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# Modeling the Interaction Between Meteorological Indicators and Electricity Production Using Machine Learning Methods: The Case of Türkiye

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## WHAT IS ALREADY KNOWN ON THIS TOPIC?

- *Electricity production exhibits strong nonlinear patterns and pronounced seasonal variability, which are significantly influenced by meteorological factors such as temperature, wind speed, and humidity.*
- *Machine learning (ML)- and deep learning (DL)-based time series models, particularly recurrent neural network (RNN) architectures, have been shown to outperform traditional statistical methods in forecasting electricity demand and production under complex and nonstationary conditions.*
- *Gated recurrent architectures, including long short-term memory (LSTM) and*

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## ABSTRACT

Accurate forecasting of electricity production has become increasingly critical for energy systems, particularly in countries where renewable energy penetration and climate variability are rapidly increasing. In this context, this study investigates the interaction between meteorological indicators and electricity production in Türkiye using machine learning–based time series forecasting methods. The analysis is conducted using daily electricity production data obtained from the Turkish Energy Market Operator (EPİAŞ) and corresponding meteorological variables—namely apparent temperature, wind speed, and humidity—sourced from the Open-Meteo platform, covering the period from late 2015 to 2024. After aggregating hourly observations into daily series and applying appropriate preprocessing steps, several forecasting models are implemented and compared, including recurrent neural networks (RNN), long short-term memory (LSTM), gated recurrent unit (GRU), and the Prophet time series model. Model performance is evaluated using mean absolute error (MAE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and the coefficient of determination ($R^2$). The results indicate that gated RNN architectures significantly outperform classical approaches in modeling electricity production dynamics. Among all models, the GRU model achieves the best performance, yielding the lowest error values (MAE = 1241.4, RMSE = 1951.5, and MAPE = 3.5%) and the highest explanatory power ($R^2$ = 76.9%). The LSTM model provides comparable but slightly weaker results, while the classical RNN and Prophet models exhibit substantially lower predictive accuracy, particularly in capturing nonlinear patterns and sudden production fluctuations. Overall, the findings demonstrate that GRU-based models offer a robust and reliable framework for electricity production forecasting in meteorologically sensitive energy systems and provide valuable insights for energy planning, grid operation, and data-driven energy policy development.

***Index Terms—***Electricity production forecasting, machine learning, meteorological indicators, time series analysis

## I. INTRODUCTION

Accurate electricity forecasting has become a critical requirement for Türkiye's energy sector in recent years due to the combined effects of rapid demand growth, increasing penetration of renewable energy sources, and intensifying climate-related impacts. Globally, climate change and international energy policies have accelerated the transition away from fossil fuels toward more sustainable energy systems [1]. Although Türkiye was not initially subject to binding emission reduction targets, strong population growth, urbanization, and economic expansion have led to a substantial rise in electricity demand. In response, the country has significantly expanded its installed capacity in wind, solar, and hydropower in order to diversify its energy mix and enhance supply security [2].

Electricity production and consumption in Türkiye are closely linked to meteorological conditions, making weather variability a key determinant of power system dynamics. Extreme weather events, in particular, can trigger abrupt and significant changes in electricity demand. For instance, Türkiye recorded its highest hourly electricity consumption in 2025 following an exceptional heatwave—the hottest July observed in 55 years—when increased air-conditioning

*gated recurrent unit (GRU) models, are widely recognized for their ability to capture long-term dependencies in energy-related time series and to mitigate the vanishing gradient problem observed in classical RNNs.*
- *Deterministic and decomposition-based forecasting models, such as Prophet, are effective in capturing long-term trends and regular seasonal components but often exhibit limited performance in modeling short-term fluctuations and sudden changes in electricity production.*

**WHAT DOES THIS STUDY ADD ON THIS TOPIC?**

- *This study provides a comprehensive comparative evaluation of classical statistical, RNN–based, and gated DL models (RNN, LSTM, GRU, and Prophet) for electricity production forecasting using a unified meteorological and production dataset for Türkiye.*
- *The findings demonstrate that the GRU model delivers the most balanced and robust performance across multiple evaluation metrics (MAE, RMSE, MAPE, and $R^2$), highlighting its effectiveness in capturing both short-term fluctuations and long-term dependencies in meteorologically sensitive electricity production series.*
- *By integrating apparent temperature, wind speed, and humidity variables into the forecasting framework, the study quantitatively confirms the critical role of meteorological indicators in improving the accuracy of electricity production predictions.*
- *The results offer practical insights for energy planning, grid operation, and policy design by showing how advanced ML-based forecasting models can serve as reliable decision-support tools in systems with increasing renewable energy penetration.*

usage pushed demand to a record level of approximately 59 GWh [3]. Empirical evidence suggests that each 1°C increase in ambient temperature may require an additional 0.77 GW of generation capacity to meet peak demand. At the same time, a growing proportion of Türkiye's electricity generation originates from weather-dependent renewable sources. Wind and solar energy alone accounted for nearly 18% of total electricity production in 2024, while the overall share of renewables has reached approximately 40%–44% in recent years. As noted by Yağmur et al. [1], climate-driven policies and market incentives have accelerated renewable deployment in Türkiye, further strengthening the interdependence between meteorological conditions and electricity generation. These developments underline the necessity of advanced forecasting approaches capable of capturing the complex interactions between weather patterns and power systems. Meteorological variables such as temperature, wind speed, and humidity play a decisive role not only in electricity demand but also directly in electricity production, particularly as renewable capacity expands. Unlike conventional thermal power plants, solar and wind generation are inherently sensitive to atmospheric conditions. Variations in photovoltaic (PV) output, for example, are strongly influenced by meteorological factors including air temperature, relative humidity, wind speed, cloud cover, and solar irradiance [4]. Similarly, wind power generation is governed by wind speed distributions, while extreme temperatures and humidity levels can affect the operational efficiency of both renewable and conventional generation units [5]. In Türkiye, the increasing share of renewables implies that weather-induced fluctuations are becoming a dominant source of variability in total electricity production, highlighting the need for forecasting models that explicitly incorporate meteorological indicators [6].

Accurate electricity production forecasting is essential for maintaining grid stability, optimizing generation planning, and ensuring efficient system operation. Although the inclusion of multiple explanatory variables increases model complexity, it also offers substantial gains in predictive accuracy. Previous studies have demonstrated that integrating environmental variables—such as temperature and humidity—significantly improves the performance of hourly and daily electricity forecasts [7]. In this context, data-driven approaches based on machine learning (ML) and deep learning (DL) have gained prominence, as they often outperform traditional statistical models in capturing nonlinear patterns and temporal dependencies inherent in energy systems. Recurrent neural networks (RNNs), along with their advanced variants long short-term memory (LSTM) and gated recurrent unit (GRU) networks, are particularly well suited for time-series forecasting due to their ability to retain information across sequential observations [8]. While LSTM networks employ memory cells to preserve long-term dependencies, GRU models offer a more parsimonious gated structure that effectively mitigates issues such as the vanishing gradient problem [9]. In parallel, the Prophet model, developed by Meta, provides a complementary framework by decomposing time series into trend, seasonality, and irregular components and has proven robust to outliers and structural changes [10]. Given Türkiye's rapidly evolving energy landscape shaped by policy reforms, economic growth, and increasing climate variability, there is a clear need for comprehensive forecasting frameworks that integrate meteorological factors with advanced modeling techniques [11]. Many previous studies focusing on Türkiye's electricity system have addressed limited time horizons or a restricted set of variables, underscoring the need for more holistic approaches [12]. To address this gap, the present study develops and compares data-driven models for daily electricity production forecasting in Türkiye by incorporating key meteorological indicators.

Using official electricity production data from the Turkish Energy Market Operator (EPİAŞ) and meteorological observations from the Open-Meteo platform covering the period from late 2015 to 2024, hourly records are aggregated into a daily time series comprising 3290 observations. Several forecasting models—including RNN, LSTM, GRU, and Prophet—are implemented and evaluated using standard performance metrics (MAE, RMSE, MAPE, and $R^2$). The results indicate that the GRU-based model achieves the highest predictive accuracy, delivering the lowest error values and an $R^2$ of approximately 77% on the test dataset. These findings highlight the effectiveness of modern ML approaches, particularly gated recurrent architectures, in modeling the complex interactions between meteorological conditions and electricity production in Türkiye.

## II. RELATED WORKS

Recent advances in energy forecasting literature increasingly emphasize the integration of ML and DL techniques for predicting electricity generation from weather-dependent renewable sources, motivated by the need to manage variability and uncertainty in power systems.

A comprehensive review by Rhafes et al. (2025) highlights that ML models, including ensemble and neural network approaches, have become essential for forecasting solar and wind energy generation, offering superior performance over traditional methods in handling nonlinearities and complex patterns in meteorological data [13]. Similarly, Benti et al. (2023) demonstrate that both ML and DL techniques significantly enhance forecasting accuracy for renewable energy outputs, underscoring their importance in grid integration and sustainable energy planning [14]. Comparative studies specifically focusing on solar power forecasting show that advanced models such as Light Gradient Boosting Machines (LGBM) and K-nearest neighbors can achieve high predictive accuracy, with LGBM outperforming simpler models in terms of RMSE and MAE metrics when using meteorological inputs like irradiance and temperature [15]. Gupta (2025) further reviews PV forecasting literature, noting the increasing adoption of DL and hybrid methods that incorporate additional data preprocessing techniques (e.g., PCA, SOM, wavelet transform) to handle dynamic solar output influenced by cloud cover and seasonal changes [16]. In the context of wind energy generation, Rajaperumal et al. (2025) employ a combination of ML techniques including XGBoost, random forest, and LSTM networks to capture complex relationships between wind speed and energy generation, demonstrating that DL can uncover patterns missed by linear approaches [17]. In another study, Şaşmaz and colleagues survey ML/optimization methods for long-term electricity forecasting in Türkiye, demonstrating that neural network models can improve predictive capability compared to statistical baselines in national energy projections [18]. Saglam (2023) applies mixed NN and optimization techniques (e.g., Whale Optimization Algorithm) to model Türkiye's electricity demand, affirming the value of ML approaches in energy system modeling even when meteorological variables are not directly included [19]. In another study on short-term demand forecasting, Kaysal et al. (2025) compare various ML methods for Türkiye's electricity load and highlight the potential of ML for capturing temporal variability, implicitly suggesting that including weather variables in future studies could further enhance model accuracy [20]. Moreover, Sorkun (2020) demonstrates the benefit of multivariate meteorological inputs (temperature, humidity, nebulosity) in LSTM models for solar radiation forecasting, reinforcing that richer weather data yield better predictions than univariate approaches—an insight that is directly relevant for energy production forecasting models that integrate weather indicators [21].

Beyond country-specific examples, broader systematic reviews and comparative studies confirm these trends. Research by Ayorinde et al. (2024) systematically reviews ML applications in renewable generation forecasting, showing that models such as GRU and LSTM consistently outperform traditional feeders across solar, wind, and hybrid energy systems due to their capacity to manage data variability and seasonality. This body of work underscores the critical role of DL in forecasting renewable outputs where meteorological uncertainty is high [22]. Alazemi et al. (2024) similarly identify ANN, deep NN, and other ML architectures as predominant in RES forecasting, highlighting their flexibility in adapting to large, noisy datasets typical of solar and wind production contexts [23]. Broader comparative research also supports that DL architectures, particularly LSTM, CNN, and GRU, outperform classical statistical and ML algorithms like Autoregressive Integrated Moving Average (ARIMA), Support Vector Machine (SVM), and random forest in renewable forecasting tasks, both in accuracy and adaptability to variable weather conditions [24]. Moreover, hybrid frameworks that combine statistical and ML/DL methods provide robust alternatives, often capturing both seasonality and nonlinear patterns inherent in renewable generation time series.

## III. MATERIAL AND METHODS

The purpose of this study is to estimate daily energy production level using the previous day's energy production level and weather values of temperature, humidity, and wind speed using neural networks and the time series-based model Prophet. Data is obtained from the real energy production amount supplied by EPİAŞ (Energy Markets AŞ), freely available by API and Open Meteo. Data is downloadable from the Kaggle platform [25]. Data consists of hourly total and categorized energy production amounts with temperature, humidity, and wind speed values starting from December 31, 2015, to January 1, 2025. The total number of observations in the dataset is 81 757, and before proceeding to modeling, the hourly dataset is converted to daily by taking the average of weather values and the sum of total energy production, making the total number of observations 3290. For better model building and prediction, outliers for energy production observations were deleted, and deleted observations were imputed. Since variables may exhibit seasonality, for the models to predict better, month and day variables were added to the dataset using the datetime variable of observations. Sequence length, which is the number of observations used for modeling to predict the first observation after the sequence, is set to 48, leaving the number of observations to 3242. The first 2632 (81.2%) of observations are used for training, and 610 (18.8%) of observations are used for testing. Since this is a time-series modeling approach, three types of neurons RNN, gated recurrent network (GRU), and LSTM are used.

In the field of time-series forecasting, RNNs, GRUs, and LSTMs represent essential RNN designs. Unlike traditional neurons, RNNs incorporate internal recurrent links, enabling them to retain data. However, the vanishing gradient issue, which arises from the gradient descent training technique, can diminish their effectiveness. To address this limitation, the GRU was developed, introducing update and forget gates to regulate data flow from prior states. Despite this improvement, GRUs lack dedicated memory cells, limiting their ability to capture long-term dependencies. Long short-term memory networks solve this by integrating input, output, and forget gates, allowing them to selectively preserve or discard information across extended sequences [8].

To avoid the exploding gradient problem, Standard Scaling (z-score normalization) is used to scale total energy and weather values. Since data has seasonality, by using feature engineering, day and month variables are extracted from the time variable. Recurrent neural network, GRU, and LSTM models have similar layers to avoid bias. After the input layer, all layers have 64, 64, and 32 neurons of RNN, GRU, or LSTM, followed by a dropout layer with a parameter of 0.2, followed by each neuron. Then 2 dense layers with 32 and 16 neurons are followed, and the output neuron is a dense neuron with an activation function of "ReLU." The optimization method is ADAM; it uses a learning rate of 0.001, and Huber loss is used. In fitting the model, a batch size of 64 and 100 epochs is used. Also used for analysis, Prophet is a time series model developed by Facebook's main company, Meta. It's like the classical time-series model ARIMA and has several components in the model: trend, seasonality, and holiday effect. Its advantages include robustness to outliers, ease of use, and detection of structural breaks and sudden changes in trend.

After building the model with the training dataset, the model is tested using the test dataset. Mean absolute error (MAE), root of mean squared error (RMSE), mean absolute percentage of error (MAPE), and R-squared ($R^2$) are used as performance metrics. Mean absolute error is the average of absolute differences between predicted and actual values. RMSE is the square root of the sum of differences between actual and predicted errors. Mean absolute percentage of error is the percentage error relative to actual value. $R^2$ is the percentage of the variability of the true value explained by the prediction.

Fig. 1 shows the flowchart of all analyses and evaluations conducted in the study.

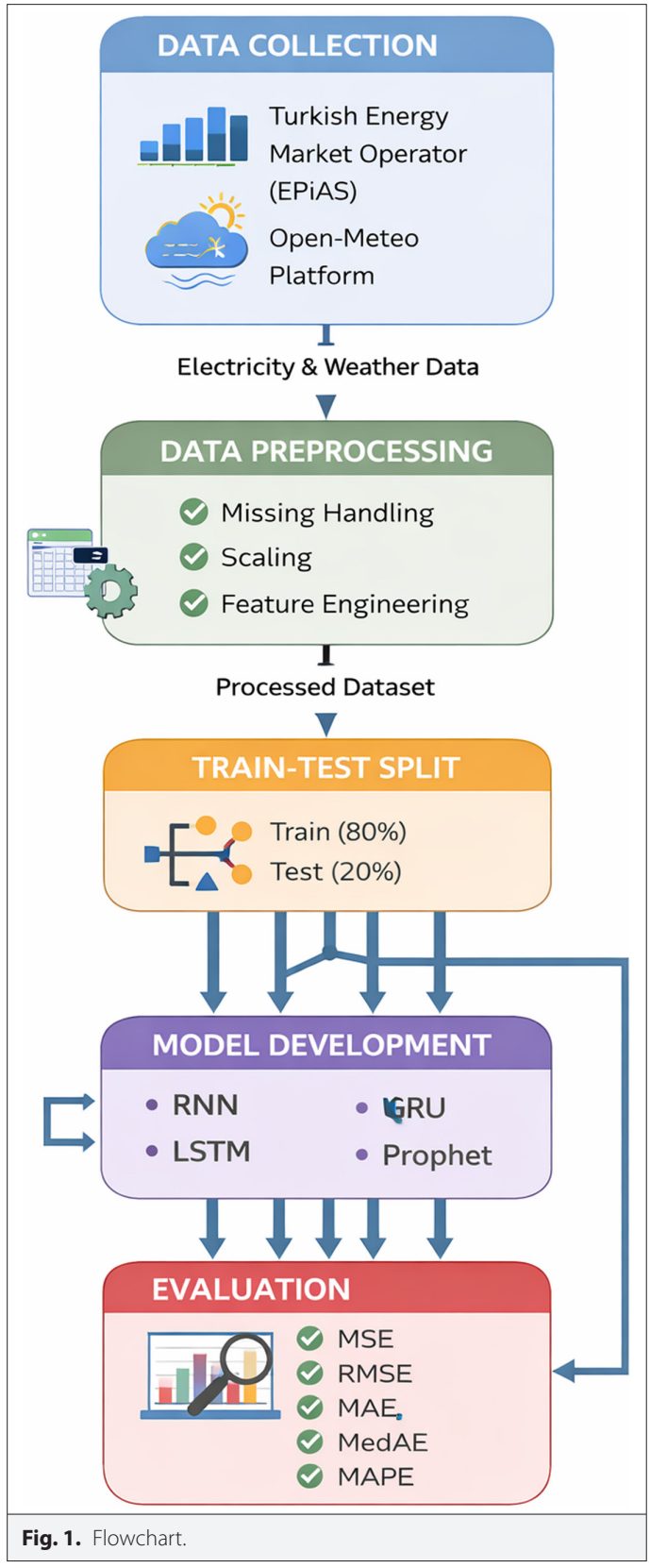


**Fig. 1.** Flowchart.

**A. Recurrent Neural Network**

Recurrent neural networks are a category of neural networks explicitly engineered to simulate sequential data characterized by temporal relationships, including time series, speech, or spoken language [26]. In contrast to feed-forward networks, RNNs integrate both present and historical inputs to capture temporal contextual information. Various input–output architectures are employed based on the task. In time series forecasting, many-to-many or many-to-one arrangements are typically favored, with input and output sequence lengths frequently varying according to the prediction horizon.

The learning mechanism of RNNs is depicted in Fig. 2, where long-term dependencies and complexity are introduced via weight updates over time steps. By updating the hidden state $h_n$ depending on both the current input $x_n$ and the preceding hidden state $h_{n-1}$, the recurrent structure with self-feedback connections enables RNNs to model sequential data, as shows Fig. 2. The network is then able to represent temporal relationships more successfully than conventional feed-forward models by computing the output $y_n$ as a function [27].

**B. Gated Recurrent Unit**

The GRU is a prevalent improvement of the RNN, formulated as a more efficient alternative to LSTM architecture [28]. The GRU, akin to LSTM in structure, consolidates the input and forget gates into a singular update gate that governs the preservation of historical information within the present state. The reset gate regulates the extent to which prior information is integrated with the current input. In contrast to LSTM, the GRU consolidates the cell state and hidden state into a unified representation, hence decreasing the parameter count. This reduction enhances computing efficiency and expedites convergence, frequently without sacrificing predictive accuracy, rendering GRUs a compelling option in practical applications [29]. The architecture of the GRU model is depicted in Fig. 3.

The functioning of a GRU cell is governed by the following equations [30]:

$$z_t = \sigma\left(x_t W^z + h_{t-1} U^z + b_z\right) \quad (1)$$

$$r_t = \sigma\left(x_t W^r + h_{t-1} U^r + b_r\right) \quad (2)$$

$$\tilde{h}_t = \tanh\left((r_t * h_{t-1})U + x_t W + b\right) \quad (3)$$

$$h_t = (1 - z_t) * \tilde{h}_t + z_t * h_{t-1} \quad (4)$$

here, $W^z$, $W^r$, and $W$ denote the weight matrices for the input vector, while $U^z$, $U^r$, and $U$ correspond to the weight matrices for the previous hidden state. $b_z$, $b_r$, and b are bias terms, σ is the sigmoid activation function, and $\tilde{h}_t$ is the candidate hidden state. The update gate $z_t$ regulates the balance between preserving past

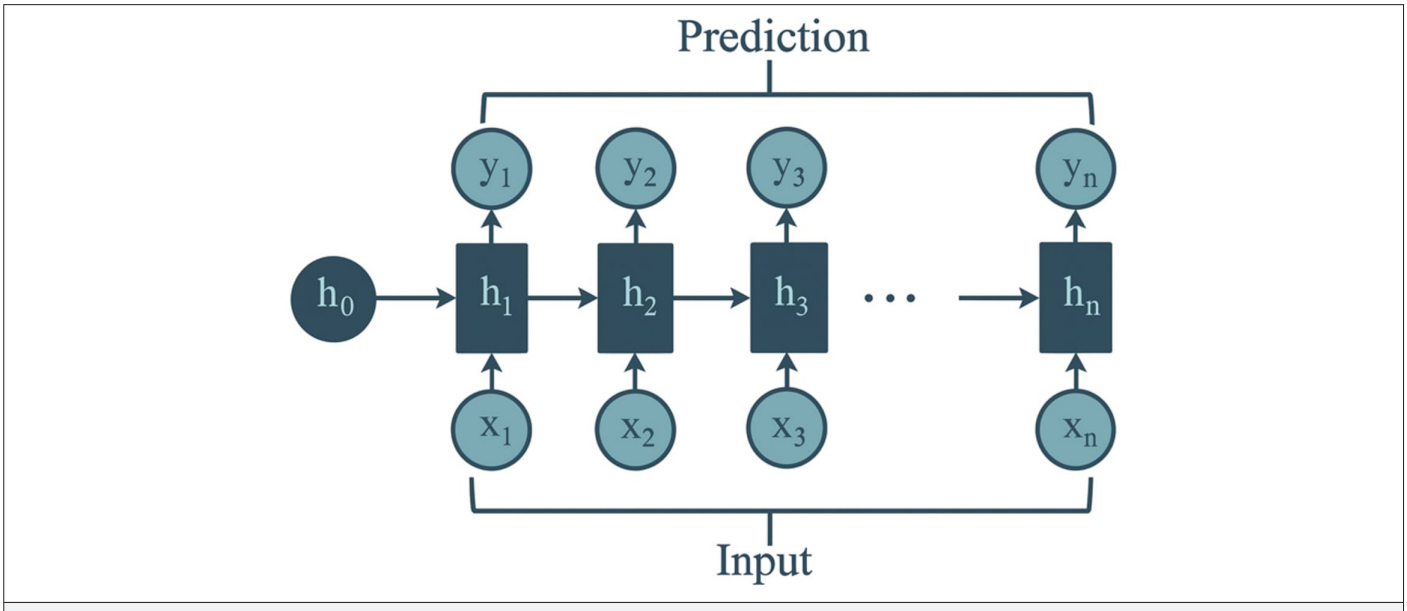


**Fig. 2.** RNN architecture.

information and incorporating new input, whereas the reset gate $r_t$ determines the degree of dependency on prior hidden states [30].

### C. Long Short-Term Memory

Among several RNN architectures, the LSTM network is distinguished by its capacity to efficiently capture long-term dependencies in time series data via its specialized memory cells [29]. The LSTM, initially introduced by Hochreiter and Schmidhuber [31], mitigates the vanishing gradient issue present in conventional RNNs when modeling prolonged temporal contexts. This is accomplished by sustaining a continuous error flow through gated mechanisms input, output, and forget gates that govern the retention or modification of information within the network. Thus, LSTM improves traditional RNNs by facilitating more precise modeling of dependencies with significant temporal intervals. The architecture of the LSTM model is depicted in Fig. 4.

At time step $t$, $x_t$ represents the LSTM input, $h_{t-1}$ is the previous hidden state, $c_t$ is the current cell state, and $h_t$ is the current hidden state. The computation proceeds as follows [32]:

Candidate Cell State:

$$\tilde{c}_t = \tanh\left(W_c\left[h_{t-1}, x_t\right] + b_c\right) \tag{5}$$

Input Gate: Controls how much of the candidate cell state is added:

$$i_t = \sigma\left(W_i\left[h_{t-1}, x_t\right] + b_i\right) \tag{6}$$

Forget Gate: Regulates how much of the previous cell state is retained:

$$f_t = \sigma\left(W_f\left[h_{t-1}, x_t\right] + b_f\right) \tag{7}$$

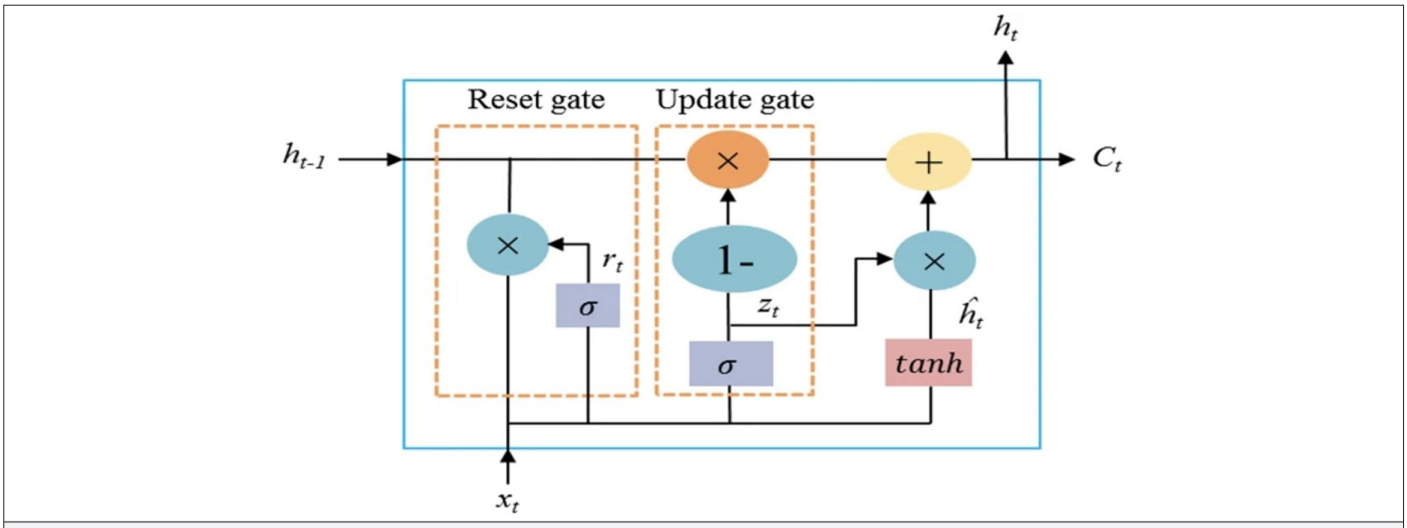


**Fig. 3.** GRU architecture.

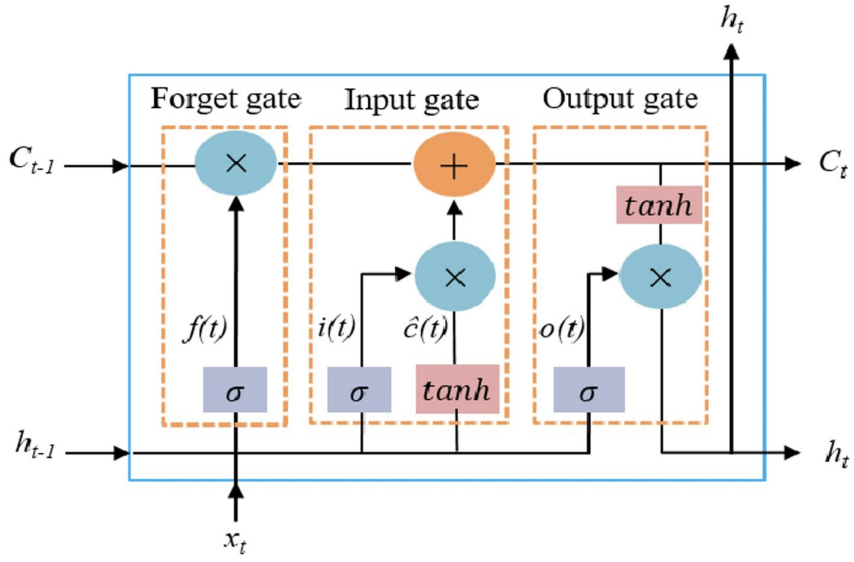


**Fig. 4.** LSTM architecture.

Cell State Update:

$$c_t = f_t * c_{t-1} + i_t * \tilde{c}_t \quad (8)$$

Output Gate: Determines the hidden state output:

$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right) \quad (9)$$

This architecture enables LSTMs to selectively store, update, and output information over long sequences, effectively mitigating the vanishing gradient problem.

### D. PROPHET

Prophet is a time series forecasting model developed by Facebook's data science team. It is specifically designed to perform well on time series that exhibit seasonality, such as daily, weekly, and yearly, and those that incorporate the effects of irregular events like holidays. Moreover, the Prophet model is a forecasting approach designed for time series data that integrates principles from classical statistical methods with ML techniques, thereby providing a balanced framework in terms of model interpretability, predictive performance, and automation [33]. Empirical evidence in the literature indicates that the Prophet model frequently demonstrates superior forecasting performance when compared to conventional time series models.

Prophet expresses time series values according to a decomposable model in the following form [33]:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \quad (10)$$

y(t): Observed value of the time series,

g(t): Trend component (usually piecewise linear or logistic),

s(t): Seasonality component (annual / weekly / daily),

h(t): Holiday and special day effects,

$\varepsilon_t$ : This is a random error term (white noise) that the model cannot explain.

In this study, the Prophet model was implemented in its standard univariate form using only historical electricity production data. Meteorological variables were not included as external regressors in order to maintain a baseline comparison with classical time series approaches and to evaluate the added value of multivariate DL models. This design allows for a clearer assessment of how incorporating exogenous variables affects forecasting performance.

### E. Evaluation Metrics

Various error measurement measures were employed to compare the basic models with those derived via hyperparameter optimization, owing to the utilization of a regression-based technique. In this context, mean squared error (MSE), root mean squared error (RMSE), MAE, median absolute error (MedAE), and MAPE were chosen as metrics for performance evaluation. The MAE and MedAE mitigate

**TABLE I.** DESCRIPTIVE STATISTICS OF VARIABLES

| Variable | Mean | Standard Deviation | Min-Max | First Quartile–Third Quartile | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| Apparent temperature | 14.6 | 9.9 | −10.3 to 59.6 | 6.6–23.0 | 0.048 | −1.005 |
| Wind speed | 11.5 | 4.0 | 0.3–48.9 | 8.7–13.6 | 0.745 | 0.493 |
| Humidity | 69.6 | 15.1 | 3.5–170.6 | 61.8–74.4 | −0.370 | −0.374 |
| Energy production | 34161.7 | 3719.4 | 23 833.6–44 799.0 | 31 782.2–36 370.6 | 0.092 | −0.232 |

the influence of outliers and represent central error patterns more equitably; conversely, RMSE allocates greater significance to substantial errors, effectively emphasizing significant discrepancies in the model's forecasts. The MAPE enables the comparison of datasets with varying scales by expressing the error rate as a percentage. The mathematical formulations for these error measures are delineated in (11–15).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(a_i - p_i\right)^2 \tag{11}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(a_i - p_i\right)^2} \tag{12}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|a_i - p_i\right| \tag{13}$$

$$MedAE = median\left(\left|a_1 - p_1\right|, \left|a_2 - p_2\right|, \ldots, \left|a_n - p_n\right|\right) \tag{14}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{a_i - p_i}{a_i}\right| \tag{15}$$

Where $a_i$ denotes the actual value, $p_i$ represents the predicted value, and n refers to the total number of observations.

## IV. ANALYSIS AND RESULTS

Table I presents the basic descriptive statistics of the dataset used in the study and provides important preliminary information on how meteorological variables are distributed in relation to electricity generation. The dataset consisted of 3290 daily observations of features of weather variables, apparent temperature, wind speed, and humidity daily averages and the target variable of total generation of energy produced. In order to provide a more comprehensive statistical characterization of the dataset, additional descriptive statistics including mean, standard deviation, min-max, first quartile, third quartile, skewness, and kurtosis were calculated for all variables. Mean apparent temperature is 14.6°C (SD 9.9), mean wind speed is 11.5 km/h (SD 4.0), average humidity is 69.6 g/m$^3$ (SD 15.1), and mean energy production is 34 161.7 (SD 3719.4).

Overall, the table shows high variance and nonlinear distributions in both meteorological variables and electricity generation. These characteristics statistically support why GRU, LSTM, and other ML-based time series models were preferred in this study, implying that traditional linear methods may be limited. Therefore, these descriptive statistics constitute the methodological justification for modeling the complex relationships between meteorological indicators and electricity generation using advanced learning algorithms.

Fig. 5 shows the prediction performance of the LSTM model on the test dataset, compared to actual electricity production values. The graph reveals that the model successfully captures general trends and significant seasonal fluctuations in electricity production. In particular, the largely accurate prediction of periodic increases and decreases in production demonstrates that the LSTM model can effectively learn long-term dependencies in the time series. The fact that the predicted values largely follow the actual observations indicates that the model exhibits strong performance in capturing both trend and seasonality components. However, it is observed that the predictions exhibit a smoother structure at some points of sudden drops and rises. This suggests that the LSTM adopts a cautious approach to extreme fluctuations, tending to partially suppress outliers.

Fig. 6 provides a close-up view of the actual and predicted values for the last 50 observations of the test dataset, allowing for a more detailed assessment of the LSTM model's short-term prediction performance. This graph shows that the model generally predicts short-term fluctuations with accurate direction and magnitude. In particular, the significant overlap in the timing of upward and downward trends demonstrates the LSTM model's ability to learn short-term dynamics. However, it is noteworthy that some observations show that the predicted values have a lower amplitude compared to the actual values, and sudden production drops are not fully captured. This situation may be due to the fact that unexpected production shocks caused by meteorological or operational reasons are difficult events to predict for learning models based on historical data.

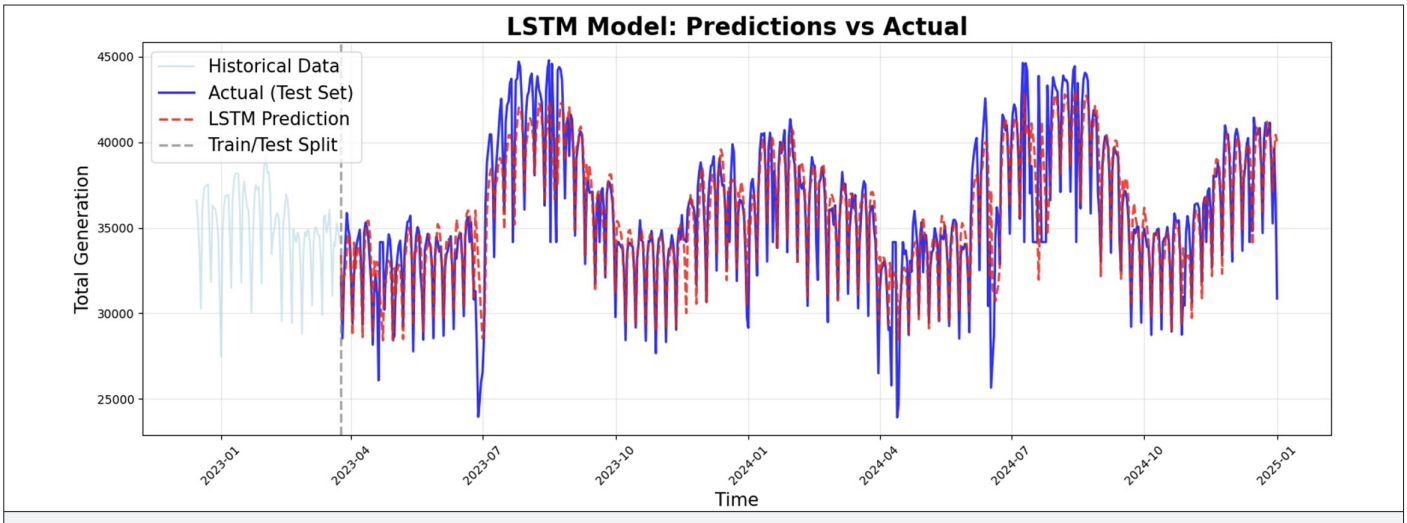


**Fig. 5.** Actual and predicted values of the LSTM model.

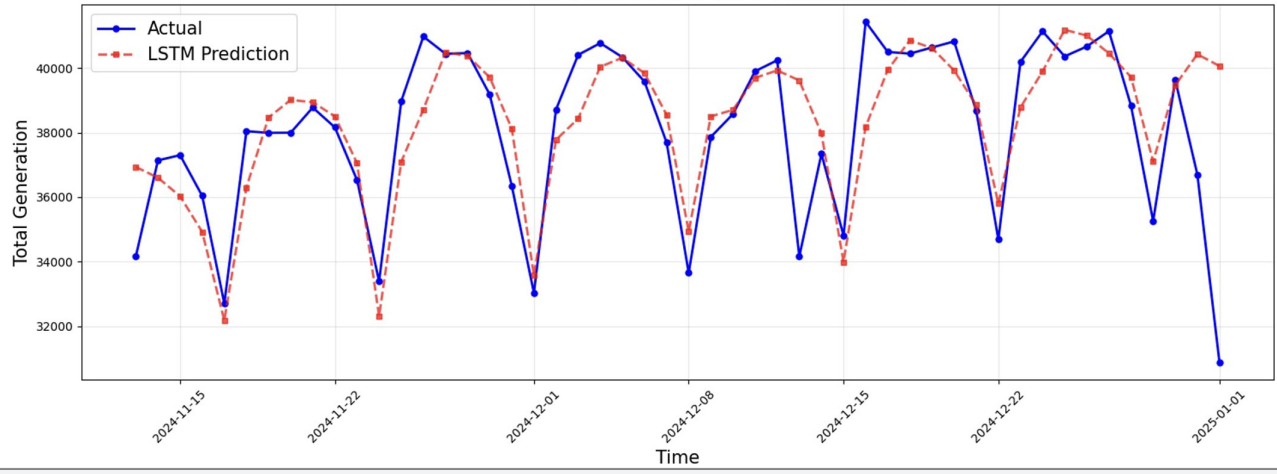


**Fig. 6.** The last 50 data points showing actual and estimated values of LSTM.

Fig. 7 shows the prediction performance of the classical RNN model on the test dataset, compared to actual electricity production values. Examining the graph, although the timing of general increases and decreases in production is largely accurately predicted, it is noteworthy that the predicted values have a more limited amplitude compared to the actual values. This situation stems from the fact that the classical RNN architecture cannot adequately represent the long-term dependencies frequently encountered in time series. Here, the prediction curve in the graph exhibits a smoother structure compared to the actual production values. This feature indicates that the RNN model is less sensitive to short-term fluctuations and tends to suppress extreme values. In this context, it can be said that the RNN model provides a certain advantage in terms of noise reduction; however, this also makes it difficult to accurately predict sudden and unexpected production changes.

Fig. 8 provides a close-up view of the actual and predicted values for the last 50 observations of the test dataset, allowing for a detailed assessment of the RNN model's short-term prediction performance. This graph clearly shows that the model accurately predicts overall trends; however, it systematically predicts rapid drops and rises in actual values with lower amplitudes than they actually are. In particular, the model's inability to capture sudden production drops observed on certain days with sufficient depth reveals that the RNN's memory mechanism is limited and weak in its ability to retain historical information for extended periods.

Fig. 9 shows the prediction performance of the GRU model on the test dataset, compared to actual electricity production values. Examining the graph reveals that the predicted values closely follow the actual observations in terms of both level and timing. This demonstrates that the GRU, thanks to its gating mechanism, effectively preserves historical information and successfully models long-term dependencies in the time series. In particular, the prediction of periodic increases and decreases in production with lower lag and less amplitude loss compared to LSTM and classical RNN models reveals that the GRU model has a strong representational capacity for this dataset. Another noteworthy aspect of the graph is that GRU predictions remain quite close to actual values, even during sudden production drops and peaks. The over-smoothing tendency observed in LSTM and especially RNN models is more limited in the GRU model. This indicates that GRU's simpler but effective memory structure

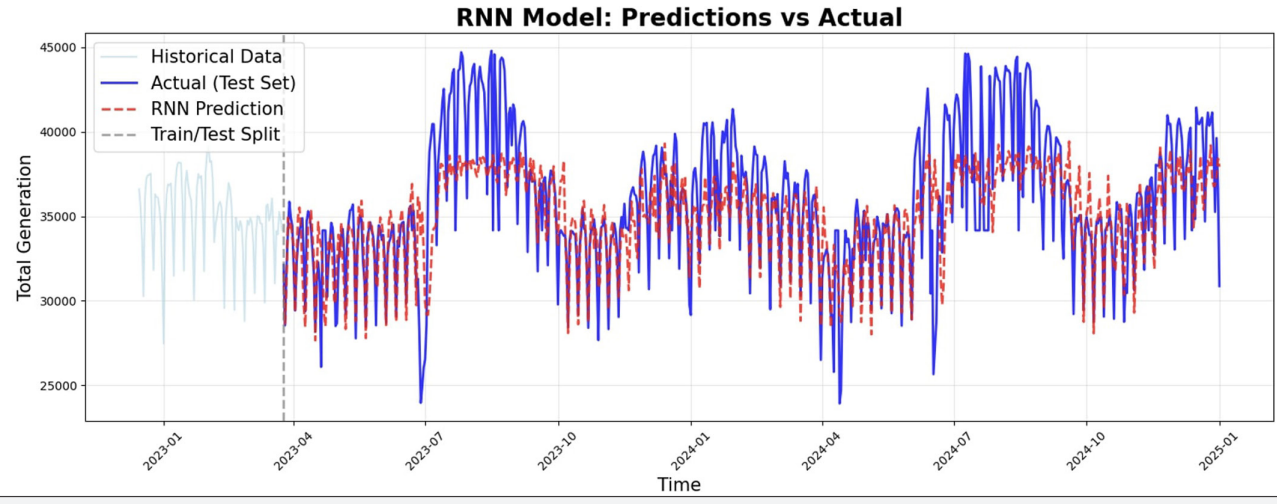


**Fig. 7.** Actual and predicted values of the RNN model.

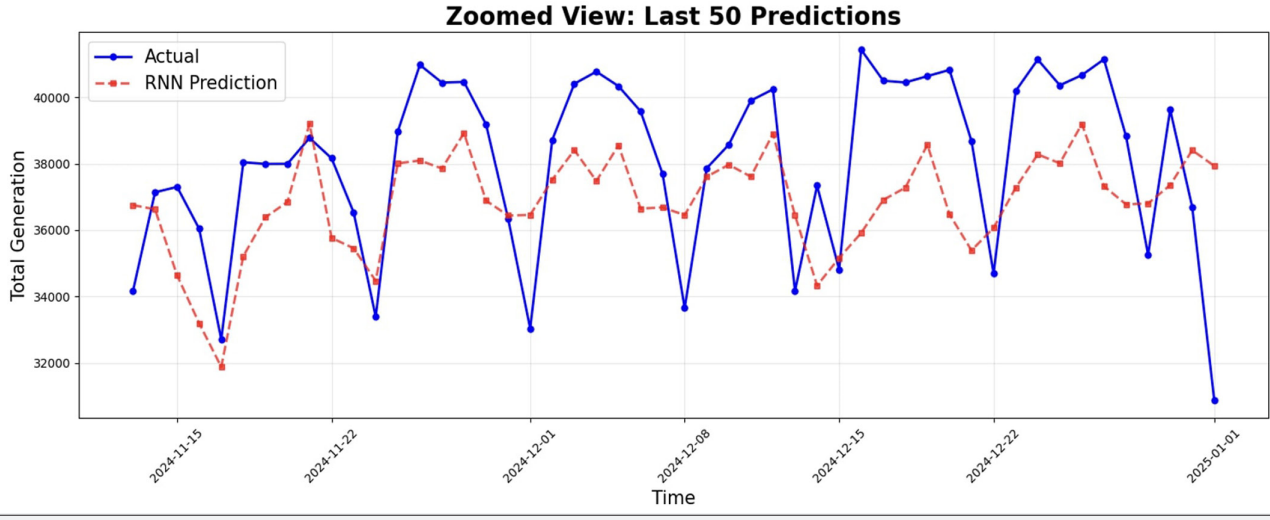


**Fig. 8.** The last 50 data points showing actual and estimated values of RNN.

allows it to learn both short-term fluctuations and long-term trends in a balanced way.

Fig. 10 details the short-term prediction performance of the GRU model for the last 50 observations of the test dataset. A close-up view shows that the model accurately predicts short-term increases and decreases in the correct direction and with largely accurate amplitudes. The high degree of convergence between the timing of sudden production drops and rapid recoveries and the actual values demonstrates the GRU's strong capacity to learn short-term dynamics. However, it is observed that the predicted values are slightly lower than the actual values at some endpoints; this difference is less pronounced compared to LSTM and especially RNN models. Furthermore, when Figs. 9 and 10 are considered together, it is concluded that the GRU model successfully represents both long-term trends and short-term fluctuations. The model is observed to be more robust against the vanishing gradient problem commonly encountered in classical RNN architectures and can provide similar performance to LSTM with fewer parameters.

Fig. 11 shows the prediction performance of the Prophet model on the test dataset, compared to actual electricity production values. The graph reveals that the Prophet model is able to capture long-term trends and regular seasonal patterns in electricity production. However, it is noteworthy that the predicted values systematically remain at lower amplitudes compared to actual production levels, exhibiting a significant underestimation trend during periods of high production. The graph also shows that sudden production drops and sharp peaks are largely over-smoothed in the Prophet predictions. This indicates that the model has limited sensitivity to short-term and unexpected fluctuations, but conversely, it produces more stable and noise-free predictions.

Fig. 12 presents a more detailed overview of the Prophet model's short-term prediction performance for the last 50 observations of the test dataset. The significant deviation of the predicted values from actual observations, particularly during sudden production increases and decreases, demonstrates the Prophet model's limitations in capturing short-term dynamics. This is due to the model's

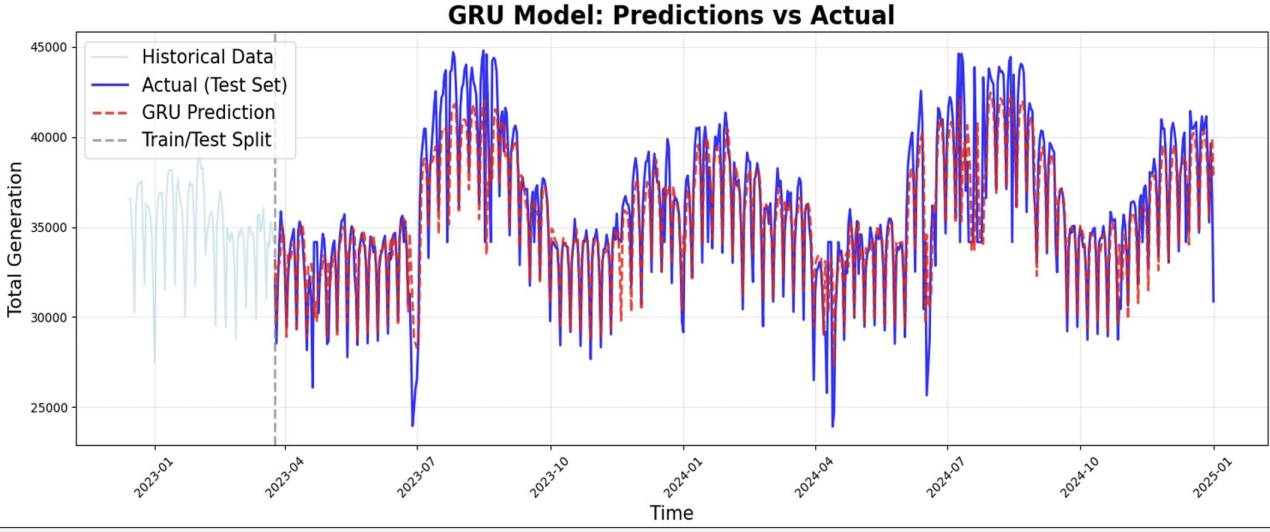


**Fig. 9.** Actual and predicted values of the GRU Model.

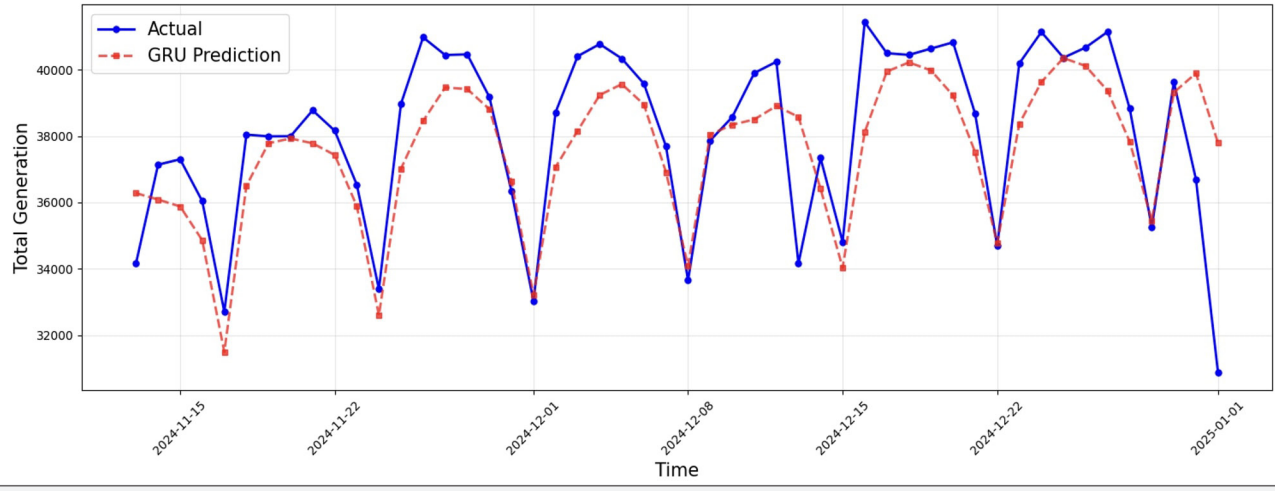


**Fig. 10.** The last 50 data points showing actual and estimated values of GRU.

deterministic nature and its strong reliance on previously observed regular components.

Table II presents a comparative analysis of the electricity generation prediction performance of the LSTM, RNN, GRU, and Prophet models used in the study, based on MAE, RMSE, $R^2$, and MAPE metrics.

The GRU model stands out as the method exhibiting the highest performance in terms of all evaluation metrics. The fact that GRU has the lowest MAE (1241.4) and RMSE (1951.5) values indicates that the predicted production values are closest to the actual observations on average. Furthermore, the $R^2$ value of 76.9% shows that the GRU model can explain approximately three-quarters of the total variance in electricity production and successfully captures the fundamental structural relationships in the dataset. The MAPE value of 3.5% indicates that the model has a relatively low error rate and provides reliable predictions for practical applications.

The LSTM model exhibits performance quite close to GRU but lags behind GRU in all metrics. The MAE (1318.7) and RMSE (2050.9) values show that LSTM has generally strong predictive capacity; however, it produces higher errors compared to GRU. While the 74.5% $R^2$ value reveals the high explanatory power of LSTM, it is noteworthy that GRU performs better despite its simpler architecture.

The classical RNN model, however, exhibits significantly lower performance compared to models with gated structures. High MAE (2211.0) and RMSE (2913.9) values indicate that the prediction errors of RNN are relatively large. The 48.5% $R^2$ value suggests that the model can explain less than half of the variance in electricity generation, revealing that RNN is limited in complex and long-term dependent time series. The 6.1% MAPE value also confirms that the relative error rate of RNN is significantly higher compared to LSTM and GRU.

The Prophet model stands out as the method with the lowest prediction success rate in terms of all performance metrics. The highest MAE (3503.6) and RMSE (4118.2) values indicate that the model's predictions are significantly far from the actual values. Specifically, the $R^2$ value of 0% reveals that the Prophet model fails to explain the production variance in the test dataset, and the predictions

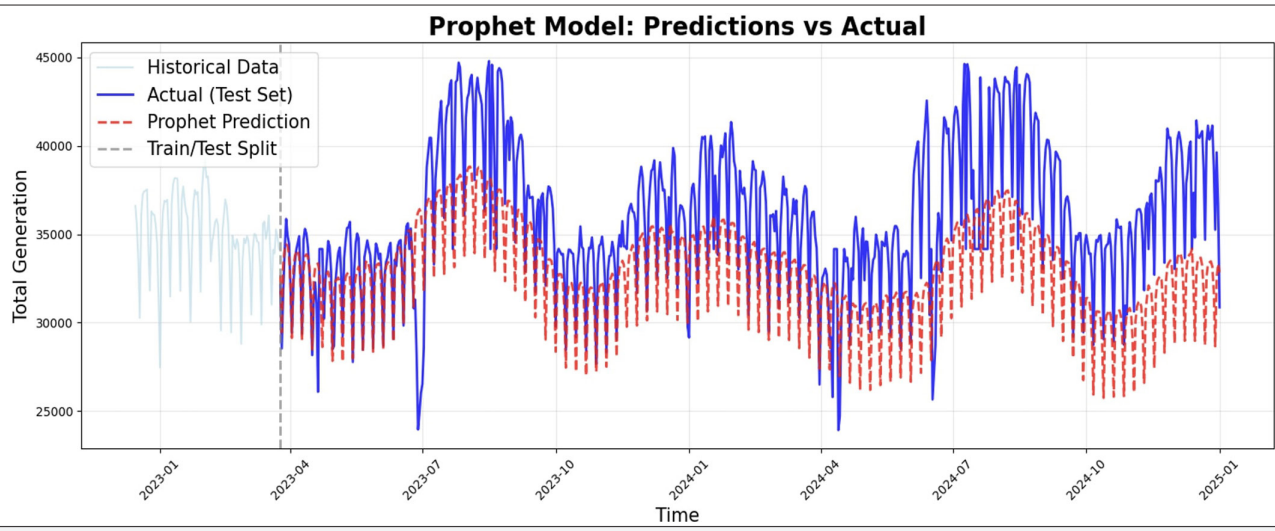


**Fig. 11.** Actual and predicted values of the PROPHET Model.

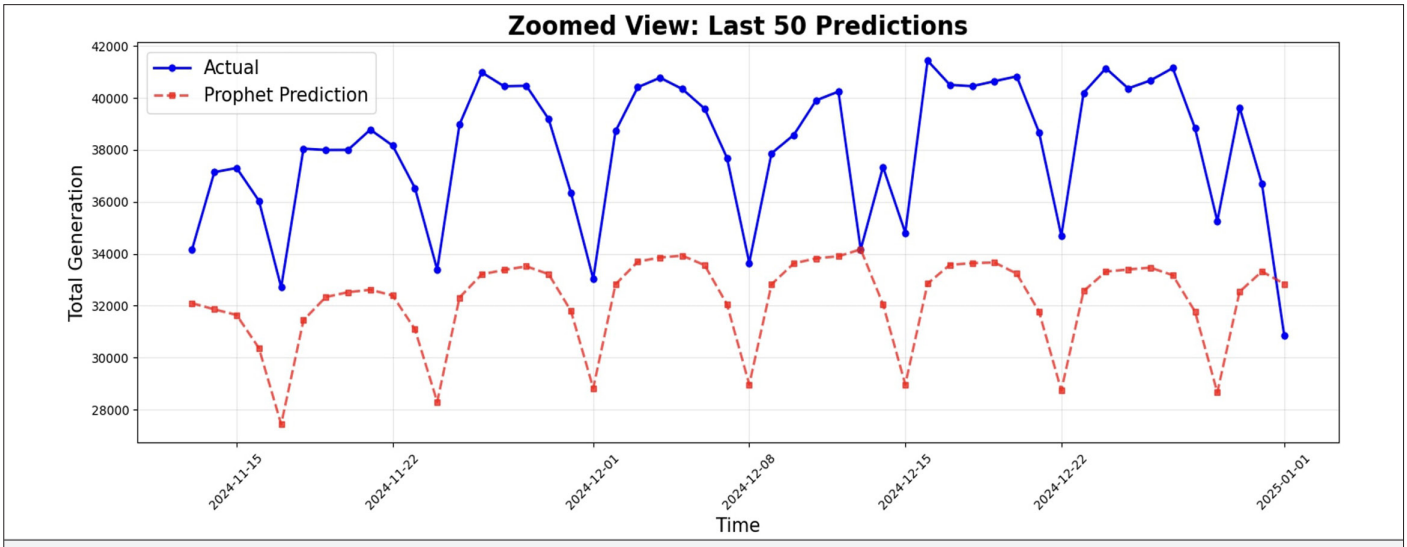


**Fig. 12.** The last 50 data points showing actual and estimated values of GRU.

converge to the average level. The 9.5% MAPE value indicates a very high relative error rate and shows that the Prophet model is insufficient for short-term electricity production predictions.

## V. DISCUSSION

When the performance of the LSTM, RNN, GRU, and Prophet models used in this study is evaluated together, it is clearly seen that model architecture plays a decisive role in forecasting time series with high volatility, seasonality, and nonlinear dynamics, such as electricity generation. Examining the performance metrics, the GRU model stood out as the method with the lowest error values (MAE = 1241.4, RMSE = 1951.5, MAPE = 3.5%) and the highest explanatory power ($R^2$ = 76.9%); this shows that GRU's simple but effective gate mechanism can learn both short-term fluctuations and long-term dependencies in a balanced way. The LSTM model exhibited performance close to GRU (MAE = 1318.7, RMSE = 2050.9, $R^2$ = 74.5%), but despite its more complex cell structure, it did not provide an additional accuracy advantage compared to GRU. This finding suggests that GRU is a more suitable alternative for this dataset in terms of parameter efficiency. In contrast, the classical RNN model failed to adequately represent long-term dependencies due to the absence of gated memory mechanisms and exhibited significantly lower performance (MAE = 2211.0, RMSE = 2913.9, $R^2$ = 48.5%). The RNN's inadequacy, particularly in the face of sudden production changes and extreme values, is consistent with the excessive smoothing and amplitude loss observed in the graphical analysis. The Prophet model, while capable of capturing trend and seasonality components, failed in the face of high-frequency fluctuations and nonlinear relationships; it reached the highest error values (MAE = 3503.6, RMSE = 4118.2, MAPE = 9.5%) and an $R^2$ = 0%. This reveals that the deterministic and limited elasticity structure of the Prophet model is insufficient to represent complex electricity production series shaped by the influence of meteorological variables. The relatively weaker performance of the Prophet model should be interpreted in light of its univariate implementation, which does not leverage meteorological information, unlike the multivariate DL models. Finally, reliable prediction models can support more efficient renewable energy investments, enhance system resilience against climate variability, and contribute to sustainable energy planning.

**TABLE II.** MODEL PERFORMANCE METRICS

| | MAE | RMSE | $R^2$, % | MAPE, % |
|---|---|---|---|---|
| LSTM | 1318.7 | 2050.9 | 74.5 | 3.8 |
| RNN | 2211.0 | 2913.9 | 48.5 | 6.1 |
| GRU | 1241.4 | 1951.5 | 76.9 | 3.5 |
| Prophet | 3503.6 | 4118.2 | 0 | 9.5 |

## VI. CONCLUSION

This study demonstrates that the relationship between electricity generation and meteorological indicators in Türkiye can be effectively modeled using ML-based time series models. The findings show that gated RNN architectures (GRU and LSTM) offer a significant advantage over classical approaches, particularly in series with high volatility and nonlinear dynamics, such as electricity generation. In terms of performance metrics, the GRU model exhibits the lowest error values and highest explanatory power, confirming its ability to learn both short-term fluctuations and long-term trends in a balanced manner. In contrast, the classical RNN model fails to adequately represent long-term dependencies, and while the Prophet model can capture trend and seasonality components, it is limited in its ability to handle sudden and high-frequency generation changes.

When the performance of the LSTM, RNN, GRU, and Prophet models applied in this study is compared using numerical metrics, it is clearly seen that there are significant differences between the models in electricity generation prediction. The results show that the GRU model provides the highest prediction success. The GRU model stands out with the lowest error values (MAE = 1241.4, RMSE = 1951.5, MAPE = 3.5%) and also achieves the highest explanatory power ($R^2$ = 76.9%). These findings show that GRU successfully explains a large part of the variance in the electricity generation time series and that the predictions converge to the actual values at a high level. Although the LSTM model showed

a performance close to GRU (MAE = 1318.7, RMSE = 2050.9, $R^2$ = 74.5%, MAPE = 3.8%), it lagged behind GRU in all metrics. In contrast, the classical RNN model produced higher error values (MAE = 2211.0, RMSE = 2913.9, MAPE = 6.1%) and achieved a lower explanatory power level ($R^2$ = 48.5%), indicating that the model has limited capacity to represent long-term dependencies. The Prophet model, on the other hand, exhibited the weakest performance among the methods used in the study; it reached the highest error values (MAE = 3503.6, RMSE = 4118.2, MAPE = 9.5%) and an $R^2$ = 0%, failing to explain the variance in the electricity generation series. Overall, these numerical findings clearly demonstrate that gated RNN-based models, especially the GRU architecture, offer the most reliable and balanced results in predicting complex and nonlinear electricity generation time series shaped by meteorological variables.

These results not only provide a methodological contribution but also contain important practical implications for energy planning and grid operation. High-accuracy generation forecasts are critical for balancing supply and demand, planning reserve capacity, and integrating renewable energy sources into the system. Especially with the increasing share of generation sources sensitive to meteorological conditions, flexible and highly learning-capable models such as GRU and LSTM are considered to contribute to maintaining grid stability and reducing operational risks. In this context, the findings of this study demonstrate that AI-powered forecasting models are powerful decision support tools that enable more efficient and reliable operation of electricity systems.

The findings of this study offer several avenues for future research. Within the scope of Future Work, incorporating meteorological data with higher spatial resolution into the model, conducting regional production-based analyses, and modeling different renewable energy sources (e.g., solar and wind) separately can further improve prediction accuracy. Furthermore, supporting GRU and LSTM models with hybrid approaches (e.g., integration with statistical methods or attention mechanisms) can contribute to more effectively capturing sudden production shocks. From a policy perspective, integrating such advanced prediction models into real-time energy management systems offers a significant area of research and application for increasing supply security, more effective planning of renewable energy investments, and the development of sustainable energy policies. In this respect, the study provides a solid foundation for both the academic literature and future research on applied energy policies.

**Data Availability Statement:** The data that support the findings of this study are available on request from the corresponding author.

**Artificial Intelligence Usage Statement:** The authors declared that no artificial intelligence tool was used in the preparation of the manuscript.

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