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

R25-065

Project Proposal Report

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BSc (Hons) in Information Technology Specializing in 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

Driven by the growing need for household energy efficiency and sustainability, this research introduces a novel, IoT-based home energy management system with integrated time series analysis and fault detection. This system empowers users to monitor, manage, and control electricity consumption at the device level while also predicting future energy usage and identifying potential appliance faults. Users can define monthly usage thresholds for individual appliances, which the system enforces through automated power cut-off mechanisms. An emergency override is accessible through a user-friendly web application.

The system leverages IoT-enabled hardware for real-time energy monitoring, AWS cloud services for secure data storage and communication, and advanced machine learning techniques for time series analysis and anomaly detection. By forecasting energy consumption and detecting deviations indicative of faults, the system enables proactive energy management and maintenance, preventing waste and unexpected costs. A web-based interface offers interactive control, detailed insights, and threshold management for individual appliances.

This research distinguishes itself through its predictive analytics, fault detection capabilities, user-centric design, and secure, scalable cloud integration, addressing limitations in existing systems. Preliminary testing indicates the system's potential to significantly enhance household energy management by reducing waste, improving appliance efficiency, and promoting sustainable practices.

In summary, this IoT-driven solution provides a comprehensive, intelligent, and intuitive energy management platform. By combining real-time monitoring, predictive analytics, and fault detection, it empowers households to adopt efficient consumption habits, minimize costs, and contribute to environmental sustainability.

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List of Abbreviations

ML	Machine Learning
AI	Artificial Intelligence
HEMS	Home Energy Management System
IoT	Internet of Things
ARIMA	Auto Regressive Integrated Moving Average
AWS	Amazon Web Services
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
SSL	Secure Sockets Layer

Table 1- List of Abbreviations

1. Introduction

1.1 Background & Literature Survey

With the global surge in energy demand and escalating electricity costs, effective energy management has become a pressing issue for both households and businesses. The economic aftermath of the COVID-19 pandemic has further underscored the importance of cost-efficient solutions to track and control energy usage. Smart home technologies, powered by the Internet of Things (IoT), artificial intelligence (AI), and machine learning (ML), have emerged as viable tools for addressing these challenges, enabling automation, real-time monitoring, and optimized energy consumption.

Existing Home Energy Management Systems (HEMS) tend to focus on overall household energy usage but often lack the capability to monitor energy consumption at the device level. This limitation prevents users from pinpointing appliances that consume excessive energy, making it difficult to take targeted actions to reduce costs. For rental property owners, the inability to track energy consumption per tenant poses challenges in managing electricity usage and billing, often resulting in disputes or inefficiencies. Current systems fail to provide solutions for allocating energy consumption based on tenant payments, leading to uncontrolled usage and financial discrepancies.

Previous researches on IoT-based energy management systems and smart home automation highlights the potential to reduce energy costs by integrating renewable sources like solar and wind power. However, existing studies reveal persistent challenges in achieving seamless integration of renewable energy with grid power, especially in balancing distribution and storage. Furthermore, there is a growing demand for user-centric, flexible energy management solutions that are tailored to individual needs while remaining scalable for larger applications, such as rental properties or shared accommodations.

This research aims to address these shortcomings by developing an IoT-enabled smart Home Energy Management System (HEMS) that provides granular, device-level energy monitoring and control. The system will enable users to track energy usage for individual appliances, set consumption limits, and allocate energy based on predefined budgets, making it especially suitable for rental settings. Incorporating AI and ML technologies, the system will offer predictive analytics and actionable energy-saving recommendations based on historical usage patterns.

Building on prior studies, this research introduces innovative features such as tenant-specific energy allocation and real-time device-level energy control. By leveraging advanced IoT and AI-driven technologies, the proposed system empowers users to make informed energy decisions, enhance cost-efficiency, and contribute to a more sustainable and transparent energy management ecosystem.

1.2 Research Gap

IoT-driven smart home energy management systems have advanced in real-time monitoring, user customization, and predictive modeling, improving energy efficiency, cost savings, and sustainability. However, a gap remains in integrating device-specific fault detection, advanced time series forecasting, and robust anomaly detection. Current approaches lack dynamic adaptation to changing energy usage and proactive identification of appliance failures, crucial for optimized consumption and fault prevention. Furthermore, the lack of seamless integration between IoT data and predictive analytics limits scalability and personalization for diverse smart home environments.

Study	Focus	Limitations
Data Analytics Challenges and Needs in Smart Grid for Smart Energy Management (Deepa K.R. et al., 2024)	This study explores the role of machine learning in smart grid demand response management, focusing on methods to balance energy supply and demand, identify system faults, and enhance energy efficiency through predictive analytics and big data tools.	While the study addresses demand response and big data analytics, it lacks focus on device-specific fault detection and the application of ARIMA models for time series analysis of energy consumption. Its primary focus is grid-level analytics, rather than appliance-specific anomaly detection for energy optimization.
Machine-Learning-Based Home Energy Management Framework via Residents' Feedback (Ebrahimi et al., 2024)	This work presents a smart home energy management system using artificial neural networks (ANN) and user feedback to prioritize energy cost and comfort. It emphasizes adaptive learning based on user dissatisfaction metrics for optimized energy usage.	While prioritizing comfort and cost optimization, this study lacks a robust focus on time series analysis, appliance fault detection, and the predictive capabilities of IoT data for anomaly identification. It also does not explore using ARIMA models for forecasting energy consumption.
Development of IoT-Based Smart Home Application with Energy Management (Prathyusha M.R. et al., 2023)	This research proposes an IoT-enabled smart home model with automated energy management for optimizing power consumption. It incorporates simulation and hardware design to monitor and analyze energy usage across devices.	While the study provides insights into energy consumption and hardware modeling, it does not address time series forecasting, anomaly detection, or the integration of ARIMA and IoT for predictive fault detection. Its focus is primarily on energy efficiency and

		system automation, rather than predictive analytics or device-specific anomaly management.
IoT Infused Residences: Advancements into Smart Home Energy Monitoring Systems (Bharadwaj K.S. et al., 2024)	This research develops a Smart Home Energy Management System (SHEMS) that leverages smart plugs, Bluetooth communication, and an API for real-time, device-level energy consumption monitoring. The study emphasizes data integrity and user empowerment through graphical trends and actionable energy usage insights.	While the system effectively monitors energy consumption and provides user-friendly interfaces, it does not incorporate predictive capabilities such as time series forecasting or anomaly detection using ARIMA. Furthermore, it does not address device-specific fault detection or proactive energy optimization strategies based on IoT data analytics.
IoT-Driven Energy Consumption Optimization in Smart Homes (Loganayagi S. et al., 2024)	This study explores IoT-based energy optimization, emphasizing user customization and predictive modeling to reduce energy consumption and carbon emissions. It incorporates machine learning to anticipate energy trends and evaluates the integration of privacy safeguards, interoperability, and sustainability.	While the study achieves commendable results in predictive energy optimization, it does not focus on detailed fault detection mechanisms for individual devices. The research also lacks the integration of ARIMA modeling for granular time series analysis, leaving out advanced techniques for anomaly detection in energy patterns.

Table 2- Research Gap

Identified Gaps:

1. Lack of Device - Specific Fault Detection and Prediction:

Existing systems such as *IoT-Infused Residences: Advancements into Smart Home Energy Monitoring Systems* focus on real-time monitoring and trend analysis but do not integrate fault detection mechanisms tailored to individual devices. This gap limits their ability to prevent appliance malfunctions proactively.

2. Absence of Advanced Time Series Forecasting Models

Research such as *IoT-Driven Energy Consumption Optimization in Smart Homes* relies on machine learning for energy optimization but does not utilize ARIMA or similar models for precise time series forecasting. This omission hinders the system's ability to predict energy consumption patterns accurately

3. Limited Anomaly Detection for Energy Usage

Studies like *Machine-Learning-Based Home Energy Management Framework via Residents' Feedback* highlight optimization through user feedback but fail to include robust anomaly detection methods to identify unusual energy consumption patterns in real time.

4. Insufficient Proactive Energy Optimization

Current frameworks focus on retrospective analysis and static settings for energy efficiency (e.g., *Development of IoT-Based Smart Home Application with Energy Management*). They do not dynamically adapt energy consumption settings using predictive insights derived from IoT data, reducing their efficiency in dynamic environments.

5. Lack of Integration Between IoT Data and Predictive Analytics

Many existing solutions emphasize data collection and visualization but do not fully exploit the integration of IoT-generated data with predictive models to provide actionable, user-centric recommendations for energy optimization and fault prevention

1.3 Research Problem

A key challenge in optimizing energy use and reducing costs, especially in shared living spaces like boarding houses, is the lack of transparency in individual device energy consumption. Generalized billing systems can lead to inaccurate and unfair charges, while undetected appliance inefficiencies can result in excessive energy waste and system failures. This research addresses this gap by proposing a time series analysis and fault detection system. This system will predict future energy usage and identify device performance anomalies, enabling proactive energy management and more equitable billing.

Problem Statement

How can a time series analysis and fault detection system be developed to predict device-specific energy consumption and identify appliance faults, and what impact does this have on energy efficiency and transparency in billing?

Key Features of the Research Problem

1. **Accurate Energy Consumption Predictions:**
   The proposed system uses ARIMA-based time series modeling to forecast device-specific energy usage. This enables users to plan their electricity consumption effectively, reducing unexpected costs.

2. **Device Fault Detection:**
   The system continuously monitors energy consumption and compares real-time data to predicted values, identifying anomalies that signal faulty appliances. Early detection minimizes energy wastage and maintenance costs.

3. **Transparency in Shared Billing:**
   For boarding houses or shared accommodations, the system provides detailed insights into device-specific energy usage, ensuring tenants are charged fairly based on actual consumption rather than generalized estimates.

Significance of the Research Problem

This component is significant because it addresses the growing demand for energy efficiency and transparency in an era of rising electricity costs. By leveraging ARIMA-based time series analysis and anomaly detection algorithms, the system empowers users to make informed decisions about their energy consumption, reducing costs and environmental impact.

Additionally, it ensures fairness in shared accommodations, enhancing tenant satisfaction. The proposed solution not only contributes to sustainable energy management but also sets the stage for future advancements in smart home technologies.

2. Objectives

2.1 Main Objective

Develop a time series analysis and fault detection system to accurately predict energy consumption and identify device-specific usage anomalies, optimizing energy efficiency and preventing appliance faults. Leveraging ARIMA modeling, anomaly detection, and IoT data, the system will provide actionable insights, empowering users to proactively manage energy consumption and reduce costs.

2.2 Specific Objectives

The following specific objectives for the time series analysis and fault detection system aim to optimize energy efficiency and proactively identify appliance faults for effective energy management. Each will be carefully addressed during system design and implementation to ensure accuracy, reliability, and usability.

1. Development of Time Series Analysis for Energy Prediction:

1.1: Design and implement an ARIMA model to predict individual appliance energy consumption based on historical data.

1.2: Incorporate seasonal and daily usage patterns to enhance predictive accuracy.

1.3: Evaluate model performance using metrics like MAE and RMSE to ensure accurate and actionable forecasts.

2. Implementation of Fault Detection Mechanisms:

2.1 Develop rule-based anomaly detection logic to identify significant deviations between actual and predicted energy consumption.

2.2 Classify anomalies (e.g., excessive/reduced usage) to pinpoint potential appliance faults.

2.3 Establish anomaly persistence thresholds to distinguish between transient and long-term faults.

3. Integration with IoT Devices for Data Collection:

3.1 Ensure seamless integration with the IoT device for real-time appliance energy consumption data collection.

3.2 Standardize data formats and preprocessing for efficient input into prediction and detection models.

3. Methodology

3.1 Project Overview

The "Time Series Analysis and Fault Detection" component of this project focuses on developing advanced analytics for device-specific energy monitoring and anomaly detection. Integrated within the Intelligent Electricity Management Unit, this component aims to optimize electricity consumption and enhance user transparency.

This component is comprised with following capabilities:

- Predictive Energy Forecasting: Utilize an ARIMA-based time series analysis model to forecast individual appliance energy consumption based on historical IoT data.
- Fault Detection: Implement an anomaly detection mechanism to identify appliances with irregular energy consumption patterns, indicating potential faults.
- Real-Time Insights: Provide users with actionable insights on predicted energy usage and detected anomalies through an intuitive dashboard or mobile application.
- Optimized Energy Management: Empower users to proactively manage their electricity consumption, preventing unexpected costs and promoting efficient appliance usage.

Real-time energy consumption data is collected for each appliance by IoT devices, including timestamps, device IDs, and units consumed. This data is then used by the ARIMA model to predict future energy usage trends, considering patterns such as daily cycles or seasonal variations. These predictions empower users to plan their energy consumption effectively.

Fault detection logic continuously compares real-time energy usage with predicted values, triggering alerts for persistent deviations (e.g., spikes or drops in usage) to help identify appliance faults early.

Users receive detailed insights via a dashboard or web application, including predicted energy usage for the next day/week and fault alerts with possible causes and recommended actions, enabling prompt action to reduce energy waste and costs.

3.2 Feasibility Study

3.2.1 Technical Feasibility

To ensure the successful development of time series analysis and fault detection functions for the Home Energy Management System (HEMS), this component will prioritize technologies that align with the team's expertise. The proposed system will leverage advanced data analysis tools, machine learning frameworks, and cloud services. A summary of the most crucial technologies and their relevance to the project follows.

1. Time Series Modelling: ARIMA

ARIMA (AutoRegressive Integrated Moving Average) is a statistical method for forecasting time series data. Python's Statsmodels library will be used for efficient implementation and analysis. ARIMA models are well-suited for handling time series data with trends and seasonality, common in household energy consumption and to predict energy usage trends for individual appliances.

2. Data Handling and Pre-processing:

Pandas and NumPy will be utilized for data manipulation and numerical operations. These libraries will be instrumental in cleaning, normalizing, and preparing energy consumption data collected from IoT devices.

3. Visualization:

Matplotlib will be used for static visualizations to evaluate model performance, while Plotly will be used for creating interactive dashboards to display energy predictions and fault detection alerts.

4. Deployment and Scalability: AWS

AWS services will be utilized to deploy the ARIMA model and manage real-time data streaming. This cloud platform provides scalability and flexibility to accommodate growing datasets from multiple IoT devices.

5. Fault Detection Logic: Python with Statistical Thresholds

Anomaly detection in appliance energy consumption will be implemented in Python. Statistical thresholds derived from ARIMA predictions will classify anomalies as potential faults

3.2.2 Economic Feasibility: Time Series Analysis and Fault Detection Component

The economic feasibility assessment of the Time Series Analysis and Fault Detection component evaluates the financial viability of its development and maintenance. This analysis ensures that the investment in development, deployment, and ongoing operation is justifiable and sustainable. It considers both initial development costs and recurring operational expenses.

Initial Development Costs

1. Software Development

- **Licensing and Tools**
  Development will leverage open-source tools such as Python and associated libraries (Statsmodels, Pandas, NumPy) for core functionality, minimizing initial costs. However, the potential use of premium features or cloud-hosted machine learning services such as AWS may introduce licensing or subscription fees.

- **Machine Learning Frameworks**
  While TensorFlow or PyTorch offer free libraries for future advanced modeling (e.g., LSTMs), their implementation and optimization may necessitate investment in specialized development expertise.

2. Data Acquisition and Management

- **IoT Device Integration**
  Data collection requires the project related IoT device, incurring costs for hardware procurement and connectivity solutions (e.g., Wi-Fi modules, sensors).

- **Data Storage**
  Initial datasets can be managed using local storage or free-tier cloud services. However, scaling the system will likely require storage upgrades and associated costs.

3. Infrastructure Setup

- **Cloud Services**
  The project will leverage AWS for deploying the ARIMA model and managing real-time energy consumption data. Initial costs will include virtual machine setup, database configuration, and network bandwidth usage on the AWS platform.

4. Testing and Deployment

- **Testing Tools**
  Testing will require tooling for unit, integration, and system validation to ensure model accuracy and reliability. While some open-source options exist, automated testing tools may incur minor costs.

- **Deployment**
  Deployment on AWS will incur costs for services like domain registration (if applicable), SSL certificates, and hosting.

Recurring Costs

1. **Cloud Hosting and Bandwidth:**

- Recurring AWS hosting fees will cover compute resources, storage, and bandwidth necessary for real-time data processing and streaming.
- These ongoing costs, while usage-dependent, can be optimized using AWS cost management tools.

2. Maintenance and Updates

- Periodic model retraining will require computational resources on AWS and developer time.
- Future system updates, such as incorporating advanced anomaly detection or scalability enhancements, will incur further development costs.

3. IoT Connectivity and Maintenance

- Maintaining accurate data collection will require regular IoT device calibration and potential hardware replacements.

3.3 System Overview Diagram

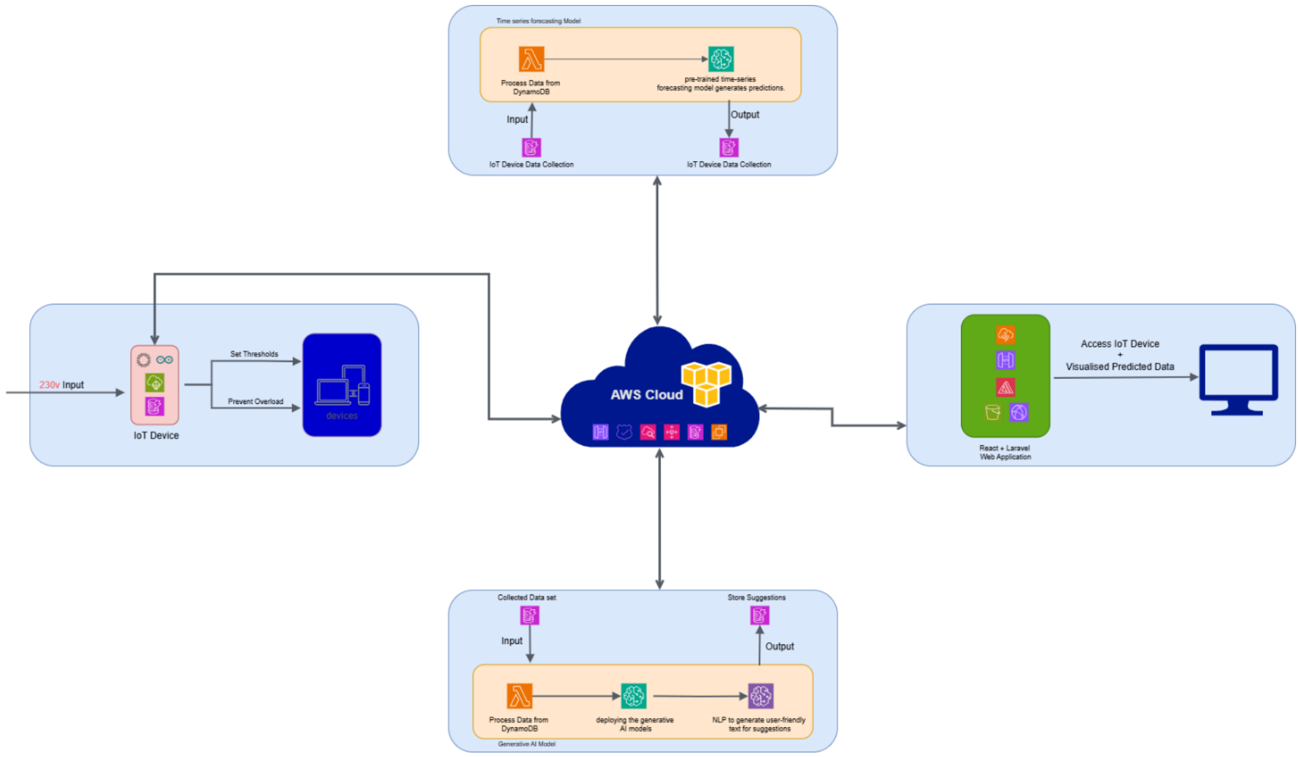

Figure 1-System Overview Diagram

3.4 Design Phase - Individual Component

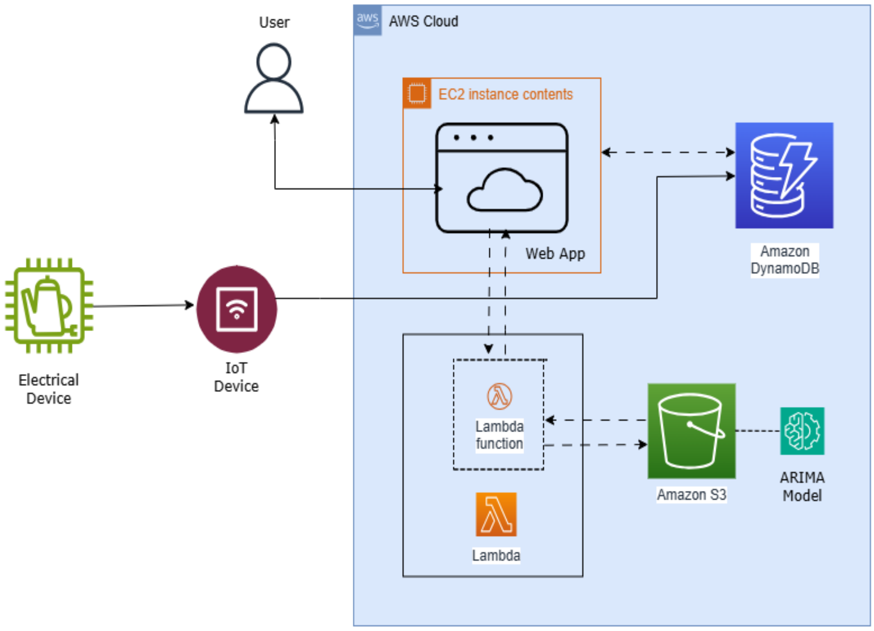

Figure 2- Machine Learning Component

3.5 Project Requirements

3.5.1 Functional Requirements

- **Data Collection**: Collect real-time energy consumption data for each appliance from the IoT device, including timestamps, device IDs, and units consumed.

- **Data Preprocessing:** Clean and normalize data to handle missing values, noise, and outliers. Decompose time series data to identify trends, seasonality, and residuals.

- **Energy Usage Prediction**: Forecast appliance energy consumption using ARIMA, including short-term (e.g., hourly/daily) and optional medium-term (e.g., weekly) predictions.

- **Fault Detection:** Compare real-time energy usage with ARIMA predictions to detect and classify anomalies (e.g., higher/lower than expected consumption). Flag persistent anomalies (e.g., 3 consecutive days) as potential faults.

3.5.2 Non-Functional Requirements

- **Performance:** Real-time data processing and predictions.

- **Reliability:** Targeting a 99.9% uptime to ensure continuous monitoring and analysis.

- **Accuracy:** ARIMA-based time series model maintains a prediction accuracy of ≥ 95% whereas fault detection identifies anomalies with a false positive rate below 5%.

- **Usability:** Users will be able to clear and intuitive visualizations of energy usage, predictions, and fault alerts.

3.6 Work Breakdown Structure and Gantt Chart

3.6.1 Work Breakdown Structure

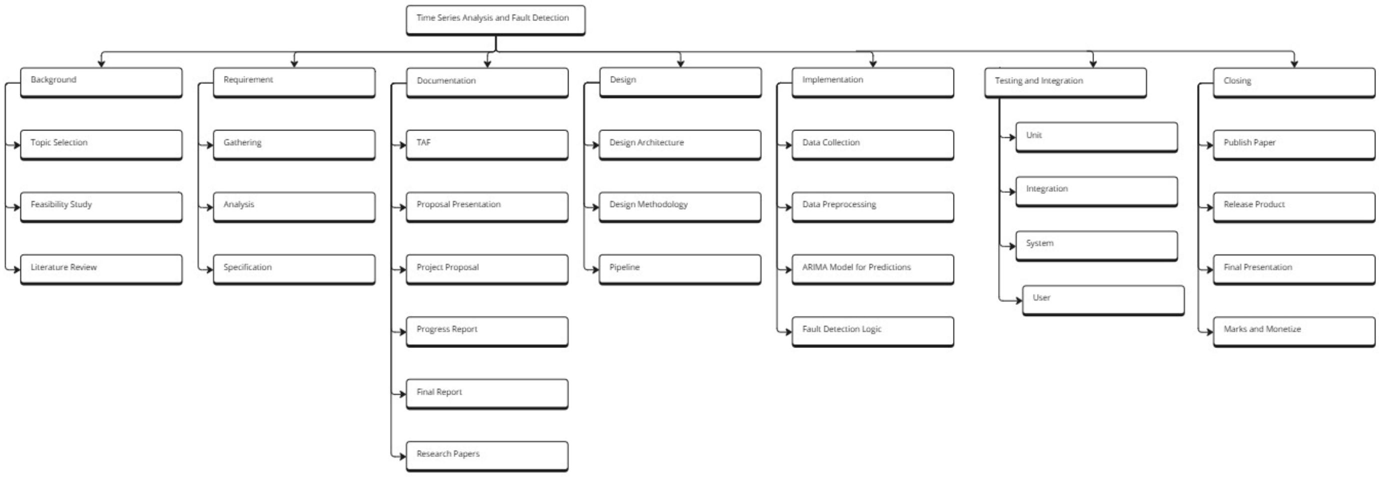

Figure 3- Work Breakdown Structure

3.6.2 Gantt Chart

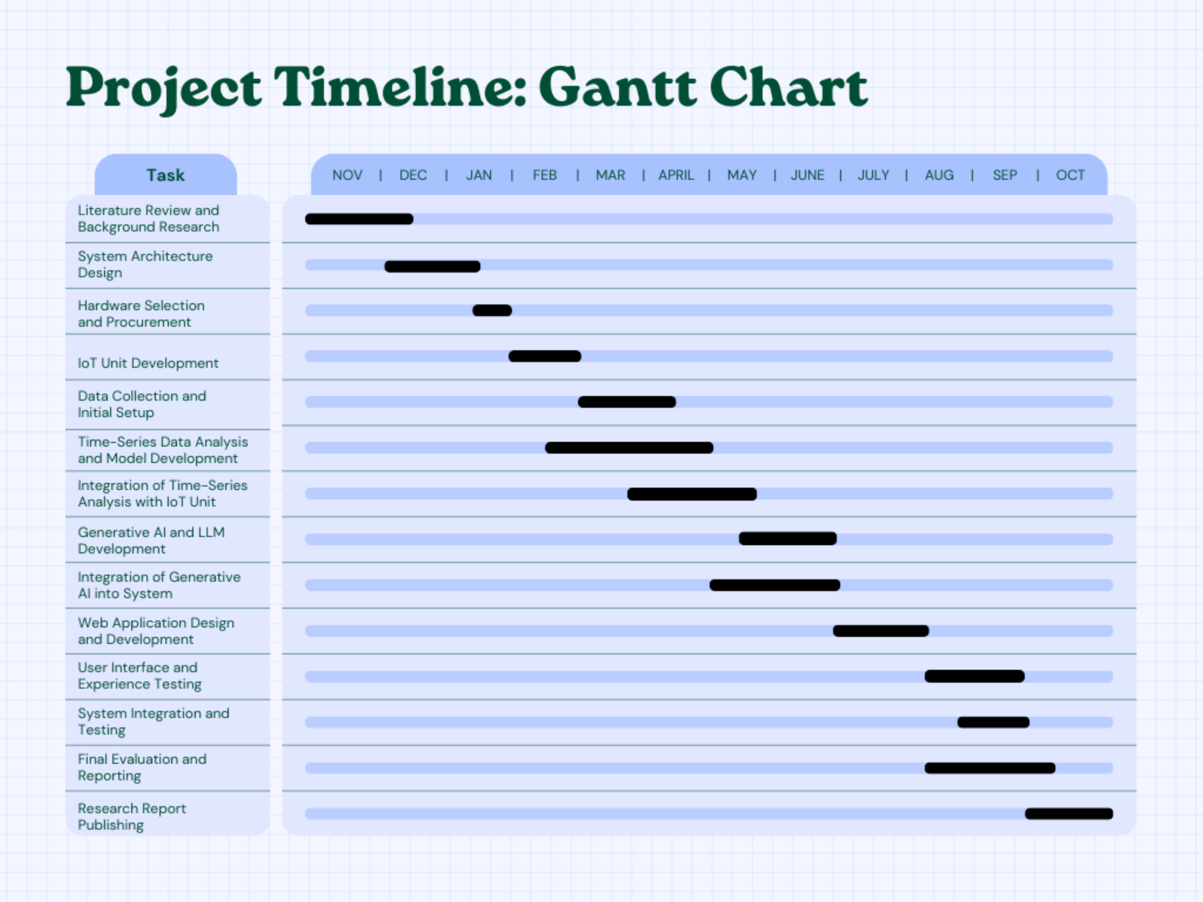

Figure 4- Gantt Chart

3.7 Deployment, Marketability and Commercialization

Deployment

- The IoT device can be deployed in individual households or rental properties with minimal installation and configuration effort.
- Users can set up the system seamlessly via a web-based application, allowing for effortless integration with existing appliances.
- The cloud-based architecture ensures scalability and reliability, making it suitable for homes with varying numbers of appliances.

Marketability

- The system appeals to households focused on energy efficiency and cost reduction, as well as landlords seeking transparent and fair billing solutions for tenants.
- Its unique features, such as time series-based energy usage predictions, fault detection, and automated threshold enforcement, differentiate it from other home energy management solutions.
- The user-friendly interface, combined with advanced predictive analytics, enhances its appeal to tech-savvy and environmentally conscious users

Commercialization

- The solution can be monetized through a subscription-based model, offering the IoT device, cloud services, and web application access as part of a bundled package.
- Collaborations with utility companies could enable integration into energy-saving programs or provide discounts for adopting the system.
- Potential expansions include incorporating advanced machine learning models, compatibility with renewable energy sources, and integration with smart home ecosystems like Alexa or Google Home.
- Additional revenue streams could be explored through premium services, such as detailed energy usage reports or predictive maintenance alerts for appliances.

4. Description of Personal and Facilities

Member	Task	Focus
Balasuriya B.L.I.S	Develop an IoT-based system that leverages time series analysis for predictive energy management and a fault detection mechanism for enhanced household energy efficiency.	Implement real-time energy usage monitoring by collecting data from sensors (e.g., current/voltage) and transmitting it to cloud storage (e.g., AWS DynamoDB) via microcontrollers (e.g., ESP32).
		Develop a time series analysis component that pre-processes IoT energy data (handling anomalies) and implements forecasting models (e.g., ARIMA) to predict future energy usage, validating model accuracy.
		Design and implement a fault detection mechanism that analyzes deviations from predicted energy consumption patterns to identify potential appliance issues and trigger corresponding alerts.
		Conduct thorough system validation and testing of the predictive and fault detection components under real-world conditions, including varying loads, environments, and scenarios, to ensure performance and reliability.

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	8000 LKR
Other	5000 LKR

Table 4- Budget

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