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Research Article

Comparative Analysis of CatBoost and BiLSTM Models for Day-Ahead Electricity Consumption Forecasting: A Case Study of Aydın, Denizli, and Muğla Regions in Turkey

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Abstract – Electricity consumption forecasting plays a crucial role in effective electricity management, particularly for city-specific predictions made by distribution and retail companies, as it enables optimized operations and efficient electricity allocation. In the context of the Turkish electricity market, inaccurate forecasts can lead to substantial financial burdens, underscoring the need for accurate and reliable predictions to ensure the smooth functioning of the market. This study focuses on forecasting hourly electricity consumption for the following day using data available up to the previous day for the Aydın, Denizli, and Muğla regions. A three-year dataset was employed to compare the performance of two powerful machine learning models, CatBoost and Bidirectional Long Short-Term Memory (BiLSTM), known for their ability to handle complex data and capture patterns over time. The results show that both models are effective in short-term electricity consumption forecasting. CatBoost demonstrated higher accuracy in capturing daily consumption fluctuations, while BiLSTM exhibited superior performance during high-demand periods, highlighting its ability to manage complex seasonal consumption patterns. This study contributes to electricity forecasting by offering insights into the application of these models in real-world scenarios, particularly in the context of the Turkish electricity market. Future work could explore additional factors influencing consumption and further refine the models for enhanced forecasting accuracy.

Keywords – Electricity Consumption Forecasting, Machine Learning, Deep Learning, Bidirectional Long Short-Term Memory, Catboost.

I. INTRODUCTION

Electric energy is a critical energy source with a wide range of applications, from daily life to industrial activities. This energy is generated by converting primary energy sources such as oil, coal, natural gas, nuclear power, hydropower, biomass, tidal, solar, and wind energy. However, the continuously growing demand for electricity, limitations on resources, and the challenges associated with electricity storage compel countries and sector participants to implement various planning strategies.[1]

With its growing population and expanding economy, Turkey faces an increasingly high demand for energy, particularly in electricity consumption. The country’s total annual electricity consumption is 289,372 GWh [2], with an average per capita electricity consumption of approximately 3,389 kWh. The development of electricity consumption in Turkey from 1970 to 2023 is shown in Figure 1.

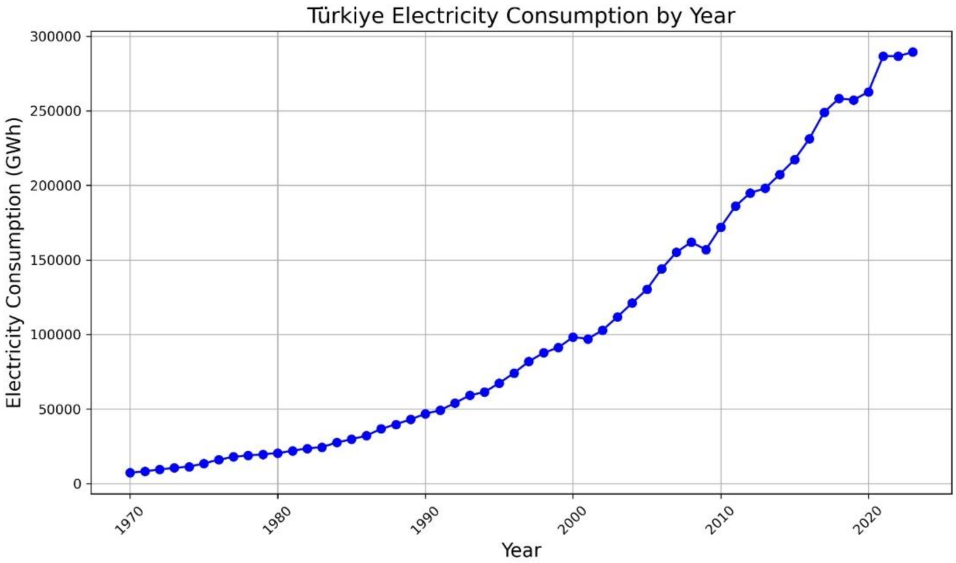

Fig. 1 Türkiye electricity consumption by year [2]

Electricity is a form of energy that must be consumed immediately after it is produced. However, the amount of consumption fluctuates over time, varying monthly, daily, and even by the hour. Electricity grids must be able to meet these instantaneous load demands and increasing energy needs in the long term [3]. On the other hand, when demand forecasts exceed supply, excessively high costs may be incurred for electricity production. At this point, predicting future electricity demand becomes a crucial step for the effective planning of electricity grids [4].

Long-term electricity consumption forecasting is essential for shaping strategic investment decisions. Investment decisions based on these forecasts play a critical role in determining the required capacity in the energy sector. However, overinvestment may result in wasted capacity and ineffective use of resources allocated for investment. Conversely, underestimating demand, leading to inaccurate system design and planning, could cause various challenges such as essential power outages. This situation would negatively impact individual welfare and economic growth. Thus, accurate and reliable long-term forecasts are vital for sustainability and efficient resource utilization in the energy sector [5].

Electric load forecasting is based on analyzing historical and current conditions in detail to identify patterns of change and predict future demand. Various factors influence electric load, including population growth, geographical conditions of the region, historical load characteristics, gross national product (GNP), and technological advancements. These factors help us understand changes in electricity demand and make more accurate future forecasts [6].

In Turkey's electricity market, privatization efforts began in the 1980s but gained significant momentum with the Electricity Market Law No. 4628, enacted in 2001. This law aimed to establish a market structure that promotes competition, ending the public monopoly and encouraging greater private sector involvement. Following its implementation, production, transmission, distribution, and retail sales were unbundled, and privatizations, particularly in production and distribution sectors, commenced. While the privatization of distribution companies was completed in 2013, the privatization of production facilities continues gradually [7].

Electricity production and trading in Turkey’s electricity market are managed through several primary market mechanisms that regulate transactions: the Day-Ahead Market (DAM), the Intra-Day Market (IDM), and the Balancing Power Market (BPM). The Day-Ahead Market (DAM) is where offers are collected, and transactions are conducted to balance supply and demand for the following day. In this market, producers and consumers submit price bids, setting the electricity price and volume one day in advance. The Intra-Day Market (IDM) offers more flexibility to respond to intraday changes in electricity supply and demand, allowing participants to conduct real-time purchases and sales as needed. The Balancing Power Market (BPM), managed by the Turkish Electricity Transmission Corporation (TEİAŞ), ensures system balance by issuing additional supply or demand instructions to address short-term imbalances. These three market mechanisms work together to maintain electricity supply security and price stability [8].

In the electricity spot market, price risk increases, and predictability decreases as real-time approaches. In other words, market clearing prices set in the Day-Ahead Market are more stable compared to system marginal prices in the Balancing Power Market, where prices are highly volatile and carry substantial risk; the primary objective here is to provide rapid solutions to ensure system reliability [8].

Accurately forecasting electricity demand is critical for efficient market operations and ensuring system security. Short-term electricity demand forecasts, in particular, directly impact the efficiency of dynamic market mechanisms such as the Day-Ahead Market (DAM) and the Intra-Day Market (IDM). While DAM and IDM help market participants balance electricity supply and demand, accurate forecasts allow energy producers and distribution companies to minimize price fluctuations due to supply-demand imbalances. In this context, the effective and rapid performance of short-term electricity demand forecasting algorithms supports the efficient and reliable operation of the energy system, providing both economic and environmental benefits [9].

Upon reviewing the literature, electricity consumption forecasting methods can be categorized into three main types: statistical methods, machine learning (ML) methods, and hybrid methods. Statistical methods include Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing (ETS), and Linear Regression. Among machine learning methods, Artificial Neural Networks (ANN) and modified neural networks—such as Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), Gated Recurrent Unit (GRU), and Convolutional Neural Networks (CNN)—are commonly used. In addition to ANN-based methods, decision tree and gradient boosting algorithms have also been employed. Furthermore, hybrid models that combine statistical and machine learning methods have been developed to improve forecasting accuracy. Table 1 below provides a summary of studies related to forecasting Turkey's electricity consumption or demand.

Table 1. Overview of the studies on electricity consumption or demand forecasting of Turkey

Forecasting Methodologies	Authors	Year
ARIMA, Regression analyses, ANN	Hamzacebi and Kutay [10]	2024
Genetic algorithm	Ozturk et al [11]	2005
Regression analyses and ANN	Topalli et al. [12]	2006
ANFIS, ARMA and ARIMA	Erdogdu [13]	2007
Curve fitting and genetic algorithm	Karabulut [14]	2008
Regression analyses, Nonlinear Regression, ANN	Bilgili [15]	2009
Optimization algorithm	Toksari [16]	2009
Fuzzy logic	Kucukali and Baris [17]	2010
ANN	Cunkas and Altun [18]	2010
ANFIS, ARMA and ARIMA	Demirel et al [19]	2010
Genetic algorithm	Yigit [20]	2011
ANN	Sözen et al. [21]	2011
Regression analyses	Kavaklioglu [22]	2011
Singh's Method	Boltürk et al. [23]	2012
ANFIS, ARMA and ARIMA	Boran [24]	2014
Regression analyses	Kavaklioglu [25]	2014
ANN, LS-SVM	Kaytez et al. [26]	2015
ANN	Esener et al. [27]	2015
ANFIS, ARMA, ARIMA, fuzzy logic	Cevik and Cunkas [28]	2015
ANN	Tanidir and Tor [29]	2015
Multiple linear regression and ANN	Gunay [30]	2016
Regression analyses	Karaca and Karacan [31]	2016
SARIMA and ANN	Hamzacebi [32]	2017
Linear model	Yükseltan [33]	2017
EPSİM-NN	Başoglu and Bulut [34]	2017
ANN	Toros and Aydın [35]	2018
Regression analyses	Haliloglu and Tutu [36]	2018
RNN, LSTM, GRU	Tokgoz [37]	2018
ANN	Hamzeçebi et al [38]	2019
ARMA, ARIMA, SARIMA	Doruk [39]	2019
ANN	Özkurt et al. [40]	2020
ARIMA and LR-SVM	Kaytez [41]	2020
Naive forecast, ridge regression and SARIMAX	Cetinkaya and Acarman [42]	2021
ANN	Ozbay and Dalcali [43]	2021
ANN	Unutmaz et al. [44]	2021
LSTM, GRU and CNN	Unlu [45]	2021
ANN	Saglam et al. [46]	2022
Regression Analysis	Emec and Akkaya [47]	2022
ANN	Comert and Yildiz [48]	2022
Extreme learning machine and ANN	Agır [49]	2022
Xgboost	Guven and Kayalica [50]	2023
ARIMA, Extreme learning machine and ANN	Pala [51]	2023
Heckman sample selection	Yarbasi and Celik [52]	2023
ANN, SVM and WOA	Saglam et al. [53]	2023
Regression analyses and ANN	Yigit et al. [54]	2024

In this study, deep learning and gradient boosting-based methods, namely BiLSTM and CatBoost, are employed to forecast the total electricity consumption of the cities of Aydın, Denizli, and Muğla one day in advance. The performance of the methods used in this study is evaluated using performance metrics such as Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

The remainder of the study is organized as follows: Section 2 provides a brief introduction to the models, including BiLSTM and CatBoost. Section 3 presents the dataset and numerical experimental results. Section 4 discusses the findings in detail. Finally, the study is concluded in Section 5.

II. MATERIALS AND METHOD

A. *Problem Statement*

In this study, we aim to forecast the total electricity consumption for the provinces of Aydın, Denizli, and Muğla using machine learning methods. Forecasting is defined as the process of predicting future values of a time series based on its historical data. Let $x = [x_1, \ldots, x_t]$ represent a time series, where each $x_t \in R^d$ and d denotes the dimensionality of the time series data. The objective of the forecasting process, then, is to predict the future values of the data as $x = [x_t, \ldots, x_{t+k}]$ where k represents the number of future values to be predicted. In this study, CatBoost and BiLSTM models are used to make 24-hour forecasts, and the performance of these models is compared using specific performance metrics.

B. *Bidirectional Long Short-Term Memory (BiLSTM)*

BiLSTM (Bidirectional Long Short-Term Memory) is a bidirectional Recurrent Neural Network (RNN) model that provides an effective approach for learning long-term dependencies in time series and sequential data. While traditional LSTM (Long Short-Term Memory) networks process information flow in a specific direction in sequential data, BiLSTM learns all dependencies in the data by utilizing connections in both the forward (past to future) and backward (future to past) directions. Figure 2 illustrates the comparison between LSTM and BiLSTM architectures.

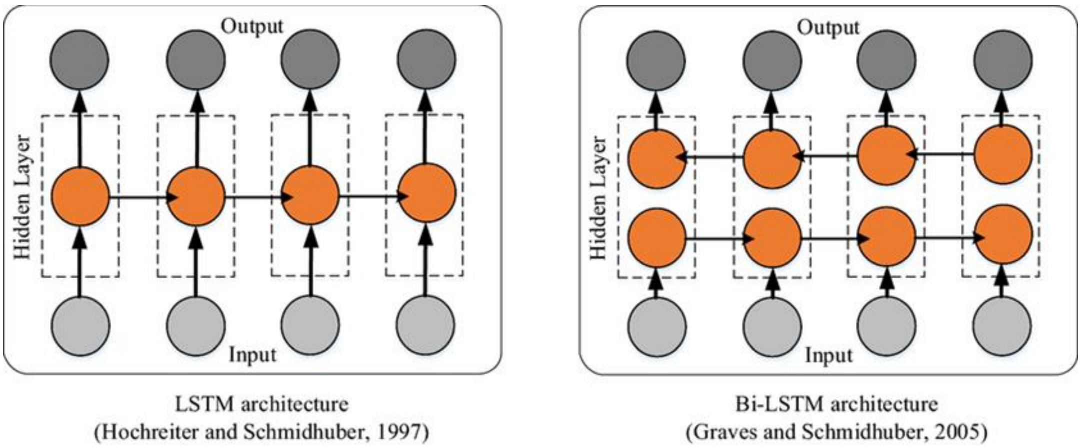

Fig. 2 Comparison between LSTM and Bi-LSTM networks [55]

The basic structure of BiLSTM consists of two LSTM layers that operate bidirectionally: a forward layer and a backward layer. The forward LSTM layer processes time steps from the beginning to the end, while the backward LSTM layer processes information in reverse, starting from the last time step. This bidirectional architecture captures temporal dependencies in both directions, enhancing prediction accuracy. The internal architecture of the BiLSTM unit is shown in Figure 3.

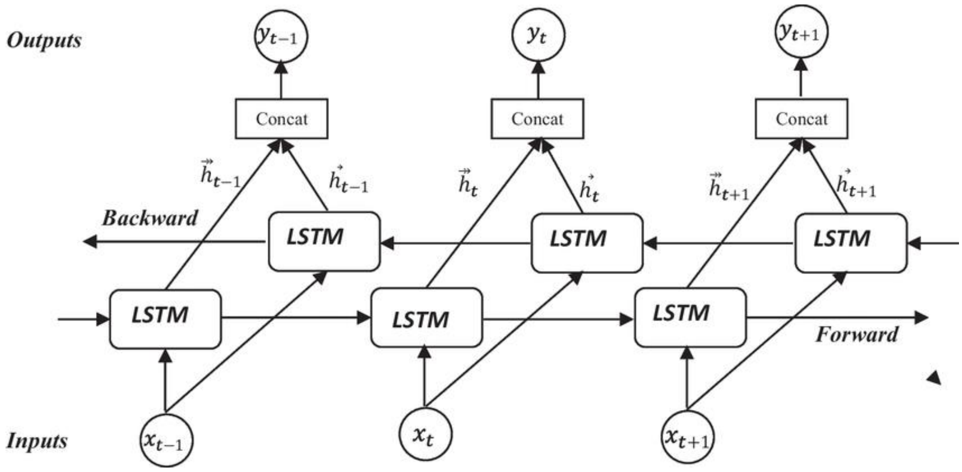

Fig. 3 Basic structure of the BiLSTM network [56]

BiLSTM utilizes the LSTM cell as its fundamental building block. Traditional RNN models may be limited in learning long-term dependencies, which can lead to the vanishing gradient problem, especially in datasets with dense sequential information flow. To address this issue, LSTM was developed [57]. LSTM layers have three gates that regulate the flow of information: the input gate, the forget gate, and the output gate. Input gates control the flow of activation information entering the cell, while output gates manage the information leaving the cell. Forget gates are used to reset the cell memory when it is no longer needed [58]. The structure of the LSTM unit is shown in Figure 4.

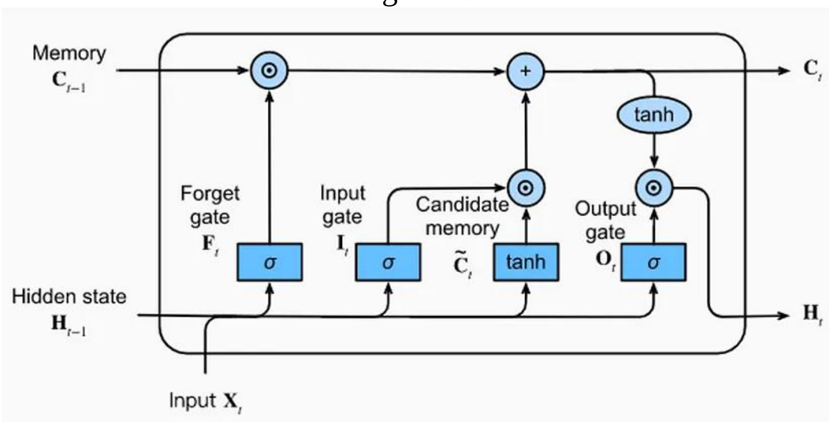

Fig. 4 The structure of the LSTM unit [57]

The Input Gate controls the proportion of new information to be added to the cell state. The Forget Gate facilitates the forgetting of unnecessary or outdated information, supporting more efficient model performance. The Output Gate adjusts the proportion of information to be sent out from the cell state, regulating the information passed to the next layers. The input time series data at a given time t is represented by x_t. W_i, W_o and W_f denote the input, output, and forget weight parameters, respectively. Accordingly, the input i_t, output o_t , and forget gates f_t in the LSTM layer are expressed as follows:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{1}$$

In Equation (1), b_i, b_o, and b_f represent the bias parameters. h_t and h_f are defined as the hidden state vectors at time step t (also referred to as the output state). In Equation (1), σ represents the sigmoid activation function. In the LSTM layer, the hidden state h_t and the cell state c_t at time step t are defined as follows:

$$c_t = f_t \odot c_{t-1} + i_t \odot \widetilde{c_t} \quad (2)$$

$$h_t = o_t \odot \tanh(c_t) \quad (3)$$

Here, $\odot$ denotes the Hadamard product, and $tanh(.)$ represents the hyperbolic tangent function. The $\widetilde{c_t}$ given in Equation (2) is written as follows:

$$\widetilde{c_t} = \tanh(W_c[h_{t-1}, x_t] + b_c) \quad (4)$$

Here, W_c and b_c represent the weight and bias parameters, respectively [59].

C. *CatBoost*

CatBoost is a gradient boosting algorithm proposed by Liudmila Prokhorenkova and other researchers in 2017. While traditional boosting algorithms are widely used in various fields such as time series analysis, classification, and regression, they encounter several limitations, particularly when handling categorical features in large datasets. The primary goal of CatBoost is to prevent prediction shift while processing categorical features and to improve model performance.

Two key innovative methods play a crucial role in CatBoost's success: Ordered Boosting and Ordered Target Encoding. These methods significantly enhance CatBoost's performance in processing categorical data compared to traditional boosting algorithms.

Ordered Boosting was developed to reduce overfitting and ensure more accurate learning by the model. In traditional boosting methods, all examples in the dataset are processed simultaneously. In contrast, CatBoost processes the data sequentially and updates weights based on information obtained from previous examples at each step. This sequential processing approach prevents data leakage, ensuring that the model produces more reliable predictions.

Another critical component in CatBoost's handling of categorical features is the Ordered Target Encoding method. This method optimizes the relationship between categorical features and the dependent variable, enabling the accurate modeling of category-specific effects. Ordered Target Encoding also reduces the risk of overfitting by preventing categorical features from becoming overly adapted to the model.

CatBoost also utilizes a symmetric tree structure for modeling. In traditional boosting algorithms, tree structures may be asymmetric, leading to different splitting conditions at each node, causing the tree structure to grow unevenly. CatBoost, however, builds symmetric trees by using the same splitting conditions at every level, ensuring uniform depth and structure across all nodes. This symmetric structure significantly reduces training and prediction times, as the trees are consistently deep and balanced. This feature enables CatBoost to work efficiently with large datasets.

Additionally, CatBoost offers advanced options for hyperparameter optimization. Fine-tuning parameters such as learning rate, tree depth, and L2 regularization can improve model performance. The GPU support in CatBoost further shortens training times, especially with large datasets, allowing for faster and more efficient model training. As a result, the features of CatBoost, including the symmetric tree structure and ordered boosting, can be leveraged more effectively [60].

D. *Performance Metrics*

The CatBoost and BiLSTM models are assessed using performance metrics, specifically RMSE and MAPE. Let y be a vector representing the future values of the sequence x, defined as $y = [x_T, \dots, x_{T+k}]$. Here, y_i and $\widehat{y_i}$ denote the actual and predicted values, respectively. The performance metrics are then calculated as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2} \quad (5)$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y_i}}{y_i}\right| \times 100 \tag{6}$$

III. RESULTS

A. *Dataset*

In this study, data analysis and modeling techniques were applied to forecast electricity consumption in the provinces of Aydın, Denizli, and Muğla, Turkey. The dataset used was provided by ADM Elektrik Dağıtım and covers the period from 00:00 on January 1, 2021, to July 15, 2024. This dataset includes the total electricity consumption values for the specified provinces in MWh (megawatt hours). The normalized version of the total consumed energy, ranging from 0 to 1, is shown in Figure 5, while the statistical information of the dataset is presented in Table 2 and Table 3.

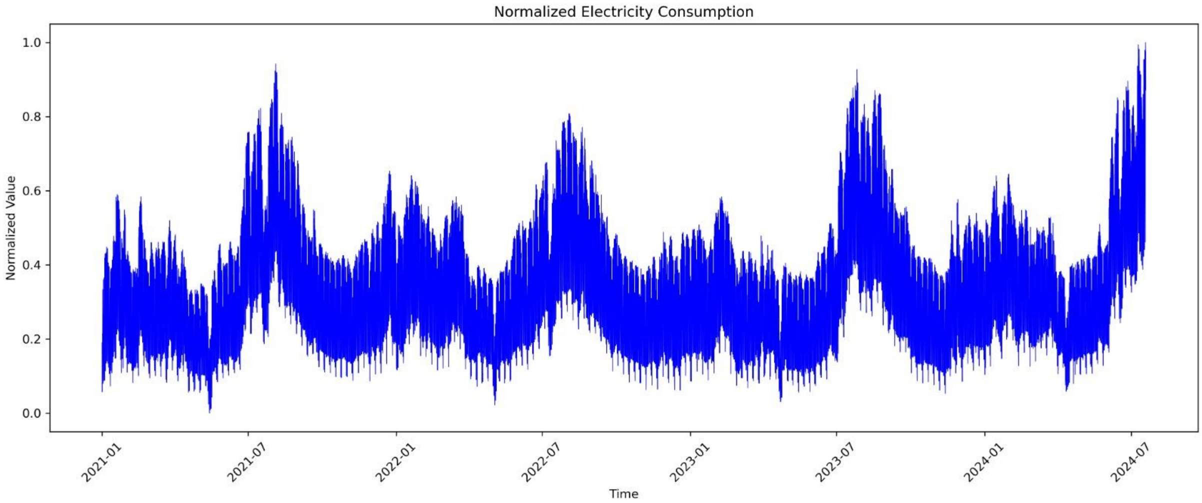

Fig. 4 Normalized electricity consumption dataset

Table 2. Statistical Summary of the Dataset

Min	Max	Mean	Median	Std	Skew	Kurtosis
509,652	2300,494	1147,961	1123,792	290,619	0,762	0,525

Upon examining the general characteristics of the dataset, it is observed that there is a large range between the minimum value of 509,652 and the maximum value of 2300,494. The mean (1147,961) and median (1123,792) values are close to each other, indicating that the central tendency of the data suggests a normal distribution. However, the positive skewness (skew = 0,762) indicates that the distribution is skewed towards higher values, suggesting the presence of outliers. The kurtosis value (0.525) suggests that the data distribution is relatively flat, meaning the peaks of the distribution are not concentrated around the mean.

Table 3. Statistical Summary of the Dataset by Year

Year	Min	Max	Mean	Median	Std	Skew	Kurtosis
2021	509,652	2196,416	1130,627	1113,864	283,0596	0,702	0,376
2022	548,725	1956,069	1144,900	1131,208	263,5447	0,412	-0,294
2023	564,272	2169,743	1133,730	1107,730	298,6005	0,839	0,559
2024	614,510	2300,494	1211,153	1160,434	326,0386	0,950	0,628

In 2021, the skewness value of the data was 0.702, indicating a right skew and the presence of significant outliers. In 2022, the skewness decreased to 0.412, making the data more symmetrical and reducing the influence of outliers. Additionally, the standard deviation decreased, and the data became more concentrated within a narrower range. In 2023, the skewness increased to 0.839, and kurtosis rose to 0.559, revealing a distribution with more pronounced right skew and outliers. In 2024, the skewness further increased to 0.950, and kurtosis reached 0.628, indicating a more right-skewed and peaked distribution. Furthermore, the average (1211,153) and median (1160,434) values in 2024 were higher, representing an increase compared to previous years.

In this study, various external factors that could affect electricity consumption were also considered. In this context, meteorological and solar energy data were included in the analyses. Meteorological data were obtained from the Enercast [61] data source, while solar energy production data were collected via the PVlib [62] Python library. These datasets were used to more accurately model the relationship between energy production and consumption.

Additionally, an extra dataset was created considering factors such as the installed capacity of unlicensed producers and public holidays (official holidays). This dataset was designed to better model the seasonal and holiday effects on electricity consumption. The variables used are presented in Table 4.

Table 4. Variables Used in the Analysis

Aydin cloud cover	Denizli elevation	Marmaris wind speed	Söke dhi
Aydin precipitation	Denizli equation	Mentese azimuth	Söke dni
Aydin radiation	Denizli ghi	Mentese dhi	Söke elevation
Aydin relative humidity	Denizli precipitation	Mentese dni	Söke equation
Aydin temperature	Denizli radiation	Mentese elevation	Söke ghi
Aydin wind direction	Denizli relative humidity	Mentese equation	Söke sun position
Aydin wind speed	Denizli sun position	Mentese ghi	Söke turbidity
Bodrum cloud cover	Denizli temperature	Mentese sun position	Söke zenith
Bodrum precipitation	Denizli turbidity	Mentese turbidity	Yatagan azimuth
Bodrum radiation	Denizli wind direction	Mentese zenith	Yatagan cloud cover
Bodrum relative humidity	Denizli wind speed	Milas azimuth	Yatagan dhi
Bodrum temperature	Denizli zenith	Milas cloud cover	Yatagan dni
Bodrum wind direction	Fethiye cloud cover	Milas dhi	Yatagan elevation
Bodrum wind speed	Fethiye precipitation	Milas dni	Yatagan equation
Cardak cloud cover	Fethiye radiation	Milas elevation	Yatagan ghi
Cardak precipitation	Fethiye relative humidity	Milas equation	Yatagan precipitation
Cardak radiation	Fethiye temperature	Milas ghi	Yatagan radiation
Cardak relative humidity	Fethiye wind direction	Milas precipitation	Yatagan relative humidity
Cardak temperature	Fethiye wind speed	Milas radiation	Yatagan sun position
Cardak wind direction	Honaz azimuth	Milas relative humidity	Yatagan temperature
Cardak wind speed	Honaz dhi	Milas sun position	Yatagan turbidity
Cine azimuth	Honaz dni	Milas temperature	Yatagan wind direction
Cine dhi	Honaz elevation	Milas turbidity	Yatagan wind speed
Cine dni	Honaz equation	Milas wind direction	Yatagan zenith
Cine elevation	Honaz ghi	Milas wind speed	Aydin non licensed electricity generation capacity
Cine equation	Honaz sun position	Milas zenith	Denizli non licensed electricity generation capacity
Cine ghi	Honaz turbidity	Mugla cloud cover	Mugla non licensed electricity generation capacity
Cine sun position	Honaz zenith	Mugla precipitation	Ramadan flag
Cine turbidity	Marmaris cloud cover	Mugla radiation	Religious day flag
Cine zenith	Marmaris precipitation	Mugla relative humidity	National day flag
Denizli azimuth	Marmaris radiation	Mugla temperature	Public holiday flag
Denizli cloud cover	Marmaris relative humidity	Mugla wind direction	
Denizli dhi	Marmaris temperature	Mugla wind speed	
Denizli dni	Marmaris wind direction	Söke azimuth	

B. *Numerical Experiments*

For training the BiLSTM model, TensorFlow v2.17.0 and Keras v3.6.0 libraries were utilized. In our numerical experiments, a four-layer network based on BiLSTM was designed. The entire network consists of four BiLSTM layers, each with a different number of hidden units, and a single output layer. The first three BiLSTM layers include 256, 128, and 64 hidden units, respectively, while the fourth BiLSTM layer has 32 hidden units. Each BiLSTM layer is equipped with a LeakyReLU activation function, a dropout rate of 0.2, and batch normalization.

Throughout the training process, the RMSE metric was selected as the model's loss function. To minimize the loss function, the Adam optimization algorithm was applied with a learning rate set to 0.0001. Additionally, early stopping and learning rate reduction mechanisms were incorporated. Various values for training parameters were tested, and those yielding the best prediction performance were selected. To identify the optimal parameters for the models, the number of epochs in the set {50, 100, 150, 200, 250, 300, 350, 400, 450, 500} and the learning rate values in $\{10^{-2}, 5 \times 10^{-3}, 10^{-3}, 5 \times 10^{-4}, 10^{-4}, 10^{-5}\}$ were explored on the validation set.

For training the CatBoost model, the CatBoostRegressor was employed. During numerical experiments, various hyperparameter combinations were examined, beginning with the identification of categorical features for the model. The final model was optimized with 10,000 iterations, a learning rate of 0.01, and a depth of 8 layers. RMSE was chosen as the loss function, and the RMSE metric was used on the validation set to assess the model's performance. To improve the model's overall performance during training, the early stopping rounds parameter was set to 50, thus halting training when validation loss did not improve.

In the experiments, the prediction of electricity consumption 24 hours in advance for the cities of Aydın, Denizli, and Muğla was conducted using the BiLSTM and CatBoost models, and their performances were evaluated using the aforementioned performance metrics. During model training, the "sliding window" approach, commonly used in time series forecasting, was applied. In this approach, after each daily prediction, the predicted value was added to the training data as time step t+24 for the next day's prediction. Thus, each day's prediction incorporated the previous day's forecast data, enhancing prediction accuracy by using information obtained from prior days.

This approach was carried out during the periods of March 1–15 and July 1–15, creating a realistic simulation environment for the predictions in both periods. Through this method, the model's performance was tested not only for independent days but also under conditions where consecutive days were interrelated.

Table 5 summarizes the performance of the CatBoost and BiLSTM models in predicting electricity consumption for the periods of March 1–15 and July 1–15. The performance is evaluated using MAPE and RMSE metrics. In the March period, CatBoost achieves a lower MAPE (2,72%) and RMSE (35,85) compared to BiLSTM (3,71% MAPE, 46,87 RMSE), indicating higher accuracy. However, in the July period, BiLSTM slightly outperforms CatBoost in terms of MAPE (2,76% for BiLSTM, 2,81% for CatBoost), though CatBoost still shows a higher RMSE (57,50) than BiLSTM (53,05).

Table 5. Performance Comparison of CatBoost and BiLSTM Models Across Different Periods

	Mape		**RMSE**	
Period	**Catboost**	**BiLSTM**	**Catboost**	**BiLSTM**
1-15 March	2,72%	3,71%	35,85	46,87
1-15 July	2,81%	2,76%	57,50	53,05

IV. DISCUSSION

A. *CatBoost's Excellence in Generalization*

CatBoost generally achieves lower MAPE values across both periods, suggesting robustness in its predictive generalization. For example, in the March period, CatBoost consistently maintains lower MAPE values on most days (e.g., March 1 with a MAPE of 1.79% for CatBoost vs. 2.01% for BiLSTM). This pattern is also observable in Figures 5 and 6, where CatBoost's predictions show a lower average error, particularly evident in daily variations in consumption, reflecting its stability and effectiveness under various conditions.

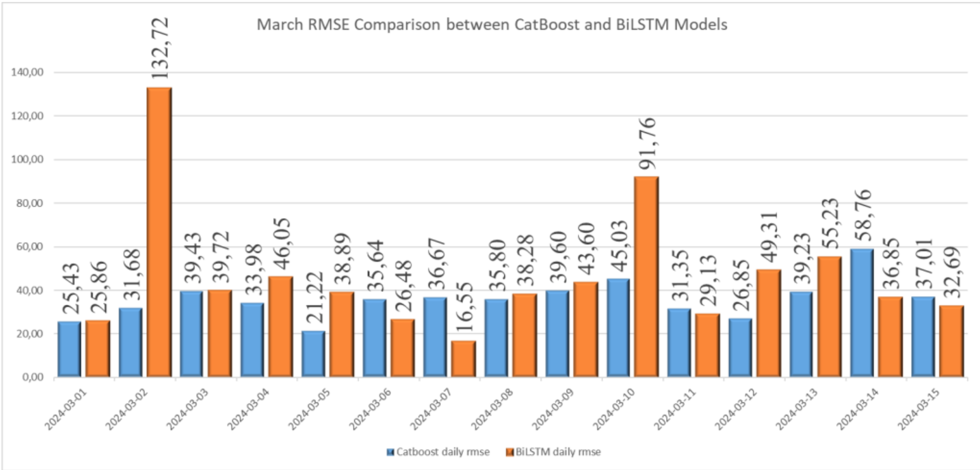

Fig. 5 March RMSE Comparison between CatBoost and BiLSTM Models

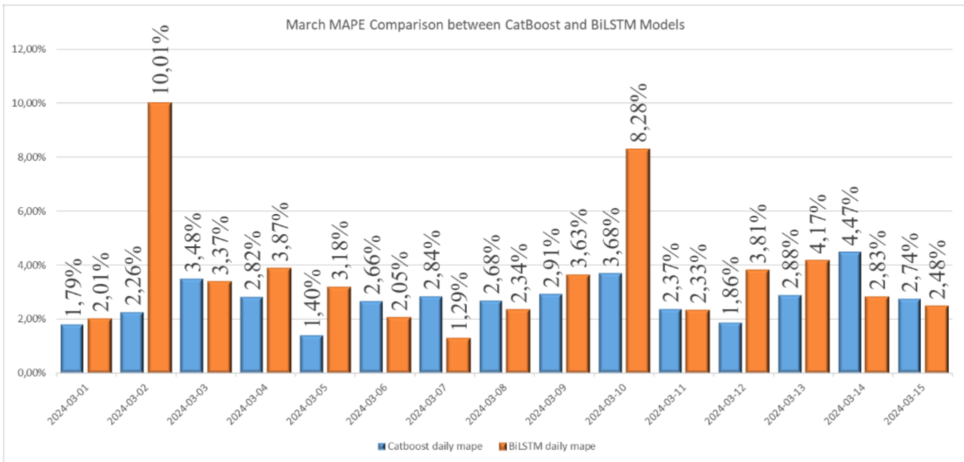

Fig. 6 March RMSE Comparison between CatBoost and BiLSTM Models

B. *BiLSTM's Superior Performance under Specific Conditions*

The BiLSTM model shows superior performance under certain conditions, particularly in handling fluctuations in high-demand scenarios. For instance, as indicated in the July period's MAPE and RMSE values (e.g., July 12 with an RMSE of 29.74 for BiLSTM vs. 60.72 for CatBoost), the model achieves lower error rates on specific days. This trend is further illustrated in Figure 3 and Figure 4, where BiLSTM's predictions closely track actual values, highlighting its ability to capture intricate seasonal consumption patterns more effectively.

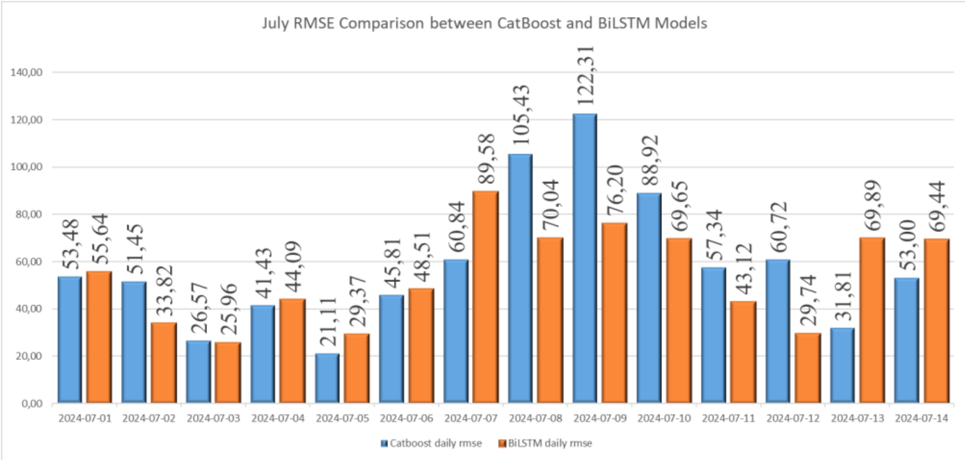

Fig 7. July RMSE Comparison between CatBoost and BiLSTM Models

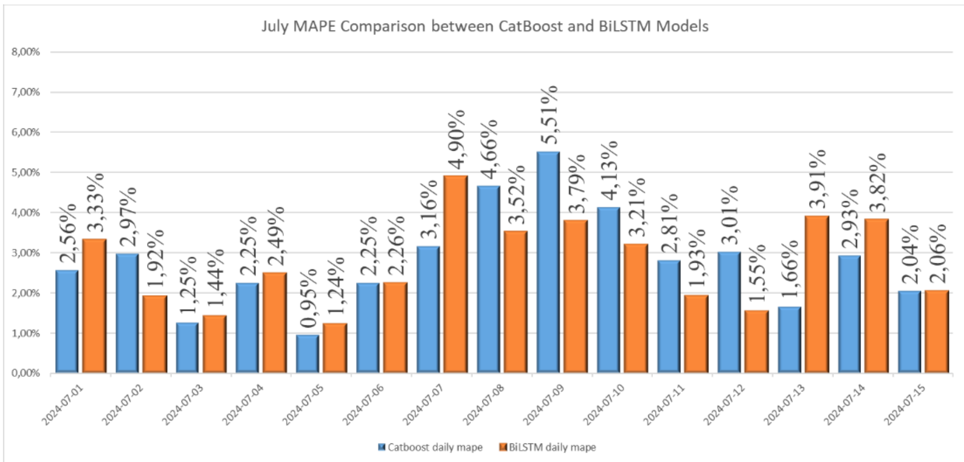

Fig. 8 July MAPE Comparison between CatBoost and BiLSTM Models

C. *Potential Benefits of Hybrid Approaches*

The distinct performance strengths of each model under specific conditions suggest potential benefits of a hybrid approach. As shown in Figure 9 and Figure 10, both CatBoost and BiLSTM predictions frequently align with observed values in March and July, indicating consistency across different demand periods. This alignment underscores the advantage of combining BiLSTM's ability to capture seasonal patterns with CatBoost's robust generalization capacity, potentially reducing both daily and seasonal error rates more effectively. A hybrid model could leverage the complementary strengths of these approaches to achieve more balanced predictions for diverse energy consumption trends.

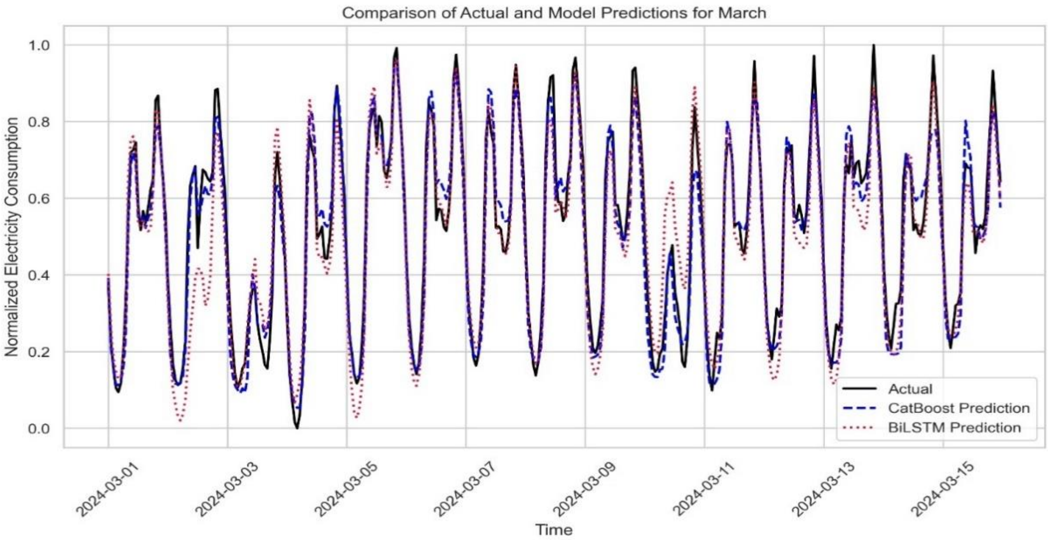

Fig. 9 Comparison of Actual and Model Predictions for March

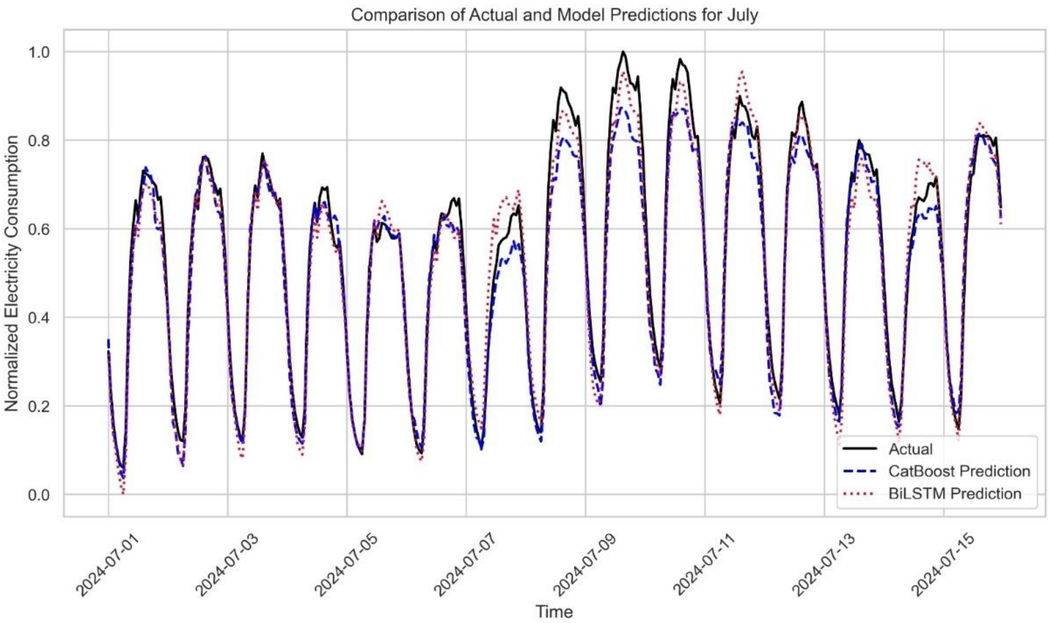

Fig. 10 Comparison of Actual and Model Predictions for July

D. *Limitations and Future Work*

The solar data used in the models were obtained from the PVlib library, and the weather data was sourced from the Enercast website. To further improve the accuracy of the models, alternative weather data providers could be utilized. More accurate weather forecasts would likely enhance the predictions.

Additionally, the study covers a large geographical area, including Aydın, Denizli, and Muğla. There are occasional power outages and maintenance activities carried out by either TEİAŞ or the distribution company, ADM Elekrik, which could lead to significant disruptions in the power grid. These outages can be classified as either unplanned (due to faults) or planned (due to maintenance work). Normalizing such outages in the dataset may help achieve more reliable results.

Future work could also explore advanced feature engineering techniques, such as lag shifts, rolling windows, and others, to further improve the models. The impact of these techniques on prediction accuracy should be evaluated to understand their effectiveness in enhancing model performance.

While the CatBoost and BiLSTM models are effective for prediction, understanding the rationale behind the models' predictions could provide more insight into system behavior. Future work could explore methods to improve model interpretability, such as SHAP (Shapley additive explanations) or LIME (Local Interpretable Model-agnostic Explanations), to better understand how specific features influence the predictions. Additionally, exploring ensemble learning methods, such as stacking or boosting, or creating hybrid models that combine the strengths of both CatBoost and BiLSTM could enhance prediction accuracy and robustness, offering a more comprehensive approach to tackling the problem.

V. CONCLUSION

The aim of this research was to predict hourly electricity consumption for the following day (t) based on data available up to the previous day (t-1), using a three-year dataset. Both CatBoost and BiLSTM models proved effective in forecasting electricity consumption, with each offering distinct advantages depending on the circumstances. CatBoost consistently provided more accurate predictions across both periods, demonstrating robustness in its ability to generalize. For example, during the March period, it outperformed BiLSTM in terms of precision, reflecting its stability and effectiveness in capturing daily consumption variations. However, BiLSTM showed superior performance in handling fluctuations during high-demand scenarios, and in certain instances, its predictions closely matched actual values, highlighting its capacity to capture intricate seasonal consumption patterns with greater accuracy.

This work contributes to the growing body of knowledge in energy forecasting by comparing two advanced machine learning models—CatBoost and BiLSTM—in short-term electricity consumption prediction. A key innovation lies in applying these models to large-scale, real-world data, offering valuable insights into how each model adapts to various consumption patterns and can be fine-tuned for better forecasting. Moreover, by assessing the models under different seasonal conditions, it sheds light on how weather-related and demand-based fluctuations impact forecasting accuracy. Additionally, the results from this research could be particularly useful for trading in Turkey's Intra-Day Market, as the models predict electricity consumption based on data up to the previous day (t-1). This aligns well with the Intra-Day Market, where forecasts are made closer to actual consumption periods, offering an opportunity to make more accurate decisions in energy distribution.

Despite the valuable contributions of this study, there are certain limitations that should be addressed in future research. One key limitation is the lack of accurate data prior to 2021, as well as the potential impact of large industrial consumers entering or leaving the distribution system, whose consumption patterns may deviate from general trends, affecting the prediction accuracy. To overcome these challenges, future work could incorporate a wider variety of data sources, including historical data from before 2021 and information from major industrial consumers. Additionally, exploring other machine learning techniques, such as ensemble learning methods or hybrid models combining CatBoost and BiLSTM, could further improve forecasting accuracy. Enhancing the interpretability of the models through methods like SHAP or LIME would also provide valuable insights into how specific features influence predictions, ultimately aiding in more informed decision-making in energy distribution.

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