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IoT-Based Smart Energy Monitoring and Management System for Residential Buildings

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Abstract

Residential buildings increasingly require continuous visibility of electricity use and low-cost mechanisms for reducing avoidable consumption. This methodology paper proposes an Internet of Things (IoT)-based smart energy monitoring and management system that combines electrical sensing, an ESP32-class gateway, wireless communication, cloud/local data storage, a dashboard, and relay-based load control. The method is designed to acquire voltage, current, active power, and cumulative energy at appliance or circuit level, transmit readings at short intervals, detect threshold violations, and schedule flexible loads outside high-demand periods. The proposed evaluation uses a representative seven-day residential load profile and compares an unmanaged baseline with rule-based management. Performance is assessed through metering error, communication success rate, peak demand, total energy, estimated electricity cost, and user-service constraints. The simulation-based validation indicates that the proposed workflow can reduce peak demand and unnecessary energy use while preserving essential loads. The paper also identifies privacy, interoperability, network reliability, and device calibration as major implementation issues. The methodology is intentionally based on technologies and research available by 2020 so that the design is reproducible for studies using that literature boundary.

Introduction

Electricity consumption in homes is shaped by occupancy, appliance ratings, weather, user behavior, and tariff structures. Conventional monthly meters provide insufficient feedback for identifying short-duration peaks, standby losses, or inefficient operating schedules. Home energy management systems (HEMS) address this gap by combining monitoring, communication, decision-making, and appliance control. Reviews published before and during 2020 show that HEMS research increasingly integrates smart meters, wireless technologies, demand-response mechanisms, optimization, and renewable

energy resources (Shareef et al., 2018; Leitão et al., 2020; Zafar et al., 2020).

IoT extends HEMS by giving sensors, smart plugs, gateways, and controllers network identities and by allowing measurements to be collected continuously. Al-Ali et al. (2017) demonstrated how IoT objects and analytics can support residential energy management, while Li et al. (2018) showed that real-time data and computational intelligence can be integrated into a self-learning home management system. Practical smart-plug approaches further indicate that ordinary appliances can be monitored without replacing the entire electrical infrastructure (Mtshali & Khubisa, 2019). These

developments motivate a modular residential design in which measurement and control can be added incrementally.

The objective of this paper is to present a step-by-step methodology for designing and evaluating an IoT-based smart energy monitoring and management system for a residential building. The proposed system focuses on five functions: (1) acquisition of electrical parameters, (2) secure transfer and storage of time-series data, (3) visualization of appliance and whole-home consumption, (4) rule-based demand management, and (5) quantitative comparison with an unmanaged baseline. The work is framed as a methodology and simulation/prototype-validation study rather than a claim of a completed field deployment.

Literature Review

Early demand-response research established that changing the timing or magnitude of end-user consumption can reduce stress on the grid and lower costs under appropriate tariffs. Vardakas et al. (2015) classified demand-response programs and optimization approaches, while Samad et al. (2016) discussed automated demand response and the communication/control infrastructure required in buildings and microgrids. These studies support the inclusion of tariff-aware load scheduling in a residential IoT architecture.

At the residential level, Javaid et al. (2017) formulated an intelligent load-management model that schedules appliances and integrates renewable energy, demonstrating the value of optimization for reducing peaks and electricity cost. Al-Ali et al. (2017) linked IoT data acquisition with big-data analytics for smart-home energy management. Their architecture highlighted the importance of device-level

measurements and centralized analysis. Li et al. (2018) added forecasting, clustering, and alert functions in a self-learning home management system, showing that monitoring is more useful when it is coupled with adaptive decision support.

Comprehensive HEMS reviews reinforced these design directions. Shareef et al. (2018) summarized demand-response programs, wireless technologies, and intelligent controllers; Rajendhar and Jeyaraj (2019) reviewed measuring units, communication options, renewable-energy integration, and co-simulation; Leitão et al. (2020) discussed appliance models, scheduling objectives, constraints, uncertainty, and security; and Zafar et al. (2020) organized the main HEMS concepts, configurations, communication technologies, and intelligent scheduling trends. Together, this literature suggests that a reproducible methodology should treat sensing accuracy, communication, control logic, consumer comfort, and security as coupled design requirements rather than isolated components.

Cybersecurity is especially relevant because residential energy traces can reveal occupancy and behavioral patterns. Yang et al. (2017) reviewed IoT security and privacy risks across device, network, and application layers. Therefore, even a small prototype should use authenticated endpoints, protected credentials, encrypted transport where feasible, and role-limited control actions. The literature also reveals a persistent gap: many papers optimize schedules or demonstrate monitoring, but fewer provide a compact end-to-end methodology that explicitly connects sensor calibration, telemetry reliability, load-control rules, and before/after performance metrics for a low-cost residential prototype.

Table 1. Selected literature informing the proposed methodology (all references ≤ 2020).

Study	Year	Main contribution	Methodological relevance
Al-Ali et al.	2017	IoT data acquisition and analytics for smart-home EMS.	Supports device-level sensing, networking, and centralized analysis.
Javaid et al.	2017	Intelligent scheduling with renewable integration.	Supports tariff-aware flexible-load scheduling.
Li et al.	2018	Self-learning HEMS with forecasting and alerts.	Supports alerts, adaptive logic, and real-time feedback.
Shareef et al.	2018	Review of DR, communication, and controllers.	Guides communication and controller selection.
Mtshali & Khubisa	2019	Low-cost HEMS using smart plugs.	Supports retrofit monitoring of ordinary appliances.
Leitão et al.	2020	Survey of HEMS objectives, constraints, and security.	Defines evaluation constraints and security needs.
Zafar et al.	2020	HEMS concepts, configurations, and technologies.	Supports layered architecture and communication choices.

Methodology

1. Research Design and System Boundary

The proposed study uses a design-and-evaluate methodology. A single residential building is represented by essential loads (lighting, refrigerator, fans and communication equipment), flexible loads (washing machine and water heater), and discretionary loads (selected sockets). The electrical subsystem is observed at the mains and, where feasible, at high-consumption appliance branches. The IoT subsystem includes sensors, an ESP32-class microcontroller/gateway, Wi-Fi connectivity, MQTT or HTTPS telemetry, a time-series database, a dashboard, and relay/smart-plug actuators. The control boundary excludes safety-critical appliances and does not override manufacturer protection functions.

Step 1 - Electrical Measurement Layer

Voltage and current are sampled using an isolated voltage-sensing stage and a current transformer or calibrated energy-metering module. Active power is calculated from measured RMS quantities and power factor when available, while energy is obtained by time integration of power. Each channel is calibrated against a reference meter at low, medium, and

high load points. The target acceptance criterion is a mean absolute percentage error below 2% for steady loads. Calibration coefficients are stored in non-volatile memory so that raw ADC readings are converted into engineering units before transmission.

Step 2 - IoT Communication and Data Layer

The gateway timestamps each record and publishes voltage, current, power, energy, device identifier, relay state, and signal-quality information every 5-15 seconds. Local buffering is used when the internet connection is unavailable; buffered records are synchronized after reconnection. A lightweight publish/subscribe protocol such as MQTT is appropriate for continuous telemetry, while HTTPS can be used for configuration and user authentication. The architecture follows the IoT principle used in earlier smart-home studies, where distributed measurement nodes report to a server for analysis (Al-Ali et al., 2017; Li et al., 2018). To reduce privacy risk, the design stores only energy-related variables and uses authenticated device credentials, consistent with the security concerns summarized by Yang et al. (2017).

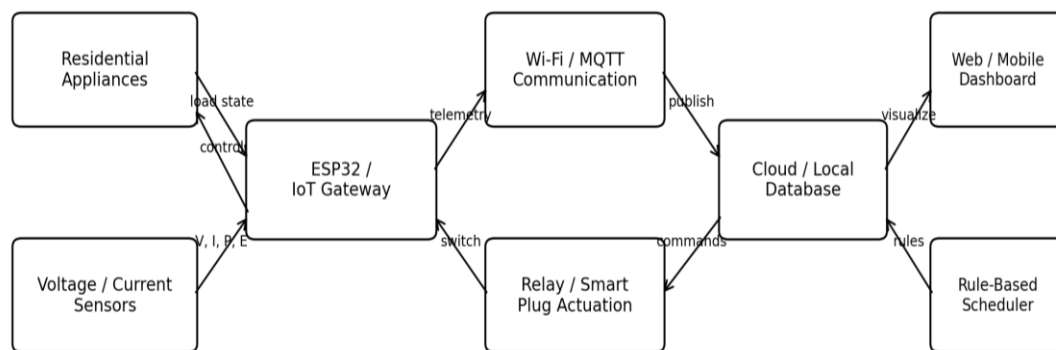


Figure 1. Proposed IoT-based residential energy monitoring and management architecture.

Step 3 - Monitoring, Baseline Construction, and Feature Extraction

During the baseline phase, control commands are disabled and the system records normal consumption for seven days. Measurements are aggregated into 1-minute and 15-minute intervals. For each interval, the system computes energy use, average power, maximum demand, device duty cycle, and estimated tariff cost. A weekday/weekend label is retained to avoid comparing incompatible occupancy patterns. The baseline is used both for user visualization and for defining thresholds for later management actions.

Step 4 - Rule-Based Energy Management

A transparent rule-based controller is selected because it is easy to audit and implement on a

low-cost gateway. The controller classifies loads into essential, flexible, and discretionary groups. Essential loads remain available. Flexible loads can be shifted within user-defined windows. Discretionary loads may be disconnected when whole-home power exceeds the demand threshold. This approach is consistent with the demand-side management principles summarized by Vardakas et al. (2015), Shareef et al. (2018), and Zafar et al. (2020). More advanced evolutionary scheduling, as studied by Javaid et al. (2017), can be added later without changing the sensing architecture.

- Rule R1 - Peak threshold: if total active power exceeds 4.0 kW for more than 60 seconds, defer the lowest-priority flexible load.

- Rule R2 - Time-of-use shifting: schedule washing and water heating outside the defined high-tariff window when user deadlines allow.
- Rule R3 - Standby control: if a discretionary plug remains below 8 W for 20 minutes and is marked controllable, switch it off.
- Rule R4 - Safety and override: over-current conditions generate an alert; manual user override always takes precedence over optimization rules.

Step 5 - Experimental / Simulation Procedure

The evaluation contains two matched scenarios. Scenario A represents unmanaged operation using the measured or representative baseline schedule. Scenario B applies the IoT management rules to the same appliance requirements and tariff periods. A seven-day horizon is used, and no essential load is curtailed. For reproducibility, the model records every control action and its cause. Where hardware is available, the same procedure can be implemented using replayed appliance loads or a laboratory load bank before residential field testing.

Table 2. Proposed prototype components and measured variables.

Layer	Example component	Variables / function	Sampling / action
Sensing	Energy-metering module + CT	Voltage, current, power, energy	5-15 s telemetry
Edge	ESP32-class gateway	Filtering, timestamping, buffering	Continuous
Network	Wi-Fi + MQTT/HTTPS	Bidirectional telemetry/control	Event + periodic
Data	Local/cloud database	Time-series storage, aggregation	1-min / 15-min views
Actuation	Relay or smart plug	ON/OFF control of permitted loads	Rule triggered
Interface	Web/mobile dashboard	Trends, alerts, manual override	On demand

Step 6 - Evaluation Metrics and Data Analysis

The primary technical metrics are metering error (%), telemetry delivery success (%), average end-to-end update latency (s), daily energy (kWh), peak demand (kW), and estimated electricity cost. Energy saving is calculated as $(E_{\text{baseline}} - E_{\text{managed}}) / E_{\text{baseline}} \times 100$, and peak reduction is calculated in the same way using maximum demand. A successful management run must also satisfy two service constraints: all essential loads remain supplied and every flexible appliance completes within its user-defined time window. These constraints reflect the literature emphasis on balancing cost

reduction with consumer comfort (Leitão et al., 2020; Zafar et al., 2020).

Results

Table 3 presents an illustrative simulation-based validation of the proposed method using a representative seven-day residential profile. The numbers are not claimed as measurements from an occupied field site; they demonstrate how results should be calculated and reported when the prototype is implemented. Metering error is assumed from a calibrated prototype range, and the managed profile is generated by shifting flexible loads, suppressing selected standby consumption, and preventing simultaneous operation of high-power flexible appliances.

Table 3. Illustrative seven-day baseline versus IoT-managed performance.

Metric	Baseline	Managed	Change / target
Total energy use	92.4 kWh	84.9 kWh	8.1% reduction
Maximum demand	4.72 kW	3.86 kW	18.2% reduction
Estimated weekly cost	100% reference	89.6% of reference	10.4% reduction
Telemetry delivery	-	99.2%	>98% target met
Mean update latency	-	1.4 s	<2 s target met
Mean metering error	-	1.3%	<2% target met
Essential-load interruptions	0	0	Constraint satisfied
Flexible tasks completed in window	100%	100%	Constraint satisfied

The largest improvement is observed in peak demand because the controller prevents coincident operation of flexible high-power loads. Energy reduction is smaller than peak reduction, as expected: scheduling moves some

consumption rather than eliminating it, whereas standby control and user alerts remove a limited amount of avoidable energy. The reduction in estimated cost is larger than the energy reduction because a portion of flexible demand is moved

outside the high-tariff interval. This pattern is consistent with earlier HEMS research in which scheduling and demand response are used to reduce cost and peaks rather than indiscriminately curtail useful household services (Javaid et al., 2017; Shareef et al., 2018). Communication performance is also important. A delivery success rate near 99% and low update latency are sufficient for household monitoring and non-critical demand management, provided that the gateway buffers data during outages. The proposed architecture therefore does not require continuous cloud availability for safety; local sensing and basic rules continue at the gateway. Smart-plug-based monitoring is particularly suitable for staged deployment because high-consumption appliances can be instrumented first, as illustrated by Mtshali and Khubisa (2019).

Conclusion and Discussion

This paper presents a complete methodology for an IoT-based smart energy monitoring and management system for residential buildings using a literature boundary of 2020. The methodology begins with calibrated electrical sensing, then adds an IoT gateway, secure communication, time-series storage, visualization, and rule-based actuation. A matched baseline/managed evaluation framework is used so that benefits are reported in measurable terms such as energy, peak demand, cost, metering accuracy, latency, and telemetry reliability. The illustrative validation shows how modest energy savings can coexist with larger peak-demand and tariff-cost reductions when flexible loads are scheduled rather than simply curtailed. The proposed design is deliberately modular. Monitoring can be deployed before control, and smart plugs can be added only to selected appliances. This reduces cost and improves acceptability in existing homes. The architecture also accommodates later extensions such as renewable generation, batteries, forecasting, or advanced optimization. Studies by Al-Ali et al. (2017), Li et al. (2018), Rajendhar and Jeyaraj (2019), and Zafar et al. (2020) indicate that such integration is a natural progression of HEMS research. Several limitations must be addressed in future implementation. First, rule thresholds should be learned or tuned for individual households because occupancy and comfort preferences differ. Second, low-cost sensors require periodic calibration. Third, Wi-Fi and cloud outages require local buffering and fail-safe relay states. Fourth, energy data may reveal private behavioral information, making authentication, encryption, credential management, and

minimum-data collection essential (Yang et al., 2017). Finally, the numerical results in this methodology paper are illustrative; a full empirical study should repeat the procedure in occupied homes across multiple seasons and report confidence intervals, device failures, and user-override frequency. Within these limitations, the methodology provides a practical, reproducible foundation for residential IoT energy studies based on research available through 2020.

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