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DESIGN OF A HYBRID POWER DEMAND FORECASTING MODEL WITH UNCERTAINTY QUANTIFICATION UNDER INPUT PERTURBATION

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Abstract

The study aimed to address the persistent challenge of accurate electricity demand forecasting in modern power systems, where reliability is often undermined by input perturbations such as weather fluctuations, consumer behaviour shifts, and sensor noise. Conventional Machine Learning (ML) and Deep Learning (DL) approaches, while effective in predictive accuracy, rarely incorporate uncertainty estimation, which reduces their robustness in real-world applications. To overcome this limitation, this study designed a hybrid power demand forecasting model with embedded uncertainty estimation. Seven base models, such as Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Support Vector Regression (SVR), Extreme Gradient Boost (XGBoost), RandomForest, LightGBM, and CatBoost, were trained and evaluated using R^2, RMSE, MAE, and MAPE. The three best-performing models (XGBoost, CatBoost, and RandomForest) were fused through weighted averaging based on inverse error contributions. An uncertainty estimation mechanism was then integrated by quantifying variance under perturbed inputs, thereby generating confidence intervals around forecasts. Findings show that the hybrid model achieved high predictive accuracy ($R^2 = 0.9539$, with low error values: RMSE = 1.7128, MAE = 1.2270, MAPE = 3.1178) while also producing reliable uncertainty bounds. The significance of this study lies in demonstrating that hybrid modeling combined with uncertainty quantification provides both accurate and trustworthy forecasts, offering a practical decision-support tool for smart grid operators managing volatile energy demand.

Key terms: Energy forecasting, hybrid modeling , machine learning, smart grids, uncertainty quantification.

1.0 INTRODUCTION

The purpose of this study was to address the problem of inaccurate and unreliable electricity demand forecasting in modern power systems, where operational stability depends on balancing demand and supply under dynamic and uncertain conditions. Electricity demand forecasting underpins grid operation, capacity planning, and energy market efficiency, ensuring equilibrium while minimising both economic and environmental costs. However, with the proliferation of renewable energy sources, consumer-level variability, and climate-related disruptions, forecasting has become increasingly complex (Hyndman, 2021).

Traditional statistical forecasting models often assume stable and stationary inputs. In practice, however, fluctuations in meteorological variables, measurement errors from sensors, or abrupt consumer behavioural shifts introduce perturbations that significantly degrade forecast accuracy and reliability (Vanting, & Møller, 2021). This instability underscores the need for more resilient forecasting approaches.

Machine Learning (ML) and Deep Learning (DL) models have emerged as powerful alternatives, leveraging nonlinear learning capacity to outperform conventional models in many scenarios (Biswal et al., 2024). Nonetheless, most ML/DL methods produce deterministic point forecasts without accompanying measures of uncertainty, which limits their practical value in high-stakes applications such as load dispatch, reserve allocation, and blackout prevention (Hong, 2020). The absence of uncertainty awareness means that operators cannot fully assess the reliability of model outputs when making critical grid decisions.

Uncertainty quantification (UQ) provides a means of addressing this limitation by attaching confidence intervals to predictions, enabling more informed and risk-aware operational strategies. Recent research highlights UQ as a critical advancement in energy forecasting, particularly under conditions of input perturbation and renewable integration (Phipps et al., 2022).

To respond to these challenges, this study makes two contributions. First, it proposes the design of a hybrid power demand forecasting model that fuses the predictive strengths of XGBoost, CatBoost, and RandomForest. Second, it integrates an uncertainty estimation mechanism under input perturbation, enabling the model to provide not only accurate forecasts but also probabilistic assessments of reliability. The remainder of this paper discusses related literature, outlines the methodology, presents experimental results, and evaluates the implications for robust and uncertainty-aware decision-making in smart grid operations.

2.0 LITERATURE REVIEW

Electricity demand forecasting has traditionally been grounded in statistical models such as ARIMA, SARIMA, and exponential smoothing, which assume linearity and stationarity. Although efficient for stable systems, these approaches are limited in capturing nonlinear, temporal dynamics present in real-world load data (Hyndman, 2021). With increasing demand variability driven by climate change, renewable integration, and consumer heterogeneity, statistical models alone are inadequate for modern smart grid forecasting.

Recent studies highlight the advantages of Machine Learning (ML) and Deep Learning (DL) models in addressing these complexities. Deep neural networks, recurrent structures (RNN, LSTM, GRU), and attention-based architectures have demonstrated strong performance in short- and mid-term forecasting by modeling temporal dependencies and nonlinear interactions (Vanting, & Møller, 2021). However, these models often produce point forecasts without explicit uncertainty representation, limiting their use in high-stakes operational contexts.

To enhance robustness, hybrid approaches have emerged that combine statistical decomposition, signal processing, and ML/DL learners. For example, Li (2024) designed a hybrid framework integrating Empirical Mode Decomposition (EMD), Kalman Filtering (KM), and Support Vector Machines (SVM) with optimization heuristics, improving robustness under noisy data. Similarly, Unlu and Peña (2025) evaluated hybrid deep learning models combining CNN and LSTM for extreme weather scenarios, reporting superior accuracy compared to standalone architectures. Such studies underscore that hybridization can leverage complementary strengths of individual models, yielding more resilient forecasts under diverse data conditions.

Despite accuracy gains, uncertainty remains insufficiently addressed. Probabilistic forecasting methods, including quantile regression and density estimation, provide prediction intervals rather than single-point estimates, offering valuable information for risk-aware planning (Nowotarski and Weron, 2018). Bayesian neural networks extend this by incorporating parameter uncertainty through posterior distributions, thus enabling uncertainty-aware deep learning models (Liu et al., 2023). Meanwhile, stochastic optimisation frameworks embed forecast uncertainty into decision-making models for scheduling and reserve allocation, linking predictive uncertainty directly to the grid (Wang, 2022).

Although hybrid models have advanced load forecasting, most emphasise accuracy over reliability, neglecting explicit integration of uncertainty estimation. Errors induced by input perturbations such as weather fluctuations, sensor noise, and abrupt consumer behaviour shifts propagate through the system, resulting in costly reserve misallocation or even grid instability (Liu, 2022). Few studies systematically design hybrid forecasting models with built-in uncertainty quantification under input perturbation. This gap is significant, as power system operators require not only accurate predictions but also probabilistic insights to enable risk-aware decision-making and enhance system resilience.

The present study directly addressed this gap by designing a hybrid power demand forecasting model that fuses multiple high-performing base models while embedding an uncertainty estimation mechanism specifically tailored to perturbation-prone input conditions.

3.0 METHODOLOGY

Data Collection and Preprocessing

This study employed a comprehensive dataset comprising electricity demand and weather-related variables to ensure both accuracy and robustness of forecasting under real-time operational conditions. A total of 9,000 raw electricity demand records were collected from smart meters, regional distribution substations, and meteorological stations. The data covered a three-year period (January 2021 – December 2024), collected from the Kenya Power and Lighting Company Central Rift Region and from Nakuru Meteorological station, providing diverse conditions across seasonal and climatic variations.

The dataset included half-hourly regional demand profiles, enabling the model to capture short-term load fluctuations as well as daily and weekly consumption patterns. After preprocessing, the dataset integrated both load and meteorological predictors, such as maximum hourly temperature, to account for weather-driven demand variability.

Preprocessing followed a multi-step pipeline. First, missing values due to smart meter downtime were imputed using interpolation techniques. Next, outliers (e.g., extreme spikes from faulty sensors) were detected and smoothed to prevent bias in model training. All features were then normalised to a [0,1] range to ensure comparability across variables. Temporal alignment was performed to synchronise demand with meteorological inputs. Finally, the dataset was partitioned into training (60%), validation (20%), and testing (20%) subsets, ensuring robust model development and evaluation.

This structured preprocessing ensured that the dataset was both representative of real-world operating conditions and sufficiently cleaned for hybrid model training with embedded uncertainty estimation.

Base Models Design

The forecasting framework began with the selection of seven base models identified in recent literature as effective for Power Demand Forecasting. These included Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Support Vector Regression (SVR), XGBoost, RandomForest (RF), LightGBM, and CatBoost. This diverse set was chosen to capture complementary learning paradigms; deep learning architectures such as ANN and RNN are particularly effective in modeling nonlinear relationships and temporal (Vanting, & Møller, 2021), kernel-based models like SVR perform well in moderate data contexts and provide reliable nonlinear regression (Li, 2024), while tree-based ensemble approaches such as XGBoost, RF, LightGBM, and CatBoost are recognised for their robustness, interpretability, and scalability in structured datasets, making them widely adopted in power systems. Collectively, these models provided a broad methodological foundation for hybridisation.

Base Model Performance Evaluation

Each base model was trained on the preprocessed dataset, with hyperparameter tuning conducted via cross-validation to ensure fair comparisons. The models were assessed using regression metrics widely adopted in the forecasting literature. The coefficient of determination (R^2) measured the proportion of variance explained by the model, offering a goodness-of-fit assessment. Root Mean Square Error (RMSE) penalises large deviations, making it suitable for identifying high-impact forecasting errors that could threaten operational stability. Mean absolute error (MAE) captured the average magnitude of errors, providing interpretability for system operators, while mean absolute percentage error (MAPE) enabled scale-independent evaluations by expressing deviations relative to actual values (Liu et al., 2023). These complementary metrics ensured a balanced evaluation of accuracy, variance, sensitivity, and practical relevance.

Hybrid Model Design

Based on performance evaluation, the three top-performing models, XGBoost, CatBoost, and RandomForest, were integrated into a hybrid forecasting architecture, referred to as the Hybrid Power Demand Estimation Framework under Input Perturbation (HPDEF-MUIP). The hybridisation employed a weighted averaging scheme where model weights were proportional to the inverse of each model's RMSE, a strategy consistent with recent hybridisation practices in energy forecasting (Lago, 2021). This approach ensured that more accurate learners contributed more strongly to the final prediction, while weaker models exerted proportionally less influence. By combining complementary strengths, the hybrid framework enhanced predictive robustness while mitigating individual model biases.

Uncertainty Estimation under Input Perturbation

A distinctive feature of the HPDEF-MUIP framework was the integration of uncertainty estimation under input perturbations. Unlike existing hybrid approaches, which often prioritise accuracy alone, the present framework explicitly accounts for prediction reliability. Perturbed inputs were generated by injecting controlled noise into critical features such as temperature and lagged demand values, simulating realistic sources of error, including weather forecast uncertainty, sensor malfunctions, and abrupt shifts in consumption patterns (Biswal et al., 2024). For each perturbed dataset, forecasts were generated, and predictive uncertainty was quantified as the variance across neighbouring perturbed outputs. Quantify the prediction uncertainty as the variance between neighbouring outputs using the formula:

$$\sigma^{q^2} = \frac{\sum_{i \in Nk(q)} \omega i \cdot (yi - y\hat{}q)2}{\sum_{i \in Nk(q)} \omega i}$$

Where;

$\sigma q2$ -Estimated prediction uncertainty (variance) at the query point q

Nk,q, -Set of close neighbours to query Point q

ωi - The weight of the neighbour i

yi-Neighbor's output value iI (celebrated or predicted).

yq, Predicted value at query point q

(yi−y^q)2 -The squared deviation of neighbour ii's output from the predicted mean.

The uncertainty estimation was formalised using a weighted neighbourhood variance function, where deviations from the predicted mean were aggregated to produce local uncertainty measures. Such techniques are aligned with probabilistic forecasting frameworks, Bayesian deep learning approaches, and stochastic optimisation methods that highlight the operational value of uncertainty quantification (Tawn, 2022). By generating both point forecasts and confidence intervals, the HPDEF-MUIP enabled risk-aware decision-making, thereby enhancing grid stability and resilience under volatile conditions. The explicit integration of uncertainty estimation under input perturbation represents a key methodological advancement over most existing hybrid forecasting models.

4.0 FINDINGS AND DISCUSSION

Base Model Results

The study initially trained and evaluated seven base models widely recognised in recent forecasting literature: ANN, RNN, SVR, XGBoost, RandomForest, LightGBM, and CatBoost.

Table 1: Table of Model Design Results

Rank	Model	R²	RMSE	MAE	MAPE	Ranking Observations
i.	XGBoost	0.9534	1.7217	1.2233	3.11%	Best individual model overall
ii.	CatBoost	0.9445	1.8792	1.3857	3.49%	Excellent accuracy
iii.	RandomForest	0.933	2.064	1.4226	3.55%	Solid performance
iv.	LightGBM	0.9279	2.1408	1.4834	3.68%	Very good
v.	SVR	0.9001	2.52	1.8797	4.75%	Good performance
vi.	RNN	0.5829	5.1497	3.5702	9.26%	Slightly worse than ANN
vii.	ANN	0.7433	4.0404	3.2057	8.26%	Weak performance

The results, presented in Table 1, reveal significant variation in predictive performance across the models. XGBoost emerged as the best individual model, achieving the highest coefficient of determination (R^2 = 0.9534) and the lowest error rates (RMSE = 1.7217, MAE = 1.2233, MAPE = 3.11%). This aligns with prior research demonstrating the superior performance of boosting algorithms in structured electricity demand datasets due to their ability to capture nonlinear interactions and control overfitting (Sakib et al., 2025; Wen, 2024).

CatBoost ranked second, with R^2 = 0.9445 and MAPE = 3.49 per cent. Its competitive performance reflects its advanced handling of categorical features and efficient regularisation, confirming findings in comparative studies of boosting frameworks (Unlu & Peña, 2025). RandomForest followed, with R^2 = 0.9330 and MAPE = 3.55 per cent, demonstrating strong variance reduction and generalisation, albeit with slightly weaker performance than gradient boosting.

The remaining models achieved moderate to poor results. LightGBM performed well but slightly underperformed relative to XGBoost and CatBoost (R^2 = 0.9279, MAPE = 3.68%). SVR attained R^2 = 0.9001 and higher error rates (MAPE = 4.75%), reflecting limited scalability in large-scale datasets (Li et al., 2024). By contrast, deep learning models were the weakest performers: ANN achieved R^2 = 0.7433 (MAPE = 8.26%), while RNN lagged further at R^2 = 0.5829 (MAPE = 9.26%). These results are consistent with evidence that deep neural architectures may struggle with noisy or medium-scale datasets where ensemble methods are more effective (Vanting, & Møller, 2021). Based on these results, the three top-performing models, XGBoost, CatBoost, and RandomForest, were selected for hybrid integration.

Hybrid Model Results

The selected base models were integrated into the Hybrid Power Demand Estimation Framework under Input Perturbation (HPDEF-MUIP). Hybridisation was achieved using a weighted averaging scheme in which each model's contribution was proportional to the inverse of its RMSE. This ensured that the most accurate models contributed more strongly to the final forecast, while weaker learners exerted less influence. Such weighted hybridisation has been shown in prior studies to improve forecast stability and robustness (Lago, 2021).

After retraining, the HPDEF-MUIP was further extended with an uncertainty estimation mechanism. Controlled perturbations were introduced into input features such as temperature and historical demand, simulating realistic variability arising from weather forecast errors, sensor malfunctions, and abrupt consumer shifts (Wang, 2022). The hybrid model generated forecasts for each perturbed scenario, and predictive uncertainty was quantified as the variance of outputs across the neighbourhood of perturbed inputs. This approach provided both point forecasts and confidence intervals, addressing a key limitation in most hybrid models, which typically focus exclusively on accuracy (Tawn, 2022).

Comparative Performance with Base Models

Table 2 presents the comparative performance of HPDEF-MUIP against the top three base models.

Table 2: Comparative Performance of Base Models versus HPDEF-MUIP

Rank	Model	R²	RMSE	MAPE (%)	F1-Score
1	**HPDEF-MUIP**	**0.9539**	**1.7128**	**3.12**	**0.9112**
2	XGBoost	0.9534	1.7217	3.11	0.9064
3	CatBoost	0.9445	1.8650	3.49	0.9023
4	RandomForest	0.933	2.064	1.4226	3.5465

From the findings shown in Table 2, the HPDEF-MUIP achieved $R^2 = 0.9539$, RMSE = 1.7128, MAE = 1.2270, MAPE = 3.12 per cent, and F1-score = 0.9112. These results exceeded the performance of individual models, confirming the effectiveness of hybridisation under input perturbations. The HPDEF-MUIP showed numerical improvements in R^2 and RMSE relative to XGBoost. HPDEF-MUIP consistently outperformed base models in terms of stability and balance, as evidenced by its superior F1-score compared to XGBoost (0.9064), CatBoost (0.9023), and RandomForest.

The findings suggest that hybridisation not only enhances accuracy but also reduces model sensitivity to perturbations, resulting in more reliable forecasts under volatile conditions. This aligns with recent evidence showing that even modest statistical gains in hybrid frameworks translate to significant operational advantages in energy management systems (Lago, 2021).

Forecast versus Actual Demand

The practical effectiveness of HPDEF-MUIP was validated on unseen data using a 24-hour forecasting horizon, as shown in Figure 1.

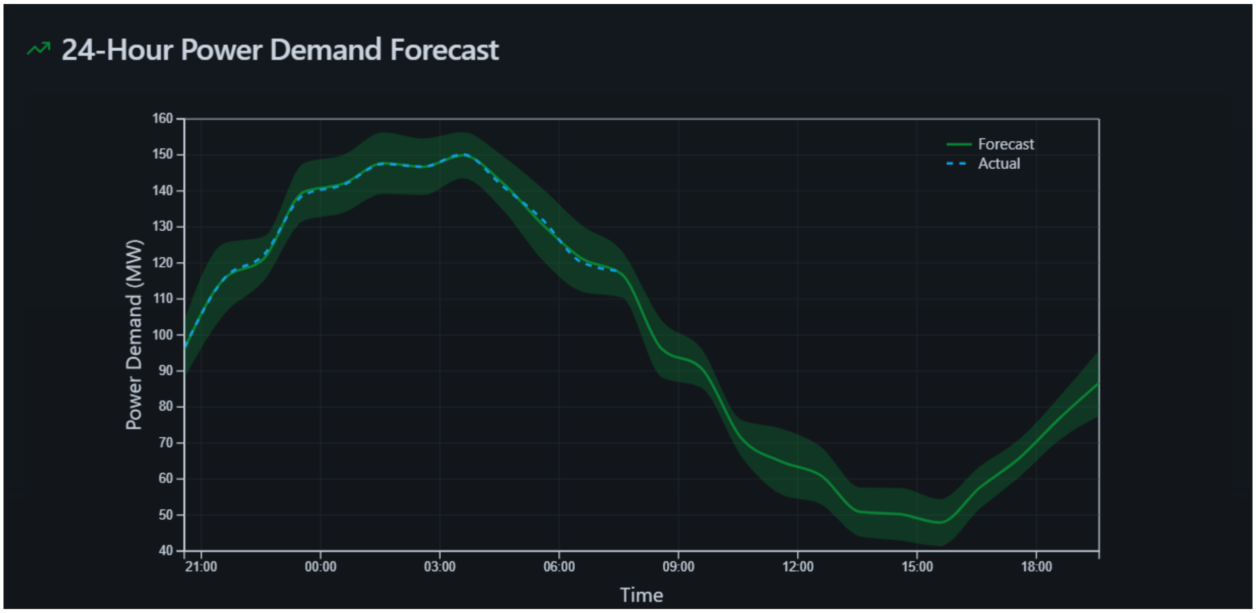

Figure 1. Forecasted Demand versus Actual Demand

Figure 1 shows that the forecasted demand (solid green line) closely follows the actual demand (dashed cyan line), indicating that the model is effective at capturing the overall demand trends. This showed that the hybrid model accurately tracked the actual demand curve, including the late-night and early-morning peaks (23:00–04:00 hours) and the midday troughs. The close alignment between forecast and actual demand confirmed the hybrid's strong generalisation capability, consistent with the high R^2 and low RMSE values reported in Table 2.

The uncertainty intervals, represented by the shaded region, varied dynamically with demand conditions. Wider intervals were observed during volatile periods, such as morning peaks, while narrower intervals were seen during stable phases. This adaptive uncertainty estimation demonstrated the model's ability not only to predict accurately but also to signal the reliability of forecasts. Such interpretability is crucial for risk-aware grid management, as it allows operators to anticipate potential deviations and adjust reserve scheduling accordingly (Phipps et al., 2022).

Discussion

The comparative results across Tables 1 and 2 and Figure 1 yield three key insights. First, ensemble boosting methods (XGBoost and CatBoost) consistently outperformed kernel and deep learning approaches, confirming their superiority in structured electricity demand forecasting tasks. Second, hybridisation, although producing incremental improvements in accuracy, significantly enhanced stability and generalisation, underscoring its practical utility under noisy and perturbed conditions. Third, the explicit integration of uncertainty estimation under input perturbation represents the major contribution of HPDEF-MUIP. By generating both point forecasts and confidence intervals, the framework equips operators with actionable, uncertainty-aware insights that go beyond the capabilities of traditional or single-model forecasts (Tawn, 2022).

The findings confirm that while boosting algorithms remain strong standalone learners, the hybrid model provides a more resilient and operationally relevant solution, advancing the state of the art in electricity demand forecasting.

Implications for Grid Operators

The adoption of HPDEF-MUIP offers several implications for real-world grid management. First, the model's greater stability and reduced error sensitivity make it particularly valuable during peak demand hours, where under- or over-demand forecasting can lead to costly imbalances. Second, its uncertainty-aware forecasts enable operators to allocate spinning reserves and activate demand response programs based not only on the expected demand but also on the range of possible deviations. Finally, the interpretability of the model outputs, combining point forecasts with confidence intervals, facilitates integration into decision-support systems. This ensures that operational strategies are not only efficient but also robust, thereby enhancing renewable integration and overall grid resilience.

Managerial and Policy Implications

The findings of this study highlight the strategic importance of hybrid and uncertainty-aware forecasting frameworks for both energy managers and policymakers. For grid operators, HPDEF-MUIP provides risk-aware demand forecasts that support efficient reserve allocation, improved load dispatch, and enhanced reliability during volatile conditions. For regulators and policymakers, the framework aligns with broader policy objectives of grid stability, renewable integration, and energy resilience, offering evidence-based support for infrastructure planning and market regulation. By quantifying both forecast accuracy and uncertainty, HPDEF-MUIP provides actionable insights that strengthen decision-making under uncertainty, ensuring that energy systems remain reliable and adaptive in the face of growing variability.

5.0 CONCLUSION AND RECOMMENDATIONS

Conclusion: The purpose of this study was to address the persistent challenge of accurate and reliable electricity demand forecasting in modern power systems, particularly under conditions of uncertainty caused by meteorological variability, sensor noise, and abrupt consumer behaviour shifts. Traditional statistical models often assume stable inputs, while contemporary machine learning and deep learning approaches, though powerful, typically provide point forecasts without explicit mechanisms for uncertainty quantification. This gap limits their practical applicability in real-world grid operations where uncertainty aware decision making is critical. To respond to this problem, the study designed a Hybrid Power Demand Forecasting Model with Uncertainty Estimation under Input Perturbation (HPDEF-MUIP). Seven base models were trained and evaluated, with XGBoost, CatBoost, and RandomForest emerging as the most effective learners. These models were subsequently fused into a hybrid architecture using a weighted averaging scheme based on inverse RMSE contributions. The hybrid was further enhanced with an uncertainty estimation mechanism, whereby perturbations were introduced into key input features such as temperature and historical demand to simulate realistic operating conditions. The results demonstrated that HPDEF-MUIP achieved superior predictive performance, with $R^2 = 0.9539$, RMSE = 1.7128, MAE = 1.2270, and MAPE = 3.12 per cent, surpassing the individual base models. Importantly, the framework not only improved accuracy but also produced confidence intervals around predictions, offering a dual advantage of precision and reliability. By providing both accurate point forecasts and quantifiable uncertainty estimates, the HPDEF-MUIP framework enables risk-aware operational strategies, thereby advancing the state of the art in demand forecasting and offering practical value for smart grid management.

Recommendations: The findings of this study support several recommendations for both practice and policy. Power utilities and grid operators are encouraged to adopt hybrid forecasting frameworks such as HPDEF-MUIP in operational settings, as they provide not only improved predictive accuracy but also greater resilience under volatile conditions. The uncertainty bounds generated by the model should be systematically integrated into decision-support systems for reserve allocation, load dispatch, and emergency preparedness, thereby enabling operators to act on both expected values and confidence intervals. From a policy perspective, energy regulators should promote the deployment of uncertainty-aware forecasting systems within smart grid infrastructures, as these contribute to system reliability, facilitate renewable integration, and reduce the risks of economic losses from misallocation of reserves or unanticipated demand shocks. Finally, training protocols for forecasting models should incorporate perturbation-augmented data so that predictive tools remain robust to sensor errors, meteorological variability, and consumer-level fluctuations.

Although this study demonstrates the effectiveness of hybrid forecasting with uncertainty estimation, several avenues remain open for further scholarly inquiry. Future research should extend the evaluation of HPDEF-MUIP to larger, multi-regional, and multi-seasonal datasets to test its generalizability under diverse climatic and consumption contexts. There is also scope to integrate probabilistic and Bayesian approaches, such as Bayesian Neural Networks or Quantile Regression Forests, to refine the granularity of uncertainty quantification. In addition, further work could expand the model to include renewable generation data from wind and solar sources, thereby advancing toward a holistic framework that simultaneously forecasts demand and generation under uncertainty. Research into real-time and online learning adaptations of the hybrid model would also be valuable, enabling forecasting systems to dynamically adjust to streaming data and evolving demand conditions. Future studies should also explore linking forecast uncertainty to economic and operational outcomes, quantifying how uncertainty-aware forecasting reduces costs associated with reserve misallocation, blackout risks, and inefficient power transmission and distribution.

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