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

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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 modern power generation [1]. Their integration, however, introduces new operational challenges due to their high intermittency, stochastic behaviour, and weather-dependent fluctuations.

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.

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 behaviour. 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 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

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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.

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.

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.

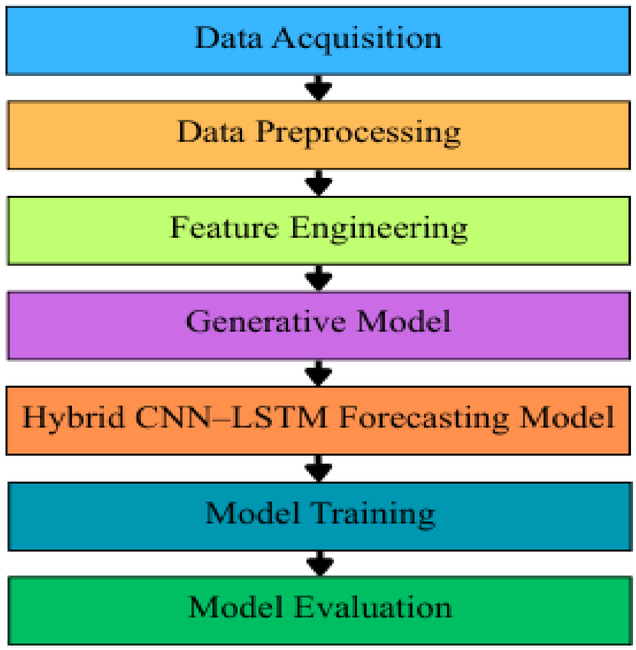

Figure 1: Proposed Hybrid GAN–CNN–LSTM Load Forecasting Framework

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

2. 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 behaviour.

3. 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. 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.

4. 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.

5. 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.

6. 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 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.

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. 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 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. 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 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.

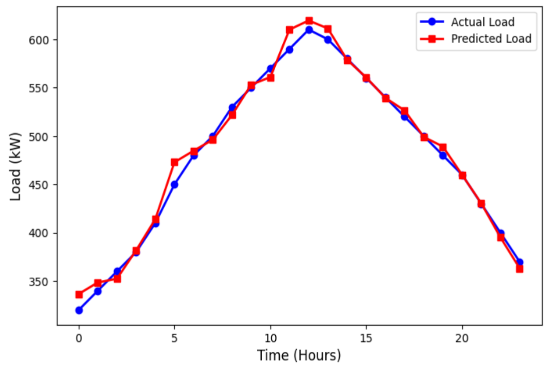

Figure 2: Actual vs Predicted Load Using Proposed Hybrid Generative AI Model

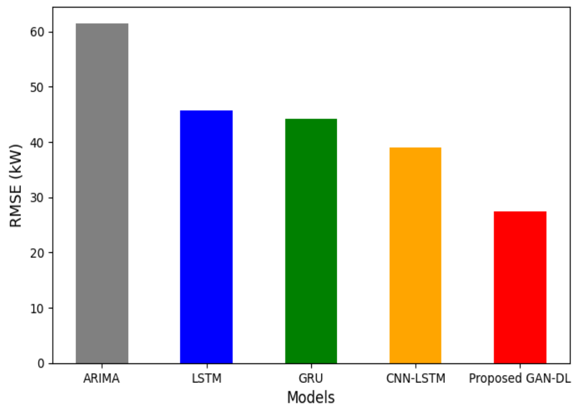

Figure 3: Comparison of Forecasting Errors Across Models

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. The results clearly show that the hybrid model provides the most stable and accurate load forecasting.

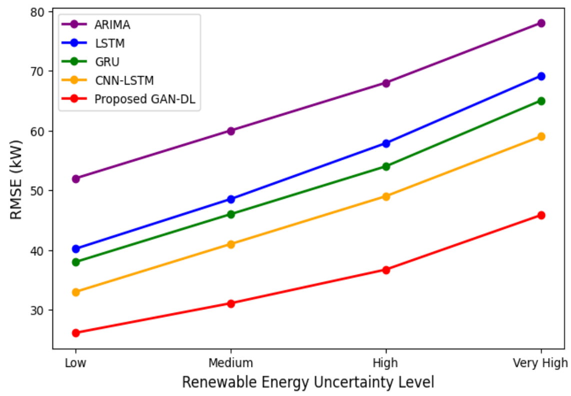

Figure 4: Renewable Uncertainty vs RMSE (Stress Analysis)

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. 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.

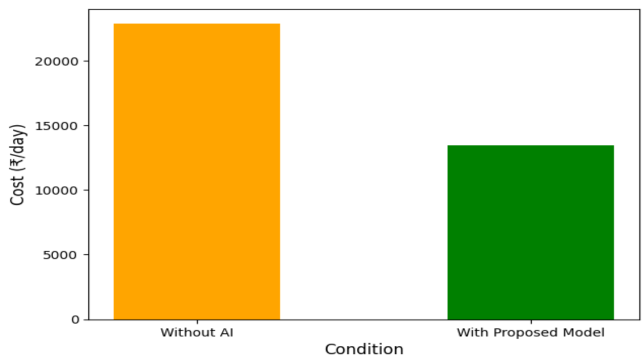

Figure 5: Cost Reduction After Model Deployment

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.

V. 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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