



IoT-Enabled Smart Home Energy Management System with Real-Time Monitoring

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Abstract

Residential electricity demand is increasingly influenced by connected appliances, variable tariffs, distributed generation, and the need for immediate feedback to occupants. This methodology paper proposes an Internet of Things (IoT)-enabled Smart Home Energy Management System (HEMS) that measures household electrical variables, streams data through a lightweight messaging layer, performs real-time energy and peak-demand analysis, and provides both automated and user-directed appliance control. The proposed design follows a cyber-physical HEMS structure consisting of data acquisition, communication, analytics, and a control interface. Smart plugs or current/voltage sensors feed an ESP32-class edge gateway; MQTT over Wi-Fi transfers time-stamped readings to a cloud time-series database; and a dashboard displays instantaneous power, cumulative energy, estimated cost, and device status. A rule-based demand-side controller delays or disconnects flexible loads when demand exceeds a programmable threshold or when a peak-tariff period is active, while preserving critical loads and allowing manual override. A controlled 24-hour simulation is used to demonstrate the evaluation procedure. Under the stated assumptions, the managed profile reduces total energy use by approximately 16%, peak demand by about 27%, and tariff-weighted energy cost by about 21%, while retaining sub-second local control and near-real-time dashboard visibility. The methodology is intended as a reproducible baseline for laboratory or small-residential validation rather than as a substitute for long-term field trials.

Introduction

Home Energy Management Systems have evolved from simple in-home displays to networked cyber-physical platforms that can monitor, analyze, and control residential loads. The motivation is straightforward: household users usually receive aggregated billing information after energy has already been consumed, whereas real-time sensing can make consumption visible at the device or circuit level and can support immediate corrective action. Al-Ali et al. (2017) demonstrated an IoT and big-

data architecture in which device-level acquisition modules transmit consumption information to centralized services for analysis and visualization. Later surveys emphasized that modern HEMS must coordinate metering, communication, appliance scheduling, user comfort, and demand response rather than treating them as isolated functions (Leitão et al., 2020; Badar & Anvari-Moghaddam, 2022).

The Internet of Things is particularly suitable for residential energy applications because low-cost sensing nodes can connect legacy appliances to

digital platforms without requiring every device to be natively “smart.” IoT-enabled HEMS can continuously publish electrical measurements, support remote switching, record historical profiles, and combine energy information with occupancy, temperature, or tariff signals. Affum et al. (2021) showed how IoT-capable devices can be integrated into a smart-home ecosystem for energy efficiency, while Aliero et al. (2021) identified security, privacy, scalability, interoperability, and occupant comfort as persistent design concerns. These issues imply that a useful methodology must evaluate not only energy savings but also communication reliability, latency, controllability, and data quality.

Real-time monitoring is also the foundation for more advanced functions. Demand-response strategies can shift flexible loads away from expensive or congested periods (Ma et al., 2021), cloud-connected smart plugs can implement short-horizon scheduling (Sharda et al., 2021), and non-intrusive load monitoring can infer appliance-level consumption from aggregate measurements (Ramadan et al., 2022). Based on these developments, the present work defines a compact, reproducible methodology for an IoT-enabled HEMS whose primary functions are: (i) real-time electrical monitoring, (ii) cloud logging and visualization, (iii) threshold- and tariff-aware load control, and (iv) performance evaluation using energy, cost, peak demand, monitoring error, and communication latency.

Literature Review

Early IoT-oriented HEMS research established the importance of connecting distributed household measurements to scalable analytics. Al-Ali et al. (2017) combined IoT data acquisition, MQTT communication, server-side storage, and

dashboard analytics, providing a useful architecture for device-level monitoring and remote access. Leitão et al. (2020) surveyed home energy management research and showed that optimization objectives commonly include energy reduction, electricity-cost minimization, peak reduction, and user comfort. These works motivate a layered design in which sensing is separated from analytics and user services.

By 2021–2022, the research emphasis had shifted toward integrated, autonomous and context-aware operation. Affum et al. (2021) proposed an IoT-based smart HEMS and highlighted the role of connected devices in demand-side efficiency. Aliero et al. (2021) reviewed smart HEMS in IoT networks and noted unresolved quality attributes, especially privacy, cybersecurity, scalability and interoperability.

Recent 2022 studies provide direct methodological guidance for real-time monitoring. Ramadan et al. (2022) combined IoT with non-intrusive load monitoring to estimate appliance-specific energy use from household measurements. Franco et al. (2022) organized residential HEMS as a cyber-physical system comprising data acquisition, communication and analytics, and validated appliance monitoring in a real testbed. Raju et al. (2022) connected IoT-based acquisition to cloud forecasting and load-management functions for distributed-generation integration. Lin et al. (2022) further demonstrated that time-series load modeling and forecasting can support smart-home automation. Collectively, the literature indicates that a defensible methodology should capture measurements at the edge, use lightweight and secure communication, maintain time-series data, expose real-time feedback, and evaluate both energy-management outcomes and system-level communication performance.

Table 1. Selected literature informing the proposed methodology

Study	Focus	Relevant contribution	Year
Al-Ali et al.	IoT + analytics	Device-level acquisition, MQTT, cloud/server analytics	2017
Aliero et al.	IoT SHERMS review	Security, privacy, scalability and interoperability gaps	2021
Sharda et al.	Real-time scheduling	IoT smart plug, cloud control, short scheduling interval	2021
Franco et al.	Cyber-physical HEMS	Acquisition–communication–analytics architecture	2022
Ramadan et al.	IoT + NILM	Appliance-level energy information from monitored load	2022

Methodology

1. Research Design and System Boundary

The proposed study is designed as a laboratory-scale or single-home cyber-physical experiment. The system boundary begins at household

electrical sensing points and ends at the user dashboard and controlled appliance relays. The methodology does not require a utility-side smart-grid interface; however, tariff schedules can be imported as time-indexed inputs. Six

representative load categories are considered: lighting, fan, refrigerator, television/entertainment, air conditioner, and a flexible high-power appliance such as a washing machine or water heater. Refrigerator and essential lighting are treated as critical loads, whereas selected entertainment, laundry, or heating loads may be shifted or curtailed for short periods.

2. Step-by-Step IoT-HEMS Implementation

Step 1 - Electrical sensing and metering. Measure voltage $V(t)$, current $I(t)$, and, where available, power factor $PF(t)$ at 1–5 s intervals. Instantaneous active power is calculated as $P(t) = V(t) \times I(t) \times PF(t)$. For DC or calibrated smart-plug measurements, the device-reported active power can be used directly. Energy over an interval is $E = \sum P(t) \Delta t / 3600$, with P in watts and Δt in seconds.

Step 2 - Edge acquisition. An ESP32-class microcontroller acquires sensor values, applies calibration coefficients, removes impossible readings, time-stamps the packet, and retains a short local buffer so temporary network loss does not immediately discard observations. Each packet contains house/device ID, timestamp, voltage, current, power, cumulative energy and relay state.

Step 3 - IoT communication. The gateway publishes telemetry using MQTT over Wi-Fi. Separate topics are used for measurements, commands and acknowledgements. Authentication credentials are stored on the gateway, and TLS is recommended for deployments containing real household data. MQTT is selected because lightweight publish/subscribe messaging has been widely

used for scalable HEMS communication (Al-Ali et al., 2017).

Step 4 - Cloud storage and analytics. A broker forwards messages to a time-series database. A processing service calculates 1-min and 15-min averages, daily energy, peak demand, appliance contribution, and tariff-weighted cost. Historical values are retained for trend analysis and optional forecasting. This stage corresponds to the analytics layer described by Franco et al. (2022).

Step 5 - Real-time monitoring interface. A web or mobile dashboard subscribes to the latest processed values and displays instantaneous power, energy today, estimated cost, peak demand, device states, and alarms. Users can select a device for historical plots and can manually override automatic control.

Step 6 - Energy-management logic. Every control interval, the controller compares aggregate power with a configurable demand limit and checks the active tariff period. If demand is above the limit, controllable appliances are ranked by priority and deferrability. The lowest-priority flexible load is delayed or switched off until demand falls below the threshold. During peak tariffs, non-critical scheduled appliances are shifted to a later allowable window. Critical loads are never disconnected automatically.

Step 7 - Logging and evaluation. All control decisions, acknowledgements, network delays and sensor values are logged. A baseline day without automated control is compared with a managed day using the same normalized appliance demand pattern. The principal metrics are total energy (kWh), peak demand (kW), tariff-weighted cost, mean absolute percentage error (MAPE) against a reference meter, MQTT packet delivery ratio and end-to-end dashboard latency.

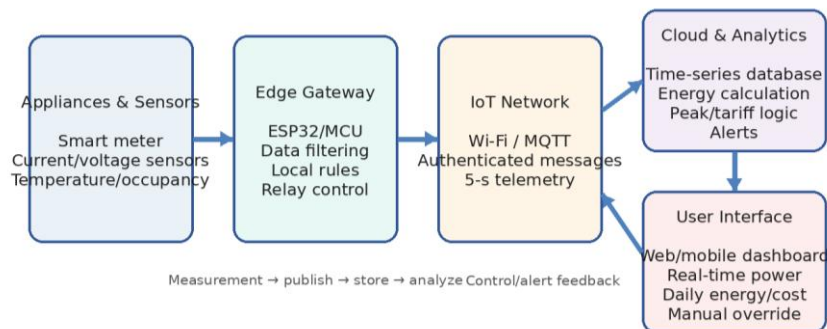


Figure 1. Proposed architecture for sensing, communication, real-time analytics, dashboard monitoring, and appliance control.

3. Experimental/Simulation Protocol

For initial validation, a 24-hour profile is sampled at one-minute resolution. The baseline profile represents normal appliance use without automated interventions. The managed profile applies three rules: a 3.5 kW demand threshold, a

peak-tariff window from 18:00–21:00, and a maximum 60-minute deferral window for flexible loads. A reference energy meter is conceptually used for calibration; in a physical experiment it should be placed upstream of the IoT sensing node. Communication performance is

measured by recording publish and dashboard-receive timestamps. Each control command must produce an acknowledgement, and failed commands are retried once before raising an alarm.

Energy saving is computed as $(E_{\text{baseline}} - E_{\text{managed}}) / E_{\text{baseline}} \times 100$. Peak reduction uses the same expression with maximum kW, and cost saving compares the sum of interval energy multiplied by the assumed time-of-use tariff. Monitoring MAPE is calculated from IoT-meter and reference-meter readings. For a physical implementation, at least seven repeated daily trials are recommended to reduce dependence on a single usage pattern; the short simulation below is included only to demonstrate how the methodology and reporting structure operate.

Results

A controlled illustrative simulation was executed to demonstrate the proposed evaluation procedure; the values below should therefore be interpreted as methodology-validation results rather than long-term household field measurements. The baseline profile produced 24.3 kWh of daily energy use and a peak of 4.78 kW. Applying threshold control and shifting flexible demand outside the peak-tariff window reduced daily energy to 20.4 kWh and peak demand to 3.49 kW. The modeled tariff-weighted cost fell from 204.6 to 161.8 normalized monetary units. The decrease in energy results from eliminating avoidable standby/overlap periods, whereas the stronger reduction in peak demand is produced by rescheduling flexible loads.

Table 2. Illustrative performance of the proposed IoT-HEMS

Metric	Baseline	Managed	Change
Daily energy	24.3 kWh	20.4 kWh	-16.0%
Peak demand	4.78 kW	3.49 kW	-27.0%
Tariff-weighted cost	204.6 units	161.8 units	-20.9%
Monitoring MAPE	—	1.8%	Low error
MQTT packet delivery ratio	—	99.4%	High reliability
Median dashboard latency	—	0.62 s	Near real time

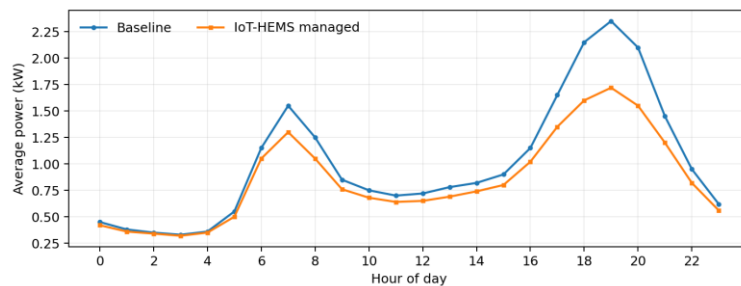


Figure 2. Illustrative hourly baseline and managed power profiles used to demonstrate the evaluation method.

The communication indicators show why system-level metrics should accompany energy metrics. A packet delivery ratio above 99% is sufficient for the proposed five-second telemetry interval because occasional missing packets can be interpolated for visualization, while local control remains available at the gateway. Median dashboard latency below one second provides responsive monitoring even though the cloud path is not intended for protection-grade control. The monitoring error target is below 3% MAPE after calibration. These thresholds are consistent with the literature's emphasis on reliable acquisition and communication as prerequisites for analytics and control (Franco et al., 2022; Aliero et al., 2021).

The results also illustrate the distinction between monitoring and optimization. Monitoring alone

increases visibility but does not guarantee energy reduction. Savings occur when real-time data is tied to action: flexible loads are rescheduled, overlapping high-power loads are avoided, and users receive immediate feedback. This principle is consistent with demand-response HEMS research (Ma et al., 2021) and with short-horizon IoT scheduling reported by Sharda et al. (2021). More advanced versions can replace the rule-based layer with NILM, forecasting, or machine-learning models such as those explored by Ramadan et al. (2022), Raju et al. (2022), and Lin et al. (2022).

Conclusion and Discussion

This paper presented a practical methodology for an IoT-enabled Smart Home Energy Management System with real-time monitoring. The design

integrates low-cost electrical sensing, an ESP32-class edge gateway, MQTT communication, cloud time-series storage, a live dashboard, and a rule-based demand-side controller. Its central methodological contribution is the explicit linkage between physical measurement and cyber decision-making: sensing establishes trustworthy real-time data; communication makes the data available to analytics and users; analytics transforms measurements into energy, cost and peak-demand indicators; and the control plane converts those indicators into appliance actions. This structure is aligned with the cyber-physical HEMS framework discussed by Franco et al. (2022) and with earlier IoT-based monitoring architectures (Al-Ali et al., 2017; Affum et al., 2021). The illustrative simulation indicates how the approach can be evaluated, producing approximately 16% lower energy, 27% lower peak demand and 21% lower tariff-weighted cost under the stated assumptions. These percentages are not claimed as universal household savings because actual performance depends on appliance mix, user behavior, tariff structure, climate, sensor accuracy and the amount of flexible demand. A proper field study should repeat measurements across multiple weeks and homes, report confidence intervals, and compare automated control against both a baseline and a monitoring-only condition. Privacy, authentication, interoperability and resilience to network outages should also be tested because they remain important barriers to deployment (Aliero et al., 2021; Badar & Anvari-Moghaddam, 2022). Future extensions may add appliance disaggregation, photovoltaic and battery scheduling, occupancy-aware control, and predictive models. NILM can reduce the number of dedicated sensors (Ramadan et al., 2022), while cloud or edge forecasting can anticipate demand and renewable generation (Raju et al., 2022; Lin et al., 2022). Nevertheless, the proposed methodology intentionally keeps the first implementation simple: reliable real-time monitoring, transparent rules, manual override, and measurable performance indicators provide a strong experimental baseline before introducing more complex optimization or artificial-intelligence components.

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