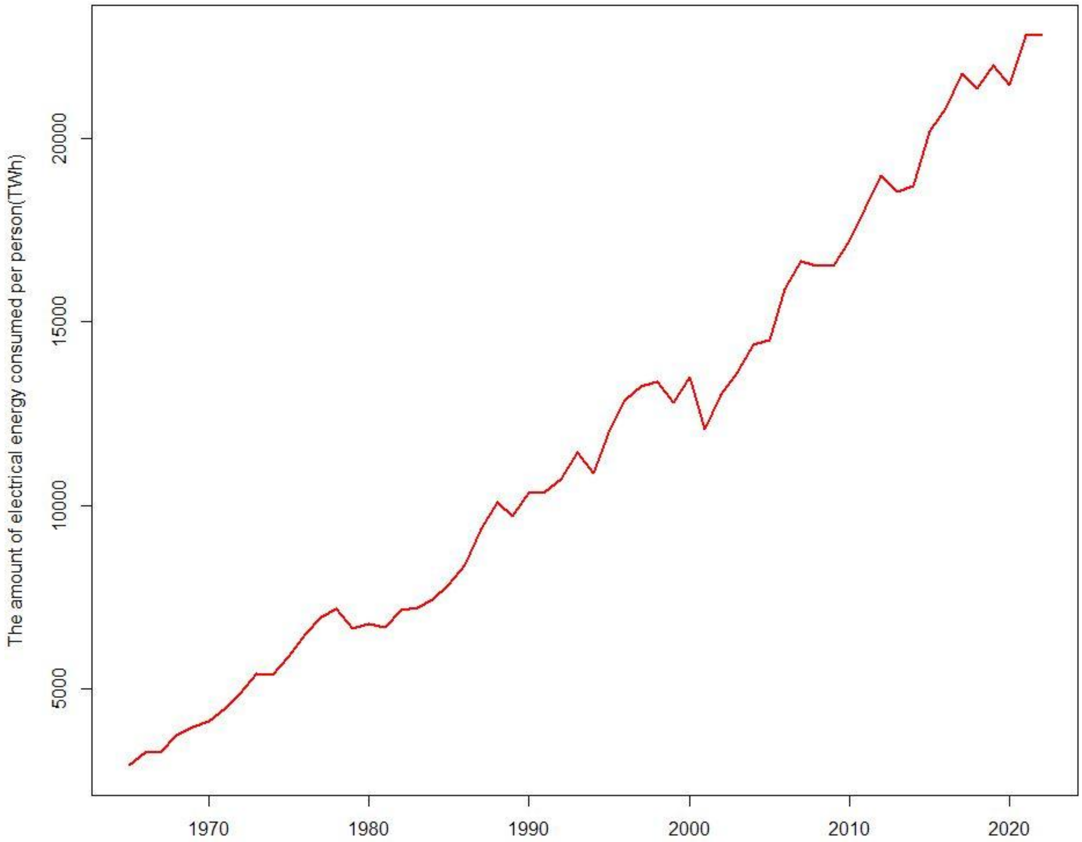

Figure 1. The amount of electrical energy consumed per capita in Turkey between 1965-2022

Those negative aspects of electricity consumption: Increased energy consumption often requires greater use of fossil fuel sources, which can increase greenhouse gas emissions and contribute to climate change. Increasing demand can strain energy supply and raise energy security concerns. It is important for the country to diversify its energy resources and use them efficiently. Increasing demand may increase the necessity for investments in energy infrastructure. This can be costly and time consuming. Turkey's energy policies can shape the increase in electricity consumption per capita. Policies such as promoting sustainable energy sources, increasing energy efficiency and increasing renewable energy production can help minimize negative impacts

3. RESULTS AND DISCUSSION

In this study, the time series given in Figure 1, including the data between 1965 and 2022, was used for forecast analysis. By dividing the time series with two different approaches, training and testing processes were trained with the help of six different models and then tested. The time series was used by dividing it into training / testing components at 79% / 21% and 75% / 25%, respectively. The MAPE values of the estimation results obtained as a result of two different approaches are given in Table 1. In Figure 2, the layer information of the MLP and ELM models and the graphs of the estimations made according to the split ratios of the dataset are given in Figure 3 and Figure 4, respectively. As seen in Figure 2, the input and output layers of the MLP model consist of one neuron, while the hidden layer consists of five neurons. Similarly, the hidden layer of the ELM model consists of 42 neurons.

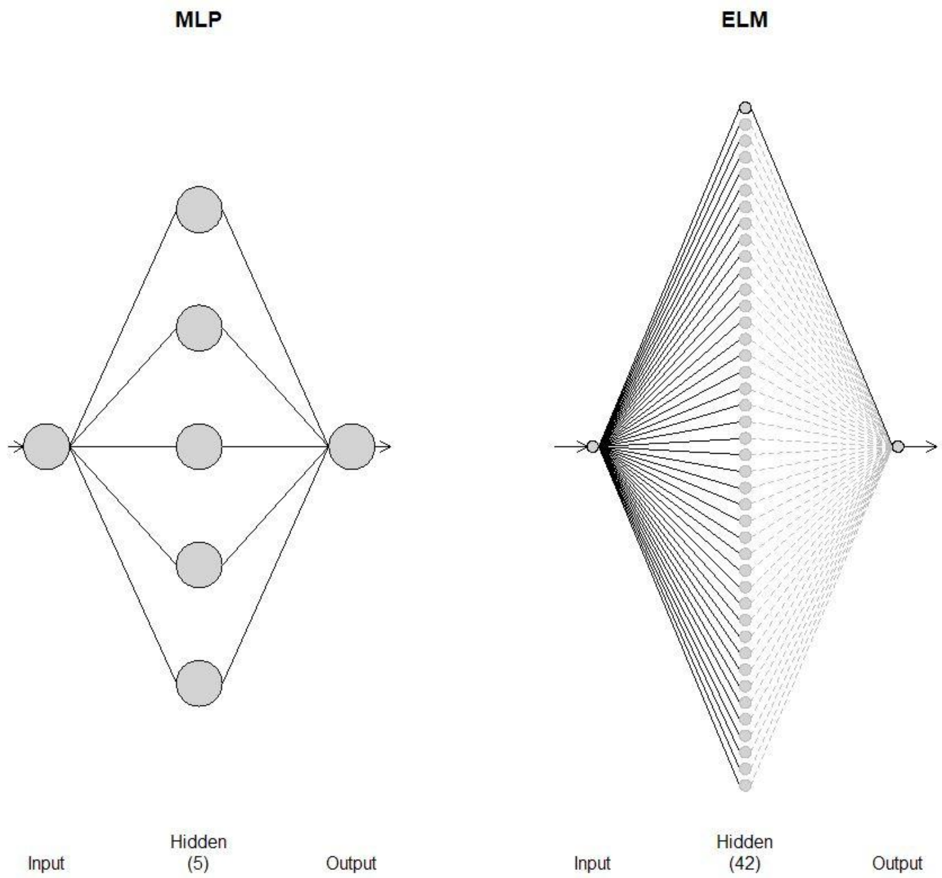

Figure 2. Layer information of MLP and ELM models

When the model graphics of the forecast results in Figure 3 and Figure 4 are examined, the first thing to see is that almost all models make an upward trending forecast.

As seen in the forecast plots, the dark shaded areas represent the predicted 80% ranges. In other words, each potential value is estimated to be in the dark shaded area with 80% probability. Light shaded areas show 95% prediction ranges. These forecast ranges are a useful way to show the variability in the forecast.

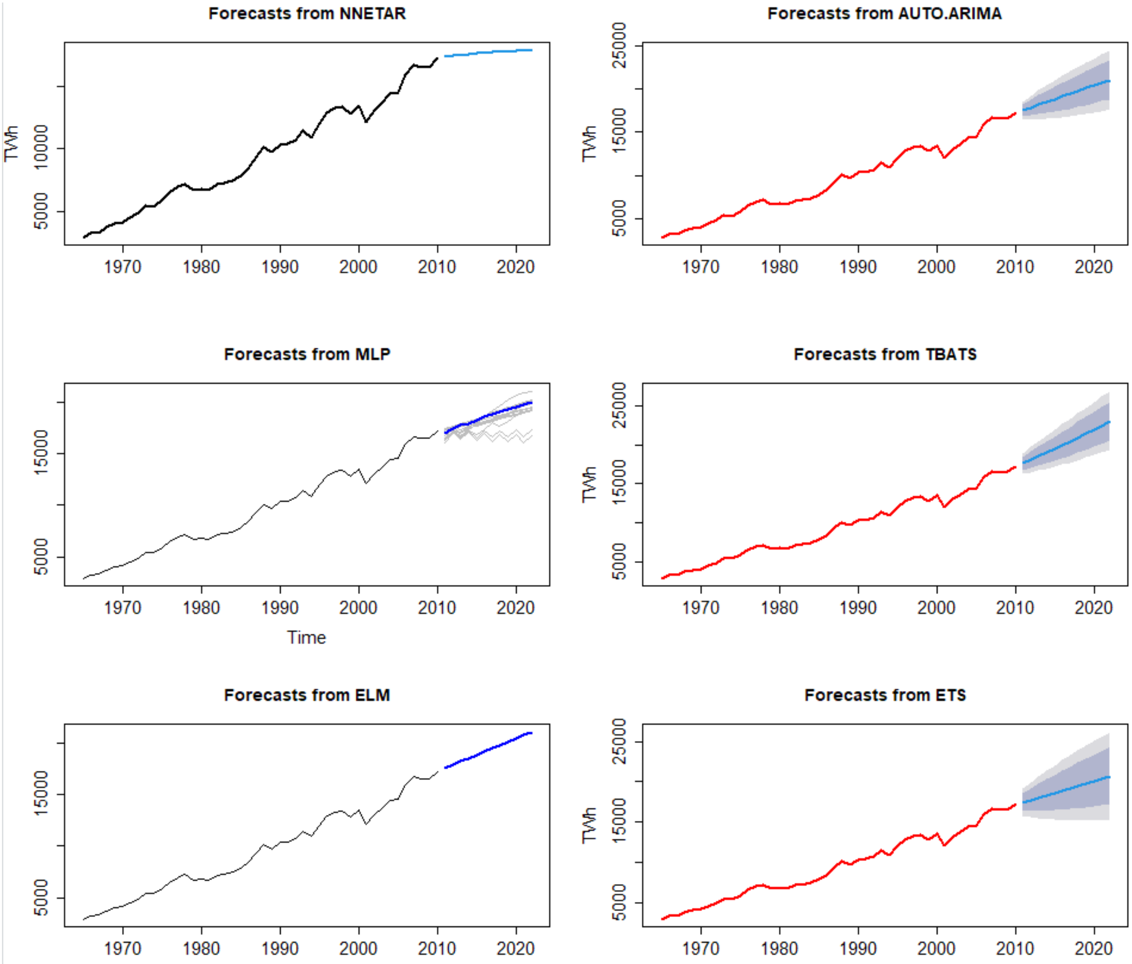

Figure 3. Prediction graphs made with the help of six different models when the data set is divided as 79% for training and 21% for testing

The MAPE values obtained in two different estimation analyzes made according to the training and test rates of the dataset used are given in Table 1. Since the MAPE metric expresses the error as a percentage, the small value obtained means that the error made is also small. In other words, the smaller the MAPE value, the better the accuracy of the model.

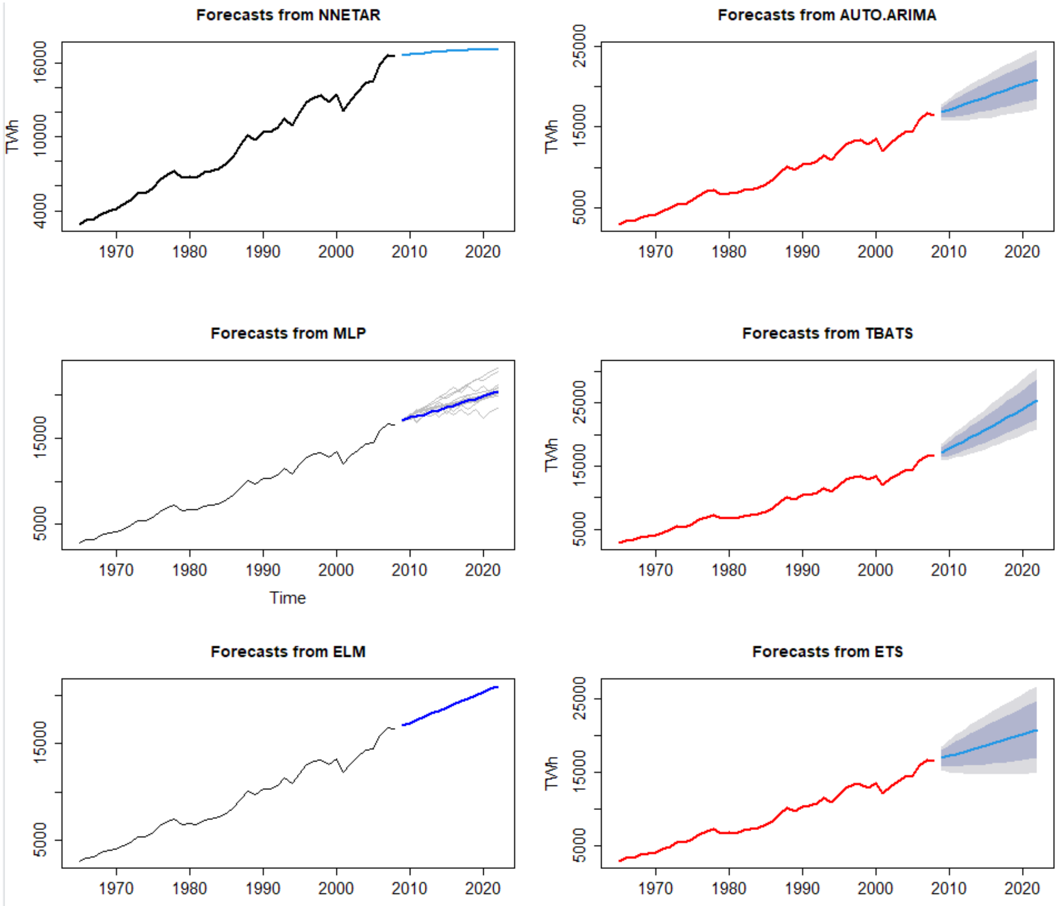

Figure 4. Prediction graphs made with the help of six different models when the data set is divided as 76% for training and 24% for testing

Table 1. MAPE values obtained from six different models because of the estimations made by dividing the data set used in two different ratios

Model	MAPE values for Training (79%) and Testing (21%)	MAPE values for Training (76%) and Testing (24%)
MLP	3.18/9.52	3.14/7.12
NNETAR	3.83/14.01	3.92/15.05
ELM	4.20/6.39	4.30/5.91
ETS	3.74/7.25	3.83/6.38
AUTO.ARIMA	3.79/6.37	3.87/5.89
TBATS	4.03/**4.66**	4.04/**5.21**

When both approaches are compared according to MAPE values in Table 1, it is seen that the results of the first approach are better than the second approach. The MAPE values of all models except the MLP model in the second approach, in other words, the error values increased. In both approaches, the best results from both deep learning and statistical-based models in the training process were obtained with the help of MLP and EST, respectively.

The order in the test processes was ELM, MLP and NNTAR in deep learning models, respectively. The same ranking was TBATS, AUTO.ARIMA and ETS in statistical based models. In the first approach, the best test results were obtained with the TBATS model with an error of 4.66%, in other words with an accuracy of 95.34%. In the second approach, the best test results were obtained with the TBATS model, with an error of 5.21%, in other words with an accuracy value of 94.79%.

When the test predictions made by both deep learning and statistical-based models are averaged for both methods and the results are compared, it can be said that the statistical-based models are better. In general, the performance of statistical-based models is better for limited data.

The fact that the dataset used in the study is very limited, consisting of 58 observation data is considered as a limitation. This particularly affects the performance of deep learning models negatively

4. CONCLUSION

In this study, future predictions were made for the amount of electricity consumed per capita (TWh) in Turkey between 1965-2022 with the help of deep learning and statistical models. Among the models used, it was seen that the TBATS model made better predictions. It has been observed that there is an increase in the electrical energy consumed per person from the past to the present. As a result, the increase in electricity consumption per capita brings both positive and negative effects. Therefore, it is important to design energy policies by considering issues such as sustainability, environmental protection and energy security.

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