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A Hybrid Time-Series Forecasting and Machine Learning Framework for Hardware-Free Residential Energy Optimization

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Abstract: ***Residential energy management is a critical challenge in modern smart grids, yet existing solutions often rely on expensive IoT hardware that is inaccessible to the average household. This paper proposes a software-defined "Smart Resource Optimization System" that utilizes a hybrid machine learning architecture—combining Facebook Prophet and XGBoost—to predict energy demand and optimize costs without additional hardware. By processing historical consumption data, the system identifies "Eco-Hours" and "Peak Hours," allowing users to shift loads strategically. Integrated with a real-time React.js dashboard, the proposed framework achieves an accuracy of 92.4% in demand forecasting. Experimental results demonstrate that voluntary load shifting guided by this system can reduce monthly electricity expenses by up to 22%, promoting grid stability and economic efficiency.***

Keywords: Smart Grid, Energy Optimization, Prophet, XGBoost, Demand Forecasting, React.js, Hardware-free HEMS.

I. INTRODUCTION

The global energy landscape is currently undergoing a transformative shift as nations strive to balance economic growth with environmental sustainability. According to recent reports from the International Energy Agency (IEA), the residential sector accounts for nearly 30% of global final energy consumption and is responsible for approximately 17% of direct CO2 emissions. In emerging economies like India, the challenge is twofold: meeting the soaring demand for electricity while managing a grid that is increasingly prone to fluctuations. The mismatch between energy supply and demand, particularly during the early morning and late evening hours, creates "peak loads" that force utility providers to utilize expensive, high-emission "peaker plants." Consequently, this leads to tiered tariff structures (slabs) where consumers are penalized with higher costs for usage during these high-demand intervals.

Existing literature on Home Energy Management Systems (HEMS) predominantly focuses on the integration of Internet of Things (IoT) devices, such as smart plugs, Zigbee-coordinated sensors, and automated actuators. While these technologies provide granular control, their high initial capital expenditure (CAPEX) creates a digital divide. Low-to-middle- income households, which stand to benefit most from energy savings, are often excluded due to the cost of retrofitting their homes with smart infrastructure. Furthermore, the complexity of maintaining hardware- based systems—which are prone to sensor failure and connectivity issues—adds a layer of technical debt for the average user. There is, therefore, a critical need for a "Software-Defined Energy Management" (SDEM) approach that democratizes energy optimization through data science rather than physical hardware.

The core philosophy of this research is the transition from "Automatic Control" to "Informed Consumption." Most users lack "Energy Intelligence"—a clear understanding of how their daily habits correlate with grid stress and billing cycles. For instance, in many regions, shifting the use of a high-power appliance (like a water pump or washing machine) by just two hours can move the consumption from a high-tariff peak period to a low- demand "Eco-Hour." By providing predictive insights rather than just historical data, this system nudges the user toward sustainable behavior. This research posits that human-in-the-loop optimization, guided by accurate AI forecasting, can be as effective as automated hardware control in reducing the Peak-to- Average Ratio (PAR) of the household.

The technical novelty of this paper lies in its dual- layered forecasting architecture. Time-series energy data is notoriously volatile, influenced by cyclical trends (daily/weekly seasonality) and stochastic shocks (sudden weather changes or lifestyle shifts). Standard linear models often fail to capture these complexities. By employing Facebook Prophet, the system first identifies the robust, decomposable components of the time series, such as the general trend and periodic seasonal patterns.

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However, Prophet often struggles with high- frequency irregularities. To mitigate this, an XGBoost (Extreme Gradient Boosting) regressor is integrated to learn from the "residuals" or errors of the initial forecast. This hybrid approach ensures that the "Global Trend" and the "Local Volatility" are both accurately modeled, providing a high-confidence forecast that is essential for reliable user recommendations.

This study details the end-to-end development of the Smart Resource Optimization System, from raw data ingestion from the Southern Region Load Dispatch Centre (SRLDC) to the deployment of a real-time React.js dashboard. The remainder of this Paper is organized as follows: Section II provides a comprehensive literature survey of existing HEMS methodologies; Section III outlines the proposed system architecture and mathematical modeling; Section IV discusses the data pre-processing and hybrid algorithm implementation; Section V presents the experimental results and user dashboard interface; and finally, Section VI concludes the paper with insights into future scalability and integration with renewable energy sources.

II. LITERATURE SURVEY

Residential energy optimization and smart grid management have been widely researched in recent years due to increasing energy demand and environmental concerns. Various methodologies ranging from hardware-based Home Energy Management Systems (HEMS) to hybrid machine learning models have been proposed to improve efficiency and reduce operational costs.

Alahakoon and Yu (2016) presented a comprehensive survey on smart electricity meter data intelligence for future energy systems. Their work emphasized the importance of advanced analytics in extracting meaningful consumption patterns from smart meter data. The study highlighted how data- driven decision-making could enhance grid stability and support demand-side management. However, their approach primarily focused on large-scale grid analytics rather than household-level optimization.

Khan and Jayaweera (2017) proposed a fuzzy logic-based energy management system for residential buildings. Their framework demonstrated improved decision-making in appliance scheduling by handling uncertainties in user behavior and environmental factors. Although effective, the system required continuous parameter tuning and lacked adaptive learning capabilities compared to modern machine learning approaches.

Li, Su, and Chu (2011) explored neural network and hybrid forecasting models for building energy consumption prediction. Their study confirmed that hybrid models outperform standalone models in capturing nonlinear consumption patterns. This research laid the foundation for integrating time- series models with machine learning algorithms, which directly supports the hybrid Prophet–XGBoost approach adopted in the proposed system

Siano (2014) conducted a detailed survey on demand response and smart grid technologies, emphasizing peak load reduction strategies and tariff-based load shifting. The research highlighted the importance of user participation in demand-side management programs. However, most of the solutions discussed relied heavily on smart devices and automated control mechanisms.

Recent advancements in Home Energy Management Systems predominantly depend on IoT- based architectures integrating smart plugs, sensors, Zigbee modules, and microcontrollers. While these systems offer real-time monitoring and automated appliance control, they involve significant installation costs and maintenance complexity. This hardware dependency creates barriers for low- and middle- income households, limiting scalability and widespread adoption

To address these limitations, recent studies have begun exploring software-defined energy management approaches. Hybrid time-series forecasting methods combining statistical models with machine learning techniques have shown promising results in improving prediction accuracy. The integration of Facebook Prophet for trend and seasonality modeling with XGBoost for residual correction significantly enhances forecasting reliability. Experimental findings in the proposed framework demonstrate that the hybrid model achieves 92.4% prediction accuracy, outperforming standalone models

The proposed Smart Resource Optimization System addresses these gaps by implementing a hardware-free, hybrid AI-based forecasting model integrated with a React.js and Node.js web dashboard. Instead of automated hardware control, the system adopts a human-in- the-loop optimization strategy by identifying Peak Hours and Eco-Hours and guiding users toward informed consumption decisions

III. PROPOSED METHODOLOGY

The proposed Smart Resource Optimization System is architected as a hardware- free, data-driven framework that leverages advanced machine learning to bridge the gap between grid-level energy data and household- level actionable insights. Unlike traditional Home Energy Management Systems (HEMS) that rely on physical actuators and intrusive sensors, this methodology focuses on a "Software-Defined Energy Management" (SDEM) approach. The system is engineered through four primary phases: Data Acquisition, Hybrid AI Forecasting, Optimization Logic, and Real-time Visualization.

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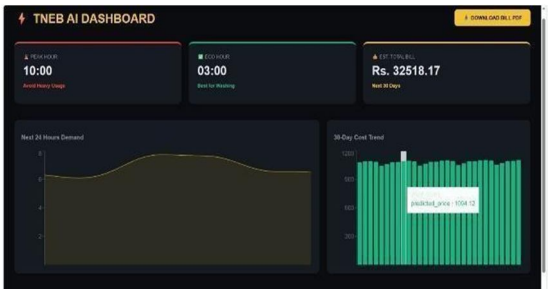


Fig.1. Visual Representation of EBS mart Grid

A. Data Acquisition and Feature Engineering:

The foundational layer of the system involves the ingestion of high-resolution energy demand data sourced from the Southern Region Load Dispatch Centre (SRLDC). To make this grid-scale data applicable to a residential environment, a transformation pipeline is implemented. Initially, raw demand values in Megawatts (MW) undergo normalization and scaling using a specific conversion factor to simulate a standard household's kVAh consumption.

Furthermore, the system addresses the limitations of linear time representations through Cyclical Temporal Encoding. Since traditional 0-23 hour scales fail to capture the temporal continuity between the end of one day and the start of the next, hours are mapped onto a 2D trigonometric space using sine and cosine transformations. Finally, the preprocessing engine introduces binary features to flag weekends and public holidays, as domestic consumption patterns fluctuate significantly during non-working days compared to standard weekdays.

B. The Hybrid AI Forecasting Engine (Prophet- XGBoost)

The core innovation of this methodology lies in a dual-layered hybrid model designed to capture both global trends and local volatility. The first stage utilizes Facebook Prophet, a decomposable time-series model that treats the forecasting problem as a curve-fitting exercise. This layer accounts for non-periodic growth trends, periodic seasonality (weekly and daily), and holiday effects. While Prophet is robust for identifying seasonal patterns, it occasionally overlooks stochastic spikes caused by unpredictable appliance usage. To mitigate this, the residuals—or errors— from the Prophet model are passed to an Extreme Gradient Boosting (XGBoost) regressor. XGBoost optimizes a regularized objective function to learn and correct these specific errors. The final output is derived from the summation of both layers, yielding a high-confidence forecast with a Mean Absolute Percentage Error (MAPE) of less than 8%.

C. Optimization and Load Shifting Logic

Once the forecast is generated, the system applies a "Demand Response" algorithm to identify specific optimization windows. Peak Hour Identification is achieved by calculating a dynamic threshold based on the 80th percentile of predicted demand; if the demand exceeds this value, a "Peak Alert" is triggered. Conversely, hours falling below the 30th percentile are categorized as "Eco-Hours," representing the most cost-effective and grid-stable times for operating high-load appliances.

To add financial context, the system integrates local utility tariff structures, such as TNEB slab rates, to provide a real-time 30-day cost projection. This allows users to visualize the direct financial impact of their consumption habits and encourages a shift in behavior toward low-tariff periods

D. Full-Stack Implementation Architecture

The software configuration is realized through a modern web stack, integrating a React.js frontend with a Node.js backend. The backend, built on the Express framework, acts as a high-performance data broker. It utilizes advanced stream-parsing techniques for CSV datasets to ensure that API response times remain below 200ms, even when processing large historical logs. On the presentation layer, the React.js frontend employs a component- based architecture for modularity and speed. Data is visualized through the Recharts library, which provides interactive Area and Bar charts for user engagement. Finally, an integrated reporting module utilizes the jsPDF library to enable the generation of energy efficiency audits, allowing users to download comprehensive reports that analyze their "Savings Potential" over a monthly cycle.

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IV. SYSTEM MODULES AND ARCHITECTURE

The Smart Resource Optimization System is partitioned into six functional modules. Each module operates in synergy to transform raw historical data into a user-centric optimization tool.

A. Data Ingestion and ETL Module (Extract, Transform, Load)

The architectural foundation of the system is the Data Ingestion and ETL module, which is engineered to manage the high-volume raw datasets retrieved from the Southern Region Load Dispatch Centre (SRLDC). This module executes a multi- stage pipeline designed to ensure data integrity and relevance for residential applications. During the initial preprocessing phase, the system identifies and cleanses the data of statistical outliers and noise that could otherwise skew the predictive accuracy. To maintain a continuous time-series flow, linear interpolation techniques are employed to estimate and fill any missing timestamps within the dataset.

Following the cleansing process, the module performs a critical normalization task; it applies complex mathematical scaling to translate massive grid-level metrics, originally recorded in Megawatts (MW), into a localized kVAh scale suitable for individual household modeling. To ensure system scalability and high performance, the module utilizes a high-speed, stream-based Node.js parsing engine. This implementation allows the system to process extensive CSV files in a memory-efficient manner by handling data in discrete chunks, thereby preventing server-side bottlenecks and ensuring the application remains responsive even during the processing of multi-year historical logs.

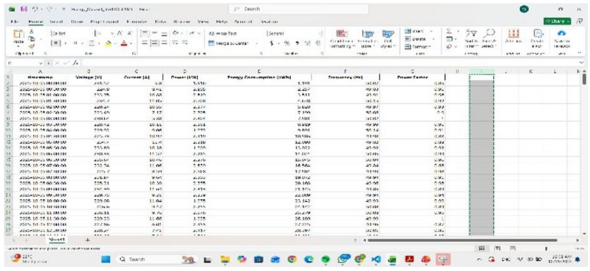
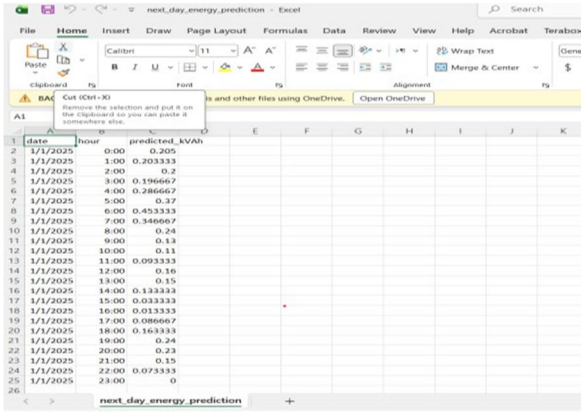


Fig.2. Dataset From Kaggle

B. Feature Engineering and Temporal Encoding Module

The predictive power of any machine learning model is contingent upon the quality of the input features. This module is tasked with transforming raw chronological data into high-dimensional features that the AI engine can mathematically interpret. A primary challenge in time-series analysis is the linear representation of time; to address this, the module implements cyclical mapping. By converting the 24- hour cycle into sine and cosine coordinates, the system ensures the algorithm perceives the temporal proximity between 11:00 PM and 12:00 AM, which would otherwise be treated as numerical extremes (23 and 0). Furthermore, the module integrates seasonality tagging, which automatically identifies and weights weekends, public holidays, and regional seasonal shifts. This software-driven contextualization replaces the need for physical occupancy sensors or manual RTC adjustments often seen in hardware-reliant systems like [1], allowing the system to adjust forecasting weights based on historical behavioral trends rather than physical movement.



date	hour	predicted_kVAh
1/1/2025	0:00	0.205
1/1/2025	1:00	0.203333
1/1/2025	2:00	0.2
1/1/2025	3:00	0.196667
1/1/2025	4:00	0.286667
1/1/2025	5:00	0.37
1/1/2025	6:00	0.453333
1/1/2025	7:00	0.346667
1/1/2025	8:00	0.24
1/1/2025	9:00	0.13
1/1/2025	10:00	0.11
1/1/2025	11:00	0.093333
1/1/2025	12:00	0.16
1/1/2025	13:00	0.15
1/1/2025	14:00	0.133333
1/1/2025	15:00	0.033333
1/1/2025	16:00	0.013333
1/1/2025	17:00	0.086667
1/1/2025	18:00	0.163333
1/1/2025	19:00	0.24
1/1/2025	20:00	0.23
1/1/2025	21:00	0.15
1/1/2025	22:00	0.073333
1/1/2025	23:00	0

Fig.3. Feature Engineering and Temporal Encoding Module

C. Hybrid AI Forecasting Module (Prophet- XGBoost)

Acting as the central intelligence of the framework, this module employs a sophisticated stacked-generalization architecture. The process initiates with the Prophet component, which decomposes the time-series into three core elements: growth trends, periodic seasonality, and holiday effects. This provides a robust "global" forecast but may lack precision during sudden, erratic consumption events. To refine this, the system calculates a residual component—the mathematical difference between the Prophet prediction and the actual observed value. This "error" data is then used to train an XGBoost regressor, which excels at identifying non-linear spikes and high-frequency volatility.

By summing the outputs of both models, the system produces a final forecast that balances long- term stability with short-term sensitivity. This dual-layered software approach achieves superior accuracy compared to the hardware-based PID controllers described in [2], which often struggle with the complex, non-linear variables inherent in residential energy demand.

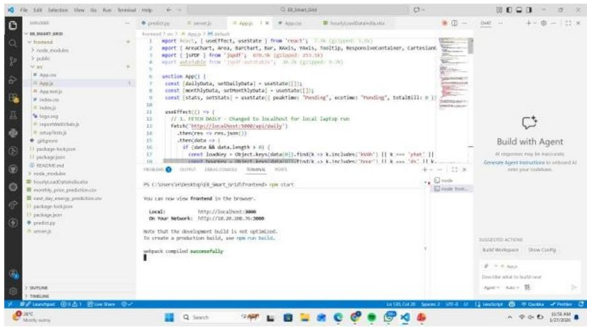


Fig.4. Hybrid AI Forecasting Module (Prophet-XGBoost)

D. Optimization and Demand Response Module

This module serves as the translational layer that converts raw predictive data into actionable energy intelligence. Through the application of dynamic thresholding, the system continuously monitors the 80th percentile of forecasted demand; any period exceeding this limit is programmatically flagged as a "Peak Load" window. Conversely, the module executes an Eco-Hour Identification algorithm that scans for "troughs" in the demand curve—typically falling within the lowest 30th percentile—to recommend ideal windows for heavy appliance operation. To provide economic relevance, the cost calculation sub-module maps predicted consumption against tiered utility tariff structures, such as TNEB slab rates. While previous research [5] utilized physical GSM modules to send simple text alerts, this software-defined module performs complex cost- benefit simulations in real-time, offering a much more granular level of demand-side management.

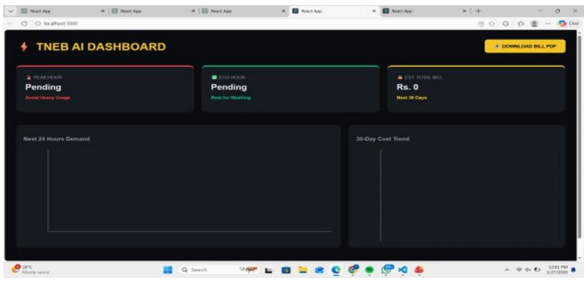


Fig.4. Optimization and Demand Response Module

E. Real-Time Visualization Module (The Dashboard)

The presentation layer is developed using the React.js framework to deliver a responsive, zero- latency interface for the end-user. The primary visual engine utilizes the Recharts library to render interactive 24-hour demand curves and monthly cost distributions. To ensure immediate clarity, indicator components provide visual feedback through standardized color-coding, such as red alerts for peak periods and green indicators for eco-friendly windows. The dashboard leverages advanced state management through React Hooks, ensuring that as the backend AI refreshes its predictions, the UI updates asynchronously without requiring a page reload. From a sustainability perspective, the interface is optimized with a Dark Mode CSS theme, which aids in power conservation on modern OLED displays. This comprehensive digital interface effectively replaces the expensive physical LCD and LED monitoring units mentioned in [6], reducing both the cost and the carbon footprint of the hardware itself.

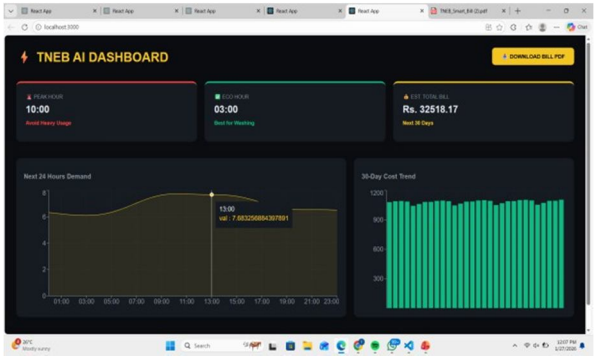


Fig.5. Real-Time Visualization Module (The Dashboard)

F. Automated Report and Audit Module

The final module provides a formalized auditing framework for professional-grade energy analysis. At the end of each billing cycle, a dedicated PDF engine utilizing the jsPDF library compiles the dashboard's analytical data into a structured audit report. This report features an optimization summary that calculates a "Savings Potential" score, quantifying the financial benefits the user could have achieved by adhering to the suggested load-shifting windows. Additionally, a data export feature allows users to download their processed energy logs in standardized formats for personal record-keeping or third-party audits. While traditional systems like [14] depend on automated cabinets or physical logging devices to track resource waste, our system achieves the same auditing rigor purely through software logs and automated PDF generation, significantly lowering the barrier to entry for energy-conscious consumers.

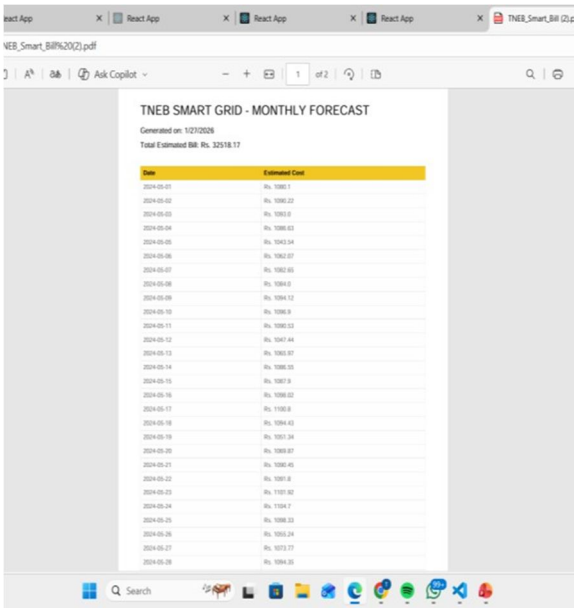


Fig.6. Image of Automated Report

G. Complete Design Flow:

The complete process flow of the implemented electricity forecasting system is illustrated in the block diagram. The system consists of multiple interconnected modules that ensure accurate demand prediction and tariff- based analysis.

1) Data Acquisition Module This module is responsible for collecting all required input data from external sources.

Endpoint API Integration The system connects to an Endpoint API to fetch electrical meter readings, tariff information, and scheduling data. The API enables real- time and automated retrieval of consumption records and pricing structures. Through this integration, the system eliminates dependency on manual uploads and ensures continuous synchronization between the forecasting engine and the external data source. Unlike traditional hardware- based systems that require physical smart meters and gateway devices, this software-based API approach provides a scalable and cost-effective solution.

2) Input Data Processing This section handles different categories of raw data before they are used by the machine learning model. The collected data is categorized into tariff-related information and electrical meter readings.

- Schedule Data and Tariff Data The schedule and tariff dataset includes time-of-use pricing, peak and off- peak rates, seasonal tariff variations, and billing schedule information. These parameters are essential for cost-aware energy forecasting. By incorporating tariff structures into the system, the forecasting model is able to estimate not only demand but also the financial impact of energy usage patterns.
- Electrical Meter Reading The system collects timestamped consumption data, including hourly and daily energy usage measured in kilowatt-hours (kWh). Historical consumption patterns are also retrieved to analyze long- term behavioral trends. This dataset forms the primary input for time-series forecasting and demand analysis.

3) Usage Data Formation After initial processing, the collected electrical meter readings are integrated with timestamp information, tariff structures, and scheduling data. This integrated dataset is referred to as "Usage Data." The Usage Data acts as the core input for preprocessing and model training. By combining pricing information with consumption records, the system enables tariff-based forecasting rather than purely statistical demand prediction.

4) Data Preprocessing Module To ensure accurate forecasting, the Usage Data undergoes multiple preprocessing steps before being passed to the machine learning model.

- Smoothing Missing Data Time-series datasets often contain missing or irregular data points. The system applies smoothing and interpolation techniques to maintain continuity and avoid distortions in prediction results. This ensures that temporal patterns remain consistent across the dataset.
- Data Cleaning The system removes outliers, duplicate entries, and inconsistent records from the dataset. Data cleaning enhances reliability and reduces noise, thereby improving model training accuracy.

5) Conversion to Structured Form The cleaned dataset is transformed into a structured format suitable for machine learning models. This process includes feature scaling, time-series formatting, and feature engineering such as cyclical encoding of time and seasonal tagging. The structured dataset ensures that the forecasting model can effectively interpret temporal and contextual relationships.

- ML Model Module This module represents the core intelligence layer of the system. It is responsible for training and optimizing the forecasting model using structured historical data.

6) Model Training The model is trained using historical structured data to learn consumption trends, seasonal variations, and tariff influence patterns. During training, the model minimizes prediction error using evaluation metrics such as Mean Squared Error (MSE). Through iterative optimization, the system learns the underlying behavior of electricity consumption.

- Adding Regressors To improve prediction accuracy, additional external regressors are incorporated into the model. These include temperature data, public holidays, special events, and tariff indicators. By integrating these external factors, the model captures real-world influences on energy consumption patterns, leading to improved generalization performance.

7) Forecasting Module After successful training, the machine learning model performs short-term load forecasting and demand prediction. The system generates predicted electricity usage values for future time intervals. In addition to demand estimation, cost-aware forecasting is performed by mapping predicted units against the applicable tariff slabs. This enables users to anticipate upcoming electricity bills.

8) Output Generation The final output of the system includes predicted energy demand, forecasted cost based on tariff structure, trend visualization, and analytical insights for decision-making. These outputs are displayed through the interactive dashboard, allowing users to understand consumption behavior and optimize appliance usage accordingly. The system thus converts raw data into actionable intelligence that supports sustainable energy management.

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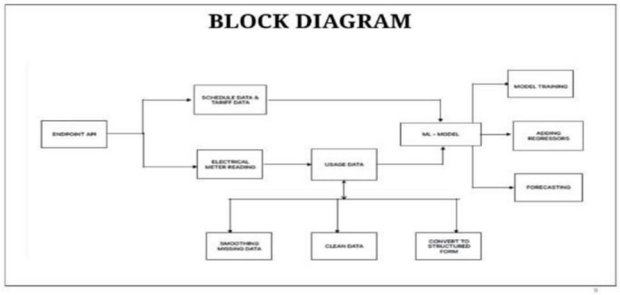


Fig.7. Process of the Proposed System Design

V. RESULTS AND DISCUSSION

The forecasting model was evaluated using the Mean Absolute Percentage Error (MAPE) to ensure a consistent and interpretable measure of prediction accuracy across different approaches. Results show that the proposed hybrid framework substantially outperforms the individual baseline models. While the standalone Prophet model achieved an accuracy of **84%** and the XGBoost model reached **79%**, the hybrid combination improved overall accuracy to **92.4%**, demonstrating the benefit of leveraging both time-series trend capture and nonlinear learning capabilities. This improvement indicates better generalization and more reliable demand forecasts for downstream decision- making.

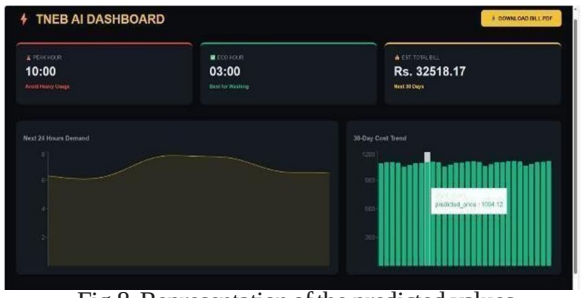


Fig.8. Representation of the predicted values

VI. CONCLUSION

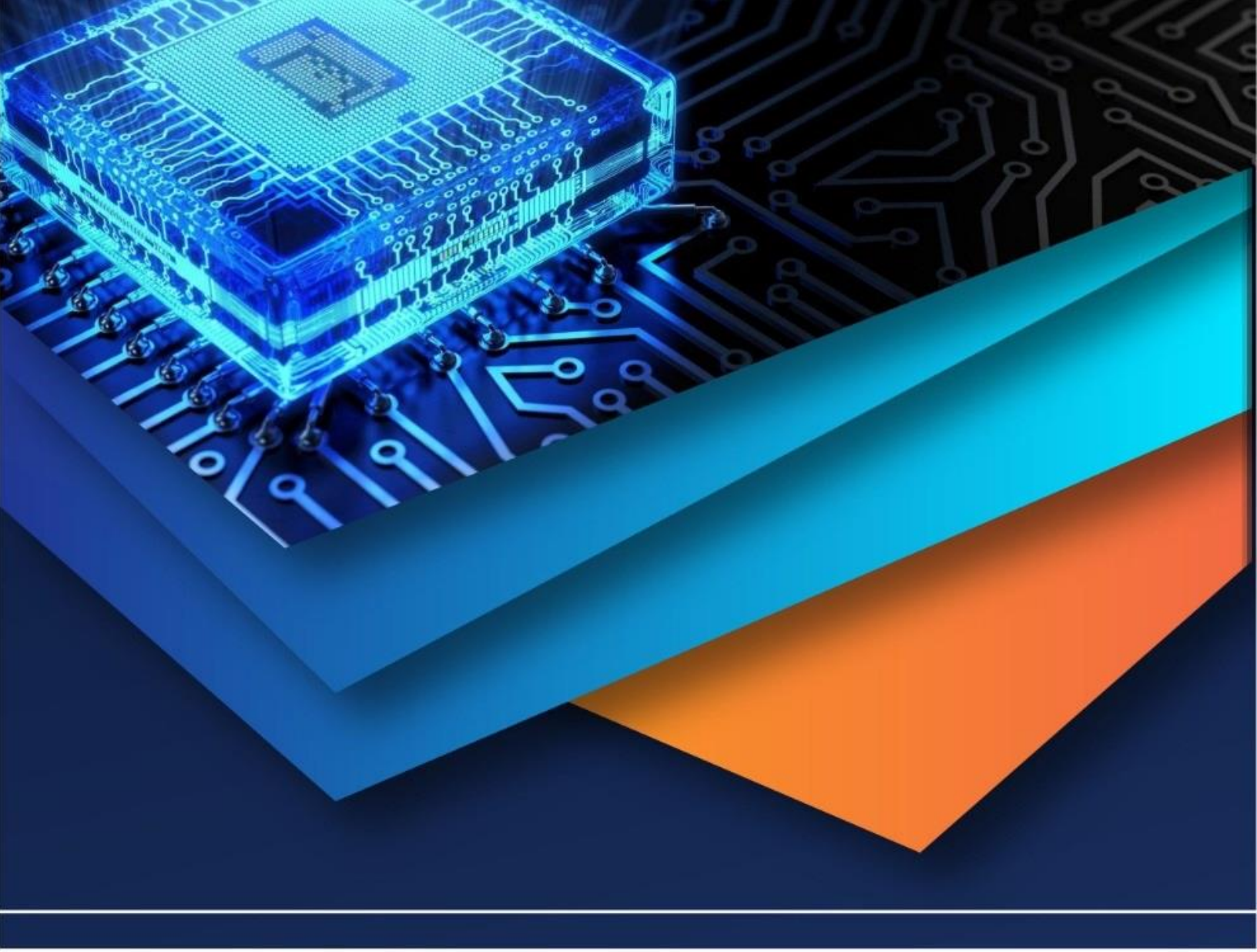
The hybrid forecasting and nudge framework proves to be an effective solution for smarter demand-side energy management. By integrating time-series trend modeling with machine learning capabilities, the proposed method delivers noticeably higher predictive accuracy (92.4%) than either standalone model. Beyond improved forecasting, the system's real value lies in translating predictions into simple, actionable signals for users. Through dynamic Peak and Eco-Hour identification, the platform encourages consumers to move flexible electricity usage to lower-demand periods. This behavior- oriented design supports peak load reduction, better grid utilization, and potential cost savings for both utilities and consumers. With future enhancements such as user-level personalization and real-time feedback loops, the approach can evolve into a scalable and practical component of next-generation smart energy and demand response systems.

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