J Inno Sci Eng, 2025, 9(2):205-215

DOI:https://doi.org/ 10.38088/jise.1635104

Research Article

Short-Term Electricity Load Forecasting and Seasonality Analysis Using Temperature and Artificial Intelligence Methods in the Southeastern Anatolia Region

Sena Çadırcı [1*], İbrahim Gürsu Tekdemir[2]

[1] *Harran University, Department of Electrical and Electronics Engineering, 63000, Şanlıurfa, Türkiye*

[2] *Bursa Technical University, Department of Electrical and Electronics Engineering, 16310, Bursa, Türkiye*

ARTICLE INFO

Received Date: 7/02/2025
Accepted Date: 2/05/2025

Cite this paper as:
Çadırcı, S., & Tekdemir, İ. G. (2025). Short-Term Electricity Load Forecasting and Seasonality Analysis Using Temperature and Artificial Intelligence Methods in the Southeastern Anatolia Region. *Journal of Innovative Science and Engineering.* 9(2), 205-215.

*Corresponding author: Sena Çadırcı
E-mail:senacadirci@harran.edu.tr

Keywords:
Electric load forecasting
Short-term load forecasting
Regression analysis
Artificial neural network
Autoregressive integrated moving average

ABSTRACT

The planning of electrical energy systems can be realized in a more efficient and sustainable way by forecasting energy demand accurately. In this context, short-term load forecasting plays a critical role in optimizing energy production and distribution processes. In this study, short-term load forecasting was conducted using hourly electricity consumption data from a facility located in the Southeastern Anatolia Region between 2019–2022. The data were integrated with meteorological parameters to evaluate the impact of temperature. The performance of Multiple Linear Regression (MLR), Artificial Neural Networks (ANN), and AutoRegressive Integrated Moving Average (ARIMA) methods were compared. According to the results, the ARIMA method was the most successful with an accuracy rate of 92%, followed by the ANN model with 90% accuracy. The MLR method demonstrated relatively lower performance, achieving an accuracy rate of 89%. Moreover, ANN showed a strong capability to model complex relationships, while ARIMA excelled in datasets with seasonality. In conclusion, this study highlights the strengths and weaknesses of different methods, providing valuable contributions to energy planning and emphasizing the importance of analyses conducted using regional datasets.

1. Introduction

Energy is an indispensable element in all aspects of human life and serves as a cornerstone for economic and social development. The rapid technological advancements and urbanization following the Industrial Revolution have significantly increased the demand for energy [1]. The consumption of energy is primarily concentrated in three main sectors: industry, transportation, and buildings. A substantial portion of energy is consumed in the construction and use of buildings, making energy-saving potential in this sector globally significant. The energy needs of buildings are met through various methods, including

electricity, water, and natural gas, depending on their structural characteristics [2]. Electricity, as a form of energy transmitted from generation centers to end-users through transmission and distribution lines, plays a critical role in meeting this demand as it cannot be stored. Therefore, planning electricity generation based on consumption demand is of great importance for energy security and economic efficiency [3]. Load forecasting serves as a fundamental tool in optimizing the production, transmission, and distribution processes of energy systems. Predicting electricity demand in advance facilitates uninterrupted and reliable service in energy production while aiming to reduce costs through efficient resource utilization [4]. Load forecasting can be categorized into three main groups: short-term, medium-term, and long-term forecasting. Short-term forecasting typically spans periods like a day or a week and provides solutions for hourly market needs. Medium-term forecasting includes monthly or annual planning, while long-term forecasting guides energy policymaking and infrastructure investments [5]. In this context, the use of artificial intelligence (AI) methods has significantly enhanced the accuracy of load forecasting and planning. Studies conducted after 2020 have made notable contributions to short-term load forecasting and have revealed the strengths and weaknesses of various approaches. For example, Somuncu and Oral (2024) achieved high accuracy in solar energy forecasting by employing a Multilayer Artificial Neural Network (ML-ANN) and an Adaptive Neuro-Fuzzy Inference System (ANFIS) using meteorological data [6]. Similarly, Kaysal et al. (2022) examined machine learning methods for Turkey's short-term electricity demand forecasting and demonstrated that Artificial Neural Networks (ANNs) outperformed Ridge Regression, Lasso Regression, and Support Vector Regression in terms of accuracy [7]. In another study, Saçlı (2020) analyzed short-term electricity demand forecasting for the Marmara Region using ARIMA and Support Vector Machines (SVM), revealing that ARIMA achieved lower error rates in datasets with seasonality [8]. Akman et al. (2018) emphasized the high accuracy of hybrid systems for short-term electricity demand forecasting by integrating ANN and expert systems [9]. Additionally, Bulut and Başoğlu (2017) developed a hybrid forecasting system combining Artificial Neural Networks and expert systems for short-term electricity demand, achieving significant success in Turkey's energy demand forecasting [10].

These studies demonstrate the effectiveness of AI-based methods and hybrid approaches in short-term electricity load forecasting. Particularly, methods such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), ARIMA, and ANFIS have been noted for their ability to improve accuracy and contribute significantly to energy planning. Building on this background, the present study aims to enhance the accuracy of short-term load forecasting by integrating temperature data with hourly electricity consumption records from a facility in the Southeastern Anatolia Region, spanning the years 2019–2022. Three different forecasting models Multiple Linear Regression (MLR), Artificial Neural Networks (ANN), and ARIMA were applied and compared using consistent datasets and evaluation metrics. Unlike many previous studies that focus on a single method or do not incorporate regional meteorological variables, this study provides a comparative analysis of three widely used models on the same real-world dataset enriched with temperature data. This makes the study a novel contribution to the literature, offering practical insights for regional energy forecasting under seasonal and environmental variability. By utilizing hourly electricity consumption data from a facility in the Southeastern Anatolia Region between 2019–2022, various forecasting models were developed. Meteorological parameters were integrated into the dataset to assess the impact of temperature on consumption. The performance of Multiple Linear Regression (MLR), Artificial Neural Networks (ANN), and ARIMA methods were compared, and error analyses were conducted.

The findings indicate that while ARIMA outperformed other methods by reducing fluctuations and providing more accurate forecasts, ANN excelled in processing speed and modeling complex structures. This study offers recommendations to improve the effectiveness of short-term load forecasting in the energy sector and highlights the growing importance of advanced technologies such as AI and machine learning in energy forecasting.

In the literature, contemporary studies on short-term load forecasting frequently employ similar methods. The commonly used techniques and their performances are summarized in Table 1.

The conducted study, when compared with previous research, demonstrates consistency in the methodology applied and the methods utilized. The success outcomes achieved in this study are corroborated by findings in the literature.

Table 1: Literature studies

Author(s) and Year	Study Title	Methods	Findings
Somuncu and Oral, 2024	Solar Energy Forecasting Based on Meteorological Data Using Artificial Neural Networks and ANFIS	Multilayer Artificial Neural Network (ML-ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS)	Both methods achieved high accuracy in forecasting solar energy production using meteorological data.
Kaysal and ark., 2022	Comparison of Machine Learning Methods in Short-Term Electricity Load Demand Forecasting in Turkey	Artificial Neural Networks (ANN), Ridge Regression, Lasso Regression, Support Vector Regression	ANN provided higher accuracy compared to other methods for short-term load forecasting.
Saçlı, M., 2020	Short-Term Electricity Load Forecasting for the Marmara Region with Seasonal Analysis	ARIMA, Support Vector Machines (SVM)	The ARIMA model demonstrated lower error rates in datasets with seasonality.
Akman and ark., 2018	Analysis of Electricity Load Forecasting Methods	ANN, Expert Systems	Hybrid systems achieved high accuracy in short-term electricity demand forecasting.
Bulut and Başoğlu, 2017	Development of a Hybrid Forecasting System Based on Artificial Neural Networks and Expert Systems for Short-Term Electricity Demand Forecasting	Artificial Neural Networks, Expert Systems	The hybrid system achieved high accuracy in forecasting Turkey's electricity demand.
Current Study	Short-Term Electricity Load Forecasting and Seasonality Analysis in the Southeastern Anatolia Region Using Artificial Intelligence Methods	Multiple Linear Regression (MLR), Artificial Neural Networks (ANN), ARIMA	The ARIMA method was the most successful for datasets with seasonality, while ANN excelled in modeling complex patterns.

2. Methodology

This study utilized hourly electricity consumption data recorded from a facility located in the Southeastern Anatolia Region between 2019 and 2022. The institution that provided the data requested not to be named due to confidentiality policies. However, the data were shared with the researchers upon formal request and used strictly for academic purposes. Additionally, temperature data corresponding to the same time period were obtained from the Turkish State Meteorological Service in order to assess its impact on electricity consumption. The final dataset was created by combining historical consumption values with these meteorological parameters, where temperature variations were considered as a critical variable [21-22].

The dataset used for the load forecasting application includes hourly electricity consumption data from a public service facility (specifically, an airport) located in the Southeastern Anatolia Region for the years 2019, 2020, 2021, and 2022. Due to confidentiality agreements, the name of the facility is not disclosed. The data were provided to the researchers strictly for academic use [21-22].

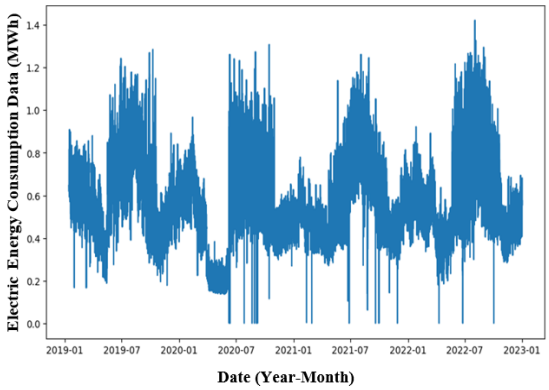

Figure 1: Hourly load consumption data for 2019, 2020, 2021, and 2022 (in MWh).

This dataset comprises hourly load values recorded over a four-year period. Additionally, temperature data for the same years were obtained from the Turkish State Meteorological Service. In cases of missing or erroneous observations, the dataset underwent preprocessing to address these issues. During the data cleaning process, erroneous records were removed, and missing values were completed using interpolation methods.

Three different methods were employed for short-term load forecasting: Multiple Linear Regression (MLR), Artificial Neural Networks (ANN), and Autoregressive Integrated Moving Average (ARIMA). The selection of these methods was based

on their contributions to data characteristics and forecasting accuracy.

2.1. Multiple Linear Regression (MLR):

MLR was used to model the linear relationship between the dependent variable (load consumption) and multiple independent variables (e.g., temperature and time). The regression model aimed to optimize forecasted load values by minimizing error rates [11]. Mathematically, the MLR model can be represented as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \quad (1)$$

where *y* denotes the dependent variable, x_i represent the independent variables, β_i are the regression coefficients estimated through the model, and ε is the random error term. The coefficients were determined by applying the Ordinary Least Squares (OLS) method, which minimizes the sum of the squared differences between the observed and predicted values.

2.2. Artificial Neural Networks (ANN):

ANN was preferred for learning complex relationships in energy consumption data and forecasting future consumption values. Variables such as temperature and prior load values were used as inputs in the input layer, processed through hidden layers, and forecasted values were obtained in the output layer. During the training process, the data were randomly divided into training and test sets [12]. The basic operation of a single artificial neuron can be mathematically formulated as:

$$\hat{y} = f\left(\sum_{i=1}^{n} \omega_i x_i + b\right) \quad (2)$$

Where x_i are the input features, ω_i are the corresponding weights, b is the bias term, and *f* is the activation function.

The learning process involves adjusting the weights and biases through the backpropagation algorithm combined with gradient descent optimization, minimizing the error between the actual and predicted outputs over successive training iterations.

2.3. ARIMA (Autoregressive Integrated Moving Average):

ARIMA was employed to forecast load by considering the trend, seasonality, and random components in the time series data. The model's parameters (p, d, q) were determined using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) [13]. Mathematically, the general ARIMA(p,d,q) model is expressed as:

$$(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)(1 - B)^d y_t = (1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta q B^p)\varepsilon_t \quad (3)$$

Where B denotes the backward shift operatör ($By_t = y_{t-1}$), ϕ_i are the autoregressive (AR) coefficients, θ_i are the moving average (MA) coefficients and ε_t represents the white noise error term. In this structure, differencing is applied *d* times to make the series stationary, while the AR and MA components respectively capture the dependencies between lagged observations and past forecast errors.

The success of the forecasting models was evaluated using the following error metrics:

1. Mean Absolute Error (MAE): The average of the absolute differences between predicted and actual values. It is mathematically defined as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \quad (4)$$

2. Mean Squared Error (MSE): The mean of the squared differences between predicted and actual values, formulated as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (5)$$

3. Root Mean Squared Error (RMSE): The square root of the mean of the squared differences, calculated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \quad (6)$$

4. Mean Absolute Percentage Error (MAPE): The mean of the absolute percentage differences between predicted and actual values, expressed as:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (7)$$

In the above equations:

- y_i denotes the actual observed value at time step *i*,
- $\hat{y}_i$ denotes the predicted value at time step *i*,
- *n* represents the total number of observations.

The forecasting performance of each model was compared and analyzed using these metrics [14].

3. Results and Discussion

This study utilized hourly electricity consumption data from a facility in the Southeastern Anatolia Region for the years 2019–2022, along with temperature variables, to perform short-term load forecasting. The performance of the forecasting models was compared based on error rates and data processing times. The findings revealed the unique strengths and weaknesses of each method. The MLR model used energy load consumption as the dependent variable and temperature and time as independent variables. Figure 2 shows the graphical comparison between actual load values and predicted load values using the MLR method.

The model successfully captured general trends in energy consumption but demonstrated sensitivity to sudden changes. The Mean Absolute Error (MAE) value was higher compared to other methods. This is primarily attributed to the model's reliance on a linear structure, which fails to adequately model complex relationships in energy consumption [15]. As illustrated in the zoomed-in view in Figure 2 (right), the MLR model shows visible lag in tracking rapid fluctuations, particularly during peak consumption intervals. This supports the conclusion that linear regression, while effective for capturing overall trends, is limited in its ability to handle nonlinear and abrupt variations in load behavior.

The ANN model utilized temperature and historical consumption data to model complex, non-linear relationships in energy consumption. Figure 3 shows the graphical comparison between actual load values and predicted load values using Long Short-Term Memory (LSTM), which is a subclass of ANN.

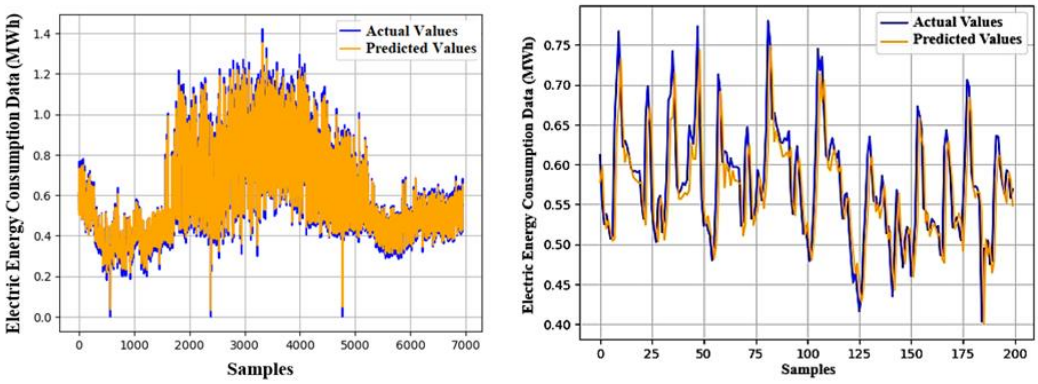

Figure 2: Comparison of actual and predicted electricity load values using the ARIMA method. The left shows annual trends, and the right displays a zoomed-in view of short-term fluctuations.

ANN demonstrated effective performance in learning and forecasting sudden changes in load data. During the data processing phase, meaningful relationships were derived from historical data using hidden layers, resulting in improved forecasting accuracy. MAPE and RMSE values were lower compared to other methods. However, the processing times for ANN were longer than those of MLR due to the size of the dataset used during the training phase [16]. As shown in the zoomed-in view in Figure 3 (right), the model was able to follow sharp load fluctuations with high precision, confirming its strength in capturing nonlinear consumption dynamics that linear models often miss.

The ARIMA model accounted for seasonality and trends in the time series data to perform load forecasting. Figure 4 shows the graphical comparison between actual load values and predicted load values using the ARIMA method.

The ARIMA model delivered stable and accurate results by minimizing fluctuations in the data. Its capability to model seasonality and trends resulted in the lowest error rates among the evaluated methods. However, determining and calibrating the model's parameters was time-consuming [17]. As illustrated in the zoomed-in view in Figure 4 (right), the ARIMA model effectively captured short-term load variations with minimal lag, particularly during rapid consumption changes. This further demonstrates the model's robustness in handling both seasonal trends and high-frequency fluctuations in electricity load behavior.

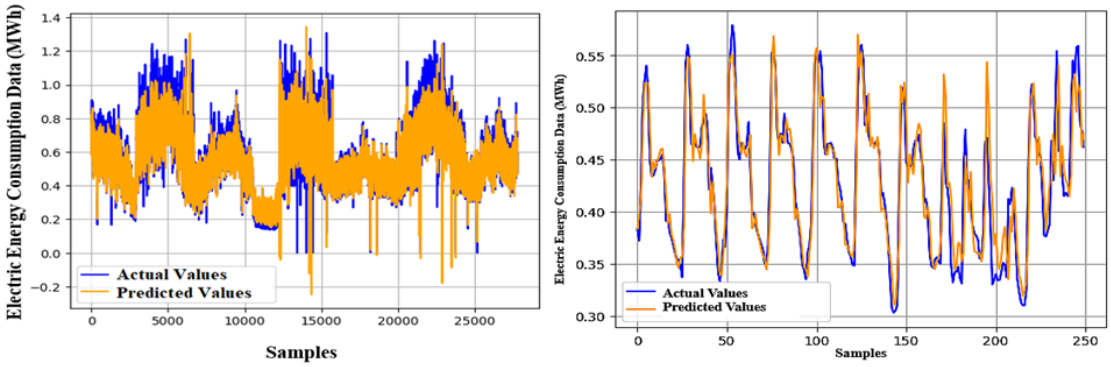

Figure 3: Comparison of actual and predicted electricity load values using the ANN method (LSTM). The zoomed-in view on the right highlights short-term variations.

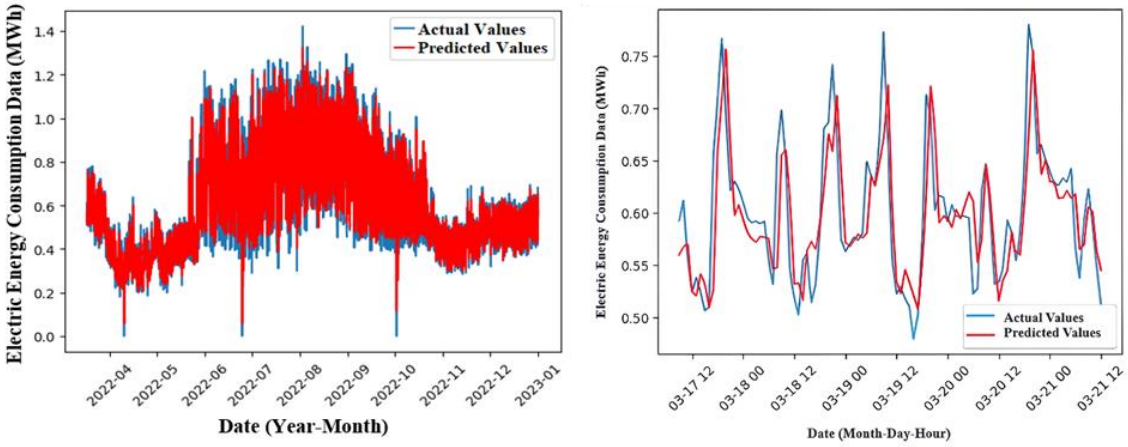

Figure 4: Comparison of actual and predicted electricity load values using the ARIMA method. The left shows annual trends, and the right displays a zoomed-in view of short-term fluctuations

3.1. Seasonality Analysis

The seasonal analysis outputs using the regression method are presented in Figure 5. The months of June, July, and August represent the summer season; March, April, and May represent the spring season; September, October, and November represent the autumn season; and December, January, and February represent the winter season.

Table 2: Seasonal analysis using the MLR method.

Multiple Linear Regression (MLR)				
Model	**MSE**	**R^2**	**MAE**	**RMSE**
Spring	0.0025	0.8900	0.0030	0.0500
Summer	0.0100	0.7402	0.0800	0.1000
Autumn	0.0036	0.8400	0.0441	0.0600
Winter	0.0016	0.8412	0.0300	0.0400

When performance evaluation criteria were examined across seasons, the season with the most successful forecasts was identified.

Table 3: Seasonal analysis using the ANN method (LSTM).

Artificial Neural Networks (ANN)				
Model	**MSE**	**R^2**	**MAE**	**RMSE**
Spring	0.0021	0.9214	0.0349	0.0458
Summer	0.0065	0.8302	0.0581	0.0807
Autumn	0.0060	0.8216	0.0490	0.0775
Winter	0.0011	0.8846	0.0251	0.0338

Upon examining Figures 5 and Table 2, a seasonal analysis of the load curves was conducted. Factors such as time of day and temperature variations were found to cause season-specific changes in the load profile. Each season demonstrated superiority in different metrics. However, given the importance of metrics like the R^2 value and the magnitude of errors such as MAE, the spring season generally performed better overall. During the spring season, the R^2 value was higher, indicating that the model explained a significant portion of the variability in the dataset. Additionally, the MAE value was notably low, showing that the model provided more accurate forecasts during this period and better captured the electricity consumption patterns [18].

In Figure 6 and Table 3, comparisons between observed actual electricity consumption data (in MWh) and values predicted by the Long Short-Term Memory (LSTM) forecasting models are presented for four seasons. The graphs are organized separately for summer, spring, winter, and autumn.

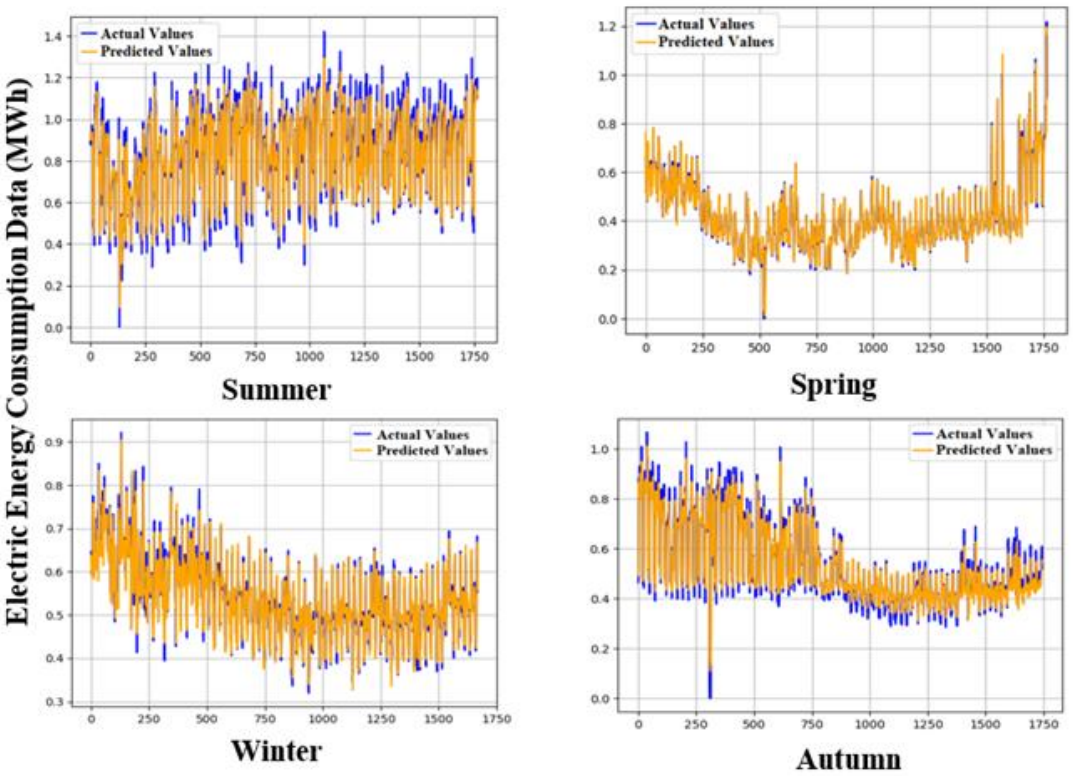

Figure 5: Seasonal analysis outputs using the MLR method.

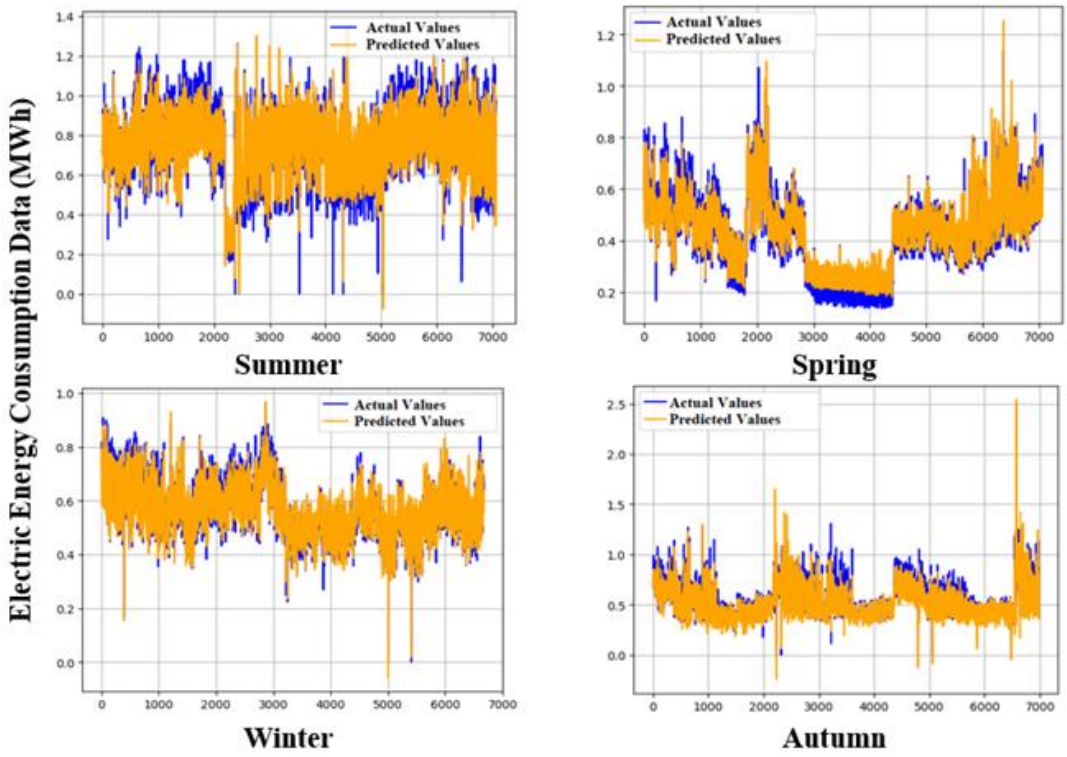

Figure 6: Seasonal analysis outputs using the ANN method (LSTM).

The LSTM model demonstrated overall success in forecasting electricity consumption. However, deviations in accuracy were observed, particularly during periods of sudden changes or extreme values.

These results indicate that the ANN model successfully predicted changes in electricity consumption during the spring season.

While the model exhibited greater errors during the summer and autumn seasons, its overall performance remained acceptable. The high R^2 value (0.8846) demonstrates strong forecasting accuracy for the winter season, indicating that the model effectively captured changes in electricity consumption during the winter months [19].

The comparison of electricity consumption forecasts and actual values across four seasons using the ARIMA (Autoregressive Integrated Moving Average) model is given in Figure 7 and Table 4. The graphs are separately organized for summer, spring, winter, and autumn. Each subgraph shows the timeline on the horizontal axis and electricity consumption values on the vertical axis. Blue lines represent actual consumption values, while red lines represent predictions made by the ARIMA model.

Table 4: Seasonal analysis using the ARIMA method.

ARIMA				
Model	**MSE**	**R^2**	**MAE**	**RMSE**
Spring	0.0020	0.9112	0.0275	0.0448
Summer	0.0033	0.8384	0.0389	0.0553
Autumn	0.0039	0.8482	0.0400	0.0624
Winter	0.0015	0.8503	0.0277	0.0387

The Autoregressive Integrated Moving Average (ARIMA) model demonstrated high performance in electricity consumption forecasting despite seasonal variations. The model showed particularly strong forecasting accuracy and explanatory power during the spring and winter seasons. Although it also performed well during the summer and autumn seasons, deviations were observed during periods of sudden changes and fluctuations. Overall, the ARIMA model can be considered as a reliable tool for electricity consumption forecasting. Future studies could focus on improving the model's performance during periods of abrupt changes [20].

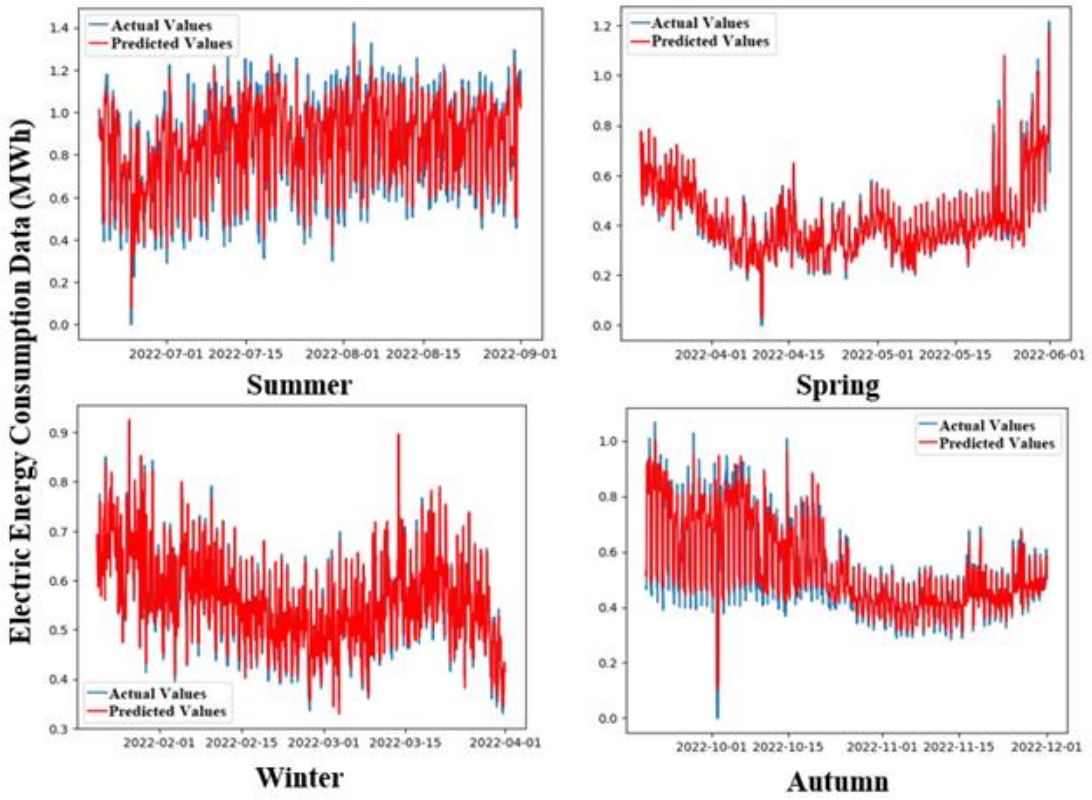

Figure 7: Seasonal analysis outputs using the ARIMA method.

3.2. Comparison of Methods

The methods used in this study were compared based on performance evaluation metrics. Table 5 summarizes the error values and other performance criteria:

Table 5: Comparison of performance evaluation metrics for the methods used.

Model	**MSE**	**R^2**	**MAE**	**RMSE**
MLR	0.0100	0.8912	0.0500	0.0802
ANN	0.0039	0.9033	0.0417	0.0624
ARIMA	0.0052	0.9162	0.0441	0.0721

The ARIMA method stands out for minimizing error rates and reducing fluctuations, while the ANN method is notable for its faster processing capability. On the other hand, the MLR method offered a simpler approach but demonstrated limited accuracy when applied to complex datasets.

3.3. Model Performance During Extreme Conditions

In addition to seasonal performance evaluations, model performances were assessed during extreme weather conditions, specifically on days when the maximum temperature exceeded 35°C or dropped below 5°C. Table 6 summarizes the results. It was observed that the ARIMA model maintained stable forecasting performance under these conditions, demonstrating resilience to temperature-driven fluctuations. The ANN model exhibited slightly decreased accuracy during these periods, likely due to its sensitivity to sudden and nonlinear consumption changes, whereas the MLR model showed the highest deterioration in performance due to its linear structure.

Table 6: Comparison of model performance on normal and extreme weather days based on MAE values.

Model	MAE (Normal Days)	MAE (Extreme Days)
MLR	0.050	0.080
ANN	0.041	0.065
ARIMA	0.044	0.050

These results underline the importance of selecting robust forecasting models for abnormal operating conditions such as extreme temperatures.

4. Conclusion

This study compared the performance of Autoregressive İntegrated Moving Average (ARIMA), Artificial Neural Networks (ANN), and Multiple Linear Regression (MLR) methods for short-term electricity load forecasting using consumption data from the Southeastern Anatolia Region. The key findings and their underlying reasons are summarized below:

ARIMA achieved the highest accuracy (92%) by effectively capturing seasonal patterns and trends in the time-series data. This success is attributed to the model's inherent structure, which allows it to handle seasonality and smooth out fluctuations, making it particularly suitable for time-dependent data with repeating patterns.

ANN, with an accuracy of 90%, demonstrated superior performance in modeling complex and nonlinear relationships, especially during periods of sudden consumption changes. Its ability to learn from historical data and adapt to hidden patterns through multiple layers of abstraction made it effective, particularly in datasets with irregular variations.

MLR, while simpler and faster, achieved a lower accuracy (89%) due to its linear structure, which limited its ability to represent nonlinear and complex interactions in the data. Nevertheless, it was still useful for providing quick baseline forecasts and was more interpretable.

The results also highlighted that meteorological variables, especially temperature, significantly improved forecasting accuracy during the spring and winter seasons. In contrast, sharp consumption spikes in summer reduced the accuracy of all methods, especially those with less flexibility in modeling rapid changes. By analyzing the strengths and weaknesses of these models under seasonal conditions, this study provides insights for selecting suitable forecasting techniques in practical applications. Unlike prior studies that focus on a single method, this research offers a comparative perspective, serving as a guide for energy planners seeking both accuracy and interpretability in regional energy forecasting. In future studies, the integration of additional meteorological variables such as humidity, wind speed, and solar radiation could be explored to improve forecasting accuracy. Moreover, incorporating operational factors like special events, holidays, and facility-specific schedules may enhance model robustness. Additionally, the development of hybrid models combining statistical and machine learning approaches could further optimize prediction performance under varying conditions.

Article Information

Financial Disclosure: The author (s) has no received any financial support for the research, authorship or publication of this study.

Authors' Contrtibution: Concept: İ.G.T., S.Ç.; Design: S.Ç., İ.G.T.; Supervision: İ.G.T.; Resources: S.Ç.; Data Collection: S.Ç.; Analysis: S.Ç., İ.G.T.; Literature Search: S.Ç.; Writing Manuscript: S.Ç.; Critical Review: İ.G.T.

Conflict of Interest/Common Interest: No conflict of interest or common interest has been declared by the authors.

Ethics Committee Approval: This study does not require ethics committee permission or any special permission.

References

[1] Zhou, X., Wang, Y., & Li, H. (2023). Advancements in Building Energy Simulation: A Comprehensive Review. Energy and Buildings, 275, 112345.

[2] Directive 2010/31/EU, Directive of the European Parliament and of the Council of 19 May 2010 on the Energy Performance of Buildings (recast), 2010.

[3] Soliman, S. A. H., & Al-Kandari, A. M. (2010). Electrical Load Forecasting: Modeling and Model Construction. Elsevier.

[4] Szostek, K., Mazur, D., Drałus, G., & Kusznier, J. (2024). Analysis of the Effectiveness of ARIMA, SARIMA, and SVR Models in Time Series Forecasting: A Case Study of Wind Farm Energy Production. Energies, 17(19), 4803.

[5] Doruk, E. (2019). Sakarya Bölgesi Hanehalkı Elektrik Tüketiminin Dinamik Lineer Model ile Tahmini. Yüksek Lisans Tezi, Sakarya Üniversitesi, Fen Bilimleri Enstitüsü.

[6] Somuncu, S., & Oral, C. (2024). Yapay Sinir Ağı ve ANFIS kullanılarak Meteorolojik Verilere Bağlı Güneş Enerjisi Tahmini. Osmaniye Korkut Ata Üniversitesi Fen Bilimleri Enstitüsü Dergisi, 7(4), 1685-1701.

[7] Kaysal, K., Akarslan, E., & Hocaoğlu, F. O. (2022). Türkiye Kısa Dönem Elektrik Yük Talep Tahmininde Makine Öğrenmesi Yöntemlerinin Karşılaştırılması. Bilecik Şeyh Edebali Üniversitesi Fen Bilimleri Dergisi, 9(2), 693-702.

[8] Saçlı, M. (2020). Dağıtım Şebekesinde Kısa Dönem Yük Tahmini. İstanbul Teknik Üniversitesi, Yüksek Lisans Tezi.

[9] Başoğlu, A. N., & Bulut, H. (2016). Kısa dönem elektrik talep tahminleri için yapay sinir ağları ve uzman sistemler tabanlı hibrit sistem geliştirilmesi. Gazi Üniversitesi Mühendislik Mimarlık Fakültesi Dergisi, 31(3), 575-583.

[10] Bulut, M., & Başoğlu, B. (2017). Kısa Dönem Elektrik Talep Tahminleri İçin Yapay Sinir Ağları ve Uzman Sistemler Tabanlı Hibrit Tahmin Sistemi Geliştirilmesi. Gazi Üniversitesi Mühendislik Mimarlık Fakültesi Dergisi, 32(2), 575-583.

[11] Khotimah, K., Sadik, K., & Rizki, A. (2020). Study of Robust Regression Modeling Using MM-Estimator and Least Median Squares. Proceedings of the 1st International Conference on Statistics and Analytics (ICSA 2019), Bogor, Indonesia. [DOI: 10.4108/eai.2-8-2019.2290533]

[12] Bouktif, S., Fiaz, A., Ouni, A., & Serhani, M. A. (2018). Optimal deep learning LSTM model for electric load forecasting using feature selection and genetic algorithm: comparison with machine learning approaches. Energies (MDPI), 11, 1–20.

[13] Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. European Journal of Operational Research, 270(2), 654–669.

[14] Chai, T., & Draxler, R. R. (2014). Root means square error (RMSE) or means absolute error (MAE)? Geoscientific Model Development, 7(3), 1247–1250.

[15] Karaca, A. (2010). Regresyon Analizi ile Günlük Elektrik Tüketiminin Tahmini. Yüksek Lisans Tezi, Erciyes Üniversitesi Fen Bilimleri Enstitüsü.

[16] Yaman, Ç., Kurt, G., & Tekdemir, İ. G. (2022). Konut tipi tüketiciler için talep tarafı yönetimi uygulaması ve enerji optimizasyonu. 8. Uluslararası Marmara Fen Bilimleri Kongresi, IMASCON 2022 BAHAR, Kocaeli, Türkiye.

[17] Zheng, A., & Casari, A. (2018). Feature Engineering for Machine Learning: Principles and Techniques for Data Scientists. O'Reilly Media.

[18] Abuella, M., & Chowdhury, B. (2015). Solar power probabilistic forecasting using multiple linear regression analysis. IEEE SoutheastCon, 1–5.

[19] Chen, K., Chen, J., & He, Y. (2019). Exploring deep learning for electric load forecasting in smart grids. IEEE Transactions on Neural Networks and Learning Systems, 30(8), 2309–2321.

[20] Almeshal, A. M., & Ahmad, F. (2021). Comparative study of short-term electricity load forecasting models for Gulf Cooperation Council countries. Energy, 219, 119610.

[21] GAP Airport. (2019–2022). Hourly Electricity Load Data (Unpublished internal data, shared upon request).

[22] Turkish State Meteorological Service. (2024). Meteorological Data for Southeastern Anatolia Region (2019–2022) (Data provided upon request).