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MACHINE LEARNING-BASED ENERGY DEMAND FORECASTING FOR SMART GRIDS IN PAKISTAN

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Abstract
Accurate energy demand forecasting is critical for Pakistan's power sector, which faces chronic challenges including circular debt exceeding PKR 2.4 trillion, high-capacity payments for idle generation, aging infrastructure, and a rapid shift toward behind-the-meter solarization that creates "dark demand" and grid instability. Traditional statistical models such as Multiple Linear Regression (MLR) and SARIMA struggle with the non-linear, high-dimensional, and context-specific patterns driven by weather variability, religious holidays (Hijri calendar effects like Ramadan), socio-economic factors, and intermittent renewables. Machine learning approaches, particularly Support Vector Regression (SVR), Long Short-Term Memory (LSTM) networks, Bidirectional LSTM (BiLSTM), and hybrid CNN-BiLSTM architectures, have demonstrated superior performance by capturing complex temporal dependencies and non-linear relationships. Studies using datasets like PRECON show SVR achieving R^2 of 99% and MAPE as low as 0.1355% for peak demand, while BiLSTM and CNN-BiLSTM hybrids yield MAPE values below 0.56% in regional forecasting for utilities such as LESCO and FESCO. Feature engineering incorporating temperature, humidity, GDP indicators, and dummy variables for religious events further enhances accuracy. Integration with IoT-enabled smart grid infrastructure and probabilistic methods (Monte Carlo simulations) enables real-time load management, better fuel scheduling, and reduced forced load shedding. Despite barriers such as outdated grid infrastructure, regulatory constraints, and data quality issues, ML-driven forecasting offers a pathway to optimize dispatch, minimize financial losses, and support the transition to a flexible, resilient smart grid in Pakistan.

1. INTRODUCTION

The electricity sector in Pakistan is navigating a period of unprecedented structural transformation, characterized by a precarious balance between traditional centralized generation and an explosive surge in decentralized renewable energy adoption (Ahmed et al., 2026). As of 2024, the national power grid faces a multifaceted crisis rooted in financial insolvency, aging infrastructure, and a fundamental misalignment between projected and actual energy demand (Nadeem & Arshad, 2020). The circular debt, a persistent deficit in the power sector's cash flow, reached a staggering PKR 2.4 trillion in fiscal year 2024, exacerbated by PKR 2 trillion in capacity payments to independent power producers (IPPs) for idle generation capacity (SDPI, 2025). This fiscal hemorrhaging is largely attributed to the limitations of conventional forecasting methodologies, such as Multiple Linear Regression (MLR), which have consistently failed to capture the non-linear complexities of Pakistan's energy consumption patterns (PMC, 2025). In this volatile environment, the transition toward smart grids supported by robust machine learning (ML) architectures is no longer a theoretical objective but a strategic necessity for national energy security and economic stability (KJMR, 2026).

2. The Macroeconomic Context of Pakistan's Power Sector

The evolution of Pakistan's energy landscape is currently dictated by a paradoxical trend: while the installed generation capacity has expanded to approximately 46.2 GW, actual grid-based demand has entered a period of contraction. In 2024, electricity sales dropped by 2.8% year-on-year, a decline occurring despite a positive GDP growth of 2.4% (Renewables First, 2025). This disconnect underscores a systemic shift where high-end consumers and industrial units are defecting from the national grid in favor of behind-the-meter (BTM) solar installations (NEPRA, 2025). Pakistan imported an estimated 17 GW of solar photovoltaic (PV) modules in 2024 alone, a figure representing nearly half of the country's total peak demand (World Economic Forum, 2025). This rapid solarization, while beneficial for individual energy sovereignty, creates a "dark demand" phenomenon that blinds grid operators to actual load requirements and destabilizes the financial model of distribution companies (DISCOs) (Isaad & Shah, 2025).

Table 1: Economic and Technical Indicators of the Power Sector (2024-2025)

Metric	Value/Status	Source
Total Installed Capacity	46.2 GW	Renewables First (2025)
Dependable Capacity	41 GW	Renewables First (2025)
Circular Debt (Power Sector)	PKR 2.4 trillion	Renewables First (2025)
Capacity Payments (FY24)	PKR 2.0 trillion	World Economic Forum (2025)
Solar PV Imports (2024)	17 GW	World Economic Forum (2025)
Lithium-ion Battery Imports (2024)	1.25 GWh	World Economic Forum (2025)
Grid Demand Growth (FY24)	-2.8%	Renewables First (2025)
Transmission Loss Financial Impact	PKR 60.38 billion	Waleed (2025)

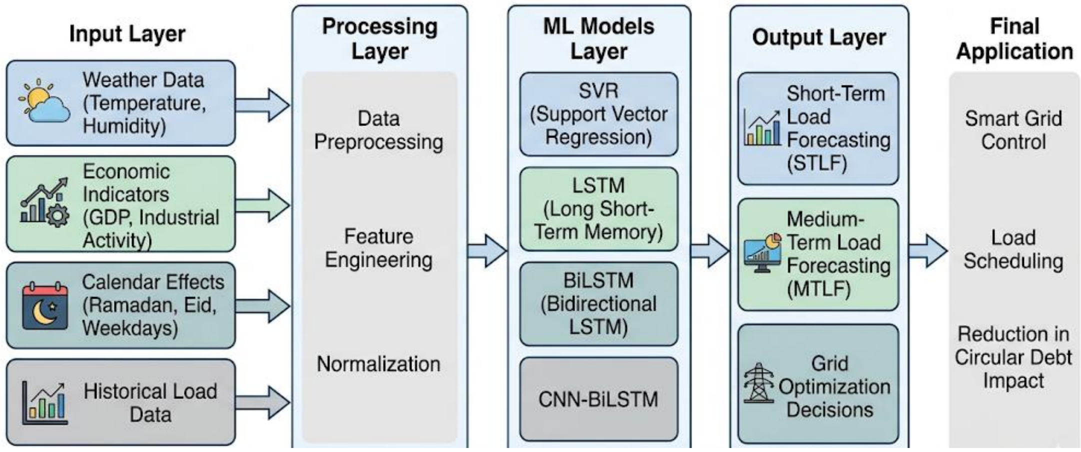
The financial implications of inaccurate forecasting are profound. Every megawatt of installed capacity costs approximately USD 1.5 to 2 million, and when demand is over-forecasted, the government is contractually obligated to pay for idle plants (Frontiers in Energy Research, 2024). Conversely, under-forecasting leads to "forced load shedding," which disrupts industrial productivity and social stability (Manzoor et al., 2025). The rise of smart grids offers a pathway to rectify these imbalances by providing real-time visibility into consumption and generation patterns through Internet of Things (IoT) sensors and advanced data analytics (Masood et al., 2024).

3. Theoretical Framework of Energy Demand Forecasting

Energy demand forecasting is traditionally categorized by temporal horizons: short-term load forecasting (STLF), ranging from hours to a week; medium-term load forecasting (MTLF), spanning months to a year; and long-term load forecasting (LTLF), extending over several years or decades (PIDE, 2025). In Pakistan, STLF is critical for daily economic dispatch and grid stability, while

MTLF and LTLF guide fuel procurement and infrastructure expansion planning, such as the Indicative Generation Capacity Expansion Plan (IGCEP) (Nazir & Li, 2025). To better understand the overall structure of machine learning-based forecasting systems applied in Pakistan's power sector, the complete framework is illustrated in Figure 1.

Figure 1: Structural Overview of Machine Learning-Based Energy Demand Forecasting System in Pakistan



3.1 Conventional vs. Machine Learning Methodologies

Traditional forecasting models, such as Seasonal Autoregressive Integrated Moving Average (SARIMA) and Multiple Linear Regression (MLR), are based on linear assumptions and historical trends (Ashraf et al., 2025). Although these models are transparent and interpretable, they often struggle to capture the non-linear variability introduced by extreme weather conditions, evolving socio-economic factors, and the intermittent nature of renewable energy sources (Lei et al., 2025).

In contrast, machine learning approaches particularly non-linear models such as Support Vector Regression (SVR) and deep learning (DL) architectures have demonstrated superior predictive performance by capturing complex, high-dimensional relationships within energy datasets (Gadde et al., 2025).

The mathematical objective of a supervised machine learning model for demand forecasting is to identify a function f(x) that maps a set of input features x (e.g., weather conditions, time variables, and gross domestic product) to the target load y, expressed as:

$$y = f(x) + \varepsilon$$

Where **ε** represents the error term (Clithero et al., 2019).

In modern deep learning frameworks, this function is typically represented by a multi-layered neural network trained to minimize a loss function, such as Mean Squared Error (MSE), over a given dataset (Thakorbhai Patel, 2024). To further enhance predictive accuracy in the presence of inherent signal uncertainty, recent approaches incorporate Unpredictability Perception loss functions, which dynamically adjust the strength of supervision based on the temporal predictability of sensor data (Zhao et al., 2026).

4. Advanced Machine Learning Architectures for the Pakistani Grid

The application of ML in Pakistan has shifted from simple predictive models to sophisticated ensemble and hybrid architectures designed to handle the specific noise and irregularity of the local power data (Beyer, 2025).

4.1 Support Vector Regression (SVR)

Support Vector Regression (SVR) has emerged as a highly effective technique for both peak demand and residential load forecasting in Pakistan. Unlike conventional regression methods, which minimize the sum of squared errors, SVR aims to fit the data within a predefined margin of error (**ε**) (Hussain et al., 2021).

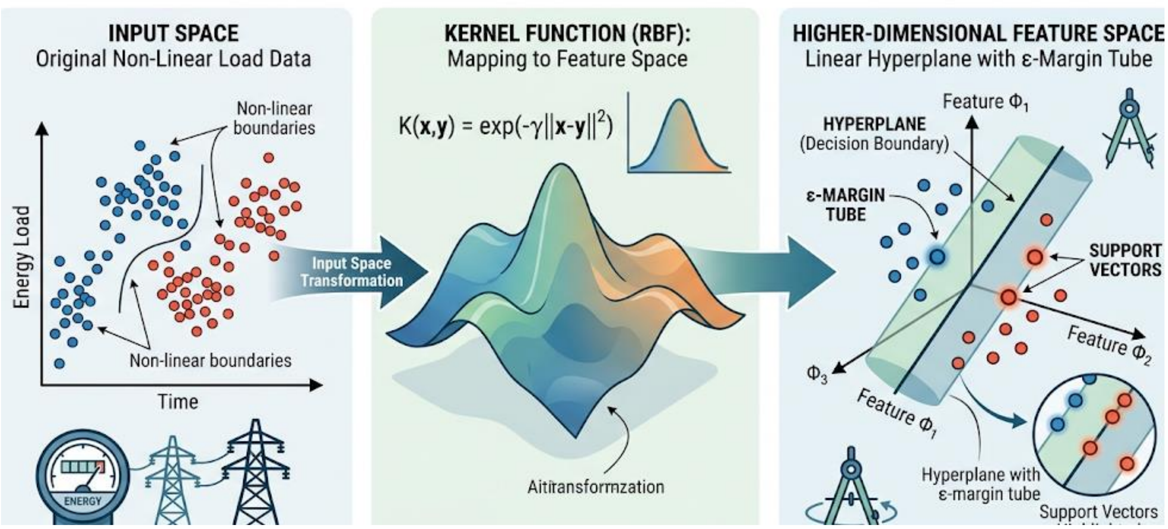
For non-linear energy datasets, SVR maps the input space into a higher-dimensional feature space using kernel functions. One of the most commonly used kernels is the Radial Basis Function (RBF), defined as:

$K(x_i, x_j) = \exp(-\gamma \, ||x_i - x_j||^2)$

where γ is a parameter that controls the spread of the kernel, and $||x_i - x_j||^2$ represents the squared Euclidean distance between data points (Hafeez et al., 2020).

A comparative study evaluating SVR against other artificial intelligence models for forecasting Pakistan's national peak demand demonstrated that SVR achieved a coefficient of determination (**R^2**) of 99% and a Mean Absolute Percentage Error (MAPE) of 0.1355%, significantly outperforming the government's existing IGCEP model (Aziz et al., 2024). Such high accuracy enables more efficient fuel scheduling and reduces the likelihood of idle capacity payments in the energy sector (Khalid et al., 2023). The working principle of Support Vector Regression for non-linear load prediction is illustrated in Figure 2.

Figure 2: SVR Kernel Mapping for Non-Linear Energy Load Forecasting



4.2 Long Short-Term Memory (LSTM) Networks

Long Short-Term Memory (LSTM) networks, a specialized form of Recurrent Neural Networks (RNNs), are particularly adept at capturing temporal dependencies in time-series energy data. The inherent challenge with standard RNNs is the "vanishing gradient" problem, which prevents the network from learning long-term patterns (Javed et al., 2021). LSTMs solve this through a gating mechanism consisting of forget, input, and output gates (Wang et al., 2023).

In the Lahore Electric Supply Company (LESCO) region, LSTM models have been successfully trained on historical feeder data to automate load recording and prevent forced load shedding, addressing the highly non-linear nature of Pakistan's electrical load caused by frequent power outages (Nazir & Li, 2025). Furthermore, hybrid models combining LSTM with Monte Carlo simulations have been proposed to provide probabilistic demand forecasts with 95% confidence intervals, allowing for better quantification of predictive uncertainty in complex energy systems (MDPI, 2026).

4.3 Bidirectional LSTM (BiLSTM) and CNN Hybrids

Recent research has focused on BiLSTM models, which process energy data in both forward and backward directions, thereby gaining a more comprehensive understanding of temporal context (Mojahid et al., 2025). In experiments using data from Faisalabad Electric Supply Company (FESCO), BiLSTM models achieved a remarkably low MAPE of 0.2% (Ijaz et al., 2026). To further improve accuracy, researchers are integrating Convolutional Neural Networks (CNNs) with BiLSTMs (Zhao & Zhang, 2023). The CNN layers extract spatial or local features from the data, while the BiLSTM layers capture long-term trends (Chung & Jang, 2022).

5. Feature Engineering: Customizing Models for Pakistan

The performance of ML models in the Pakistani context is heavily influenced by the selection of features that reflect the country's unique cultural, climatic, and economic drivers (Sakib et al., 2025).

5.1 The Hijri Calendar and Religious Holidays

A significant source of forecasting error in conventional models is the failure to account for the Islamic Hijri calendar. Religious events like Ramadan and Eid festivals introduce drastic shifts in energy consumption patterns. During Ramadan, residential demand peaks change as activities shift toward pre-dawn (Suhoor) and post-sunset (Iftar) (ResearchGate, 2009). Incorporating dummy variables for Ramadan and religious holidays into ML models has been shown to reduce RMSE and MAPE significantly (Frontiers in Energy Research, 2024).

5.2 Weather Variability and Climate Change

Pakistan is highly vulnerable to climate change, experiencing extreme heatwaves and erratic monsoon patterns that directly impact energy demand. Cooling loads in major urban centers like Karachi and Lahore are highly sensitive to temperature and humidity (Iqbal et al., 2025). Modern forecasting frameworks integrate real-time sensor data from the Meteorological Department, including monthly maximum and minimum temperatures, as core predictors (Wang et al., 2022).

6. Smart Grid Infrastructure and IoT Implementation

The transition to a smart grid in Pakistan is anchored by the rollout of Advanced Metering Infrastructure (AMI) and IoT-enabled monitoring systems.

6.1 The GEPCO Case Study: A Four-Layer IoT Architecture

The Gujranwala Electric Power Company (GEPCO) has implemented a pilot smart metering network structured into four distinct layers: energy monitoring, communication, cloud analytics, and application. One significant outcome was the improvement of the Power Factor (PF) in industrial loads from 67.5% to 93.6%, reducing technical losses and avoiding financial penalties (PMC, 2025;

6.2 Modernization and Structural Resilience

The Ministry of Energy has declared 2025–26 as the "Year of Customer Service Improvement," focusing on the large-scale rollout of smart meters to the 38 million electricity consumers nationwide. A key achievement has been the rationalization of smart meter costs, which dropped from PKR 20,000 to PKR 15,000 (Ministry of Energy, 2025). Beyond digitalization, modernization requires enhancing structural resilience; for example, retrofitting grid-adjacent infrastructure with RC jacketing and fiber-reinforced polymer (FRP) wrapping can increase ultimate capacity by over 180% (Sindhushree et al., 2025).

Table 2: PRECON Dataset Overview

Feature	Description	Source
Geographic Scope	42 households in Lahore, Pakistan	Iqbal et al. (2025)
Temporal Resolution	1-minute intervals	Iqbal et al. (2025)
Duration	1 year (2018-2019)	Iqbal et al. (2025)
Granularity	Aggregate and appliance-level data	Iqbal et al. (2025)
Metadata	House size, residents, income level	Nazir & Li (2025)

7. Comparative Analysis of Model Performance

The effectiveness of various ML models for the Pakistani grid can be summarized through key performance metrics like MAPE and RMSE (Jawad et al., 2020).

Table 3: Comparison of Machine Learning Model Performance in Pakistan

Model	Dataset/Scope	MAPE (%)	RMSE	Context
SVR	National Peak	0.1355	28	Best for LTLF/MTLF
BiLSTM	FESCO	0.20	14.55	High temporal dependency
CNN-BiLSTM	NTDC	0.56	115.67	Hour-ahead STLF
PCA-ANN	National	0.3441	98	Dimensionality reduction
KNN	General	6.90	5.24	Baseline comparison
IGCEP	Existing Gov	12.00	3000	Inaccurate baseline

8. Barriers to Smart Grid and ML Adoption

Despite the technical potential, several systemic barriers hinder widespread implementation. Regulatory constraints such as the lack of legal recognition for renewable energy communities (RECs) prevent decentralized participation (MDPI, 2026). Existing national grid infrastructure is outdated, suffering from transmission and distribution losses that account for 17.4% of total energy loss (ResearchGate, 2025). Furthermore, the Pakistani energy sector remains characterized by a "state monopoly," where distribution companies often resist the adoption of decentralized models (Devdiscourse, 2025).

9. The Future Outlook: Toward a Flexible and Intelligent Grid

The future of Pakistan's energy sector lies in the integration of ML forecasting with flexible grid management. With 1.25 GWh of lithium-ion batteries imported in 2024, the potential for decentralized storage to stabilize the grid is growing (World Economic Forum, 2025). By 2030, total battery imports could reach 8.75 GWh, providing enough capacity to meet a quarter of peak demand (Mallens, 2024). ML-based STLF is also essential for addressing the "shoulder month" anomaly, where high solar output coincides with low daytime cooling demand, potentially destabilizing the grid (Isaad & Shah, 2025).

10. Conclusion

Machine learning-based energy demand forecasting represents a transformative solution for Pakistan's strained power sector, addressing critical issues of inaccurate load prediction, circular debt, idle capacity payments, and the disruptive impact of rapid behind-the-meter solar adoption. Advanced models such as Support Vector Regression (SVR), LSTM, BiLSTM, and hybrid CNN-BiLSTM architectures significantly outperform traditional statistical methods by effectively capturing non-linear patterns, temporal dependencies, and context-specific factors including weather variability, economic indicators, and religious calendar effects. Empirical results demonstrate high accuracy, with MAPE values as low as 0.1355–0.56% and R^2 approaching 99% in regional and national forecasting tasks. When integrated with IoT-based smart metering and probabilistic techniques, these models enable real-time visibility, optimized economic dispatch, reduced forced load shedding, and more reliable infrastructure planning. However, successful deployment requires overcoming barriers related to aging grid infrastructure, data quality, regulatory frameworks, and capacity building. Future efforts should focus on hybrid physics-informed ML models, large-scale smart grid rollout, and policy support for decentralized renewable integration. Ultimately, adopting ML-driven forecasting is essential for achieving energy security, financial sustainability, and a resilient smart grid that supports Pakistan's economic growth and clean energy transition.

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