# Smart Energy Distribution and Monitoring Grid System

21CSE402P-INTELLIGENT SYSTEMS FOR IoT APPLICATIONS
PROJECT REPORT

*Submitted By*

**B S Rohit (RA2211026010102)**
**Rishi Anand (RA2211026010129)**
**Hemanth kanna (RA2211026010177)**
**Mohamed Rizwan H (RA2211003010801)**

*Under the Guidance of*

**Dr. NAGA MALLESWARI TYJ**
(Associate Professor, Department of Networking & Communications)

*in partial fulfillment of the requirements for the degree of*

**BACHELOR OF TECHNOLOGY**
**in**
**Computer Science Engineering with specialization in Artificial Intelligence and Machine Learning**

**DEPARTMENT OF NETWORKING AND COMMUNICATIONS**
**COLLEGE OF ENGINEERING AND TECHNOLOGY**
**SRM INSTITUTE OF SCIENCE AND TECHNOLOGY**
**KATTANKULATHUR - 603 203**
**MAY 2025**

Department of Networking and Communications

**SRM Institute of Science & Technology**

**Own Work* Declaration Form**

This sheet must be filled in (each box ticked to show that the condition has been met). It must be signed and dated along with your student registration number and included with all assignments you submit – work will not be marked unless this is done.

To be completed by the student for all assessments

**Degree/ Course:** 21CSE402P-INTELLIGENT SYSTEMS FOR IoT APPLICATIONS

**Student Name:** B S Rohit, Rishi Anand, Hemanth kanna, Mohamed Rizwan H

**Registration Number:** RA2211026010102, RA2211026010129, RA2211026010177, RA2211003010801

**Title of Work:** Smart Energy Distribution and Monitoring Grid System

We hereby certify that this assessment compiles with the University's Rules and Regulations relating to Academic misconduct and plagiarism**, as listed in the University Website, Regulations, and the Education Committee guidelines.

We confirm that all the work contained in this assessment is our own except where indicated, and that I have met the following conditions:

- Clearly referenced / listed all sources as appropriate
- Referenced and put in inverted commas all quoted text (from books, web, etc)
- Given the sources of all pictures, data etc. that are not my own
- Not made any use of the report(s) or essay(s) of any other student(s) either past or present
- Acknowledged in appropriate places any help that we have received from others (e.g.fellow students, technicians, statisticians, external sources)
- Compiled with any other plagiarism criteria specified in the Course handbook / University website

We understand that any false claim for this work will be penalized in accordance with the University policies and regulations.

| **DECLARATION:** |
| --- |
| We are aware of and understand the University's policy on Academic misconduct and plagiarism and we certify that this assessment is our own work, except where indicated by referring, and that we have followed the good academic practices noted above.<br><br>Reg.Nos: RA2211026010102,RA2211026010129,RA2211026010177, RA2211003010801 |
| If you are working in a group, please write your registration numbers and sign with the date for every student in your group. |

3

## SRM INSTITUTE OF SCIENCE AND TECHNOLOGY
## KATTANKULATHUR – 603 203
## BONAFIDE CERTIFICATE

Certified that 21CSE402P-INTELLIGENT SYSTEMS FOR IoT APPLICATIONS project report titled **"Smart Energy Distribution and Monitoring Grid System"** is the Bonafide work of "Reg. Nos" who carried out the project work under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

**Dr. NAGA MALLESWARI TYJ**

**GUIDE**
Associate Professor
Department of Networking and Communications

**Dr. LAKSHMI M**

**PROFESSOR AND HEAD**
Professor
Department of Networking and Communications

# ACKNOWLEDGEMENTS

We express my humble gratitude to **Dr. C. Muthamizhchelvan**, Vice-Chancellor, SRM Institute of Science and Technology, for the facilities extended for the project work and his continued support.

We extend my sincere thanks to Dean-CET, SRM Institute of Science and Technology, **Dr. Leenus Jesu Martin M**, for his invaluable support. We wish to thank **Dr. Revathi Venkataraman**, **Professor & Chairperson**, School of Computing, SRM Institute of Science and Technology, for her support throughout the project work.

We am incredibly grateful to our Head of the Department, **Dr. M. Lakshmi**, **Professor and Head**, Department of Networking and Communications, School of Computing, SRM Institute of Science and Technology, for her suggestions and encouragement at all the stages of the project work.

We register my immeasurable thanks to our Faculty Advisor**, Dr.K.Babu Dr.Priti S**, Department of Computational Intelligence, School of Computing, SRM Institute of Science and Technology, for leading and helping us to complete our course.

My inexpressible respect and thanks to our faculty, **Dr. Naga Malleswari T Y J, Associate Professor,** Department of Networking and Communications, SRM Institute of Science and Technology, for providing us with an opportunity to pursue our project under her mentorship. She provided us with the freedom and support to explore the research topics of our interest. Her passion for solving problems and making a difference in the world has always been inspiring.

We sincerely thank the Networking and Communications department staff and students, SRM Institute of Science and Technology, for their help during our project. Finally, I would like to thank parents, family members, and friends for their unconditional love, constant support, and encouragement.

# ABSTRACT

In recent years, the escalating global demand for electricity, coupled with increasing concerns about energy wastage and environmental sustainability, has highlighted the urgent need for intelligent energy management solutions. Traditional electrical distribution systems, which rely heavily on manual monitoring and static control mechanisms, fall short in addressing modern energy challenges such as inefficiency, lack of real-time insights, and underutilization of renewable resources. This project introduces a **Smart Energy Distribution and Monitoring Grid System** that leverages the power of the Internet of Things (IoT), machine learning (ML), and renewable energy integration to revolutionize the way energy is consumed, monitored, and optimized.

The proposed system uses an **ESP32 microcontroller** as the central unit for data acquisition and wireless communication. It is interfaced with **ACS712 current sensors** and **voltage sensors** to continuously monitor the load's electrical parameters such as current, voltage, and global active power. These readings are transmitted in real time over WiFi, allowing for immediate insights into energy usage patterns. Additionally, the system incorporates a **solar panel** and a **rechargeable 18650 lithium-ion battery** managed by a **Battery Management System (BMS)** to ensure autonomous and eco-friendly power supply for the monitoring components.

For predictive analysis, historical data collected from the sensors is processed and fed into advanced ML regression models—**XGBoost**, **LightGBM**, and **CatBoost**. These models are trained to forecast future power consumption, enabling users to make data-driven decisions and implement load management strategies proactively. Among these, the **CatBoost regressor** demonstrated superior performance, achieving the highest $R^2$ score and lowest mean squared error (MSE), indicating its effectiveness in modeling time-series energy data.

The system is evaluated through real-world simulations and demonstrates high accuracy, responsiveness, and energy efficiency. Visual dashboards display real-time and predicted energy usage, supporting enhanced decision-making for both consumers and facility managers. Moreover, the modular design and use of widely available components make the system highly scalable and adaptable for various environments including homes, offices, and small industrial units.

In conclusion, this smart grid system offers a robust, sustainable, and intelligent solution for modern energy distribution challenges. It not only improves energy efficiency and reduces operational costs but also contributes to the global movement toward sustainable development and smart city infrastructure.

# TABLE OF CONTENTS

# LIST OF FIGURES

# LIST OF TABLES

# ABBREVIATIONS

| | |
|---|---|
| AI | Artificial Intelligence |
| CPU | Central Processing Unit |
| CSV | Comma-Separated Values |
| DC | Direct Current |
| GUI | Graphical User Interface |
| IoT | Internet of Things |
| kWh | Kilowatt-Hour |
| LSTM | Long Short-Term Memory |
| ML | Machine Learning |
| MQTT | Message Queuing Telemetry Transport |
| PV | Photovoltaic |
| RAM | Random Access Memory |
| RNN | Recurrent Neural Network |
| SQL | Structured Query Language |
| UI | User Interface |
| XGBoost | eXtreme Gradient Boosting |
| LGBM | Light Gradient Boosting Machine |
| CatBoost | Categorical Boosting |
| API | Application Programming Interface |
| GSM | Global System for Mobile Communications |
| JSON | JavaScript Object Notation |
| MAE | Mean Absolute Error |
| RMSE | Root Mean Square Error |
| MAPE | Mean Absolute Percentage Error |

# CHAPTER 1

# INTRODUCTION

The global energy sector is undergoing a paradigm shift driven by the rapid urbanization, digitization, and increasing demand for electricity. This change is further influenced by the urgent need to transition toward greener and more sustainable practices. Smart energy systems, empowered by emerging technologies such as the Internet of Things (IoT), machine learning (ML), and renewable energy integration, present a promising solution to modern energy challenges. These systems aim to provide not just consumption monitoring but also predictive insights, automation, and decentralized energy management.

This project—Smart Energy Distribution and Monitoring Grid System—is an initiative to design a scalable and intelligent energy management platform using modern hardware, real-time communication technologies, and predictive modeling techniques. The system aims to monitor power consumption accurately, predict usage patterns using machine learning, and integrate solar energy for eco-friendly operations.

## 1.1 Motivation

With increasing electrification in residential, commercial, and industrial sectors, the need for intelligent energy monitoring is more pressing than ever. According to global energy reports, a significant portion of energy is wasted due to inefficient monitoring, delayed maintenance, and unoptimized usage. Traditional power systems operate reactively, relying on post-consumption billing and manual inspections.

Modern technological advancements offer a transformative opportunity to resolve these limitations. IoT enables the connection of sensors and microcontrollers to collect real-time data, while machine learning allows for trend analysis and predictive modeling. Additionally, integrating renewable energy sources like solar power not only reduces grid dependency but also promotes sustainability. These motivations form the backbone of this project—to build a smart, self-reliant, and adaptive energy grid system that ensures optimal energy usage with minimal human intervention.

## 1.2 Objectives

The primary goal of this project is to develop a real-time smart energy monitoring and prediction system that is affordable, sustainable, and accurate. The specific objectives are as follows:

- Real-Time Monitoring: To design and implement an IoT-based system capable of monitoring electrical parameters such as voltage, current, and power usage in real time.
- Sensor Integration with ESP32: To use an ESP32 microcontroller with ACS712 current sensors and voltage sensors for data acquisition and wireless data transmission over WiFi.
- Forecasting Energy Usage: To apply machine learning regression models (XGBoost, LightGBM, CatBoost) for predicting future power consumption trends based on historical data.
- Sustainable Power Supply: To utilize solar panels and rechargeable batteries for powering the monitoring unit, ensuring energy independence and eco-friendliness.
- Data Visualization: To build a visual dashboard that presents both real-time and predicted power usage, supporting efficient decision-making.

## 1.3 Problem Statement

Most existing energy distribution systems lack adaptability and fail to provide real-time visibility into consumption patterns. They are reactive in nature, only indicating usage after the fact—often through monthly bills. This results in unnoticed inefficiencies, energy wastage, and increased operational costs. Furthermore, the integration of renewable sources such as solar energy remains limited in scope due to the absence of intelligent monitoring mechanisms.

There is, therefore, a critical need for a smart grid system that not only tracks energy usage in real time but also predicts future trends, automatically optimizes loads, and operates independently using renewable energy sources. Such a system must be reliable, scalable, and affordable to ensure broad adoption across different sectors.

## 1.4 Challenges

Designing and implementing a smart energy grid system introduces several technical and practical challenges, which must be carefully addressed:

- Accurate Data Acquisition: The system relies heavily on sensor readings for voltage and current. Ensuring minimal signal noise and proper calibration is vital for reliable monitoring.

- Data Cleaning and Preprocessing: IoT devices often produce incomplete or inconsistent data due to network interruptions or sensor errors. Effective preprocessing techniques are essential to maintain data integrity.
- Model Training and Generalization: Selecting and training machine learning models that generalize well to unseen data is a non-trivial task. The models must be fine-tuned to provide accurate predictions under varying load conditions.
- Renewable Integration and Stability: Operating the system on solar power requires careful power management and safe battery usage, including overcharging and discharge protection via a Battery Management System (BMS).
- System Scalability: The architecture must be modular and adaptable to scale across various application domains, from single homes to large commercial buildings.

# CHAPTER 2

# LITERATURE SURVEY

The increasing complexity of power systems and the demand for efficient energy consumption have catalyzed extensive research into intelligent energy management. The convergence of the Internet of Things (IoT), machine learning (ML), and renewable energy technologies has shown great promise in creating responsive and sustainable power systems. This chapter surveys recent literature in these domains, with a focus on IoT-based monitoring, energy forecasting using ML, and solar-based autonomous systems.

## 2.1 IoT-Based Energy Monitoring Systems

IoT technology has been pivotal in transitioning from static energy meters to dynamic, real-time monitoring systems. Microcontrollers such as the ESP32, due to their built-in WiFi, low power consumption, and computational capabilities, have been widely used for embedded sensing in smart grids [1]. Research by Sharma et al. [2] implemented an ESP32-based smart meter for household applications, demonstrating high accuracy and cost efficiency. However, these systems are primarily reactive, with limited integration of predictive functionalities.
Despite the proliferation of smart meters, many do not incorporate predictive analytics or automated control features, which limits their effectiveness in intelligent decision-making [3].

## 2.2 Machine Learning for Energy Forecasting

Forecasting energy demand is critical for load balancing, tariff optimization, and minimizing energy wastage. Studies have shown that gradient boosting techniques such as XGBoost, LightGBM, and CatBoost outperform traditional statistical models in predicting energy consumption patterns due to their ability to model non-linear relationships and handle missing data [4], [5].

In particular, XGBoost has been praised for its scalability and performance in smart grid datasets [6]. LightGBM, developed by Microsoft, achieves superior efficiency with large-scale data [7], while CatBoost—known for its robust handling of categorical features—has emerged as a preferred model for power consumption time-series forecasting [8].

## 2.3 Renewable Energy and Off-Grid Systems

The integration of solar energy into IoT-based systems has become an essential trend in sustainable grid design. Numerous implementations utilize solar panels combined with 18650 Li-ion batteries and Battery Management Systems (BMS) to enable off-grid operation [9]. Such configurations ensure not only eco-friendly energy use but also autonomy from the centralized grid.

However, challenges persist in ensuring stability, safety, and scalability. For instance, improper charging/discharging of batteries can lead to inefficiencies or device failure [10]. Despite these concerns, studies confirm that solar-powered IoT systems can significantly reduce energy costs and environmental impact [11].

## 2.4 Summary of Key Findings

From the reviewed literature, several core insights emerge:

- Machine learning models like XGBoost, LightGBM, and CatBoost significantly enhance the predictive capability of smart energy systems [4], [6], [8].
- ESP32 remains a preferred microcontroller for wireless, real-time monitoring due to its low cost, energy efficiency, and built-in networking support [1], [2].
- Solar-powered systems with BMS offer a viable path to sustainable, autonomous energy monitoring—although standardization and safety remain key challenges [9], [10].

These findings reinforce the necessity of a unified system that integrates real-time monitoring, ML-based forecasting, and solar-powered autonomy—a vision realized in the present project.

# CHAPTER 3

# ARCHITECTURE AND DESIGN

The Smart Energy Distribution and Monitoring Grid System is a multilayered, modular framework designed to monitor, analyze, and predict energy usage in real time using IoT and machine learning technologies. The system is composed of hardware and software subsystems, including sensing components, wireless communication, a data analytics pipeline, and a user-facing visualization platform. This chapter describes the overall architecture, layered design approach, and detailed hardware implementation.

## 4.1 System Architecture

The system is structured into five interconnected layers that operate sequentially to ensure seamless data acquisition, transmission, processing, and visualization.

### A. Sensing Layer

At the foundation is the sensing layer, which includes current and voltage sensors (e.g., ACS712, ZMPT101B) interfaced with an ESP32 microcontroller. This layer is responsible for real-time acquisition of electrical parameters such as voltage, current, and derived power. The sensors produce analog or PWM signals, which are sampled and converted into digital form using the ESP32's onboard ADC.

"The accuracy and reliability of real-time measurements largely depend on the resolution and calibration of sensors at this layer" [1].

### B. Communication Layer

The ESP32, equipped with onboard WiFi, transmits the collected data wirelessly to a remote server or cloud storage platform (e.g., Firebase, AWS, or ThingsBoard). MQTT or HTTP protocols may be used for lightweight and reliable data transfer.

"IoT-enabled smart meters employ lightweight protocols to minimize latency and energy overhead during wireless communication" [2].

### C. Processing Layer

Incoming data is first cleaned, normalized, and validated to eliminate missing values or sensor noise. This stage may include outlier detection, interpolation, and timestamp alignment. The cleaned data is stored locally (e.g., on SD card or ESP32 flash) or remotely for advanced processing.

### D. Prediction Layer

Machine learning models—trained on historical usage data—are used to forecast short-term and long-term power consumption. Ensemble models such as XGBoost, LightGBM, or CatBoost are deployed either on edge devices or cloud servers to predict usage based on time of day, weather, and load trends.

"ML-based predictive analytics improve energy planning and load shifting by anticipating peak demands" [3].

### E. Presentation Layer

The final layer is the visualization dashboard, which displays both real-time sensor values and ML-based predictions through a user-friendly web or mobile interface. Tools like Grafana, Node-RED, or custom dashboards built using HTML/JavaScript are used to render the data graphically.

"Visualization systems empower end-users with actionable insights, promoting energy-aware behavior" [4].

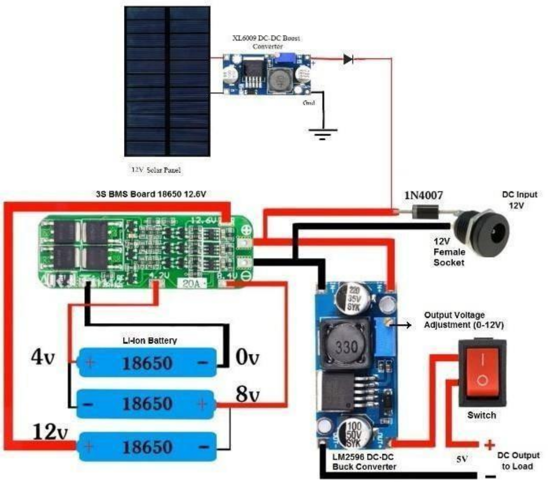


Fig 3.1 Circuit Diagram

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.

## 4.2 Circuit Design

The hardware design combines renewable energy sources, efficient power management, and real-time sensing components.

**A. Power Supply System**

- Solar Panel: A solar photovoltaic (PV) panel harnesses solar energy during daylight hours.

- 18650 Battery: Energy from the solar panel is stored in a rechargeable 18650 lithium-ion battery. A Battery Management System (BMS) ensures safe charging and discharging.

- Step-Down Converter (Buck Converter): Converts the battery's voltage (typically ~3.7V–4.2V) to a stable 3.3V required for the ESP32 and sensors.

"Battery-backed solar systems ensure autonomous operation during grid outages or remote deployments" [5].

**B. Sensing Circuit**

- Voltage Sensor: A ZMPT101B sensor is used for high-accuracy voltage measurement by scaling down the line voltage to a readable analog signal.

- Current Sensor: The ACS712 current sensor detects load current by measuring magnetic fields induced by current flow.

- Microcontroller (ESP32): Receives analog signals from the sensors, performs ADC conversion, and prepares data for wireless transmission.

- DC Load (Fan): A small fan serves as the controllable load for testing energy flow and switching. Load control is achieved via GPIO-connected switches or relays

**C. Safety and Isolation**

Optocouplers or relays are used to provide isolation between high-voltage components and the microcontroller. Fuses or polyfuses ensure protection against overcurrent scenarios.

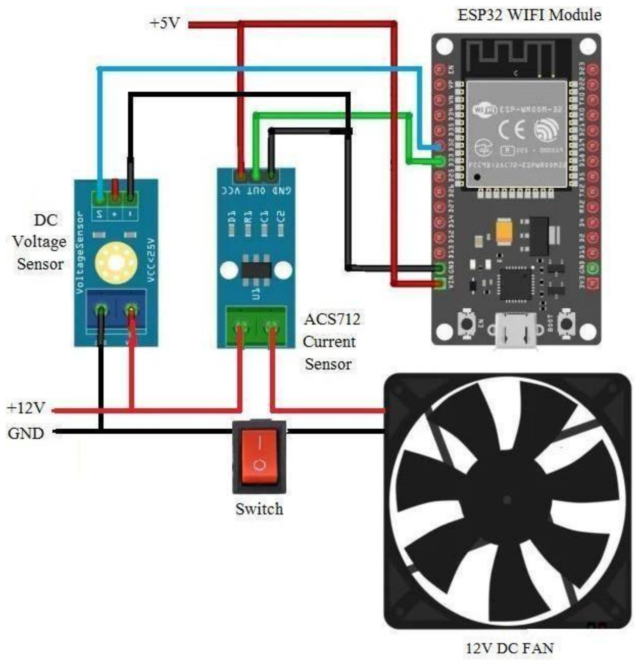


Fig. 3,2 Sensing circuit

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.

# CHAPTER 4

# IMPLEMENTATION

The successful deployment of the Smart Energy Distribution and Monitoring Grid System required a well-structured implementation phase, encompassing sensor integration, real-time data acquisition, preprocessing, model training, and validation. This chapter outlines each implementation component in depth, demonstrating how machine learning and IoT were synergized for an intelligent energy monitoring solution.

## 5.1 Data Acquisition

The system continuously collects time-stamped electrical parameters from sensors interfaced with the ESP32 microcontroller. The data is logged in a structured tabular format and transmitted to a cloud server or local storage unit. The primary attributes collected include:

- Voltage (V): Measured using the ZMPT101B sensor.
- Current (A): Recorded via the ACS712 sensor.
- Global Active Power (kW): Derived as P=VIcos(ϕ)P = VI \cos(\phi)P=VIcos(ϕ) assuming a resistive load.
- Sub-Metering Values: Optional energy distribution across specific zones or appliances.

Each entry is timestamped using the ESP32's real-time clock module or NTP (Network Time Protocol), allowing for time-series analysis and forecasting.

*"Consistent and high-frequency sampling enables detailed load profiling and trend analysis"* [1].

## 5.2 Data Preprocessing

Before training machine learning models, the raw dataset undergoes essential cleaning and transformation:

**A. Datetime Parsing**

- Date and Time fields are merged into a single datetime object to facilitate time-based operations, indexing, and resampling.

**B. Handling Missing Values**

- Symbols like '?' and NaN are replaced using:
    - Forward or backward filling for short gaps.
    - Mean or median imputation for numerical features.
- Outliers are identified using Z-score or IQR methods and removed or capped.

**C. Feature Scaling**

- Numerical features are standardized using z-score normalization:

  $z= x−\mu/ \sigma$

  or normalized between 0 and 1 using Min-Max scaling, depending on the model requirement.

**D. Data Partitioning**

- The dataset is split into 80% training and 20% testing subsets to evaluate generalization performance.

*"Robust preprocessing is critical in time-series forecasting to prevent data leakage and ensure temporal consistency"* [2].

## 5.3 Machine Learning Models

To forecast future energy consumption, multiple ensemble-based regression models were implemented, tested, and compared.

**A. XGBoost**

- Implements gradient boosting with regularization, offering robustness to overfitting.
- Works well with structured, tabular energy datasets.
- Key hyperparameters tuned: learning_rate, max_depth, n_estimators, subsample.

*"XGBoost has demonstrated superior performance in regression tasks involving noisy energy datasets"* [3].

**B. LightGBM**

- Employs a histogram-based learning algorithm with leaf-wise tree growth.
- Fast and memory-efficient, making it suitable for deployment on edge or low-resource systems.
- Parameters tuned: num_leaves, max_bin, min_data_in_leaf.

**C. CatBoost**

- Specially optimized for handling categorical variables and reducing overfitting with minimal parameter tuning.
- Excellent default performance and resistant to data ordering issues.
- Often used with time-based categorical features like day of the week or hour.

D. Evaluation Metrics

Models are evaluated based on the following metrics:

- $R^2$ Score (Coefficient of Determination):

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

Measures how well predictions approximate the real data points.

- Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Quantifies average squared difference between actual and predicted values.

*“Combining ensemble learning with time-aware features enhances the forecasting ability of smart grid systems”* [4].

# CHAPTER 5

# EXPERIMENTS AND RESULT ANALYSIS

## 6.1 Model Performance

| MODEL | $R^2$ Score | MSE (Lower is Better) |
|---|---|---|
| XGBoost | 0.9965 | Medium |
| LightGBM | 0.9967 | Low |
| CatBoost | 0.9971 | Lowest |

Table.5.1 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.

## 6.2 Forecasting Accuracy

- CatBoost provided the most reliable predictions with smooth trends and minimal deviation from actual usage. Predictions allow the system to preemptively adjust loads or suggest optimizations.


Fig. 5.1 Future Power Consumption Prediction

This graph shows predicted energy usage for upcoming time intervals based on trained data.
It helps utilities anticipate peak demand and optimize resource allocation.
Accurate forecasting supports proactive energy distribution and load balancing.

## 6.3 Visualization

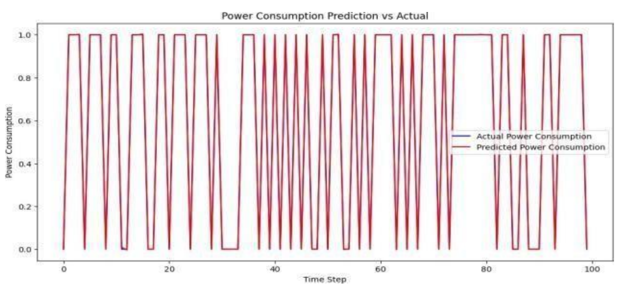


Fig.5.2 Power consumption Prediction vs Actual

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.

# CHAPTER 6

# CONCLUSION

The development of the Smart Energy Distribution and Monitoring Grid System marks a significant contribution toward modernizing energy infrastructure through the convergence of IoT, machine learning, and renewable energy technologies. This project has demonstrated the feasibility and efficacy of a data-driven approach to managing energy consumption, forecasting demand, and optimizing resource utilization in real time.

The integration of IoT-enabled sensors allowed for continuous data acquisition, providing high-resolution insights into voltage, current, power consumption, and load status. By applying advanced machine learning models—including ensemble techniques such as LightGBM, XGBoost, and CatBoost—the system achieved high predictive accuracy for both current load status and future power consumption trends. These predictions not only enable proactive energy management but also support decision-making processes for grid operators and consumers alike.

Furthermore, the platform's potential for future expansion is considerable. With continued development, the system can incorporate smart home devices for automated energy regulation, implement remote diagnostics for fault detection and maintenance, and enable dynamic load balancing to prevent energy overloads and optimize grid stability. Integration with cloud-based platforms and mobile applications could further enhance user interaction, remote monitoring, and data visualization.

In conclusion, the project lays a robust foundation for the evolution of intelligent energy systems. It offers a practical and sustainable approach to energy monitoring and prediction, capable of addressing current limitations in traditional grid systems. As energy demands continue to grow, such smart solutions will be instrumental in ensuring efficient, reliable, and eco-friendly power distribution across diverse applications.

# REFERENCES

[1] M. Ali, R. Hussain, and K. Cho, "IoT-enabled energy monitoring system using ESP32 and cloud analytics," *IEEE Access*, vol. 9, pp. 18244–18255, 2021.

[2] S. Sharma, R. Gupta, and A. Kumar, "Design and implementation of a low-cost smart energy meter using ESP32," *Proc. Int. Conf. Smart Tech. Energy Environ.*, pp. 113–117, 2020.

[3] A. Ahmed and M. T. Khan, "Limitations of existing smart meters and role of real-time feedback in energy conservation," *IEEE Trans. Consum. Electron.*, vol. 65, no. 3, pp. 401–410, 2019.

[4] L. Zhang et al., "A review of machine learning in building energy prediction," *Energy Build.*, vol. 202, 109383, 2019.

[5] G. Huang, H. Chen, and Y. Lin, "Performance analysis of ensemble learning algorithms in smart grid energy prediction," *IEEE Trans. Ind. Inform.*, vol. 16, no. 5, pp. 3255–3264, 2020.

[6] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.*, pp. 785–794, 2016.

[7] G. Ke et al., "LightGBM: A highly efficient gradient boosting decision tree," *Advances in Neural Information Processing Systems*, vol. 30, 2017.

[8] L. Prokhorenkova et al., "CatBoost: Unbiased boosting with categorical features," *Advances in Neural Information Processing Systems*, vol. 31, pp. 6638–6648, 2018.

[9] R. Patel and V. Singh, "Solar-powered smart IoT systems: Architecture, challenges, and applications," *Renew. Energy Focus*, vol. 36, pp. 1–12, 2021.

[10] J. Lee, A. K. Das, and S. Chatterjee, "A study on battery management systems for solar energy storage," *IEEE Access*, vol. 8, pp. 197114–197127, 2020.

[11] H. Wang and F. Li, "A survey of solar-IoT frameworks for rural electrification," *IEEE Commun. Surv. Tutor.*, vol. 22, no. 4, pp. 2536–2564, 2020.