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IoT System for Residential Energy Monitoring and Management: Design and Implementation

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Abstract This study addresses the lack of integrated, secure, and scalable Home Energy Management Systems (HEMS) that combine appliance-level and circuit-level control while providing pilot-scale statistical analysis of energy savings under real-world conditions. We design and deploy a cloud-enabled IoT-based HEMS using ESP32 microcontrollers and PZEM-004T sensors, integrated through MQTT and Home Assistant on AWS. The system was evaluated in two residential households over several months. Compared with related work, the proposed solution integrates circuit-level actuation at the electrical distribution board, vendor-agnostic interoperability through Home Assistant, and a secure end-to-end data pipeline based on TLS encryption and broker-level authorization. In this pilot-scale evaluation (N=2), we observed a 9–10% reduction in monthly residential electricity consumption ($p < 0.05$), with a 95% confidence level, within the monitored households. An illustrative difference-in-differences (DiD) estimator suggests an additional reduction of 3.17 kWh/month under a single treated–control pairing. Measurement accuracy remained below 3% relative error when compared with official utility bills. These findings should be interpreted as preliminary evidence and technical validation rather than generalizable proof of population-wide energy savings. Overall, the proposed HEMS constitutes a reproducible reference implementation for secure monitoring and control, demonstrating its feasibility and potential for residential energy optimization in pilot-scale deployments.

Keywords: Internet of Things (IoT), energy management, smart homes, residential electricity consumption, cloud computing.

1 Introduction

According to the Latin American Energy Organization (OLADE), the largest energy-consuming sectors worldwide are transportation (38%), industry (29%), and the residential sector (16%), highlighting the significant contribution of households to overall energy demand in Latin America and the Caribbean [Ramos-Males and Bautista-Segovia, 2022]. In Ecuador, the National Electricity Operator (CENACE) reported a total electricity consumption of 30,389.70 GWh in 2023, representing a 15.75% increase compared to 2022 [CENACE, 2023]. The National Energy Balance indicates that residential electricity consumption accounted for 13.5% of total demand, with an average monthly residential consumption of 143.36 kWh, reflecting an 8.4% increase year over year [Ministry of Energy and Mines, 2024].

Residential electricity consumption is influenced by several factors, including the number and type of household appliances, dwelling size, and user behavior. In many homes, limited technological integration prevents effective monitoring and management of electricity use. Smart home technologies can enable remote control of appliances, lighting, and electrical circuits, leading to reported savings of 20–30% on monthly electricity bills [Cuatin and Azuero, 2022]. However, the lack of integrated monitoring and control solutions limits users' ability to track real-time consumption, detect inefficient appliances, and implement personalized energy-saving strategies [Palacios, 2020; Arroyo and Angulo, 2022].

In this context, there is a clear need for technological solutions that support real-time monitoring and remote management of residential electricity consumption. The guiding research question of this study is: How can an IoT-based system enhance energy efficiency in residential environments through remote monitoring and management of electricity consumption? To address this question, this work presents the design and implementation of an IoT-based system capable of recording residential electricity consumption while enabling remote control of appliances and electrical circuits.

The remainder of this paper is structured as follows. Section 2 reviews related work on IoT-based residential energy management systems. Section 3 describes the system architecture and development methodology. Section 4 details the system implementation in residential environments. Section 5 presents functionality testing results. Section 6 discusses the results and their implications. Finally, Section 7 concludes the paper and outlines future research directions.

2 Related Works

The Internet of Things (IoT) has enabled the development of diverse architectures for residential energy monitoring and management. These architectures are commonly applied in Smart Grid environments and adapted to residential contexts through Home Energy Management Systems (HEMS). Previous studies indicate that no standardized IoT architecture exists for residential energy management. Instead, architectural choices, such as the number of layers and communication protocols, are driven by performance, scalability, and application-specific requirements [Jakhar *et al*., 2022; Taghizad-Tavana *et al*., 2022].

Several IoT-based systems focus on monitoring residential electricity consumption at either the appliance level or the household level. Reported implementations demonstrate that IoT technologies can achieve acceptable measurement accuracy and promote energy-efficient behavior through real-time visualization and automation [Cuzme-Rodríguez *et al*., 2020; Wongwut and Angamnuaysiri, 2024]. More recent studies integrate monitoring and control functionalities within unified HEMS platforms, combining smart meters, smart plugs, and cloud services to support residential energy management [Condon *et al*., 2022; Joha *et al*., 2023].

Other works explore intelligent monitoring and automation using ESP32-based platforms and advanced control strategies, such as load disconnection and data-driven optimization [El-Khozondar *et al*., 2024; Shaban and Alsharekh, 2022]. These studies confirm the feasibility of IoT-based HEMS and highlight the role of automation and data analytics in improving residential energy efficiency.

Table 1 summarizes the main characteristics of representative IoT-based HEMS reported in the literature. Building on these contributions, the system proposed in this study integrates household-level and appliance-level monitoring with circuit-level control in a single open-source framework, enabling interoperable, scalable, and real-world deployment.

2.1 Data Security and Privacy

Data security represents a critical challenge in IoT environments due to the large number of interconnected devices and the sensitive nature of transmitted information. MQTT, a widely used protocol in HEMS, presents inherent vulnerabilities related to the absence of default encryption, weak authentication mechanisms, and topic exposure. These weaknesses can be exploited through sniffing, man-in-the-middle, or denial-of-service attacks [Laghari *et al*., 2024].

To mitigate these risks, existing literature recommends the use of TLS-based secure channels, access control lists (ACLs), strong authentication mechanisms, and broker hardening techniques [Heredia-Andrango *et al*., 2024]. Additionally, lightweight intrusion detection and prevention systems, such as Suricata, have proven effective in identifying anomalous behavior with minimal impact on system resources.

These measures contribute to ensuring data confidentiality, integrity, and availability in IoT platforms designed for residential energy monitoring.

3 Materials and Methods

This section describes the methodology adopted for the development of the proposed system. The project follows the Waterfall model, which structures development into four sequential phases: requirements definition, system design, implementation, and testing (Figure 1) [Luna *et al*., 2022]. The process begins with the specification of hardware and software requirements in accordance with the ISO/IEC/IEEE 29148:2018 standard, followed by the design of the IoT architecture and system deployment in a controlled or residential environment.

The Waterfall methodology was selected due to the stable and well-defined nature of the system requirements and the need for detailed upfront planning. The integration of embedded devices, fixed electrical installations, and cloud services introduces hardware–software dependencies and electrical safety constraints that limit iterative changes. Under these conditions, Waterfall provides a more reliable and traceable development framework than Agile methodologies [Khan and Mahadik, 2022].

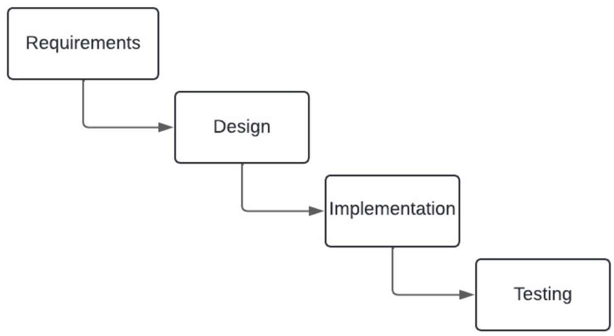

Figure 1. Applied Waterfall Model.

3.1 IoT System Architecture

The IoT architecture for the Residential Electricity Consumption Monitoring and Management System is illustrated in Figure 2. The architecture consists of four layers—devices, network, services, and application—which collectively support household energy monitoring and control.

- **Devices Layer:** This layer hosts the components responsible for acquiring electricity consumption data, including sensors and actuators. Actuators, such as relays and solid-state relays, enable the remote activation and deactivation of electrical outlets and circuits within the household distribution panel.
- **Network Layer:** The network layer manages wireless communication between devices and the gateway using Wi-Fi technology. It also handles data transmission to cloud-hosted services over the Internet, enabling real-time monitoring and remote control.
- **Services Layer:** This layer comprises cloud-based services responsible for processing, storing, and visualizing electricity consumption data at both the household and appliance levels.
- **Application Layer:** The application layer provides end users with tools for monitoring residential electricity consumption, managing devices remotely, and receiving alerts triggered by abnormal consumption patterns.

Table 1. Comparative Summary of Representative IoT-based HEMS Proposals

Work	Technology	HEMS Scope	Limitations	Contributions
[Cuzme-Rodríguez *et al.*, 2020]	ESP-01S; MQTT; AWS	Appliance monitoring	MQTT security; ZigBee/LoRa; hardware compatibility	Full HEMS
[Wongwut and Angamnuaysiri, 2024]	PZEM-004T MQTT; Local server	Residential Consumption	MQTT security; Single-phase meters	Single-phase and two-phase meters
[Condon *et al.*, 2022]	Sonoff POW R2; eGauge EG4115; Cloud server	Full HEMS	AWS Iot Core; circuit control hardware compatibility	Circuit control; Wi-Fi/ZigBee interoperability
[Joha *et al.*, 2023]	ESP32-8266; Cloud server	Full HEMS	ZigBee/LoRa incompatible; Lab test	Wi-Fi/ZigBee. interoperability
[El-Khozondar *et al.*, 2024]	ESP32; Cloud server	Residential monitoring	Battery use; hardware compatibility	Operability continuous
[Shaban and Alsharekh, 2022]	ESP32; SSRs; Cloud server	Residential monitoring	Internet-dependent; Blynk cost	Full HEMS

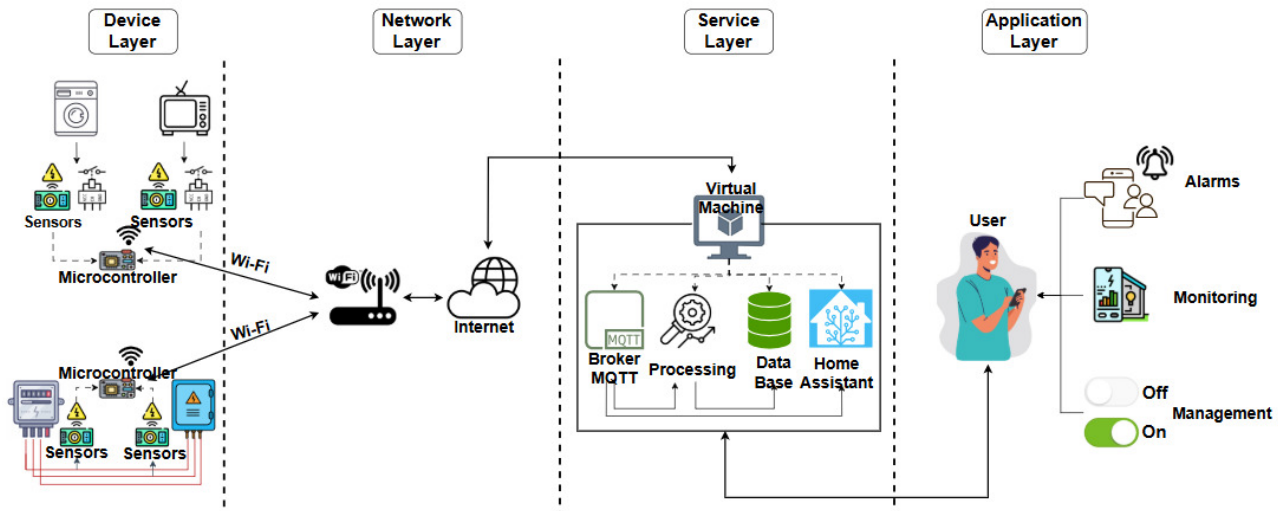

Figure 2. IoT Architecture of the Proposed System

3.2 System Block Diagram

Figure 3 presents the overall system block diagram, illustrating the functional structure of the residential electricity monitoring and management system. The system consists of five main blocks: power supply, electrical consumption data acquisition, transmission, cloud services, and application. The interaction among these blocks enables the system's core functionalities.

- **Power Supply Block:** This block provides stable power to the information acquisition nodes.
- **Electrical Consumption Data Acquisition:** This block collects electrical variables through two nodes. Node 1 measures appliance-level consumption and enables remote management of two appliances. Node 2 monitors total residential electricity consumption and controls electrical circuits at the distribution board. Microcontrollers process and transmit data using the MQTT protocol, selected for its low resource requirements and efficient bandwidth usage. Communication is secured through TLS encryption to ensure data confidentiality and integrity.
- **Transmission Block:** The transmission block includes the gateway, which connects to the data acquisition nodes via Wi-Fi and forwards information to cloud-hosted services through the Internet. Wi-Fi was selected due to its wide availability and higher data transfer rates compared to Bluetooth, ZigBee, and Z-Wave, making it suitable for residential environments.
- The **Cloud Services Block:** Cloud services are deployed on AWS, selected for its robust infrastructure-as-a-service capabilities and wide range of preconfigured operating systems. A virtual machine hosts the Mosquitto MQTT broker, InfluxDB, Node-RED, and Home Assistant. Home Assistant was chosen for its open-source nature, adaptability, and compatibility with MQTT and a broad range of IoT hardware.
- **Application Block:** This block corresponds to the user interface developed in Home Assistant. It enables real-time visualization of electricity consumption, remote management of appliances and circuits, and access to historical data.

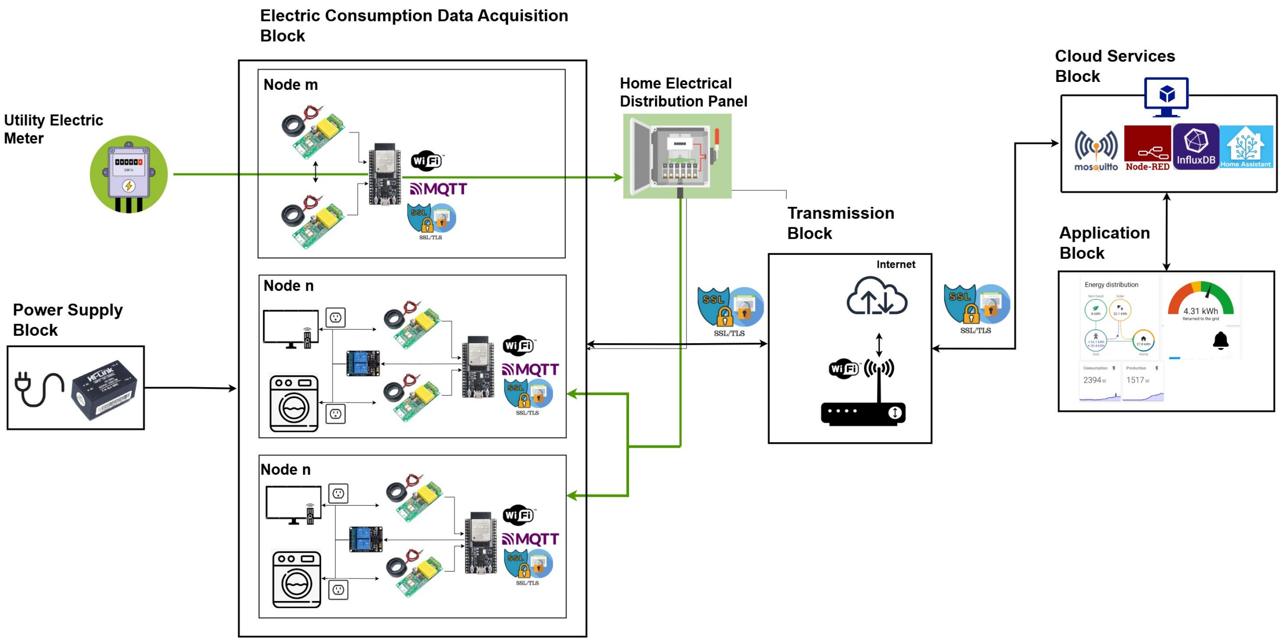

Figure 3. System Block Diagram

Figure 4 presents the use case diagram, which illustrates the interactions between the user and the Energy Monitoring Platform, highlighting core functionalities such as real-time consumption visualization, remote control of appliances and circuits, and access to historical data. The platform manages background processes including message publishing and database queries to ensure seamless communication between devices and services.

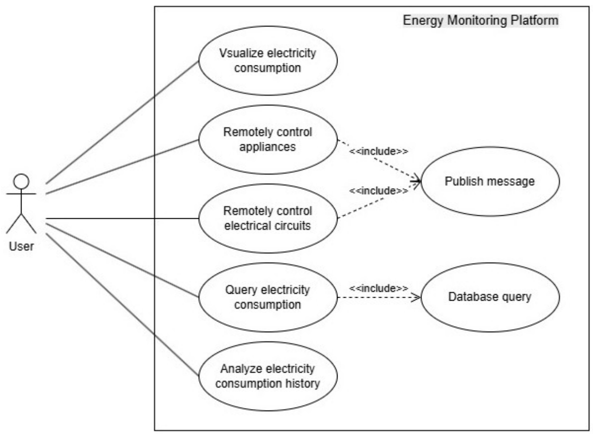

Figure 4. Use Case Diagram of the Proposed Platform

Figure 5 presents the sequence diagram illustrating the end-to-end data transmission and processing flow of the proposed IoT system. The diagram describes how the electrical measurements acquired by the sensor nodes are securely transmitted via MQTT over TLS, processed in real time by Node-RED to structure the incoming data into measurements, tags, and fields compatible with InfluxDB, and subsequently queried for monitoring and analysis purposes.

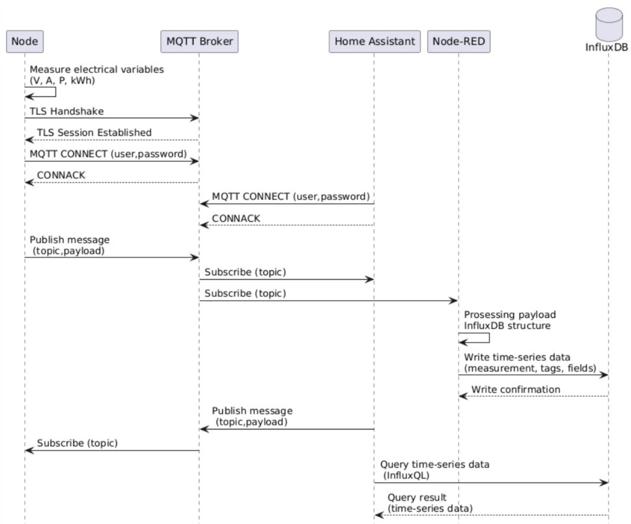

Figure 5. Sequence Diagram of Data Acquisition and Storage

3.3 Nodes Design

The proposed system includes two information acquisition nodes with distinct functionalities. Node 1 measures electricity consumption and enables remote control of two individual appliances. Node 2 monitors total residential electricity consumption and allows remote control of electrical circuits at the distribution panel.

Table 2 lists the electronic components used in both nodes, including sensors for measuring electrical parameters and microcontrollers responsible for data processing and MQTT communication.

Based on the electrical characteristics of the components listed in Table 2, Node 1 consumes approximately 0.7 kWh per month, while Node 2 consumes about 0.6 kWh per month. The total system self-consumption is therefore approximately 2 kWh per month, which is negligible when compared to the average residential electricity consumption in Ecuador (≈143 kWh/month).

Table 2. Hardware Components Used in Node 1 and Node 2

Components	Quantity	Voltage (VDC)	Current (mA)
Node 1			
ESP32	1	5	80
PZEM-004T v3	2	5	20
Relay module	1	5	65
LED	1	5	20
Hi-Link PM-01	1	–	–
Node 2			
ESP32	1	5	80
PZEM-004T v3	2	5	20
SSR-40A	1	3.3	20
SSR-60A	3	3.3	20
Hi-Link PM-01	1	–	–

3.3.1 Electrical Connections Model of Node 1

During the design phase, the electrical model of Node 1 was defined to establish connections among the microcontroller, sensors, relays, and power supply. As shown in Figure 6, the node operates at 110 VAC, which is converted to 5 VDC using a Hi-Link PM-01 module to power the ESP32 and sensors.

Two PZEM-004T v3 sensors are connected in parallel to the phase and neutral conductors of the monitored appliances and communicate with the ESP32 via UART. A dual-channel relay module, connected to GPIO pins, enables remote control of each appliance.

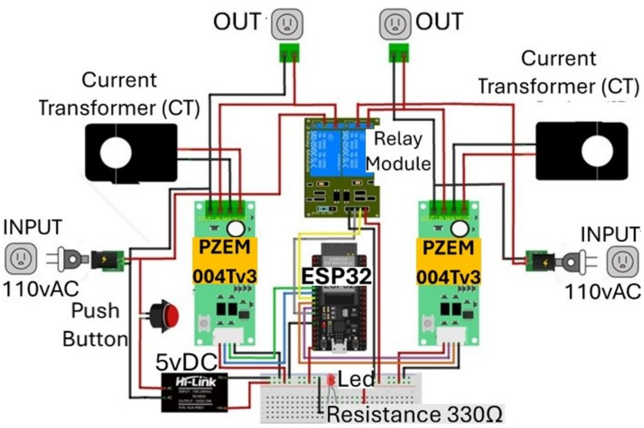

Figure 6. Connection Diagram of Node 1

3.3.2 Electrical Connections Model of Node 2

Figure 7 illustrates the electrical model of Node 2. The Hi-Link PM-01 module provides a 5 VDC power supply. The node integrates two PZEM-004T v3 sensors and current transformers for phase-by-phase voltage and current measurement.

Solid-state relays (SSR-40A and SSR-60A), controlled through ESP32 GPIO outputs, enable remote switching of lighting circuits, outlets, and special electrical loads at the distribution panel.

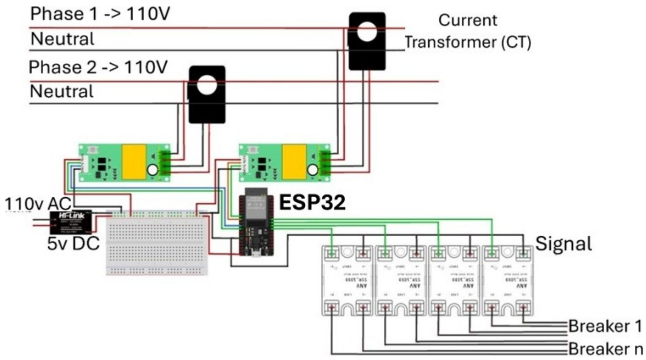

Figure 7. Connection Diagram of Node 2

3.4 Design of the Electricity Consumption Monitoring and Management Interface

This section describes the conceptual design of the interface used to visualize and manage electricity consumption. The interface displays total household consumption and appliance-level data while enabling remote control of connected devices and circuits.

The interface is organized into four panels: **Overview, IoT System – Smart Meter, IoT System – Plugs**, and **Queries**. Figure 8 shows the Summary panel, which includes navigation tools for accessing phase-based consumption data and a histogram that visualizes monthly consumption trends. MQTT-based switches are also integrated to enable remote control of lighting, outlets, and special loads.

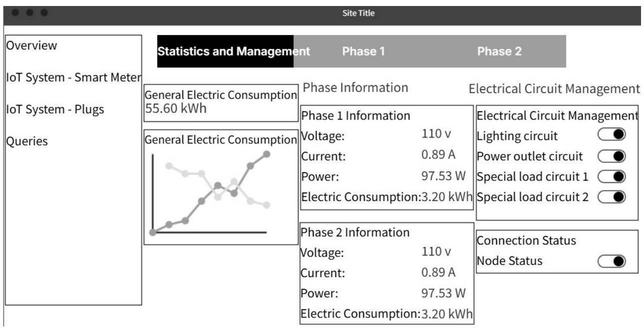

Figure 8. Dashboard Design for Residential Energy Monitoring and Management

3.5 Database Design for Energy Consumption Data Storage

Electricity consumption data are stored on an AWS virtual server using an InfluxDB time-series database. As illustrated in Figure 9, the InfluxDB instance runs on the server and handles database management and administration.

Within this instance, the database **smart_grid_home** contains two measurements: **plugs** and **smart_meter**. Each data point includes a timestamp, tags, and fields. Tags store metadata, where the tag key defines the identifier type and the tag value corresponds to a pseudonymous node identifier (**id_node**). Fields store the measured electrical variables, with the field key indicating the variable type (voltage, current, power, or consumption) and the field value representing the corresponding numerical measurement. No personally identifiable user information is stored.

To manage the data lifecycle, retention policies are applied. High-frequency raw measurements are retained for 30 days, daily aggregated consumption data (kWh/day) for 12 months, and monthly aggregated consumption records for up to three years. After these periods, the database engine automatically deletes the data, limiting long-term storage within the cloud infrastructure.

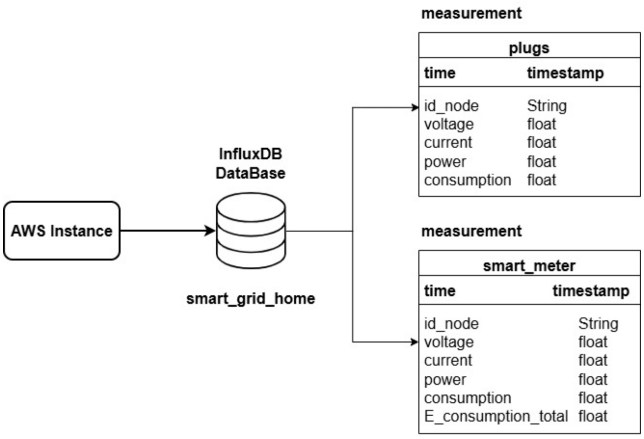

Figure 9. InfluxDB Database Design for Energy Measurements

3.6 Development of Node 1

Node 1 was assembled as a compact unit designed for appliance-level energy monitoring and management. As shown in Figure 10, the enclosure integrates all electronic components and electrical connections, ensuring electrical safety, accessibility, and stable long-term operation in residential environments.

The physical layout supports flexible installation near household appliances while maintaining adequate insulation and protection for continuous residential use.

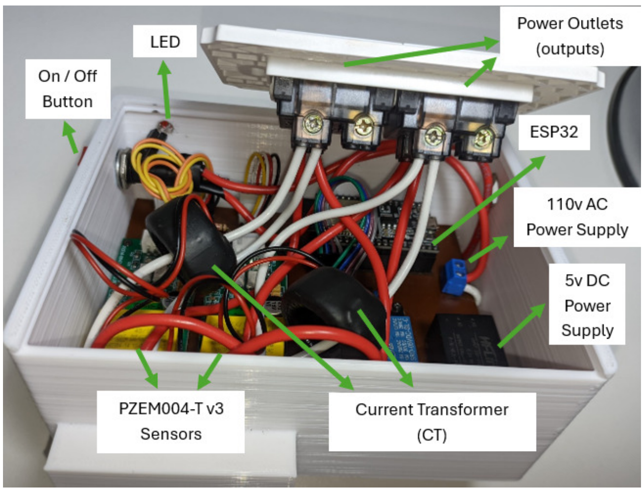

Figure 10. Assembled Prototype of Node 1

3.7 Development of Node 2

Node 2 was assembled based on the previously defined electrical and functional design. As illustrated in Figure 11, the enclosure incorporates dedicated terminal blocks that facilitate electrical connections between the node and the residential distribution panel.

This design allows secure installation adjacent to the distribution panel while preserving adequate electrical isolation and supporting continuous operation under real residential conditions.

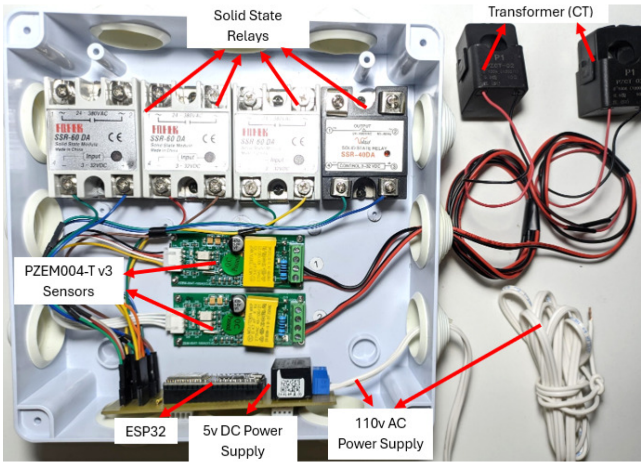

Figure 11. Assembled Prototype of Node 2

4 System Implementation

Following the development of Nodes 1 and 2, the system was deployed in residential environments to collect data on total residential electricity consumption and selected appliances. This deployment enabled validation of the system's functionality under real operating conditions.

The households selected for the study were chosen using purposive sampling to represent typical urban social-interest housing in Ecuador. Selection criteria included stable occupancy, conventional electrical installations, and spatial layouts representative of standard family dwellings.

Both households are two-story single-family residences with built areas ranging from 100 to 120 m^2 and occupancy of three to four residents. INEC's 2023 building-permit statistics report a national median of 113 m^2 per planned dwelling, supporting this size range as typical in Ecuador [National Institute of Statistics and Census (INEC), 2024]. Each dwelling includes three bedrooms, multiple bathrooms, a living room, a dining area, a kitchen, and a laundry area, reflecting common residential configurations and appliance usage patterns.

Although the limited sample size restricts broad statistical generalization, the selected households provide a representative baseline for evaluating residential electricity consumption and system performance in comparable urban environments. To reduce the influence of resident-specific habits and other external drivers, the study prioritizes comparable households (size, occupancy, and appliance context) and uses energy consumption (kWh) as the primary outcome, which is independent of the billing structure and allows direct comparison across periods.

4.1 Appliance Selection and System Deployment

Selecting appliances for monitoring is a critical step in system deployment. Table 3 lists the selected appliances along with their rated power consumption. High-power appliances such as the iron (1200 W), microwave oven (700 W), and washing machine (700 W) were identified; however, these devices are typically used for short durations.

In contrast, lower-power devices such as the television (135 W), stereo system (120 W), and refrigerator (113.5 W) operate for extended periods. Notably, the refrigerator runs continuously, making it a significant contributor to total residential electricity consumption.

Table 3. Monitored Appliances and Rated Power

N.º	Appliance	Power (Watts)
1	Refrigerator	113.5
2	Washing machine	700
1	TV	135
3	Stereo system	120

Node 1 was installed at a household electrical outlet. The two available sockets were used to connect the refrigerator (Appliance 1) and the washing machine (Appliance 2). After installation, stable wireless connectivity with the household access point was verified (Figure 12).

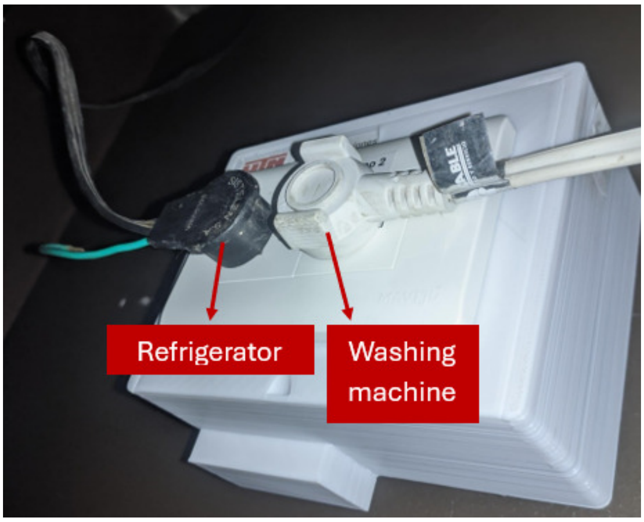

Figure 12. Node 1 Deployment (Appliance Level)

Node 2 was installed adjacent to the household electrical distribution panel. The phase conductors (L1 and L2), neutral bar, ground, and four electrical circuits were identified and connected according to the wiring diagram shown in Figure 7. Stable wireless connectivity with the access point was also confirmed (Figure 13).

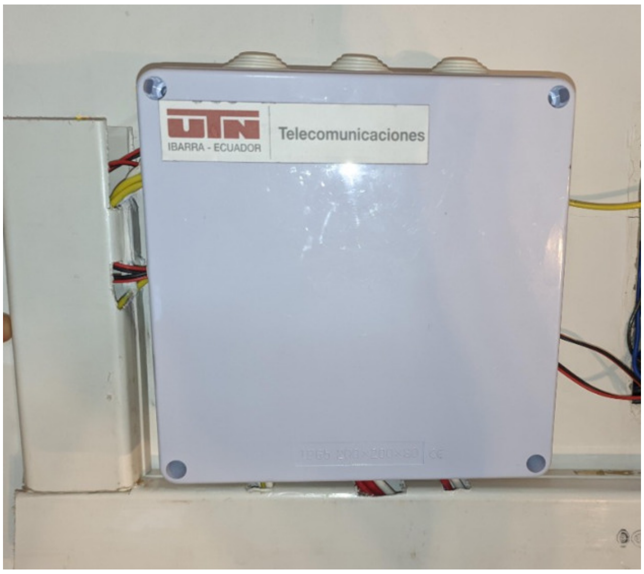

Figure 13. Node 2 Deployment (Distribution Panel)

4.2 Security in MQTT Communication

Based on recent studies [Laghari *et al.*, 2024; Heredia-Andrango *et al.*, 2024], MQTT-based systems face several security risks, including insecure data transmission, unauthorized access, and vulnerabilities related to human factors. To mitigate these risks, the system implements encrypted communication, authenticated access, and broker-side access control mechanisms.

MQTT communication is secured end-to-end using TLS v1.3. The Mosquitto broker is configured with an X.509 server certificate based on RSA-2048 (valid for 360 days) and establishes encrypted sessions using the AEAD cipher suite TLS_AES_256_GCM_SHA384, ensuring strong encryption and message integrity.

Each ESP32 node is assigned unique credentials for broker authentication, preventing anonymous access and restricting message publication to authorized devices. Credential lifecycle management is enforced through periodic rotation every 90 days or immediately in the event of suspected compromise. Although MQTT 3.1.1 supports mutual TLS with per-device certificates, this implementation adopts credential-based authentication over TLS to balance security requirements with the computational and energy constraints of the ESP32 platform [Tagliaro *et al.*, 2024; Al-muqarm *et al.*, 2022]. Mutual TLS and automated certificate provisioning are identified as future enhancements.

5 System Functionality Testing

In accordance with the Waterfall methodology, the final phase focused on validating the operational performance of the Residential Electricity Consumption Monitoring and Management System. The tests verified core system functionalities and user-facing operations, as defined in the use case diagram (Figure 4).

Specifically, the evaluation covered real-time visualization of household- and appliance-level electrical variables (voltage, current, power, and consumption), remote management of connected appliances and electrical circuits, and access to historical electricity consumption data stored in the database.

Figure 14 shows the Smart Meter panel, which provides real-time monitoring of total residential electricity consumption. The interface displays the current month's accumulated consumption (kWh), a dynamically updated histogram of consumption trends, and electrical parameters for each phase. In addition, the panel includes switches that allow remote control of lighting, outlets, and special electrical loads. During testing, all circuits remained active, indicating normal system operation.

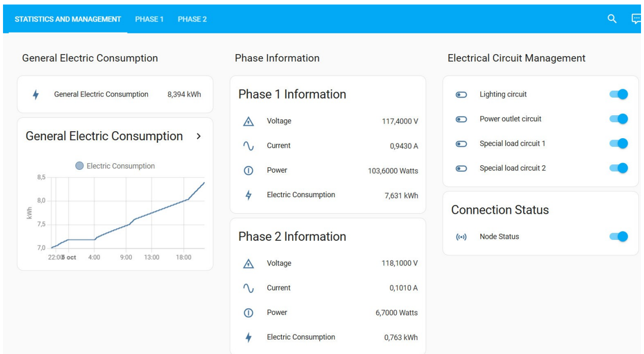

Figure 14. Smart Meter Dashboard

Remote management tests were conducted from two geographically separated locations. The first corresponded to the residence where the system was deployed, located in the Santa Lucía del Retorno area of Ibarra. The second location was approximately 4 km away, in the Pilanqui area, from which the user accessed the Home Assistant platform remotely.

These tests evaluated the system's ability to execute control commands reliably without physical presence at the deployment site. Each test verified correct command execution, stable communication, and consistent system response under real residential conditions. Table 4 summarizes the defined test cases and their objectives.

Table 4. Remote-Control Test Cases and Objectives

Test code	Test objective
T1	Remote control of lighting circuit
T2	Remote control of outlets circuit
T3	Remote control of special load circuit 1
T4	Remote control of special load circuit 2
T5	Remote control of refrigerator
T6	Remote control of washing machine
T7	Remote control of television
T8	Remote control of stereo system

The results confirm that the system supports reliable remote management of both electrical circuits and household appliances. Table 5 reports successful execution for all tested elements.

To validate access to historical electricity consumption data, queries were executed through the Home Assistant interface to retrieve household- and appliance-level consumption records. The queried periods matched the billing cycles used by the electricity utility company, enabling direct comparison with official electricity bills.

Table 5. Remote-Control Execution Results for Circuits and Appliances

Test Code	Managed element type	Result
T1	Lighting circuit	Successful
T2	Outlets circuit	Successful
T3	Special load circuit 1	Successful
T4	Special load circuit 2	Successful
T5	Refrigerator	Successful
T6	Washing machine	Successful
T7	TV	Successful
T8	Stereo system	Successful

As shown in Table 6, system-recorded values closely match utility billing data. For Household A, the system measured an average monthly consumption of 78.47 kWh, compared to 80.00 kWh billed, yielding a mean difference of 1.53 kWh (1.9%). For Household B, the system measured 89.49 kWh versus 91.17 kWh billed, resulting in a mean difference of 1.68 kWh (1.83%). In both cases, relative errors remained below 3%, confirming measurement accuracy and system stability.

Table 6. Utility Bills Versus System-Measured Monthly Consumption

Month	Invoice (kWh)	System (kWh)	Relative Error (%)
Household A			
August	80.00	78.03	2.46
September	80.00	78.82	1.47
December	77.00	75.68	1.71
January	82.00	81.32	0.83
February	80.00	78.52	1.85
March	81.00	78.42	3.19
Mean	80.00	78.47	–
Standard D.	2.47	–	–
Household B			
January	86.00	84.65	1.57
February	92.00	90.22	1.94
March	99.00	97.11	1.91
April	87.00	85.41	1.83
May	94.00	92.01	2.12
June	89.00	87.53	1.65
Mean	91.17	89.49	–
Std. dev.	5.02	–	–

6 Results and Discussion

A six-month comparative analysis was conducted to evaluate the impact of the proposed system on residential electricity consumption. Post-implementation data for Household A and Household B were compared with the same calendar months from the previous year.

October and November were excluded due to a national power crisis in Ecuador that led to electricity rationing and could have biased the results. Comparisons were aligned by calendar months across years to reduce seasonal variability.

While habit-level variables (e.g., exact occupancy schedules) were not instrumented, confounding was minimized by focusing on stable-occupancy households with similar characteristics and by relying on the treatment–control DiD structure reported later in this section.

As shown in Figure 15, Household A reduced average monthly electricity consumption from 89.3 kWh to 80.0 kWh, corresponding to a reduction of 9.3 kWh (10.4%). Household B reduced consumption from 102.7 kWh to 91.1 kWh, equivalent to 11.6 kWh (11.3%).

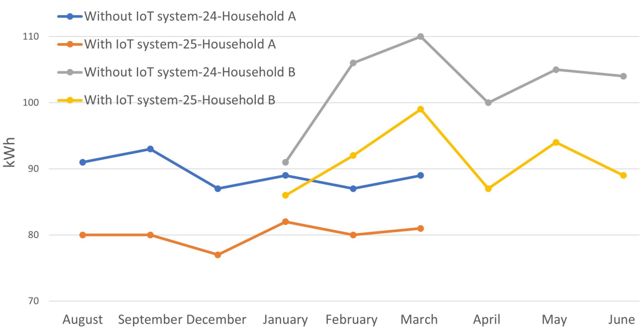

Figure 15. Monthly Consumption Before/After Deployment

To assess whether these reductions were statistically significant, paired-sample Student's t-tests were performed. The null hypothesis (H_0) assumed no difference between pre- and post-implementation consumption, while the alternative hypothesis (H_1) assumed a significant difference. Using a 95% confidence interval ($\alpha = 0.05$), the calculated t values for Household A (9.44) and Household B (7.90) exceeded the critical value (2.01). Therefore, the null hypothesis was rejected in both cases, indicating statistically significant pre–post differences within the two monitored households (Table 7). Given the pilot nature and the use of repeated measurements within a limited number of households, these results should be interpreted as within-sample evidence consistent with system deployment, rather than as generalizable causal claims.

Table 7. Paired-sample Student's t-test Results for Both Households

Parameter	Household A	Household B
Difference mean of the pairs	9.33	11.5
Standard Deviation	2.42	3.56
Sample size	6	6
T-statistics	9.44	7.90
Critical t-value	2.01	2.01

To minimize seasonal effects, a winter-based comparison was also conducted under similar climatic conditions. As shown in Figure 16, Household A exhibited an average reduction of approximately 9%, while Household B showed a reduction of about 10.5%. These results suggest that, within this pilot deployment, the observed savings are more likely associated with system use than with seasonal variability.

A difference-in-differences (DiD) estimator was used to further isolate the system's impact. One household was assigned as the treatment group, where the IoT system was deployed, and another served as the control group without intervention (Figure 17). The analysis compared monthly consumption before and after deployment for both groups.

The results (Table 8) indicate that the treatment household reduced average consumption from 85.83 kWh/month to 79.00 kWh/month, while the control household decreased from 104.67 kWh/month to 101.00 kWh/month. The DiD estimator suggests an additional reduction of 3.17 kWh/month under this single treated–control pairing; this value is presented as illustrative and does not support broad generalization or population-level causal inference.

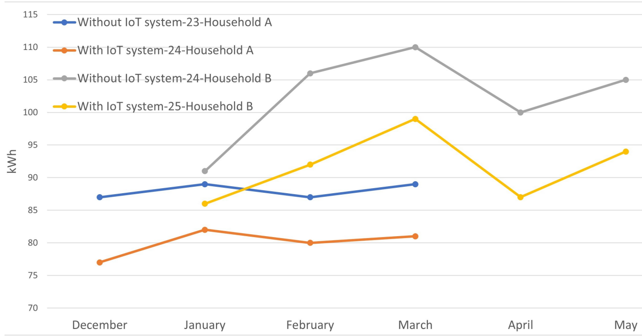

Figure 16. Winter-Month Consumption Comparison

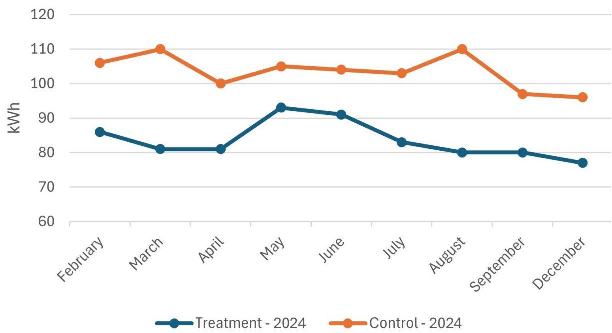

Figure 17. Monthly Electricity Consumption for Treatment and Control Groups

Table 8. Difference-in-Differences (DiD) Analysis of Residential Electricity Consumption

Group	Pre	Post	Difference (Post-Pre)
Treatment (kWh)	85.83	79.00	-6.83
Control (kWh)	104.67	101.00	-3.67
DiD	-3.17		

From an economic perspective, average monthly savings of 9.3 kWh and 11.6 kWh correspond to cost reductions of approximately USD 0.90 and USD 1.12 for Households A and B, respectively, based on the local electricity tariff.

Since residential billing may vary due to subsidy tiers, consumption brackets, and tariff updates, the kWh reduction is reported as the primary outcome and the monetary estimate is provided only as contextual interpretation.

The estimated payback period ranges from ≈13–17 years; however, integration into new residential constructions or deployment at larger scales could improve economic feasibility. For the indicative payback calculation, we used a local electricity tariff of USD 0.097/kWh and an estimated system cost C_0 = USD 182 (hardware: USD 102; software: USD 74; installation: USD 6), as summarized in Table 9. The payback period was estimated as

$$PB = \frac{C_0}{12 \cdot S_n} \tag{1}$$

where C_0 is the system cost and S_n represents the estimated monthly monetary savings derived from the observed energy reduction and the local electricity tariff. The calculation does not explicitly subtract the system's own electricity consumption (approximately 2 kWh/month), since this load is relatively small compared to the measured savings and remains nearly constant across households. Therefore, its impact on the payback estimate is considered negligible at this stage.

Table 9. Summary of Economic Assumptions Used for Payback Estimation

Parameter	Household A	Household B	Units
Energy reduction (ΔE)	9.3	11.6	kWh/month
Electricity tariff (p)	0.097		USD
Monthly savings	0.90	1.12	USD
System cost			
Hardware	102		USD
Software	74		USD
Installation	6		USD
Total (C_0)	182		USD
Payback period	16.8	13.4	years

Beyond economic considerations, it is also important to assess whether the monitoring infrastructure adds a meaningful environmental burden. The three-node IoT system consumes about 2 kWh/month and is built from low-power components with an expected lifespan of 5–7 years. Given this modest overhead and the observed reduction in residential electricity consumption, the system is expected to deliver a net positive environmental impact over its lifetime.

The system's communication performance was evaluated by measuring round-trip time (RTT) latency for 50 MQTT packets (Figure 18). The average RTT was 192.86 ms, with no packet loss observed. Given the system's 10-second sampling interval, this latency represents approximately 2% of the update period and is therefore acceptable for residential energy monitoring applications.

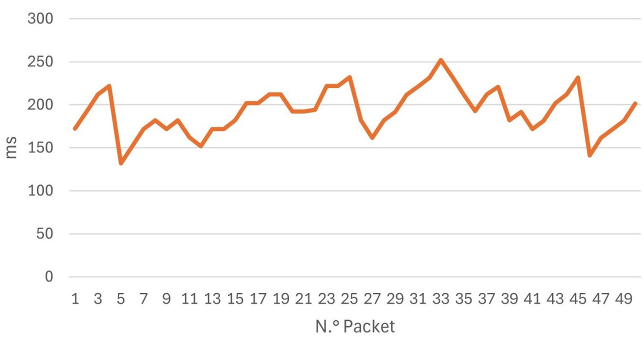

Figure 18. MQTT Round-Trip Latency (RTT) Across 50 Packets

In this pilot deployment (N = 2), the results indicate a consistent reduction of approximately 9–10% in monthly electricity consumption, supported by statistical testing and a seasonal alignment strategy. While encouraging, these findings should be interpreted as preliminary evidence; larger studies are required to confirm external validity across different household profiles, tariffs, and usage behaviors.

Compared with previous studies that report short observation windows or limited statistical reporting, this work contributes a transparent, replicable case-study evaluation under real household conditions. Nonetheless, broader deployments are required before generalizing effectiveness claims.

The evidence in Table 1 shows that many IoT-based HEMS contributions remain fragmented, typically emphasizing monitoring or partial automation rather than an integrated monitor-and-control workflow. Studies such as [Cuzme-Rodríguez *et al.*, 2020; Wongwut and Angamnuaysiri, 2024; El-Khozondar *et al.*, 2024; Shaban and Alsharekh, 2022] illustrate this gap in integration. In contrast, our implementation delivers a full HEMS workflow in real homes, combining measurement and control across appliances and electrical circuits to support holistic, actionable residential energy management.

To support real residential deployment, the system strengthens security and privacy at the communication layer. MQTT over TLS/SSL with node-level authentication reduces eavesdropping and tampering risks and enforces controlled access to consumption data. The platform also supports single-phase and two-phase meters and adds circuit-level zone control, going beyond appliance-only management in [Cuzme-Rodríguez *et al.*, 2020; Wongwut and Angamnuaysiri, 2024; Condon *et al.*, 2022].

Adopting Home Assistant strengthens interoperability while avoiding tight coupling to proprietary ecosystems. Unlike closed solutions [Condon *et al.*, 2022; Shaban and Alsharekh, 2022], this choice enables multi-vendor integration through standard protocols (e.g., Wi-Fi and ZigBee), which is essential for scalable HEMS growth over time. The modular architecture and AWS-backed services support incremental expansion (more nodes/devices) without redesign, directly tackling scalability and maintainability issues common in real-world IoT-HEMS deployments.

Operational reliability improves because the nodes avoid battery dependence, unlike [Shaban and Alsharekh, 2022]. Grid-powered operation via AC–DC conversion enables continuous 24/7 monitoring and control, which is critical in HEMS. This increases service availability for long-running deployments and reduces maintenance interruptions, supporting sustained data collection and stable actuation in real households.

6.1 Limitations and Future Work

Despite the positive results, several limitations must be acknowledged. We did not explicitly model external drivers (e.g., occupancy patterns, appliance changes, or tariff variability); future work will incorporate lightweight habit tracking and tariff sensitivity analyses.

Because the evaluation was conducted as a pilot-scale case study (N = 2), the external validity of the findings is limited. In addition, the Hawthorne effect may have influenced the observed reductions, as residents could modify their behavior when aware of being monitored. Although seasonal alignment and a treatment–control difference-in-differences (DiD) structure were used to reduce potential confounding, unmeasured behavioral or contextual factors may still influence the results.

Importantly, the DiD analysis is included for methodological illustration only: it relies on a single treated household and a single control household, and therefore it should not be interpreted as a generalizable causal estimate or evidence of population-level effectiveness.

Future work will address these limitations through larger samples and longer monitoring periods. The system depends on continuous internet connectivity, which may affect performance in areas with unstable or limited network coverage. Temporary communication disruptions could impact real-time monitoring and remote control functionalities.

From a security perspective, although the system incorporates TLS-encrypted communication, authenticated access, and broker-side access control, it does not include active penetration testing against common IoT attacks such as man-in-the-middle or denial-of-service attacks. Such evaluations require dedicated threat modeling and controlled experiments and are therefore identified as future work.

Interoperability with proprietary smart home ecosystems also presents challenges, as many commercial platforms operate within closed architectures, cloud services or licensing policies. To address this limitation, the proposed system adopts an open-source approach based on Home Assistant and standardized protocols, enhancing long-term flexibility and compatibility.

Future work will explore additional communication protocols (e.g., ZigBee and LoRaWAN) to overcome the current reliance on Wi-Fi/MQTT, which may limit scalability in deployments with many devices and reduce robustness in areas with inadequate coverage. We also plan to incorporate machine-learning models for residential electricity demand forecasting, building on prior results that report strong performance for Gaussian SVM in load prediction [Shaban and Alsharekh, 2022].

7 Conclusions

This work presented a dual-granularity Home Energy Management System that integrates appliance-level and circuit-level monitoring and control over a secure, cloud-enabled pipeline. In two real households and multi-month operation, monthly residential electricity consumption decreased by 9–10% ($p<0.05$), with an illustrative difference-in-differences estimate of ≈3.17 kWh/month under a single treated–control pairing. Measurement accuracy remained within <3% relative error compared with utility bills, and the system sustained sub-second responsiveness (median MQTT RTT ≈ 193 ms). Together, these pilot-scale results ($N = 2$) support the technical feasibility and provide preliminary evidence of effectiveness for combining circuit-level actuation with vendor-agnostic orchestration in Home Assistant under real household conditions.

Beyond performance, the work articulates a deployment-grade security posture (TLS 1.3 with broker-side authentication, periodic credential rotation) and data management practices (pseudonymized identifiers, and tiered retention—raw high-frequency data 30 days, daily aggregates 12 months, monthly aggregates 3 years) that together enable trustworthy operation and privacy-preserving analysis. The system's own energy footprint (≈ 2 kWh/month) is quantified, and an indicative payback range under local tariff scenarios is provided, clarifying economic significance alongside environmental impact. The open, modular stack—and the adoption of Home Assistant—supports interoperability and scalability beyond Wi-Fi, providing a clear roadmap toward Zigbee/LoRaWAN and heterogeneous device fleets without vendor lock-in. All artifacts (code, schematics, configurations, and anonymized datasets) are made available to promote reproducibility and technology transfer.

Limitations include the number and profiles of households, the monitoring period, and reliance on credential-based device authentication in the current prototype; additionally, while statistical validation is provided, the results should be interpreted with caution because they are based on a limited number of households. Future work will incorporate certificate-based device identity (mTLS). In addition, lightweight predictive analytics will be added for short-term forecasting and anomaly detection, including automation that requires user confirmation before executing actions. Finally, multi-protocol support will be expanded to improve scale and coverage, and broader deployments across diverse dwelling types and tariff structures will be conducted to strengthen the generalizability of the findings. Overall, the contribution advances a measured and reproducible basis for further HEMS evaluation and potential adoption, linking quantified pilot-scale efficiency gains to data protection and vendor-agnostic integration.

This work should be interpreted as a pilot-scale technical validation and reference implementation; broader effectiveness and behavioral impact claims require larger and longer deployments.

Declarations

Authors' Contributions

Juan Martínez-Morocho, Fabián Cuzme-Rodríguez, and Hernán Domínguez-Limaico made substantial contributions to the conception and design of the work. Juan Martínez-Morocho: Conceptualization, Methodology, Software, Writing—Original Draft. Fabián Cuzme-Rodríguez: Data Curation, Formal Analysis, Writing—Review and Editing; and Hernán Domínguez-Limaico: Project Administration, Supervision, and Validation. All authors read and approved the final manuscript.

Competing interests

The authors declare that they have no competing interests.

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Availability of data and materials

The datasets and software generated and/or analyzed during the current study are publicly available in the project GitHub repository. Additionally, the source code used in this research is openly accessible at the following link: `https://github.com/juanmm24/Smart_Grid_Home_IoT.git`.

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