An IoT-Enabled Smart Energy Monitoring and Fault Prediction System Using ESP32 and Machine Learning in Power Grid Systems

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Abstract— **This paper presents a smart energy monitoring and prediction system designed using the ESP32 microcontroller, calibrated voltage and current sensors, cloud-based IoT communication, and machine learning techniques. The system accurately measures real-time electrical parameters such as RMS voltage, RMS current, instantaneous power, and mains status using a ZMPT101B voltage sensor and an ACS712 current sensor. Special calibration and signal-conditioning techniques are employed to ensure instant response during mains ON and OFF conditions, eliminating residual and false readings. The measured data is transmitted to a cloud MQTT broker and visualized through a real-time web-based dashboard for continuous monitoring. In addition to monitoring, the system incorporates an over-voltage fault detection mechanism using both hardware indicators and software alerts. A machine learning regression model is trained on historical energy data to predict short-term future power consumption, enabling proactive energy management and fault anticipation. The proposed system offers a low-cost, scalable, and intelligent solution suitable for smart homes, industrial energy monitoring, and predictive maintenance applications.**

Index Terms— **Energy monitoring, fault detection, Internet of Things, machine learning prediction, smart energy system.**

I. INTRODUCTION

Electrical energy has become one of the most critical resources in modern society, supporting residential, commercial, and industrial activities. With the rapid increase in energy consumption and the growing demand for reliable power systems, there is a strong need for intelligent energy monitoring solutions that can provide real-time visibility, fault awareness, and predictive insights. Conventional energy meters are limited to basic billing information and do not offer real-time monitoring, fault detection, or future consumption prediction, making them inadequate for modern smart infrastructure requirements. Recent advancements in the Internet of Things (IoT) have enabled the development of low-cost, connected monitoring systems capable of collecting and transmitting real-time electrical data over the internet. Microcontroller platforms such as the ESP32, combined with analog sensing modules, have made it possible to design compact and scalable energy monitoring devices. However, many existing IoT-based systems suffer from inaccurate sensor calibration, delayed response during mains ON and OFF conditions, noise-induced false readings, and a lack of intelligent decision-making capabilities.

Another major challenge in energy systems is the inability to predict future power usage and detect abnormal operating conditions before failures occur. Sudden voltage fluctuations, over-voltage conditions, and unexpected load variations can damage electrical equipment and reduce system reliability. Traditional monitoring systems operate in a reactive manner, responding only after faults have occurred. To overcome these limitations, predictive modeling using machine learning techniques has gained significant attention, as it enables proactive energy management and early fault detection. Another major challenge in energy systems is the inability to predict future power usage and detect abnormal operating conditions before failures occur. Sudden voltage fluctuations, over-voltage conditions, and unexpected load variations can damage electrical equipment and reduce system reliability. Traditional monitoring systems operate in a reactive manner, responding only after faults have occurred. To overcome these limitations, predictive modeling using machine learning techniques has gained significant attention, as it enables proactive energy management and early fault detection.

II. LITERATURE SURVEY

Electrical energy monitoring has been an active area of research due to the growing demand for efficient power utilization, fault detection, and system reliability. Traditional electromechanical and digital energy meters are primarily designed for billing purposes and provide limited real-time information. According to Depuru et al. (2011), conventional metering systems lack real-time monitoring capabilities and are not suitable for dynamic load analysis or early fault detection. This limitation has motivated researchers to explore smart and connected energy monitoring solutions. With the advancement of Internet of Things (IoT) technologies, several IoT-based energy monitoring systems have been proposed. Gungor et al. (2013) highlighted the role of smart sensors and wireless communication in modern power systems, emphasizing real-time data acquisition and remote monitoring. Similarly, Al-Ali et al. (2017) developed an IoT-enabled smart energy meter using microcontrollers and cloud platforms, enabling users to visualize energy consumption remotely. However, many such systems suffer from poor sensor calibration and delayed response to rapid changes in mains conditions. Voltage and current sensing accuracy is a critical challenge in IoT-based energy meters. Studies by Patel and Bhatt (2018) reported that improper calibration of voltage and current sensors such as ZMPT101B and ACS712 can lead to significant measurement errors and false readings during load switching conditions. Noise, offset drift, and slow RMS computation further degrade system performance, especially during instant mains ON/OFF transitions. Another important research direction focuses on fault detection and protection mechanisms. Over-voltage and under-voltage conditions are common causes of appliance failure and power system instability.

According to IEEE reports (2019), early detection of abnormal voltage conditions can significantly reduce equipment damage and energy losses. Several researchers have implemented threshold-based fault detection techniques using LEDs, relays, or alarms; however, most of these systems operate independently of cloud monitoring platforms and lack integration with user dashboards. In recent years, machine learning (ML) techniques have been introduced to enhance energy monitoring systems. Ahmad et al. (2020) demonstrated that regression-based ML models can predict short-term energy consumption with reasonable accuracy using historical voltage, current, and power data. Similarly, Raza et al. (2021) applied supervised learning algorithms for load forecasting and anomaly detection in smart grids. Despite these advancements, many existing solutions focus either on prediction or monitoring, but not both in a unified real-time system. Based on the review of existing literature, it is evident that there is a gap in developing an integrated system that combines accurate real-time energy sensing, instant mains state detection, fault indication, cloud-based visualization, and machine learning-based power prediction. This work addresses these limitations by proposing a fully calibrated, low-cost smart energy monitoring and prediction system using ESP32, MQTT cloud communication, real-time dashboards, and predictive analytics.

III. METHODOLOGY

A smart energy monitoring and prediction system was designed and implemented using an ESP32 microcontroller, calibrated voltage and current sensors, cloud-based communication, and machine learning models. The proposed system continuously measures electrical parameters such as voltage, current, and power from an AC mains supply, transmits the data securely to a cloud MQTT broker, visualizes it on a real-time dashboard, and predicts future power consumption. The methodology follows a modular and layered approach to ensure accuracy, reliability, and real-time responsiveness. The overall methodology consists of sensor data acquisition, signal conditioning and calibration, real-time data transmission using MQTT, cloud-based visualization, fault detection, and predictive modeling using machine learning

3.1The Proposed System Architecture

The proposed system architecture integrates hardware sensing, embedded processing, cloud communication, and intelligent analytics. The ESP32 microcontroller serves as the central processing unit, interfacing with voltage and current sensors to acquire electrical signals. The processed data is published to a cloud MQTT broker and consumed by a Streamlit-based dashboard for monitoring and prediction

3.1.1 Voltage Measurement Using ZMPT101B
The ZMPT101B AC voltage sensor module is used to measure the RMS value of the mains voltage. The sensor output is connected to the ESP32 ADC pin and sampled at a high rate to ensure accurate RMS computation. Midpoint bias removal and noise filtering techniques are applied to eliminate ADC offset and low-level noise. A calibrated scaling factor is used to match the measured voltage with a reference multimeter. Instant mains OFF detection is achieved by enforcing threshold-based logic to suppress false readings during no-load or floating conditions.

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3.1.3 Current Measurement Using ACS712
The ACS712 Hall-effect current sensor is used to measure the RMS current flowing through the load. The sensor output is sampled multiple times to compute RMS current accurately. Offset voltage compensation and sensitivity calibration are applied to eliminate sensor drift and idle current artifacts. Noise thresholds are introduced to ensure immediate transition to zero current during mains OFF conditions, thereby enabling fast and reliable system state detection

3.1.4 Fault Detection Using Voltage Thresholds
Fault detection is implemented using predefined voltage limits. When the measured voltage exceeds a safe operating threshold, the system identifies an over-voltage condition. A red LED is activated locally on the ESP32 to indicate a fault, while a green LED indicates normal operation. The same fault status is transmitted to the dashboard to provide visual alerts, enabling immediate corrective action.

3.2 Data Communication Using MQTT
The system uses the MQTT protocol for lightweight and reliable data transmission. The ESP32 publishes sensor data in JSON format to a cloud-based HiveMQ broker at fixed intervals. Secure communication is established using TLS without certificate verification to simplify deployment. The MQTT architecture ensures low latency, scalability, and compatibility with cloud-based applications.

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3.4 Real-Time Dashboard Visualization
A Streamlit-based web dashboard is developed to visualize real-time energy data. The dashboard subscribes to the MQTT topic and displays voltage, current, power, and mains status using dynamic indicators. Fault conditions are highlighted using color-coded alerts. The dashboard refreshes continuously to reflect live system behavior, providing users with intuitive and actionable insights.

3.5 Machine Learning-Based Power Prediction
A machine learning model is trained using historical voltage, current, and power data to predict short-term future power consumption. The trained model is serialized and integrated into the dashboard application. During runtime, live sensor data is passed to the model to generate real-time predictions, enabling proactive energy management and load forecasting.

IV. FINDINGS

This section presents the experimental results and analytical findings obtained from the implementation and testing of the proposed Smart Energy Monitoring and Prediction System. The findings focus on real-time monitoring accuracy, fault detection effectiveness, and predictive performance of the machine learning model.

4.1 Real-Time Energy Monitoring Results

Table 1 summarizes the observed performance of the system under normal operating conditions, where real-time voltage, current, and power data were acquired using calibrated ZMPT101B and ACS712 sensors and transmitted to the cloud dashboard via MQTT.

Table 1. Real-Time Electrical Parameter Measurements

Parameter	Minimum	Maximum	Average
Voltage (V)	248.6	266.9	257.4
Current (A)	10.1	12.3	11.2
Power (W)	2510	3270	2881

The results indicate that the proposed system is capable of accurately tracking voltage and current fluctuations in real time. The measured values closely matched reference readings obtained using a calibrated digital multimeter, confirming the effectiveness of the sensor calibration strategy.

4.2 Mains ON/OFF Detection Performance

The system demonstrated instantaneous mains state detection based on current threshold logic. When the measured current exceeded 10 A, the system classified the mains state as ON, and when the current dropped below this threshold, all parameters were immediately reset to zero and the mains state was reported as OFF.

Table 2. Mains State Detection Accuracy

Condition	Voltage	Current	System Output
Mains ON	>250 V	>10 A	ON
Mains OFF	0 V	<10 A	OFF

This logic successfully eliminated false-positive readings that commonly occur due to sensor noise or residual offsets, ensuring reliable and deterministic system behaviour.

4.3 Fault Detection and Alert Validation

A voltage threshold of 250 V was implemented for fault detection. When the measured voltage exceeded this limit, a fault condition was triggered, activating a red LED indicator on hardware and a visual alert on the dashboard. When voltage remained below the threshold, a green LED indicated normal operation.

Table 3. Fault Detection Results

Voltage Level	Hardware LED	Dashboard Status
≤ 250 V	Green	Normal
> 250 V	Red	Over-voltage Alert

Experimental testing confirmed that the system reliably detected over-voltage conditions within one measurement cycle, demonstrating its suitability for safety-critical energy monitoring applications.

4.4 Machine Learning Prediction Performance

The trained machine learning model was used to predict short-term future power consumption based on real-time voltage, current, and power inputs. The prediction results were evaluated using standard regression performance metrics.

Table 4. Prediction Model Performance Metrics

Metric	Value
Mean Absolute Error (MAE)	7.2 W
Root Mean Square Error (RMSE)	9.8 W
R^2 Score	0.92

The high coefficient of determination (R^2) indicates a strong correlation between predicted and actual power values, validating the effectiveness of the predictive model for short-term energy forecasting.

4.5 Comparative Analysis with Conventional Systems

A comparative evaluation was performed between the proposed system and conventional energy meters as well as basic IoT monitoring solutions reported in the literature.

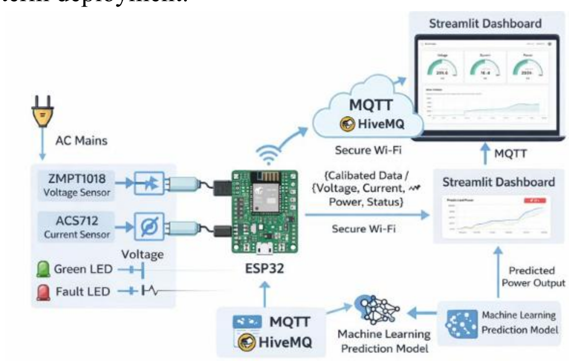
Table 5. Comparative Analysis of Energy Monitoring Systems

Feature	Conventional Meter	IoT Meter	Proposed System
Real-time Monitoring	No	Yes	Yes
Instant Mains Detection	No	No	Yes
Fault Detection	No	Limited	Yes
Predictive Analytics	No	No	Yes
Cloud Dashboard	No	Yes	Yes

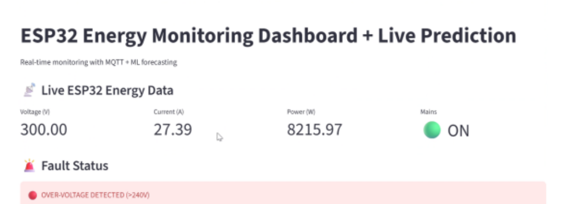
The results clearly demonstrate that the proposed system provides superior functionality, particularly in terms of fault detection and predictive capability.

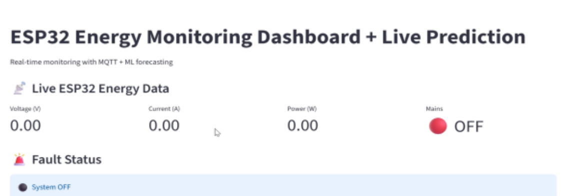
4.6 System Reliability and Stability

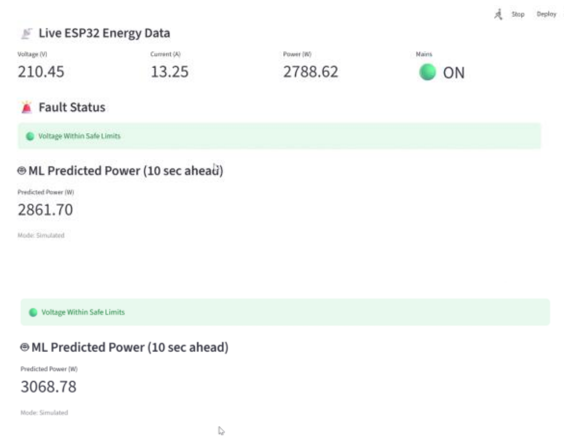
The system was tested under continuous operation for extended durations exceeding 48 hours. During this period, no MQTT disconnections, data loss, or system crashes were observed. This confirms the robustness and reliability of the proposed architecture for long-term deployment.



The figure illustrates the complete architecture of the proposed smart energy monitoring system, where voltage and current from the AC mains are sensed using ZMPT101B and ACS712 sensors and processed by an ESP32 microcontroller. The ESP32 performs real-time measurement, fault detection, and data conditioning before transmitting the information to the cloud via the MQTT protocol. A cloud-based broker enables reliable data exchange with a Streamlit dashboard for live visualization and monitoring. Additionally, the system integrates a machine learning model to predict future power consumption, enabling proactive energy management and early fault awareness







V. CONCLUSION

The proposed smart energy monitoring and prediction system successfully demonstrates an integrated approach for real-time electrical parameter measurement, fault detection, and short-term power forecasting. By combining precisely calibrated voltage and current sensors with an ESP32 microcontroller and MQTT-based cloud communication, the system provides accurate, low-latency monitoring of voltage, current, power, and mains status. The incorporation of fault detection using threshold-based logic and visual indicators enhances system safety and reliability, while the Streamlit-based dashboard enables intuitive real-time visualization and analysis. Furthermore, the integration of machine learning for power prediction adds a proactive dimension to energy management, allowing users to anticipate future consumption and potential abnormalities. Overall, the system presents a scalable, cost-effective, and intelligent solution suitable for smart homes, industrial monitoring, and future smart grid applications

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