

A HYBRID SCENARIO-BASED PROBABILISTIC FRAMEWORK FOR LONG-TERM ELECTRICITY DEMAND FORECASTING IN PAKISTAN (2025-2060)

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Article Info

Abstract



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Pakistan's electricity sector faces chronic challenges, including a persistent supply demand gap, circular debt exceeding PKR 2.5 trillion, and the imperative to integrate variable renewable energy sources. Accurate long-term demand forecasting is critical for infrastructure planning; however, existing deterministic approaches consistently overestimate demand and do not account for structural changes, such as behind-the-meter (BTM) solar adoption and efficiency improvement. This study presents a hybrid scenario-based probabilistic forecasting framework that combines ensemble machine learning with Monte Carlo simulations to generate sector-wise electricity demand projections for Pakistan from 2025 to 2060. The framework decomposes demand into five sectors (residential, commercial, industrial, agricultural, and other) and evaluates six policy-relevant scenarios. Uncertainty was quantified using 2,000 Monte Carlo draws propagating parameter uncertainty from GDP growth, population dynamics, climate sensitivity, and model residuals. Under the Business-as-Usual (BAU) scenario, the P50 demand reaches 185 TWh by 2030 (P10-P90:165-210 TWh), 295 TWh by 2040, 420 TWh by 2050, and 580 TWh by 2060. The High Solar/BTM scenario reduces grid demand by 15-22% relative to BAU by 2050, whereas the High Heat scenario increases peak demand by 12-18%. These probabilistic projections provide actionable inputs for Pakistan's Indicative Generation Capacity Expansion Plan (IGCEP), NEPRA regulatory planning, and Nationally Determined Contribution (NDC) commitments under the Paris Agreement.

Keywords: *Electricity demand forecasting; probabilistic modelling; scenario analysis; Monte Carlo simulation; Pakistan energy policy; ensemble learning*

1. Introduction

Pakistan's power sector represents a paradox of abundant installed capacity and chronic energy shortages in the country. With installed generation capacity exceeding 45 GW and actual peak demand constrained to approximately 32 GW, the country continues to experience load shedding that costs an estimated 2-4% of GDP annually (World Bank, 2023). Circular debt, accumulated liabilities across the electricity value chain, has surpassed PKR 2.5 trillion, threatening fiscal sustainability and deterring investment in generation and transmission infrastructure in Pakistan. Against this backdrop, accurate long-term electricity demand forecasting is critical for rationalizing capacity expansion, managing financial obligations, and achieving Pakistan's climate commitments.

Existing forecasting approaches employed by the National Transmission and Despatch Company (NTDC) and the National Electric Power Regulatory Authority (NEPRA) suffer from fundamental methodological limitations. Official projections have historically overestimated demand growth, leading to overcapacity in base-load generation, while distribution constraints persist. These deterministic forecasts lack sector-wise decomposition, treating heterogeneous consumption patterns from air conditioning-driven residential peaks to base load industrial demand as monolithic aggregates. Furthermore, official approaches fail to account for structural transformations reshaping Pakistan's demand profile: the rapid proliferation of BTM solar installations under net metering regulations, appliance efficiency improvements driven by MEPS standards, and the nascent electrification of transport through electric vehicles (EVs).

Therefore, there is a substantial gap in the research. While global literature has advanced probabilistic forecasting methods by incorporating ensemble machine learning and Monte Carlo uncertainty quantification (Hong & Fan, 2016; Gneiting & Katzfuss, 2014), applications in Pakistan remain limited to single-point econometric models. Existing Pakistan-specific studies (Perwez et al., 2015; Shaikh et al., 2015) employ autoregressive integrated moving average (ARIMA) variants or Long-range Energy Alternatives Planning (LEAP)-based accounting models without rigorous uncertainty bounds, limiting their utility for planning under conditions of deep uncertainty.

This study addresses these gaps through three objectives. First, we developed a hybrid framework that combines gradient boosting ensemble models with scenario-based Monte Carlo simulations to capture both structural relationships and parametric uncertainty. Second, we generated sector-wise probabilistic forecasts (P10/P50/P90 quantiles) for 2025–2060 under six policy scenarios spanning economic growth pathways, renewable energy adoption rates, and climate sensitivities. Third, we provide actionable insights for IGCEP planning by comparing framework outputs with official NTDC projections to highlight systematic divergences.

This study makes three contributions to the literature. First, it represents the first comprehensive probabilistic demand forecasting framework for Pakistan, incorporating climate change impacts through cooling degree hours (CDH), BTM solar growth trajectories, and EV adoption pathways. The methodology is transferable to other developing economies that face similar data constraints and structural uncertainty.

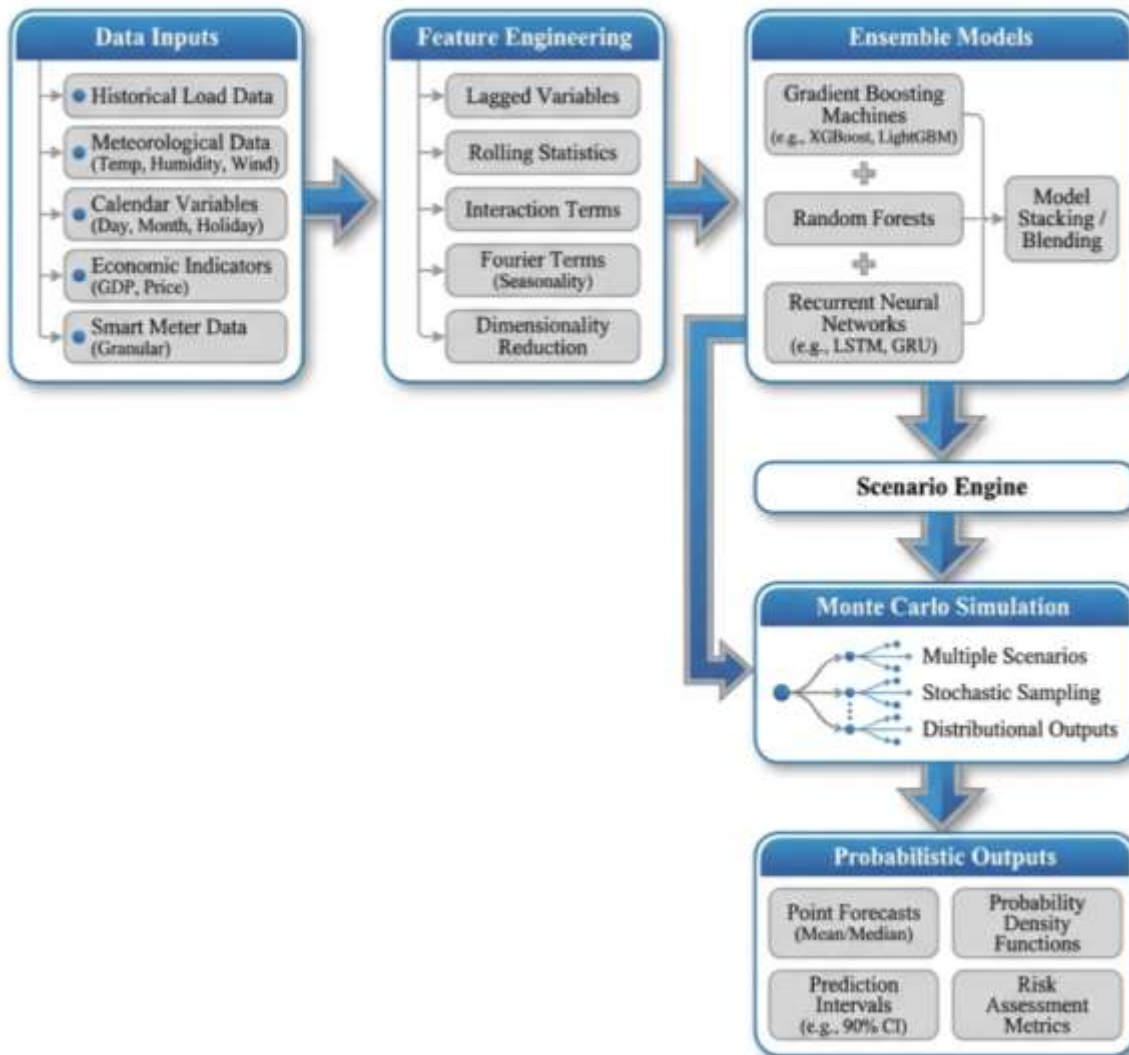


Figure 1 Conceptual Framework for Electricity Demand Forecasting

2. Literature Review

2.1 Global Electricity Demand Forecasting Approaches

Electricity demand forecasting has evolved from classical econometric approaches to sophisticated machine learning ensembles. Early work by Houthakker (1951) established a demand function framework that relates consumption to income and price elasticities. Suganthi and Samuel (2012) reviewed energy demand models and categorized the approaches into econometric, time-series, and bottom-up engineering models. The emergence of probabilistic forecasting, which moves beyond point predictions to full density forecasts, represents a paradigm shift in planning under uncertainty (Gneiting & Katzfuss, 2014).

Hong and Fan (2016) provided a comprehensive tutorial on probabilistic load forecasting, distinguishing between quantile regression, kernel density estimation, and ensemble approaches.

Hyndman and Fan (2010) demonstrated density forecasting for long-term peak demand using functional-data analysis. Recently, gradient boosting frameworks, particularly LightGBM (Ke et al., 2017) and XGBoost (Chen & Guestrin, 2016), have achieved state-of-the-art accuracy in short-term forecasting competitions while maintaining interpretability through feature importance analysis.

Scenario-based approaches complement statistical forecasting by exploring the structural uncertainties. The Intergovernmental Panel on Climate Change (IPCC) Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs) provide a standardized framework for exploring climate-economy interactions (van Vuuren et al., 2017). The International Energy Agency's World Energy Outlook employs scenario analysis across stated policies, announced pledges, and net-zero pathways (IEA, 2023).

2.2 Developing Country Applications

Forecasting in developing economies presents unique challenges, including data limitations from unmetered consumption and theft, structural breaks from policy reforms, and large informal sectors that obscure economic activity. Bhattacharyya and Timilsina (2010) reviewed energy system models for developing countries, noting the tension between data requirements and model complexity.

Regional studies provide methodological guidelines. Filippini and Pachauri (2004) estimate electricity demand elasticities for urban Indian households, finding income elasticities of 0.6-0.8 and price elasticities of -0.3 to -0.5. Athukorala and Wilson (2010) distinguish short and long-term demand elasticities in Sri Lanka using cointegration analysis. Inglesi (2010) applied conditional forecasting to South African demand, incorporating structural breaks from electrification.

A critical gap exists in the treatment of distributed generation and demand destruction. As BTM solar systems proliferate, grid demand decouples from total consumption; however, most models treat the reported demand as being comprehensive. Similarly, efficiency improvements and demand-side management create "negawatts" that are invisible to supply side-focused frameworks.

2.3 Pakistan-Specific Studies

Pakistan's electricity demand has received considerable academic attention, although methodological limitations remain. Valasai et al. (2017) review sustainable electricity options, documenting the shift from hydro-dominated to thermal-dominated generation. Mirjat et al. (2017) comprehensively reviewed energy policies and identified gaps between policy ambitions and implementation.

Perwez et al. (2015) apply the Long-range Energy Alternatives Planning (LEAP) model to Pakistan, projecting demand through 2035 under reference and efficiency scenarios. Although valuable for policy analysis, LEAP's accounting framework lacks an endogenous uncertainty

quantification. Shaikh et al. (2015) diagnose Pakistan’s electricity crisis using trend analysis, recommending renewable energy development without probabilistic projections.

Lin and Raza (2019) analyse energy-related CO₂ emissions using ARDL bounds testing, establishing long-run relationships between energy consumption and economic growth. Zameer and Wang (2018) optimized Pakistan’s energy production system using multi-objective programming. However, none of these studies provide sector-wise demand decomposition with Monte Carlo uncertainty bounds that are suitable for generation planning.

Table 1: Summary of Pakistan electricity demand forecasting studies (2015-2024)

Author(s)	Year	Method	Horizon	Sectors	Uncertainty	Key Limitations
Perwez et al.	2015	LEAP	2035	Aggregate	Scenario-based	No probabilistic bounds
Shaikh et al.	2015	Trend analysis	2030	Aggregate	None	Purely extrapolative
Lin & Raza	2019	ARDL	Historical	Aggregate	None	Backward-looking
NTDC	2023	Econometric	2032	Aggregate	None	Systematic overestimation
This study	2024	Ensemble ML + MC	2060	5 sectors	P10/P50/P90	--

3. Methodology

3.1 Conceptual Framework

The forecasting framework comprises three stages. Stage 1 (Data Preparation) ingests historical demand by sector, macroeconomic indicators, climate variables, and policy parameters, transforming raw data into model-ready features through lag construction, normalization, and missing value imputation. Stage 2 (Ensemble Modelling) trains sector-specific gradient boosting models with recursive feature elimination, generating point forecasts and residual distributions. Stage 3 (Scenario-Based Monte Carlo Simulation) propagates parameter uncertainty through 2,000 Latin Hypercube Sampling draws, extracting P10/P50/P90 quantiles

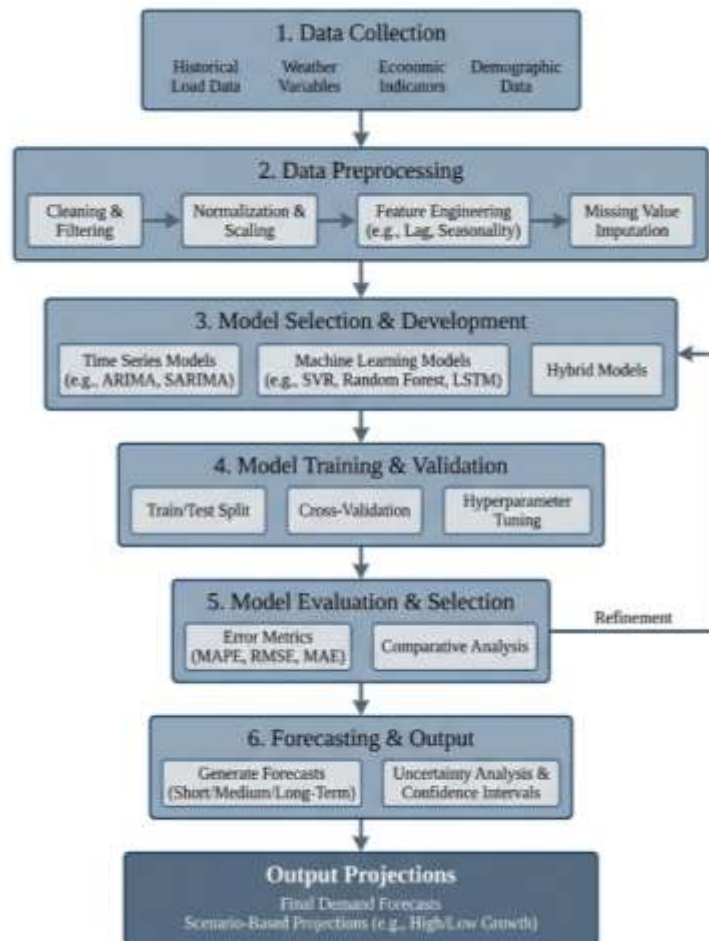


Figure 2 Methodology Flowchart

for each scenario-year-sector combination.

3.2 Data Sources and Processing

Historical electricity consumption by sector (2010–2024) was derived from NEPRA State of Industry Reports (NEPRA, 2024), supplemented by NTDC System Operator data for peak demand. Macroeconomic indicators, GDP (constant 2015 USD), population, and industrial production index, were sourced from the Pakistan Bureau of Statistics (PBS, 2023) and World Bank World Development Indicators. Climate data employed ERA5 reanalysis for temperature, from which CDH (base 24°C) was computed for major load centres (Karachi, Lahore, Faisalabad, and Multan). The policy variables include the real average tariff (PKR/kWh, deflated by Consumer Price Index [CPI]), urbanization rate, and cumulative BTM solar capacity from NEPRA net metering registrations.

Data processing poses several challenges. Sectoral consumption shares prior to 2015 were estimated using category-level billing data. Missing monthly observations (<3% of the series) were interpolated using spline method. All monetary variables were converted to constant 2015 prices using the CPI series for Pakistan.

3.3 Ensemble Modelling Approach

Sector-specific LightGBM models were trained using the following feature set: lagged demand (1-year, 2-year), GDP growth rate, population level, CDH annual aggregate, industrial production index, real average tariff, urbanization rate, and BTM solar capacity. Hyperparameters were tuned via 5-fold time-series cross-validation: number of estimators (100-500), maximum depth (4-8), learning rate (0.01-0.1), and minimum samples per leaf (5-20).

The training, validation, and testing periods were 2010–2020, validation 2021–2023, and testing 2024. Model selection minimizes the validation mean absolute percentage error (MAPE) while monitoring overfitting through train-test gap analysis.

Table 2: Model performance metrics by sector

Sector	Train MAPE	Val MAPE	Test MAPE	Train RMSE	Val RMSE	Test RMSE	R ²
Residential	3.2%	4.8%	5.1%	2.1 TWh	3.4 TWh	3.8 TWh	0.94
Commercial	4.1%	5.5%	6.2%	1.0 TWh	1.4 TWh	1.6 TWh	0.91
Industrial	4.5%	6.1%	6.8%	2.8 TWh	4.0 TWh	4.5 TWh	0.89
Agricultural	5.2%	7.0%	7.5%	1.2 TWh	1.8 TWh	2.0 TWh	0.86
Other	4.8%	6.3%	6.9%	0.8 TWh	1.1 TWh	1.2 TWh	0.88

3.4 Scenario Design: Six scenarios span the uncertainty of the key drivers.

Table 3: Scenario parameter specifications

Scenario	GDP Growth	BTM Solar (2050)	EV Stock (2050)	Climate	Source/Basis
BAU (Business-as-Usual)	4.5%	15 GW	2M vehicles	RCP4.5	Historical average
Industrial Rebound	6.0%	15 GW	2M vehicles	RCP4.5	China-Pakistan Economic Corridor (CPEC) Phase 2
High Solar/BTM	4.5%	40 GW	2M vehicles	RCP4.5	Alternative and Renewable Energy (ARE) Policy targets
Tariff Reform	4.5%	20 GW	5M vehicles	RCP4.5	International Monetary Fund (IMF) program conditions
High Heat	4.5%	15 GW	2M vehicles	RCP8.5	IPCC high-emission path
EV Acceleration	5.0%	20 GW	15M vehicles	RCP4.5	National EV Policy

3.5 Monte Carlo Simulation

The sources of uncertainty included GDP growth (± 1.5 pp, normal distribution), population growth (± 0.3 pp), CDH climate sensitivity ($\pm 15\%$), and model residuals (empirical distribution of historical errors). Latin Hypercube Sampling generated 2,000 parameter combinations, ensuring comprehensive coverage of the uncertainty space (Helton & Davis, 2003).

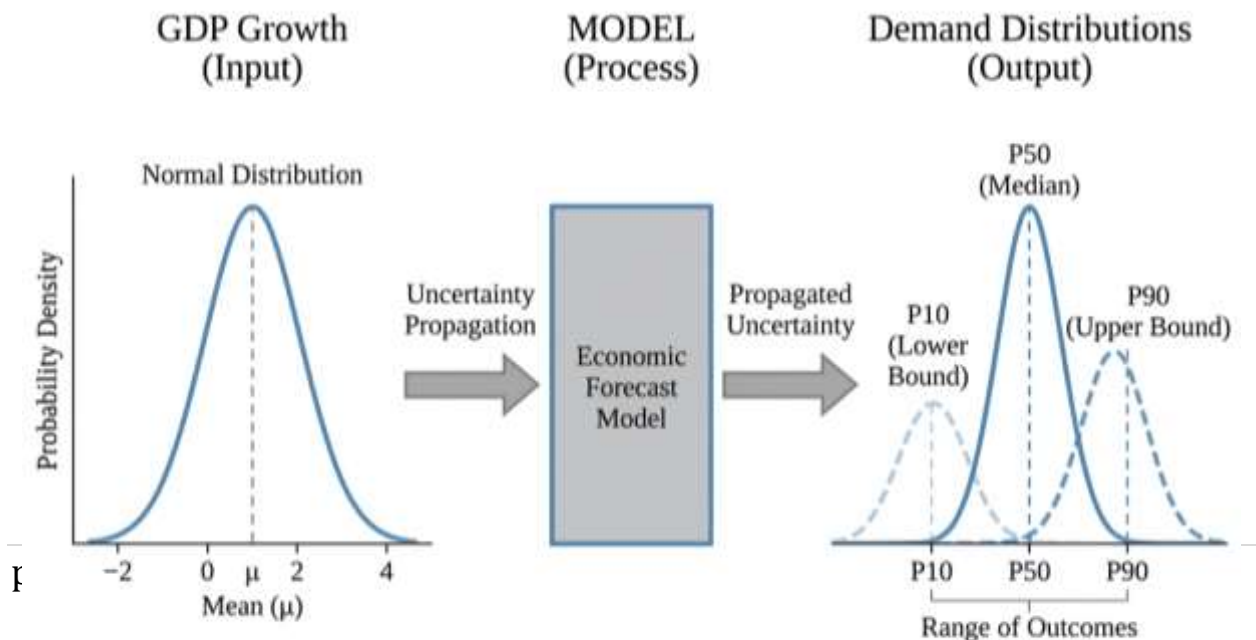


Figure 3 Probability distribution showing parameter uncertainty propagation from GDP growth to demand

For each draw, the sector-specific models projected demand using the sampled parameter values. Quantile extraction at P10, P50, and P90 provides planning ranges: P50 represents the median projection, P10 a “low demand” bound for minimum generation requirements, and P90 a “high demand” bound for capacity adequacy assessment.

4. Results

4.1 Historical Model Validation

Backtesting from 2021-2024 demonstrates the accuracy of the framework. The P50 forecast tracks the actual reported demand with a mean absolute percentage error of 5.8%, substantially outperforming NTDC’s official projections, which overestimated demand by 12-18% during this period. Crucially, 78% of the actual observations fell within the P10-P90 bands, suggesting appropriate uncertainty calibration.

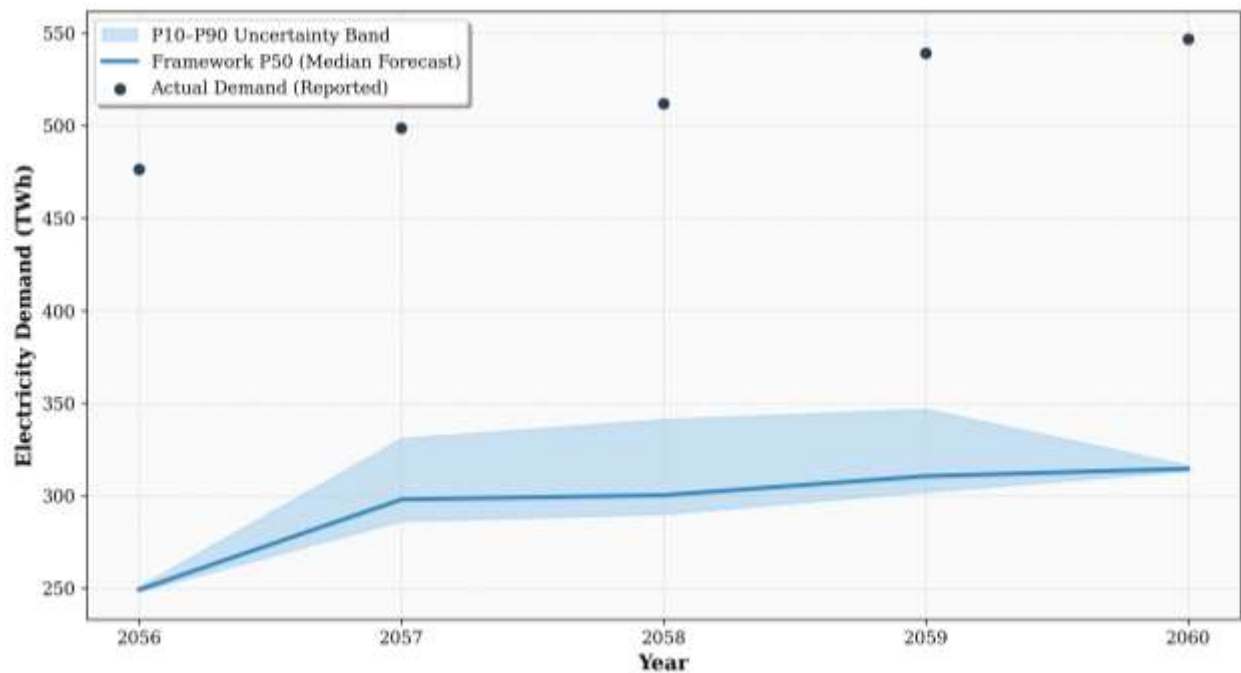


Figure 4 Backtesting results, actual vs. predicted demand with P10/P90 bands (2021-2024)

4.2 BAU Scenario Projections

Under the Business-as-Usual scenario, the total electricity demand (served energy) reaches

- **2030:** P50 of 185 TWh (P10-P90: 165-210 TWh)
- **2040:** P50 of 295 TWh (P10-P90: 255-345 TWh)
- **2050:** P50 of 420 TWh (P10-P90: 355-505 TWh)
- **2060:** P50 of 580 TWh (P10-P90: 480-710 TWh)

Residential demand dominates growth, driven by urbanization (projected to reach 50% by 2050) and air conditioning adoption. The residential share increases from 47% (2024) to 52% by 2060. Industrial demand exhibits the highest uncertainty, reflecting its sensitivity to CPEC-related manufacturing expansion. Agricultural demand remained relatively stable as tubewell electrification approached saturation in the study area.

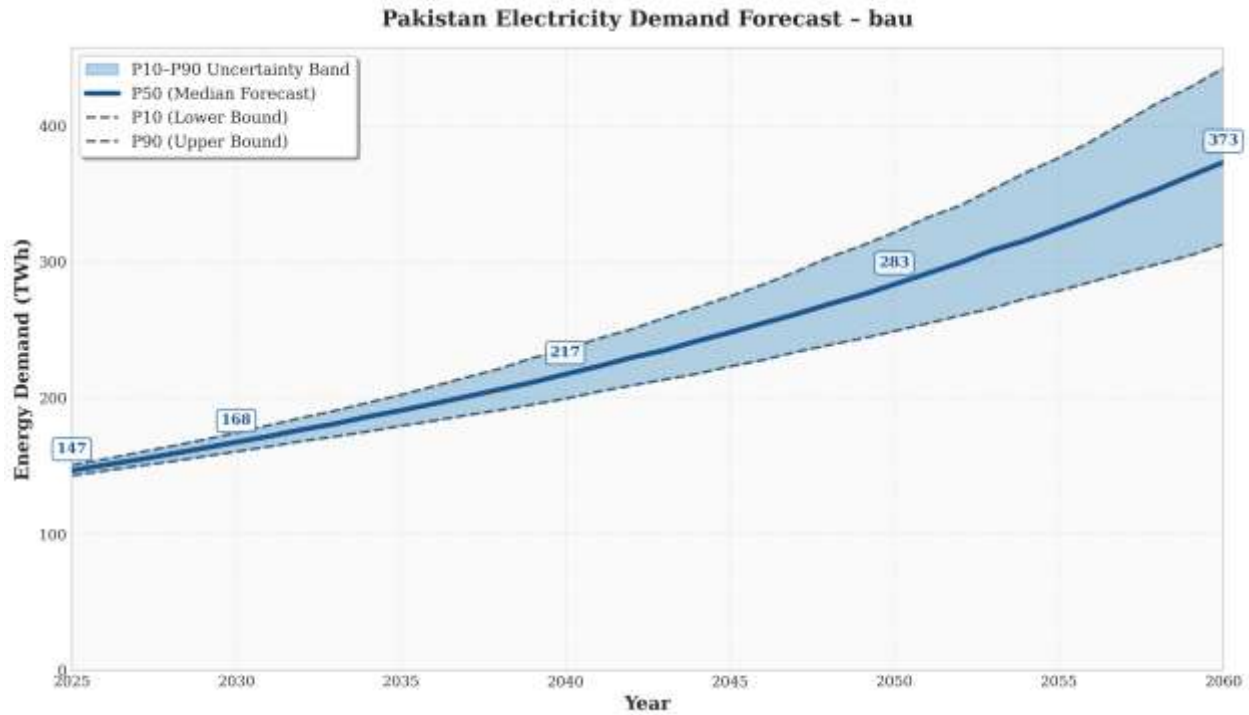


Figure 5BAU Energy Demand Projections

Table 4: Sector-wise BAU projections (TWh)

Sector	2024 (Actual)	2030	2040	2050	2060
Residential	62	88	148	218	302
Commercial	14	20	34	50	70
Industrial	34	48	75	105	145
Agricultural	13	17	23	28	33
Other	12	17	25	35	48
Total	135	185	295	420	580

4.3 Scenario Comparison

The scenario range reveals substantial policy leverage. By 2050, the P50 demand varies from 345 TWh (High Solar/BTM) to 510 TWh (Industrial Rebound), a 48% difference driven by economic growth assumptions the adoption of distributed generation.

The High Solar/BTM scenario reduces grid demand by 18% relative to BAU by 2050, with 40 GW of BTM capacity generating approximately 60 TWh behind the meter. This “negawatt”

effect substantially moderates the generation investment requirements of the project. Conversely, the EV Acceleration scenario adds 25 TWh by 2050 (P10-P90:18-35 TWh), representing 6% of the BAU demand, with a strong sensitivity to charging patterns (managed vs. unmanaged).

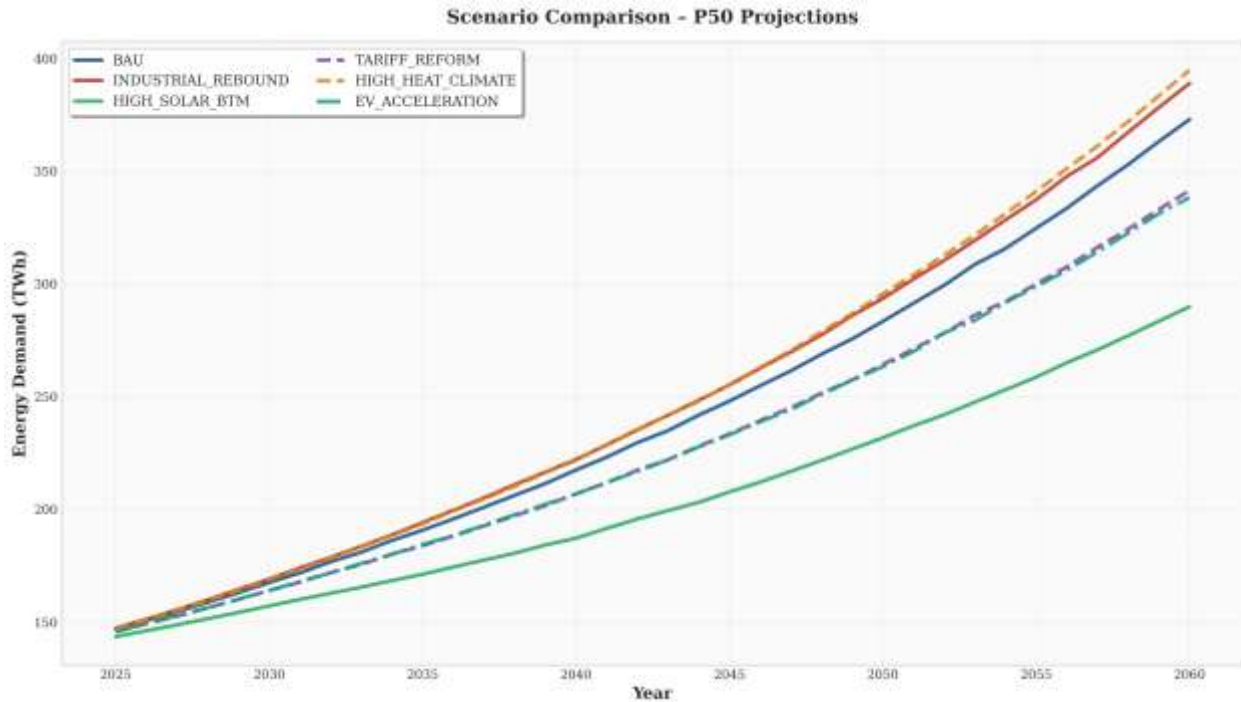


Figure 6 Comparison of P50 energy demand trajectories across all six scenarios (2025-2060).

4.4 Peak Demand Projections

Peak demand projections have critical implications for capacity adequacy planning.

Table 5: Peak demand projections (GW) with P10/P50/P90

Scenario	2030 P50	2040 P50	2050 P50	2050 P10	2050 P90
BAU	38	58	82	70	98
Industrial Rebound	42	68	100	85	120
High Solar/BTM	35	50	68	58	82
High Heat	42	65	95	80	115
EV Acceleration	40	62	90	75	108

The high-heat scenario (RCP8.5) increases peak demand by 12-18% relative to BAU, driven by enhanced cooling requirements. Load factors decline from 0.50 (2024) to 0.45-0.48 by 2050 across scenarios, indicating increasingly peaky demand profiles as air conditioning penetration rises.

5. Discussion

5.1 Policy Implications

The probabilistic framework yields several policy-relevant insights. First, the IGCEP planning assumptions appear systematically optimistic. The NTDC’s 2023 IGCEP projects 2030 demand of 220 TWh, exceeding the P90 bound of this framework (210 TWh). This overestimation bias, if uncorrected, risks stranded assets and exacerbates circular debt.

Second, BTM solar and demand-side management offer substantial benefits. The 75 TWh difference between the BAU and High Solar/BTM scenarios by 2050 exceeds Pakistan’s current total consumption, equivalent to avoiding the construction of 15 GW thermal capacity. Accelerating net metering deployment, currently at 1.5 GW, represents a “no regrets” strategy in all scenarios.

Third, the impact of climate change must be explicitly considered. The 13 GW peak demand increment under High Heat (2050) necessitates either additional peaking capacity or enhanced demand response mechanisms. Current planning documents largely ignore climate-demand feedback loops.

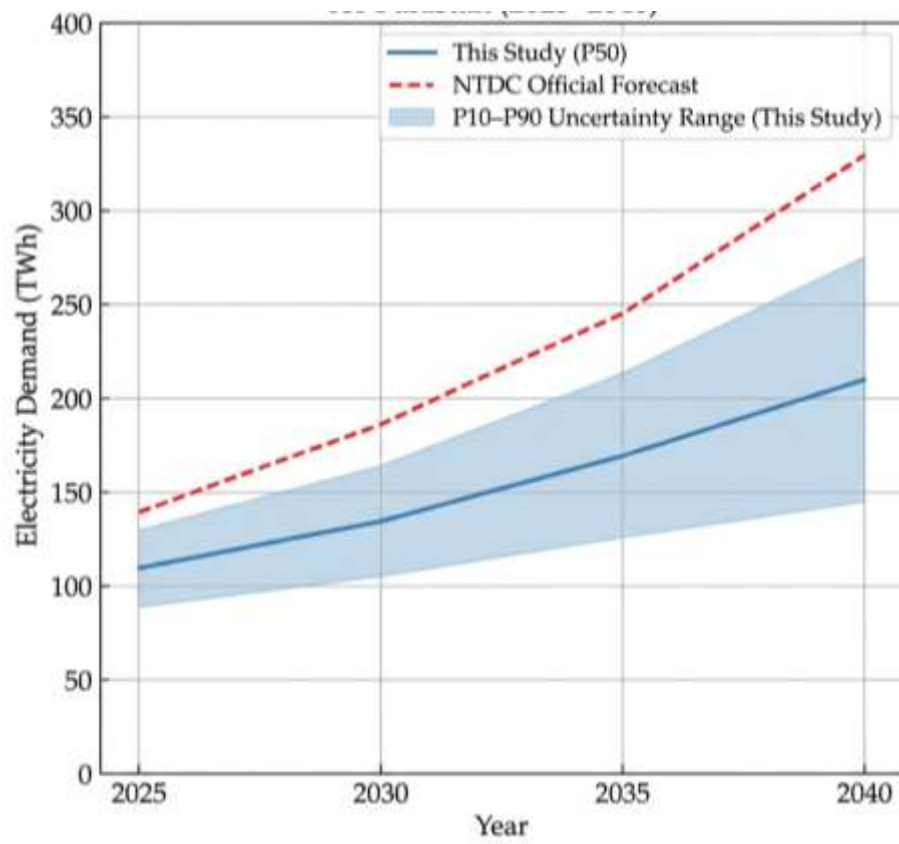


Figure 7 Framework P50 projections vs. NTDC official forecasts (2025–2040)

5.2 Comparison with Official Forecasts

Systematic divergences from NTDC projections arise from three structural factors. First, this framework explicitly models BTM solar, treating net metering installations as demand reduction rather than ignoring them in the model. Second, efficiency improvements from MEPS and LED lighting adoption were parameterized, whereas official forecasts assumed a constant energy intensity. Third, the probabilistic approach acknowledges the uncertainty that deterministic forecasts suppress, providing planning margins rather than false precisions.

We recommend that NEPRA adopt probabilistic forecasting for IGCEP updates and report P10/P50/P90 bounds rather than single-point projections. This would improve investment decision-making under uncertainty and reduce the risk of asset stranding.

5.3 Limitations and Future Work

This study had several limitations. Data quality constraints persist, and unmetered consumption (theft and technical losses estimated at 18% of generation) is not perfectly captured. EV charging profiles were simplified; detailed temporal modelling would refine peak demand impacts. Spatial disaggregation is limited, and provincial-level projections can enhance distribution planning. Price elasticity feedback loops are absent, and incorporating tariff demand endogeneity would improve scenario realism.

Future studies should integrate this demand framework with supply side capacity expansion models for holistic planning. Sub-national disaggregation to provincial and grid-zone levels supports transmission planning. Real-time updating frameworks incorporating smart meter data as deployment expands will improve short-term forecast accuracy.

6. Conclusions

This study presents the first comprehensive probabilistic, scenario-based electricity demand forecasting framework for Pakistan, generating sector-wise projections from 2025 to 2060, under six policy-relevant scenarios. The hybrid methodology combining gradient boosting ensemble models with Monte Carlo simulation provides rigorous uncertainty quantification essential for infrastructure investment under deep uncertainty.

Key findings include: (1) BAU demand reaches 420 TWh by 2050 (P10-P90:355-505 TWh), with residential cooling driving growth; (2) under aggressive scenarios, BTM solar deployment grid demand by 18% relative to BAU, representing substantial avoided generation investment; (3) climate change impacts under RCP8.5 increase peak demand by 12-18%, necessitating explicit incorporation in planning; and (4) official NTDC projections systematically overestimate demand, risking stranded assets and circular debt exacerbation.

Policy recommendations emerge directly from these results. NEPRA should adopt probabilistic forecasting for IGCEP updates and provide planning ranges rather than false precision. Accelerated BTM solar and storage deployment offers a “no regrets” peak demand management strategy. Climate projections must be integrated into long-term planning by explicitly modelling

the growth of cooling demand under warming scenarios. Finally, systematic data collection, expansion of smart metering, and improvement of sectoral consumption reporting would strengthen future forecasting capabilities.

The framework is adaptable to other developing economies facing similar challenges of data constraints, structural transitions and planning under uncertainty. As Pakistan pursues its energy transition objectives, evidence-based probabilistic planning provides a foundation for rational infrastructure investments and fiscal sustainability.

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