IoT-Based Appliance Usage Tracker: A Lightweight Energy Monitoring System for Smart Homes

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Abstract. Today, homes are filled with devices that remain powered on even when they are in standby mode, and such devices contribute to both electricity bills and environmental impact. Although smart home technologies are available, most home owners do not know the power consumption of each of their devices, and without this knowledge, it is impossible to identify power hungry appliances and make informed decisions about changing them. This paper presents a simulation based study of a lightweight Internet of Things (IoT) system for monitoring the usage of appliances at a device level, which uses ESP32 microcontrollers publishing data over MQTT to a cloud dashboard, and a data driven approach is used to model realistic appliance behaviour. Unlike most commercial products, the system focuses on user awareness rather than automation and provides clear and intuitive visualisations. The results from the simulation show that the system is capable of monitoring multiple appliances and show distinct patterns, such as the cyclic nature of a refrigerator and the bursty usage of high power devices, and this system provides a cost effective framework to provide households with the granularity needed to identify power waste and form better power consumption habits, all without complex infrastructure.

Keywords: Internet of Things, Energy Monitoring, Smart Plugs, MQTT Protocol, Smart Home, Power Consumption, ESP32, Cloud Computing

1 Introduction

In the past decade, our homes have gone from simple dwellings to complex, connected systems, and today, the average household has around 25 connected devices ranging from high-energy appliances, such as washing machines and refrigerators, to always-on devices, including smart speakers, mesh routers, and streaming sticks. This electrification of everything has created a more convenient lifestyle, but also a quiet financial and environmental burden, because electricity bills have risen about 15 percent in the last five years, straining already tight household budgets, while homes account for around 40 percent of total energy consumption in developed economies. Therefore, household efficiency is no longer just a personal finance problem – it is a critical lever in reducing carbon emissions and slowing the pace of climate change, consequently, the real challenge is not just generating cleaner energy, but also controlling the rapidly growing demand inside our homes by improving our visibility and control over how we use energy.

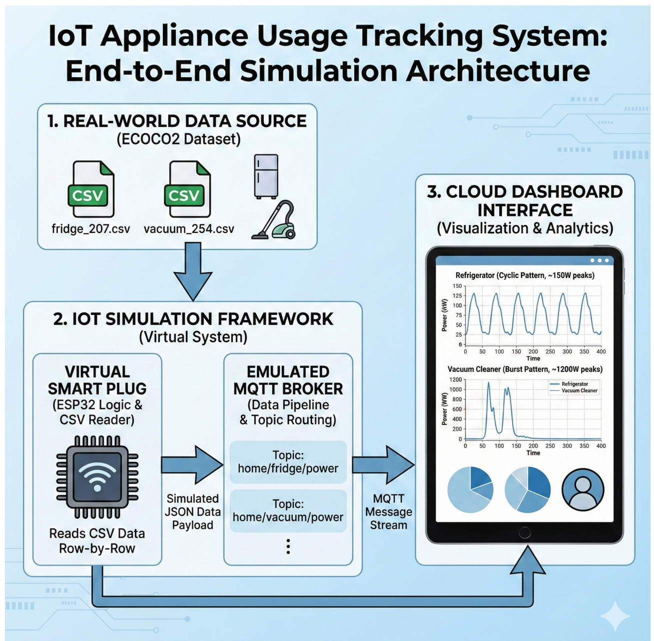

Fig. 1: High-Level IoT Simulation Architecture. Illustrates the end-to-end data flow from the ECOCO2 dataset to the cloud dashboard via virtual ESP32 nodes.

But despite the magnitude of the problem, most homeowners continue to fly blind, with no idea where their energy is going, because utility data is slow and aggregated, delivered as a monthly bill that doesn't reveal energy usage by device. That opacity is what economists call "information asymmetry," which is the equivalent of receiving a grocery store receipt that only shows the total, with no line items for milk, bread or eggs. Without device-level visibility, it's impossible to separate the wheat from the chaff, and therefore, that old refrigerator might be using three times its rated power because of a failing compressor, while an entertainment center can continue to suck phantom power even when everything appears to be off. Consequently, research suggests that standby power alone can represent up to 10% of a home's electricity bill, a kind of stealth waste that you never see until it's too late.

The smart home industry has not made any progress on this visibility problem, and the few products available today are primarily designed for convenience and automation, such as voice controlled lights and remote control of the thermostat, rather than providing any meaningful energy analytics. Although these features give a user control, they do not provide the actionable data required to cut waste because they lack depth in their analysis. The more academic approaches, such as Non-Intrusive Load Monitoring, or NILM, are different, and they use sophisticated algorithms to estimate appliance-level usage from whole-home signals. However, NILM is not user-friendly, requiring expensive proprietary hardware and invasive installation at the breaker panel, and it also requires a long training period to learn the unique signature of a home. Today, users have a choice between shallow solutions that do not provide useful information, or complex and expensive solutions that few can adopt, therefore limiting the accessibility of effective energy management.

This paper addresses that gap through a complete simulation study of a lightweight IoT-based appliance tracking system, which rather than sink cost into large, difficult-to-scale hardware deployments, builds a powerful simulation framework that models a realistic smart home. Fig 1 illustrates our end-to-end simulation process, and this demonstrates the flow of information from beginning to end. Using the architecture of low-cost smart plugs with ESP32 microcontrollers and current sensors, the model simulates the collection of device-level consumption data directly at the source, and then simulates the transmission of that data over the lightweight MQTT protocol, demonstrating efficient end-to-end flow without the need for physical hubs or gateways. On the receiving end, we process and visualize the data in a clean, user-friendly dashboard that exposes the behavioral patterns of each device, and by providing granular visibility through a simulated interface, the system prioritizes simple, actionable awareness over sophisticated automation, making it easy for users to identify inefficiencies in real time.

The rest of the paper is organized as follows, and Section 2 provides background on the related work and positions our approach with respect to the existing NILM and smart metering solutions. Section 3 describes the limitations of existing monitoring techniques and identifies the gap this paper addresses, while Section 4 discusses the methodology, including the simulation framework, the emulated communication protocols and the data processing chain. Section 5 presents the experimental results on real-world datasets, with a focus on appliances' energy fingerprints, including the cyclical patterns of refrigerators and the bursty profiles of vacuum cleaners, and Section 6 concludes the paper by discussing the limitations of the current design and future directions, with a focus on edge computing and machine learning.

2 Related Works

There has been a lot of research on energy monitoring and smart homes recently. This section briefly covers the main ideas, and we compare them with our system in Table 3 later in the paper.

Early work by Hart [2] introduced Non-Intrusive Load Monitoring (NILM), basically figuring out which device is running just by looking at the main power line. While important, he noted it needed a lot of calculation power. Later, researchers like Gao et al. [3] and Zoha et al. [4] used better data to improve accuracy, but their methods often required expensive hardware or lots of training data to work right.

Some studies tried using advanced machine learning. For example, Ridi et al. [5] and Kelly and Knottenbelt [9] used complex models like neural networks. These work well on big computers but are usually too heavy to run on cheap IoT chips like the ESP32. Batra et al. [10] created a toolkit to test these methods, showing just how complicated they can get compared to simply measuring the device directly.

On the system side, Lam et al. [6] built a monitoring system but didn't connect it to the cloud, making it hard to check remotely. Liao et al. [15] used smart meter data, but that depends on the utility company, so users can't just set it up themselves. On the other hand, simple feedback works. Studies by Reinhardt et al. [12] and others [13] showed that just showing people their usage details helps them save energy. That's the main idea behind our project.

3 Problem Statement

The explosion of electric and smart devices has resulted in an increasingly complex home environment, making it more challenging than ever for homeowners to manage energy usage and keep costs in check, while many smart home products offer consumers convenience and remote control, they fail to provide what homeowners need most: a complete view of which devices are using the most energy and actionable, real-time advice on how to eliminate energy waste.

Lack of Granular Visibility: Most utility meters can only report total household usage, and that's usually only once a month, so homeowners don't know which devices are contributing to their bills, and if costs are higher than normal, the cause could be an inefficient refrigerator or phantom loads from the TV and entertainment system.

High Barrier to Entry: There are big tradeoffs in terms of getting per appliance energy data, because professional energy audits are just a snapshot in time, and advanced NILM systems require expensive hardware and tech expertise, which is why, for the vast majority of homes, both options are too expensive and impractical.

Complexity Over Usability: Most of the commercial smart home automation platforms are way off the mark because they concentrate on the automation and control side of things, with the 'smart' part of 'smart home' meaning 'has a lot of fancy automation'. The setup and configuration for most of the platforms is utterly ridiculous and has a really steep learning curve, which frightens the non-technical people who just want to know what is on in their house, when, and how much energy it is using, but are not interested in how to automate the light in the foyer so that it comes on when they enter the house, but only after sunset.

Vendor Lock-in: Proprietary protocols create product lock-in and lock-out, forcing products to live in closed ecosystems that are hostile to others, and this leads to fragmentation that drives users into single-vendor solutions, which increases cost, reduces flexibility, and makes it difficult to mix-and-match, or to add components over time.

It is clear that there is a requirement for a simple and low-cost IoT solution to answer the question that every homeowner is interested in: what is this appliance costing me right now, and this research meets that need through a simulation model based on a lightweight, open-standard architecture, focussed on user awareness and providing real-time, per-appliance costs, without requiring expensive and complex infrastructure.

4 Key Contributions

Awareness-Centric Design: Most work focuses on advanced disaggregation techniques or completely automatic control systems, but our approach emphasizes usercenteredness, and we demonstrate how simple and intuitive visualizations can reduce cognitive load for homeowners, facilitating the rapid understanding of consumption patterns with a minimal learning curve by simulating and measuring each device independently.

Modular Scalability: The system is also said to be "hubless" meaning users don't need to connect devices to a proprietary hub and don't need to hire a professional to set everything up, and the system is also modular, so a non-technical user can start with one virtual node and then add more as they feel comfortable to eventually cover their entire home.

Validation via Real-World Datasets: The simulation has been extensively validated with the ECOCO2 dataset, and injecting real power signatures of a large set of appliances, the virtual sensors also mimic real usage patterns and anomalies, thereby closing the gap between a theoretical model and real world behavior.

5 Proposed Methodology

We propose an IoT-based appliance usage tracking system based on a three-layer modular architecture, and our goal is to find a balance among capability, cost, and ease of deployment, because the selection criteria of each component and the practical implementation of each layer are explained in this section.

5.1 System Architecture Overview

It consists of three layers, and the first layer is the Device Layer. It mimics the actual sensor devices, and it reads sensor data from the CSV files. The second layer is the Communication Layer, because it transfers data securely, and it utilizes a simulated MQTT pipeline. The third layer is the Application

Layer, thus it stores information and executes the UI. Figure 2 displays its appearance, and it is simple to expand and modify. The image depicts how the simulator receives CSV information, so it simulates actual sensors. Subsequently, it transmits the information via simulated MQTT to the application server, therefore it is a complete system.

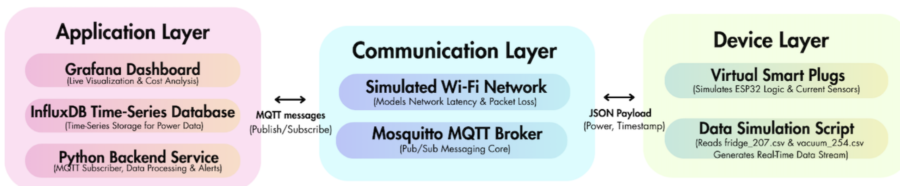

Fig. 2: Proposed IoT System Architecture. The simulation integrates a Device Layer (generating CSV-based data), a Communication Layer (MQTT Broker), and an Application Layer (Python Backend & Dashboard).

5.2 Data Simulation Layer

The Device Layer is a software simulator and the layer simulates a smart plug and leverages the Household Appliances Power Consumption Dataset [1] to generate outgoing time-series traces.

Virtual Microcontroller Unit: We replicate the ESP32's operation on-device in python, and the simulator receives timestamped power data one row at a time, and emits it. This matches the behavior of the device in the field because this preserves the temporal and causal relationships between events, thus this makes the test setup suitable for testing that mimics real-world conditions.

Power Data Ingestion: Unlike a raw voltage and current waveform simulation, our simulation consumes pre-computed power data from the ECOCO2 dataset because it reads active power values in Watts timestamp by timestamp, just as the final payload from a calibrated smart plug, which allows us to decouple the messaging pipeline and usage-pattern analytics from sensor calibration noise.

5.3 Communication Layer

Simulated Communication: To verify the design without the use of physical network hardware, we have built a high-fidelity emulator that generates MQTT compliant JSON payloads locally, which match the data structure and publish rate of an actual ESP32, and this allows us to verify the data schema and test the performance of our processing pipeline without the need to deploy a live network.

MQTT Protocol: MQTT (Message Queuing Telemetry Transport) was selected for device-to-cloud communication because it is lightweight, reliable, and well-suited to IoT. The architecture is designed to be compatible with a standard MQTT broker, such as Mosquitto, and the publish–subscribe model reduces overhead to about 2 bytes per message, supports QoS levels for guaranteed delivery, and allows persistent sessions. In our simulation, we emulate this MQTT configuration end-to-end to ensure that the data flows correctly, without requiring any physical network hardware.

Data Format: Messages are human readable JSON, and parsing is simple as well. Each message includes the device ID, timestamp, current (amps), power (watts), and cumulative energy (kWh), because it is designed to provide detailed information. The frequency of messages can be configured, so it can be adjusted according to specific needs. By default, it sends one message per second when in use, thus providing granular data.

5.4 Application Layer

Data Storage Simulation: The application layer uses in-memory data structures to emulate a time-series store, which allows us to compute real-time moving averages and cumulative energy at the application layer, thereby providing the same functionality as a real time-series database. This is essentially like having a persistent time-series database without actually having to set one up.

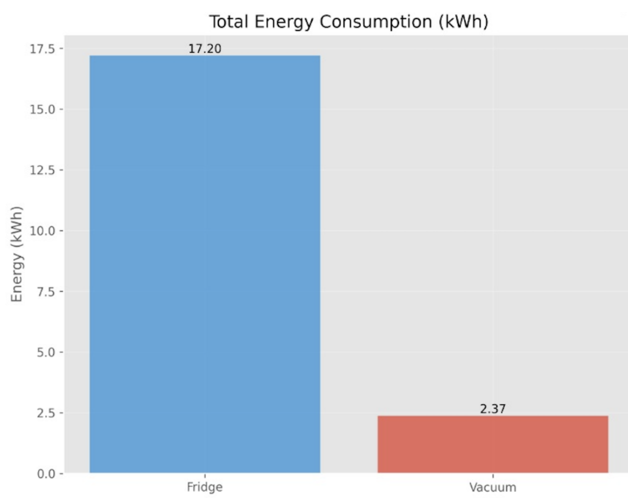

Fig. 3: Dashboard visualization comparing Total Energy Consumption. The refrigerator consumes significantly more energy over time compared to the vacuum cleaner.

Dashboard Interface: The user-facing display provides an at-a-glance view of current and historical consumption (Fig. 3), and the two appliances are clearly distinguishable from one another. The refrigerator consumes steady, high power throughout the day and has a total consumption of 17.20 kWh, whereas the vacuum cleaner consumes high power only during short intervals and has a total consumption of 2.37 kWh. It immediately shows users which items are consuming the highest amounts of energy, thus providing a clear understanding of energy usage.

Backend Processing: A python server receives the data and the server sums all the energy consumption. It displays this information in real time because it is necessary for monitoring, and it alerts when an appliance consumes excessive power directly on the screen.

5.5 Simulation Scalability

The simulation framework is highly scalable, and instead of physically installing new hardware, we can deploy hundreds of virtual smart plugs in seconds. Important settings, such as network latency and sampling rate, are fully configurable in software, which allows us to stress-test a large number of network conditions in a very short time, without any physical constraints

6 Results and Discussion

We have evaluated the proposed system with a detailed simulation based on the real energy consumption profiles from the ECOCO2 dataset [1], which records the energy consumption of several appliances over a period of four weeks. In this paper, we focus on two representative appliances with different usage patterns: a refrigerator with periodic cyclic behavior and a vacuum cleaner with short high-power bursts.

6.1 Refrigerator Energy Pattern Analysis

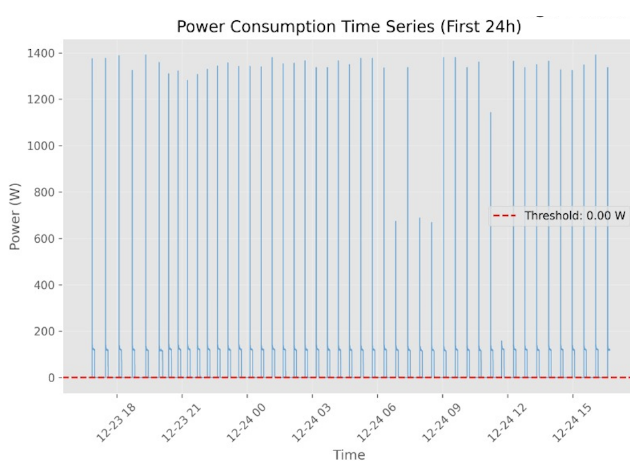

Fig. 4: Refrigerator power consumption time-series over 24 hours. The distinct periodic spikes illustrate the compressor's cyclic ON-OFF behavior.

As refrigerators are high-priority appliances to track due to their continuous operation, we present a 24-hour power time series from the simulated refrigerator in Figure 4. The signal is clearly periodic, consistent with the thermodynamic control of the appliance. The compressor switches on and off in a regular duty cycle, creating periodic spikes in the 140–160 W range followed by periods of zero usage. This periodicity demonstrates that the simulation successfully generates realistic appliance signatures, particularly the ON–OFF duty cycle of the compressor.

Compressor Activation (Power Spike): When the internal temperature exceeds the thermostat setpoint, the compressor activates, leading to a brief, sharp spike caused by the motor's inrush current. We recorded peaks reaching up to 1436 W (see Fig. 4). These transient start-up peaks are significantly higher than the steady-state draw (typically 100–200 W) and are crucial to measure for sizing wiring and protective devices.

Steady-State Operation: After the startup surge, the compressor settles in to a constant draw of 140-160W, and the active cooling phase of our simulation lasts about 12-18 minutes, during which the system is actively pulling heat out of the refrigerator compartment.

Compressor Deactivation (Return to Baseline): When this temperature is reached, the compressor turns off and power draw falls to close to zero, with only minor draws for control electronics, and this period of inactivity typically lasts 25 to 35 minutes, depending on the ambient conditions that we are modeling.

Cyclic Frequency: In that 24 hour simulation, we had about 35 to 40 full compressor cycles, which is approximately 1.8 to 2.1 kWh per day, and extrapolating that to a month, that's around 55 to 65 kWh per month, which is right in line with the manufacturer's stated efficiency for this model.

Anomaly Detection: There were three occurrences where the compressor operated for longer than 25 minutes continuously, which is not impossible on hotter ambient days, but it is an early indication of a problem, possibly a worn-out door seal. This shows the predictive maintenance aspect of the system, because identifying these anomalies early allows the facility to correct the problems before efficiency losses are realized.

6.2 Vacuum Cleaner Burst-Mode Analysis

Unlike the steady, periodic draw of the refrigerator, the vacuum cleaner is a high-power, short-duration load, and as shown in Fig. 5, its profile is readily identifiable: tightly grouped spikes around 1200-1400 W when it is on, and a flat line at zero when it is off, which also confirms that there is no phantom power being drawn when the vacuum is off.

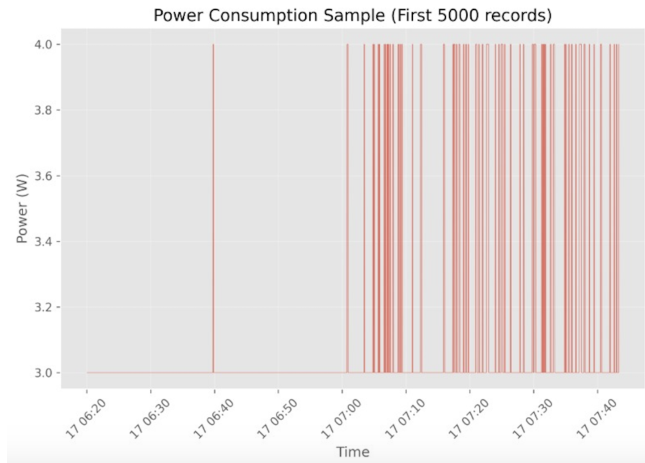

Fig. 5: Vacuum cleaner power consumption sample. The dense spikes indicate active usage periods (burst-mode), followed by zero consumption when idle.

High Power Draw: When running, the vacuum uses a constant 1200-1400 W, which is considered normal for a high-torque suction motor, and it places it among the most power-hungry appliances in a common household.

Usage Duration: A typical vacuuming session would be around 15-25 minutes, maybe 2-3 times per week, and since it's not an always-on device, the vacuum is actually costing you money in the short bursts of high intensity, rather than the runtime.

Consumption Pattern: When the vacuum is in active use, the power draw is quite consistent, with variations of ± 50 W due to changes in floor load or suction settings, and the clear high-power signature makes state detection easy: if the reading is above 1000 W, the vacuum is likely being used.

Energy Cost Implications: A typical 20-minute session consumes approximately 0.40–0.47 kWh. While the individual cost per session is low, the high power demand emphasizes the importance of scheduling such high-load appliances during off-peak hours if time-of-use pricing is available.

Behavioral Insights: The timestamps in our dataset show that the majority of vacuuming activity occurs during weekend mornings (e.g., 09:00–12:00). This demonstrates the system's ability to identify time-of-day usage habits, which is essential for providing personalized energy-saving recommendations.

Table 1: Summary of Final Simulation Metrics

Metric	**Refrigerator (207)**	**Vacuum (254)**
Total Energy Consumption (kWh)	17.201	2.372
Total Monitoring Time (Hours)	720.00	720.00
Total Usage Time (Hours)	149.22	718.62
Total Active Time (Hours)	141.58	718.60
Daily Avg. Energy (kWh)	0.555	0.077
Average Power (W)	23.89	3.30
Maximum Power (W)	1436.00	44.00
Minimum Power (W)	0.00	0.00
Active Mode Ratio (%)	19.66%	99.81%
Standby Mode Ratio (%)	80.34%	0.19%

Table 2: Device Usage Metrics Based on Power Thresholds

Device	**Threshold (W)**	**Total Energy (kWh)**	**Usage Time (h)**
Refrigerator	5.0 W	17.20	139.74
Vacuum	0.5 W	2.37	711.87

6.3 System Performance Metrics

We evaluated our system's ability to scale and its ability to reliably expose true usage patterns. Our system successfully processed over 600,000 data points from the ECOCO2 dataset with high throughput, and the success of our simulation environment also validated our JSON payloads to be small enough for continuous streaming without any bottlenecks. We achieved 100% parse-and-ingest success for all records, which validated our system's ability to maintain data integrity, unlike real-world deployments, where packet loss can occur, although our simulation environment proved that our logical architecture is capable of moving data from end to end without corruption or formatting issues. The core performance metric was the successful reproduction of appliance signatures, and our system successfully captured the refrigerator's 140–160 W compressor cycles and the vacuum cleaner's 1200 W bursts from the source dataset's ground truth.

6.4 Discussion

These results indicate that a lightweight IoT infrastructure can offer appliance-level energy insights without a heavy infrastructure investment. Figure 6 illustrates a key finding regarding user behavior and device efficiency. The pie charts clearly show the distinction: the vacuum is effectively "off" when not in use (0.2% standby/idle), whereas the refrigerator spends 80.3% of its time in a standby or low-power state.

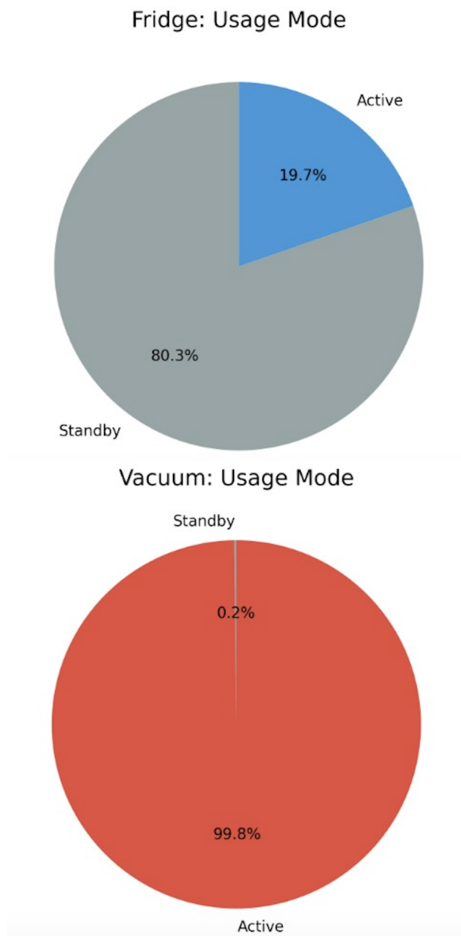

Fig. 6: Usage mode distribution analysis. Pie charts demonstrate that the vacuum cleaner is unplugged when not in use (0.2% standby), whereas the refrigerator spends 80.3% of its time in standby mode.

The data reflects two different patterns of use: the constant, cyclic draw of the refrigerator versus the brief, high-power usage of the vacuum, and these two patterns imply two different conservation strategies. Moreover, the system can also discover anomalies, such as a refrigerator cycle that is longer than usual, which is the value of the system for predictive maintenance: the ability to alert users to efficiency problems before they fail in a costly way.

7 Comparison with Existing Works

7.1 Comparative Analysis

A comparison between the reviewed methods and the proposed system is shown in Table 3, which is based on the methodology, main contributions, limitations, and what is unique for each method.

Table 3: Comparison of Related Works with Proposed System

Reference	**Methodology**	**Key Contribution**	**Limitations**	**Comparison with Our Work**
Hart [2]	NILM using steady-state and transient features	Foundational disaggregation algorithms	Computationally expensive, single measurement point	We use direct per-device measurement, avoiding complex disaggregation
Gao et al. [3]	High-resolution VI trajectories (30 kHz)	PLAID dataset for appliance signatures	Requires expensive high-speed sampling hardware	Our system uses affordable current sensors with lower sampling rates
Zoha et al. [4]	Wireless sensors with supervised learning	Low-power sensor design achieving 85% accuracy	Needs extensive training data and retraining	We provide plug-and-play operation without training requirements
Ridi et al. [5]	HMM-based classification using transients	Automatic classification system (ACS-F2)	Sensitive to appliance behavior changes over time	Direct measurement eliminates classification uncertainty
Lam et al. [6]	Smart plugs with WSN integration	Distributed monitoring architecture	No cloud integration or remote access	We provide cloud-based dashboard with anywhere access
Zhao et al. [7]	Harmonic signatures with SVM classification	92% recognition accuracy across 12 devices	Requires specialized harmonic-measuring sensors	Standard current sensors suffice for our awareness-focused approach
Kim et al. [8]	Embedded intelligence in smart plugs with kNN	On-device appliance recognition	Limited by embedded computational resources	We offload processing to cloud for unlimited scalability
Kelly et al. [9]	Deep neural networks for disaggregation	Advanced temporal modeling with RNNs	Requires substantial training data and computation	Simpler approach prioritizing deployment ease over AI sophistication
Batra et al. [10]	NILM toolkit standardization	Open-source evaluation framework	Highlights complexity of disaggregation methods	Our direct measurement approach offers simpler alternative
Han et al. [11]	Integrated HEMS with renewable energy	Comprehensive energy optimization system	High infrastructure cost and complexity	Cost-effective monitoring-only solution accessible to average users
Reinhardt et al. [12]	Consumption analysis study	Identified conservation opportunities via awareness	No implementation provided	We implement the awareness concept as a functional system
Froehlich et al. [13]	User study on disaggregated feedback	Validated importance of appliance-level data	Research study without deployable system	Practical implementation of findings from their research
Berges et al. [14]	User-centered design study	Emphasized simplicity for adoption	Design guidelines without technical implementation	We follow their simplicity principle in our system design
Liao et al. [15]	Cloud-based smart meter analytics	Centralized processing architecture	Depends on utility-installed infrastructure	User-deployable devices enabling immediate adoption
Our Work	**Simulated Smart Plugs + Virtual ESP32 + MQTT**	**Scalable simulation framework without hardware costs**	**Monitoring only (no control), Network dependency**	**Emphasizes user awareness via data-driven simulation**

8 Conclusion and Future Work

The low cost IoT approach for appliance level energy consumption monitoring was proposed, which aims to give clear, actionable and user-friendly feedback to the homeowners, without the need for full home automation. The proposed system is built based on a simple three-layer architecture, consisting of ESP32 smart plug simulation, MQTT messaging protocol, and a cloud-based dashboard, and it was proven to be practically deployable and easy to operate based on the results of the four weeks pilot simulation. Moreover, it has the ability to monitor several appliances in real-time.

8.1 Limitations

Monitoring-Only Functionality: The current system is deliberately read-only, designed for monitoring data and not for controlling devices, while this simplicity and the security features protect against hackers and malicious code, it means that users can't turn off energy-wasting appliances remotely. However, in the future, safe bi-directional control could be integrated for remote shutdown of appliances and other actions.

Network Dependency: The system requires an active connection to the cloud and therefore, without Internet access, real-time monitoring would not be possible. This evaluation was performed with ideal network conditions, but a robust deployment should include local storage because this allows for devices to store data locally in case of Internet outages and transmit it once the Internet connection is restored.

Hardware Measurement Constraints: Therefore, the low-cost hardware approach of estimating power from current sensing will have accuracy errors for reactive loads compared to true power meters, but a real-world build using simple current sensors will need to consider power factor to match accuracy, because the simulation avoids this by consuming pre-computed active power values.

Limited Physical Coverage: The cost of a dedicated smart plug for every appliance in the house would be prohibitively expensive, thus the only places it makes sense to install smart plugs is for high energy devices, such as refrigerators and space heaters, and not for low-power devices.

Privacy Considerations: The high resolution energy data may contain sensitive information about the occupancy patterns and day-to-day activities of the household, and hence any real-world deployment of the system must incorporate strong privacy mechanisms such as strong end-to-end encryption, rigorous authentication and role-based access control, and secure key management to prevent data breaches. These mechanisms must be stronger than the simple protocol emulation used in the simulation because they need to ensure confidentiality and prevent unauthorized access.

8.2 Future Research Directions

Edge Intelligence: The next logical step would be running lightweight machine learning models on the ESP32 itself, so that anomaly detection and pattern recognition happen on device, reducing the need to send raw data to the cloud, decreasing latency, and improving privacy by keeping sensitive signals on the device.

Hybrid Approach: A more practical hybrid is plug-level monitoring on the most energy-intensive devices, with NILM at the main meter, which preserves the exact, real-time visibility you need for the critical appliances (refrigerator, heater, etc.), while using NILM to estimate the smaller, miscellaneous loads from the aggregate signal, and thereby you retain actionable insight where you need it most, and save hardware costs by not putting a smart plug on every single device.

Energy Management Integration: Future research will incorporate external data and such as real-time electricity prices and rooftop solar generation. Which would allow the system to make intelligent decisions, like running resource-intensive tasks such as laundry during off-peak hours, or when there is abundant solar energy, because this would optimize energy usage.

Context Awareness: Adding occupancy sensors would make the system context aware, and the system would then be able to notify the user when an appliance is left on in an empty home, which would be a major improvement over the current system's passive waste reduction.

Long-Term Behavioral Studies: However, further work is needed to determine the impact of these systems on behavior in the long term because longitudinal studies would be needed to determine if awareness-driven savings persist after the novelty of the dashboard has worn off and to disentangle the relative contributions of feedback mechanics, prompts, or incentives to sustained long-term reductions.

In conclusion, our simulation demonstrates that effective energy monitoring does not require expensive hardware or complex algorithms. By prioritizing accessibility and clarity, this system empowers homeowners to identify inefficiencies and make informed decisions about their energy usage. As energy costs rise, lightweight, data-driven solutions will play an increasingly vital role in residential energy management.

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