An Intelligent Electricity Management Unit: AI-Driven Power Forecasting and Personalized Consumption Insights with Application Integration

R25-065

Project Proposal Report

Welikalage R.Y.W.

BSc (Hons) in Information Technology Specializing in Information Technology

Department of Information Technology

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Declaration

I declare that this is our own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made the text.

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Signature of the Co-Supervisor	Date

Abstract

The growing need for sustainable energy consumption in households has prompted the development of an Integrated Intelligent Electricity Energy Management Unit aimed at monitoring, predicting, and optimizing energy usage. This study focuses on addressing inefficiencies in household electricity consumption using IoT device tracking, machine learning forecasting, and generative AI for personalized recommendations. The research aims to empower users to enhance energy efficiency, reduce costs, and support environmental sustainability.

The system integrates four components: IoT devices for real-time usage monitoring, machine learning algorithms for analyzing consumption patterns, predictive models for forecasting energy use, and generative AI for providing personalized recommendations. A web application serves as an interface, offering actionable insights, interactive simulations, and progress-tracking dashboards.

The study involves collecting real-time data from IoT devices, developing machine learning models, and implementing generative AI for personalized suggestions. Real-time feedback and gamified features visualize energy savings, further engaging users.

Preliminary findings indicate that combining these technologies improves user engagement, fosters proactive energy management, and motivates behavior change.

In conclusion, the system overcomes existing energy management solution limitations by offering a user-centric, comprehensive platform that optimizes household energy use. This research aids sustainability efforts by encouraging households to adopt energy-efficient practices, reduce costs, and lower their carbon footprint.

Keywords – Sustainable energy consumption, IoT devices, Machine learning forecasting, Generative AI, Energy efficiency

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List Of Abbreviations

HEM	Home Energy Management
LLM	Large Language Model
AI	Artificial Intelligence
IoT	Internet of Things

Table 1. List of Abbreviations

1. Introduction

1.1 Background & Literature Survey

The increasing demand for electricity, rising costs, and growing environmental concerns have amplified the need for efficient and intelligent energy management systems in households. Current energy management solutions often fall short, primarily focusing on aggregated energy consumption metrics without offering granular insights into individual device usage. This lack of specificity leaves users unable to make informed decisions about optimizing their electricity consumption, leading to higher bills and increased environmental impact. Research in this domain has explored IoT-based systems for real-time energy monitoring, which enable device-level data collection and pave the way for more precise management of energy usage [1]. Similarly, predictive modeling techniques, including machine learning algorithms such as neural networks and decision trees, have been applied to energy consumption forecasting to improve accuracy and identify patterns in energy usage [2]. However, these systems typically fail to integrate intelligent feedback mechanisms that provide actionable recommendations tailored to the unique behaviors of individual users.

In parallel, advancements in artificial intelligence, particularly in the domain of generative AI, have introduced new opportunities for personalization in various fields. Large language models (LLMs), such as GPT-3 and GPT-4, have demonstrated remarkable capabilities in delivering context-aware and personalized suggestions across diverse domains, including healthcare, education, and e-commerce [3]. These advancements hold immense potential for revolutionizing energy management by leveraging real-time data to offer dynamic, user-specific recommendations that encourage energy-efficient practices. Furthermore, recent studies in personalized home energy management systems highlight the importance of integrating IoT, AI, and behavioral insights to promote sustainable energy use and optimize household energy consumption [4].

Despite these developments, a significant research gap remains in combining device-level energy monitoring, predictive analytics, and AI-driven personalized insights into a single, unified platform. The proposed research aims to address this challenge by developing an Intelligent Electricity Management Unit that integrates IoT-based real-time device monitoring, machine learning-powered time-series forecasting, and generative AI-driven recommendations. This system will not only enhance energy management but also empower users to make data-driven decisions that reduce electricity consumption, lower costs, and minimize carbon emissions. The user-friendly web application will serve as a central interface, displaying detailed energy analytics, predictive insights, and personalized recommendations through an intuitive design that emphasizes accessibility and ease of use. This holistic approach aligns with global sustainability goals by fostering energy-conscious behaviors while leveraging cutting-edge technologies like IoT, AI, and human-computer interaction principles.

By mastering IoT sensor networks, developing advanced machine learning frameworks for forecasting, applying generative AI techniques for personalized recommendations, and adhering to user-centered design principles, this research promises to contribute significantly to the field of home energy management while addressing critical environmental and economic concerns.

This research aims to bridge the gap in household energy management systems by integrating IoT-based real-time device monitoring, machine learning for predictive analytics, and generative AI to deliver personalized energy-saving recommendations. By leveraging advanced technologies and user-friendly interfaces, the proposed system seeks to empower users to optimize energy consumption, reduce costs, and contribute to global sustainability goals through informed and energy-conscious decision-making.

1.2 Research Gap

The integration of AI into HEMS has advanced significantly in areas such as energy forecasting, device-level monitoring, and basic energy-saving suggestions. However, significant gaps remain in developing a truly integrated and user-centric energy management system. Current solutions lack the ability to combine real-time IoT-based tracking, predictive energy forecasting, and generative AI for providing personalized recommendations that adapt to individual user behavior and preferences.

Study	Focus	Limitations
IoT-HEMS Framework (Singh et al., 2021) [5]	Real-time energy monitoring using IoT devices, providing notifications for energy-saving actions to optimize energy consumption.	Lacks advanced predictive models and fails to provide recommendations based on long-term user behavior or contextual data.
SmartHomeEnergyAI (Kumar et al., 2023) [6]	A generative AI-based approach for creating basic energy-saving suggestions tailored to general household patterns.	SmartHomeEnergyAI is limited in its adaptability and fails to incorporate real-time IoT data streams or simulate potential outcomes for user engagement.
Design and Implementation of Cloud-IoT-Based HEMS [7]	This study presents the design and implementation of a home energy management system (HEMS) that collects and stores energy consumption data using IoT devices.	While the system supports real-time monitoring and data storage, it does not integrate advanced machine learning models or provide personalized recommendations.
Real-time personalized energy saving recommendations (EM)3 [8]	This work introduces a recommendation engine that provides real-time personalized suggestions for energy saving, using sensors and actuators to monitor and control devices.	While (EM)3 supports real-time recommendations and user interaction, it relies heavily on user input for decision-making and lacks advanced predictive modeling for long-term optimization.

Table 2. System Comparison

Identified Gap:

1. Lack of Real-Time Personalization:
   Solutions like the Cloud-IoT-Based HEMS focus on real-time energy monitoring but do not provide actionable, personalized recommendations tailored to individual users' consumption behaviors.

2. Absence of Long-Term Adaptation and Learning:
   Systems such as the IoT-HEMS Framework and SmartHomeEnergyAI lack the capability to learn from historical user interactions or adapt recommendations over time, limiting their ability to evolve with user behavior.

3. Insufficient Context-Aware Recommendations:
   The (EM)3 Recommendation Engine provides real-time suggestions but does not integrate advanced contextual data like external environmental conditions or pricing structures for more impactful energy-saving advice.

4. Limited Predictive Modeling Capabilities:
   Studies such as the Design and Implementation of a Cloud-IoT-Based HEMS focus on forecasting or monitoring but fail to leverage predictive machine learning models for long-term optimization of energy consumption.

5. Fragmented Integration of Generative AI and IoT:
   While systems like SmartHomeEnergyAI employ generative AI, they do not integrate IoT data streams with predictive modeling or provide simulations of energy-saving outcomes, reducing engagement and practical value.

While current energy management systems lack real-time personalization, long-term adaptation, context-aware recommendations, and an integrated approach combining IoT, machine learning, and generative AI, the system proposed in this research aims to address these gaps. By integrating IoT-based real-time tracking, machine learning for energy forecasting, and generative AI-driven personalized recommendations, this project will deliver an efficient and adaptive energy management solution. This approach has the potential to significantly improve household energy optimization, encourage proactive user engagement, and contribute to long-term sustainability goals.

1.3 Research Problem

One of the major challenges in household electricity management is enabling users to monitor, predict, and optimize energy consumption for individual appliances effectively. Current systems lack the ability to provide granular, personalized, and actionable recommendations, leaving users unable to make informed decisions that can significantly reduce electricity costs and environmental impact. This research aims to address this gap by developing an integrated system that combines IoT-enabled device monitoring, predictive analytics, and generative AI to offer real-time, tailored insights for electricity management.

Problem Statement:

How can an intelligent energy management system be developed to provide personalized, real-time, and actionable recommendations for individual household appliances, and what impact does it have on optimizing electricity usage and fostering sustainable practices?

Key Features of the Research Problem:

1. IoT-Enabled Appliance Monitoring:
   The system will utilize IoT devices to measure and manage energy consumption at the individual appliance level, offering users precise control and insights into their usage patterns.
2. Predictive Analytics with Time-Series Models:
   Advanced machine learning models will predict future energy consumption patterns, enabling users to plan and optimize their electricity usage proactively.
3. Generative AI for Personalized Recommendations:
   A custom large language model (LLM) will analyze energy consumption trends and provide personalized, context-aware suggestions tailored to specific devices and user behavior.
4. Context-Aware Insights:
   The system will integrate external factors such as time-of-use tariffs, weather, and household occupancy patterns to deliver contextually relevant and actionable energy-saving recommendations.
5. User-Friendly Web Application**:**
   An intuitive web interface will display real-time data visualizations and actionable insights, ensuring effective human-computer interaction for energy optimization.

Significance of the Research Problem:

This research aims to revolutionize household energy management by addressing the limitations of existing systems and delivering a comprehensive, user-centric solution. The proposed system has the potential to empower users with the tools and insights needed to reduce electricity bills, minimize carbon footprints, and adopt sustainable energy practices. By leveraging IoT, machine learning, and generative AI, this tool not only enhances energy optimization but also contributes to global sustainability goals, making it a valuable innovation for future smart homes.

2. Objectives

2.1 Main Objective

The project aims to create an advanced Intelligent Electricity Energy Management Unit that helps households monitor, predict, and optimize electricity usage. This system will integrate IoT-based device tracking to monitor real-time energy consumption of appliances and devices. Machine learning algorithms will be used for energy forecasting, analyzing historical consumption data to predict future usage patterns, which enables proactive management. Additionally, generative AI will provide personalized recommendations based on individual household energy usage habits, suggesting ways to save energy and reduce costs. All of this will be accessible through a user-friendly web application, offering an intuitive platform for efficient energy management.

2.2 Specific Objectives

1. Data Collection and Preprocessing**:**
   1.1: Develop a robust data collection framework to gather real-time electricity usage data from IoT-enabled devices across various household devices.
   1.2: Clean and preprocess the collected data to ensure consistency and accuracy for subsequent analysis.
   1.3: Implement privacy and security protocols to safeguard user data during the collection and preprocessing phases.

2. Personalized Recommendation Model Development:
   2.1: Utilize AI algorithms to analyze individual electricity consumption patterns and identify key factors influencing energy usage.
   2.2: Design and implement machine learning models that provide tailored energy-saving recommendations based on user consumption habits, time-of-day usage, and appliance efficiency.
   2.3: Ensure the recommendation engine continuously learns from new data to refine its suggestions over time.

3. Model Validation and Fine-Tuning:
   3.1: Conduct extensive testing and validation of the AI models to ensure their recommendations are accurate, practical, and aligned with user preferences.
   3.2: Fine-tune the models by incorporating user feedback and real-world performance data, optimizing for energy efficiency and user satisfaction.

4. Energy-Saving Simulation and Visualization:

4.1: Develop an interactive simulation tool that allows users to visualize the potential energy savings and environmental impact of following the recommendations.
4.2: Incorporate gamification elements into the visualization tool to encourage user engagement, participation, and proactive energy-saving behaviors.

5. Generative AI Integration and Real-Time Recommendations**:**
    5.1: Seamlessly integrate the generative AI-based recommendation system into the platform for real-time, actionable suggestions on energy usage optimization.
    5.2: Ensure the system is adaptable and responsive to real-time data inputs, offering timely recommendations as user habits evolve.
    5.3: Enable accessibility features that make the platform easy to use for diverse user groups, fostering inclusive participation and promoting sustainability goals.

3. Methodology

3.1 Project Overview

The proposed system, **"Intelligent Electricity Management Unit"**, is designed to address the challenges of household energy management by integrating IoT-based monitoring, predictive analytics, and generative AI to offer personalized, actionable insights for efficient electricity usage. The system is comprised of the following capabilities:

- **IoT-Enabled Real-Time Monitoring:** Monitor electricity consumption of individual appliances and manage their usage through threshold-based controls.
- **Time-Series Analysis for Prediction:** Predict future electricity consumption patterns based on past usage trends using machine learning models.
- **Personalized Recommendations:** Generate tailored, actionable electricity-saving suggestions using a custom-built generative AI model (LLM).
- **Data-Driven Contextual Insights:** Incorporate factors like weather, time-of-use tariffs, and occupancy patterns to provide contextually relevant recommendations.
- **Web-Based User Interface:** Display analytical visualizations, real-time data, and AI-driven insights through an intuitive, user-friendly web application.

The proposed system will enable users to track energy consumption in real time through the web platform. Users will be required to input necessary details such as device configurations and thresholds for efficient energy management.

Additionally, the system empowers users by providing detailed energy-saving suggestions that are device-specific, promoting informed decision-making. The system's intuitive web application ensures that users can easily understand the insights provided, fostering proactive energy-conscious behavior.

By integrating IoT monitoring with machine learning and generative AI capabilities, the Intelligent Electricity Management Unit aims to help households reduce unnecessary electricity wastage, lower electricity bills, and contribute to sustainability goals. This innovative solution will act as a comprehensive tool for optimizing household energy usage and improving overall energy efficiency.

3.2 Requirement Gathering

The IoT device collects historical data by continuously monitoring appliances' power consumption (in watts) and timestamping each reading. This data is transmitted in real-time to a central database via communication protocols like Wi-Fi. Each record includes the device ID, timestamp, and wattage value, forming a comprehensive dataset. The data is then stored in a database for long-term analysis. Historical patterns, such as peak usage times or overconsumption trends, are derived from this data. It is used as input for a Generative AI model, delivering personalized energy-saving recommendations.

3.3 Feasibility Study

3.3.1 Technical Feasibility Study

1. Input Requirements

- Data Sources:
  - Real-time and historical energy usage data collected via IoT devices.
  - External datasets for electricity tariffs and seasonal consumption trends.
- Preprocessing:
  - Data cleaning to remove anomalies or incomplete records.
  - Normalization to standardize input data for the AI model.
- Data Storage:
  - Raw Data Storage: Stored in AWS DynamoDB, which provides scalability and fast read/write performance for IoT device data. External datasets for electricity tariffs and seasonal consumption trends.
  - AI Model Storage: The fine-tuned AI model is stored in an AWS S3 bucket for secure and efficient access during inference.

2. Generative AI Model

- Model Selection:
  - Use a pre-trained Large Language Model (e.g., Hugging Face Transformers) fine-tuned with domain-specific data for energy management.
  - Integrate features for contextual and numerical reasoning, enabling accurate energy-saving recommendations.

- Capabilities:
    - Generate personalized schedules and tips for energy usage based on user-specific patterns.
    - Adapt recommendations dynamically based on changing factors like time of day, seasonal demands, and tariffs.

3. Computational Requirements

- Infrastructure:
    - Using cloud platform named AWS is used for training and deployment due to high computational needs.
- Scalability:
    - Design the system to handle multiple user profiles simultaneously without latency.

4. Integration

- Web Application:
    - Integrate the AI module with the web application to deliver recommendations in real time.
- APIs:
    - Create APIs for seamless data flow between IoT devices, the database, and the AI module.
- Real-time Updates:
    - Ensure the AI module receives live data from IoT sensors for dynamic insights.

3.3.2 Economic Feasibility Study

1. Initial Development Cost:

- Covers the procurement of IoT devices, model fine-tuning, and AI system development, including data preprocessing and training.

2. Data Acquisition and Management:

- Costs for collecting, cleaning, and storing energy usage data via IoT devices, as well as external datasets (e.g., electricity tariffs, seasonal trends).

3. Infrastructure Setup:

- Initial setup of AWS services (S3 for model storage, DynamoDB for raw data) and cloud resources (e.g., GPUs/TPUs for model training).

4. Testing and Deployment:

- Includes testing the AI model, integrating it with IoT devices and the web application, and deploying the system to the cloud for real-time use.

5. Recurring Costs:

- Ongoing expenses for cloud services (data storage, model inference), API maintenance, and updates for system scalability and model retraining.

3.4 Testing

Testing is crucial to ensure the AI-driven system delivers personalized, accurate energy-saving recommendations. The testing strategy will include the following key approaches:

1. Unit Testing:
   - Objective: Test individual components (e.g., AI model functions, data preprocessing) to ensure correctness.
   - Tools: PyTest for Python algorithms.
2. Integration Testing:
   - Objective: Ensure different system parts, like the AI module, IoT device data, and web application, work together as expected.
   - Tools: Postman for API testing and integration scripts for CI/CD pipeline.
3. System Testing:
   - Objective: Test the complete system, from IoT data collection to real-time recommendation delivery via the web app.
   - Tools: Selenium for automated testing and manual tests for user experience validation.
4. User Acceptance Testing (UAT):
   - Objective: Confirm the system meets user needs, especially for energy-saving recommendations and ease of use.
   - Testing: Involve a small group of users for real-world feedback.
   - Tools: Feedback forms and surveys.
5. Performance Testing:
   - Objective: Ensure the system can handle the expected load and provide recommendations without performance issues.
   - Tools: JMeter for load testing and AWS monitoring tools for real-time performance tracking.

Test Phases

1. Alpha Testing: Internal testing by the development team, focusing on unit and integration testing.
2. Beta Testing: Testing with real users (e.g., homeowners) to identify issues missed in alpha testing.
3. Final Testing: Final validation, ensuring all bugs from previous phases are resolved before deployment.

3.4 System Overview Diagram

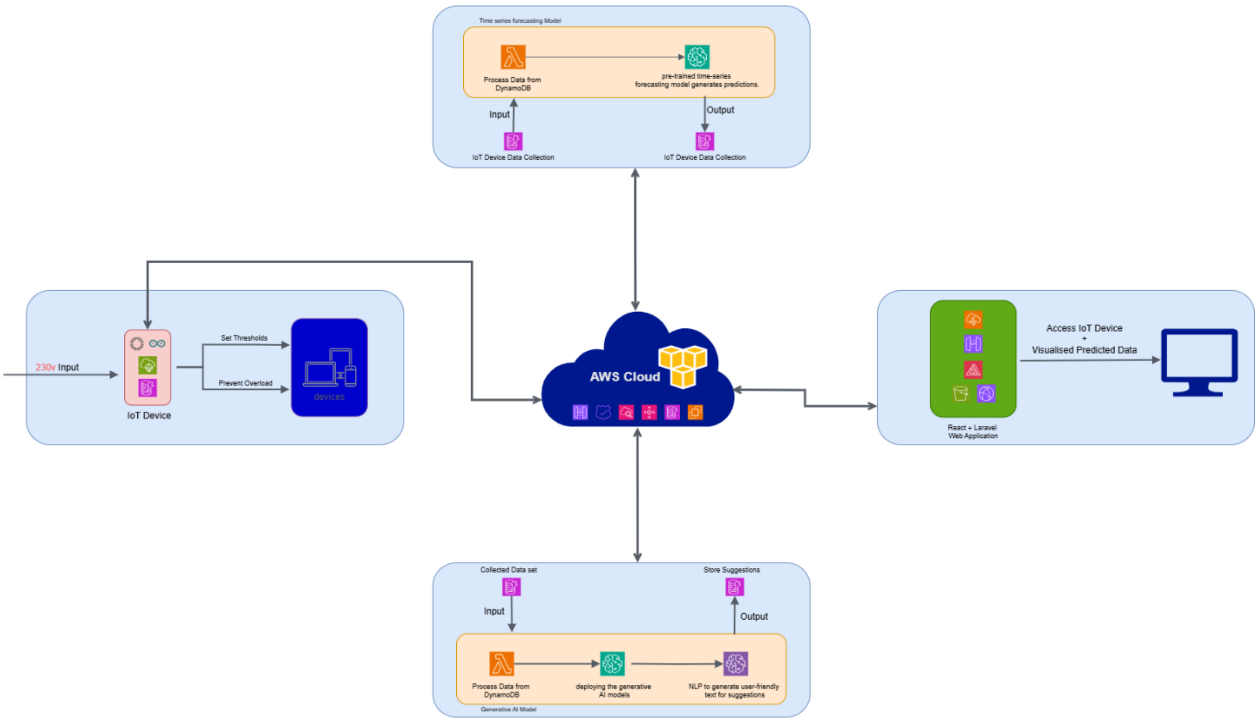

Figure 1.System Overview Diagram

3.5 Design Phase - Individual Component

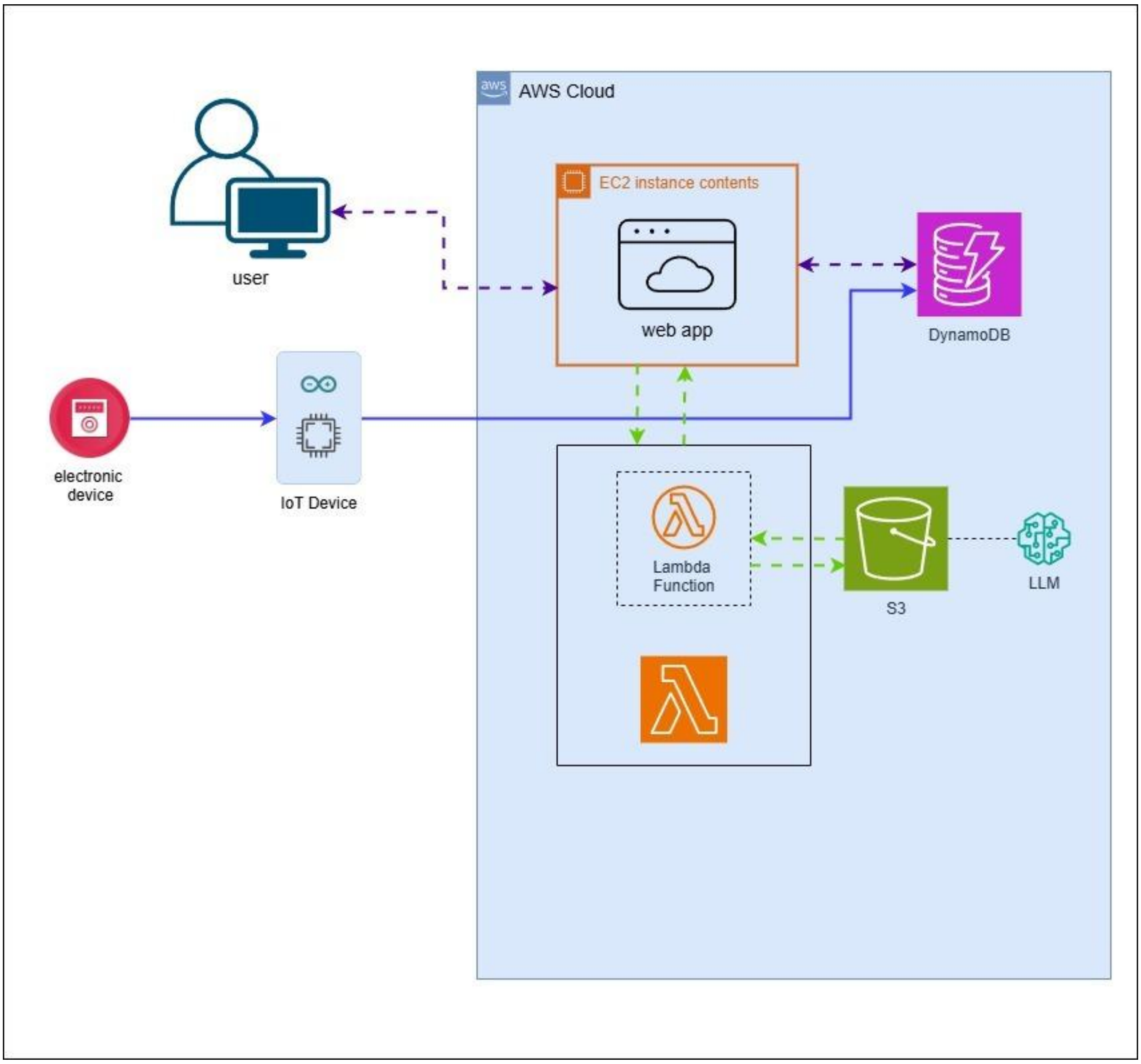

Figure 2.Individual Component Overview Diagram

3.6 Project Requirements

3.6.1 Functional Requirements

The functional requirements outline the specific behaviors and features that the **Generative AI-based Intelligent Electricity Management System** must perform to deliver personalized energy-saving recommendations tailored to individual user consumption patterns. These requirements focus on achieving the system's goal of optimizing electricity usage while encouraging sustainability and cost reduction.

1. Data Collection and Preprocessing

- Real-Time Electricity Usage Data:
  Collect electricity consumption data from IoT-enabled devices in real time.
- Data Cleaning and Transformation:
  Ensure raw data is cleaned, formatted, and organized for effective analysis.
- Integration with IoT Devices:
  Establish seamless connectivity with household IoT devices to gather device-specific consumption metrics.

2. Personalized Recommendation Engine

- User Behavior Analysis:
  Analyze individual energy consumption patterns and identify inefficiencies.
- Contextual Recommendation Generation:
  Use Generative AI models to create personalized, actionable energy-saving suggestions based on user-specific consumption data, time-of-use tariffs, and external factors (e.g., weather, occupancy).
- Dynamic Adjustment:
  Continuously refine recommendations based on updated consumption data and user feedback.

3. Model Validation and Fine-Tuning

- Performance Testing:
  Test AI models on diverse data sets to ensure accuracy and reliability.
- Iterative Improvement:
  Regularly validate and optimize the AI models to improve the quality and effectiveness of recommendations.

- Error Handling:
  Incorporate mechanisms to address anomalies or inaccuracies in energy usage data.

4. Simulation and Visualization of Outcomes

- Interactive Simulations:
  Provide users with visualized scenarios of potential energy savings based on implementing recommendations.
- Outcome Prediction:
  Display estimated reductions in electricity bills, energy usage, and carbon footprint through intuitive graphs and charts.
- User Feedback Integration:
  Allow users to evaluate and customize recommendations based on simulated outcomes.

5. Generative AI Deployment

- Real-Time Recommendations:
  Integrate AI models into the system pipeline to generate recommendations dynamically in response to live energy usage data.
- Scalable Architecture:
  Ensure the system can handle multiple users and large volumes of IoT data efficiently.
- Energy-Saving Gamification:
  Incorporate gamification elements, such as badges or progress trackers, to motivate users to implement recommendations.

3.6.2 Non-Functional Requirements

The non-functional requirements define the quality attributes, performance benchmarks, and constraints that ensure the **Generative AI-based Intelligent Electricity Management System** is efficient, reliable, secure, and user-friendly. These factors are essential for achieving the system's objectives and delivering optimal user experience.

1. Accuracy

- High-Precision Analytics:
  Ensure AI models deliver highly accurate energy-saving recommendations tailored to individual user consumption patterns.
- Error Minimization:
  Implement robust validation mechanisms to minimize inaccuracies in data collection, analysis, and recommendation generation.

2. Performance

- Real-Time Data Processing:
  The system should process electricity usage data and generate recommendations with minimal delay to support real-time decision-making.
- Low Latency:
  Maintain system responsiveness below 500ms for data visualization, recommendation updates, and simulations to enhance user engagement.

3. Scalability

- Flexible Architecture:
  Design the system with a modular and scalable architecture to accommodate growing user bases and integrate new features or data sources without performance degradation.
- Cloud Integration:
  Leverage cloud infrastructure to handle large volumes of electricity usage data from IoT devices efficiently.

4. Security

- Data Encryption:
  Ensure all user data is encrypted during storage and transmission to maintain privacy and confidentiality.
- Access Control:
  Implement role-based access control to ensure only authorized users can access sensitive data and system features.

5. Reliability

- Error Handling:
  Incorporate robust error detection and recovery mechanisms to ensure system stability during unforeseen issues, such as data transmission failures or model errors.
- High Availability:
  Design the system for 99.9% uptime to ensure consistent availability for users.

6. Maintainability

- Modular Codebase:
  Develop the system with a modular codebase to facilitate easier updates, debugging, and component replacements without disrupting the overall functionality.
- Comprehensive Documentation:
  Provide detailed documentation, including system architecture, user guides, and troubleshooting manuals, to assist developers and administrators in managing and upgrading the system.
- Automated Testing:
  Implement automated testing frameworks to regularly test bugs, vulnerabilities, and performance issues, ensuring the system remains robust over time.

3.7 Work Breakdown Structure and Gantt Chart

3.7.1 Work Breakdown Structure

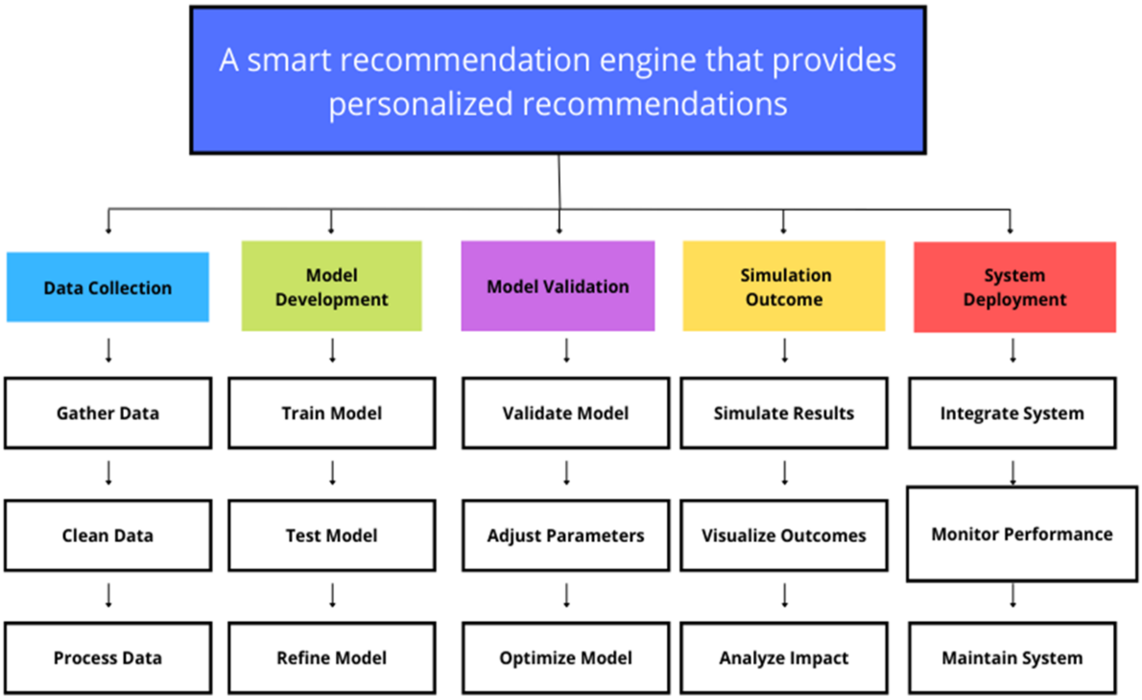

Figure 3. Work Break Down Chart

1. Requirement Gathering (January - March)

Task Breakdown:

- Collect electricity usage data from IoT devices.
- Finalize the project scope and system requirements.
- Prepare a detailed project plan and allocate resources.

Key Milestones:

- Data collection will be completed by the end of February.
- Project scope and requirements finalized by mid-March.
- Project plan approved by end of March.

2. System Design (March - May)

Task Breakdown:

- Design system architecture.
- Design front-end framework and back-end services.
- Design AI models and algorithms for recommendations.
- Finalize database structures (e.g., MongoDB, DynamoDB).

Key Deliverables:

- Finalized system architecture by mid-April.
- AI model and algorithm designs completed by the end of April.
- Database structures are finalized by the end of May.

3. Implementation (May - August)

Task Breakdown:

- Develop front-end using React.
- Develop back-end services with Node.js and Express.
- Integrate AI models into the system.
- Set up database and cloud infrastructure on AWS.

Key Milestones:

- Front-end development will be completed by the end of June.

- Back-end services implemented and tested by the end of July.
- AI model integration is completed by the end of August.

4. Testing and Refinement (August - October)

Task Breakdown:

- Perform unit, integration, and user acceptance testing.
- Optimize AI models and refine the system based on feedback.
- Enhance system performance and user experience.

Key Milestones:

- Initial testing phase completed by mid-September.
- AI model optimization will be completed by the end of September.
- Final refinements and performance optimizations are completed by the end of October.

3.7.2 Gantt Chart

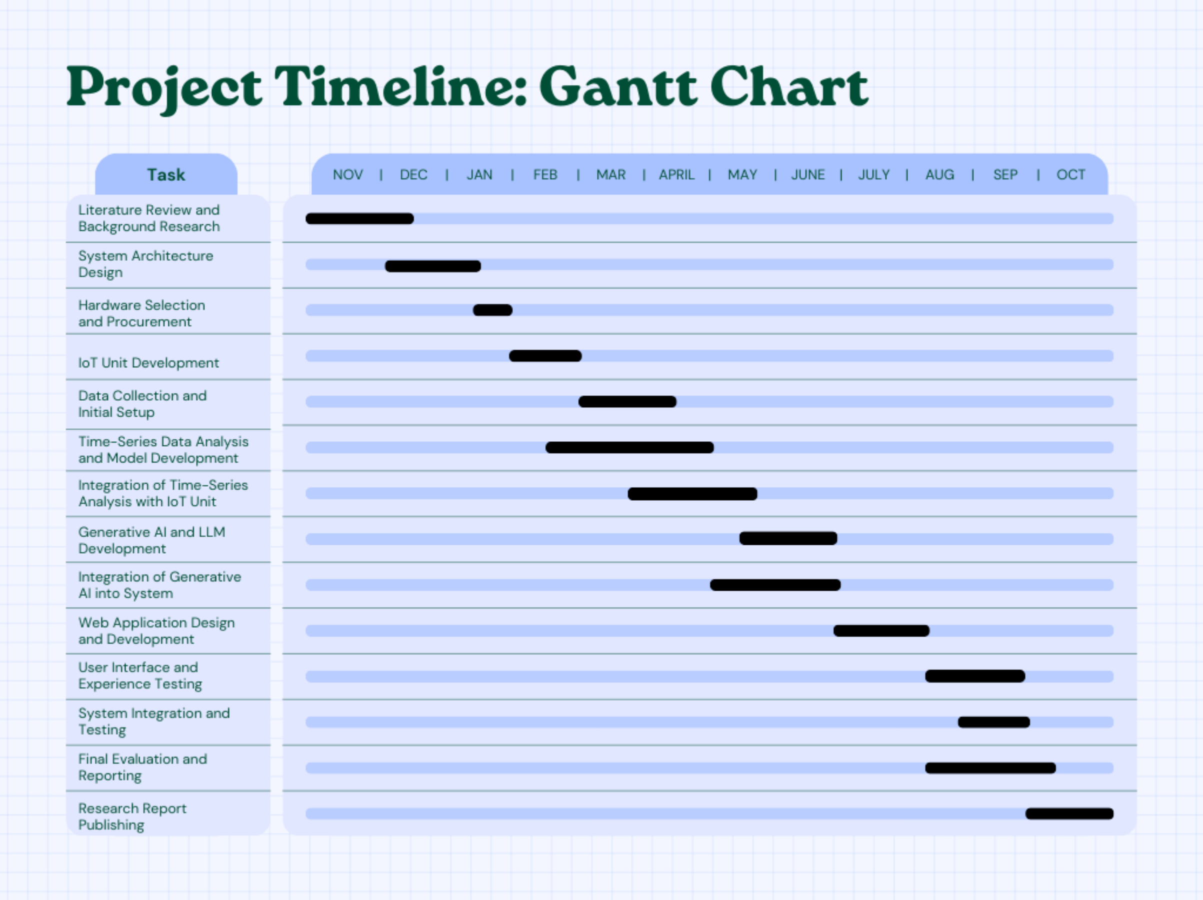

Figure 4.Gantt Chart

3.8 Deployment, Marketability and Commercialization

Deployment

- Model Integration: Deploy the trained Generative AI model into the website to provide real-time energy-saving recommendations.
- Platform Launch: Ensure the AI system is integrated seamlessly into the website or app, allowing users to access personalized suggestions.
- Ongoing Updates: Regularly update the AI model based on new data and user feedback to improve recommendation accuracy.

Marketability

- Unique Selling Proposition: Promote the AI's ability to offer personalized, data-driven energy-saving suggestions tailored to individual consumption patterns.
- Target Market: Market the AI solution to tech-savvy homeowners, energy-conscious users, and businesses looking to optimize energy usage.
- Marketing Channels: Use online marketing, social media, and partnerships with eco-conscious brands to reach potential customers.

Commercialization

- Subscription Model: Offer the AI-powered recommendations as part of a subscription-based model for continuous access to personalized insights.
- Freemium Model: Provide basic recommendations for free, with advanced AI-driven features available for premium users.
- Partnerships: Collaborate with energy providers or smart home brands to integrate the AI system into broader ecosystems or offer as a bundled service.

4. Description of Personal and Facilities

Member	Component	Task
Welikalage R.Y. W	Implement a Generative AI-based system to provide personalized energy-saving recommendations tailored to individual user consumption patterns.	Gather real-time electricity usage data from IoT devices and preprocess it for analysis.
		Develop AI models (e.g., supervised learning, deep learning) to generate personalized energy-saving recommendations based on user consumption patterns
		Test and refine the AI models to ensure they provide accurate, relevant, and actionable energy-saving suggestions.
		Create simulations that show potential energy savings based on user actions.
		Integrate AI models into the energy management system to provide real-time, personalized recommendations.
		Use real-time user feedback to continuously improve the AI models.
		Implement the energy-saving recommendation system in a scalable production environment for broad user access.
		Detection of the object and the child's head using an object detector
		Generate personalized reports automatically based on user behavior and energy savings over time

Table 3.Description of Personal and Facilities

5. Budget and budget justification (if any)

Resource	Cost
Hardware:	
Microcontroller	1800 LKR
Current Sensor (ACS712)	800 LKR
Voltage Sensor (ZMPT101B)	550 LKR
Relay Module (5V Single Channel Relay)	300 LKR
LEDs and Buzzer (Standard LED + Buzzer)	250 LKR
DC Power Adapter (5V/3.3V DC Adapter)	1700 LKR
Cloud Services:	
IoT Core	\$5–10/month
DynamoDB	\$5–10/month
Lambda	\$2–5/month
S3	\$3–5/month
CloudWatch	\$1–3/month
API Gateway	\$2–5/month
Others:	
Internet	7000 LKR
Travelling	10000 LKR
Other	8000 LKR

Table 4.Budget Table

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