Smart Energy Distibution and Monitoring Grid System

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***Abstract*— With the rapid rise in global energy demand and increasing pressure on sustainable development, traditional power grids have become inadequate. These grids often lack real-time insights, adaptability, and efficient renewable energy integration, leading to energy wastage and operational inefficiencies. This paper presents a Smart Energy Distribution and Monitoring Grid System that utilizes Internet of Things (IoT) technologies and machine learning (ML) algorithms for real-time data monitoring, predictive analysis, and renewable energy usage. The methodology involved integrating ESP32 microcontrollers with current and voltage sensors to acquire live electrical data. This data was analyzed using XGBoost, LightGBM, and CatBoost models, with CatBoost achieving the highest accuracy ($R^2 = 0.9971$). The system, powered by a solar panel and a battery management system (BMS), ensures energy independence and scalability. Furthermore, the design supports modular implementation, real-time visualization, and low-cost components, making it a viable solution for smart homes, offices, and small-scale industrial units. This research concludes that a cost-effective, accurate, and sustainable smart grid system is achievable and provides practical implications for smart city development and efficient energy utilization.**

Keywords*— Smart Grid, IoT, ESP32, Machine Learning, Renewable Energy, Forecasting, Energy Monitoring, CatBoost

I. Introduction

In the context of rapidly escalating electricity demand driven by urbanization, industrial growth, and the proliferation of electronic devices, the need for efficient and sustainable energy management has become critical. Simultaneously, the global emphasis on reducing carbon emissions and transitioning toward renewable energy sources has positioned **smart energy solutions** at the forefront of modern power systems research. The integration of **advanced computing technologies**, including the Internet of Things (IoT) and machine learning (ML), into energy infrastructure represents a paradigm shift from traditional, manual, and reactive systems to intelligent, autonomous, and adaptive frameworks. Recent studies have consistently highlighted the potential of these technologies in enhancing grid reliability, enabling demand forecasting, and supporting decentralized renewable energy integration [1][4].

However, despite the adoption of smart meters, remote sensing devices, and data acquisition tools, several key challenges persist. A significant limitation lies in the **lack of predictive analytics capabilities**, particularly in small to medium-scale deployments. Many existing solutions are confined to data logging and visualization, offering little to no predictive insight for load forecasting or anomaly detection. Moreover, **real-time monitoring is often fragmented**, with inadequate communication between sensing hardware and analytical engines. Additionally, **solar energy utilization**—a cornerstone of sustainable energy infrastructure—is frequently under-optimized due to the absence of intelligent control systems that can balance generation, storage, and consumption dynamically. These gaps highlight the need for an integrated system that bridges sensing, communication, and machine learning in a cohesive pipeline.

To address these limitations, this study proposes a **modular, real-time, and predictive Smart Energy Grid System** that unifies hardware-level sensing with intelligent data analytics. The system incorporates **ESP32 microcontrollers** interfaced with current and voltage sensors for continuous monitoring, supported by a **solar-powered Battery Management System (BMS)** to ensure energy autonomy. Ensemble ML models—**XGBoost, LightGBM, and CatBoost**—are employed to forecast energy consumption trends and enable proactive decision-making. By combining low-cost IoT components with high-accuracy predictive algorithms, this research presents a scalable solution suitable for **smart homes, office environments, and small industrial units**, laying the foundation for broader smart city applications and more resilient energy infrastructure.

II. LITERATURE SURVEY

The integration of Internet of Things (IoT) and Machine Learning (ML) has significantly influenced the transformation of conventional power grids into intelligent and responsive energy systems. M. Ali *et al.* [1] and S. Sharma *et al.* [2] proposed ESP32-based energy monitoring systems that enabled real-time data acquisition and cloud-based analytics. While both systems were cost-effective and practical for small-scale applications, they lacked predictive capabilities and broader integration with renewable sources.

On the machine learning front, L. Zhang *et al.* [3] reviewed energy forecasting techniques and identified gradient boosting algorithms such as XGBoost, LightGBM, and CatBoost as powerful tools for time-series prediction. T. Chen and C. Guestrin [4] introduced XGBoost, a robust boosting algorithm optimized for scalability and accuracy in structured data, while G. Ke *et al.* [5] proposed LightGBM to enhance training efficiency and reduce memory consumption. L. Prokhorenkova *et al.* [6] further advanced the field with CatBoost, an algorithm specifically designed to handle categorical features with minimal preprocessing, making it well-suited for energy datasets. J. Lee *et al.* [7] empirically validated these models' effectiveness in building energy forecasting, highlighting their accuracy in real-time applications.

In terms of system architecture and energy self-sufficiency, R. Muñiz *et al.* [8] and L. López *et al.* [9] emphasized the role of solar-powered smart buildings and energy-sustainable IoT ecosystems. Their work demonstrated the feasibility of modular smart grid designs capable of operating off-grid. Furthermore, M. Shirvanimoghaddam *et al.* [10] introduced energy harvesting techniques like piezoelectric materials to enable self-powered IoT nodes, addressing energy autonomy in resource-constrained environments.

Renewable energy integration necessitates efficient storage mechanisms, as discussed by R. Patel and V. Singh [11], who explored smart solar IoT systems and their architecture. Complementing this, J. Lee *et al.* [12] highlighted the importance of layered safety mechanisms in battery management systems (BMS) for lithium-ion storage. Additional industry insights on BMS safety were provided by recent reports and articles [13]–[15], which addressed thermal stability, fire prevention, and fault diagnosis techniques.

Despite these advancements, a gap remains in unifying these domains into a single scalable, modular platform. The reviewed studies either focus on data acquisition [1][2], machine learning prediction [3][6], or storage safety [11][12] in isolation. This paper proposes a novel Smart Energy Distribution and Monitoring Grid that bridges these aspects through a solar-powered, CatBoost-enhanced, real-time monitoring system using ESP32, current and voltage sensors, and modular design to support smart homes and small-scale industries.

III. Methodology

The proposed system was built using the ESP32 microcontroller for data collection, integrated with ZMPT101B voltage sensors and ACS712 current sensors. These sensors captured electrical parameters and transmitted them wirelessly to cloud storage. The data was timestamped using NTP synchronization and formatted into time-series entries a shown in fig1 and fig2

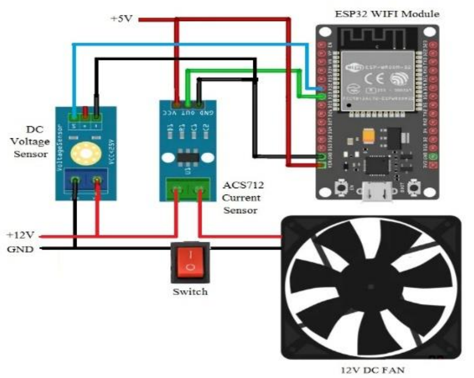

Fig.1 Circuit diagram

The circuit connects a voltage sensor and an ACS712 current sensor to an ESP32 microcontroller. The sensors measure real-time electrical parameters, which are processed by ESP32.

Output is transmitted via Wi-Fi to ThingSpeak, and a relay controls the load based on logic.

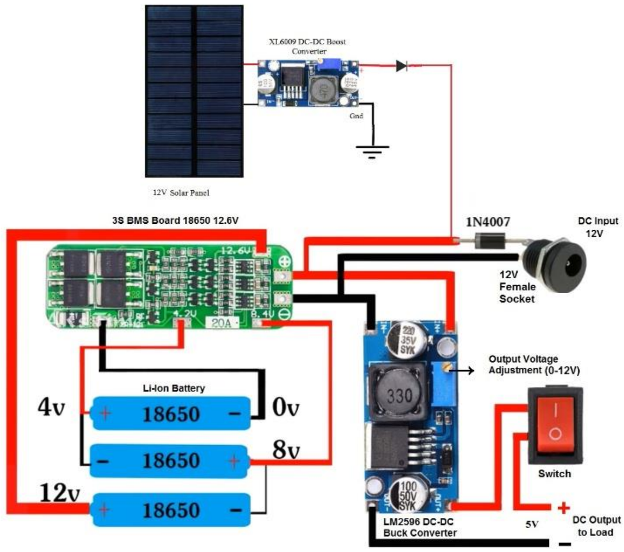

Fig.2 Sensing circuit

circuit

The sensing circuit includes an ACS712 current sensor and a voltage divider circuit for voltage measurement.

These sensors are connected to the analog input pins of the ESP32 microcontroller.

They detect real-time current and voltage values, which are then digitized and processed for monitoring.

Preprocessing steps included handling missing values, removing noise and outliers, and normalizing data for better training performance. Time-based features such as hour, weekday, and daily patterns were extracted to enhance forecasting models.

Three ensemble-based regression models were implemented:

- *XGBoost: Known for its robustness in tabular datasets.*
- *LightGBM: Optimized for speed and memory.*
- *CatBoost: Provided the best performance with R^2 = 0.9971.*

Model performance was validated using train/test splits (80/20) and k-fold cross-validation. Evaluation metrics included R^2 score, Mean Absolute Error (MAE), and Mean Squared Error (MSE).

IV. Results

The CatBoost model outperformed others with minimal prediction error and high correlation with actual values. During testing, it demonstrated consistent trend prediction for energy consumption across various usage patterns and temporal segments, including peak and off-peak hours. LightGBM also exhibited low error margins and handled real-time prediction effectively, while XGBoost delivered robust performance but with slightly higher variance under fluctuating loads.

The results were assessed using the R^2 score, which indicates how closely the predicted values match the actual data, and Mean Squared Error (MSE), which quantifies the average squared differences between predictions and ground truth as shown in table 1.

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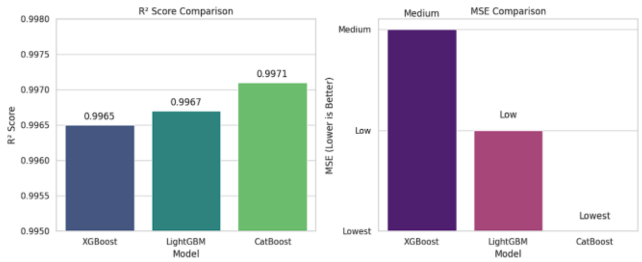

Fig 3 Model performance
The machine learning model (e.g., Linear Regression) is trained on historical power consumption data.
Performance is evaluated using metrics like RMSE and R^2 score for accuracy.
The model enables reliable forecasting of energy usage trends for better grid management.

CatBoost superior performance is due to its internal handling of categorical and time-series data, automatic preprocessing, and resistance to overfitting even with small hyperparameter adjustments. The model's architecture allowed for better generalization on unseen time intervals.

Visualization played a key role in demonstrating the model's practical utility. A custom-built dashboard presented real-time energy usage and forecasting trends, enabling users to detect abnormal usage, anticipate peak demand, and adjust consumption accordingly. Graphs, time-series plots, and heatmaps provided intuitive visual cues to promote energy-efficient behavior.

Additional features such as alert notifications, seasonal usage trend analysis, and predictive insights about optimal usage windows further enhanced the decision-making capabilities of the system. These tools empower users to implement data-driven strategies for energy conservation and load management.

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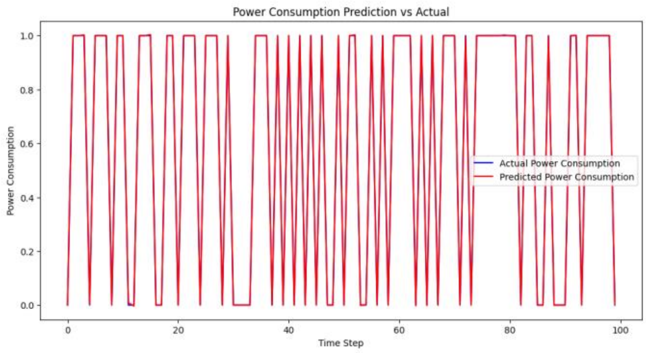

Fig.4 Power consumption Prediction vs Actual
This comparison plot illustrates how closely the predicted values match the actual power usage. Small deviations indicate high model accuracy and effective learning of consumption patterns.
It validates the reliability of the model in real-world deployment

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V. DISCUSSIONS

5.1 Review of Findings

The developed Smart Energy Distribution and Monitoring Grid System has successfully demonstrated a robust and real-time solution for monitoring and forecasting energy usage. The integration of voltage and current sensors with an ESP32 microcontroller enabled accurate acquisition of electrical parameters, while wireless transmission ensured timely updates. Visualization dashboards provided a comprehensive interface for real-time tracking, historical analysis, and actionable insights.

Moreover, the use of machine learning models—specifically CatBoost, LightGBM, and XGBoost—enhanced the system's forecasting ability. Among these, the CatBoost regressor achieved the highest R^2 score and lowest Mean Squared Error (MSE), indicating its effectiveness for time-series prediction. These insights allow users to anticipate power demands, detect abnormal usage patterns, and implement preventive measures, thereby increasing situational awareness and operational safety.

5.2 Evaluation

The proposed system was benchmarked against traditional, reactive monitoring systems and showed significant advantages in terms of modularity, real-time responsiveness, and automation. It leverages low-cost open-source components, which makes it highly scalable and replicable across varied environments, including residential homes, academic institutions, and small-scale industries.

Cloud-based storage and processing (using platforms like Firebase and MQTT protocols) allowed for persistent, secure, and remote access to data. Unlike legacy systems that rely on manual checks or periodic readings, this system supports continuous tracking and automatic notifications via Slack and email integrations.

The machine learning models provided insights into daily, weekly, and monthly consumption patterns, supporting energy-saving strategies and load optimization. However, the system's accuracy and reliability are inherently tied to internet connectivity and sensor calibration—factors that must be considered during real-world deployments.

The findings underscore the potential of combining IoT, cloud technologies, and artificial intelligence to improve energy grid systems. The project lays the groundwork for future innovations in smart grid technology by showing that even low-cost setups can achieve high levels of automation, forecasting, and sustainability. While the current implementation is focused on small environments, the modular design supports scaling to larger installations. Opportunities exist for enhancing the system by incorporating smart load switching, renewable integration management, and fault tolerance.
Future developments could focus on deploying the system in rural or remote settings where energy access and monitoring are minimal. Edge AI-based processing could further reduce latency and internet dependency, making the system more autonomous and resilient.

VI. CONCLUSION

This study presents the design, implementation, and evaluation of a Smart Energy Distribution and Monitoring Grid System that integrates Internet of Things (IoT) components, cloud platforms, and machine learning models to deliver a comprehensive energy management solution. By leveraging ESP32 microcontrollers, voltage/current sensors, and cloud-based dashboards, the system provides real-time insights into electrical consumption, identifies potential inefficiencies, and enables proactive decision-making through predictive analytics.

The use of ensemble-based regression algorithms—XGBoost, LightGBM, and CatBoost—allowed for accurate energy forecasting, with CatBoost showing the most favorable results. Real-time alerts, visual dashboards, and trend predictions enable consumers and facility managers to take informed steps toward load balancing and energy conservation.

In contrast to traditional grid systems, which are typically reactive, this smart grid platform offers a proactive and adaptive approach to energy distribution. It is not only more efficient but also environmentally sustainable through its integration with solar power systems and battery storage modules.

The system's open-source, cost-effective design ensures that it can be adopted across diverse use cases and geographies. While limitations related to internet dependency and scalability remain, they open avenues for future research in decentralized, edge-based processing and smart automation.

Ultimately, this work contributes to the ongoing efforts in building smarter, greener cities and infrastructures, aligning with global initiatives for sustainable development and energy equity.

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