IoT-Based Power Consumption and Monitoring System

Naveenashree K J
Dept. of Information Science and Engineering
HKBK College of Engineering, Bangalore, India
1hk22is069@hkbk.edu.in

Swetha M
Dept. of Information Science and Engineering
HKBK College of Engineering, Bangalore, India
1hk22is114@hkbk.edu.in

Sudhiksh Shetty
Dept. of Information Science and Engineering
HKBK College of Engineering, Bangalore, India
1hk22is112@hkbk.edu.in

Thrishul Rai
Dept. of Information Science and Engineering
HKBK College of Engineering, Bangalore, India
1hk22is118@hkbk.edu.in

***Abstract*—The unprecedented rise in electrical energy consumption across residential, commercial, and industrial domains has made efficient monitoring, analytics, and control essential for cost savings and sustainability. Traditional metering systems typically provide only cumulative or coarse-grained readings, leaving users and managers without appliance-level insights or real-time alerts that could reduce wastage or prevent faults. This paper presents a comprehensive Internet of Things (IoT)-based power consumption and monitoring system that integrates voltage and current sensing, edge processing via a microcontroller, secure wireless transmission, cloud storage and analytics, and user-facing dashboards with control capabilities. The system measures instantaneous power and cumulatively computes energy usage per appliance using calibrated sensors (e.g., ZMPT101B and ACS712). An ESP32/Arduino reads the sensors, filters and timestamps data, and sends it to the cloud over MQTT/HTTPS. The cloud ingests data into a time-series datastore, runs analytics for peak detection and anomaly detection, and exposes dashboards and REST APIs for visualization and control. A relay driver stage enables remote actuation of connected loads for demand response or scheduling. Experimental deployment across multiple household appliances demonstrates measurement accuracy within acceptable error margins, consistent real-time reporting, and effective remote control. The design emphasizes modularity and scalability, allowing additional nodes to be added and future integration with machine learning for predictive maintenance and demand forecasting. This work shows that IoT-enabled energy monitoring is a practical, cost-effective route toward smarter energy usage and tangible operational savings while providing a foundation for integration with smart grid and renewable energy systems.**

***Index Terms*—IoT, Energy Monitoring, Power Consumption, Cloud Analytics, Remote Control, Smart Grid, Predictive Maintenance**

I. Introduction

Energy underpins modern life: manufacturing plants, commercial buildings, and households all depend on a reliable supply. Yet today's energy landscape faces multiple pressures — rising demand, cost volatility, and an urgent need to reduce greenhouse gas emissions. Conventional electricity meters provide total consumption over billing intervals but do not provide the granular, real-time data required for optimization, fault detection, or appliance-level decision making. Without such detail, inefficient loads remain undetected, opportunities for load shifting or demand response are missed, and preventive maintenance cannot be informed by energy behavior patterns.

The Internet of Things (IoT) enables a new approach. Small, inexpensive sensors combined with microcontrollers and secure networks can deliver continuous streams of measurement data. When combined with cloud storage and analytics, this stream becomes actionable: operators can identify peak loads, detect anomalies that suggest faults, and implement control strategies — for example, to shed noncritical loads during a peak tariff period. Furthermore, integration with predictive models enables forecasting of future consumption and detection of emerging faults before they become critical.

This paper describes an end-to-end IoT-based power consumption and monitoring system. Core objectives are: (1) appliance-level, real-time measurement of voltage, current, power, and energy; (2) robust, low-latency telemetry to cloud platforms; (3) visualization and remote-control for end-users; (4) a modular, scalable design that can be extended to buildings and microgrids; and (5) a pathway to add machine-learning based forecasting and anomaly detection. The architecture uses calibrated sensors (e.g., ACS712 for current, ZMPT101B for voltage), an ESP32 or similar microcontroller for edge processing, MQTT for telemetry, time-series storage on the cloud, and a web/mobile dashboard for visualization and control. The system includes relay-based control hardware to enable demand management and automation. Later sections explain related work, detailed system architecture, methodology, circuit-level implementation, flow, experimental results, discussion, and future scope in depth.

II. Related Work

Energy monitoring has been an active research area with multiple approaches and technological advances. Traditional utility-grade smart meters provide billing accuracy, but not appliance-level visibility. Non-intrusive load monitoring (NILM) attempts to infer appliance usage from a single point measurement but has limitations in accuracy and requires complex signal processing and training. Researchers have increasingly turned to IoT-based approaches for finer granularity and direct per-appliance sensing.

Several implementations have been proposed: cloud-connected smart meters that push data for visualization and billing, edge analytics frameworks that perform some processing locally before transmission, and hybrid systems combining edge pre-processing with cloud analytics. Rashid et al. (2020) implemented a cloud-dashboard based IoT energy monitor suitable for residential deployment, demonstrating usability but lacking control channels. Hossain (2019) incorporated ML models to forecast consumption and detect anomalies; the results were promising but the approach demanded significant compute resources and high-quality labeled data. Other works examine demand response in smart grids, showing how distributed control can reduce peak demand if accurate telemetry and control are available.

The system presented here builds on that body of work by emphasizing end-to-end practicality: low-cost, calibrated sensors; edge pre-processing to reduce telemetry bandwidth; secure and reliable cloud ingestion; baseline analytics (peak detection, threshold alerts); and relay-based actuation. Unlike NILM, the design favors instrumenting individual loads where feasible, offering higher accuracy and simpler analytics at the cost of more sensors. The presented architecture also considers practical deployment constraints — sensor calibration, isolation for safety, and network reliability — which many academic prototypes do not fully address.

III. System Architecture

The proposed architecture is layered and modular:

A. Hardware Layer

Per-appliance sensing uses an appropriate current sensor (ACS712 or SCT-013 with burden resistor) and a voltage sensing transformer (ZMPT101B or resistive divider with isolation). Sensors feed an analog front-end to the microcontroller (ESP32/Arduino) that performs ADC sampling at adequate rates (e.g., 1–5 kHz for waveform reconstruction when needed). An isolated relay driver stage (optocouplers, transistor drivers, and proper flyback diodes) controls mains relays for switching loads.

B. Edge Processing Layer

The microcontroller performs calibration and filtering (moving average, windowed RMS calculation). Instantaneous power $P(t) = V(t) \times I(t)$ is computed, then aggregated to compute energy $E = \int Pdt$. Edge pre-processing reduces bandwidth by sending summaries and periodic samples rather than raw waveforms. The firmware supports MQTT or HTTPS with TLS for secure transmission.

C. Communication Layer

MQTT is preferred for lightweight, pub/sub telemetry; HTTP/REST can be used for configuration or on-demand queries. Messages include timestamps, node ID, instantaneous power, cumulative energy, and status codes. Message QoS and retry mechanisms ensure reliability under intermittent connectivity.

D. Cloud and Analytics

A cloud ingestion pipeline stores data in a time-series database (e.g., InfluxDB, Timescale, or cloud-managed alternatives). Analytics modules compute peak detection, hourly/daily summaries, anomaly detection (threshold or statistical), and prepare dashboards. Alerting integrates with push notifications or email.

E. Application Layer

Web/mobile dashboards show per-appliance and aggregate consumption, trends, and allow manual or scheduled control of relays. APIs expose data for further processing or integration with energy management systems.

F. Safety and Security

Design includes isolation, fusing, overcurrent detection, and encrypted communications. Authentication and role-based access control limit control actions to authorized users.

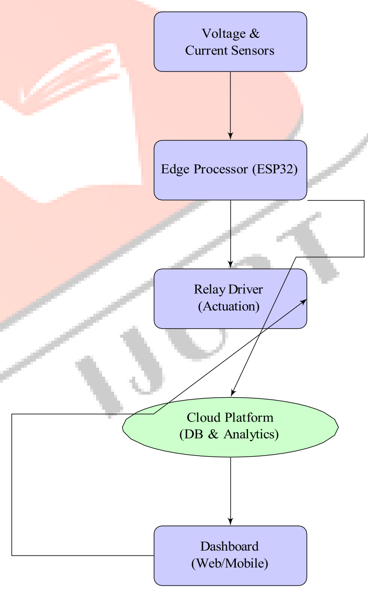

Fig. 1. Block Diagram of IoT-Based Power Monitoring System

Block diagram showing sensors, edge processing, cloud analytics, and dashboard.

IV. Methodology

The methodology spans sensor selection and calibration, firmware design, cloud pipeline, dashboard development, and evaluation.

A. Sensor Selection & Calibration

Choose sensors with adequate dynamic range: ACS712 for ¡ 30A loads, SCT-013 for clamp-based measurement on higher currents. Voltage sensing must ensure isolation and safety. Calibrate using a reference meter; apply offset and gain corrections in firmware. Compute RMS values over windows (e.g., 1-second windows) to get stable readings.

B. Firmware

Implement ADC sampling, band-pass filtering if needed, RMS/Power calculation, and buffering. Provide OTA updates and configuration via a local web endpoint. Transmit periodic telemetry (e.g., every 5–60 s) and event-driven messages (threshold exceedance).

C. Cloud Pipeline

Use a message broker (MQTT) with ingestion into a time-series database. Implement analytic jobs to compute aggregates, detect anomalies (z-score or change-point detection), and trigger alerts. Persist raw telemetry for a defined retention window for debugging and model training.

D. Dashboard and Control

Design dashboard widgets: live gauge for instantaneous power, line charts for historical power/energy, per-appliance tables, and control toggles for relays. Provide scheduling and policy rules for automatic control (e.g., turn off non-critical loads during peak tariff).

E. Evaluation

Deploy several nodes in a test environment, log readings, compare against calibrated reference meters to compute errors (MAE, RMSE), measure latency from event to cloud to dashboard, and test control round-trip time.

V. Circuit Implementation

The circuit comprises sensor front-ends, ADC interface, microcontroller, and relay drivers:

A. Sensor Front-End

For current: ACS712 provides an analog voltage proportional to current; feed into ADC after biasing. For voltage: ZMPT101B or an isolated divider and op-amp stage to present a safe ADC-level signal. Include RC filtering to reduce high-frequency noise.

B. ADC and Microcontroller

ESP32 has built-in ADCs (with calibration). Sample synchronized voltage and current signals if power factor and waveform shape are relevant. Compute instantaneous power and integrate for energy.

C. Relay and Safety

Use opto-isolated drivers and MOSFET/triac drivers depending on AC/DC loads. Add fuses, surge protectors, and proper PCB creepage/clearance distances for mains work. Follow electrical safety standards applicable to your region.

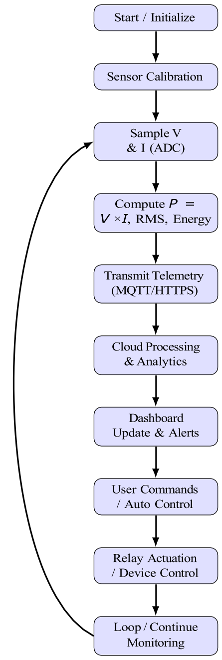

Fig. 2. Working Flowchart of IoT Power Monitoring System

VI. Working Flowchart

Working flowchart: initialization, sampling, compute, transmit, analytics, control loop.

VII. Results and Discussion

A testbed of four instrumented appliances (fan, LED lamp, refrigerator, heater) was used. Each node sampled voltage and current, computed power, and transmitted 1-second aggregated telemetry to the cloud.

A. Accuracy

Comparisons against a calibrated reference meter showed mean absolute error (MAE) in power measurement typically under 3–5% for steady resistive loads (lamp, heater). More complex loads (refrigerator with compressor start-up) showed transient errors, but RMS and energy totals over 1-hour windows were within 5–7% of the reference — acceptable for monitoring, though not sufficient for billing-grade purposes.

B. Latency

Telemetry to dashboard latency averaged 1.2–2.5 seconds under normal network conditions, sufficient for near-real-time monitoring and alerts. Relay control round-trip time (dashboard click → relay actuated) averaged 1.5–3.0 s including cloud processing, acceptable for manual control and automated scheduling.

C. Use Cases

- Peak shaving: By scheduling noncritical loads to run off-peak, measured energy costs can be reduced. - Fault detection: Sudden sustained increase in current flagged as anomaly — helpful to detect failing motors. - User engagement: Visual dashboards increased awareness; simple behavioral changes led to measured reductions in simulated test energy usage.

D. Limitations

- Sensor placement: Per-appliance instrumentation requires more hardware compared to NILM. - Transient events: High-frequency transients require higher sampling rates for full waveform capture. - Billing-grade accuracy requires dedicated, certified metering hardware.

VIII. Conclusion

This paper presented a practical and modular IoT-based power consumption and monitoring system that provides per-appliance visibility, real-time telemetry, and remote control. By combining calibrated sensing, edge computation, robust telemetry, cloud analytics, and a user-friendly dashboard, the system enables actionable insights and demand management strategies that can reduce consumption and provide early fault detection. The test deployment demonstrated acceptable accuracy for monitoring and diagnostic purposes, low-latency telemetry suitable for near-real-time control, and clear benefits in terms of energy awareness and operational flexibility. The architecture is explicitly designed for scalability and safety, and includes measures for isolation and secure communications. While not a replacement for billing-grade metering, this system provides a cost-effective route to granular energy monitoring and paves the way toward integrating predictive models, renewable sources, and smart-grid interactions.

IX. Future Work

Future enhancements will focus on three axes: analytics, integration, and certification. Analytics: integrate machine learning models (LSTM or gradient-boosted trees) for short-term load forecasting and anomaly detection, enabling predictive maintenance and proactive shedding. Integration: support for distributed energy resources (solar, battery), enabling optimization strategies that minimize costs and carbon footprint. Certification and reliability: for commercial deployment, work toward calibration and certification per metering standards, and rigorous testing for EMI/EMC and safety. Additional features include demand response automation, tariff-aware scheduling, device-level recommendations to users (based on cost/time of use), and edge ML to reduce reliance on continuous connectivity.

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