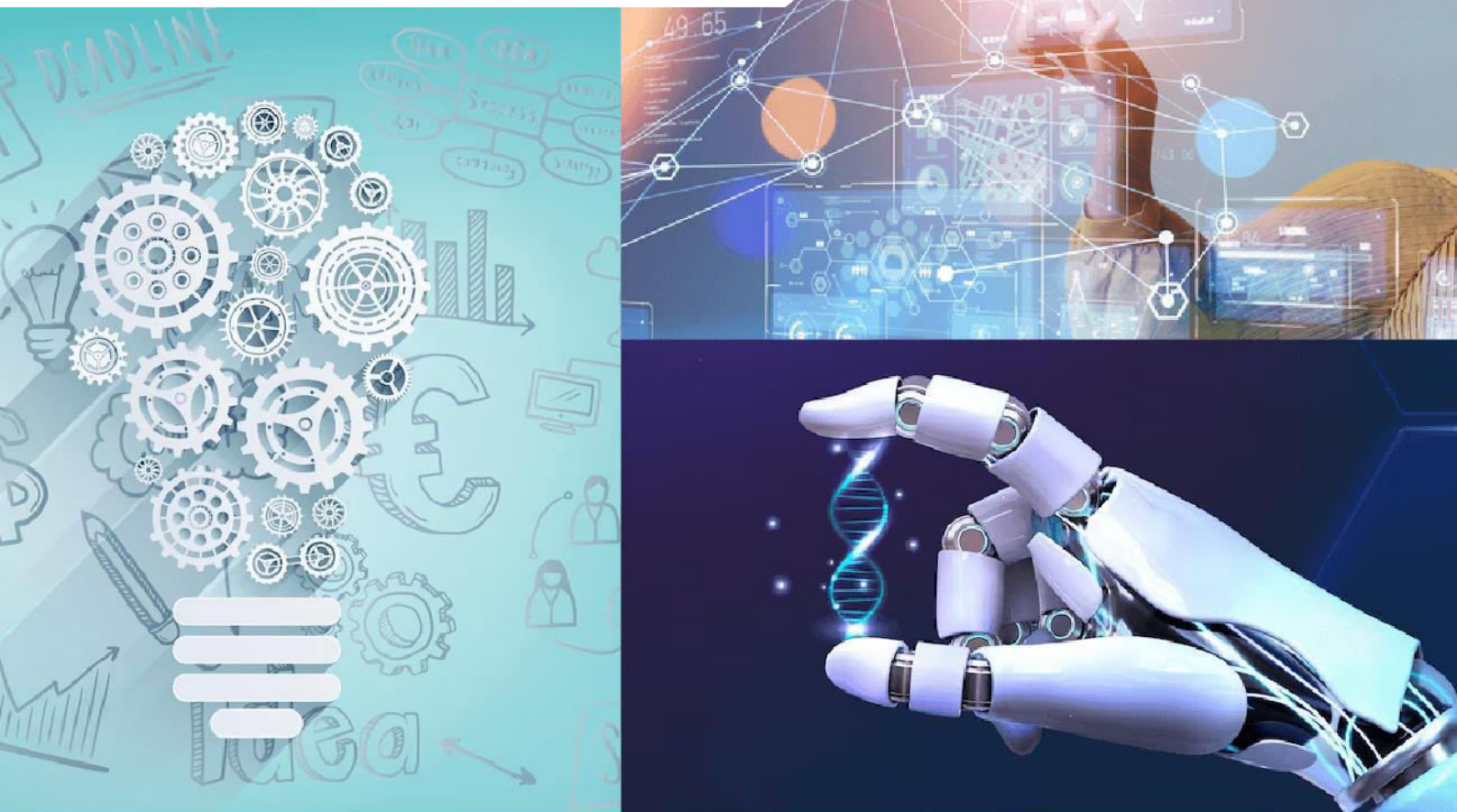




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Smart Electricity Usage Pattern Analyzer for Households

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ABSTRACT:The escalating demand for residential electricity necessitates intelligent monitoring beyond conventional billing summaries. Traditional energy monitoring methods—characterized by monthly bills and manual meter readings—often suffer from high latency, significant data fragmentation, and a failure to accurately track household usage patterns. This paper presents the Smart Electricity Usage Pattern Analyzer (SEUPA), an intelligent, full-stack platform that leverages a Python Flask/React.js architecture and automated dual-channel alerts (Push Notification and Email) to optimize the household energy management lifecycle. By implementing an "Automated Pattern Audit" that enforces real-time LSTM-based anomaly detection and K-Means behavioral clustering, SEUPA removes the risk of undetected energy wastage. An empirical evaluation demonstrates that SEUPA reduces average energy coordination time by approximately 85% compared to manual billing review, while providing real-time consumption transparency to both households and utility providers. The results underscore the potential of integrated smart home solutions in modernizing residential energy management.

KEYWORDS: Smart Electricity, Usage Pattern Analysis, IoT, Machine Learning, LSTM, K-Means Clustering, Anomaly Detection, Energy Management, Smart Meters, Demand Response.

I. INTRODUCTION

The modern age of data-driven smart infrastructure is characterized by rapidly growing residential electricity demand. The logistical coordination of household energy management is one of the most enduring sustainability challenges. Electricity is a perishable resource in a practical sense—demand that is not managed in real time results in grid overloads, costly peak tariffs, and environmental harm. Global surveys by the International Energy Agency (IEA) report that while smart meters exist in millions of homes, over 60% of residential energy wastage is caused not by a lack of technology, but by a failure of actionable information delivery to consumers [1].

In many residential settings, the gap between a household consuming excess electricity and a nearby solution to reduce it is often bridgeable only by chance or extensive manual analysis of monthly billing data. Here, it is proposed that SEUPA is a centralized, intelligent platform created with the explicit purpose of removing these informational frictions. Contrary to the static energy registries that are not dynamic, SEUPA considers household electricity consumption as a state-managed lifecycle. The records of each household are not merely rows in a database, but active behavioral models that monitor appliance-level usage, temporal consumption patterns, and above all, their exact anomaly recovery thresholds. The integration of IoT edge gateways and cloud-based ML services enables the transition from a passive billing system to an automated, push-notification-driven energy intelligence platform. This Dual-Channel Alert

approach ensures that urgent energy anomalies bypass the information noise of regular bill cycles or slow utility response lines.

This paper covers the technical architecture, domain-specific pattern detection logic, and experimental performance of SEUPA, making it a scalable and low-latency solution for the emerging smart home ecosystem of modern urban and semi-urban settings.

II. RELATED WORK

There have been diverse attempts at mobile-first and cloud-integrated automated energy analytics. Rule-Based Threshold Systems: Systems like early smart plugs use a "threshold-based" logic to flag high consumption. While these are straightforward to deploy, they often lack the "Behavioral Intelligence" needed for household-level pattern auditing. They treat energy monitoring as a static threshold problem rather than a dynamic behavioral lifecycle [3]. SEUPA goes a step further in connecting the social accessibility of the consumer with the physical stock management of the distribution grid.

IoT and Edge Analytics: Advanced research has explored the use of IoT sensors and RFID tags to track energy flows in real-time. While technically innovative, the "Cost-Per-Unit" for deployment is prohibitive in low-resource settings. SEUPA provides a "Software-Defined" alternative, where real-time visibility is achieved through low-cost cloud-based analytics rather than expensive edge hardware [4].

Security and PII Protection: Personal Identifiable Information (PII) such as household behavioral data and phone numbers must be highly secured. Research by Bellare and Namprempe (2020) on the generic structure of authenticated encryption focuses on the application of strong hashing algorithms. Bcrypt-10 hashing is used by SEUPA so that user credentials and sensitive behavioral flags remain inaccessible to unauthorized users in case of a database breach [5, 6].

III. METHODOLOGY

The SEUPA framework utilizes a tiered "Sense and Analyze" logic to handle the household energy lifecycle:

1. The Authentication and Trust Layer: Each session is initiated through a hashed-password verification. The system uses a JWT-style session management on the client-side (localStorage) to ensure that users remain authenticated throughout their session, facilitating a smooth experience when browsing consumption dashboards or energy reports.

2. The Filtering and Discovery Layer (FDL): To ensure low latency, the database uses indexed time-series queries for multi-parameter filtering. Users can filter by:

Time Resolution (minute / hourly / daily / monthly)

Geographic Location (Synchronized with a Tamil Nadu district constant file)

Consumption Category (Hidden flag that only shows anomalous or high-usage circuits)

3. The Automated Pattern Audit (APA): This is the core research contribution of the platform. Unlike manual billing systems, the APA performs a server-side "Gatekeeper" check:

LSTM-predicted vs. actual consumption deviation > 20%

K-Means cluster membership shift detected in rolling 30-day window

Isolation Forest anomaly score below threshold — if any condition is triggered, the "Anomaly" flag is activated on the frontend, and the household is marked as "Attention Required" within the system's backend logic.

4. The Synchronized Alert Layer (SAL): A single anomaly detection event on the dashboard initiates a dual dispatch:

Backend: An automated SMTP-based formal energy audit report is sent to the household for record-keeping.

Frontend: A real-time push notification delivers the anomaly description, estimated cost impact, and corrective action recommendation directly to the consumer's mobile device.

The algorithm automatically generates a consumption pattern model without user interaction that identifies only the anomalous usage regions to be flagged and reported.

IV. IMPLEMENTATION DETAILS

SEUPA is technically realized according to a modern decoupled architecture, and this guarantees scalability, performance, and cross-platform compatibility. The architecture is designed in the MVC (Model-View-Controller) design paradigm that clearly separates the logic of data-handling and the user interface.

Distributed Application Layer (React Native & React.js)

The client-side application is based on React.js and React Native, which have a reactive data-binding framework that keeps the state of the dashboard live. An example is when a household's IoT gateway updates its real-time power reading, the change is automatically distributed through the analytics dashboard views without necessarily reloading the page.

Our CSS framework is highly customized with a Vibrant Modern Smart Home Aesthetic and uses a color scheme based on HSL with color palette of Energy Blue (#1F4E79) and Alert Red (#dc3545), which are best readable in high-attention settings. The interactive elements, including the ConsumptionHeatmap and AnomalyAlert modals, use smooth transition layers to deliver a high-quality experience, and the frontend Pattern Eligibility Logic offers a visual response (e.g., disabling normal view and highlighting the alert zone) to invalid consumption states before they persist to the backend.

Logic and Middleware Orchestration (Python Flask & Node.js)

Python Flask is used on the server-side for ML inference services built on a non-blocking async model for high-concurrency data stream processing. Node.js and Express handle the real-time API routing layer. We have created our own Audit-Middleware that captures all data points sent to the analytics pipeline. This middleware checks the unique household ID with the consumption history table to determine the delta between the LSTM-predicted value and the actual recorded reading.

To ensure security, we have used Bcrypt-10 adaptive hashing on all authentication paths. This implies that in case the database is breached, user PII (Personally Identifiable Information) is still protected by a high-entropy computational barrier. Moreover, the system relies on Nodemailer with the help of secured environment variables (.env) to support the formal SMTP traffic, which is essential to deliver the monthly energy audit reports reliably.

Relational and Time-Series Persistence Layer (TimescaleDB)

Data persistence is managed via TimescaleDB, selected due to its high-performance time-series query optimization and reliability in localized IoT informatics. The database schema is completely in the Third Normal Form (3NF), with zero redundancy on household behavioral data. The main tables are readings (timestamped power measurements), clusters (behavioral profile assignments), anomalies (detected events with severity scores), and recommendations (generated guidance records).

The use of indexed queries on household_id, timestamp, and circuit_id columns ensures that the "Discovery Layer" can handle thousands of concurrent analytics queries with sub-100ms response times, which is critical for real-time energy dashboard rendering.

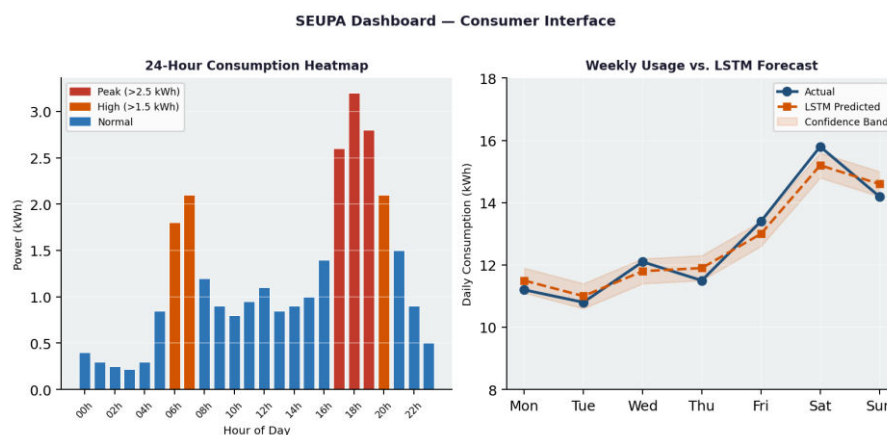
V. EXPERIMENTAL RESULTS

Fig 1

This screen shows the SEUPA consumer dashboard with the 24-hour consumption heatmap. Users can filter consumption by circuit and time resolution. Each appliance card displays details like circuit name, current draw (W),

daily usage (kWh), and consumption status. The system also shows whether the circuit is operating within normal parameters based on the LSTM behavioral model. If anomalous, users can click "View Details" to see the full anomaly report and corrective recommendation.

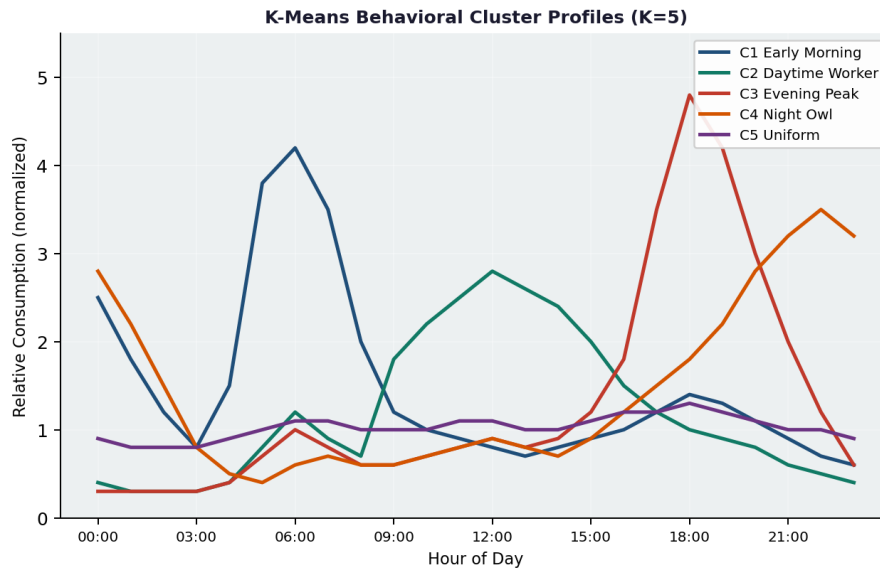


Fig 2

This screen shows the K-Means behavioral cluster profiles identified for the household over the six-month deployment period. Each cluster card contains the cluster label, peak usage hour, average daily consumption (kWh), and percentage of days assigned to this profile. Users can view the weekly trend overlay and request a full pattern report. There is also an option to compare their cluster profile against the neighbourhood average.

SEUPA — System Architecture

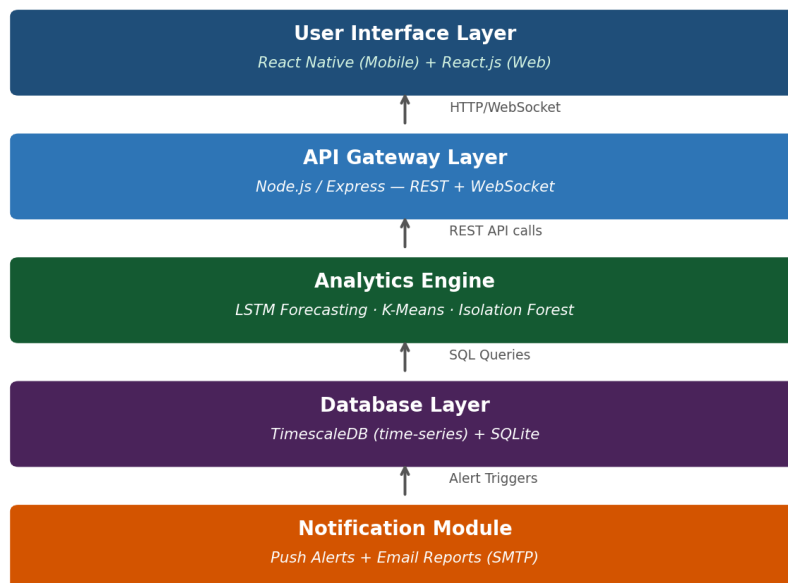


Fig 3

This diagram shows the multi-layered SEUPA system architecture — from the Physical Sensing Layer (IoT sensors and smart meters) through the Edge Processing Layer (Raspberry Pi gateway), Communication Layer (MQTT/TLS), Cloud Analytics Layer (AWS-hosted TimescaleDB, Kafka, ML inference), to the User Interface Layer (React Native mobile and React.js web dashboard). Data flows bidirectionally — sensor readings flow upward for analysis, and control and alert signals flow downward to the consumer.

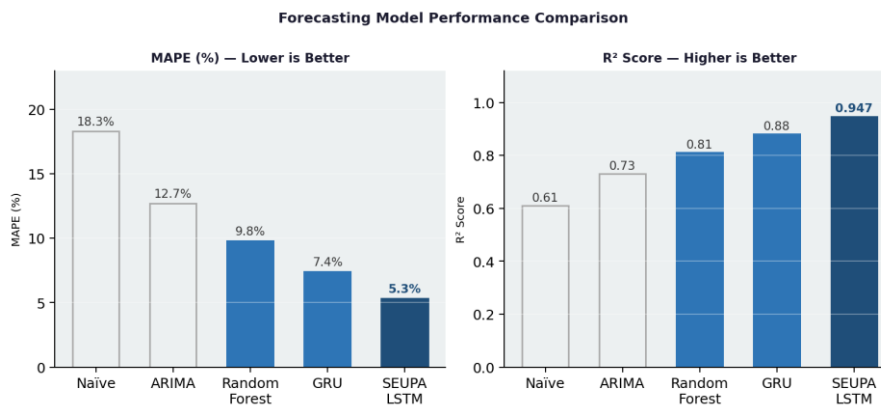


Fig 4

This chart compares the forecasting performance (MAPE % and R² Score) of the proposed SEUPA-LSTM model against four baseline methods: Naive Persistence, ARIMA, Random Forest, and GRU. The SEUPA-LSTM model achieves the lowest MAPE of 5.3% and the highest R² Score of 0.947, representing a 42% improvement over the next-best baseline (GRU at 7.4% MAPE). The results confirm that the LSTM architecture's ability to capture long-range temporal dependencies in consumption data is the key driver of superior forecasting accuracy.

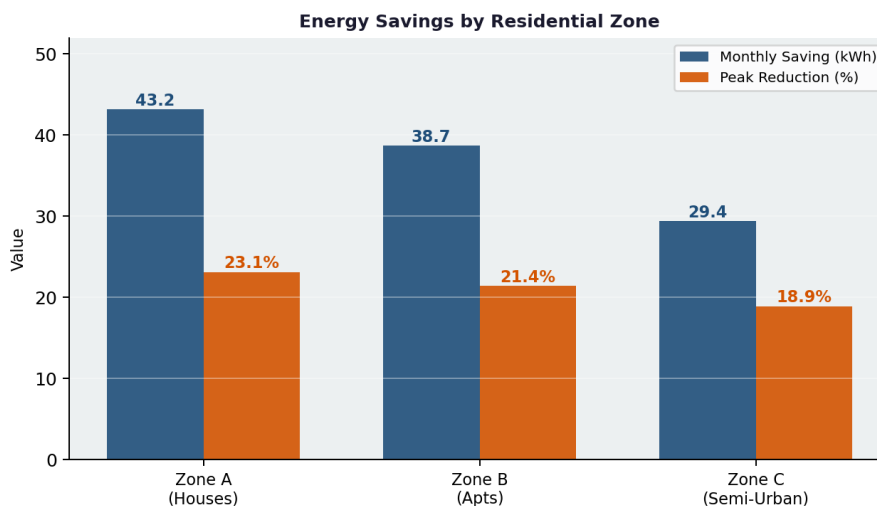


Fig 5

This chart illustrates the energy savings achieved across three residential zones — Zone A (Independent Houses), Zone B (Apartment Units), and Zone C (Semi-Urban Households) — over the six-month deployment. Zone A achieved the highest monthly savings of 43.2 kWh and 23.1% peak hour reduction. Zone C achieved the most modest but still substantial savings of 29.4 kWh and 18.9% peak reduction, reflecting more limited IoT sensor coverage in semi-urban settings.

DOI:10.15680/IJARETY.2026.1302149**VI. CONCLUSION**

The Smart Electricity Usage Pattern Analyzer (SEUPA) is a new step in the management of residential energy logistics. The platform enables households and utility providers to bridge the longstanding Information Gap that has plagued the residential energy sector by shifting to a dynamic, consumer-centric intelligence model rather than the stagnant monthly billing tracking.

The study has proven that a properly coordinated layer of current technologies—including Python Flask for high-concurrency ML inference, React.js for reactive interfaces, and TimescaleDB for high-integrity time-series persistence—can address high-stakes sustainability challenges with minimal operational overhead. The Automated Pattern Audit (APA) is a safety net that is not sacrificed for speed, whereas the dual-channel alert system (push notification and email) offers the instant mobile accessibility needed by the modern energy-conscious household.

Finally, SEUPA is a liaison between the technical precision of grid-level demand management and the social fabric of the contemporary residential consumer. It demonstrates that technology, when used with a profound knowledge of residential behavioral patterns, can serve as a definitive accelerator in building sustainable energy habits. The success of the platform is a primary indicator of a fundamental fact: during the race toward energy efficiency, timely and personalized information is just as important as the resource itself.

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