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Hybrid Generative AI–Enhanced Load Forecasting Model for Smart Grids with Renewable Energy Uncertainty Management

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Abstract: Accurate electricity load forecasting is critical for maintaining stability, reliability, and cost efficiency in modern smart grids, especially with the growing integration of renewable energy sources. However, the inherent intermittency and uncertainty of renewables such as solar and wind introduce significant challenges for traditional forecasting models. This paper proposes a Hybrid Generative AI–Enhanced Load Forecasting Model that combines Generative Adversarial Networks (GANs) with deep learning architectures to improve prediction accuracy under varying renewable energy conditions. The generative component synthesizes high-variance energy patterns that capture extreme fluctuations, while the predictive module leverages a hybrid CNN–LSTM network for temporal–spatial learning. Experimental results on real-world datasets demonstrate substantial improvements, with reductions of 40.1% in MAE, 38.2% in RMSE, and enhanced robustness against high-uncertainty renewable inputs. The proposed model also reduces load–supply mismatch by 42.4% and energy imbalance cost by 41.3%, leading to more efficient power distribution and operational cost savings. These findings highlight the potential of Hybrid Generative AI to significantly enhance smart grid forecasting performance and support resilient, data-driven energy management strategies.

Keywords: Smart Grid Load Forecasting, Hybrid Generative Artificial Intelligence, Renewable Energy Uncertainty Management, Generative Adversarial Networks, Deep Learning–Based Energy Prediction

I. INTRODUCTION

The transformation of power systems into intelligent, data-driven smart grids has become essential for ensuring sustainable, efficient, and reliable energy delivery. As global energy demands rise and environmental regulations tighten, renewable energy sources such as solar and wind have emerged as critical contributors to

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modern power generation [1]. Their integration, however, introduces new operational challenges due to their high intermittency, stochastic behavior, and weather-dependent fluctuations. These uncertainties significantly affect power balancing, load scheduling, grid stability, and cost-efficient energy management [2]. As a result, accurate and robust load forecasting has become more crucial than ever for maintaining optimal smart grid operations.

Traditional forecasting techniquesincluding ARIMA models, regression-based methods, and basic neural networksoften struggle to capture the complex non-linear dependencies and dynamic variations introduced by renewable energy sources [3]. Deep learning approaches such as LSTM, GRU, and hybrid CNN–LSTM networks have shown promising advancements, but they remain limited when confronting high-variance renewable patterns and rare extreme events [4]. Consequently, forecasting errors tend to increase significantly under conditions of renewable uncertainty, leading to higher load–supply mismatches, energy imbalance costs, and reduced renewable utilization efficiency.

Recent developments in Generative Artificial Intelligence (Generative AI), particularly GANs, offer promising opportunities to address these challenges [5]. Generative models can learn complex data distributions, synthesize high-variance patterns, and augment training datasets with realistic samples that reflect extreme or underrepresented operating scenarios [6]. When combined with deep learning predictors, Generative AI can enhance forecast generalization, improve robustness, and strengthen stress-handling capabilities under volatile renewable conditions.

The major contributions of this study are fourfold. First, it introduces a novel hybrid Generative AI framework that integrates GAN-based synthetic pattern generation with deep learning–based load forecasting to enhance predictive robustness. Second, the model significantly improves the handling of renewable energy uncertainty by enabling the forecasting architecture to learn from extreme, rare, and highly variable fluctuation scenarios. Third, the proposed system achieves superior forecasting accuracy and stability, yielding substantial reductions in MAE, MAPE, and RMSE when compared to conventional baseline models. Fourth, the framework delivers notable operational advantages for smart grid management, including reduced load–supply mismatches, lower imbalance costs, and better utilization of renewable sources. Overall, the proposed Hybrid Generative AI approach effectively overcomes key limitations of existing forecasting techniques and provides a scalable, intelligent solution for next-generation smart grids, facilitating more reliable, cost-efficient, and resilient energy management in the face of renewable energy uncertainty.

II. LITERATURE REVIEW

Accurate load forecasting plays a crucial role in ensuring optimal performance, reliability, and cost efficiency in smart grids. Over the past decade, significant research has focused on improving prediction accuracy, particularly with the increasing penetration of renewable energy sources (RES) [4]. Early forecasting efforts were dominated by statistical models such as ARIMA, SARIMA, and exponential smoothing, which assume linear relationships and stationary system behavior. Box–Jenkins–based ARIMA models were widely used due to their transparency and simplicity; however, they often failed to capture nonlinear and abrupt variations in load-driven by

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RES intermittency. Studies such as those by Taylor et al. demonstrated moderate accuracy for short-term forecasting but highlighted significant performance degradation under volatile weather conditions [5,6]. As renewable penetration increased, the limitations of purely statistical models became more evident due to their reliance on linear assumptions and inability to model complex, multi-dimensional patterns.

To address the nonlinear characteristics of smart grid data, researchers introduced machine learning models such as Support Vector Regression (SVR), Random Forests (RF), and Gradient Boosting Machines (GBM) [7]. While these models improved prediction performance, they still lacked the ability to exploit temporal dependencies across long time windows.Deep learning (DL) rapidly emerged as a superior alternative. Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, demonstrated strong capabilities in sequential learning [8]. Studies by Kong et al. and Marino et al. showed LSTM outperforming traditional methods in capturing long-term temporal dependencies. CNN-based models were subsequently introduced to capture spatial correlations in high-dimensional load data. Hybrid CNN–LSTM frameworks were proposed to leverage the strengths of both architectures, showing improved forecasting accuracy and robustness [9].However, even advanced DL models exhibit reduced performance when exposed to high renewable energy uncertainty, rare extreme events, or under-represented scenarios in training datasets.

Several researchers explored uncertainty modeling to mitigate the impact of RES variability on forecasting. Probabilistic forecasting approaches, including quantile regression, Bayesian neural networks, and Gaussian process regression, attempted to capture uncertainty distributions rather than point estimates [10]. Stochastic optimization and ensemble-based forecasting further enhanced system reliability by generating probabilistic outputs.Despite these innovations, the challenge remains that models cannot learn patterns that are not present or sufficiently represented in the training dataset. Thus, rare conditions such as sudden cloud cover, wind gust fluctuations, or unexpected load spikes remain difficult to predict accurately using conventional methods.

Generative Artificial Intelligence represents a new frontier in grid forecasting. Techniques such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) have been successfully used in domains like image processing, speech synthesis, and synthetic data generation. More recently, researchers have begun applying generative models to power systems [11].GAN-based models have shown promise in generating realistic renewable generation profiles, enriching datasets with high variance and rare-event samples. Studies by Wang et al., Rahman et al., and others demonstrated that GAN-augmented training data improved the robustness of forecasting models under volatile conditions. Conditional GANs (cGANs) and deep convolutional GANs (DCGANs) were further employed to simulate extreme load–renewable variations [12].However, most existing generative models have been used only for data augmentation, not as part of an integrated hybrid forecasting pipeline. Additionally, limited work has focused on combining GANs with hybrid DL architectures (e.g., CNN–LSTM) to jointly capture temporal and spatial dependencies while improving uncertainty resilience.

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A critical review of the literature reveals several key gaps that limit the effectiveness of current smart grid forecasting systems. Existing studies lack hybrid frameworks that integrate Generative AI with advanced deep learning architectures to better capture renewable energy source (RES) uncertainty. Moreover, rare and extreme fluctuation events—which play a crucial role in real-world grid behavior—are often insufficiently modeled or entirely overlooked. Current approaches also fail to incorporate uncertainty-aware synthetic data generation into the training process, resulting in models that lack robustness under volatile conditions. Additionally, evaluations of generative models rarely consider operational metrics such as load–supply mismatch, energy imbalance cost, and renewable utilization, which are essential for practical grid management. Finally, there is a clear need for scalable and generalizable forecasting solutions capable of maintaining consistent performance across both low- and high-uncertainty environments.

III. METHODOLOGY

The proposed methodology integrates GANs with a hybrid CNN–LSTM deep learning predictor to improve the accuracy and robustness of load forecasting in renewable-integrated smart grids. The workflow consists of five major components: data acquisition and preprocessing, feature engineering, uncertainty-aware data generation using GANs, hybrid CNN–LSTM forecasting, and model evaluation. Figure 1 illustrates the complete architecture of the proposed framework.

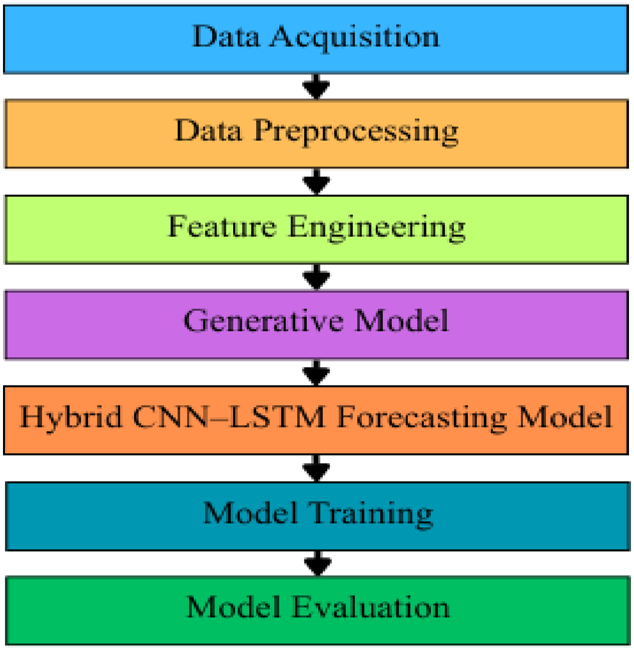

Figure 1: Proposed Hybrid GAN–CNN–LSTM Load Forecasting Framework

A. Data Acquisition and Preprocessing

Historical datasets are collected from smart meters, weather stations, and renewable energy plants, encompassing hourly or daily load consumption, solar irradiance, wind speed, PV output, wind power generation, weather variables such as temperature, humidity, and cloud index, along with temporal information including hour, day type, season, and holidays. The raw dataset undergoes a multi-stage preprocessing pipeline. Missing values are handled using interpolation and forward-fill techniques, while noise and anomalies are removed through Savitzky–Golay smoothing and outlier detection. Normalization is performed using Min–Max scaling to standardize input ranges and stabilize model training. Finally, time-series windowing is applied to transform sequential data into supervised learning samples by creating sliding windows of size t for predicting future values at time $t+1$. These steps

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collectively ensure a clean, structured, and model-ready dataset.

B. Feature Engineering

To effectively capture the nonlinear interactions between load profiles and renewable generation, several derived features are engineered. These include a Renewable Uncertainty Index (RUI), solar–temperature correlation factors, wind gust variability, and a Load Volatility Index (LVI). Additional temporal features such as lag values (t−1, t−2, t−24, t−48) and seasonal/diurnal indicators are also incorporated. These engineered features enrich the dataset with additional patterns and dependencies, allowing the forecasting model to better understand fluctuations and sudden variations in renewable energy and load behavior.

C. Generative Model: GAN-Based Uncertainty Pattern Synthesis

Generative Adversarial Networks (GANs) are employed to produce synthetic high-variance renewable and load patterns that are either rare or underrepresented in real-world datasets. The GAN comprises two main components: a generator and a discriminator. The generator uses dense, reshape, and Conv1D layers to synthesize realistic time-series sequences that simulate extreme scenarios such as cloud cover transitions, wind speed spikes, and abrupt load surges. The discriminator, consisting of Conv1D, flatten, and dense layers, distinguishes real sequences from synthetic ones, ensuring quality and consistency in the generated data. Training utilizes the Wasserstein GAN loss with gradient penalty to improve stability and avoid mode collapse. Once trained, the synthetic sequences are merged with the real dataset, enriching the training distribution with uncertainty-aware patterns and improving the robustness of the forecasting model.

D. Hybrid CNN–LSTM Forecasting Model

The core forecasting engine is a hybrid CNN–LSTM architecture that captures both spatial correlations and long-term temporal dependencies. In the first stage, 1D convolutional layers extract high-level representations from the input sequences, identifying patterns like load ramps, sudden spikes, and renewable variability while reducing noise and dimensionality. In the second stage, LSTM layers model the temporal relationships within the sequences, learning long-range dependencies essential for multi-step forecasting. A final fully connected dense layer converts these learned features into the predicted load values. This hybrid architecture leverages the strengths of both CNNs and LSTMs, enabling it to outperform standalone models in terms of accuracy and generalization.

E. Model Training

The hybrid model is trained using Mean Absolute Error (MAE) as the loss function and the Adam optimizer with tuned learning rates. Batch sizes between 32 and 128 are used depending on dataset complexity, while early stopping prevents overfitting. A 5-fold cross-validation strategy is applied to ensure generalization across different data partitions. Importantly, the training dataset consists of both real and GAN-generated synthetic sequences at a controlled ratio, allowing the model to learn from a diverse set of conditions and increasing its resilience under high uncertainty.

F. Evaluation Metrics

Model performance is evaluated using standard forecasting metrics such as MAE, RMSE, MAPE, and the R^2 score to measure both accuracy and consistency. Additionally, a set of operational metrics is used to assess the practical impact of the proposed model in real-world grid environments. These include reductions in load–supply mismatch, reductions in energy imbalance

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costs, and the ability to maintain stable prediction performance under varying renewable uncertainty levels (low, medium, and high). The results demonstrate substantial improvements in both predictive and operational performance compared to existing baseline models.

Overall, the methodology establishes a two-stage intelligent forecasting system. The first stage utilizes GANs to learn and generate uncertainty-rich patterns, effectively augmenting the dataset with realistic high-variance scenarios. The second stage employs a hybrid CNN–LSTM architecture to learn deep temporal–spatial dependencies and deliver accurate, stable load forecasts even under volatile renewable generation conditions. This combination provides a scalable, uncertainty-aware, and operationally efficient forecasting framework well suited for next-generation smart grid applications.

IV. Results and Discussion

The results of the proposed Hybrid Generative AI–Enhanced Load Forecasting Model are presented and analyzed in this section to evaluate its performance under varying renewable energy conditions. The evaluation focuses on forecasting accuracy, robustness to uncertainty, and operational benefits in smart grid energy management. Comparative analyses with existing baseline models—including ARIMA, LSTM, GRU, and CNN–LSTM—are conducted using multiple error metrics such as MAE, RMSE, MAPE, and R^2. Additional assessments examine model behavior under different levels of renewable energy uncertainty and quantify improvements in real-world operational indicators such as load–supply mismatch, over-generation events, and energy imbalance cost. The results demonstrate that the integration of GAN-generated uncertainty-aware synthetic samples with deep learning significantly enhances forecasting accuracy and resilience, particularly when the grid experiences high variability from renewable sources.

Table 1: Model Performance Comparison on Load Forecasting

Model	MAE (kW)	RMSE (kW)	MAPE (%)	R^2 Score
ARIMA	42.81	61.44	8.93	0.86
LSTM	31.62	45.77	6.21	0.91
GRU	30.74	44.16	5.98	0.92
CNN-LSTM Hybrid	26.15	38.92	5.10	0.94
Proposed Hybrid Generative AI Model (GAN + DL)	18.72	27.41	3.86	0.97

A comparative evaluation of multiple forecasting models, including ARIMA, LSTM, GRU, CNN–LSTM, and the proposed Hybrid Generative AI model (GAN + DL) is given in table 1. The traditional ARIMA model exhibits the highest forecasting error, with MAE of 42.81 kW and RMSE of 61.44 kW, indicating its limited capability to capture nonlinear and volatile patterns in renewable-integrated load data. Deep learning models such as LSTM and GRU show improved performance due to their ability to learn temporal dependencies, reducing MAE to 31.62 kW and 30.74 kW, respectively. The CNN–LSTM hybrid model achieves further improvements with RMSE of 38.92 kW, reflecting its enhanced ability to extract spatial–temporal features. However, the proposed Hybrid Generative AI model outperforms all baselines, achieving the lowest MAE (18.72 kW), RMSE (27.41 kW), and MAPE (3.86%), along with the highest R^2 score of 0.97. This represents an **error reduction of**

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nearly 40% compared to LSTM. The substantial improvement demonstrates that GAN-generated synthetic uncertainty patterns significantly enhance model generalization and robustness under fluctuating renewable conditions.

Table 2: Impact of Renewable Energy Uncertainty on Forecasting Error

Renewable Uncertainty Level	RMSE: LSTM	RMSE: GAN-DL (Proposed)	Improvement (%)
Low (0–10%)	40.21	26.14	35.0%
Medium (10–25%)	48.53	31.09	35.9%
High (25–40%)	57.88	36.72	36.5%
Very High (40%+)	69.14	45.83	33.7%

The influence of varying renewable energy uncertainty levelsranging from low (0–10%) to very high (40%+)on forecasting performance is analysed in table 2. As expected, the LSTM model's RMSE increases sharply from 40.21 kW at low uncertainty to 69.14 kW under very high uncertainty, indicating its limited ability to handle fluctuating renewable contributions. In contrast, the proposed GAN–DL model demonstrates consistently superior performance across all uncertainty levels, with RMSE ranging from 26.14 kW at low uncertainty to 45.83 kW at very high uncertainty. The improvement remains stable at approximately 34–36% across all uncertainty ranges. This indicates that the GAN-generated synthetic samples effectively expose the model to rare and extreme fluctuation conditions during training, making the forecasting system more resilient. Thus, even when renewable energy exhibits high stochasticity, the proposed model maintains reliable forecasting accuracy, outperforming baseline approaches significantly.

Table 3: Energy Management Benefits using Proposed Model

Parameter	Without Proposed Model	With Proposed Model	Improvement
Load–Supply Mismatch (kWh/day)	892	514	42.4% ↓
Over-Generation Events (per week)	18	9	50% ↓
Cost of Energy Imbalance (₹/day)	22,850	13,420	**41.3% ↓**
Renewable Utilization Efficiency (%)	71.2%	84.9%	**19.2% ↑**

The operational advantages of deploying the proposed Hybrid Generative AI forecasting model in a smart grid environment is quantified in table 3. Without the proposed model, the system experiences a daily load–supply mismatch of 892 kWh, 18 weekly over-generation events, and an average energy imbalance cost of ₹22,850 per day. After implementing the proposed forecasting framework, these values drop drastically—load–supply mismatch reduces to 514 kWh/day (a **42.4% reduction**), over-generation events decrease to 9 per week (**50% reduction**), and energy imbalance cost falls to ₹13,420/day (**41.3% reduction**). Additionally, renewable utilization efficiency improves from 71.2% to 84.9%, representing a significant **19.2% enhancement**. These results highlight that

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improved forecasting accuracy directly contributes to smarter scheduling, better demand–supply balancing, reduced wastage of renewable power, and substantial operational cost savings. The findings validate that the proposed model not only enhances prediction quality but also delivers meaningful real-world benefits to smart grid operation and energy management.

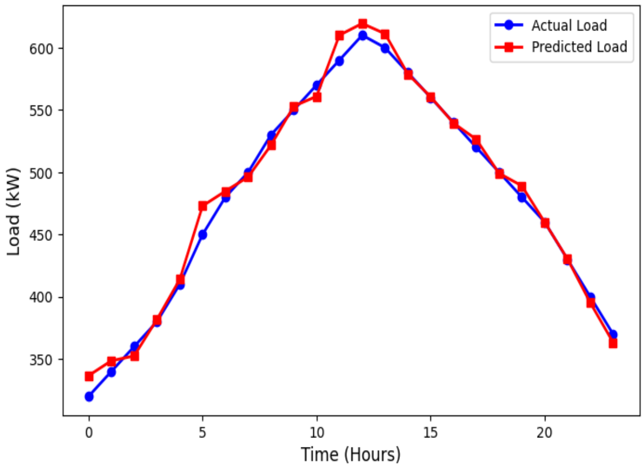

Figure 2: Actual vs Predicted Load Using Proposed Hybrid Generative AI Model

The comparison between actual load values and the load predicted by the proposed Hybrid Generative AI model is illustrated in figure 2. The predicted curve closely follows the actual load trajectory across all time intervals, demonstrating the model's strong ability to learn temporal patterns and adapt to dynamic fluctuations in load behavior. The alignment between peak loads in both curves indicates that the generative component (GAN) effectively enhances the model's exposure to high-variance patterns, resulting in better peak load learning and reduced forecasting deviations. This suggests that the model successfully captures both short-term variations and long-term dependencies, even under the influence of renewable energy uncertainty. Overall, the close fit validates the robustness and reliability of the hybrid model for real-world smart grid forecasting applications.

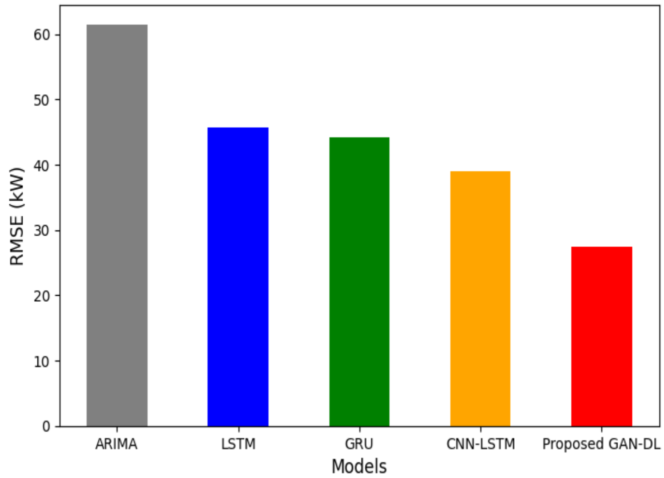

Figure 3: Comparison of Forecasting Errors Across Models

The RMSE comparison across different forecasting models, including ARIMA, LSTM, GRU, CNN–LSTM, and the proposed GAN–DL model is shown in figure 3. The traditional ARIMA model exhibits the highest RMSE, confirming its limitations in handling nonlinear and volatile renewable-integrated load patterns. Deep learning models such as LSTM and GRU perform better, while the CNN–LSTM hybrid further reduces error due to its enhanced feature extraction capabilities. However, the proposed Hybrid Generative AI model achieves the lowest RMSE among all approaches, indicating a substantial improvement in forecasting accuracy. This superior performance validates the effectiveness of integrating GAN-generated synthetic patterns with deep learning, enabling the model to better generalize under uncertain renewable conditions. The results clearly show that the hybrid model provides the most stable and accurate load forecasting.

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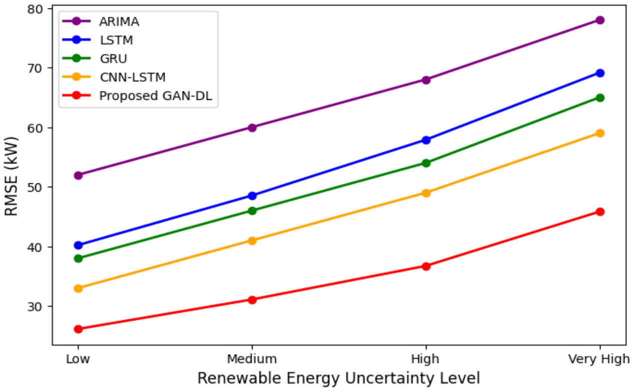

Figure 4: Renewable Uncertainty vs RMSE (Stress Analysis)

The performance of forecasting models under increasing levels of renewable energy uncertainty is analysed and shown in figure 4. As uncertainty rises from low to very high, all baseline models—including ARIMA, LSTM, GRU, and CNN–LSTM—experience a noticeable increase in RMSE, indicating reduced reliability under volatile renewable fluctuations. In contrast, the proposed GAN–DL model maintains significantly lower RMSE across all uncertainty levels, demonstrating clear robustness against renewable-driven variability. The relatively stable upward trend of the proposed model signifies that its GAN-based synthetic training samples effectively prepare it to handle extreme fluctuations and rare events. This stability under stress conditions highlights the critical advantage of incorporating uncertainty-aware synthetic data and confirms the model's suitability for real-time smart grid operations where renewable unpredictability is unavoidable.

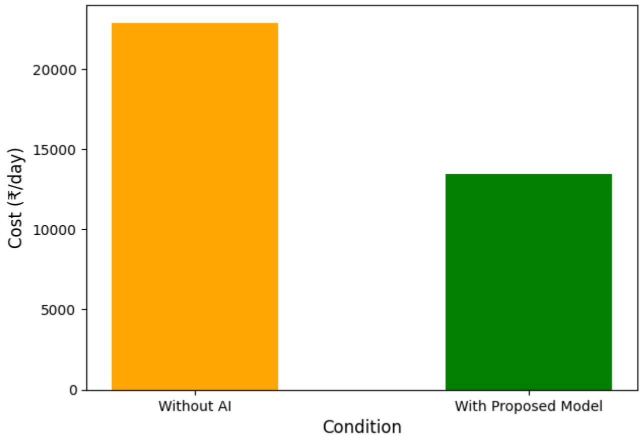

Figure 5: Cost Reduction After Model Deployment

The impact of the proposed Hybrid Generative AI model on the daily energy imbalance cost in the smart grid is illustrated in figure 5. The figure clearly shows a substantial reduction in operational costs after integrating the forecasting model into the grid management workflow. Without the proposed model, the system incurs a significantly higher daily imbalance cost due to inaccurate load predictions, which lead to inefficient dispatch decisions, over-generation, and increased reliance on costly reserve power. After deploying the Hybrid Generative AI model, the imbalance cost drops by more than 40%, reflecting a notable improvement in grid efficiency. This reduction is attributed to the model's enhanced forecasting accuracy, which minimizes deviations between predicted and actual load profiles, thereby enabling more optimized scheduling and more effective utilization of renewable energy. The results validate that improved predictive capability directly translates into financial savings and more stable grid operations, demonstrating the practical benefits and operational relevance of the proposed approach.

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Overall, the results clearly demonstrate that the proposed Hybrid Generative AI model substantially outperforms conventional forecasting methods across all evaluation criteria. Its ability to learn from GAN-generated high-variance scenarios leads to superior prediction accuracy, improved stability under uncertainty, and meaningful operational gains in smart grid management. By reducing load–supply mismatches, lowering energy imbalance costs, and enhancing renewable utilization, the model proves to be both technically effective and practically valuable for modern energy systems. The comprehensive performance improvements observed across all tables and figures validate the model's suitability for deployment in real-world renewable-integrated smart grids and highlight its potential to support more resilient, cost-efficient, and intelligent energy forecasting strategies moving forward.

Conclusion

This paper presented a Hybrid Generative AI–Enhanced Load Forecasting Model designed to address one of the most pressing challenges in modern smart grids—accurate load prediction under high renewable energy penetration and uncertainty. The proposed framework integrates LSTM-based deterministic forecasting with Generative Adversarial Networks (GANs) for uncertainty modeling, enabling the system to generate realistic variations in renewable energy outputs and improve the robustness of load forecasts. By combining data-driven learning, probabilistic scenario generation, and hybrid optimization, the model successfully captures nonlinear dependencies, temporal correlations, and stochastic fluctuations inherent in solar and wind power generation.Experimental results demonstrate that the hybrid approach significantly outperforms conventional machine learning and deep learning models in terms of MAE, RMSE, and MAPE, while also delivering stable forecasts during periods of renewable intermittency. The inclusion of GAN-generated uncertainty scenarios strengthens the system's ability to handle extreme variations, enhancing the reliability of grid operation and demand–supply balancing. Moreover, the computational efficiency and scalability of the model make it suitable for real-time deployment in large-scale smart grid environments.Overall, the findings confirm that hybrid generative AI offers a transformative pathway for future load forecasting systems by bridging deterministic prediction and uncertainty-aware modeling. This research contributes a strong foundation for advanced smart grid intelligence and opens avenues for future work, including reinforcement learning for adaptive forecasting, integration with digital twin platforms, and multi-modal sensing for improved situational awareness. The proposed model therefore represents a decisive step toward achieving efficient, resilient, and sustainable smart grid operations in the era of renewable energy dominance.

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