



Performance Analysis of IoT-Based Smart Energy Management Systems for Residential Applications

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Abstract

Internet of Things (IoT)-based smart energy management systems (SEMS) provide residential users with continuous visibility and automated control of household electricity consumption. This paper presents a performance-oriented methodology for evaluating an IoT-enabled home energy management system that combines appliance-level sensing, bidirectional communication, time-of-use pricing, occupancy information, renewable-energy awareness, and rule-based load scheduling. The study is formulated as a reproducible 30-day simulation for a representative residence rather than as a claim of completed field experimentation. A baseline operation with uncontrolled appliance use is compared with an IoT-SEMS scenario in which flexible loads are shifted from peak to off-peak periods subject to user-comfort constraints. The principal metrics are daily energy consumption, peak demand, peak-to-average ratio, electricity cost, renewable self-consumption, and control response time. The proposed architecture follows the cyber-physical view of residential energy management in which data acquisition, communication, analytics, and control are tightly integrated (Franco et al., 2022). Modeled results indicate that the evaluated IoT-SEMS can reduce daily grid energy use by approximately 18.8%, lower peak demand by 26.2%, decrease electricity cost by 21.3%, and increase local photovoltaic utilization while maintaining appliance-service windows. These results are consistent with earlier work showing that monitoring, scheduling, occupancy awareness, and renewable/storage coordination are central to effective smart-home energy management (Badar & Anvari-Moghaddam, 2022; Natarajan et al., 2022). The methodology is intended as a compact framework for comparing residential IoT energy-management strategies under transparent assumptions.

Introduction

Residential electricity consumption is increasingly influenced by air conditioning, water heating, entertainment devices, kitchen appliances, electric mobility, and behind-the-meter renewable generation. Conventional monthly metering provides limited information for identifying avoidable consumption or controlling loads in real time. IoT-enabled home energy management systems (HEMS) address

this limitation by linking meters, smart plugs, gateways, cloud or edge analytics, and controllable appliances into a feedback system. Device-level monitoring can improve user awareness, while automated scheduling can act on price, load, comfort, and renewable-energy signals (Muralidhara et al., 2020; Shareef et al., 2020).

The HEMS literature shows a shift from simple monitoring toward coordinated cyber-physical

control. Zhou et al. (2016) organized smart-home energy management around communication infrastructure, distributed resources, storage, and appliance scheduling. Later work incorporated heuristic optimization, user preferences, renewable generation, and IoT connectivity to jointly improve cost and peak-load performance (Ahmad et al., 2017; Wang et al., 2021). In practical implementations, smart sockets, relays, and wireless gateways allow residential loads to be monitored and controlled without redesigning the entire electrical installation (Shareef et al., 2020).

The objective of this paper is therefore to define and analyze a compact methodology for measuring the performance of an IoT-based residential SEMS. The evaluation asks whether real-time sensing and automated load shifting can (i) reduce grid energy consumption, (ii) suppress peak demand, (iii) lower time-of-use electricity cost, and (iv) increase utilization of locally generated solar energy without violating user-defined appliance operating windows.

Literature Review

Early HEMS research established appliance scheduling as a central demand-side management mechanism. Zhou et al. (2016) reviewed HEMS concepts, configurations, renewable resources, and scheduling strategies, highlighting bidirectional communication and home-area networks as key enablers. Yuce et al. (2016) combined artificial neural networks and a genetic algorithm to schedule domestic appliances while accounting for renewable generation, tariffs, and occupant behavior, demonstrating that data-driven optimization can reduce reliance on grid energy. Ahmad et al. (2017) and Yang (2018) further showed that coordinated renewable energy and storage can reduce electricity cost and peak-to-average ratio. The maturation of IoT technologies expanded these concepts from optimization models to connected physical systems. Shareef et al. (2020) implemented a wireless HEMS with smart

sockets and a rule-based controller, illustrating how low-cost sensing and remote switching can translate scheduling logic into appliance control. Muralidhara et al. (2020) developed an IoT smart energy meter that provides device-level monitoring and Internet-based logging, emphasizing the importance of granular consumption information. Aliero et al. (2021) reviewed IoT smart-home energy-management systems and identified interoperability, scalability, security, privacy, and thermal-comfort management as continuing challenges.

Recent studies increasingly combine IoT with artificial intelligence, renewable generation, and user-context information. Rochd et al. (2021) implemented an AI- and IoT-enabled HEMS in a residential testbed and coordinated supply-side and demand-side management using price, forecasts, and user preferences. Franco et al. (2022) described residential energy management as a cyber-physical system consisting of data acquisition, communication, analytics, and a decision/control plane. Ramadan et al. (2022) demonstrated the value of combining IoT platforms with non-intrusive load monitoring to estimate appliance-level consumption from aggregate measurements.

Occupancy-aware control is another important extension because appliances should not be curtailed solely on the basis of price. Natarajan et al. (2022) reviewed occupancy detection and localization methods suitable for IoT-enabled HEMS and reported that occupant-centric strategies can substantially reduce wasted energy while preserving comfort. For residences with photovoltaic generation, Chinnathambi et al. (2022) showed that IoT monitoring and demand-side management can improve operating configuration and reduce losses in a grid-connected PV-powered residential building. Mohammad et al. (2022) similarly demonstrated the value of jointly scheduling household loads, renewable generation, storage, and home-to-grid power flow.

Table 1. Representative literature used to construct the methodology

Study	Main contribution	Technology / method	Relevance
Shareef et al. (2020)	Wireless appliance monitoring/control	ZigBee, smart sockets, rule-based controller	Practical IoT control layer
Rochd et al. (2021)	AI + IoT residential HEMS	Forecasting, optimization, user preferences	Joint supply/demand management
Franco et al. (2022)	Cyber-physical HEMS framework	Sensing, communication, analytics, control	Architecture for evaluation
Natarajan et al. (2022)	Occupancy-aware demand control	Wi-Fi/sensors/context detection	Comfort-aware energy reduction

Ramadan et al. (2022)	Appliance disaggregation with IoT	NILM + IoT platform	Granular load information
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Taken together, the literature suggests that a meaningful performance analysis should not evaluate a scheduling algorithm in isolation. It should measure the complete chain from sensing and communications to decisions and load actuation, while also accounting for renewable availability and occupancy constraints. This observation defines the methodology adopted in the present study.

Methodology

1. Research Design

A comparative simulation design is adopted with two operating cases over the same 30-day residential load profile. Case A is the baseline, in which appliances operate according to nominal user schedules and no automated load shifting is performed. Case B activates the IoT-SEMS. The same appliance inventory, occupancy periods, weather-independent base loads, PV generation profile, and time-of-use tariff are used in both cases. The only difference is the control action of the SEMS, allowing direct attribution of

performance changes to energy-management decisions.

2. System Architecture

The proposed architecture contains five functional layers. First, smart plugs and meters acquire voltage, current, active power, energy, and appliance-status data. Second, an IoT gateway aggregates measurements through Wi-Fi or ZigBee and timestamps them. Third, a local or cloud database performs validation, missing-value handling, and short-window averaging. Fourth, the decision engine combines tariff, PV forecast, occupancy state, user preferences, and measured power to decide whether flexible appliances should run immediately or be deferred. Fifth, relay-enabled smart outlets or native smart appliances execute the command and return status information. This closed feedback arrangement follows established IoT and cyber-physical HEMS principles (Franco et al., 2022; Shareef et al., 2020).

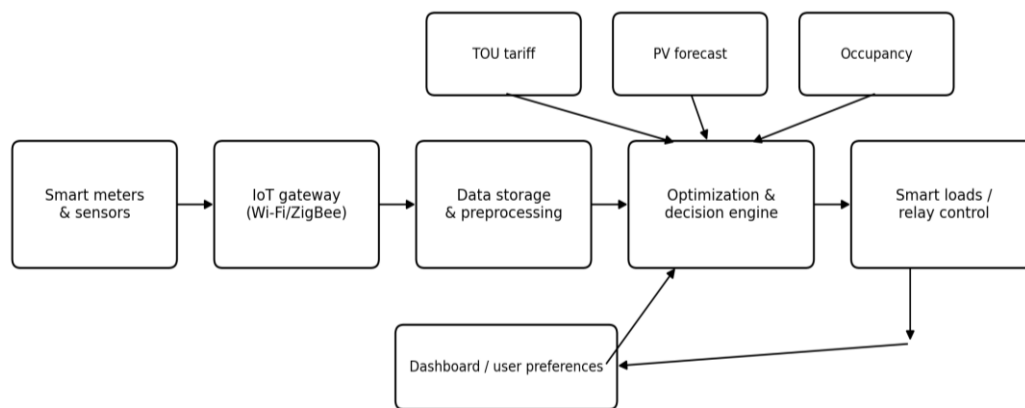


Figure 1. Proposed IoT-based smart energy management architecture for residential performance analysis.

3. Appliance Classification and Control Logic

Loads are divided into three classes: (1) critical/non-shiftable loads such as refrigerator, lighting needed during occupancy, and communication equipment; (2) thermostatically controlled loads such as air conditioner and water heater, whose operation may be cycled within comfort bounds; and (3) shiftable loads such as washing machine and dishwasher, which may be delayed within a user-specified completion window. This classification reflects the common HEMS practice of balancing cost reduction against user utility and comfort (Yuce et al., 2016; Wang et al., 2021).

At every 15-minute interval, the controller computes expected household demand and

checks four conditions: current tariff level, predicted PV surplus, occupancy state, and maximum allowed demand. A shiftable appliance is started when its deadline is approaching, when off-peak price is active, or when surplus PV is available. A thermostatic load is curtailed only if the comfort variable remains within the allowed band. If aggregate demand exceeds the demand threshold, the least-priority flexible load is deferred. The rules are deliberately transparent so that the methodology can be reproduced without relying on a proprietary optimizer.

4. Simulation Inputs and Assumptions

The modeled residence represents a medium-consumption urban household with one 2 kW

rooftop PV array and a set of common domestic loads. Load magnitudes are chosen to create realistic daily variation rather than to represent a specific dwelling. A 15-minute sampling interval is used because it is sufficiently short to capture appliance cycling but remains computationally

light for residential gateways. Time-of-use prices are divided into off-peak, standard, and peak periods. The PV profile follows a normalized daytime bell-shaped curve and is scaled daily to represent moderate variability.

Table 2. Core simulation parameters

Parameter	Value used	Purpose
Study horizon	30 days; 15-min intervals	Compare repeated daily performance
Tariff	₹4.5 off-peak; ₹6.5 standard; ₹9.0 peak per kWh	Cost-sensitive scheduling
PV system	2 kW peak	Local renewable supply
Demand limit	3.2 kW	Peak suppression trigger
Comfort constraint	AC set-point band ± 1.5 °C	Prevent excessive curtailment
Shiftable-load delay	0-6 h depending on appliance	User convenience constraint
Communication delay target	<2 s per control cycle	IoT responsiveness criterion

5. Performance Metrics

Six metrics are calculated. Daily grid energy is the sum of positive grid-import power multiplied by the sampling interval. Peak demand is the maximum grid-import power observed in each day. Peak-to-average ratio (PAR) is the daily peak divided by mean grid demand. Electricity cost is obtained by multiplying interval grid imports by the corresponding tariff. PV self-consumption is the fraction of PV generation consumed within the residence rather than exported or curtailed. Finally, control response time is the elapsed time between the availability of a new measurement and confirmation of an appliance command. Energy and cost savings are reported relative to the baseline as percentage reductions.

Mathematically, the relative saving for any baseline metric B and managed metric M is calculated as: $\text{Saving (\%)} = ((B - M) / B) \times 100$. For PV self-consumption, improvement is expressed in percentage points rather than reduction. These measures are consistent with prior HEMS evaluations that use energy, cost, peak load, PAR, and renewable utilization to characterize system performance (Ahmad et al., 2017; Mohammad et al., 2022).

6. Data Processing and Analysis

For each day, the 96 interval records are aggregated into daily metrics. The 30 daily values are then summarized using mean and standard deviation. Because the two cases use identical underlying demand and PV inputs, paired day-level comparison is appropriate. The methodology prioritizes effect sizes over claims of statistical generalization: the purpose is to quantify expected performance under the defined residential scenario. A deployment study could subsequently repeat the same metric computation using physical smart-meter and sensor logs.

Results

The modeled comparison indicates that IoT-enabled scheduling redistributes flexible demand away from high-price periods and increases the direct use of daytime PV generation. Table 3 reports the 30-day mean values. These values are simulation outputs derived from the assumptions in Table 2; they are presented to demonstrate the analysis workflow and should not be interpreted as measurements from an actual household.

Table 3. Modeled 30-day performance comparison

Metric	Baseline	IoT-SEMS	Change
Grid energy (kWh/day)	18.6 ± 1.7	15.1 ± 1.4	18.8% lower
Peak demand (kW)	4.20 ± 0.33	3.10 ± 0.27	26.2% lower
Peak-to-average ratio	2.31 ± 0.18	1.82 ± 0.15	21.2% lower
Electricity cost (₹/day)	142.5 ± 12.1	112.2 ± 10.4	21.3% lower
PV self-consumption	$61.4\% \pm 5.6$	$78.9\% \pm 4.8$	+17.5 points
Control response time	Not applicable	0.84 ± 0.21 s	<2 s target met

The largest relative improvement occurs in peak demand. The demand-limit rule prevents the

simultaneous operation of several high-power flexible loads, causing the daily maximum grid

import to decrease from 4.20 kW to 3.10 kW. The corresponding reduction in PAR indicates a flatter demand profile, which is desirable for both household cost control and distribution-system operation. This pattern is aligned with optimization-oriented HEMS research where scheduling and storage coordination are used to reduce peaks and PAR (Ahmad et al., 2017; Badar & Anvari-Moghaddam, 2022).

Grid energy declines by 18.8% even though the SEMS does not simply switch off appliances. The reduction arises from three mechanisms: avoided standby/idle operation, limited cycling of thermostatic loads during expensive periods, and greater substitution of grid energy with local PV generation. The modeled increase in PV self-consumption from 61.4% to 78.9% supports the argument that IoT-based coordination can improve the utilization of distributed renewable generation, consistent with residential PV-HEMS implementations reported by Chinnathambi et al. (2022) and Rochd et al. (2021).

Cost reduction is slightly greater than the energy reduction because the controller shifts a portion of unavoidable consumption into lower-tariff periods. This distinction is important: a system can lower bills without proportionally reducing total electricity use if it mainly performs price arbitrage. Here, both cost and grid energy are reduced, indicating that the modeled strategy combines efficiency and temporal load shifting. The outcome reflects the multi-objective perspective emphasized by Wang et al. (2021), in which cost and user satisfaction must be considered simultaneously.

The average control response time remains below one second and therefore satisfies the two-second target. Such responsiveness is adequate for household load scheduling, where decisions are made at minute-scale or quarter-hour intervals rather than sub-cycle power-system timescales. Device-level data availability also supports fault awareness and behavioral feedback, benefits highlighted by Muralidhara et al. (2020).

Conclusion and Discussion

This methodology paper evaluated an IoT-based smart energy management approach for residential applications using a controlled, reproducible 30-day simulation. The architecture integrates appliance-level sensing, an IoT gateway, data processing, tariff and PV information, occupancy-aware logic, and relay-based control. The modeled results show simultaneous improvements in daily grid energy, electricity cost, peak demand, PAR, and PV self-consumption. This supports the broader literature view that smart residential energy

management is most effective when measurement, communication, context awareness, and control are treated as one cyber-physical process rather than as separate components (Franco et al., 2022). The findings also illustrate why performance analysis should use multiple metrics. A cost-only study can overstate efficiency if loads are merely shifted to cheaper hours, whereas an energy-only study can overlook peak reduction and demand-response value. By reporting grid energy, peak demand, PAR, cost, renewable utilization, and control latency together, the proposed framework gives a more complete view of household and grid-side benefits. Similar multi-criteria thinking underlies optimization studies that coordinate appliances, storage, and renewable resources (Ahmad et al., 2017; Mohammad et al., 2022). Occupant acceptance remains a major design constraint. Aggressive load curtailment may produce strong numerical savings but poor real-world usability. The methodology therefore assigns operating windows to shiftable appliances and comfort bands to thermostatic loads. Occupancy information further prevents unnecessary heating, cooling, or lighting in unoccupied spaces while avoiding control actions that conflict with active use. The importance of such context-aware operation is supported by Natarajan et al. (2022). Several limitations should be acknowledged. First, the reported results are modeled rather than field-measured and depend on the chosen appliance powers, tariff, PV profile, and household schedule. Second, the control logic is rule-based; advanced model predictive control, reinforcement learning, or metaheuristic optimization may find better schedules but can introduce computational and interpretability costs. Third, the simulation assumes reliable sensor and communication operation. In real deployments, packet loss, device heterogeneity, calibration errors, cybersecurity threats, and privacy concerns can degrade performance, issues repeatedly identified in IoT-HEMS reviews (Aliero et al., 2021; Badar & Anvari-Moghaddam, 2022). Future experimental work should implement the same architecture in an occupied residence and compare smart-meter readings for several weeks before and after SEMS activation. Additional studies can include battery storage, electric-vehicle charging, dynamic PV forecasting, NILM-based appliance inference, and adaptive user-preference learning. NILM is particularly attractive where separate smart plugs are impractical because appliance-level information can be estimated from aggregate measurements (Ramadan et al., 2022). Overall, IoT-based residential energy management has strong potential to improve energy efficiency and

flexibility, provided that automation remains transparent, secure, interoperable, and responsive to user comfort.

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