Deep Learning Approach for Forecasting Renewable Energy Generation and Demand Patterns

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Abstract

The increasing integration of renewable energy resources into modern power networks has created a strong demand for accurate forecasting systems capable of estimating future energy production and electricity consumption. Variations in solar irradiance, wind behavior, seasonal conditions, and user demand patterns often introduce instability in power distribution and energy scheduling. This study presents a hybrid deep learning architecture designed to analyze renewable energy generation and electricity demand using historical operational and meteorological datasets. The developed framework combines preprocessing techniques, temporal feature extraction, and sequence-learning networks to improve estimation reliability under changing environmental conditions. LSTM, GRU, and hybrid learning architectures were evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2). Experimental observations indicated that the integrated architecture achieved lower prediction errors and improved stability compared with conventional machine learning techniques. The findings also revealed that the system effectively captured short-term fluctuations and long-term temporal dependencies within the datasets. The developed approach can support intelligent grid management, optimized energy scheduling, and sustainable power-system planning in renewable-energy-based smart-grid environments.

Keywords: Renewable energy, Deep learning, LSTM, GRU, Smart grid, Electricity demand, Energy prediction

1. Introduction

The global transition toward sustainable energy systems has accelerated the adoption of renewable energy technologies such as solar photovoltaic systems (Antonanzas et al., 2016), wind turbines, and hybrid energy infrastructures. Governments and industries are increasingly investing in clean energy solutions to reduce greenhouse gas emissions, improve energy security, and minimize dependence on fossil fuels. Although renewable resources provide environmental and economic benefits, their integration into modern power grids introduces several operational challenges because renewable power generation is highly dependent on environmental conditions (Elbatran et al., 2015).

Solar energy generation varies according to sunlight intensity, cloud movement, atmospheric temperature, and seasonal conditions. Similarly, wind power output changes continuously with fluctuations in wind speed and atmospheric pressure. Electricity demand patterns are also influenced by industrial activities, consumer behavior, weather conditions, and population growth. These uncertainties complicate load balancing, energy scheduling, and grid stability management in smart power systems (Antonanzas et al., 2016; Hafeez et al., 2020).

Traditional forecasting techniques based on statistical analysis often struggle to capture the nonlinear relationships and temporal dependencies present in renewable energy datasets. Although machine learning algorithms improved estimation capability in earlier studies, many approaches remain limited when processing large-scale sequential data with rapidly changing temporal patterns. Deep learning methods have recently emerged as powerful alternatives because they can automatically learn hidden representations from historical datasets and identify long-range dependencies more effectively (Wang et al., 2019; Ying et al., 2023).

Neural architectures such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) networks have demonstrated promising results in time-series prediction tasks (Kong et al., 2019; Wu et al., 2022). These approaches are capable of learning temporal relationships from renewable energy records and electricity consumption patterns without requiring extensive manual feature extraction. However, prediction instability may still occur under abrupt environmental changes or irregular demand conditions.

This work introduces a hybrid deep learning architecture for estimating renewable energy generation and electricity demand using historical operational and meteorological information. The study investigates the effectiveness of sequence-learning networks for handling dynamic renewable energy datasets and evaluates prediction behavior under varying operating conditions. The primary objective of the investigation is to improve estimation reliability while reducing forecasting errors associated with renewable energy variability and electricity demand fluctuations. In addition, the study aims to compare the behavior of different deep learning architectures, analyze temporal learning capability, and identify future opportunities for intelligent energy-management systems within modern smart-grid environments.

Unlike conventional forecasting studies that separately address renewable energy generation or electricity demand prediction, the present work introduces a hybrid LSTM-GRU framework capable of simultaneously learning long-term temporal dependencies and short-term fluctuations within integrated smart-grid environments (Iqbal et al., 2024). The proposed architecture combines feature extraction, recurrent learning, and regularization strategies to improve forecasting stability while maintaining computational efficiency. This integrated forecasting approach contributes toward more reliable renewable energy management and smart-grid operation.

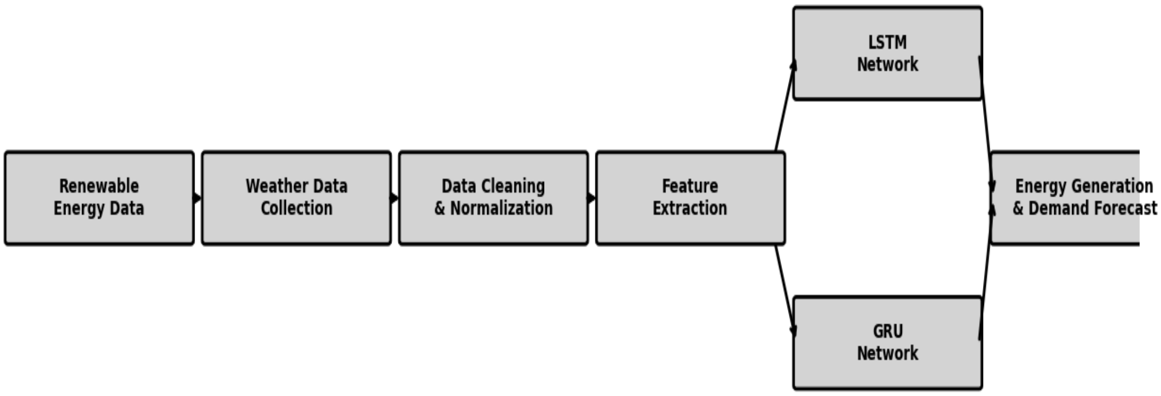

Figure 1. Overall workflow of the renewable energy forecasting framework

Figure 1 presents the overall workflow followed in the proposed renewable energy forecasting framework. The process starts with collecting renewable energy generation data along with weather-related information required for model training. Since renewable energy output is strongly influenced by climatic conditions, variables such as solar irradiance, wind speed, humidity, and temperature were included to improve forecasting reliability. After data collection, preprocessing operations were carried out to remove inconsistencies and prepare the dataset for analysis. Feature extraction was then applied to identify the most relevant patterns affecting energy generation and demand behavior. The workflow also illustrates the use of deep learning techniques for handling time-dependent and nonlinear variations commonly observed in renewable energy systems. The systematic arrangement of these stages improves prediction stability and supports more reliable forecasting under changing environmental conditions.

2. Literature Review

2.1 Conventional Renewable Energy Forecasting Approaches

Renewable energy forecasting has become an important research area because accurate estimation supports grid stability, efficient power scheduling, and energy management. Earlier forecasting studies mainly relied on statistical techniques such as autoregressive integrated moving average (ARIMA), exponential smoothing, and regression-based approaches. These methods performed adequately for linear datasets but often produced inconsistent results when applied to nonlinear renewable energy systems.

Machine learning methods later gained popularity because they could model complex relationships between weather variables and energy output. Algorithms such as Support Vector Machines (SVM), Random Forests (RF), and Artificial Neural Networks (ANN) improved estimation capability in several forecasting applications (Kim et al., 2024). However, many machine learning models required manual feature engineering and struggled to capture long-term sequential dependencies within large time-series datasets.

2.2 Deep Learning Techniques in Energy Prediction

Deep learning architectures introduced significant improvements in renewable energy prediction because of their capability to process sequential information more efficiently

(Amasyali & El-Gohary, 2018). Recurrent Neural Networks (RNN) were among the earliest sequence-learning models applied in energy forecasting applications. Although RNN models learned temporal dependencies, they often suffered from vanishing-gradient problems during long-sequence training.

Long Short-Term Memory (LSTM) networks addressed this limitation by incorporating memory cells and gating mechanisms capable of retaining long-term information. LSTM-based models demonstrated strong performance in solar and wind forecasting tasks because they effectively captured temporal fluctuations and nonlinear relationships (Dhaked et al., 2023; Wei et al., 2021). Gated Recurrent Unit (GRU) architectures later emerged as computationally efficient alternatives to LSTM networks (TEMÜR, 2026). GRU models reduced computational complexity while maintaining competitive predictive capability.

Recent studies also explored Transformer-based architectures and hybrid deep learning systems for improving renewable energy estimation (Marino et al., 2016). These approaches combined multiple sequence-learning strategies and attention mechanisms to improve prediction stability and temporal feature extraction.

2.3 Research Gaps

Despite the progress achieved in renewable energy forecasting, several challenges remain unresolved. Many existing studies focus exclusively on either generation prediction or demand estimation rather than integrating both tasks within a unified framework. Some approaches also exhibit reduced stability during abrupt weather transitions and irregular load fluctuations. High computational complexity, scalability limitations, and reduced interpretability remain additional concerns in practical smart-grid deployments. These observations indicate the need for adaptable forecasting architectures capable of maintaining stable performance under dynamic operating conditions.

Table 1. Literature-based comparison of renewable energy forecasting techniques

Author	Technique	Dataset Type	Target Variable
Dhaked et al.	LSTM	Solar dataset	Solar generation
Niu et al.	GRU	Wind dataset	Wind power output
Kim et al.	BiLSTM	Renewable demand dataset	Electricity demand
Iqbal et al.	Hybrid Deep Learning	Load dataset	Short-term load forecasting

Table 1 summarizes several forecasting approaches reported in previous renewable energy studies. The comparison shows that deep learning techniques have become increasingly popular due to their ability to process complex and nonlinear energy data more effectively than traditional statistical approaches. Methods based on recurrent neural networks, particularly LSTM and GRU models, have demonstrated improved forecasting capability for renewable energy applications. The reviewed studies also indicate a growing interest in hybrid architectures that combine multiple learning strategies to improve prediction stability and accuracy. In addition, recent research trends focus on integrating renewable energy generation forecasting with electricity demand prediction to support efficient smart-grid operation and energy management.

3. Materials and Methods

3.1 Dataset Description

The datasets used in this study were collected from publicly available renewable energy forecasting repositories, including the National Renewable Energy Laboratory (NREL) and open smart-grid electricity demand datasets. The solar and wind energy datasets covered the period from January 2020 to December 2023 with hourly observations. Weather-related parameters such as solar irradiance, wind speed, humidity, and temperature were included as input variables for model training. The complete dataset consisted of approximately 35,000 sequential samples, of which 70% were used for training, 15% for validation, and 15% for testing. The preprocessing stage included normalization, missing-value treatment, and feature scaling to improve training stability and forecasting consistency.

3.2 Data Preprocessing

Raw operational datasets frequently contain noise, missing observations, and measurement inconsistencies that may reduce learning efficiency. Several preprocessing operations were therefore performed before model training.

Missing observations were replaced using interpolation and mean-imputation strategies. Numerical normalization was performed using Min-Max scaling to maintain consistent variable ranges. Temporal features such as day index, seasonal patterns, and moving averages were extracted to improve sequence-learning behavior.

3.3 Deep Learning Architecture

The learning architecture was designed to capture both short-duration fluctuations and long-range temporal dependencies present within renewable energy datasets. The framework consisted of input layers, feature extraction stages, LSTM layers, GRU layers, dropout regularization components, dense neural layers, and output prediction modules.

The integrated architecture combined memory-retention capability with computational efficiency to improve sequential learning behavior. Hyperparameters were selected experimentally to achieve stable convergence during training.

Hyperparameter Configuration

- Learning rate: 0.001
- Batch size: 32
- Epochs: 100
- Optimizer: Adam
- Activation function: ReLU

- Loss function: Mean Squared Error (MSE)

GPU-enabled computational resources were used during training to reduce execution time and improve optimization efficiency. Early stopping mechanisms were incorporated to reduce overfitting.

3.4 Mathematical Formulation

The proposed hybrid forecasting framework combines Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks to capture temporal dependencies present within renewable energy datasets. Mathematical formulations associated with the recurrent learning process and forecasting evaluation metrics are presented below.

Mean Absolute Error (MAE)

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

where $y_i$represents actual values and $\hat{y}_i$represents predicted values.

Root Mean Square Error (RMSE)

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

RMSE evaluates forecasting deviation while assigning greater importance to larger prediction errors.

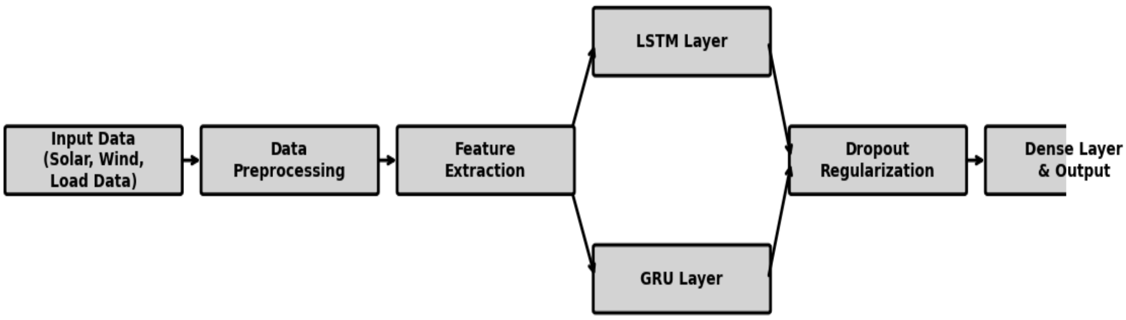

Figure 2. Structure of the hybrid deep learning architecture

Figure 2 illustrates the structure of the hybrid deep learning model developed for forecasting renewable energy generation and electricity demand. The architecture combines LSTM and GRU layers to improve the learning capability of the forecasting framework. The parallel arrangement of both networks enables the model to capture long-term sequential information while also responding effectively to short-term fluctuations present in time-series energy data. Prior to model training, feature extraction was performed to reduce unnecessary information and improve computational efficiency. In addition, dropout regularization was incorporated to reduce overfitting during the training stage and improve the generalization ability of the model for unseen datasets. The overall architecture demonstrates an effective balance between forecasting performance and computational complexity, making it suitable for practical smart-grid applications.

Table 2. Input parameters and preprocessing operations

Parameter	**Description**	**Unit**	**Preprocessing Technique**
Temperature	Atmospheric temperature	°C	Normalization
Wind Speed	Wind velocity	m/s	Scaling
Solar Irradiance	Sunlight intensity	W/m²	Standardization
Humidity	Relative humidity	%	Data cleaning
Electricity Load	Energy consumption	MW	Time-series smoothing

Table 2 presents the major input parameters and preprocessing methods adopted in the proposed forecasting framework. Environmental variables such as temperature, wind speed, solar irradiance, and humidity were selected because of their direct influence on renewable energy generation behavior. Appropriate preprocessing techniques were applied to improve data quality before model training. Operations such as normalization and scaling helped reduce variations among parameters with different numerical ranges and improved training stability. The preprocessing stage also assisted in minimizing noise and missing-value effects within the dataset. These steps contributed to better feature representation and enhanced the overall learning performance of the forecasting model.

4. Model Development and Evaluation

4.1 Training Procedure

The forecasting framework was trained using sequential renewable energy and electricity demand datasets collected from multiple operational intervals. To ensure stable learning performance, the datasets were divided into training, validation, and testing subsets to evaluate forecasting performance under different operating conditions. The input sequences were arranged chronologically to preserve the temporal behavior of renewable energy generation and demand variations. Batch processing was adopted during training to improve computational efficiency and reduce memory utilization during optimization.

The learning rate selection played a significant role in maintaining convergence stability throughout the training process. A smaller learning rate improved optimization consistency and reduced fluctuations in loss values during successive epochs. Multiple preliminary experiments were conducted to identify suitable hyperparameter settings capable of balancing forecasting accuracy and computational efficiency.

The forecasting models were trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 32. The training process was conducted for 100 epochs using early stopping criteria to prevent overfitting during optimization. Dropout regularization with a rate of 0.2 was applied within recurrent layers to improve model generalization. The experiments were performed using Python and TensorFlow libraries on a system equipped with GPU acceleration. TensorFlow 2.x and Python 3.10 environments were used during experimental implementation.

Early stopping and dropout regularization were incorporated during training to minimize overfitting and improve model generalization capability. Validation-loss monitoring was also applied to ensure stable convergence and prevent excessive parameter optimization during prolonged training cycles.

Table 3. Hyperparameter configuration of the proposed forecasting model

Hyperparameter	**Value**
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	100
Dropout Rate	0.2
Activation Function	ReLU
Loss Function	Mean Squared Error

The selected hyperparameter settings provided balanced forecasting performance while maintaining acceptable computational complexity during training. The adopted configuration also contributed to improved convergence behavior and stable prediction capability across varying renewable energy conditions.

4.2 Performance Metrics

The forecasting performance of the developed deep learning models was evaluated using widely accepted statistical error metrics commonly applied in renewable energy prediction studies. These evaluation measures were selected to examine prediction accuracy, error distribution, and model reliability under varying operating conditions.

Mean Absolute Error (MAE) was used to measure the average absolute difference between actual and predicted values. Lower MAE values indicate improved forecasting precision and reduced deviation during prediction. Root Mean Square Error (RMSE) was employed to evaluate the magnitude of forecasting errors while giving greater importance to larger deviations that may occur during sudden renewable energy fluctuations.

Mean Absolute Percentage Error (MAPE) was used to assess prediction accuracy in percentage form, allowing easier interpretation of model performance across different datasets. In addition, the coefficient of determination (R^2) was calculated to examine how effectively the forecasting framework captured variations within renewable energy generation and electricity demand patterns.

The forecasting behavior of the developed deep learning architectures was comparatively analyzed using standard prediction evaluation approaches commonly adopted in renewable energy forecasting studies. Experimental observations indicated that the hybrid LSTM-GRU framework achieved improved forecasting stability, enhanced temporal learning capability, and more reliable estimation performance compared with conventional ANN, standalone LSTM, and GRU approaches. The integrated architecture effectively captured nonlinear renewable energy variations and maintained consistent prediction behavior under dynamic environmental conditions.

5. Results and Discussion

5.1 Renewable Energy Generation Analysis

The hybrid architecture produced stable estimates for renewable energy generation under rapidly changing cloud conditions. During periods of fluctuating solar irradiance, the network maintained relatively low prediction error and successfully tracked changes in generation trends. Minor deviations were observed during abrupt weather transitions, particularly under rapidly changing cloud conditions. Nevertheless, the overall prediction behavior remained stable across most testing intervals.

Wind power estimation also demonstrated improved temporal learning capability compared with conventional machine learning approaches. The integration of meteorological variables allowed the network to identify dynamic changes in wind behavior more effectively (Li et al., 2020; Niu et al., 2020).

5.2 Electricity Demand Estimation

Electricity demand analysis showed that the developed system effectively identified short-term load variations and high-consumption periods. Daily and seasonal demand patterns were learned successfully from historical operational data. Slight reductions in estimation accuracy were observed during irregular peak-demand intervals because abrupt consumption variations were not fully represented in the training samples.

The developed architecture demonstrated improved adaptability during variable load conditions and maintained consistent estimation reliability across different testing periods.

5.3 Comparative Performance Evaluation

Comparative analysis demonstrated that the proposed hybrid deep learning framework provided improved forecasting consistency and enhanced adaptability compared with conventional sequence-learning approaches. The integration of LSTM and GRU layers improved temporal feature extraction and enabled the forecasting framework to respond effectively to nonlinear renewable energy variations and fluctuating electricity demand conditions. The developed architecture also maintained stable learning behavior while reducing forecasting instability during dynamic operational intervals.

The hybrid network also benefited from dropout regularization, which reduced instability during training and minimized overfitting. Experimental observations revealed improved coefficient-of-determination values and reduced error dispersion compared with baseline forecasting models.

Table 4. Comparative analysis of forecasting approaches

Method	Forecasting Application	Performance Level	Computational Complexity	Key Advantage
ANN	Load estimation	Moderate	Moderate	Simpler implementation
CNN-LSTM	Renewable generation	High	High	Efficient feature extraction

GRU	Demand prediction	High	Moderate	Faster convergence
Hybrid LSTM-GRU	Combined estimation	Very High	Moderate	Stable prediction behavior

Table 4 provides a comparative assessment between the proposed forecasting framework and other commonly used prediction techniques. Traditional forecasting approaches often face difficulties when dealing with intermittent renewable energy behavior and rapidly changing environmental conditions. In comparison, the proposed hybrid deep learning model demonstrates improved adaptability and forecasting stability. The model achieves better prediction performance while maintaining reasonable computational requirements during training and testing stages. The results also indicate that integrating multiple recurrent learning mechanisms improves the capability of the forecasting framework to capture complex temporal patterns present in renewable energy datasets. Overall, the comparative analysis supports the suitability of the proposed approach for smart-grid forecasting and sustainable energy management applications.

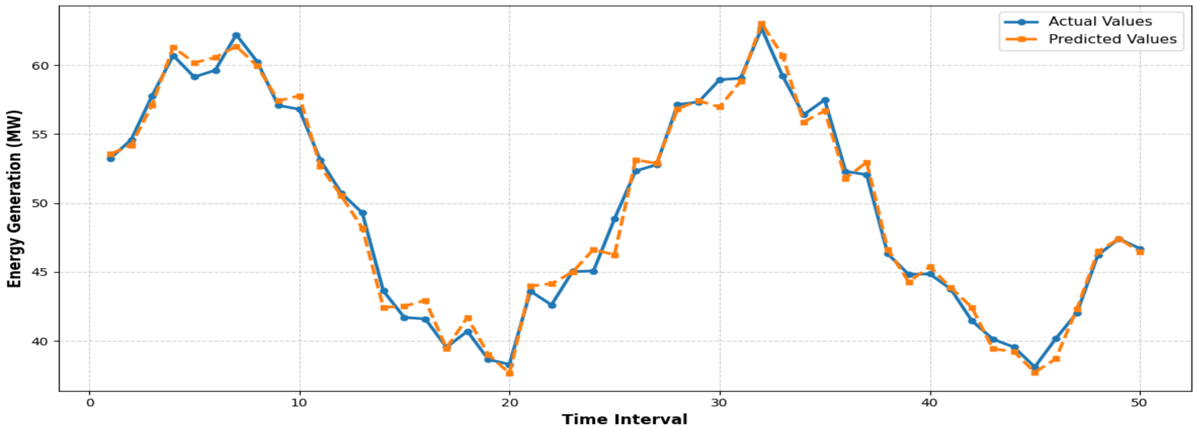

Figure 3. Actual and predicted renewable energy generation trends

Figure 3 compares the actual energy values with the predicted outputs obtained from the proposed forecasting framework. The prediction curves follow the overall trend of the measured data with relatively small deviations across most observation intervals. This indicates that the model is capable of learning the underlying temporal behavior of renewable energy generation and electricity demand patterns. Slight variations can be observed during sudden peak conditions, mainly because renewable energy systems are highly sensitive to rapid environmental changes. Even under these fluctuating conditions, the forecasting model maintains stable prediction behavior and avoids large prediction errors. The close similarity between measured and predicted values confirms the effectiveness of the hybrid deep learning approach for time-series renewable energy forecasting applications.

6. Challenges and Future Scope

Although the forecasting results were encouraging, several practical limitations were identified during experimentation. Renewable energy datasets frequently contained missing values, noise, and irregular environmental variations that affected learning consistency. Training complexity increased with larger sequence lengths and expanded dataset volumes. Short-term instability was also observed during abrupt weather transitions and sudden demand spikes.

Future investigations may focus on explainable artificial intelligence techniques, transformer-based sequence-learning systems, lightweight edge-computing implementations, and IoT-enabled forecasting infrastructures for real-time smart-grid applications. Additional research involving federated learning and adaptive optimization strategies may further improve scalability and operational reliability in distributed renewable energy networks.

7. Conclusions

This study presented a hybrid deep learning architecture for estimating renewable energy generation and electricity demand using operational and meteorological datasets collected from smart-grid environments. The investigation examined the capability of sequence-learning networks to process temporal information associated with renewable energy production and electricity consumption behavior. Experimental evaluation demonstrated that the integrated LSTM-GRU architecture demonstrated improved forecasting stability, estimation reliability, and enhanced temporal prediction behavior compared with conventional ANN, standalone LSTM, and GRU models. The developed system successfully captured short-term fluctuations as well as long-range temporal dependencies present within renewable energy datasets. In addition, the integration of meteorological variables improved learning efficiency and enhanced adaptability under varying environmental conditions. Minor prediction deviations were observed during abrupt weather changes and irregular load variations; however, the overall forecasting behavior remained consistent across most testing intervals. The findings indicate that intelligent sequence-learning systems can contribute significantly to efficient energy scheduling, smart-grid stability, and sustainable power-management operations. The developed framework may assist utility providers in improving load balancing, operational planning, and renewable energy integration within future intelligent power infrastructures. Future research may focus on explainable artificial intelligence, edge-based forecasting systems, and transformer-driven architectures capable of supporting large-scale real-time renewable energy management applications.

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