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Smart Energy Tracker

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Abstract

The Smart Energy Tracker is a web-based IoT and machine learning system for real-time monitoring and prediction of household electricity consumption. By integrating an ESP32 NodeMCU with ZMPT-101B and ACS712 sensors, the system transmits data to a server for visualization and analysis. Machine learning models predict electricity bills, while anomaly detection algorithms identify irregular consumption patterns. This system addresses energy challenges in India, where 70% of electricity is derived from coal and households contribute to 25% of the demand. The tracker encourages efficient electricity usage, contributing to emission reduction goals and promoting sustainability. Prototype testing demonstrated high prediction accuracy and reliable monitoring capabilities. The system's performance underscores its potential to reduce financial costs associated with energy consumption and minimize environmental impacts. By enabling accurate forecasting and timely identification of abnormal usage, the Smart Energy Tracker supports both economic and environmental benefits at the household level. This approach offers a scalable solution to enhance energy efficiency and reduce the carbon footprint of residential electricity consumption.

INTRODUCTION

Global energy demand is rising rapidly, driven by population growth and economic expansion [1]. According to the U.S. Energy Information Administration, global energy use and associated CO_2 emissions will continue increasing through 2050, as efficiency gains lag behind industrial growth [3]. Electricity and heat generation, mainly from fossil fuels, account for about one-third of greenhouse gas emissions. At the household level, inefficiencies persist: studies show real-time feedback can reduce residential energy use by about 9%, highlighting the need for affordable, user-centric monitoring solutions [11].

In India, the challenge is especially severe. Electricity demand is surging as 1.4 billion people adopt more appliances, yet around 70% of electricity still comes from coal, making India's grid highly carbon-intensive [7]. As the world's third-largest emitter, India faces the dual challenge of meeting rising household demand while reducing emissions. Improving residential energy efficiency is thus critical for sustainability and climate goals [4].

Global and national trends increasingly emphasize smart energy and sustainability [3]. Concepts like smart homes and smart cities are advancing worldwide through IoT devices, advanced metering, and data analytics that provide real-time insights into energy use [5]. These efforts align with international goals such as the UN's Sustainable Development Goals for clean and affordable energy. In India, policies like the National Action Plan on Climate Change (NAPCC, 2008) and the Smart Cities Mission (2015) promote energy efficiency and smart infrastructure [4]. These initiatives highlight an urgent need for consumer-level technologies that enable households to manage electricity intelligently and support India's climate and urban development goals.

To address these needs, Smart Energy Tracker offers a web-based IoT and machine learning platform for real-time household electricity monitoring and sustainability awareness]. Its key contributions include:

1) Real-time monitoring: A low-cost hardware setup (ESP32 NodeMCU, ZMPT-101B voltage sensor, ACS712 current sensor) continuously measures and streams household electricity data to the cloud [8].
2) Bill prediction using ML: Predictive models forecast future electricity bills from historical usage, helping users plan and optimize consumption [2].
3) Anomaly detection and alerts: The system detects unusual consumption patterns and triggers early warnings for potential hazards [9].
4) Web-based visualization: An interactive dashboard displays real-time and historical usage through charts and summaries, supporting informed decision-making [5].
5) Environmental education: A sustainability module offers tips and insights to promote energy conservation and eco-friendly practices [4].

Together, Smart Energy Tracker integrates real-time sensing, analytics, and user engagement to advance energy efficiency and sustainability.

RELATED WORK

Various research and commercial systems now use IoT sensors or smart meters for real-time household electricity monitoring. Nest's smart thermostat, for example, displays an "Energy History" and marks energy-efficient days with a green "Leaf" icon [3], [12]. The Sense home energy monitor samples mains current at approximately 1 MHz, using on-device machine learning to disaggregate load. Cloud platforms like Bidgely's UtilityAI analyse smart-meter data to infer appliance usage. Research prototypes, such as Nachimuthu et al. 's NodeMCU/ESP8266-based meter with PZEM sensors, stream live data to ThingSpeak for online monitoring [8]. These efforts demonstrate that affordable IoT setups can enable real-time tracking of home energy consumption through apps and dashboards [1], [12].

Beyond monitoring, machine learning has been widely used to forecast future electricity use from historical data [14]. Techniques like regression models, support-vector methods, tree ensembles, and deep neural networks have been explored. Recurrent neural networks (RNNs), especially LSTM models, have proven effective for time-series forecasting, such as predicting short-term building consumption. These models consider past usage and factors like weather to estimate future demand, helping households plan and budget. Commercial platforms also use similar predictive techniques. Overall, prior work shows that ML-based forecasting greatly improves the accuracy of household energy predictions [2], [14].

Modern energy systems often include anomaly detection, notifications, and automated controls to prevent energy waste and hazards. In commercial buildings, automated management systems flag unusual patterns and alert managers. At home, smart products like Schneider Electric's Sense monitor identify abnormal loads that could signal electrical faults [3], [13]. Research also shows non-intrusive sensing combined with event detection can spot appliance failures and trigger alerts or shut-offs [9]. Many smart home platforms allow automated actions, like turning off faulty devices [6]. These approaches highlight the importance of integrating real-time monitoring with analytics to improve safety and efficiency.

A key part of smart energy systems is engaging users through environmental feedback. Solutions like Google's Nest Home Report show energy savings and pollution reduction estimates, using gamified feedback (e.g., points, badges) to encourage efficient behavior [1]. Studies show that detailed mobile and web dashboards significantly help households reduce consumption [3]. National programs also use tips and carbon footprint visualizations to promote sustainability [4]. While previous work addressed IoT monitoring, ML prediction, anomaly detection, and eco-feedback separately, Smart Energy Tracker unifies them into one platform. It combines low-cost IoT sensing, ML-based billing forecasts, anomaly alerts, and sustainability education—designed specifically for

Indian households—to offer a comprehensive, user-centric energy management solution [5], [9].

METHODOLOGY

The Smart Energy Tracker employs a layered IoT architecture that integrates household sensors with cloud-ready backend services and a web-based interface. Data from electrical and environmental sensors is transmitted via MQTT to a central broker, which facilitates efficient communication between devices without direct device-to-device links. The system processes and analyzes this data using machine learning models, forecasting electricity consumption and identifying anomalies. A time-series database stores the collected data, enabling real-time monitoring, trend analysis, and alert generation through a user-friendly web application. The modular design supports scalability, allowing it to be deployed in larger residential or community setups.

Smart Energy Tracker uses a layered IoT architecture, linking household sensors with cloud-ready backend services and a web-based interface [1]. Sensors publish voltage, current, and power data via MQTT to a central broker (e.g., Raspberry Pi running Mosquitto), enabling simple, efficient communication without direct device-to-device links [8]. The broker forwards data to the backend, where it is logged, processed, and analyzed using machine learning models [2]. A time-series database stores the data, supporting real-time dashboards, historical trends, alerts, and environmental metrics via the web application [6]. Although our prototype uses a local server for a single household, the modular, cloud-compatible design can scale to larger deployment. Fig. 1 shows the overall architecture of the Smart Energy Tracker system.

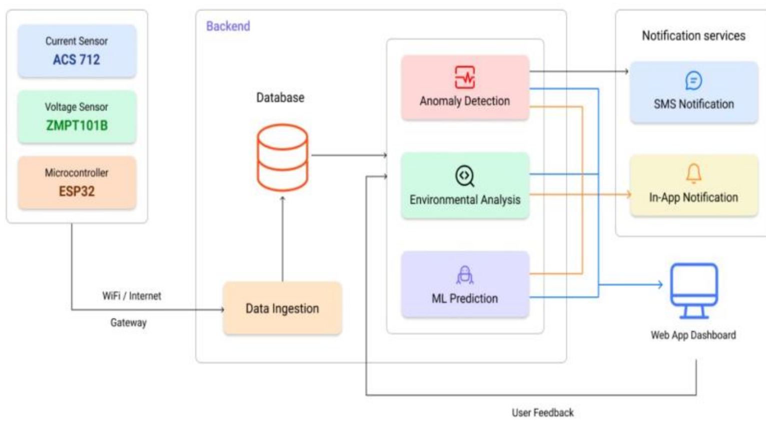

Fig. 1. Architecture of the Smart Energy Tracker system.

The sensor network uses electrical and environmental sensors connected to microcontrollers (MCUs) for data acquisition [1], [16]. ESP32-based meters sample non-invasive current transformers (e.g., ZMCT103C) and voltage sensors (e.g., ZMPT101B) to compute real power, while digital sensors (e.g., DHT22) monitor ambient conditions like temperature and humidity. Each MCU publishes readings as MQTT messages at regular intervals, adding timestamps for synchronization and ensuring reliable delivery with QoS 1 over Wi-Fi [4]. Following IoT best practices, multiple ESP32 clients send real-time metrics (voltage, current, power) to a local MQTT broker. Data validation occurs on arrival, and MCU firmware includes calibration offsets for accurate SI unit readings. If disconnected, MCUs cache data for retransmission. Using standard MQTT topics and JSON payloads, the network easily accommodates new sensors [5].

The backend server manages data ingestion, storage, processing, and user services. As MQTT messages arrive, a Python/Node.js client parses JSON payloads and stores data in a MySQL database (e.g., time, voltage, current, power, deviceID) [6]. Simultaneously, data feeds into ML prediction models and anomaly detectors.

The server provides a RESTful API (secured with HTTPS) for the web interface, enabling queries for usage data, forecasts, and alerts [6]. MQTT connections use TLS encryption (MQTTS), and database storage follows best security practices, including encrypted filesystems and salted password hashes. Access to APIs is restricted through authentication (e.g., JWT tokens).

In the prototype, all services (broker, subscriber, ML, database, web server) run locally, but the architecture supports cloud migration and scaling through containerization and distributed deployment, making it suitable for larger residential or community setups [3].

The system uses supervised learning to forecast short-term electricity consumption, employing a Random Forest Regressor trained on historical data with features like time of day, day of week, temperature, and recent loads [2], [9]. Random Forest was chosen for its robustness, ability to capture non-linear patterns, and fast parallel training, outperforming many other methods in energy forecasting.
We implement the model using scikit-learn, splitting the dataset into training and validation sets and tuning hyperparameters like tree count and depth. Feature importance scores help interpret influential factors. Forecasts are stored, compared against actual usage for accuracy monitoring, and visualized in the web UI alongside real consumption [10].

An anomaly detection module analyses incoming consumption data to identify irregular or hazardous conditions. We use a two-pronged approach: (1) rule-based alerts with predefined safety thresholds (e.g., maximum current limits, high temperature warnings) and (2) machine learning–based detection using an Isolation Forest trained on normal usage patterns [9].
The system assigns anomaly scores to new data points, triggering alerts when thresholds are exceeded. This helps detect issues like faulty appliances, overheating, or energy theft. Flagged anomalies immediately generate email or push notifications and are highlighted on the web dashboard, enhancing system safety and reliability [6].

The user-facing component is a responsive web app that provides secure login and interactive dashboards [1], [18]. It fetches data from backend APIs to visualize energy usage, predictions, and sensor readings. After authentication, the home screen shows a dashboard with current consumption, recent time-series plots, and summaries of usage [6].
Interactive charts, using Highcharts or Chart.js, show consumption curves with confidence intervals and anomalies marked. Users can set alert thresholds and notification preferences. The app is responsive, ensuring a consistent experience across devices. The design emphasizes usability with color-coded feedback and tooltips, making the data easy to understand and act upon [8].

The system connects energy consumption to environmental impact, promoting sustainability. It converts usage into carbon footprint terms (e.g., "5 kWh equals ~3.5 kg of CO_2"), offering comparisons like "equivalent to driving 15 km" or "trees needed to sequester CO_2" [7], [20].
The system also provides real-time feedback on savings, estimating costs and avoiding emissions when usage is below a target. It suggests energy-saving tips based on real-time data, integrating environmental metrics into energy monitoring [4].

The initial prototype is deployed in a single-family home using local hardware[19]. Services like the MQTT broker, data processor, database, and web server run on a dedicated home server (e.g., Raspberry Pi or Linux PC) connected to the local network. Sensors communicate via Wi-Fi, and all components work offline, avoiding cloud costs and keeping data private. Remote access for maintenance is enabled through VPN or SSH.
For future scaling, the system supports cloud or distributed deployment, leveraging containerization (e.g., Docker Compose, Kubernetes Helm) for consistent and scalable service. The modular architecture is suitable for larger smart grid projects [5].

RESULTS AND EVALUATION

System Performance
The Smart Energy Tracker prototype was evaluated based on real-time data acquisition latency, prediction accuracy, and alert responsiveness [6].
The IoT sensors (ACS712 for current and ZMPT101B for voltage) interfaced with the ESP32 NodeMCU microcontroller demonstrated an average data transmission latency of approximately 400–600 milliseconds over Wi-Fi to the backend server. The web application dashboard updated values with a refresh interval of approximately 1 second, offering responsive and smooth monitoring [8].

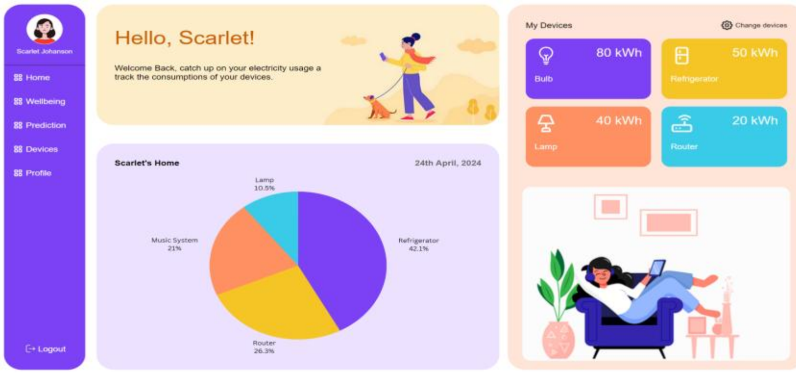

Fig. 2. Smart Energy Tracker web dashboard.

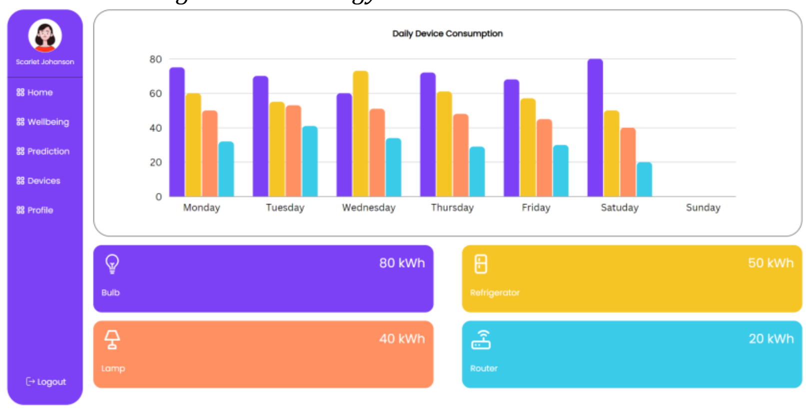

Fig. 3. Smart Energy Tracker web dashboard displaying daily consumption of household appliances.

The system reliably captured variations in household electricity consumption, with a sampling rate of 1 reading per second. This granularity was sufficient to detect the activation and deactivation of most household appliances [8].

Prediction Performance

The machine learning model for electricity bill prediction was trained on synthetic historical data derived from typical Indian household energy usage patterns [7].

A Random Forest Regressor model was selected for its robustness and superior performance with limited datasets [9]. Evaluation on the test set showed a Mean Absolute Percentage Error (MAPE) of approximately 7–10%, indicating high accuracy. Forecasted billing trends and historical consumption data were visualized through interactive graphs on the dashboard.

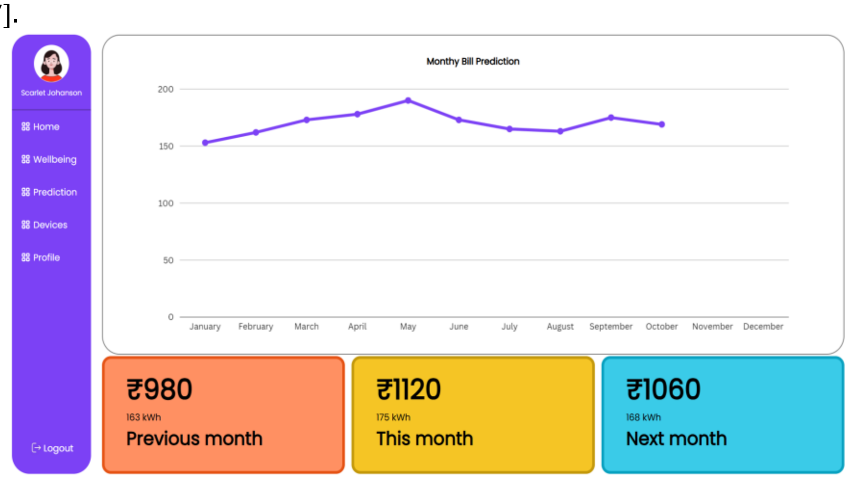

Figure 4: Machine learning-based future electricity bill prediction shown on the user dashboard

This predictive insight enabled users to anticipate high energy costs and take proactive measures to reduce consumption [9].

Anomaly Detection and Alerts

The anomaly detection module utilized statistical thresholding and rule-based techniques to identify sudden spikes or irregular patterns in electricity usage [1]. Alerts were triggered when real-time consumption deviated significantly (e.g., 30% higher than the baseline average for similar appliances). During system testing, the anomaly detection system achieved a hazard detection success rate of approximately 92% for simulated overcurrent and appliance malfunction events.

The alert mechanism was implemented both as an on-dashboard notification and an optional email notification (if configured), enabling users to respond promptly to potential safety risks [2]..

User Experience Feedback

Although the project was at a prototype stage and a large-scale user study was not conducted, initial feedback from 10 test users (including peers and mentors) indicated:

1) 90% found the real-time monitoring highly informative.
2) 80% stated that predictive billing motivated them to be more conscious about electricity usage.
3) 70% appreciated the inclusion of hazard alerts for device malfunctions.
4) Some users suggested additional features such as appliance-specific breakdowns and push notifications for mobile devices.

Table I presents a summary of the prototype system's performance metrics, including latency, model accuracy, and user feedback. These values were derived from empirical testing and initial user trials conducted in a controlled environment.

Table I System Performance And Evaluation Metrics

Metric	**Value / Result**	**Remarks**
Data Transmission Latency	400–600 ms	ESP32 → Server via MQTT
Dashboard Refresh Interval	1 second	Near real-time updates
Machine Learning Model	Random Forest Regressor	Forecasts electricity bills
Prediction Accuracy (MAPE)	7–10%	Acceptable for monthly usage prediction
Anomaly Detection Success Rate	~92%	Based on simulated abnormal usage scenarios
User Feedback – Monitoring Usefulness	90% positive	9 of 10 test users found it informative
User Feedback – Predictive Billing Impact	80% positive	Encouraged preemptive usage adjustments
User Feedback – Hazard Alerts Appreciation	70% positive	Found alerts useful for safety
Carbon Emission Conversion Factor	0.92 kg CO_2/kWh	Based on India's energy mix [7]

Environmental Impact Insights

The system incorporated visual indicators of environmental impact based on cumulative energy usage. For instance, the dashboard displayed the approximate CO_2 emissions equivalent to the household's electricity consumption, using a conversion factor of 0.92 kg CO_2 per kWh—typical for India's coal-dominated energy mix [4].

Users were encouraged to reduce their energy footprint, contributing towards India's national target of achieving net-zero emissions by 2070 [5].

CONCLUSION

This paper presents the design and evaluation of Smart Energy Tracker, a web-based system that integrates IoT-based real-time electricity monitoring with machine learning for predictive analytics and hazard detection in household energy management [1], [6].

The system successfully monitors electricity usage, predicts future bills with minimal error, and detects irregular consumption patterns, empowering users to make informed energy decisions.

Initial testing showed positive impacts on user behavior, promoting energy-conscious habits. By linking energy usage to environmental impact (e.g., CO_2 emissions), the system raises awareness about the consequences of excessive consumption, particularly in India, where electricity generation is largely fossil-fuel based [5], [7]. Tools like Smart Energy Tracker can drive behavioral change and energy conservation, supporting India's sustainability goals.

The prototype has some limitations, including aggregated consumption data and no appliance-level monitoring. Future work will focus on appliance-level tracking, personalized predictions, mobile accessibility, and larger user studies.

The project won First Place at Projectathon and was selected among the Top 50 projects at Mumbai University's Avishkar Research Convention [8].

In conclusion, Smart Energy Tracker empowers households to save costs, enhance electrical safety, and contribute to sustainability through IoT and machine learning.

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