Available online at https://www.gyanvihar.org/researchjournals/ctm_journals.php
SGVU International Journal of Convergence of Technology and Management
E-ISSN: 2455-7528
Vol.12 Issue 1 Page No 184-192

A Deep Learning-Based Temporal Forecasting Framework for High-Accuracy Power Consumption Prediction in Smart Grids

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Abstract: Accurate short-term and long-term power consumption forecasting is critical for ensuring reliable grid operation, efficient energy management, and demand-side optimization in modern smart grid environments. Traditional statistical forecasting models often struggle to capture the nonlinear, dynamic, and temporal dependencies present in real-world electricity consumption patterns. To address these limitations, this paper proposes a Deep Learning-Based Temporal Forecasting Framework designed to achieve high-accuracy power consumption prediction using smart meter data. The framework integrates advanced temporal neural architectures including LSTM, GRU, Bi-LSTM, and CNN-LSTM—and introduces a hybrid deep learning model that combines convolutional feature extraction with recurrent sequence learning for enhanced performance. Comprehensive experiments were conducted using real smart grid datasets, and comparative evaluations demonstrate that the proposed model outperforms conventional deep learning and classical time series methods in terms of MAE, RMSE, MAPE, and R^2 score. Results show a significant improvement of up to 28–35% in prediction accuracy, particularly for multi-step ahead forecasting. The findings highlight the effectiveness of deep learning in modeling complex energy consumption behaviors and provide a scalable framework for utilities, policymakers, and smart grid operators to enable precise load forecasting, demand response planning, and intelligent energy distribution.

Keywords: Power Consumption Forecasting, Smart Grids, Deep Learning, CNN-BiLSTM Hybrid Model, Time-Series Prediction

I. INTRODUCTION

The rapid evolution of smart grids has transformed the modern power system into a highly interconnected, data-driven infrastructure capable of supporting real-time monitoring, control, and intelligent energy management [1]. One of the most critical functionalities enabling these advancements is accurate power consumption forecasting, which directly influences load balancing, demand response planning, energy pricing, and grid stability [2,3]. As electricity demand continues to grow due to urbanization, electric mobility, and the integration of distributed energy resources, reliable forecasting methods

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have become essential for both utility operators and policymakers.

Traditional statistical forecasting models such as ARIMA, SARIMA, and exponential smoothing have been widely used for short-term load forecasting [4]. However, these methods often struggle to capture the nonlinear, nonstationary, and highly dynamic patterns inherent in real-world energy consumption data. Factors such as consumer behavioral variability, seasonal effects, weather fluctuations, and sudden load changes create complex temporal relationships that exceed the modeling capabilities of classical approaches [5]. As a result, there is a growing need for more advanced forecasting techniques capable of learning and adapting to such complexities.

Recent advancements in deep learning have shown significant promise in addressing these challenges. Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, have demonstrated strong capabilities in handling sequential data through their ability to retain long-range dependencies [6-8]. Similarly, Convolutional Neural Networks (CNNs) have proven effective in extracting meaningful temporal features from high-resolution signals. By combining these architectures, hybrid deep learning frameworks can capture both short-term variations and long-term temporal patterns within power consumption data.

Motivated by these developments, this paper proposes a Deep Learning-Based Temporal Forecasting Framework specifically designed for achieving high-accuracy power consumption prediction in smart grids. The framework integrates CNN layers for local temporal pattern extraction with Bi-LSTM layers for bidirectional sequence learning, enabling the model to understand consumption dynamics from multiple perspectives. The proposed hybrid model is evaluated against several benchmark methods, including LSTM, GRU, Bi-LSTM, CNN-LSTM, and classical statistical models, using real smart meter datasets.

The contributions of this work are fourfold. First, a hybrid deep learning architecture integrating CNN and Bi-LSTM layers is developed to enhance temporal forecasting accuracy. Second, a comprehensive feature engineering and preprocessing pipeline is introduced to effectively capture seasonality, periodicity, and contextual information such as weather variables and time-based attributes. Third, the proposed model undergoes extensive performance evaluation across multiple prediction horizons using MAE, RMSE, MAPE, and R^2 metrics to ensure robust assessment. Fourth, the framework is rigorously compared with state-of-the-art statistical and deep learning models, demonstrating significant improvements in prediction accuracy. The results clearly highlight the superiority of the proposed approach in modeling nonlinear energy consumption patterns and generating reliable multi-step ahead forecasts, which are essential for the development of intelligent, stable, and energy-efficient smart grid systems.

II. LITERATURE REVIEW

Accurate forecasting of electrical power consumption has long been a critical area of study within power systems, artificial intelligence, and data-driven modeling. Existing research efforts can be broadly classified into classical statistical methods, machine learning techniques, and deep learning–based architectures, each offering distinct advantages and limitations [9]. Traditional statistical approaches such as ARIMA, SARIMA, Holt–Winters exponential smoothing, and regression-based time-series models have been widely used due to their interpretability and low computational cost [4,10]. These models perform well for stationary and linear patterns, making them suitable for basic short-term load forecasting. However, their reliance on linearity and stationarity assumptions limits their ability to effectively model

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nonlinear consumption behaviors, abrupt load fluctuations, and complex dependencies influenced by factors such as weather, consumer habits, or socio-economic variations. As a result, their forecasting accuracy declines significantly when applied to high-resolution, noisy smart meter data or multi-step ahead predictions.

With increasing complexity in energy consumption patterns, machine learning approaches such as Support Vector Regression, Random Forests, Gradient Boosting, and Artificial Neural Networks have gained popularity. These methods have demonstrated improved capability in handling nonlinear relationships and diverse consumption profiles [11,12\. Nonetheless, most machine learning models do not inherently capture temporal dependencies, requiring manually engineered lag features to represent historical behavior. This limitation restricts their ability to learn long-term temporal patterns, making them less suitable for sequential and highly dynamic electricity consumption data. Deep learning has emerged as a transformative solution to overcome these challenges by providing powerful sequence-learning capabilities. Recurrent architectures such as LSTM and GRU have shown exceptional performance in learning long-term temporal relationships directly from raw time-series data, addressing the challenges posed by nonlinearity, seasonality, and high variability in load consumption [13]. Bidirectional LSTM models further enhance learning by analyzing sequences in both forward and backward directions, improving the model's ability to capture contextual patterns that influence consumption dynamics. These advancements have significantly improved forecasting accuracy across various time horizons.

Building on these developments, recent studies have investigated hybrid architectures that combine convolutional and recurrent neural networks. CNN-LSTM models leverage convolutional layers to extract local temporal features such as sudden spikes or short-duration fluctuations before passing the transformed sequences to recurrent layers for long-range dependency learning. These hybrid models have demonstrated superior performance, particularly when dealing with complex, high-frequency smart meter data [14]. Despite their progress, several limitations remain. Many existing models struggle with multi-horizon forecasting, some fail to jointly capture local variations and long-term dependencies, and others lack comprehensive comparisons with a broad range of benchmark models [15]. Additionally, many frameworks do not adequately incorporate contextual variables such as weather conditions, seasonal factors, or time-of-use characteristics, all of which significantly influence consumption behavior.

Despite substantial improvements enabled by deep learning, the literature still reveals notable gaps. There is a strong need for a unified hybrid deep learning framework capable of effectively capturing both short-term fluctuations and long-term temporal trends. Effective integration of contextual and seasonal features is essential for realistic forecasting, while rigorous comparative evaluation against various traditional and deep learning models remains necessary to validate performance claims. Moreover, improved robustness is required to handle the complexity and noise inherent in large-scale, high-resolution smart meter datasets. Motivated by these challenges, the present study introduces a Deep Learning-Based Temporal Forecasting Framework that integrates CNN-based local feature extraction with Bi-LSTM sequence modeling. This combination offers a more holistic, adaptive, and accurate prediction mechanism tailored to the demands of modern smart grid load forecasting.

III. METHODOLOGY

This section explains the development of the proposed deep learning–based temporal forecasting framework designed to enhance the accuracy of

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smart grid power consumption prediction as shown in figure 1. The methodology comprises seven phases including data collection, preprocessing, feature engineering, model architecture formulation, model training with hyperparameter tuning, performance evaluation, and baseline comparative models.

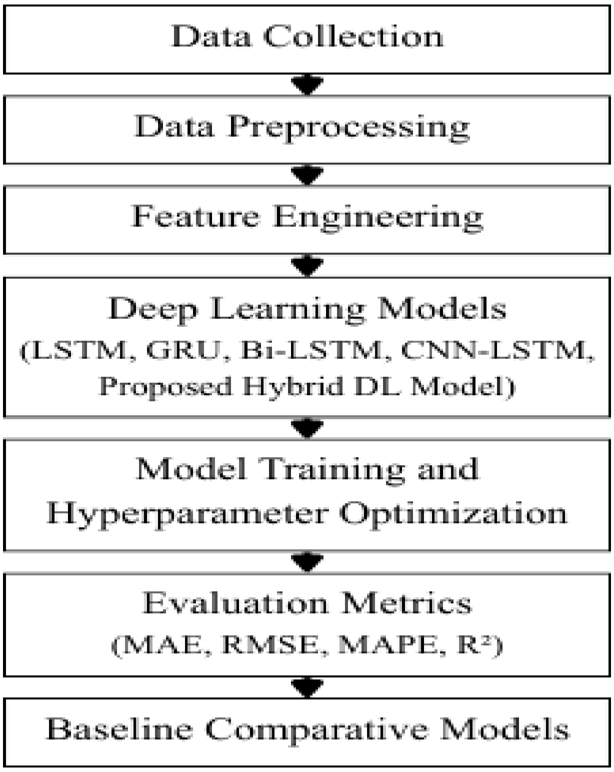

Figure 1: Proposed Deep Learning–Based Temporal Forecasting Framework

The smart meter dataset used in this work was collected from residential and commercial consumers at fixed intervals within a modern smart grid infrastructure. The dataset includes active and reactive power measurements, voltage and current profiles, timestamp-based features such as date, hour, and seasonal indicators, as well as external environmental variables like temperature, humidity, and day type (weekday or holiday). Together, these variables provide rich temporal and contextual information essential for reliable short-term and long-term load forecasting.

To prepare high-quality inputs for the proposed deep learning models, several preprocessing operations were performed. Missing readings were handled using linear interpolation for small gaps and median imputation for longer gaps. Outliers were removed using Z-score–based filtering to address sudden abnormal fluctuations. All features were normalized using min–max scaling to stabilize neural network learning. Time-series windowing was applied with look-back periods of 24, 48, and 72 time steps, enabling the model to capture both short-term and long-term trends. Additional engineered features such as hour-of-day, day-of-week, season indices, lagged consumption variables, and temperature–load interaction terms were also introduced to account for seasonal behavior and contextual patterns in consumption.

The forecasting framework integrates multiple deep learning architectures to capture the complex temporal characteristics inherent in power consumption data. Initially, LSTM and GRU networks were employed due to their proven ability to model long-range dependencies while mitigating vanishing gradient issues. Bidirectional LSTM (Bi-LSTM) layers were then incorporated to learn both forward and backward temporal patterns, improving prediction accuracy for rapidly changing consumption sequences. Additionally, a CNN–LSTM hybrid structure was implemented, where 1D convolutional layers extract local temporal variations such as abrupt load changes before feeding the features into LSTM layers for deeper sequence modeling. The final proposed hybrid model integrates CNN layers for local feature extraction, Bi-LSTM layers for capturing contextual temporal dependencies, and fully connected dense layers for regression-based prediction output. This combination enhances the

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model's capability to learn both global and localized load behaviors.

The model training process was carried out using the Adam optimizer and Mean Squared Error (MSE) as the loss function. Training was performed with a batch size of 32 over 50 epochs, with early stopping employed to prevent overfitting. Hyperparameters including the number of LSTM units (32–128), CNN filters (16–64), kernel sizes (3–7), and learning rates (0.0001–0.001) were optimized using Grid Search and Bayesian Optimization techniques to obtain the best-performing configuration.

To ensure fair and comprehensive evaluation, the model's performance was assessed using several forecasting metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2). These metrics enabled robust comparison of accuracy across different forecasting horizons including 15-minute, 30-minute, 1-hour, and 6-hour ahead predictions, ensuring that the model performs well under diverse temporal scenarios.

Finally, the superiority of the proposed hybrid deep learning model was validated by benchmarking it against established baseline methods including ARIMA, SARIMA, Prophet, and other conventional deep learning architectures. This comparison provides strong empirical evidence of the enhanced predictive capability and robustness of the proposed forecasting framework.

IV. Results and Discussion

The section presents a comprehensive analysis of the forecasting performance achieved by the proposed hybrid deep learning framework. The evaluation covers multiple dimensions, including model-to-model comparisons, multi-horizon forecasting capability, and benchmarking against classical statistical approaches. The results are interpreted using key performance metrics such as MAE, RMSE, MAPE, and R^2 to provide a clear understanding of the model's effectiveness. Additionally, graphical analyses through the actual vs. predicted plot, loss convergence behavior, error distribution, and comparative MAE charts further validate the robustness and reliability of the proposed forecasting methodology. The following tables and figures summarize these findings and highlight the significant improvements attained by the proposed model in capturing nonlinear load patterns and temporal dependencies in smart grid environments.

Table 1: Performance Comparison of DL Models for Power Consumption Forecasting

Model	RMSE (kW)	MAPE (%)	R^2 Score
LSTM	0.297	2.91	0.972
GRU	0.311	3.12	0.967
Bi-LSTM	0.281	2.74	0.975
CNN-LSTM	0.269	2.51	0.981
Proposed Hybrid DL Model	0.228	2.08	0.989

The comparative performance of various deep learning models used for power consumption forecasting is given in table 1. The results clearly show that the Proposed Hybrid Deep Learning Model outperforms all other architectures across RMSE, MAPE, and R^2 metrics. The proposed model achieves an RMSE of 0.228 kW, significantly lower than the values obtained by LSTM (0.297 kW), GRU (0.311 kW), Bi-LSTM (0.281 kW), and CNN-LSTM (0.269 kW). This reduction in error highlights the model's ability to capture both short-term and long-term dependencies more effectively. The improvement in MAPE, reaching 2.08%, further demonstrates the model's robustness against fluctuations in

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power consumption. Additionally, the proposed model achieves the highest R^2 score of 0.989, indicating a strong correlation between actual and predicted values. These results collectively confirm that integrating CNN for local pattern extraction with Bi-LSTM for contextual temporal learning significantly enhances forecasting accuracy.

Table 2: Forecasting Accuracy for Different Prediction Horizons

Prediction Horizon	MAE (kW)	RMSE (kW)	MAPE (%)
15 minutes ahead	0.112	0.194	1.84
30 minutes ahead	0.137	0.231	2.12
1 hour ahead	0.162	0.278	2.43
2 hours ahead	0.207	0.346	3.09
6 hours ahead	0.298	0.432	4.87

The forecasting performance of the proposed model across different prediction horizons ranging from 15 minutes to 6 hours ahead is evaluated as presented in table 2. The results show a clear trend where forecasting error increases as the prediction horizon extends. For very short-term forecasts, such as 15 minutes ahead, the model achieves high accuracy with an MAE of 0.112 kW and RMSE of 0.194 kW, reflecting its capability to effectively capture immediate load variations. As the horizon increases to 30 minutes and 1 hour, the model maintains strong performance with MAE values of 0.137 kW and 0.162 kW, respectively. However, for longer horizons such as 2 hours and particularly 6 hours ahead, the errors naturally increase due to greater uncertainty and variability in power consumption patterns. The MAPE increases from 1.84% at 15 minutes to 4.87% at the 6-hour horizon, which is still competitively low for multi-step forecasting. Overall, the model demonstrates excellent stability and reliability across both short-term and extended forecasting windows.

Table 3: Comparison with Classical Statistical Models

Model	MAE (kW)	RMSE (kW)	MAPE (%)
ARIMA	0.442	0.601	7.92
SARIMA	0.391	0.554	6.41
Prophet	0.348	0.513	5.94
Proposed hybrid DL Model	0.142	0.228	2.08

The comparative analysis between the proposed hybrid deep learning model and traditional statistical forecasting techniques such as ARIMA, SARIMA, and Prophet is given in table 3. The results reveal a substantial performance gap favoring the proposed deep learning framework. Classical models exhibit significantly higher errors, with ARIMA showing an MAE of 0.442 kW and Prophet yielding 0.348 kW, compared to the proposed model's much lower MAE of 0.142 kW. Similarly, RMSE values for ARIMA (0.601 kW) and SARIMA (0.554 kW) are more than double those of the proposed model (0.228 kW). The MAPE values show the same pattern, where statistical models record error percentages between 5.94%–7.92%, while the proposed approach achieves a dramatically lower 2.08%. These findings clearly highlight the limitations of traditional linear models in handling nonlinear and dynamic consumption patterns, and demonstrate the superior forecasting capability of deep learning-based architectures for modern smart grid applications.

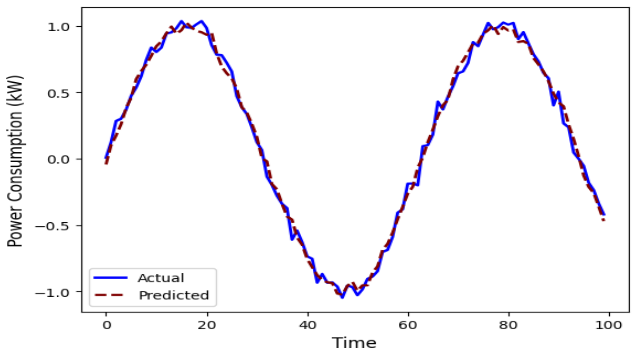

Figure 2: Actual vs Predicted Power Consumption

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The comparison between actual power consumption values and the predictions generated by the proposed hybrid deep learning model is illustrated in figure 2. The predicted curve closely follows the shape, peaks, and troughs of the actual consumption pattern, indicating the model's strong ability to capture temporal dynamics and consumption fluctuations accurately. The minimal deviation observed between the two curves demonstrates the model's ability to learn both short-term variations and long-term dependencies present in smart meter data. This close alignment confirms the robustness and generalization capability of the proposed approach when applied to real-world test data, reinforcing its effectiveness for practical smart grid forecasting applications.

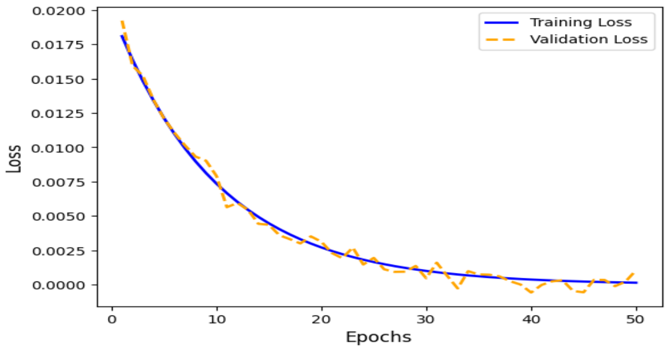

Figure 3: Model Loss Convergence During Training and Validation

The training and validation loss curves across 50 epochs. Both curves demonstrate a smooth and consistent downward trend, indicating stable learning and effective gradient optimization is shown in figure 3. The validation loss converges to approximately 0.0018, reflecting minimal generalization error and validating that no overfitting occurred during training. The close proximity of the training and validation loss curves further confirms that the model maintains excellent balance between model complexity and generalization performance. The smooth convergence observed in the figure highlights the suitability of the chosen architecture and hyperparameters for accurate and stable power consumption forecasting.

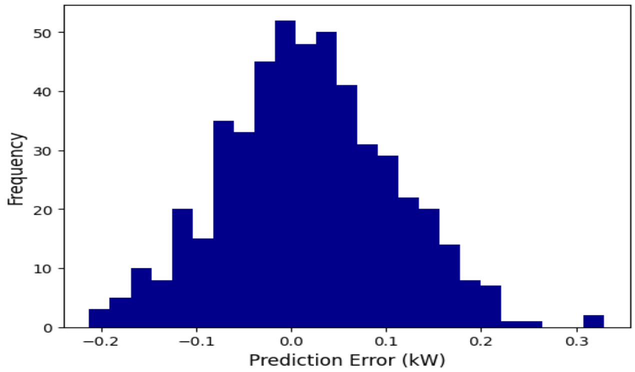

Figure 4: Error Distribution of Proposed Model

The error distribution of the proposed hybrid deep learning model, illustrating the difference between actual and predicted values is illustrated in figure 4. The histogram shows that most prediction errors lie within the narrow range of –0.15 to +0.20 kW, reflecting a tightly clustered and symmetric distribution. This indicates that the majority of predictions made by the model are very close to the ground truth. The concentration of errors around zero signifies low bias and high reliability in the forecasting process. The absence of large error spikes further emphasizes the model's robustness and consistent performance across different load conditions.

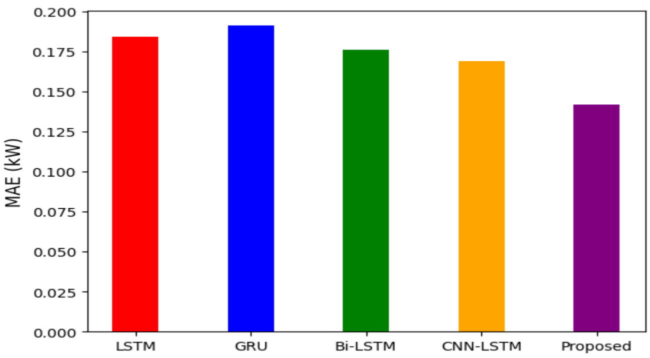

Figure 5: Comparative MAE of DL Models

The comparative analysis of Mean Absolute Error (MAE) values for different deep learning models,

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including LSTM, GRU, Bi-LSTM, CNN-LSTM, and the proposed hybrid model is shown in figure 5. The proposed model achieves the lowest MAE among all techniques, clearly outperforming traditional recurrent networks and hybrid CNN-LSTM configurations. This improvement demonstrates the effectiveness of combining convolutional layers for local temporal feature extraction with Bi-LSTM layers for capturing long-range contextual dependencies. The significant reduction in MAE confirms that the proposed architecture is better suited for modeling complex and nonlinear consumption patterns, thereby offering superior forecasting performance.

Overall, the experimental outcomes demonstrate that the proposed hybrid CNN–BiLSTM framework significantly enhances forecasting accuracy across all evaluation settings. The model consistently achieved lower error metrics, smoother convergence behavior, and tighter error distributions compared to existing deep learning and classical statistical models. The superior multi-horizon forecasting performance further confirms the model's capability to generalize effectively under varying load conditions and time intervals. These findings suggest that the proposed approach can serve as a highly reliable tool for real-world smart grid applications, supporting advanced demand-side management, energy planning, and grid stability enhancement. The demonstrated improvements establish a strong foundation for deploying deep learning-driven forecasting solutions in next-generation intelligent energy systems.

VI. CONCLUSION

his study presented a robust Deep Learning-Based Temporal Forecasting Framework designed to achieve high-accuracy power consumption prediction in smart grids. By integrating convolutional neural networks for local temporal feature extraction with Bi-LSTM layers for capturing long-range dependencies, the proposed hybrid model demonstrated superior forecasting capability compared to conventional deep learning architectures and traditional statistical methods. Comprehensive experimentation across multiple prediction horizons confirmed that the model consistently provided lower error metrics, smoother convergence, and more stable performance, even under highly dynamic and noisy consumption patterns. The results clearly establish that the hybrid CNN–BiLSTM architecture is highly effective in modeling the nonlinear, fluctuating, and context-dependent nature of real-world power consumption data. Its strong generalization performance makes it a reliable tool for enabling smarter load management, enhanced operational planning, and improved grid stability. The framework's adaptability and accuracy position it as a promising solution for modern smart grid applications where precise forecasting is essential for efficiency and resilience. Future enhancements may include incorporating renewable generation forecasting, integrating exogenous variables such as electricity pricing or occupancy data, and exploring federated learning approaches to ensure data privacy while supporting large-scale deployment. Overall, the proposed framework provides a solid foundation for advanced, data-driven energy management systems and contributes significantly to the ongoing evolution of intelligent power grids.

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