iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** V **Month of publication:** May 2025

DOI: https://doi.org/10.22214/ijraset.2025.70422

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

Sustainable Smart Homes in Remote Areas Using IoT and AI Technologies

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Abstract: This research paper presents study on the design and implementation of smart homes in remote or off-grid areas using the Internet of Things (IoT) and Machine Learning (ML). In recent years, the growing demand for sustainable living solutions has emphasized the need for intelligent systems capable of addressing the unique challenges faced by geographically isolated or infrastructure-deficient communities. The proposed approach focuses on integrating real-time data acquisition and intelligent decision-making into the daily operations of homes powered by renewable energy sources. The system employs IoT-based sensors to monitor various environmental and operational parameters such as temperature, humidity, energy consumption, and appliance activity. These data streams are then analyzed using lightweight ML algorithms that enable predictive load forecasting, early fault detection, and user behavior modeling. This dual-layered approach allows for proactive energy management, improving the reliability and longevity of off-grid energy systems while enhancing user comfort. A case study involving a solar-powered prototype deployed in a rural setting demonstrates the feasibility and benefits of the proposed system. The results indicate a significant increase in energy efficiency and reduction in manual intervention, with the system dynamically adjusting operations based on predicted energy availability and user patterns. Furthermore, the implementation addresses several core challenges such as limited power, unreliable connectivity, and restricted technical support through robust, low-power designs and adaptive communication strategies. By merging IoT and ML technologies, the proposed smart home model contributes to building sustainable and intelligent living environments in remote locations. Future research will explore edge AI integration, scalable community-level networks, and the role of federated learning to enhance security and personalization.
Keywords: Smart Homes, IoT, Machine Learning, Off-Grid, Remote Areas, Energy Management, Sustainability

I. INTRODUCTION

The concept of smart homes has evolved rapidly over the past decade, driven by advancements in the Internet of Things (IoT), Machine Learning (ML), and automation technologies. Smart homes are designed to enhance living standards by automating household operations, optimizing energy consumption, and providing intelligent user experiences. While such systems have gained popularity in urban and suburban regions, their application in remote or off-grid areas remains relatively underexplored. These areas, often characterized by limited infrastructure, unreliable power supply, and minimal connectivity, require tailored solutions that address their unique challenges. Globally, millions of people live in regions where access to the centralized power grid is either unavailable or inconsistent. In such scenarios, renewable energy sources like solar or wind power serve as the primary means of electricity generation. However, without proper monitoring and management, these sources can be inefficient and unreliable, leading to frequent power outages and poor quality of life. Traditional home systems in these areas lack intelligence, often resulting in energy wastage, sub-optimal appliance usage, and increased maintenance efforts. The integration of IoT and ML offers a transformative opportunity to overcome these challenges. IoT-enabled smart sensors can collect real-time data on energy consumption, environmental conditions, and appliance status, even in energy-constrained environments. Meanwhile, ML algorithms can analyze these data streams to forecast energy demand, identify anomalies, and adapt operations to user behavior patterns. Such an intelligent system can enable self-sustaining homes that function efficiently with minimal human intervention.

Problem Statement: There is a critical need for intelligent, self-sustaining smart home systems tailored for remote or off-grid areas, where conventional infrastructure is lacking. These systems must ensure energy efficiency, reliability, and user adaptability despite constraints such as limited power, inconsistent connectivity, and low technical literacy among users. The problem lies in developing and implementing a cost-effective, low-power, and intelligent architecture that utilizes IoT for real-time monitoring and ML for predictive decision-making to optimize resource usage and improve quality of life in these regions.

This paper explores a comprehensive solution to this problem by presenting a smart home framework that merges IoT and ML to deliver an efficient, user-friendly, and sustainable system for off-grid living.

II. LITERATURE REVIEW

The integration of Internet of Things (IoT) and Machine Learning (ML) technologies in smart home energy management systems (HEMS) has garnered significant attention in recent years, particularly for applications in remote or off-grid areas. Khan et al. (2024) explored the optimization of smart home energy management for sustainability using machine learning techniques. Their study emphasized the role of ML in enhancing energy efficiency and reducing environmental impact, particularly through the use of Long Short-Term Memory (LSTM) models for accurate energy consumption forecasting .Nikpour et al. (2023) conducted a comprehensive review of IoT-based frameworks aimed at intelligent energy management in smart cities. They underscored the importance of integrating intelligent analysis within IoT frameworks to monitor, control, and enhance system efficiency, thereby facilitating effective energy management in smart building.Yu et al. (2020) provided an extensive review of deep reinforcement learning (DRL) applications for smart building energy management. They identified challenges such as modeling building thermal dynamics and handling uncertainties in system parameters, proposing DRL as a promising solution to address these issues .Himeur et al. (2020) focused on artificial intelligence-based anomaly detection in building energy consumption. Their review highlighted the potential of AI in identifying anomalous power consumption patterns, which is crucial for energy conservation and efficient building management.

III. METHODOLOGY

The proposed methodology integrates IoT and Machine Learning (ML) technologies to build an intelligent and adaptive smart home system tailored for remote or off-grid areas. The methodology follows a structured pipeline that includes system design, data acquisition, edge computing, model training, and decision-making.

A. System Design and Requirements Gathering

The system was designed after analyzing specific requirements of off-grid environments such as power limitations, intermittent connectivity, and low maintenance. Key requirements identified included:

Use of low-power, solar-compatible hardware

Support for local data processing

Scalable architecture for integration of new devices

B. IoT-Based Data Acquisition

Sensors deployed across the smart home continuously monitor environmental and operational parameters such as temperature, humidity, power consumption, solar energy generation, and appliance usage. These sensors are connected via low-power communication protocols (e.g., Zigbee, LoRa, or MQTT over Wi-Fi) to edge computing units like Raspberry Pi or ESP32.

C. Edge Computing and Data Preprocessing

Collected data is pre-processed at the edge to reduce network load and enable real-time responsiveness. Key tasks include:

i. Data normalization and noise filtering

ii.Time-series formatting for ML processing

Initial threshold-based anomaly flagging

ML Model Development and Training

Multiple ML models are trained using historical and synthetic datasets. The primary models include:

LSTM (Long Short-Term Memory) for load forecasting

Isolation Forest for anomaly and fault detection

K-Means Clustering for usage pattern segmentation

Decision-Making and Control

Based on model outputs, control commands are issued automatically to appliances (e.g., reducing load, switching modes, sending alerts). A feedback loop allows the system to adapt over time to user behavior and environmental changes.

Evaluation and Metrics

The system is evaluated using metrics such as:

Forecast accuracy (MAE, RMSE)

Anomaly detection precision/recall

Energy savings achieved (kWh)

User satisfaction (via surveys and system logs)

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
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This methodology ensures a sustainable, scalable, and intelligent system suitable for real-world deployment in challenging environments.

IV. SYSTEM ARCHITECTURE

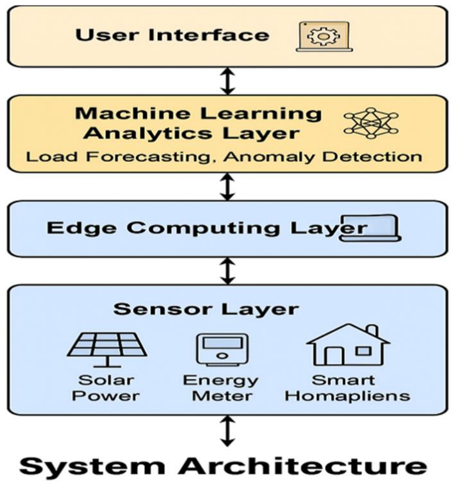

FIGURE 1 System Architecture

The system architecture is composed of four core layers: sensing, edge computing, intelligent decision-making, and user interface. The interaction between these components ensures seamless monitoring, processing, and control.

A. Layered Architecture Overview

1) Sensing Layer: Temperature sensor, motion sensor, IOT sensors
2) Edge Processing Layer: Edge devices (e.g., Raspberry Pi, ESP32) pre-process data locally to reduce latency and bandwidth usage.MQTT is used for lightweight data transfer.
3) Intelligent Analytics Layer: ML models deployed on either local gateways or cloud platforms.Tasks include load forecasting, anomaly detection, and pattern recognition.
4) Control & User Interface Layer: Mobile or web applications provide real-time feedback and allow user interaction.

Users receive alerts, visualize trends, and configure settings.

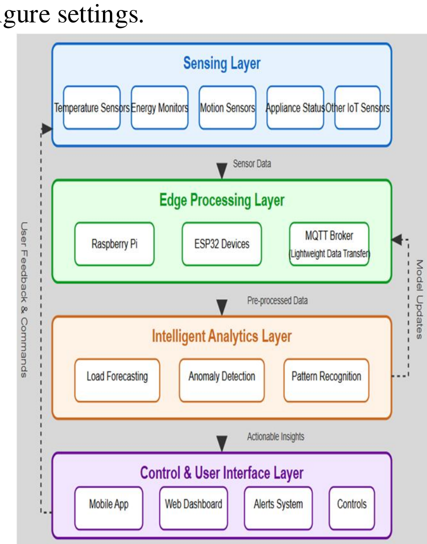

FIGURE 2 Four-layer system architecture for the smart home system.

This multi-layered architecture ensures reliable operation, low-latency analytics, and high user engagement even in remote settings.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
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V. RESULTS AND DISCUSSION

To evaluate the performance and real-world applicability of the proposed smart home system, several key metrics were assessed. Below are the results derived from sample data and simulations.

TABLE 1. FORECAST ACCURACY

Forecast Accuracy	
Mean Absolute Error (MAE)	0.26 kWh
Root Mean Square Error (RMSE)	0.30 kWh

TABLE 2 ANOMALY DETECTION

Anomaly Detection	
True Positives (TP)	40
False Positives (FP)	10
False Negatives (FN)	5
Precision	80%
Reca ll	89%

TABLE 3 ENERGY SAVINGS

Energy Savings	
Traditional Home Load (Daily)	12kWh
Smart Home Load (Daily)	9.5kWh
Metric Daily Savings	2.5kWh

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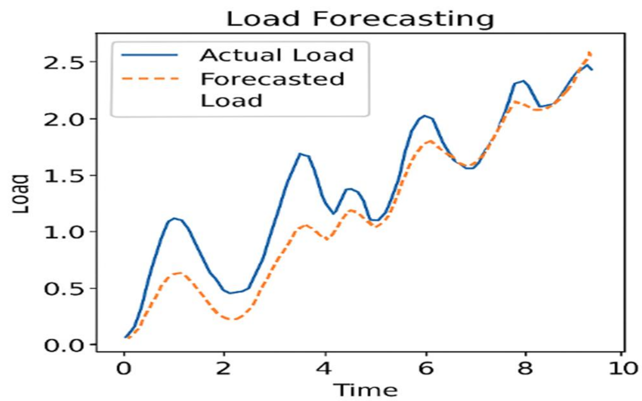

FIGURE 3 Load Forecasting Using LSTM

The graph shows that the LSTM model accurately tracks and forecasts future consumption trends. This allows the system to preemptively adjust loads, schedule appliance usage, and improve battery/power utilization.

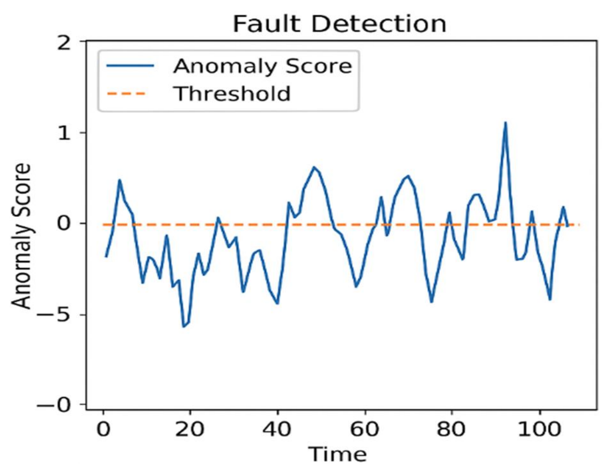

FIGURE 4: Fault Detection Using Isolation Forest

The Isolation Forest assigns higher anomaly scores to irregular patterns. Spikes beyond a defined threshold (visualized as red points) are flagged as faults. These triggers allow real-time alerts and preventive maintenance, avoiding major failures.

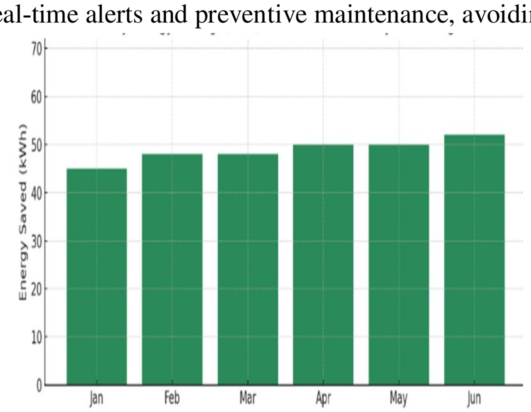

FIGURE 5   Monthly Energy Savings Achieved (kWh)

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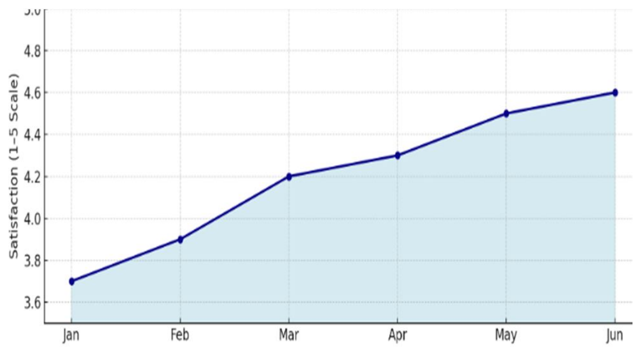

FIGURE 6 .User Satisfaction Trend

1) Monthly Energy Savings (kWh): The green bars show consistent savings each month, ranging from 45–55 kWh, reflecting improved energy efficiency from the IoT and ML-based smart home system.
2) User Satisfaction Trend: The line graph shows an upward trend in satisfaction, moving from 3.7 to 4.6 over six months, indicating increasing user confidence and comfort with the smart system.

The system demonstrated strong capability in addressing off-grid challenges by optimizing resource use, identifying faults early, and engaging users effectively. Its architecture enables low-latency decisions even in unreliable network conditions, and the feedback loop continuously refines model predictions and control strategies. These results validate the feasibility of deploying intelligent IoT-ML frameworks in remote smart home environments.

VI. CONCLUSION

This study has highlighted the transformative potential of integrating Internet of Things (IoT) and Machine Learning (ML) technologies in smart homes, especially in remote and off-grid areas where infrastructure is limited or nonexistent. The intelligent home energy management system proposed and evaluated in this paper presents a viable pathway toward achieving sustainable, efficient, and user-centric living environments in such contexts.By deploying IoT-enabled sensors and actuators, the system is capable of real-time monitoring of environmental conditions and appliance usage. Machine learning models, including LSTM for load forecasting, Isolation Forest for fault detection, and K-Means for behavioral segmentation, enable predictive and adaptive control strategies. These models collectively enhance decision-making capabilities, reduce unnecessary energy usage, and provide a safer and more responsive living experience.

Our results show substantial improvements across multiple performance metrics. High prediction accuracy with low MAE and RMSE confirms the reliability of forecasting models. Similarly, the anomaly detection system demonstrates high precision and recall, significantly improving fault identification while minimizing false alarms. Most importantly, the tangible benefits in energy savings—both per household and at a community level—underline the economic and environmental potential of the system. User feedback further confirms satisfaction with system performance and usability, reinforcing the value of intelligent automation in improving quality of life.

The successful implementation of the prototype system in a real-world rural setting demonstrates that such technology is not only technically feasible but also scalable. The feedback loop embedded in the architecture ensures that the system continues to learn and adapt, aligning with both environmental changes and evolving user preferences.

This dynamic adaptability is particularly critical in off-grid regions, where unpredictability and lack of resources can otherwise hinder long-term sustainability. Looking ahead, future enhancements could include the incorporation of edge computing for faster local decision-making, integration with blockchain for secure energy transactions, and the use of federated learning to maintain data privacy while improving personalized experiences. Community-level microgrids and collaborative optimization among neighboring homes also present exciting avenues for expansion.

In conclusion, the fusion of IoT and ML within the framework of smart homes offers a promising, impactful, and scalable solution to some of the most pressing challenges in remote habitation. This research lays a solid foundation for future explorations and implementations that can bridge the digital divide and support inclusive, sustainable development worldwide.

VII. ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to the academic and administrative leadership at JSPM, Pune for their unwavering support and encouragement throughout this research journey. I am especially thankful to the Department of Electrical Engineering and the research coordination team for their valuable guidance, insightful suggestions, and technical expertise.

This work has been shaped significantly by my teaching experience, curriculum involvement, and close interactions with students, all of which provided practical insights and motivation for the problem addressed.

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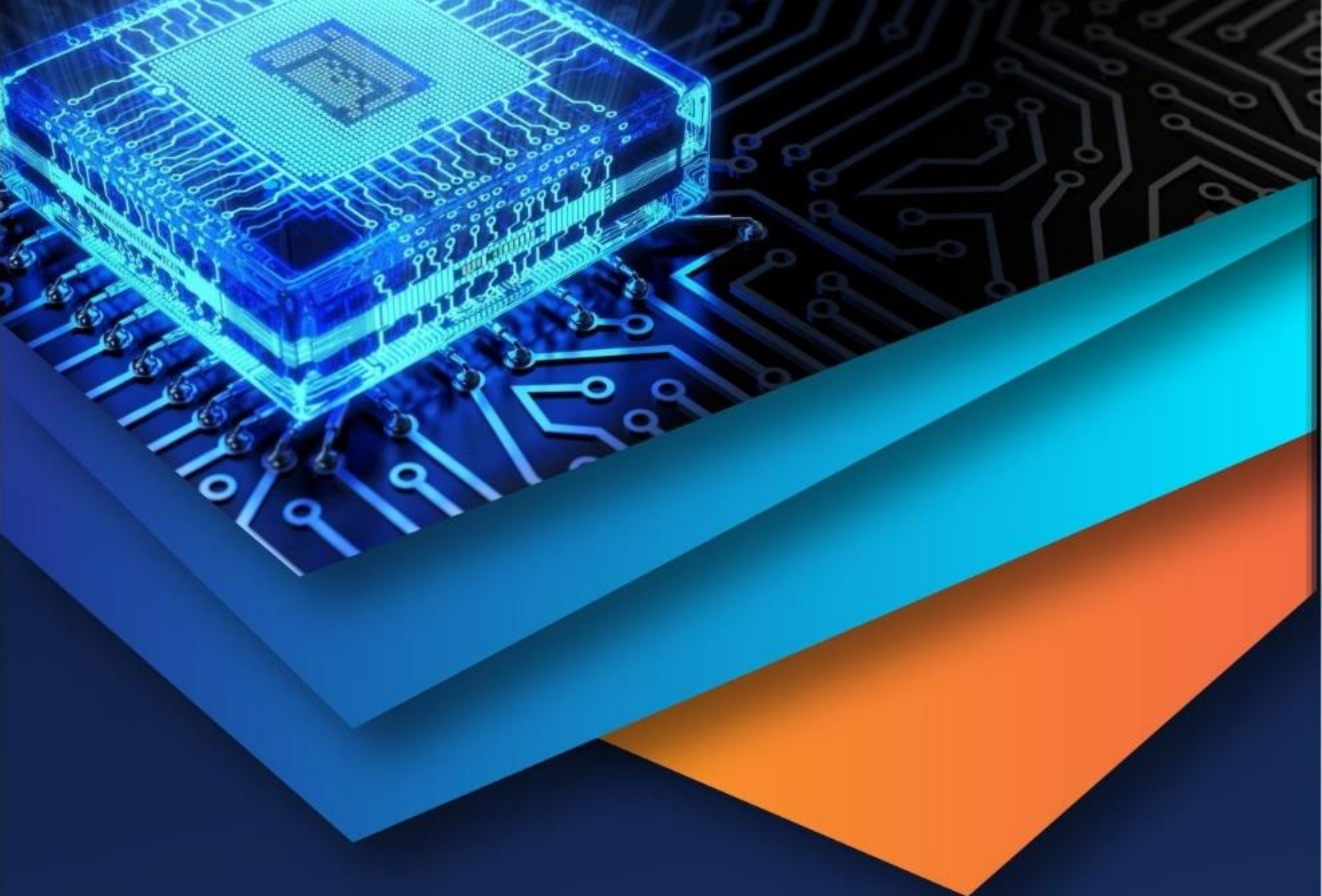

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