

IoT and Machine Learning Based Smart Energy Monitor with Consumption Prediction and Automatic Cutoff Alerts

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Abstract: *The increasing adoption of connected technologies and rapid urban growth have made efficient energy utilization an important concern across residential and industrial environments. Conventional energy monitoring approaches generally provide limited visibility into real-time consumption patterns and lack intelligent decision-making capabilities, resulting in inefficient energy usage. This study proposes an Internet of Things (IoT) and Machine Learning (ML) driven Smart Energy Monitoring System designed to support continuous monitoring, predictive analysis, and automated protective actions.*

The developed framework combines IoT sensing devices with cloud-based analytics to collect and process electrical consumption data in real time. An ESP32 controller integrated with current, voltage, and temperature sensors measures critical electrical parameters including voltage, current, power consumption, power factor, and total energy usage. The captured data is transmitted through MQTT communication to a cloud platform where machine learning models analyze usage trends and predict future consumption. To enable intelligent decision-making, an LSTM-based forecasting model estimates short-term and long-term energy demand, while a Random Forest algorithm identifies irregular consumption behavior and potential anomalies. When energy consumption exceeds predefined or dynamically generated thresholds, the system issues alerts and activates relay-based cutoff mechanisms to prevent excessive load conditions. Performance evaluation through prototype implementation demonstrates reliable prediction accuracy, efficient anomaly detection, and low communication delay. The proposed solution provides a scalable and cost-effective approach suitable for residential, commercial, and industrial energy management applications..

Keywords: Internet of Things, Machine Learning, Smart Energy Management, Energy Forecasting, LSTM, Random Forest, ESP32, MQTT, Consumption Prediction, Automated Protection

I. INTRODUCTION

Energy availability plays a major role in supporting economic growth, industrial development, and daily human activities. With increasing dependence on electrical devices, smart appliances, and automated infrastructure, electricity demand continues to rise globally. The growth in consumption places additional pressure on existing power distribution systems and increases the need for efficient energy management strategies.

Despite technological progress in energy generation and distribution, energy wastage remains a common issue across both residential and commercial sectors. Many existing monitoring solutions rely on periodic meter readings and provide users with limited information about how and when electricity is consumed. Such approaches do not support immediate decision-making or proactive control of energy usage.



The advancement of the Internet of Things (IoT) has introduced new possibilities for collecting and transmitting real-time operational data from connected devices. When IoT technologies are integrated with Machine Learning methods, energy systems can move beyond simple monitoring and begin predicting future demand, identifying abnormal behavior, and responding automatically to changing conditions.

This research presents a Smart Energy Monitoring System that combines IoT infrastructure with predictive machine learning techniques to improve energy visibility and operational efficiency. The system is designed to continuously measure electrical parameters, transmit data to cloud services, forecast future energy usage, detect anomalies, and initiate automatic alerts or protective cutoff actions whenever abnormal consumption patterns are detected.

1.1 Motivation

Current smart energy solutions often focus on isolated functions rather than offering a complete energy management workflow.

Consumer-grade monitoring devices generally operate at the appliance level, while industrial monitoring platforms involve high implementation costs and complex deployment requirements. In addition, many analytical tools still require manual data handling from traditional meters.

To address these limitations, this work proposes an integrated and affordable system capable of combining sensing, communication, prediction, and automated response within a single architecture suitable for different deployment environments.

1.2 Scope and Objectives

The primary objectives of this study include:

- Develop an IoT-based sensing unit for continuous measurement of electrical parameters using ESP32 and energy monitoring hardware.
- Establish an MQTT-enabled communication framework for efficient cloud data transfer.
- Implement machine learning models for forecasting future energy consumption.
- Detect unusual energy usage patterns and system abnormalities using intelligent algorithms.
- Generate automated alerts and execute relay-based protective actions.
- Evaluate overall system performance through practical implementation and testing.

1.3 Organization of the Paper

The remaining sections of this paper discuss previous research, system architecture, hardware implementation, machine learning methodology, software infrastructure, experimental observations, and concluding findings.

II. LITERATURE REVIEW

Research related to smart energy systems has expanded significantly with developments in IoT, wireless communication, and intelligent data analytics. Existing studies have explored energy monitoring, forecasting approaches, and automated control mechanisms. This section summarizes previous contributions and highlights areas that still require improvement.

2.1 IoT-Based Energy Monitoring Approaches

IoT technologies have transformed energy monitoring by enabling continuous collection and exchange of electrical data through connected devices. Early smart grid studies emphasized the importance of two-way communication for improving energy distribution efficiency and demand management.

Later developments introduced wireless sensor-based monitoring systems for residential environments that provided near real-time updates of energy usage. These solutions improved visibility into consumption behavior but generally focused only on monitoring and lacked predictive or automated control capabilities.



Other low-cost implementations using microcontrollers and cloud dashboards demonstrated practical deployment possibilities for home energy tracking.

However, most of these systems remained limited in terms of scalability, intelligent analytics, and automatic intervention during abnormal energy conditions.

Recent work introduced MQTT-based monitoring frameworks with threshold-driven notifications. Although such systems successfully generated alerts, fixed thresholds often caused unnecessary warnings and reduced reliability under changing usage conditions.

The present work addresses these limitations by integrating monitoring, forecasting, anomaly detection, and automated response into a unified architecture.

2.2 Machine Learning for Energy Forecasting

Energy consumption forecasting has become an active research area due to increasing demand for intelligent resource management.

Traditional statistical approaches such as ARIMA and exponential smoothing methods have been widely used because of their simplicity and interpretability. However, these techniques often struggle when handling nonlinear patterns and changing user behavior.

Deep learning approaches, particularly Long Short-Term Memory (LSTM) networks, have shown improved forecasting performance because of their ability to learn temporal dependencies from sequential data. Several studies demonstrated that LSTM models outperform conventional forecasting methods for short-term load prediction. More advanced hybrid architectures combined convolutional and recurrent layers to capture both local and long-term consumption characteristics.

For anomaly identification, machine learning algorithms such as Isolation Forest and Random Forest have been widely adopted. These models can identify unusual usage behavior more effectively than rule-based approaches.

Building upon these developments, the proposed framework combines LSTM forecasting with Random Forest anomaly detection to create an intelligent and responsive energy management environment.

2.3 Automated Alert and Cutoff Mechanisms

Automatic cutoff systems have traditionally relied on predefined safety rules implemented directly in hardware.

Recent developments introduced predictive approaches capable of estimating future demand and initiating corrective actions before overload conditions occur. Such predictive control methods improve energy efficiency but often require substantial computational resources and complex deployment.

To maintain practical deployment and lower hardware requirements, the proposed system performs advanced analytics in the cloud while preserving essential safety operations at the edge device level.

This architecture allows intelligent decision-making without overloading the embedded hardware.

2.4 Identified Research Gap

After reviewing existing approaches, several limitations become evident:

- Many systems provide either monitoring or prediction but rarely combine both in a complete operational framework.
- Adaptive threshold generation remains limited in affordable smart energy platforms.
- Real-world deployment conditions such as sensor inaccuracies and communication delays are insufficiently explored.
- Research addressing electrical usage behavior under Indian residential conditions remains comparatively limited.

The proposed study attempts to bridge these gaps through an integrated IoT and ML-based solution.

III. PROPOSED SYSTEM ARCHITECTURE

The Smart Energy Monitoring System follows a layered architecture designed to support data acquisition, intelligent processing, and automated control. The complete framework consists of three major layers:



1. Edge Sensing Layer
2. Communication and Cloud Processing Layer
3. Application and Actuation Layer This structure supports scalable deployment while maintaining efficient communication and decision-making.

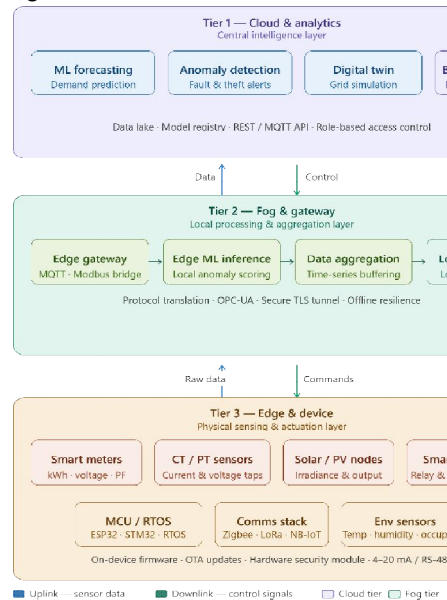


Figure1: Three-Tier IoT-ML Smart Energy Monitoring Architecture

3.1 Edge Sensing Layer

The sensing layer serves as the physical interface between electrical infrastructure and the monitoring platform.

Each sensing node contains:

- PZEM-004T Energy Sensor: Measures electrical parameters including voltage, current, active power, power factor, and total energy usage.
- ESP32 Controller: Performs local data collection, preliminary processing, and wireless communication.
- Temperature Sensor: Tracks operating temperature to identify overheating conditions.
- Relay Unit: Executes automatic load disconnection during abnormal operating conditions.
- LCD Display: Displays current measurements locally for user convenience.

Sensor measurements are collected continuously and packaged into structured data messages before transmission.

3.2 Communication and Cloud Processing Layer

The communication layer is responsible for transferring sensor data and executing intelligent analytics.

Collected readings are transmitted using the MQTT protocol to a cloud-based processing environment.

Cloud processing modules perform:

Data Preparation

- Handling incomplete records
- Removing abnormal values
- Normalization and aggregation

Forecasting Engine

- Predicting short-term energy demand
- Estimating long-term consumption trends



Anomaly Detection

- Identifying unusual consumption behavior
- Detecting overload or faulty appliance activity

Threshold Management

- Applying user-defined and adaptive limits
- Generating alerts and initiating control actions

This architecture enables real-time monitoring while reducing computational load on edge hardware.

3.3 Application and Actuation Layer

The final layer provides interaction and control capabilities.

Main features include:

Mobile Application

Users can:

- View real-time measurements
- Monitor historical trends
- Access prediction reports
- Receive alerts

Web Dashboard

Administrators can:

- Monitor multiple nodes
- Generate reports
- Manage devices

Notification System

The system delivers:

- Mobile notifications
- SMS alerts
- Email notifications

Relay Control

Automatic load control commands are transmitted to the sensing unit whenever unsafe operating conditions are detected.

IV. HARDWARE DESIGN AND IMPLEMENTATION (REWRITTEN)

4.1 Hardware Components

The hardware platform was selected to balance cost, performance, and ease of deployment.

Major components include:

Component	Function
ESP32	Data processing and wireless communication
PZEM-004T	Electrical parameter measurement
DS18B20	Temperature monitoring
Relay Module	Automatic power control
LCD Display	Local information display
Power Supply	Device operation

The overall design remains cost-effective while supporting real-time operation.

4.2 Circuit Design

The system integrates sensing and control hardware through dedicated communication interfaces.



- PZEM-004T communicates with ESP32 using UART.
 - Temperature sensing uses a single-wire communication interface.
 - Relay modules receive digital control signals.
 - LCD display communicates through I2C.
- All components are assembled to ensure stable measurement and reliable response.

4.3 Firmware Implementation

The embedded firmware controls sensor reading, communication, and actuation.

The main operational sequence includes:

1. Collect electrical measurements
2. Read temperature values
3. Convert measurements into structured data
4. Send data to cloud services through MQTT
5. Receive commands for relay control
6. Execute emergency protection when overload conditions occur

Local protection remains active even if cloud connectivity becomes unavailable.

and identify abnormal electrical usage. The proposed framework combines predictive analytics with intelligent monitoring to improve decision-making and system responsiveness.

V. MACHINE LEARNING METHODOLOGY

This section explains the machine learning process used to forecast energy consumption

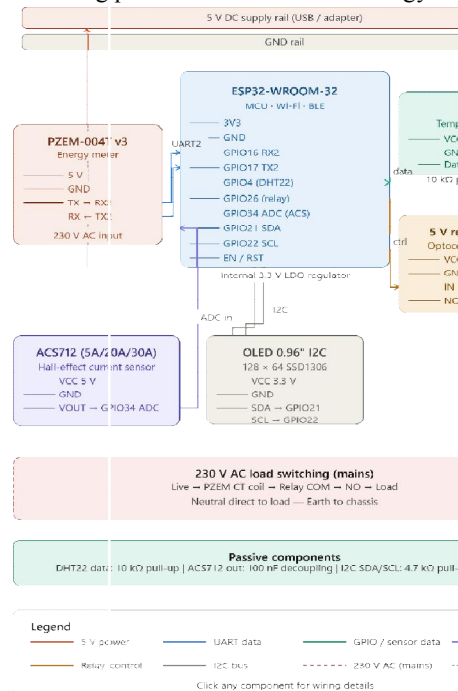


Figure 2: ESP32 circuit schematic showing every pin connection

5.1 Dataset Preparation

The development of the prediction and anomaly detection models relied on two primary data sources.



The first dataset consisted of publicly available household energy consumption records used for initial model training.

The second dataset was collected directly from the developed prototype during practical deployment over multiple weeks.

The collected records included electrical and environmental parameters such as:

- Voltage (V)
- Current (A)
- Active Power (W)
- Reactive Power
- Apparent Power
- Energy Consumption (kWh)
- Temperature
- Time and date information
- Usage behavior indicators

Combining public and real-world datasets improved the ability of the models to generalize across operating conditions.

5.2 Data Preprocessing

Raw sensor data required preprocessing before training and prediction.

The preprocessing pipeline included:

Missing Value Handling

Incomplete observations were corrected using appropriate replacement strategies depending on the duration of missing intervals.

Outlier Processing

Extremely abnormal values were reduced to minimize noise and improve model stability.

Feature Scaling

Numerical values were normalized into a consistent range to improve convergence during training.

Sequence Generation

Sequential input windows were created to preserve temporal relationships between energy measurements.

These preprocessing operations improved prediction consistency and reduced training instability.

5.3 Energy Consumption Forecasting Using LSTM

To predict future electricity usage, a Long

Short-Term Memory (LSTM) neural network was selected.

LSTM networks are effective for time-series analysis because they retain useful historical information while reducing problems

associated with traditional recurrent models.

The forecasting model follows a multi-layer structure:

- Input Layer for sequential energy data
- First LSTM layer for learning long-term temporal relationships
- Second LSTM layer for feature refinement
- Dense layer for output processing
- Prediction layer for estimated consumption values

The model was trained using an optimization algorithm designed to reduce forecasting error and improve learning efficiency.

Predictions were generated at two levels:

Short-Term Forecasting

Estimate upcoming hourly energy demand.



Long-Term Forecasting

Generate projected monthly consumption trends.

These predictions allow users to anticipate future usage and manage energy proactively.

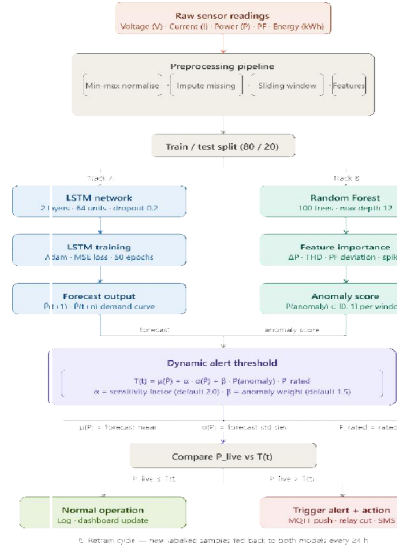


Figure 3: ML pipeline (LSTM + Random Forest → DATA)

5.4 Random Forest-Based Anomaly Detection

In addition to forecasting, the system incorporates anomaly detection to identify unusual electrical activity. A Random Forest classifier was selected because of its strong performance on structured sensor datasets and its ability to reduce overfitting.

The model analyzes features such as:

- Average consumption trends
- Consumption variation
- Sudden changes in demand
- Time-based behavior patterns
- Deviation from predicted consumption
- Unexpected energy spikes
- Appliance malfunction
- Continuous overload conditions
- Energy wastage due to unattended devices

The anomaly detection mechanism supports early intervention and improved operational safety.

5.5 Dynamic Threshold Mechanism

Instead of relying entirely on fixed limits, the system introduces adaptive thresholds.

Threshold values are generated dynamically based on:

- Predicted energy demand
- Historical forecasting errors
- Recent usage behavior

This approach allows alert sensitivity to change according to real operating conditions.

Dynamic thresholding provides several benefits:

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- Fewer false alarms
- Improved adaptability
- Better user experience
- Increased reliability during changing demand conditions

By combining prediction and adaptive decision-making, the proposed system achieves more intelligent energy management.

VI. CLOUD AND SOFTWARE INFRASTRUCTURE

The cloud infrastructure supports data communication, model execution, storage, and user interaction.

6.1 MQTT-Based Communication

MQTT was selected as the communication protocol because of its lightweight architecture and suitability for IoT environments.

Its advantages include:

- Low bandwidth requirements
- Publish–subscribe communication
- Reduced transmission overhead
- Reliable message delivery

Sensor nodes continuously transmit readings to cloud services for processing and storage. Secure communication methods are implemented to protect transmitted information.

6.2 Cloud Processing Backend

The cloud backend performs data processing and machine learning inference.

Its major responsibilities include:

Data Collection

Receiving sensor streams in real time.

Data Storage

Maintaining historical records for analysis.

Prediction Execution

Running trained forecasting models.

Alert Generation

Triggering notifications and relay actions.

Device Management

Supporting remote monitoring and control. Cloud deployment enables scalability and reduces processing load on edge devices.

6.3 Mobile and Dashboard Application

User interaction is supported through mobile and web platforms.

Core application features include:

Real-Time Monitoring

Display current electrical measurements.

Historical Analytics

Visualize energy trends over time.

Forecast View

Present expected future consumption.

Alert Center



Show warnings and system events.
Configuration Settings
Allow users to customize thresholds and reporting options.
The interface is designed to simplify energy monitoring and improve user accessibility.

VII. EXPERIMENTAL RESULTS AND EVALUATION

7.1 Experimental Environment

To validate the system, a prototype deployment was performed under real operating conditions.

The evaluation focused on:

- Continuous monitoring capability
- Prediction accuracy
- Communication performance
- System responsiveness
- Reliability during long-term operation

Data collected during deployment was used to measure model performance and overall system effectiveness.

7.2 Forecasting Performance

Multiple forecasting approaches were compared to evaluate prediction quality. Performance indicators included:

- Mean Absolute Percentage Error (MAPE)
- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- Coefficient of Determination (R^2)

Results showed that deep learning models produced more accurate predictions than traditional forecasting approaches.

The selected LSTM configuration achieved strong balance between accuracy and computational efficiency.

7.3 Anomaly Detection Performance

The anomaly detection module was evaluated against conventional threshold methods.

Performance metrics included:

- Precision
- Recall
- F1 Score
- Overall Accuracy

The Random Forest model demonstrated improved capability in identifying genuine abnormal events while reducing unnecessary alerts.

7.4 System-Level Performance

Additional performance indicators included:

- End-to-end response delay
- Communication reliability
- Energy consumption of embedded hardware
- Relay activation speed
- Dashboard update frequency
- Overall operational uptime



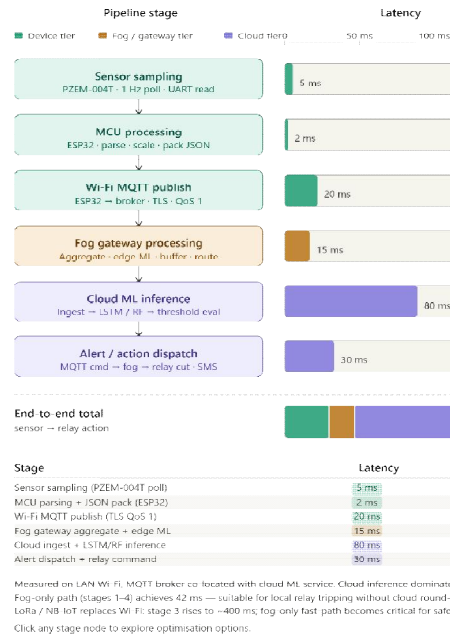


Figure 4: Real-time data flow with latency bar

Experimental observations confirmed that the proposed architecture supports efficient and reliable real-time monitoring.

VIII. DISCUSSION

8.1 Practical Implications

The proposed Smart Energy Monitoring

System demonstrates how the integration of IoT technologies and machine learning can support more efficient and intelligent energy management at a relatively low implementation cost. By combining real-time monitoring with predictive analytics and automated control, the system provides users with greater awareness of electricity usage and enables timely intervention when abnormal conditions occur.

During practical deployment, continuous monitoring and alert mechanisms encouraged improved energy usage behavior and contributed to reduced unnecessary power consumption. The ability to forecast future demand and detect irregular patterns allows users to take preventive actions before energy waste or overload situations develop. For larger environments such as commercial buildings and industrial facilities, the system can support centralized monitoring and provide insights into operational efficiency across multiple locations. Dynamic threshold generation also improves alert reliability and reduces excessive notifications compared with static rule-based systems.

8.2 Limitations

Although the developed system achieved promising performance, several limitations remain.

Single-Phase Monitoring

The current implementation focuses on single-phase electrical systems. Extending support to three-phase infrastructure would increase applicability for industrial environments.

Dependence on Cloud Processing

Advanced prediction and intelligent decision-making rely on cloud services. Internet interruptions may reduce access to forecasting features, although local protection mechanisms remain operational.



Limited Deployment Diversity

Model evaluation was performed under a restricted deployment environment. Broader testing across multiple households and different usage profiles is required to confirm generalization.

Security and Data Protection

While secure communication protocols are applied, additional work in areas such as data encryption, vulnerability assessment, and access control can further strengthen overall system security.

8.3 Future Work

Several enhancements can improve the capabilities of the proposed system.

Planned future developments include:

- Implementation of appliance-level energy identification using advanced load monitoring methods.
- Deployment of edge-based machine learning to reduce dependence on cloud infrastructure.
- Integration with renewable energy systems for optimized energy balancing.
- Development of intelligent voice-assisted monitoring interfaces.
- Expansion of testing across multiple residential and commercial environments.

These improvements may increase system adaptability and support broader adoption of intelligent energy management solutions.

IX. CONCLUSION

This research introduced an IoT and Machine Learning based Smart Energy Monitoring System designed to improve energy visibility, prediction capability, and automated protection.

The proposed framework combines real-time sensing, cloud communication, intelligent forecasting, anomaly detection, and automatic relay control into a unified platform. Through continuous monitoring and predictive analysis, the system enables proactive energy management rather than relying solely on traditional consumption reporting methods.

Experimental evaluation demonstrated effective forecasting performance, reliable anomaly identification, and responsive system behavior under practical operating conditions.

The integration of adaptive thresholds and automated alerts further improved operational efficiency and reduced unnecessary intervention.

Overall, the developed solution offers a scalable and cost-effective approach for residential and small-scale commercial energy management. By enabling informed decision-making and reducing energy waste, the proposed system contributes toward smarter and more sustainable energy utilization.

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