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Research Article

Comparative Analysis of Electricity Consumption Forecast

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ABSTRACT

This study aims to make a comparative analysis of electricity consumption forecast using artificial intelligence (AI) and statistical models. In order to reduce the current deficits of countries, it is of great importance to predict the future electricity consumption amount and plan the power plant capacities accordingly. Electricity is an energy source that is extremely difficult to store when used in sectors such as industry and housing. Therefore, the electricity produced must be consumed immediately without causing energy losses and waste. In this context, ensuring the balance between electricity production and consumption can correctly contribute to the management of the current deficit by increasing economic efficiency. In the current study, Türkiye's hourly electricity consumption data between 2016 and 2024 were examined. These data were transformed into a 108-month consumption data set. Seven different models, namely Auto-ARIMA, Holt-Winters, Theta, ETS, TBATS, NNETAR and MLP, were used in the analyses. Among the models, NNETAR and MLP are AI based, and the others are statistical-based models. In this way, the effectiveness of different model types in electricity consumption estimations was compared. In this study, the Auto-ARIMA model stood out with a 3.77% MAPE error rate. When such studies are considered within the framework of countries' energy policies, they can make a significant contribution to reducing the current deficit of the country's economy. As a result of the study, it was concluded that the Auto-ARIMA model should be taken into consideration when making estimates on how many Megawatt power plants should be built in order to meet future energy needs in shaping energy policies in Türkiye.

1. Introduction

Energy is the most basic and indispensable need of today's modern societies. It plays a critical role in both economic growth and social welfare. Today, many devices and systems operate on energy. Energy is used as a fundamental resource for sustainable development and operational efficiency in various sectors such as homes, industry, transportation, production, and healthcare. Developing countries in particular experience a constant outflow of foreign currency because they import a large portion of their energy needs from abroad in foreign currency. This situation leads to a current account deficit in the country's economy. Meeting energy needs through imports negatively affects the economic development of these countries. In this context, it is of critical importance for developing countries to meet their energy needs with domestic and national resources in order to reduce their current account deficits and ensure their sustainable development. It can be said that the most widespread and most used type of energy is electrical energy. The production of electrical energy at low cost is of great importance in terms of closing the current account deficit in the national economy. Meeting the excessively consumed electricity need in the industrial and residential sectors with domestic and national resources is a critical step in terms of both economic efficiency and reducing foreign exchange outflow. Providing fuel through imports for electricity needs that cannot be met with domestic and national resources increases external dependency, resulting in a high amount of foreign exchange outflow and thus a current account deficit. Therefore, investments in electricity production with domestic and national resources should be continuously increased in order to meet the energy need. In Türkiye, especially in recent years, efforts to meet the energy need with domestic and national resources instead of imported oil and natural gas have gained momentum, and this process makes significant contributions to energy supply security [1]. However, it can be said that the electricity produced with domestic and national resources in Türkiye is currently not enough to meet the country's total electricity needs. In addition, in order to close the current account deficit in the country's economy, the production capacity in the industry should also be increased. On the other hand, increasing the production capacity will naturally create a greater need for electricity in the industry. In this case, the energy need should be met by increasing electricity production with domestic and national resources, and the production volume in the industrial sector should be increased. This approach aims to both provide foreign exchange inflow to the country and close the current account deficit in the country's economy. Thus, by ensuring energy independence, it will be possible to reduce external dependency and strengthen economic sustainability [2]. Figure 1 shows that 46% of electricity production is provided by imported energy sources, as stated in the 2024 Energy Statistics Bulletin of the Ministry of Energy and Natural Resources. The amount of electricity produced with domestic and national resources consists of 11% wind, 3% waste, 15% HES (Hydroelectric Power Plant) dam, 6% HES river, 3% geothermal and 14% lignite [3].

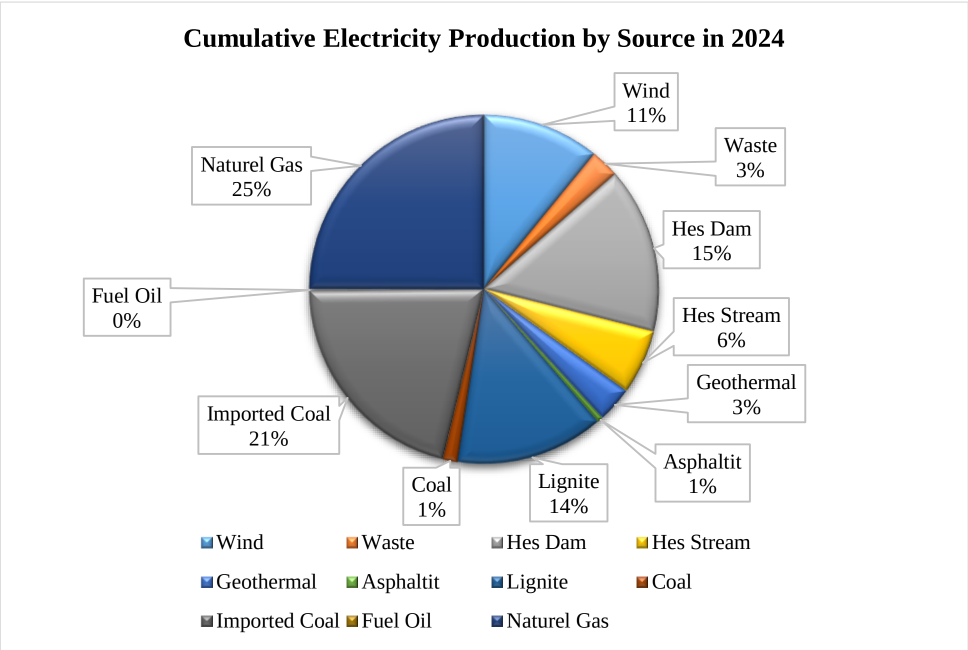

Figure 1. EIGM Reports [3].

The aim of this research is to encourage energy production with domestic and national resources instead of import-based energy resources and to contribute to closing the current deficit by ensuring that the budget allocated for energy remains within the country. In this context, the research emphasizes the importance of effective use of domestic energy resources. In a period when global energy crises and economic uncertainties are increasing, domestic energy production is of critical importance for the sustainability of the country's economy. In line with this goal, the research aims to reduce energy costs, create domestic added value and ensure more efficient use of the country's budget. As a result, reducing dependency on imports and encouraging domestic energy production emerge as an important step to ensure the country's economic and environmental sustainability.

1.1. Related Works

Energy is a critical factor for a country's economic growth and sustainable development. Therefore, energy production is at the core of economic and strategic decisions around the world. Many countries are developing various policies aimed at reducing energy dependency and using their domestic resources more efficiently. However, externally dependent energy production can threaten economic stability and prevent the efficient use of resources. Therefore, increasing domestic and national energy production is of great importance in terms of both economic and environmental sustainability. Studies in the literature on the contributions of domestic energy production to economic development and reducing external dependency reveal the importance of policies and strategies in this area. For example, Karaman and Bektaş (2023) [4] estimated energy consumption for the period 2020-2040 by using Türkiye's population, import, export and gross domestic product data between 1980-2019. Researchers used Particle Swarm Optimization (PSO), Gaussian Process Regression (GSR), Linear Regression (LR) models in their studies. As a result of the study, they found the coefficient of determination (R^2) of the models they used as GSR 0.9983, LR 0.9923 and PSO 0.9938, respectively [4]. Ekinci (2019) [5] made predictions by comparing the Artificial Neural Network (ANN) and Adaptive Network Based Fuzzy Logic Inference System (ANFIS) models, using electricity consumption data in Türkiye between 1970-2015. As a result of the study, the Mean Absolute Error Percentage (MAPE) for the test data of the ANN model was calculated as 3.69, and the ANFIS model as 3.35 [5]. Özden and Öztürk (2018) [6] applied the ANN model, using the electricity data consumed in the OSTİM Organized Industrial Zone between the years 2014-2016 and estimated the possible electricity consumption of the region [6]. Zeng et al. (2018) [7] estimated the electricity consumption for the period 2009-2015 by using the electricity consumption data between the years 1997-2008 in the commercial sector in Hong Kong. In the study, the possible electricity consumption for 2020 was calculated as 108,050 terajoules [7]. Similarly, Pençe et al. (2019) [8] examined the data between the years 1970-2016 in order to estimate the electricity consumption in the Turkish industry and made estimates for the period 2017-2023. As a result of the study, the RMSE value measuring the accuracy of the estimates was found to be 8.99 [8]. Işık and Şeker (2021) [9] estimated the future electricity demand by using an ANN model with data between 1985-2019, considering the electricity generation capacity in Türkiye. In this study, an ANN model consisting of 6 inputs, 4 outputs and 10 hidden layers was designed [9]. Lee et al. (2022) [10] estimated the electricity consumption in 2016 by using the ANN model, using 10-year electricity consumption data of Switzerland, Norway, Malaysia, Egypt and some other countries. In this study, it was determined that the Fuzzy Time Series (FTS) model showed the best performance for Algeria, Norway, Bulgaria and Kenya in short-term forecasts, while the ANFIS model was found to be more successful for Switzerland [10]. Tarmanini et al. (2023) [11] randomly selected 709 households in Ireland and applied 18-month daily electricity consumption data to ANN and ARIMA (Autoregressive Integrated Moving Average) models. As a result, they predicted that a better performance would be achieved when a hybrid model structure was used [11]. Lazzari et al. (2022) [12] examined the behavior of users on electricity consumption and established an ANN-based behavior clustering. Then, they tested it on 500 users in Spain and predicted future electricity consumption [12]. Ramos et al. (2020) [13] predicted future electricity consumption, using an ANN model with 16-month data of an industrial facility [13]. Pala (2023) [14] examined the electricity consumed per capita in Türkiye between 1965-2022. In the study, MLP (Multilayer Perceptron), NNETAR (Neural Network Time Series Forecasts), ELM (Extreme Learning Machine), ETS (Exponential Smoothing), Auto-ARIMA, TBATS (Trigonometric Seasonal + Exponential Smoothing Method + Box-Cox Transform + ARMA) models were used. In the analysis, the most successful model was found to be TBATS and the MAPE performance of the model was obtained with an error of 4.66% [14]. After examining the electricity consumption data on a sectoral basis between 1970-2004 in Türkiye, Hamzaçebi (2017) [15] estimated the total electricity consumption for 2020 as 499588.2 GWh with the ANN model. However, the total electricity consumption data announced by TÜİK for 2020 is 262702.1 GWh, which shows that there is a significant deviation in the researcher's estimate [15]. Qureshi et al. (2024) [25] emphasized that building energy management systems increase and optimize efficiency by monitoring energy consumption. In the study, electricity consumption was predicted by using LSTM-based time series analysis, and it was shown that the model achieved 95% accuracy [25]. On the other hand, Liu et al. (2024) [26] proposed a new gray Fourier model augmented with Fourier functions and fractional time-varying terms to accurately model seasonal fluctuations in electricity consumption. The study shows that the proposed model offers higher accuracy and flexibility compared to other traditional forecasting methods [26]. Peteleaza et al. (2023) [27] showed that the proposed time series dense encoder model for short and long-term forecasts of electricity consumption at the city level exhibits superior performance compared to traditional approaches [27]. Matos et al. (2024) [28] use machine learning techniques to forecast energy consumption of communities by addressing the transformation in the energy sector with the integration of renewable energy sources and the decentralization of electricity markets. The study shows that forecasts made with the eXtreme Gradient Boosting (XGBoost) algorithm are effective in reducing energy expenditures of communities and their dependence on the central distribution grid [28]. Kim et al. (2025) [29] studied the effect of data normalization on electricity consumption estimates in buildings with four different ANN algorithms. The study highlights that proper use of data normalization techniques can significantly increase the accuracy of electricity consumption estimates [29]. Leite Coelho da Silva et al. (2025) [30] emphasized that forecasting industrial sector electricity consumption is important for energy planning and control. The study reveals that the integration of classical forecasting models with Seasonal and Trend decomposition using Loess method can significantly increase the accuracy of electricity consumption forecasting [30]. Nazir and Li (2025) [31] stated that the quality of Pakistan's electricity consumption forecasts is critical for energy planning. The study demonstrates the effectiveness of a combined forecasting model based on LSTM and Monte Carlo simulation in accurately predicting the country's electricity consumption [31]. On the other hand, Zhang et al. (2020) [32] proposed a new gray model that takes into account spatial effects in electricity consumption estimates. The model exhibits higher accuracy and robustness compared to existing methods by using dynamic interaction matrix and Bayesian Optimization [32].

As a result, when the studies on electricity consumption estimation are examined, it is seen that both traditional statistical methods and machine learning-based approaches are widely used. While previous studies in the literature mainly focused on statistical techniques such as time series analysis and regression, in recent years it has been shown that deep learning and hybrid models offer significant advantages in improving the estimation performance. In this study, different statistical and artificial intelligence-based models for electricity consumption estimation were compared, and their performances were evaluated in detail. Auto-ARIMA, Holt-Winters, Theta, ETS, TBATS, NNETAR and MLP models were used in the study. These models offer different advantages and limitations in electricity consumption estimation. For example, Auto-ARIMA works efficiently with automatic parameter selection in small data sets, while it may have difficulty in large data sets. Holt-Winters is effective in pronounced seasonal patterns and may be weak in sudden changes. Theta adapts to both seasonal and non-seasonal components, but is sensitive to weak seasonal data. ETS performs well in simple data, but may be limited in complex data. TBATS is robust on multi-seasonal patterns but may suffer from performance degradation on small datasets. NNETAR and MLP are good at capturing nonlinear relationships but require large data and careful parameter tuning.

2. Material and Methods

Electrical energy consumption estimations are made with various techniques such as time series analysis, regression methods and machine learning. In this study, deep learning methods were used in addition to time series analysis in estimating electrical energy consumption. In the study, Auto-ARIMA, Holt-Winters, Theta, ETS and TBATS were used as statistical models, and MLP and NNTAR models were used as AI based models.

Time series, which are used in many sectors such as statistics, engineering, finance and energy, contain records of past observations taken according to a certain period. These series can be in seconds, minutes, hours, daily, weekly, monthly, seasonal, annual and periodic periods. Time series generally contain four elements: trend, conjectural fluctuation, seasonal fluctuation and random fluctuation. Time series consist of two parts: stationary and non-stationary. Statistical models are generally applied to stationary time series. However, in business life, industry and economy, time series are non-stationary at a certain average but rather have an up-and-down trend. In time series analysis, non-stationary series are made stationary and then applied to models [16][17][19].

2.1. ARIMA Model

ARIMA is a statistical model that allows estimating future values based on past data. This model is effectively used to predict future trends by analyzing time series data. ARIMA is preferred to solve unpredictable problems in many areas such as economy, finance, and energy demand. This model is used with the Auto.ARIMA function in the forecast library in the R programming language.

The ARIMA model is shown in the format ARIMA(p,d,q); p (AR) indicates the number of past values of the series, d (I) indicates the degree of difference iteration (how much difference is taken to make it stationary), and q (MA) indicates the component degree (the number of past errors). When applying the ARIMA model to time series data, determining the correct parameters is critical for prediction accuracy. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots indicate which ARIMA model to use. Akaike Information Criterion (AIC) and Schwarz Information Criterion or Bayesian Information Criterion (BIC) are used to evaluate the accuracy of the selected ARIMA model. Since there are many forms of the ARIMA model, the Auto.ARIMA function in the R programming language automatically selects the relevant ARIMA form for us to use. The mathematical formula of the general ARIMA(p,d,q) model [16][17] is as follows:

$$Y'_t = c + \phi_1 Y'_{\{t-1\}} + \cdots + \phi_p Y'_{\{t-p\}} + \theta_1 \varepsilon_{\{t-1\}} + \cdots + \theta_q \varepsilon_{\{t-q\}} + \varepsilon_t \quad (1)$$

Here Y'_t represents the differenced time series, ϕ_i AR parameters, θ_j MA parameters, ε_t error term.

2.2. Holt-Winter Model

Holt (1957) and Winters (1960) is a model used in the forecast analysis of time series with seasonality. This model creates observations and makes forward-looking predictions by taking into account the trend, level and seasonal effects in the time series. There are three components in the Holt-Winter additive model, which are level l_t, trend b_t and seasonality s_t. The correction parameters are α, β and γ. The additive formula of the model is shown below [17]:

$$Y_{(t+h|t)} = l_t + hb_t + s_{t+h-m(k+1)} \quad (2)$$

$$l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}) \quad (3)$$

$$b_t = \beta^{*(l_t - l_{t-1})} + (1-\beta^*)b_{t-1} \quad (4)$$

$$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m} \quad (5)$$

2.3. Theta Model

Theta model is a model used in the prediction of time series. The model is based on changing the local trends of the time series. The trend of the time series is smoothed with a number called theta coefficient. Theta coefficient is given values that continuously decrease towards zero, and the trend curve is made a linear line. The mathematical formula of the model is shown below [17][18]:

$$X''^{(\theta)}_{\mathrm{new}} = \theta \cdot X''_{\mathrm{data}}, \text{where} X''_{\mathrm{data}} = X_t - 2X_{t-1} + X_{t-2} \text{at time} t \quad (6)$$

2.4. ETS Model

ETS (Error-Trend-Seasonality) model is a statistical model used in time series forecasting. The model, which considers Error, Trend and Seasonality, can express these components in additive or multiplicative forms. The general mathematical formula of the model is shown below [21]:

Formula in the observation equation:

$$y_t = l_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t \quad (Additive) \quad (7)$$

$$y_t = (l_{t-1} + b_{t-1}).s_{t-m}.\varepsilon_t \quad (Multiplicative) \quad (8)$$

$$\begin{gathered} y_t, observations; \\ l_{t-1}, level; \\ b_{t-1}, trend; \\ s_{t-m}, seasonality; \\ \varepsilon_t, error\ term. \end{gathered} \quad (9)$$

The formula in the level equation:

$$l_t = l_{t-1} + \alpha\varepsilon_t \quad (Additive) \quad (10)$$

$$l_t = l_{t-1}.(1 + \alpha\varepsilon_t) \quad (Multiplicative) \quad (11)$$

α is the correction coefficient for the level.

Formula in trend equation:

$$b_t = b_{t-1} + \beta\varepsilon_t \quad (Additive) \quad (12)$$

$$b_t = b_{t-1}.(1 + \beta\varepsilon_t) \quad (Multiplicative) \quad (13)$$

β is the trend correction coefficient.

Formula in seasonal equation:

$$s_t = s_{t-m} + \gamma\varepsilon_t \quad (Additive) \quad (14)$$

$$s_t = s_{t-m}(1 + \gamma\varepsilon_t) \quad (Multiplicative) \quad (15)$$

γ is the adjustment coefficient for seasonality.

2.5. TBATS Model

TBATS model is designed to model complex seasonal structures and nonlinear time series. The model has a wide range of time series applications by combining trigonometry-based Fourier series, Box-Cox transformation, ARMA error terms, trend and seasonality components. In particular, it can effectively model fractional and irregular seasonal cycles and double calendar effects. TBATS provides more accurate estimates, using maximum likelihood estimates and requires less computational load than other methods. The general mathematical formula of the model is shown below [20]:

$$y_t^{(\omega)} = \ell_{t-1} + \emptyset b_{t-1} + \sum_{i=1}^{T} s_{t-m_i}^{(i)} + d_t \qquad (16)$$

$y_t^{(\omega)}$, Box-Cox transformed observation; l_{t-1}, Previous period trend component (level); ϕb_{t-1}, Previous period trend (trend growth rate), multiplied by the damping parameter (ϕ\phiϕ); $s_{t-mi}^{(i)}$, i'th seasonal component; d_t, represents the values coming from ARMA errors.

2.6. NNAR Model

NNAR (Neural Network Auto Regressive) is an ANN model used to predict time-dependent data. This model is designed specifically for univariate time series and consists of a feed-forward layer. NNAR takes past observations (lag) as input and predicts future values based on these data. It is called with the nnetar() function in the forecast package in the R programming language. It is called nnetar (p, k), p represents the delayed input values, i.e. past observations, and k represents the number of neurons in the hidden layer. The general form of the model is NNAR(p,P,k)m, consisting of inputs $(y_{t-1}, y_{t-2}, \dots, y_{t-p}, y_{t-m}, y_{t-2m}, y_{t-pm})$ and k is the number of neurons in the hidden layer. If k is not specified, k=(p+P+1)/2 is set [17].

2.7. MLP Model

MLP (Multi-Layer Perceptron) is a deep learning model used in time series and other fields. MLP is a forward-learning ANN model with at least three layers. The data received from the input unit is multiplied by a specified weight, and summed, and passed through the activation function and transmitted to the next layer or output. The mathematical formula of the model is shown below [22][23]:

$$Y = f(net) = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \qquad (17)$$

$(x_1, x_2 \ldots x_n)$ data inputs; $(w_1, w_2 \ldots w_n)$ weights; b, bias, a fixed value: f, activation function; Y, output.

2.8. Performance Measurement Metrics

MAPE (Mean Absolute Percentage Error), RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) metrics were used to evaluate the performance of the models.

$$MAE == \frac{1}{N} \sum_{t=1}^{N} \left| Y_t - \hat{Y}_t \right| \qquad (18)$$

$$MAPE = \frac{100}{N} \sum_{t=1}^{N} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \qquad (19)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^{N} \left(Y_t - \hat{Y}_t\right)^2} \qquad (20)$$

Y_t represents the actual value, $\hat{Y}_t$ represents the predicted value, and N represents the number of samples.

MAE is the absolute average of the differences between the predicted value and the actual values. As a result of this process, negative values and positive values are prevented from canceling each other out. MAE is calculated by taking the sum of the absolute values of the errors and dividing the total error by the number "n".

MAPE expresses the percentage of the ratio of the prediction errors to the actual values. It is used especially when the units of the variables are different or when an error measure independent of the unit is desired. Since the results are presented as a percentage, comparisons between units can be made. The closer the MAPE value to zero, the more successful the result is considered. However, MAPE can only be calculated when applied to positive data.

RMSE is the square root of the mean square of the errors. It not only measures the magnitude of the errors but also gives more weight to large errors. Due to its sensitivity to large errors, it emphasizes the effect of errors more strongly, and since it penalizes large errors, it can ignore the importance of small errors [17][24].

2.9. Dataset

In the current study, Türkiye's hourly electricity consumption data between 2016-2024 were examined. The data were obtained from https://seffaflik.epias.com.tr (Energy Markets Operation Joint Stock Company). The data were obtained from hourly consumption data. These hourly data were converted to monthly consumption data. There is no loss in the data. No missing data filling or data reduction was done. As a result, 108 months of electricity consumption data were calculated.

3. Analysis

In the study, electricity consumption data were handled with statistical and AI based models. The estimates of each model on the consumption data were carried out, and the results obtained were analyzed and measured.

The data set was divided into 80% training and 20% test data. As a result of the analyses performed on the data set, the model with the highest performance was determined. Figure 2 shows Türkiye's monthly electricity consumption between 2016 and 2024 (108 months).

When the graph is examined, it is observed that there are significant fluctuations. Fluctuations are an indicator of seasonality rather than stationarity of the data. Each black dot shows the electricity consumption of that month. An increasing consumption trend is observed in the graph over time. Consumption, which was at lower levels in 2016, increased significantly by 2024. A short-term decrease is seen around 2020. In May 2020, less than 20 thousand MWh was consumed and consumption decreased. This situation may be related to the economic slowdown caused by the pandemic. However, the graph shows higher fluctuations and sudden increases in consumption starting from 2021. This may be related to economic growth, industrialization, population growth or changes in energy policies. These are important data in terms of planning energy policies, sustainability strategies and demand forecasting.

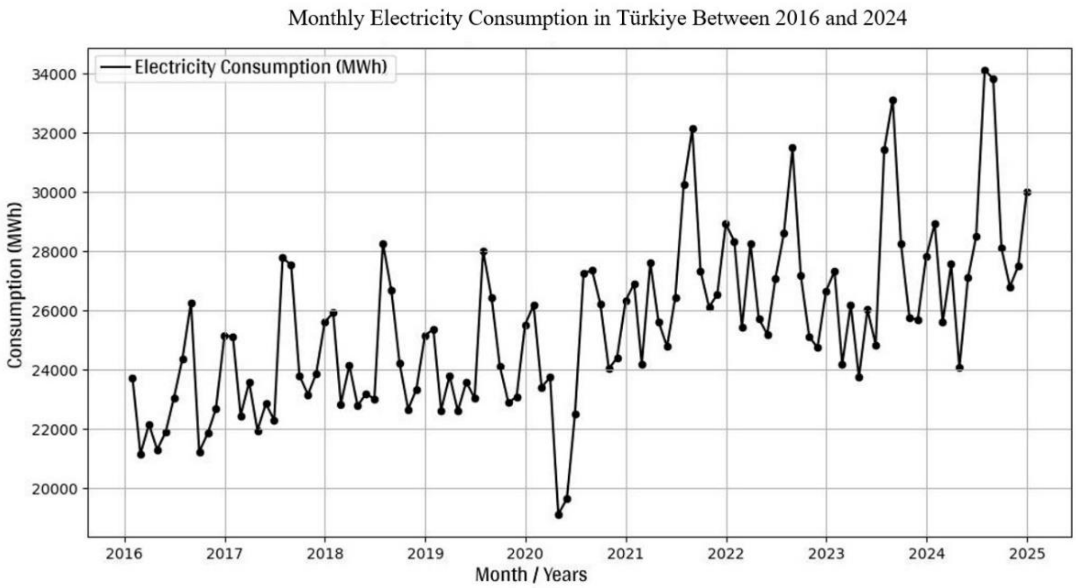

Figure 2. Monthly Electricity Consumption in Türkiye Between 2016 and 2024

4. Results and Discussion

In this study, the analyses made on electricity consumption data are visualized with separate graphs for each model. Figure 3 shows the analysis of the Auto-ARIMA model on the data, Figure 4 shows the analysis of the Holt-Winters model, Figure 5 shows the analysis of the Theta (THETAF) model, Figure 6 shows the analysis of the ETS model, Figure 7 shows the analysis of the TBATS model, Figure 8 shows the analysis of the NNETAR (NNAR) model, and Figure 9 shows the analysis of the MLP model. In the visuals in the figures, the black lines show the training data, the red lines show the test data, and the blue lines show the predictions of the relevant model. The light and dark gray areas represent the 95% and 80% confidence intervals of the model. Among the models used in the study, the Auto-ARIMA model was the model that approached the red test line the closest with the blue line compared to other models. Therefore, the model with the highest prediction rate is the Auto-ARIMA model.

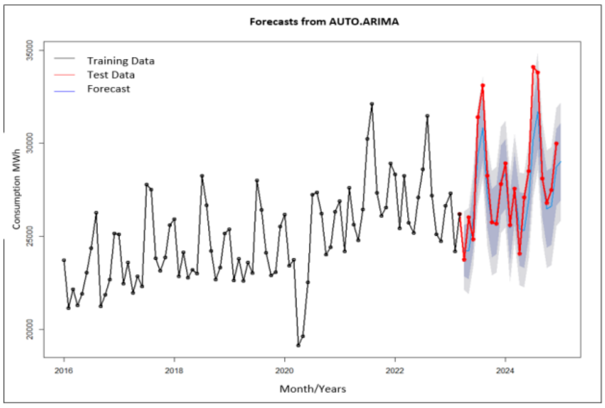

Figure 3. Performance Graph of Auto-ARIMA Model

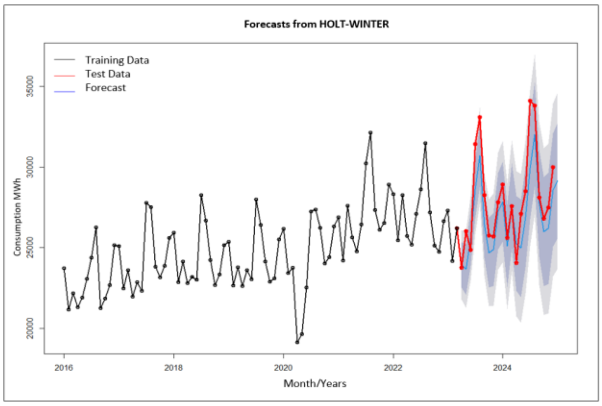

Figure 4. Performance Graph of Holt-Winter

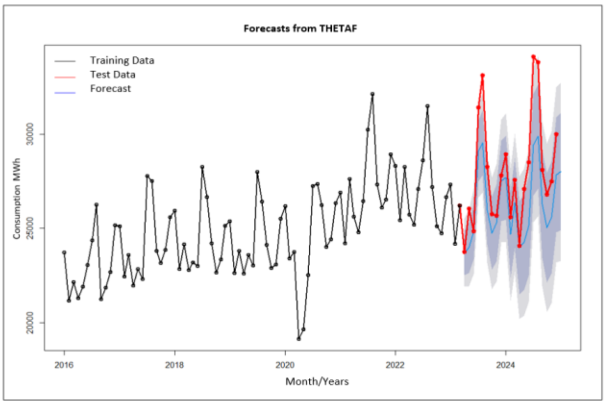

Figure 5. Performance Graph of Theta

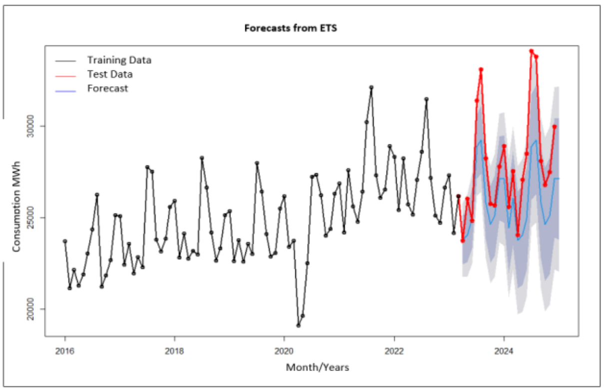

Figure 6. Performance Graph of ETS

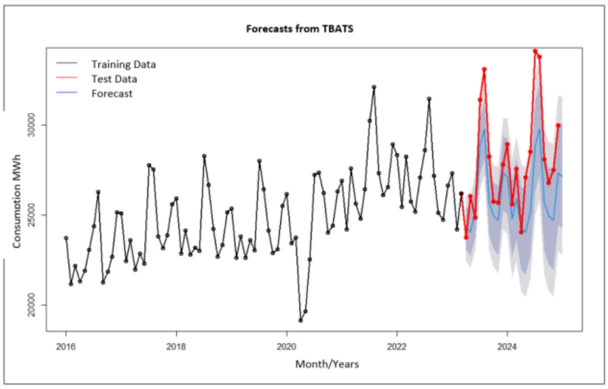

Figure 7. Performance Graph of TBATS

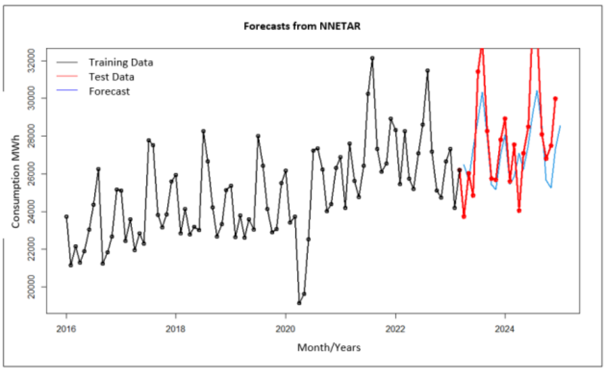

Figure 8. Performance Graph of NNETAR

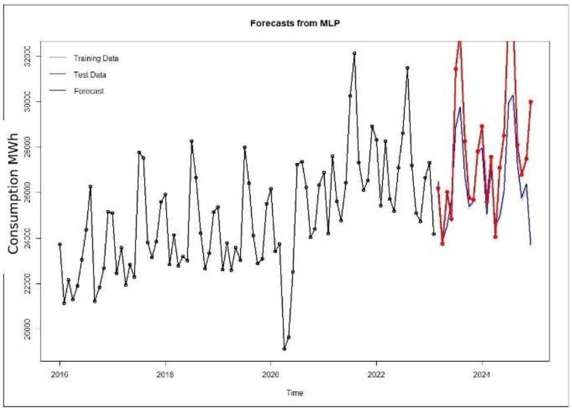

Figure 9. Performance Graph of MLP

Figure 10 shows the results of the time series analysis performed by using the Auto.ARIMA model. The model analyzed past data and made a 12-month consumption forecast for the future. The training data shown with black dots represent the consumption values of the past years (2016-2024). The data set shows a seasonal and general increasing trend. The blue line shows the estimated consumption values, while the gray shades around it represent the uncertainty range. The uncertainty range widens as time progresses. This indicates that the estimated values may vary more in the future and the uncertainty increases. When the graph is examined, although there are fluctuations in consumption according to the 12-month forecast result, a certain trend is maintained.

Performance measurements in all analyses were measured with RMSE, MAE and MAPE metrics. Table 1 presents the performances of all models together. Auto-ARIMA shows the highest accuracy by providing the lowest error rates among all models. It exhibits a significant superiority over other models in both training and test sets, especially in terms of RMSE and MAE values. On the other hand, THETAF, ETS, TBATS models attract attention with higher error values. NNETAR and MLP models have larger error rates, falling behind Auto-ARIMA in terms of prediction accuracy. This shows that Auto-ARIMA is a more robust and reliable option in time series predictions.

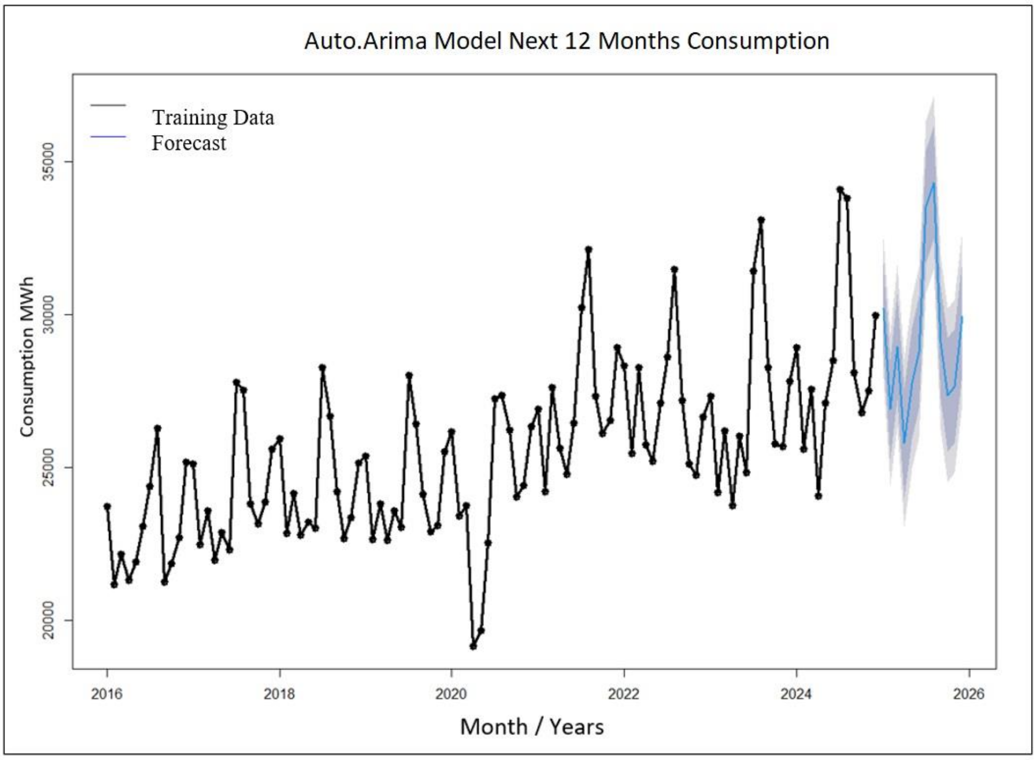

Figure 10. Auto-ARIMA Model Next 12 Months Consumption Forecast

Table 1: Error Measurement Performance Analysis of Models

Data Set	Training / Test Sets			
Türkiye Electricity Consumption 2016-2024 (108 Units)	Training / Test Length 80%-20%	RMSE Training / Test	MAE Training / Test	MAPE (%) Training / Test
Auto-ARIMA	86 - 22	**969.53 / 1470.09**	**622.33 / 1107.33**	**2.48 / 3.77**
Holt Winter	86 - 22	1092.90 / 1695.51	790.41 / 1386.16	3.15 / 4.77
THETAF	86 - 22	921.91 / 2225.95	676.41 / 1802.43	2.74 / 6.10
ETS	86 - 22	940.38 / 2512.18	729.60 / 2089.38	2.97/7.09
TBATS	86 - 22	933.70 / 2448.19	696.40 / 2068.11	2.83 / 7.05
NNETAR	86 - 22	1234.84 / 2107.46	897.83 / 1676,54	3.56 / 5.84
MLP	86 - 22	844.19 /2208.34	639.06 / 1573.37	2.59 / 5.28

The last 3-year monthly consumption average between 2022-2024 and the monthly consumption forecast of the Auto-ARIMA model for 2025 are shown in Table 2.

Table 2: 12 Months Electricity Consumption Forecast for 2025

Month	Monthly Average Consumption of the Last Three Years 2022-2024 (MWh)	Auto-ARIMA 2025 Consumption Forecast (MWh)
January	28.187	30.196
February	25.073	26.912
March	27.336	28.952
April	24.512	25.796
May	26.103	27.757
June	26.810	28.766
July	31.376	33.519
August	32.795	34.317
September	27.846	29.088
October	25.886	27.366
November	25.972	27.654
December	28.149	29.931

When Table 2 is examined, it is seen that electricity consumption reaches the highest levels especially in July (31.376 MWh → 33.519 MWh) and August (32.795 MWh → 34.317 MWh) and peaks in these months in the 2025 estimates. This can be associated with the widespread use of cooling systems along with the increasing temperatures in the summer months. Similarly, it is observed that consumption is high in January (28.187 MWh → 30.196 MWh) and December (28.149 MWh → 29.931 MWh). This trend can be evaluated as a result of the increased use of electricity for heating purposes in the winter months. On the other hand, it is observed that consumption levels are lower in April (24.512 MWh → 25.796 MWh) and October (25.886 MWh → 27.366 MWh) compared to other months. This decrease can be explained by the decrease in demand for air conditioning systems during seasonal transition periods. In addition, estimates made by the Auto.ARIMA model predict an average increase of 5-7% based on the data of the previous three years. This trend shows that there is a continuous increase in electricity consumption and that energy demand will increase even more in 2025. It is evaluated that this increase may be due to various socioeconomic factors such as industrialization, population growth and technological advances. These findings are of critical importance in terms of effective planning of energy policies and the development of sustainable electricity production strategies. Taking the necessary measures to ensure energy supply security, especially during peak demand periods, stands out as an important requirement in terms of energy management.

5. Conclusion

As a result of the study, it was determined that there are significant seasonal fluctuations in electricity consumption in Türkiye. It is understood that electricity consumption should be compatible with its production because storing the electricity produced is extremely difficult and costly. In this context, it is important to examine seasonal fluctuations in more detail, and to conduct studies on sectors where electricity consumption increases due to these fluctuations, and to optimize power plant capacities accordingly.

It is emphasized that power plants to be established in the future should be powered by renewable energy sources (such as wind, solar, wave energy and nuclear energy) instead of fossil fuels. In addition, meeting the electricity need with domestic and national resources will contribute to the country's economy becoming more sustainable by preventing foreign exchange outflow. This situation can also help reduce budget deficits based on energy imports.

In recent years, wars around the world have posed serious threats to energy security and supply, and this issue has become a priority for countries. For example, Russia's restriction of natural gas to Europe has led to a major energy crisis in western countries. In this context, energy supply security is a critical priority, especially for industrial countries that are dependent on foreign energy. In countries with high external dependency, economic problems such as disruption of industrial production, decrease in export revenues and increase in budget deficits may arise. Therefore, it is clear that domestic resources for energy supply must be increased and diversified.

To recap, in this study, electricity consumption estimates were compared by using AI and statistical-based models. The study shows that it can be an important reference source in determining Türkiye's future energy needs. The study is limited to hourly electricity consumption data between 2016-2024. In the future studies, it is recommended to use datasets belonging to different countries and organizations. Broader and longer-term data can contribute to the examination of various electricity consumption models and to obtaining more reliable results. Increasing the amount of data will also improve the accuracy of the forecast models.

Studies on electricity consumption prediction focus on determining the methods with the highest accuracy rate by comparing different models and approaches. Similar to our study results, in some studies, statistical-based models were found to be successful in short-term estimations [7][26][32][33]. However, machine learning and deep learning-based approaches provide an advantage in long-term forecasting by better capturing complex consumption patterns [25][27][28][29]. On the other hand, in some studies, it is emphasized that hybrid models using statistical and AI based methods together increase estimation accuracy [4][5][6][30][31]. These findings reveal that model selection is critical in terms of energy planning and management.

In this study, seven different models (Auto-ARIMA, Holt-Winter, Theta, ETS, TBATS, NNETAR, MLP) were used to estimate Türkiye's electricity consumption in 2025. The models used in the study showed different performances in electricity consumption estimates. As a result, the Auto-ARIMA model stood out with a MAPE error rate of 3.77%. The prominence of this model is based on several important factors. First, the small size of the dataset used in our study, combined with the ability of Auto-ARIMA to adapt to the available data, allowed successful results to be obtained. This model generally provides statistical accuracy when working with limited data. Second, the seasonal characteristics of the dataset helped Auto-ARIMA to make accurate predictions by taking seasonal components into account. Finally, Auto-ARIMA's ability to automatically select the optimum parameters increased prediction accuracy by ensuring the correct configuration of the model. When these factors came together, Auto-ARIMA exhibited strong performance even on small datasets, and showed superior results compared to other models. In future studies, it is recommended to improve electricity consumption estimates by using different models and methods. This study does not consider external variables such as economic indicators and weather patterns, which could influence electricity consumption. Future research could benefit from incorporating larger datasets and accounting for the effects of such external factors to enhance the robustness and accuracy of forecasting models.

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Authors' Contrtibution

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