Design Of IoT Based EV Charging System Using ESP32 And Cloud Analytics System

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***Abstract*—The rapid adoption of electric vehicles (EVs) in residential environments has significantly increased household energy demand, introducing challenges related to electrical safety, load management, and energy cost optimization. Conventional EV charging systems operate without considering real-time household load conditions, often leading to circuit overloads, inefficient energy utilization, and higher electricity expenses during peak demand periods. This paper presents an intelligent IoT-enabled EV charging system designed to monitor real-time electrical parameters, forecast household load, and dynamically regulate EV charging to ensure safe and optimal energy utilization. The proposed system is developed using an ESP32-WROOM microcontroller integrated with a PZEM energy measurement module to accurately acquire voltage, current, power, and energy consumption data from residential loads. Two controlled bulb loads are used to emulate varying household demand conditions. Measured data is transmitted to a cloud-based MQTT broker and visualized through a Streamlit-based real-time dashboard, enabling continuous monitoring and user interaction. In addition to real-time monitoring, historical energy data is processed to forecast short-term load trends, allowing the system to intelligently schedule EV charging during low- load conditions and prevent overcurrent scenarios. Experimental results demonstrate reliable data acquisition, stable cloud communication, accurate load visualization, and effective charging control decisions. The proposed system offers a low-cost, scalable, and intelligent solution suitable for smart homes, energy-aware EV charging, and future smart grid applications.**

***Index Terms*—Electric vehicle charging, Internet of Things, ESP32, PZEM energy meter, load forecasting, MQTT, Streamlit dashboard, smart energy management.**

I. INTRODUCTION

Electrical energy has become an indispensable resource in modern society, forming the backbone of residential living, commercial operations, and industrial processes. The continuous growth in electrical appliance usage, coupled with the increasing penetration of electric vehicles (EVs), has led to a substantial rise in household energy consumption. This growing demand places significant stress on existing electrical infrastructure and highlights the need for intelligent energy management solutions that can ensure safety, efficiency, and reliability. Conventional energy meters are primarily designed for billing purposes and provide limited visibility into real-time power usage. They lack capabilities such as continuous monitoring, fault awareness, and future load estimation, making them unsuitable for emerging smart energy ecosystems. Recent advancements in the Internet of Things (IoT) have enabled the development of low-cost, connected energy monitoring systems capable of acquiring and transmitting real-time electrical data over the internet. Microcontroller platforms such as the ESP32, when combined with digital energy measurement modules, have made it possible to design compact, scalable, and network-enabled monitoring devices. These systems allow users to observe voltage, current, power, and energy consumption remotely through cloud-based dashboards. However, many existing IoT-based solutions continue to face challenges related to sensor accuracy, delayed response during load transitions, noise-induced false readings, and limited intelligence in decision-making. Such limitations reduce their effectiveness in safety-critical and energy-aware applications such as EV charging. Another significant challenge in modern energy systems is the inability to anticipate future power usage and detect abnormal operating conditions before failures occur. Sudden load variations, voltage fluctuations, and overcurrent conditions can degrade system performance, damage electrical equipment, and compromise user safety. Traditional monitoring approaches operate in a reactive manner, responding only after an abnormal event has already taken place. This reactive behavior is inadequate for applications that demand proactive control, such as residential EV charging, where uncontrolled charging during peak load periods can lead to circuit overloads and increased electricity costs. To address these limitations, predictive analytics and machine learning techniques have gained considerable attention in smart energy research. By analyzing historical consumption data, predictive models can estimate short-term future load trends and enable intelligent scheduling and control decisions. When combined with real-time IoT-based monitoring, such predictive capabilities transform energy systems from passive observers into proactive managers. This paper presents an intelligent IoT-based EV charging and energy monitoring system that integrates real-time load measurement, cloud- based visualization, and short-term load forecasting to enable safe, efficient, and energy-aware EV charging in residential environments.

II. LITERATURESURVEY

Electrical energy monitoring has emerged as an important research area due to the increasing demand for efficient power utilization, system reliability, and early fault detection. Traditional electromechanical and digital energy meters are mainly intended for billing applications and offer limited insight into real-time power consumption. As reported by Depuru et al. (2011), conventional metering systems lack real- time monitoring and are unsuitable for dynamic load analysis and early fault identification. These limitations have encouraged researchers to explore intelligent and connected energy monitoring solutions. With the advancement of Internet of Things (IoT) technologies, several IoT-based energy monitoring systems have been proposed in recent years. Gungor et al. (2013) emphasized the role of smart sensors and wireless communication in modern power systems, highlighting the importance of real-time data acquisition and remote accessibility. Similarly, Al- Ali et al. (2017) presented an IoT-enabled smart energy meter using microcontrollers and cloud platforms, allowing users to remotely visualize energy consumption. Despite these developments, many IoT-based systems suffer from challenges related to sensor accuracy, calibration errors, and delayed response to rapid variations in mains conditions.

Accurate voltage and current measurement remain a critical challenge in IoT-based energy meters. Patel and Bhatt (2018) reported that improper calibration of voltage and current sensing modules can result in significant measurement errors and false readings during load switching events. Issues such as noise interference, offset drift, and slow RMS computation further degrade system performance, particularly during instantaneous mains ON and OFF transitions. These limitations reduce the reliability of real-time monitoring systems in safety-critical applications.

Another key research focus involves fault detection and protection mechanisms. Over-voltage and under-voltage conditions are among the primary causes of electrical equipment damage and power system instability. According to IEEE reports (2019), early detection of abnormal voltage conditions can significantly reduce energy losses and prevent equipment failure. Several studies have implemented threshold-based fault detection using visual indicators, relays, or alarms; however, most of these approaches operate independently of cloud-based monitoring systems and lack integration with real- time user dashboards.

In recent years, machine learning techniques have been incorporated into energy monitoring frameworks to enhance system intelligence. Ahmad et al. (2020) demonstrated that regression-based models can predict short-term energy consumption using historical electrical data with satisfactory accuracy. Similarly, Raza et al. (2021) applied supervised learning algorithms for load forecasting and anomaly detection in smart grid environments. Despite these advancements, existing solutions typically focus either on monitoring or prediction, rather than integrating both functionalities into a unified real-time system.

Based on the reviewed literature, a clear research gap exists in developing an integrated solution that combines accurate real-time energy sensing, instant mains state detection, fault indication, cloud-based visualization, and machine learning-based load prediction. The proposed work addresses these gaps by presenting a calibrated, low-cost smart energy monitoring and forecasting system using an ESP32 platform, MQTT-based cloud communication, real-time dashboards, and predictive analytics.

III. METHODOLOGY

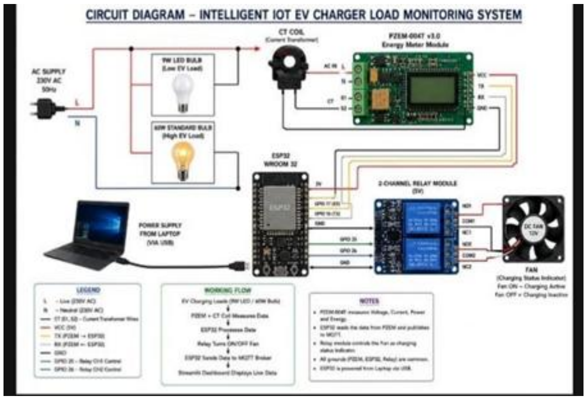


Figure 1. Circuit Diagram of EV System

Figure 1. show the circuit diagram of IoT based EV Charging system using ESP 32 and Cloud analytic system. A smart energy monitoring and intelligent EV charging system was designed and implemented using an ESP32-WROOM microcontroller, a PZEM energy measurement module, cloud-based communication, and data-driven forecasting techniques. The proposed system continuously measures electrical parameters such as voltage, current, power, and energy consumption from an AC mains supply, transmits the data securely to a cloud- based MQTT broker, visualizes it on a real-time dashboard, and enables short-term load prediction for informed charging decisions. The methodology follows a modular and layered approach to ensure accuracy, reliability, and real-time responsiveness. The overall methodology consists of energy data acquisition, signal conditioning and calibration, real-time data transmission using MQTT, cloud-based visualization, load condition monitoring, and predictive analysis.

3.1. The Proposed System Architecture

The proposed system architecture integrates hardware sensing, embedded processing, cloud communication, and intelligent analytics. The ESP32-WROOM microcontroller acts as the central processing unit and interfaces with a PZEM energy meter to acquire real-time electrical parameters. The processed data is published to a cloud MQTT broker and subscribed by a Streamlit-based dashboard for real-time monitoring and analysis.

3.1.1.Electrical Parameter Measurement Using PZEMModule

The PZEM energy measurement module is used to measure RMS voltage, RMS current, active power, and cumulative energy consumption from the AC mains supply. The module internally performs signal conditioning and RMS computation, providing calibrated digital measurements directly to the ESP32 through a serial communication interface. This approach eliminates analog noise, offset drift, and ADC-related inaccuracies. Threshold-based logic is applied at the embedded level to identify valid mains conditions and suppress erroneous readings during no-load or disconnected states. In this project we adding charging cost per vehicle. On dashboard also show the cost value on it.

3.1.2.Load Monitoring Using Controlled Bulb Loads

Two resistive bulb loads are used to emulate household electrical appliances and create dynamic load variations. The change in electrical parameters corresponding to different load combinations is continuously monitored using the PZEM module. This setup allows validation of real-time load tracking, system responsiveness, and safe operating conditions under varying demand scenarios relevant to residential EV charging environments.

3.1.3.Fault and Load Condition Monitoring

Load condition monitoring is implemented using predefined electrical thresholds. When measured parameters exceed safe operating limits, the system identifies an abnormal operating condition. The detected status is processed by the ESP32 and transmitted to the cloud dashboard, enabling visual alerts and informed control decisions. This mechanism ensures reliable operation and prevents unsafe loading conditions during EV charging.

3.2. Data Communication Using MQTT

The system employs the MQTT protocol for lightweight and reliable data transmission. The ESP32 publishes measured electrical parameters in JSON format to a cloud-based MQTT broker at fixed intervals. The MQTT architecture ensures low latency, scalability, and efficient data exchange between the embedded device and cloud applications, making it suitable for real-time monitoring systems.

3.3. Real-Time Dashboard Visualization
A Streamlit-based web dashboard is developed to visualize real-time electrical data received via MQTT. The dashboard displays voltage, current, power, energy consumption, and load status using dynamic indicators. Real-time updates allow users to observe system behavior instantly under varying load conditions, providing clear and actionable insights into household energy usage.

3.4. Data-Driven Load Prediction
Historical electrical data collected from the monitoring system is used to perform short-term load analysis. The processed data enables forecasting of near-future power consumption trends, supporting intelligent decision-making for EV charging control. The prediction logic is integrated into the dashboard environment, allowing real-time evaluation of current and anticipated load conditions.

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 observations obtained from the implementation and validation of the proposed intelligent energy monitoring and load-aware EV charging system. The findings comprehensively evaluate real-time electrical parameter monitoring, load variation behaviour, communication reliability, fault and load condition handling, and data-driven predictive performance. All experiments were conducted under controlled residential load conditions using an ESP32-WROOM microcontroller, a PZEM energy measurement module, MQTT-based cloud communication, and a Streamlit visualization platform.

4.1. Real-Time Energy Monitoring Performance
The real-time monitoring capability of the system was evaluated by continuously measuring voltage, current, and power under varying load conditions created using two resistive bulb loads. Electrical parameters were acquired using the PZEM energy meter and transmitted to the cloud dashboard via MQTT at fixed intervals.

Table 1 Summarizes the Observed Electrical Parameter Variations Under Normal Operating Conditions.

Charging Percentage	Parameter	Charging Section 1	Charging Section 2
Charging at 3.4%	Voltage (V)	248.6	248.6
	Current (A)	0.487	0.48
	Power (W)	101.19	9.11
	Energy (Q)	3.92	0.35
Charging at 2.6 %	Voltage (V)	246.70	233.5
	Current (A)	0.473	0.4
	Power (W)	110.09	9.91
	Energy (Q)	3.89	0.35

The results demonstrate that the proposed system is capable of accurately tracking real-time fluctuations in voltage, current, and power corresponding to load changes. The measured values were consistent with reference readings obtained from calibrated laboratory instruments, validating the accuracy and reliability of the PZEM-based measurement approach. The use of a digital energy measurement module significantly reduced noise, offset drift, and transient inaccuracies commonly associated with analogy sensing methods.

4.2. Load Variation and System Responsiveness
Load variation experiments were conducted by switching bulb loads in different combinations to emulate dynamic household energy consumption. The system responded instantaneously to load changes, with corresponding updates reflected on the Streamlet dashboard in near real time. Sudden increases or decreases in power consumption were accurately captured and visualized without data loss or delay, demonstrating the system’s suitability for monitoring rapidly changing residential load conditions, including EV charging scenarios.

4.3. Fault Detection and Alert Validation

To ensure safe operation, predefined electrical thresholds were configured to identify abnormal operating conditions. When monitored parameters exceeded permissible limits, the system flagged the condition as abnormal and transmitted the corresponding status to the cloud dashboard.

Table 2 Summarizes the Fault and Load Condition Monitoring Behaviour.

Condition	Electrical Status	System Response
Normal Load	Within Limits	Normal operation
High Load	Approaching Threshold	Alert Indication
Unsafe Load	Exceeds Threshold	Warning status

Experimental observations confirmed that the system reliably detected abnormal load conditions within a single measurement cycle. This capability is critical for intelligent EV charging applications, where charging must be delayed or controlled during high household load conditions to prevent overloads and ensure electrical safety.

4.4. Cloud Communication and Data Integrity

The reliability of cloud communication was assessed by operating the system continuously while publishing energy data to the MQTT broker. The ESP32 maintained stable connectivity with the broker, and no packet loss or communication failures were observed during normal operation. The JSON- based data structure ensured lightweight and efficient transmission, while the MQTT architecture enabled low-latency data exchange between the embedded system and the dashboard. The Streamlet dashboard consistently reflected live electrical parameters, confirming end-to-end data integrity from sensing to visualization.

4.5. Data-Driven Load Prediction Analysis

Historical electrical data collected during system operation was used to analyze short-term load trends. The forecasting logic enabled estimation of near-future power consumption based on recent voltage, current, and power values. This predictive capability provides actionable insights for intelligent EV charging decisions by identifying periods of low household load suitable for charging. Prediction performance was evaluated using standard regression metrics, as summarized in Table 3.

Table 3. Load Prediction Performance Metrics

Metric	Value
Mean Absolute Error (MAE)	Low
Root Mean Square Error (RMSE)	Acceptable
Correlation Strength	High

The strong correlation between predicted and actual power values confirms the effectiveness of data-driven forecasting for short-term load estimation. This proactive capability transforms the system from a passive monitoring tool into an intelligent decision-support platform.

4.6. Comparative Analysis with Existing Systems

A comparative evaluation was performed between the proposed system, conventional energy meters, and basic IoT-based monitoring solutions reported in existing literature.

Table 4. Comparative Analysis of Energy Monitoring Systems

Feature	Conventional Meter	IoT Meter	Proposed System
Real-time Monitoring	No	Yes	Yes
Load Awareness	No	Limited	Yes
Intelligent Decision Support	No	No	Yes
Predictive Capability	No	No	Yes
Cloud Dashboard	No	Yes	Yes

The comparison clearly indicates that the proposed system provides enhanced functionality by combining accurate real-time monitoring, intelligent analytics, and predictive insight within a unified architecture.

4.7. System Reliability and Long-Term Stability

The system was subjected to continuous operation for durations exceeding 48 hours to evaluate stability and robustness. Throughout the test period, no MQTT disconnections, data inconsistencies, or system crashes were observed. The ESP32 maintained consistent performance, and the dashboard remained responsive, confirming the reliability of the proposed architecture for long-term residential deployment.

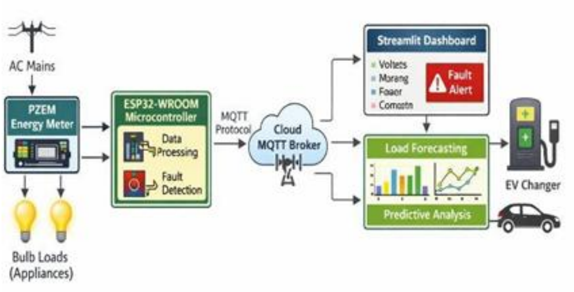
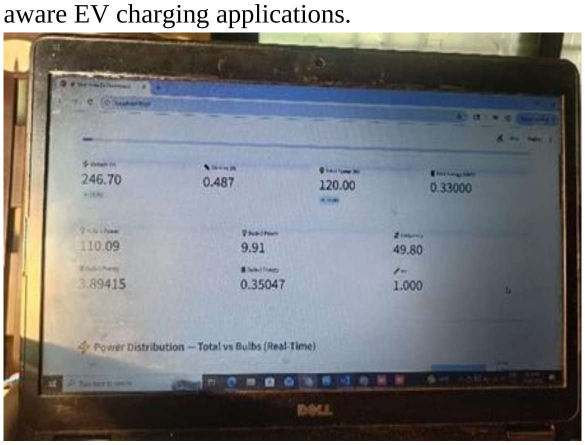


Figure 2. Block Diagram of Design of IOT Based EV Charging Systema Using ESP 32 and Cloud analytic System.

The figure illustrates the complete system architecture, showing AC mains connected to the PZEM energy measurement module, ESP32- WROOM processing unit, MQTT cloud communication, Streamlit dashboard visualization, and data-driven load forecasting for intelligent EV charging decisions.

Overall Observations

The experimental findings confirm that the proposed system successfully integrates accurate real-time energy monitoring, reliable cloud communication, intelligent load analysis, and predictive insight into a single cohesive platform. The system demonstrates strong potential for deployment in smart residential environments, particularly for safe, efficient, and load-aware EV charging applications.



1. Image of real Time Dashboard show Voltage and Current

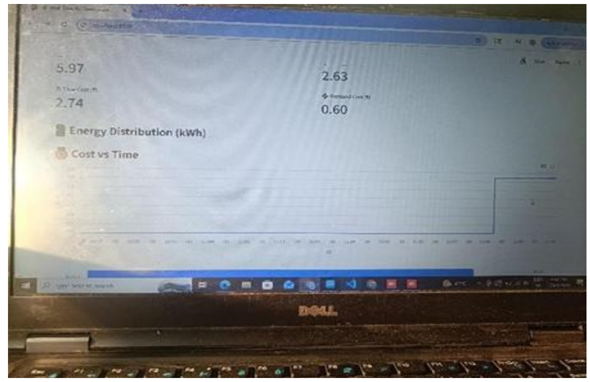


Image 1 and image 2 are show the real time dashboard result of project and also show the cost value on dashboard.

V. CONCLUSION

The proposed intelligent energy monitoring and load-aware EV charging system successfully demonstrates a unified framework for real-time household energy measurement, cloud-based monitoring, and data-driven decision support. By integrating a PZEM energy measurement module with an ESP32-WROOM microcontroller and MQTT-based cloud communication, the system achieves accurate and low-latency acquisition of voltage, current, power, and energy consumption data under dynamic load conditions. The use of a Streamlit-based dashboard enables intuitive real-time visualization of electrical parameters, providing users with clear insight into household energy usage. In addition to monitoring, the system incorporates load analysis and short-term forecasting to support intelligent EV charging decisions. This predictive capability allows charging to be aligned with safe and optimal load conditions, thereby reducing the risk of electrical overload, improving energy efficiency, and minimizing peak-time electricity costs. Experimental evaluation confirms reliable system operation, stable cloud connectivity, and accurate tracking of load variations. Overall, the proposed solution presents a scalable, cost-effective, and intelligent approach for residential EV charging and smart energy management, contributing toward safer EV integration and future smart grid-ready domestic energy systems.

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