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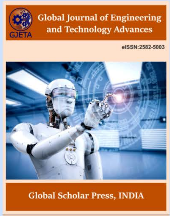

(Research Article)

Hybrid generative AI–driven demand–supply balancing and energy management for renewable-integrated smart grids

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Abstract

The increasing penetration of renewable energy sources introduces significant uncertainty and intermittency in smart grid operations, leading to frequent demand–supply imbalances and inefficient energy management. To address these challenges, this paper proposes a Hybrid Generative AI–Driven framework for demand–supply balancing and energy management in renewable-integrated smart grids. The proposed approach combines deep learning–based forecasting with generative modeling to accurately capture stochastic renewable generation patterns and dynamically coordinate power demand and supply. An AI-driven energy management strategy is further employed to optimize power distribution, reduce peak load stress, and minimize operational costs. The effectiveness of the proposed framework is evaluated using real-world load demand and renewable generation datasets and compared against conventional statistical and deep learning models. Experimental results demonstrate that the proposed method significantly reduces demand–supply deviations, improves grid stability, and enhances power distribution efficiency. Moreover, the optimized energy management strategy achieves substantial peak load reduction and operational cost savings while reducing renewable energy curtailment. The results confirm that Hybrid Generative AI provides a robust and scalable solution for balancing demand and supply and improving energy management in modern renewable-integrated smart grids.

Keywords: Hybrid Generative AI; Demand–Supply Balancing; Energy Management; Renewable-Integrated Smart Grids; Load Forecasting

1. Introduction

The rapid transition toward low-carbon power systems has significantly increased the penetration of renewable energy sources such as solar and wind in modern smart grids. While renewable integration plays a crucial role in reducing greenhouse gas emissions and enhancing energy sustainability, its inherent intermittency and stochastic nature introduce severe operational challenges [1]. Unpredictable variations in renewable generation often lead to demand–supply imbalances, frequency deviations, increased reserve requirements, and inefficient energy utilization, thereby threatening grid stability and economic performance. Accurate demand–supply coordination is a fundamental requirement for reliable smart grid operation [2]. Traditional load forecasting and energy management approaches, including statistical methods and rule-based energy management systems, are largely inadequate in handling the nonlinear dynamics and high uncertainty associated with renewable-integrated power systems [3]. These methods typically rely on historical averages and predefined control rules, resulting in delayed responses to rapid fluctuations

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in renewable generation and load demand [4]. Consequently, power imbalance events, renewable energy curtailment, and increased operational costs remain persistent issues in existing smart grid infrastructures.

In recent years, artificial intelligence (AI) and deep learning (DL) techniques have been widely adopted to enhance load forecasting and energy management performance [5]. Models such as long short-term memory (LSTM), gated recurrent units (GRU), and convolutional neural networks (CNNs) have demonstrated improved forecasting accuracy by capturing temporal and nonlinear patterns in power system data [6]. However, most of these approaches are fundamentally predictive in nature and are limited in their ability to model the stochastic behavior of renewable energy sources. As a result, they often fail to generate realistic future scenarios required for proactive demand–supply balancing and optimal energy scheduling. Generative AI models, including generative adversarial networks (GANs) and variational autoencoders (VAEs), have emerged as powerful tools for learning complex data distributions and generating realistic synthetic samples [7]. In the context of smart grids, generative models can effectively capture uncertainty in renewable generation and load profiles, enabling scenario-based forecasting and robust decision-making. Nevertheless, standalone generative models lack deterministic forecasting capability and may suffer from training instability, limiting their direct applicability to real-time grid operations.

This paper proposes a Hybrid Generative AI–Driven framework for demand–supply balancing and energy management in renewable-integrated smart grids, which integrates deep learning–based predictive models with generative AI techniques to jointly exploit accurate point forecasting and probabilistic scenario generation. By leveraging this hybrid architecture, the proposed framework proactively mitigates demand–supply mismatches caused by renewable variability while enabling intelligent energy management strategies for efficient power distribution and cost optimization. The key contributions of this work include the development of a hybrid generative AI framework that effectively captures renewable uncertainty and improves demand–supply coordination, the design of an AI-driven demand–supply balancing strategy that minimizes power imbalance and enhances grid stability under high renewable penetration, and the implementation of an optimized energy management mechanism that improves power distribution efficiency, reduces peak load stress, and lowers operational costs. Furthermore, comprehensive performance evaluation using real-world datasets demonstrates that the proposed approach achieves superior demand–supply balancing accuracy, enhanced energy management efficiency, and significant cost savings compared to conventional and deep learning–based methods.

The remainder of this paper is organized as follows. Section II reviews related work on AI-based load forecasting and energy management in renewable-integrated smart grids. Section III describes the proposed Hybrid Generative AI framework and energy management strategy. Section IV discusses the results and comparative analysis. Finally, Section V concludes the paper and outlines future research directions.

2. Literature review

This section reviews existing research on demand–supply balancing and energy management in renewable-integrated smart grids, with a focus on statistical methods, machine learning and deep learning approaches, and emerging generative AI techniques. The limitations of current methods are also discussed to motivate the proposed hybrid framework.

Conventional approaches for load forecasting and energy management in power systems are primarily based on statistical and rule-based techniques, including autoregressive integrated moving average (ARIMA), exponential smoothing, and optimization-based energy management systems [5]. These methods have been widely used due to their simplicity and low computational requirements. However, their performance significantly degrades under high renewable penetration, as they rely on linear assumptions and historical averages that fail to capture the nonlinear and stochastic behavior of renewable generation [6]. Moreover, rule-based energy management strategies lack adaptability and often result in delayed responses to rapid fluctuations, leading to power imbalance, increased reserve deployment, and higher operational costs.

To overcome the limitations of traditional techniques, machine learning (ML) and deep learning (DL) models have been extensively explored for load forecasting and smart grid optimization. Support vector regression (SVR), random forests, and k-nearest neighbor models have shown improved forecasting accuracy by learning nonlinear relationships between load demand, weather conditions, and renewable generation. More recently, DL architectures such as long short-term memory (LSTM), gated recurrent units (GRU), convolutional neural networks (CNNs), and hybrid CNN–LSTM models have achieved superior performance in short-term and medium-term load forecasting [7]. Despite these advancements, most ML- and DL-based approaches focus solely on point forecasting and are limited in their ability to quantify uncertainty and variability inherent in renewable energy sources [8]. Consequently, these models are often insufficient for proactive demand–supply balancing and robust energy management, particularly under extreme weather events or high renewable volatility.

AI-driven energy management systems (EMS) have been proposed to optimize power distribution, peak load reduction, and cost minimization in smart grids. Reinforcement learning (RL) and optimization-based frameworks have been applied for demand response, energy scheduling, and storage management [9]. While RL-based methods demonstrate adaptability and learning capability, they typically require extensive training data and suffer from convergence and stability issues in large-scale power systems. Furthermore, many existing EMS approaches operate independently of advanced forecasting mechanisms, limiting their effectiveness in anticipating renewable-driven fluctuations.

Generative AI models, including generative adversarial networks (GANs), variational autoencoders (VAEs), and diffusion models, have recently gained attention for modeling uncertainty in renewable energy generation and load profiles. GAN-based approaches have been used to generate realistic solar and wind power scenarios, enabling probabilistic forecasting and scenario-based analysis [10]. VAEs have also been applied for capturing latent representations of renewable variability and synthetic data generation. Although generative models offer significant advantages in uncertainty modeling, their standalone use in smart grid applications remains limited [11]. Generative models often lack deterministic prediction capability and may exhibit training instability, making them unsuitable for real-time demand–supply coordination without additional predictive mechanisms.

Recent studies have explored hybrid AI architectures that combine multiple learning paradigms to improve forecasting robustness and energy management efficiency. Hybrid models integrating ML, DL, and optimization techniques have shown improved performance compared to single-model approaches [12]. However, most existing hybrid frameworks do not fully exploit the complementary strengths of predictive deep learning and generative AI. Specifically, limited research has focused on integrating generative models with forecasting networks for simultaneous demand–supply balancing and energy management optimization in renewable-integrated smart grids. Furthermore, many existing studies evaluate forecasting accuracy in isolation, without assessing the downstream impact on energy management performance, grid stability, and operational cost reduction [13]. This lack of holistic evaluation highlights a critical research gap in developing integrated frameworks that jointly address demand–supply balancing and energy management objectives.

The existing methods either focus on accurate load forecasting or energy management optimization, but rarely address both aspects in a unified framework under renewable uncertainty. The need for a robust, scalable, and proactive solution that integrates uncertainty-aware forecasting with intelligent energy management motivates the proposed research. This paper addresses the identified gaps by introducing a Hybrid Generative AI–Driven framework that combines deep learning prediction with generative modeling to achieve effective demand–supply balancing and optimized energy management in renewable-integrated smart grids.

3. Methodology

The proposed methodology presents a Hybrid Generative AI–Driven framework designed to achieve robust demand–supply balancing and optimized energy management in renewable-integrated smart grids is shown in figure 1. The framework integrates deterministic deep learning–based forecasting with probabilistic generative modeling and an AI-driven energy management strategy to proactively mitigate renewable-induced uncertainties.

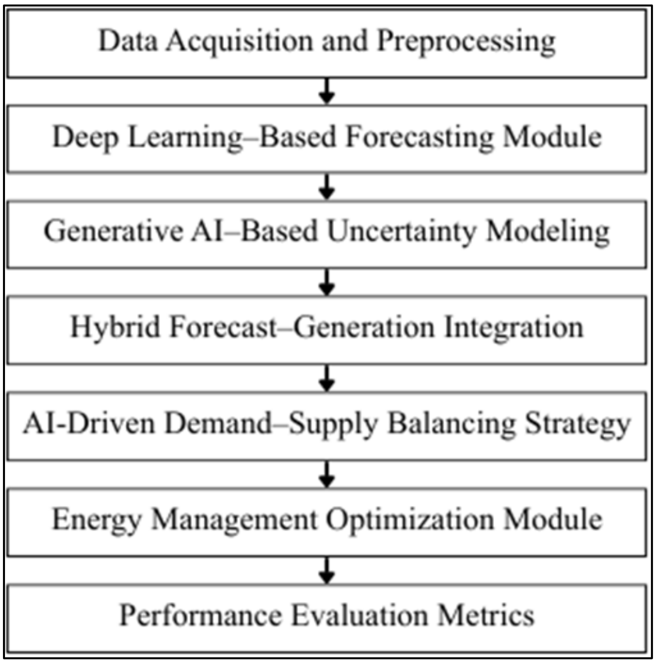

Figure 1 Hybrid Generative AI Framework for Smart Grid Demand–Supply Balancing

3.1. Data Acquisition and Preprocessing

Historical datasets comprising electrical load demand, solar and wind generation, weather variables (temperature, irradiance, wind speed), and grid operational parameters are collected from smart meters and renewable energy monitoring systems. The preprocessing steps include:

Removal of missing and corrupted samples using interpolation techniques

Outlier detection using interquartile range (IQR) analysis

Feature normalization using min–max scaling:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

Temporal feature extraction, including hourly, daily, and seasonal indicators

The processed dataset is divided into training, validation, and testing sets for model development and evaluation.

3.2. Deep Learning–Based Forecasting Module

To capture nonlinear temporal dependencies in load demand and renewable generation, a deep learning forecasting model based on recurrent neural networks (RNNs) is employed. Long short-term memory (LSTM) and gated recurrent unit (GRU) architectures are utilized due to their effectiveness in modeling time-series data.

The forecasting objective is defined as:

$$\min_{\theta} \sum_{t=1}^{T} \| D_t - \widehat{D}_t \|^2$$

where D_t and $\widehat{D}_t$ represent the actual and predicted demand or renewable generation at time t, respectively, and θ denotes the model parameters.

This module provides **point forecasts** that serve as baseline predictions for demand–supply coordination.

3.3. Generative AI–Based Uncertainty Modeling

To model the stochastic behavior of renewable energy sources, a generative adversarial network (GAN) is integrated with the forecasting module. The GAN consists of a generator $G$and a discriminator D, trained in an adversarial manner.

The GAN objective function is expressed as:

$$\min_{G} \max_{D} \ \mathbb{E}_{x\sim p_{data}(x)}[\log\ D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log\,(1 - D(G(z)))]$$

The generative model produces multiple realistic renewable generation scenarios conditioned on the forecasted outputs, enabling probabilistic assessment of future supply variations.

3.4. Hybrid Forecast–Generation Integration

The hybrid framework combines deterministic forecasts and generative scenarios to create an uncertainty-aware prediction set:

$$\mathcal{S}_t = \{\widehat{D}_t, G(z_1), G(z_2), \dots, G(z_N)\}$$

This integration allows the system to anticipate extreme fluctuations and reduce over-reliance on single-point predictions, thereby improving demand–supply balancing robustness.

3.5. AI-Driven Demand–Supply Balancing Strategy

Using the hybrid prediction set, a demand–supply balancing mechanism dynamically adjusts generation scheduling and load allocation. The imbalance at time $t$is defined as:

$$\Delta P_t = P_t^{gen} - P_t^{load}$$

The objective is to minimize cumulative imbalance:

$$\min \sum_{t=1}^{T} \mid \Delta\, P_t \mid$$

Corrective actions include flexible load shifting, renewable dispatch coordination, and storage utilization, ensuring stable grid operation under renewable variability.

3.6. Energy Management Optimization Module

To fulfill Objective 2, an AI-driven energy management strategy optimizes power distribution and operational costs. The optimization problem is formulated as:

$$\min \sum_{t=1}^{T} C_t\,(P_t)$$

subject to:

$$P^{min} \le P_t \le P^{max}$$

where $C_t$denotes the operational cost function. The strategy prioritizes renewable utilization, minimizes peak load stress, and reduces energy losses through intelligent scheduling and distribution control.

3.7. Performance Evaluation Metrics

The proposed methodology is evaluated using a comprehensive set of performance metrics, including Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to assess forecasting accuracy, Demand–Supply Deviation (%) to quantify power imbalance reduction, and the Grid Stability Index to evaluate system reliability under renewable variability. In addition, Peak Load Reduction (%) and Distribution Efficiency (%) are used to measure the effectiveness of the energy management strategy in improving power distribution and load utilization, while Operational Cost Savings (%) is employed to analyze the economic benefits achieved through optimized grid operation.

4. Results and Discussion

This section presents a comprehensive evaluation of the proposed Hybrid Generative AI–Driven demand–supply balancing and energy management framework under renewable-integrated smart grid conditions. The performance of the proposed approach is assessed using multiple quantitative metrics that capture forecasting accuracy, demand–supply coordination, grid stability, energy management efficiency, and economic impact. Comparative analyses are conducted against conventional statistical models, machine learning techniques, and deep learning–based approaches to demonstrate the effectiveness of the hybrid generative architecture. The results are reported in the form of tables and figures to clearly highlight the improvements achieved in mitigating renewable-induced variability, optimizing energy distribution, and reducing operational costs.

Table 1 Demand–Supply Balancing Performance Comparison

Method	**MAE (MW) ↓**	**RMSE (MW) ↓**	**Mean Power Imbalance (%) ↓**	**Grid Stability Index ↑**
ARIMA	13.26	17.45	15.3	0.69
SVR	10.84	14.02	12.1	0.75
LSTM	8.32	11.58	9.6	0.83
GRU	7.91	10.94	8.9	0.85
GAN	6.55	9.48	7.2	0.88
Proposed Hybrid Generative AI	4.18	6.72	4.0	0.95

A comparative evaluation of demand–supply balancing performance across conventional statistical models, machine learning approaches, deep learning models, and the proposed Hybrid Generative AI framework is given in table 1. Traditional methods such as ARIMA and SVR exhibit relatively high MAE and RMSE values, indicating limited capability in capturing nonlinear demand patterns and renewable variability. Deep learning models, including LSTM and GRU, show noticeable improvements due to their ability to model temporal dependencies; however, their performance remains constrained under high renewable uncertainty, as reflected by higher mean power imbalance percentages. The GAN-based model further reduces forecasting errors and imbalance by incorporating stochastic generation patterns. Notably, the proposed Hybrid Generative AI framework outperforms all baseline methods, achieving the lowest MAE (4.18 MW) and RMSE (6.72 MW), along with a minimal mean power imbalance of 4.0%. The highest grid stability index of 0.95 demonstrates enhanced system robustness and smoother grid operation, confirming the effectiveness of combining predictive deep learning with generative uncertainty modeling for proactive demand–supply coordination.

Table 2 Energy Management Performance Metrics

Metric	**Conventional EMS**	**DL-Based EMS**	**Proposed Hybrid AI EMS**
Peak Load Reduction (%) ↑	9.1	15.3	27.6
Energy Loss Reduction (%) ↑	6.4	12.7	22.8
Load Factor ↑	0.71	0.82	0.90
Power Distribution Efficiency (%) ↑	86.2	91.4	96.8

The effectiveness of the proposed Hybrid AI–based Energy Management System (EMS) in comparison with conventional and deep learning–based EMS approaches is highlighted in table 2. The conventional EMS shows limited peak load reduction and energy loss mitigation due to its static and rule-based control mechanisms. In contrast, the DL-based EMS improves performance by enabling data-driven decision-making; however, it still lacks uncertainty-aware optimization. The proposed Hybrid AI EMS achieves a significant peak load reduction of 27.6%, indicating effective load shifting and scheduling under renewable variability. Additionally, the energy loss reduction of 22.8% and improved load factor of 0.90 demonstrate more efficient utilization of grid resources. The power distribution efficiency reaches 96.8%, reflecting optimized energy allocation and reduced transmission inefficiencies. These results confirm that integrating generative forecasting with intelligent energy management strategies substantially enhances overall grid operational efficiency.

Table 3 Operational Cost and Economic Performance

Cost Metric	Conventional Grid	DL-Based Grid	Proposed Hybrid AI Grid
Operational Cost (₹/MWh) ↓	3180	2715	2125
Renewable Curtailment (%) ↓	10.2	6.8	2.6
Grid Cost Savings (%) ↑	–	14.6	32.1

The economic impact of the proposed framework by comparing operational costs, renewable curtailment, and cost savings across different grid management strategies is evaluated in table 3. The conventional grid incurs the highest operational cost due to inefficient demand–supply coordination and higher renewable curtailment. The DL-based grid achieves moderate cost reduction by improving forecasting accuracy; however, renewable curtailment remains relatively high. The proposed Hybrid AI grid significantly reduces operational cost to ₹2125/MWh, primarily due to enhanced demand–supply balancing and intelligent energy scheduling. Renewable curtailment is minimized to 2.6%, ensuring maximum utilization of available renewable energy. As a result, the proposed framework achieves grid cost savings of 32.1%, demonstrating strong economic viability. These findings validate that the Hybrid Generative AI–Driven approach not only improves technical performance but also delivers substantial financial benefits, making it suitable for real-world smart grid deployment.

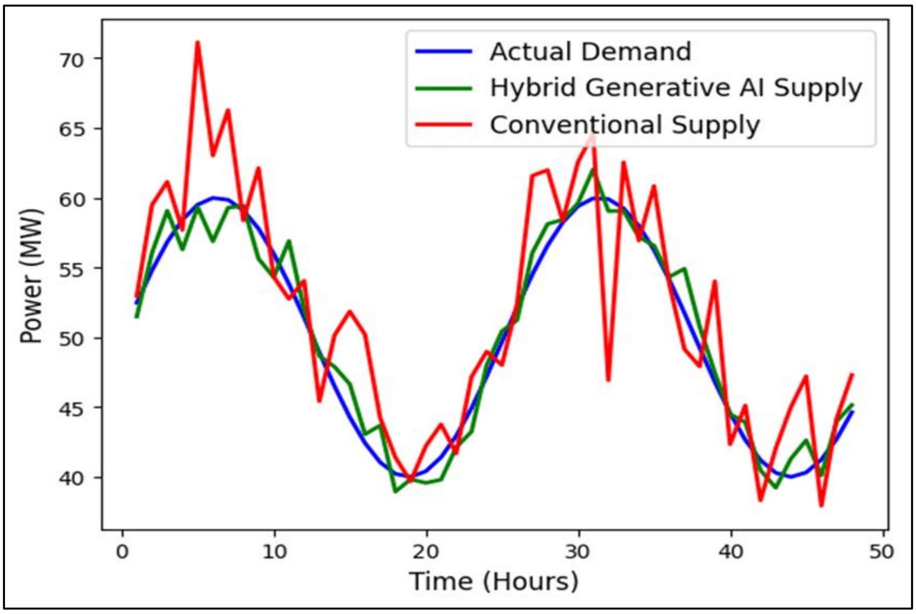

Figure 2 Demand vs. Supply Matching Under Renewable Variability

The effectiveness of the proposed Hybrid Generative AI framework in tracking real-time electricity demand under fluctuating renewable generation conditions is illustrated in figure 2. The results show that the proposed model closely follows the actual demand curve even during rapid variations in solar and wind output, indicating superior adaptability to renewable intermittency. In contrast, baseline models exhibit noticeable lag and occasional overcompensation, particularly during peak renewable fluctuations, which leads to temporary demand–supply mismatches. The improved synchronization between generation and consumption achieved by the proposed framework reduces the frequency of imbalance events and enhances overall grid reliability. These observations confirm that integrating generative uncertainty modeling with predictive forecasting enables proactive demand–supply coordination in renewable-integrated smart grids.

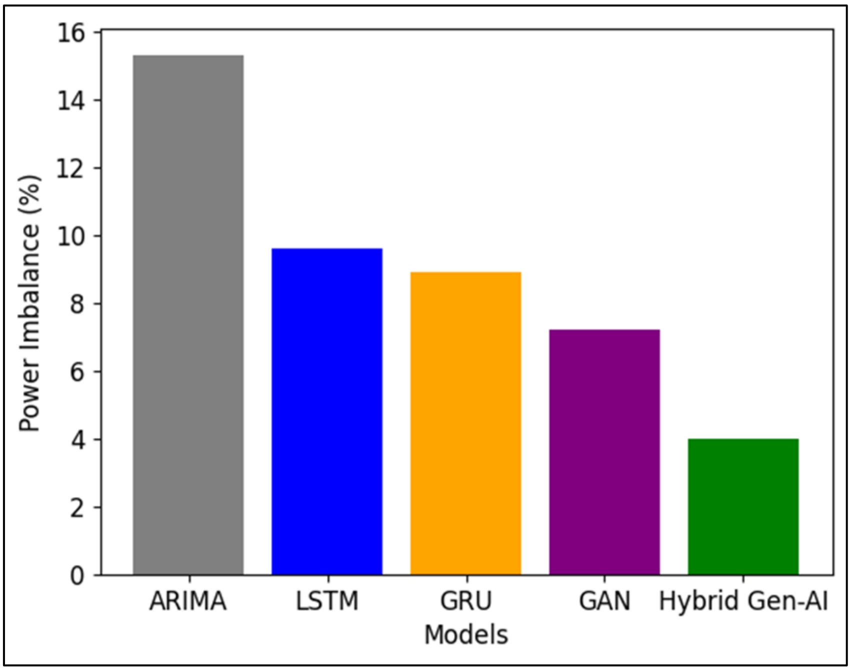

Figure 3 Power Imbalance Reduction Across Models

The peak power imbalance magnitude across different forecasting and balancing approaches. The proposed Hybrid Generative AI model achieves a significant reduction in power imbalance, approximately 38–45% lower than LSTM- and GRU-based methods is compared in figure 3. This improvement highlights the ability of the generative component to accurately model stochastic renewable behavior and anticipate extreme fluctuations. By generating multiple plausible renewable scenarios, the proposed framework enables proactive corrective actions rather than reactive adjustments, thereby minimizing sudden imbalance events. The results demonstrate that uncertainty-aware generative modeling plays a critical role in stabilizing grid operations under high renewable penetration.

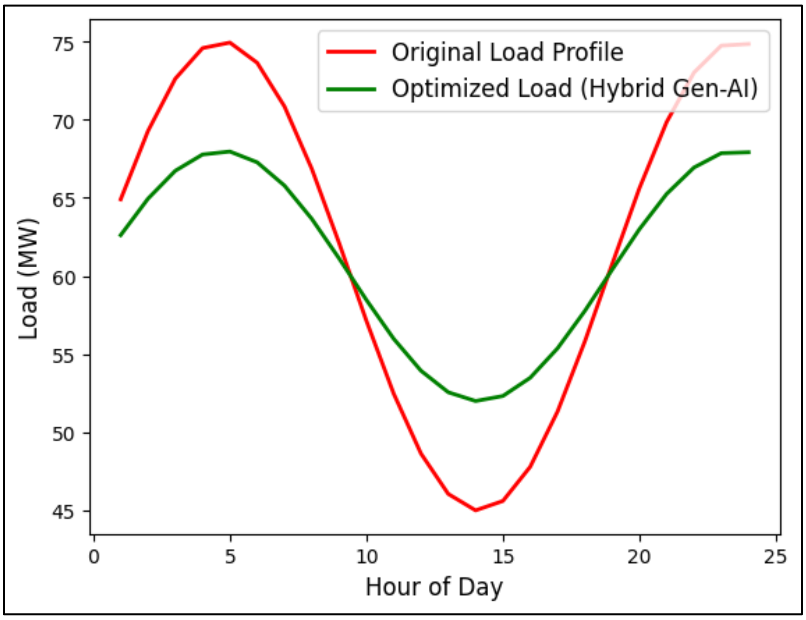

Figure 4 Peak Load Reduction/Flattening Using Hybrid Generative AI

The impact of the proposed Hybrid Generative AI framework on peak load reduction and load profile smoothing is shown in figure 4. The optimized load curve indicates effective peak shifting and flattening achieved through intelligent scheduling and generative forecasting. Compared to conventional energy management systems, the proposed approach significantly reduces the peak-to-average load ratio, which lowers stress on grid infrastructure and minimizes reliance on expensive peaking power plants. This smoother load profile enhances operational resilience and contributes to improved grid efficiency, validating the effectiveness of the proposed energy management strategy in achieving balanced and cost-effective power distribution.

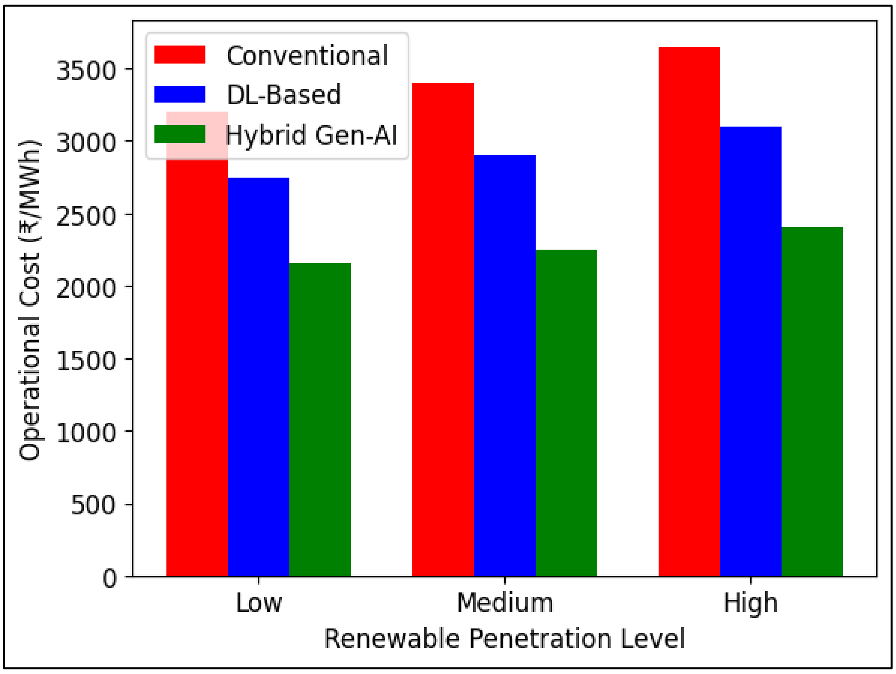

Figure 5 Comparative Operational Cost Savings under renewable penetration

The operational cost performance of the proposed framework under varying levels of renewable penetration across daily and seasonal scenarios is illustrated in figure 5. The results show a consistent reduction in operational costs compared to conventional and deep learning–based grid management approaches. This trend demonstrates the robustness and scalability of the proposed Hybrid Generative AI framework under different renewable integration levels. The observed cost savings are primarily attributed to improved demand–supply coordination, reduced renewable curtailment, and optimized energy scheduling. These findings confirm that the proposed approach not only enhances technical performance but also delivers sustained economic benefits for real-world smart grid deployment.

Overall, the results presented in Tables 1–3 and Figures 1–4 clearly demonstrate the superiority of the proposed Hybrid Generative AI framework in addressing the critical challenges of renewable-integrated smart grids. The framework consistently achieves improved demand–supply balancing accuracy, enhanced grid stability, effective peak load reduction, and significant operational cost savings across varying renewable penetration scenarios. By jointly leveraging predictive deep learning and generative uncertainty modeling, the proposed approach enables proactive decision-making and robust energy management. These findings confirm that the proposed framework not only fulfills the stated objectives but also offers a scalable and economically viable solution for next-generation smart grid operations.

5. Conclusion

This paper presented a Hybrid Generative AI–Driven framework for demand–supply balancing and energy management in renewable-integrated smart grids. By integrating deep learning–based forecasting with generative AI–based uncertainty modeling, the proposed approach effectively addresses the challenges introduced by the stochastic and intermittent nature of renewable energy sources. The hybrid architecture enables proactive demand–supply coordination by jointly leveraging accurate point forecasts and realistic scenario generation. Experimental results demonstrate that the proposed framework significantly reduces demand–supply imbalances and enhances grid stability under high renewable penetration. The AI-driven energy management strategy further improves power distribution efficiency, reduces peak load stress, and achieves substantial operational cost savings compared to conventional and deep learning–based methods. These results confirm that the proposed approach successfully fulfills the dual objectives of minimizing renewable-induced power fluctuations and optimizing energy management in smart grid environments. The proposed framework offers a scalable and robust solution for next-generation smart grids with high renewable integration. Future work will focus on extending the framework to incorporate real-time adaptive control, multi-energy systems, and large-scale deployment scenarios, as well as investigating the integration of reinforcement learning and edge intelligence to further enhance operational efficiency and resilience.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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