# Non-Intrusive Load Monitoring (NILM)

Project Proposal

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# Chapter 1

# Introduction

**Non-Intrusive Load Monitoring (NILM)** is a transformative technology that has gained considerable attention in recent years. This novel approach to energy management promises to bestow residential and commercial users with deep insights into their **energy consumption patterns**, eliminating the need for intrusive and often prohibitively expensive hardware installations [1]. Instead, NILM harnesses the power of advanced signal processing techniques to **disaggregate** and **identify** individual appliances' energy consumption from the aggregate energy usage data, providing a more detailed and granular understanding of electricity consumption. While numerous countries have already harnessed the advantages of NILM technologies, Malaysia is on the brink of embracing this revolutionary paradigm.

In recent times, Malaysia has witnessed a significant upswing in electricity costs, primarily driven by the government's introduction of a 10 cent per kilowatt hour (kWh) electricity tariff surcharge for domestic users consuming over 1,500 kWh per month, translating to a monthly bill of RM708 [2]. Starting from the second half of 2023, these users will no longer enjoy the previously granted 2 cent/kWh rebate. Consequently, their monthly electricity bills are anticipated to increase by at least RM187 or 25% [2]. This underscores the growing importance of effective energy management solutions.

Comprehensive knowledge of energy consumption patterns is crucial, enabling individuals to optimise energy use, reduce expenses, and enhance energy efficiency [3]. Implementing NILM in Malaysia holds the potential to empower users with a deeper understanding of their energy consumption patterns. This, in turn, enables more informed decision-making regarding energy habits, as users can pinpoint energy-intensive appliances, fine-tune usage schedules, and ultimately play a role in fostering a more sustainable and economically efficient energy environment [4]. The introduction of NILM in Malaysia could usher in a new era of energy management, providing users with a tool to monitor and control their energy consumption effectively. As the country explores and integrates NILM into its energy management landscape, it holds the promise of not only addressing current energy challenges but also contributing to global efforts toward sustainable and efficient energy consumption practices.

For the forthcoming summer semester, our project is geared towards delving into the dataset provided by MIMOS Berhad and tuning our selected machine-learning model accordingly. Our main goals encompass **identifying appliances**, **optimising usage behaviours**, and **detecting energy wastage**, all tailored to resonate with the unique energy consumption patterns inherent to Malaysia. The expected outcome of our project is a trained NILM model with at least a **0.80 M-FScore** and a user-friendly **Graphical User Interface (GUI)** that allows our stakeholders to visualise the electrical energy usage behaviours.

Our team, comprising four members: **Chong Ming Sheng** helming as the project manager, **Martin Ung Chee Hong** and **Wang Kai Jie** spearheading technical operations, and **Pang Wai Qi** overseeing quality assurance, is deeply committed to the NILM project's success.

To facilitate a structured discourse, this project proposal unfolds as follows: **Section 2** provides an in-depth review of our literature review on the related works about NILM recently. In **Section 3**, we present our project management plan. **Section 4** delves into the external design of our project. **Section 5** outlines the methodology employed in our NILM system. **Section 6** discusses our approach to test planning. Finally, **Section 7** offers the concluding remarks for our proposal.

# Chapter 2

# Literature Review

In this section, we delve into the NILM realm starting with its background, progressing towards contemporary methodologies. The discussion encompasses signal processing tactics, energy disaggregation strategies, appliance identification techniques, and evaluation metrics. Figure 8.1 shows an overview of our literature review.

## 2.1 Background

### 2.1.1 Introduction

NILM technology facilitates the disaggregation and monitoring of energy consumption at the appliance level without necessitating individual energy meters. Utilising a single sensor to measure voltage and current at the primary electrical inlet of a building, NILM systems approximate the power consumption of individual appliances within. This technology is significant for energy management and conservation, aiding in reducing energy consumption in residential and commercial settings, assisting utilities in managing demand during peak periods, and fostering the development of home automation systems that autonomously regulate appliances to conserve energy.

### 2.1.2 Evolution of NILM

The NILM technology originated in the 1980s with Hart et al., introducing a method to estimate individual appliance power consumption through a single smart meter, leveraging changes in electrical admittance and employing cluster analysis for appliance group categorisation [5].

In the 1990s, researchers experimented with various methods to improve appliance identification and energy disaggregation, exploring features like current and voltage distortion and steady-state current and power harmonic features, although challenges arose in distinguishing appliances with similar power consumption due to overlapping signatures [6].

Transitioning to the mid-2000s and early 2010s, the focus shifted towards new features including steady-state and transient features, with transient features proving effective in distinguishing events of overlapping, similar-power appliances. However, the requirement for high-sampled signals rendered the trained NILM system less transferable to other households [7]. EMI signals and voltage-current (VI) waveform trajectories demonstrated potential in enhancing the accuracy of NILM systems [8]. A retrospective glance reveals a sluggish advancement in NILM technology during its nascent stages, attributed to sparse smart meter adoption in households and the subpar performance of appliance identification plus energy disaggregation algorithms.

From mid-2010s onwards, machine learning and deep learning techniques were employed to enhance NILM performance, showing effectiveness in accurately identifying and disaggregating appliances with similar power consumption profiles. This period marked a significant stride towards leveraging advanced computational techniques to improve NILM system performance.

The aforementioned timelines depict a gradual evolution of NILM technology, initially hampered by limited smart meter adoption and algorithmic constraints, but later accelerated by the advent of machine learning and deep learning paradigms.

## 2.2 Signal Processing

In NILM, signal processing is key for extracting meaningful features from electrical waveforms representing aggregate power consumption, aiding in appliance energy usage pattern identification.

### 2.2.1 Sampling Frequency

Breaking down the combined energy signal necessitates transforming appliance signatures into multidimensional feature vectors. The sampling frequency is crucial here, with two types, **low-frequency** and **high-frequency**, for steady-state and transient-state features extraction respectively [9]. To enhance real-time operation, principal component analysis (PCA) can be employed to obtain lower dimensional power feature vectors without information loss [10]. Table 8.1 in Appendix showcases feature categorisation based on sampling frequency [9].

### 2.2.2 Windowing Techniques

Existing NILM methods based on neural networks often attempt to boost feature extraction capabilities by increasing the network's depth, leading to issues like gradient vanishing and overfitting. A method proposed in this paper [11] aims to optimise load disaggregation in NILM via **multi-overlap sliding windows**.

The sliding windows at input and output stages, by segmenting and reconstructing sequences, facilitate parallel data processing and reduce time complexity. However, to address the "break" in sequence due to these normal sliding windows, the paper [11] again suggests multiple overlapping sliding windows to improve data smoothness at edges between consecutive windows, enhancing appliance recognition accuracy and efficiency.

The accuracy of disaggregation and appliance identification at the edge points between two adjacent windows diminishes when the value of sliding step size $S$ equals the sliding window's size $W$, as illustrated in Figure 2.1. Conversely, reducing the value of $S$, leading to a larger $Y$ value as shown in Figure 2.2, enhances the appliance recognition accuracy and efficiency. This implies that a smaller sliding step size S results in a greater overlap between consecutive windows, thereby improving recognition accuracy.

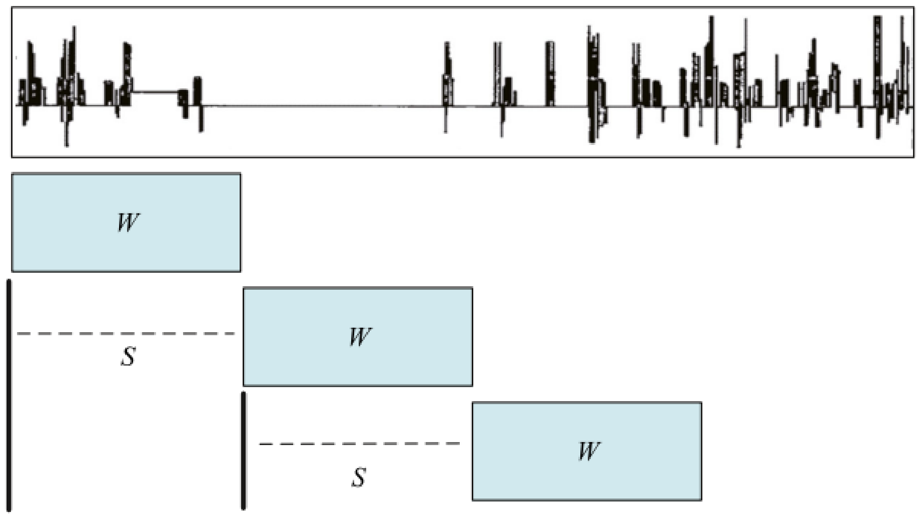


Figure 2.1: Use of normal sliding windows, where sliding window's size $W$ denotes the length of running time for the particular appliance, whereas $S$ denotes the sliding step size. [11]

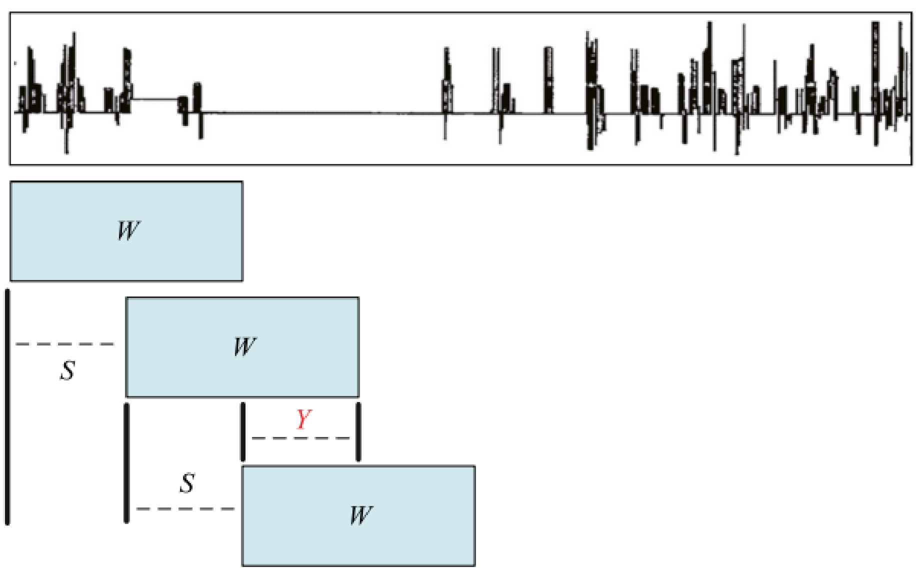


Figure 2.2: Use of multiple overlapping sliding windows, where $Y$ denotes the overlapping proportion between two consecutive sliding windows. [11]

### 2.2.3 Noise and Outlier Detection and Handling

In practical scenarios, electrical signals harvested from domiciles or buildings often harbour undesired noises, distorting the electrical waveforms and posing challenges for the NILM model in accurate appliance identification and disaggregation. Filters serve to mitigate or attenuate these noises, enabling NILM algorithms to operate on cleaner, more reliable data, and enhancing signal quality.

This part delineates a comparative analysis of four distinct filtering techniques employed for noise elimination in digital signals, with their merits and demerits summarised in Appendix (Table 8.2).

- ***Evaluation***:
  The application of **moving average filters** stands out as a potent strategy for signal preprocessing, especially within the ambit of an event-based approach. With a particular edge sharpness, these filters are capable of minimising noise significantly while concurrently rendering more accurate temporal information regarding an appliance's operation. The sharp step responses engendered by this filtering technique yield distinct and readily detectable transitions in the appliance's signal, which is instrumental for NILM algorithms to accurately pinpoint these events in an event-based approach, as the integrity of the original signal remains unaltered [12]. Furthermore, the high computational speed characteristic of moving average filtering mitigates latency, making real-time signal processing viable. Additionally, its commendable performance in time domain analysis is invaluable for scrutinising electrical signals over time, identifying ON/OFF transitions of appliances, and discerning temporal patterns of energy consumption.

  $$y[i] = \frac{1}{M} \sum_{j=0}^{M-1} x[i+j]$$

  The equation above elucidates the formula utilised for moving average filtering, where $M$ denotes the number of data points employed in the moving average [13].

### 2.2.4 Dataset Format

To optimise data handling and evaluation processes within the typical NILM framework, studies found that **Hierarchical Data Format (HDF5)** dataset format will be preferred over CSV, given its myriad advantages [14] [15]. Some advantages are as follows:

- Expedited read and write speed
- Ampler storage capacity
- Provision for storing NILM-relevant metadata
- Adaptation into NILMTK data format (NILMTK-DF), facilitating the evaluation of NILM algorithm with the NILMTK toolkit

## 2.3 Disaggregation

Disaggregation entails the partitioning of the aggregate energy signal into sub-signals that align with the consumption patterns of individual appliances. Disaggregation methodologies predominantly fall into two categories: event-based and non-event-based approaches.

### 2.3.1 Event-Based Disaggregation

Event-based disaggregation concentrates on identifying distinct events within the aggregate energy signal, signalling a state change – typically an appliance being turned **on or off**. These techniques vigilantly monitor electrical activities (e.g., power measurements) within a household, aiming to detect **state transitions of appliances** by noting variances in the signal, an endeavour known as event detection. Through event detection, it becomes feasible to ascertain the appliance responsible for the signal shift, thus monitoring its power consumption [16].

A notable model in event-based disaggregation is the **Factorial Hidden Markov Model (FHMM)**, introduced by Michael I. Jordan in 1996 as a derivative of the traditional Hidden Markov Model (HMM), tailored for modelling **multiple independent hidden state sequences** [17].

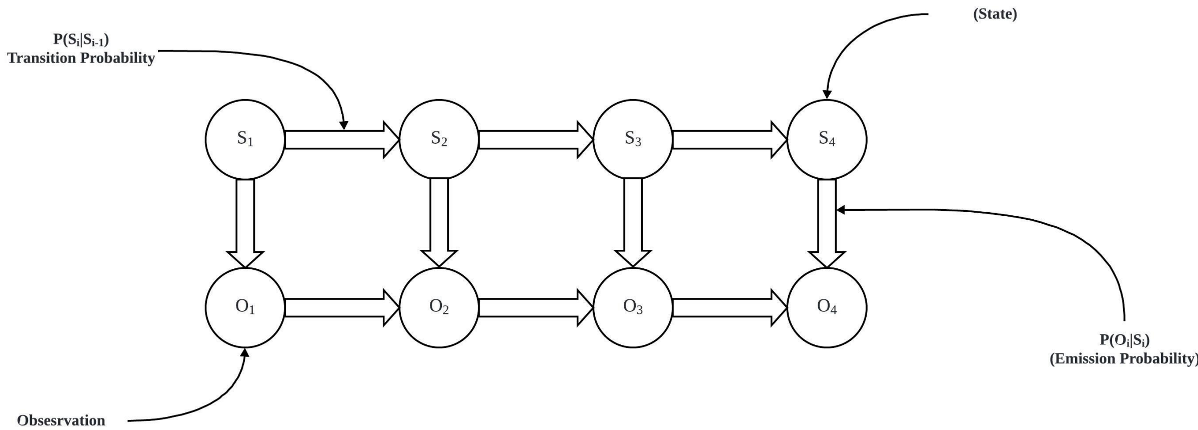


Figure 2.3: Working principle of FHMM

By employing **probabilistic models** of individual appliances in conjunction with aggregate power measurements, it becomes possible to deduce each appliance's **operational state** [18]. Both [18] and [19] have demonstrated the capability of FHMM in identifying the most probable sequence of appliance states given an observed aggregate power signal, notably by implementing the **Viterbi Algorithm**.

Analysis of FHMM parameters, like **transition and emission probabilities**, elucidates its operational dynamics. Transition probabilities indicate appliance state transitions, while emission probabilities reflect the chance of observing specific power signal patterns. Various studies affirm FHMM's effectiveness in NILM load disaggregation tasks [18] [19] [20].

The employment of FHMM can be either supervised (with the availability of labelled data) or unsupervised (necessitating algorithmic data generation like **Expectation-Maximisation**), contingent on the data availability.

### 2.3.2 Non-Event-Based Disaggregation

Diverging from event-based methodologies, non-event-based disaggregation employs **statistical or machine learning** instruments to perpetually analyse the aggregate signal, aspiring to gauge each appliance's operational state across its operative span.

**Long Short-Term Memory (LSTM)** networks, a branch of Recurrent Neural Networks (RNN), have been scrutinised for their promise in non-event-based disaggregation, particularly within the NILM schema. A cardinal strength of LSTMs lies in their prowess in processing sequential data, which dovetails well with time-series energy consumption data. Their architectural framework empowers them to seize temporal patterns and dependencies typically witnessed when appliances toggle states over time [21]. A salient trait of LSTMs is their memory cells capable of preserving information over extended durations. This faculty is pivotal for NILM, aiding in differentiating the operations of appliances that may exhibit similar yet distinct consumption patterns [22]. Moreover, the innate **gating mechanisms** of LSTMs - encompassing input, forget, and output gates - refine the management of information, adjudicating what's retained or jettisoned from the sequence [23]. Recent scholarly ventures have underscored the viability of LSTMs in NILM tasks.

Upon deployment, LSTMs render **probability distributions of plausible states** for each appliance, with the state boasting the highest probability being selected as the most likely current state of the appliance. Performance refinement is attainable by tuning the LSTM's hyperparameters, as elucidated in [24].

### 2.3.3 Summary

Table 8.3 in Appendix provides a thorough comparison of the event-based approach, specifically FHMM, with non-event-based methods— LSTM across various pivotal aspects relevant to NILM research. Despite both FHMM and LSTM presenting their own merits, empirical analysis showcases a slight performance edge in favour of FHMM.

## 2.4 Identification

The core of appliance identification lies in discerning the operational state of an appliance. This identification task can be approached via two main approaches: the **pattern recognition approach** and the **optimisation approach**.

### 2.4.1 Pattern Recognition Approach

Appliances generally exhibit unique electrical signatures delineated by attributes such as magnitude, frequency, and duration of load alterations. The pattern recognition approach hinges on contrasting real-time power consumption patterns with previously recorded signatures peculiar to different appliances. This necessitates the preliminary establishment of load signatures for each appliance, encapsulating distinct power consumption events tied to their operation. The extracted features are subsequently juxtaposed against a repository of load signatures housed in the appliance feature database [25]. This comparative analysis facilitates the discrimination and identification of appliance operation. To attain precise load identification, ample load information is imperative, thus the espousal of high-frequency data acquisition becomes vital to preserve relatively intact waveforms and signatures of mixed load signals [26]. Both supervised and unsupervised methods find application in load identification. The supervised modality demands training data to craft models for appliance identification, whereas the unsupervised modality, requiring one-time labelling of appliances, can construct models with minimal training data. Common techniques encompass Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Hidden Markov Model (HMM), and Decision Trees [27].

### 2.4.2 Optimisation Approach

This methodology aspires to align observed power measurements with potential amalgamations of appliance power signals catalogued in the database, thereby diminishing errors in the residual sum between estimated and actual aggregate consumption. The optimal match is ascertained when the discrepancy between the database entry and the extracted feature is minimised [28]. A variety of combinatorial search methods, inclusive of genetic algorithms, segmented integer quadratic constrained programming, and mixed-integer linear programming, are employed to this end [29]. While this methodology may hold feasibility for a limited appliance count, a significant hurdle materialises as the count of unknown loads in power measurements escalates. This elevates the complexity of the optimisation problem since the method endeavours to find a solution grounded on the combination of known appliances [30].

## 2.5 Evaluation Metrics

Evaluating machine learning models is crucial for gauging their performance and real-world applicability. In NILM projects, assessing the models' efficacy in disaggregating and identifying individual appliance-level energy consumption is vital. Employing suitable evaluation metrics is indispensable for comprehending these models' performance.

### 2.5.1 Energy Disaggregation Evaluation

A cardinal metric used in energy disaggregation evaluation is the **Root Mean Square Error (RMSE)**, employed to compare estimated and actual energy consumption at each timestamp. RMSE can defined as:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{y}_m^t - y_m^t)^2}$$

However, RMSE's significant limitation lies in its **lack of normalisation** to the total energy consumed, leading to potential discrepancies in RMSE values even when two NILM approaches exhibit identical energy estimation accuracy [31]. This is due to varying total energy consumption in the datasets utilised.

To counter this limitation, the **Normalised Disaggregation Error (NDE)** emerges as a notable alternative [32]. NDE, by comparing the predicted and actual energy consumption of each appliance and normalising by the total energy consumption of all appliances [31], facilitates a more equitable assessment of estimation accuracy, and it can be defined as

$$\text{Est. Acc.} = 1 - \frac{\sum_{t=1}^{T}\sum_{m=1}^{M}|\hat{y}_m^t - y_m^t|}{2\sum_{t=1}^{T} y_m^t}$$

For a more granular accuracy estimation for each appliance, the sum over the number of appliances M can be omitted as shown in the subsequent formula:

$$\text{Est. Acc.}_m = 1 - \frac{\sum_{t=1}^{T}|\hat{y}_m^t - y_m^t|}{2\sum_{t=1}^{T} y_m^t}$$

However, NDE might sometimes exhibit inflated accuracies as noted in previous research [33]. Various factors including the quality of training data, disaggregation algorithm complexity, and the nature of appliances in focus, can affect NDE's accuracy portrayal.

### 2.5.2 Appliance Identification Evaluation

Evaluating the model's performance in appliance identification necessitates assessing its accuracy in predicting each appliance's state, extending beyond mere energy disaggregation to correctly identifying active appliances at any given time. Essential metrics for this evaluation include accuracy and F-score.

$$\text{Acc.} = \frac{TP + TN}{TP + TN + FP + FN}$$

**Accuracy** is a foundational metric measuring the model's capability in predicting specific appliances' on/off states, quantifying the algorithm's proficiency in discerning individual appliances' operational status. However, the **class imbalance problem**, arising from varying usage frequencies among appliances, poses a challenge. This imbalance can lead to algorithm performance overestimation, especially for more frequently used appliances.

$$\mathrm{F}_1 = 2\frac{precision * recall}{precision + recall}$$

$$\text{precision} = \frac{TP}{TP + FP}, \text{ recall} = \frac{TP}{TP + FN}$$

**F-score**, a common alternative among NILM researchers, represents the harmonic mean of precision and recall. Unlike accuracy, the F-score mitigates class imbalance issues and provides a more robust assessment of the model's performance. It is particularly well-suited for **binary classification tasks**, like classifying appliances as active or inactive [34].

To cater to **non-binary outcomes**, the **Modified F-Score (M-FScore)** extends the F-score concept, introducing a threshold T to differentiate true positives into Accurate True Positives (ATP) and Inaccurate True Positives (ITP) [32]. This threshold, calculated by dividing an appliance's whole ground truth mean, is applied to precision and recall while retaining the F-score definition. M-FScore combines appliance state classification and power estimation accuracies [34], proving invaluable in NILM scenarios aimed at both correct appliance identification and accurate power consumption estimation.

### 2.5.3 Evaluation Tools and Framework

The assessment of NILM models significantly benefits from the utilisation of dedicated evaluation tools and frameworks. This section delves into two prominent frameworks, NILMTK and NILM-Eval, scrutinising their features and current maintenance status.

**NILMTK**, encompassing various Python-based software components, avails a wide array of performance metrics specifically curated for NILM endeavours. Significantly, the framework's most recent update was on June 7, 2021, reflecting its ongoing relevance and sustained engagement from the user community [35].

Conversely, **NILM-Eval** is a Matlab-centric framework for performance assessment. However, the last recorded update on June 26, 2015, casts doubt regarding its continued support and maintenance by the original author [36].

### 2.5.4 Summary

In summary, **NILMTK** emerges as our primary evaluation tool, with the intention to utilise **all discussed metrics**. Additionally, there's a potential incorporation of the NILM-Eval framework into the evaluation regime, subject to time and resource availability, facilitating a thorough appraisal of our model's performance in NILM projects.

## 2.6 Conclusion

This literature review elucidates the NILM field, traversing its evolution and current methodologies including signal processing, energy disaggregation, and appliance identification. The discussion extends to evaluation metrics essential for NILM model assessment. The journey from NILM's early steady-state signal processing to contemporary machine learning techniques highlights the significant strides towards improved accuracy. This review is pivotal for our NILM system's development. Figure 8.2 provides a glimpse of a portion of our synthesis table, which summarises gathered insights from various research papers.

# Chapter 3

# Project Management Plan

## 3.1 Project Overview

In today's technologically advanced era, rising energy costs and heightened environmental awareness have underscored the importance of optimising energy consumption. While direct appliance-level monitoring offers precise readings, it requires an intensive setup with sensors attached to every individual appliance—a challenge for broad-scale implementation. Our project introduces a solution through **Non-Intrusive Load Monitoring (NILM)**.

Utilising the cutting-edge techniques of data science and machine learning, we have adopted the event-based NILM approach. This method simplifies the energy monitoring process by analysing aggregated main meter readings, eliminating the need for individual appliance sensors. Our project revolves around **three core objectives**:

1. Identification of active appliances from aggregated data
2. Analysis and optimisation of usage behaviours
3. Detection and elimination of superfluous energy consumption

Fortified by a collaborative agreement with **MIMOS Berhad**, we have secured a specialised dataset from their lab processes. To ensure compatibility with notable international datasets, this dataset will be converted into the universally recognised HDF5 format, making it comparable with databases such as the UK-Dale.

Our major milestones include Project Kickoff, Business Case Study on NILM, Project Management Planning, Data Preprocessing and Analysis, NILM Model Architecture Design, NILM Model Implementation Phase, GUI development, NILM model Evaluation, NILM model Integration and Testing, and Project DocumentationTable 8.4 in the Appendix shows the **major milestones** in our project.

## 3.2 Project Scope

### 3.2.1 Project Deliverables

Deliverables are categorised into two distinct categories - **project deliverables** and **product deliverables**.

#### 3.2.1.1 Project Deliverables

Our project deliverables consist of:

- Business Case Study
- MindMap and Project Management Planning
- Project Concept and Design
- Data Analysis Report
- Project Scope Statement
- Requirement Traceability Matrix
- Gantt Chart
- Work Breakdown Structure
- Stakeholder Analysis Matrix
- Communication Matrix
- Risk Register
- Required Resources
- Project Proposal

Table 8.5 in the Appendix shows the project deliverables.

#### 3.2.1.2 Product Deliverables

Our product deliverables include:

- NILM model source code
- Visualization of user data
- Interactive Graphical User Interface
- Test plan and test cases
- Code documentation for NILM model

Table 8.6 in the Appendix shows the product deliverables.

### 3.2.2 Project Scope Categories

Our project scopes have been categorised into four categories:

- Data Collection and Analysis
- Model Development and GUI

- Appliances and Energy Types
- Project Compliance and External Collaboration

Tables 8.7 and 8.8 in the Appendix show the **scope, limitations, and assumptions** for the different aspects of our NILM project.

### 3.2.3 Product Characteristics and Requirements

#### 3.2.3.1 Product Characteristics

Our energy disaggregation software is designed for **scalability** to cater to expanding datasets. Emphasising **high performance**, it processes data efficiently, even at low sampling rates. The system's **user-friendly GUI** facilitates straightforward interactions, while the incorporated visualisation tools transform intricate data into clear insights. With a commitment to precision, our NILM model targets a **90% disaggregation accuracy**. Recognising the innovative realm of our project, flexibility is embedded in the software design, allowing adaptability to evolving needs.

#### 3.2.3.2 Product Requirements

Our NILM project represents a harmonious blend of cutting-edge technology with today's pressing energy challenges, characterised by both functional and non-functional requirements.

In terms of functional requirements, we identified the **MIMOS datasets** as a cornerstone. Knowing the inherent challenges this dataset presented, we outlined rigorous data cleaning processes to ensure inconsistencies are addressed and missing values are rectified. Once the data is primed, our strategy incorporates a meticulous phase of **data processing and analysis**. Additionally, the decision to adopt the HDF5 format stands as a testament to our commitment to data interoperability and processing efficiency. Recognising the potential challenges of low-frequency data, our approach is sculpted to proficiently address these intricacies. This diligent preparation then sets the stage for **building, training, and optimising** our NILM model. On the interaction front, we plan to develop an intuitive GUI. This platform is designed not merely as a conduit for data input but as a comprehensive tool, enabling users to derive profound insights into their energy consumption. An exhaustive testing phase will ensure the GUI's robustness. At the heart of our project lies the development and fine-tuning of the NILM model, which remains the nucleus of our energy disaggregation ambition.

When we pivot to non-functional requirements, our aspirations are clear. **Performance** sits atop our priority list with the NILM model targeted to achieve an accuracy benchmark of 90 percent. This target underscores our unwavering commitment to technical excellence and meeting practical user expectations. Enhancing the user experience is paramount. As such, our GUI is meticulously designed to **deliver insights promptly**, ideally within **two seconds** post data input. The theme of quality is pervasive and will be evident in the detailed documentation of our model. This ensures longevity, provides clarity, and guarantees accessibility for future stakeholders.

The derivation of these requirements was an exhaustive process. **Collaborative sessions with MIMOS Berhad** played a pivotal role, affording us an in-depth understanding of the nuances of energy consumption patterns. Our project supervisor's insights and guidance acted as anchors, helping us navigate the waters between academic rigor and industry benchmarks. Finally, our reconnaissance of prevailing NILM tools in the market informed our strategy, inspiring us not just to contribute to the field but to set new benchmarks and truly resonate in the industry.

#### 3.2.3.3 Requirement Traceability Matrix (RTM)

The project's requirements, rooted in its scope, are set by both our supervisor and MIMOS Berhad. They're categorised as functional (specific system actions) and non-functional (system quality attributes). The RTM, detailing these, is available in the Appendix (Table 8.9 & Table 8.10).

### 3.2.4 Product User Acceptance Criteria

In Appendix (Table 8.11), each user acceptance criterion is systematically associated with its respective user story and aligned with the corresponding project requirement for comprehensive traceability.

## 3.3 Project Organisation

The team comprises 4 members, as detailed in Appendix (Table 8.12), consisting of a project manager, two technical leads, and a quality assurance. This project is supervised by Dr. Lim Wern Han and supported by industry lead, MIMOS Berhad.

### 3.3.1 Process Model


Figure 3.1: Agile methodology workflow [37]

For the management of our NILM project, we have chosen the Agile methodology. This decision was driven by the project's intrinsic demand for adaptability, given its complexities. Agile's iterative nature ensures that as we confront challenges, especially those related to MIMOS datasets, we can seamlessly integrate feedback from our stakeholders like MIMOS Berhad and Dr. Lim [38]. This iterative development offers a dual benefit: it keeps the project aligned with user needs and enables quick pivots in response to unforeseen challenges.

Moreover, the technical challenges of handling low-frequency data and our commitment to achieving high accuracy in the NILM model reinforced the need for an adaptive approach. Predictive methodologies, while structured, might leave us ill-prepared to address real-time challenges. In contrast, Agile empowers us to be proactive, making data-driven decisions while continuously integrating stakeholder feedback [39].

The collaborative spirit of Agile is further amplified by our choice of tools. Jira is an instrumental ally, aiding in organising our tasks, backlogs, and sprints. It allows us to maintain a clear view of our progress and ensures the timely delivery of our commitments. Meanwhile, Git serves as our collaborative code management backbone. It streamlines our codebase's evolution, ensuring that team members can work cohesively, track modifications, and integrate their contributions without hitches. These tools, under the Agile umbrella, ensure continuous stakeholder engagement and promote shared vision throughout our project's lifecycle.

In essence, our choice of Agile methodology, combined with the strategic deployment of tools, ensures our NILM project remains dynamic, responsive, and consistently aligned with both technical and practical benchmarks.

### 3.3.2 Project Responsibilities

Clearly defined roles and responsibilities in a project help team members focus on their tasks and objectives, reducing conflicts and redundant efforts. Table 8.13 in Appendix shows the primary responsibilities for each role.

To ensure clear roles and responsibilities in our NILM project, we implement the RACI Matrix to minimise disputes and conflicts among team members. The RACI Matrix is shown in Appendix (Table 8.14)

## 3.4 Management Process

### 3.4.1 Risk Management

Risk management proactively identifies, analyses, and mitigates project threats and opportunities [40]. Addressing risks early minimises negative impacts and maximises positive outcomes, facilitating improved decision-making, resource allocation, and project resilience. Some strategies that we will utilise are:

- ***Brainstorming:***
  Brainstorming promotes diverse viewpoints by enabling team members to share insights, enriching risk assessment from various angles [41]. In our sprint planning meetings, we collaboratively identify potential project risks and benefits, which are then documented in the SWOT Analysis, and our Risk Register is updated accordingly.
- ***SWOT Analysis:***
  SWOT Analysis is a strategic tool that categorises project risks into internal (strengths and weaknesses) and external (opportunities and threats) factors, guiding informed risk management choices [41]. Strengths denote our project's internal resources and capabilities, while weaknesses represent internal vulnerabilities. Opportunities and threats are external factors that can respectively help or hinder our project goals. Risks pinpointed in the SWOT Analysis are documented in the Risk Register. The SWOT Analysis is shown in Appendix (Table 8.15).
- ***Risk Register:***
  Risk Register dynamically and systematically logs project risks, detailing their root causes, impacts, likelihood, assigned risk managers, and management strategies throughout the project's lifecycle, etc [42]. This tool aids in monitoring and addressing potential risks, ensuring informed decisions for effective risk mitigation and successful project completion. Our team's Risk Register is shown in Figure 8.3 and it will be updated during every sprint planning phase.
- ***Probability/Impact Matrix:***
  Probability/Impact Matrix, used in our qualitative risk analysis, ranks the risks based on their potential impact and occurrence likelihood. This method allows us to prioritise and address the most consequential risks proactively, ensuring unforeseen challenges do not derail our project [42]. Our team's Probability/Impact Matrix is shown in Figure 8.4.

### 3.4.2 Stakeholder Analysis and Communication Plan

Recognising individuals and groups with a stake in our project ensures stakeholder alignment with our objectives, promoting collaboration [43]. This alignment helps meet stakeholder requirements by continuously adapting our project plan based on their feedback.

Stakeholder analysis categorises our stakeholders by influence and interest, streamlining engagement, resource allocation, and expectation management for project success [43]. We employ both Stakeholder Analysis Matrix and Stakeholder Management Matrix to systematically identify, prioritise, and manage our stakeholders. These matrices aid in defining roles and responsibilities, tracking stakeholder interests, and ensuring their needs are met throughout the project's lifecycle. Appendix (Table 8.16 & 8.17) shows our Stakeholder Analysis Matrix. Figure 8.5 shows our Stakeholder Management Matrix.

- ***MIMOS Berhad*** **(High interest, High impact):**
  As our project collaborator, they bring real-world context, resources, and expertise to our project, such as providing experimental dataset, relevant source code samples, and tutorials on using NILMTK toolkit.
- ***Project Supervisor*** **(High interest, High impact):**
  Dr. Lim Wern Han serves as a direct mentor and evaluator, holding significant authority in our project-related decisions and outcomes His close involvement and constructive feedback on our project makes him a key stakeholder of our project.
- ***Monash University FIT3161/62/63/64 Teaching Team*** **(High interest, High impact):**
  The teaching team defines the project's academic requirements and grading criteria, holding significant authority in evaluating our project and overseeing our project management progress.
- ***MDS23 Team Members*** **(High interest, High impact):**
  Team members have direct roles in project planning, project execution and decision-making, collectively impacting the project outcomes. Our high level of involvement and shared interest in the project are extremely important for the project success.

Communication Matrix details our project's communication plan, including meeting frequencies, reporting mechanisms, report formats, etc. In essence, we hold weekly Microsoft Teams meetings with our project supervisor to share progress, seek clarifications, and obtain feedback for improvement. The Communication Matrix is shown in Appendix (Table 8.18, 8.19).

### 3.4.3 Monitoring and Controlling Mechanisms

#### 3.4.3.1 Communication Plan and Task Allocation

The communication plan for our team is included in the same Communication Matrix shown in Appendix (Table 8.18, 8.19). Adhering to Agile methodology, we schedule different meetings for each sprint: stand-up, planning, review, and retrospective. We also schedule weekly physical team meetings to discuss and work on our project together, bolstering effective real-time communication. Samples of our sprint planning meeting agenda (Figure 8.6) and minutes (Figure 8.7 & 8.8) are shown.

Task distribution within our team is equitable, factoring in team roles, availability, capabilities, and progress. This ensures optimal workload distribution, amplifying our collective efficiency.

- ***Role:***
Tasks are primarily designated based on roles, though **flexibility** exists. For instance, project manager (Ming Sheng) concentrates on management specifics, requirements collection, milestone deliverables, and liaising with our supervisor. Quality assurance (Wai Qi) handles test planning, test cases execution, and document structuring. Technical leads (Martin and Kai Jie) focus on NILM model development, research into NILM algorithms, and other technical project requirements.

- ***Availability:***
Every member's schedule is integrated into a shared **Google Calendar**, providing visibility into team availability. This assists Ming Sheng in aligning tasks with individual timelines, forestalling work congestion and scheduling overlaps.

- ***Capability:***
We apply the **Weighted Scoring Model** to gauge members' technical and interpersonal skills. Ming Sheng uses these insights to align tasks with each member's strengths, leading to quality task performance.

- ***Progress:***
Our team uses **Clockify** software to access every team member's task progression. This offers real-time insights on task engagement and performance, facilitating Ming Sheng to allocate new tasks to members with available capacity, ensuring fair task distribution and deadlines can be met proficiently.

#### 3.4.3.2 Monitoring of Project Progress Against Planned Milestones etc.

In our Agile project management approach, we employ a range of collaborative mechanisms to effectively monitor and control our team's project progress.

We conduct **sprint reviews** at the end of each sprint, to submit and showcase our work to stakeholders, particularly the teaching team and Dr. Lim, and to obtain their valuable feedback. During **sprint retrospective** meetings, we internally reflect on our team's performance throughout the particular sprint and identify areas for improvement, ensuring continuous enhancement in our project execution in consequent sprints. We will evaluate individual performance and give peer feedback so that we can learn from our mistakes. Furthermore, we will review the current project schedule via Gantt chart, identifying causes of delays in tasks (if any), updating the delayed tasks with realistic deadlines based on the current situation, and reallocating human resources to critical and behind-schedule tasks. This accelerates our team's progress and aligns us with the original team schedule. Our team also schedules **weekly stand-up meetings** (10:00am-10:30am every Friday via Zoom) to update individual and team progress, identify and address any roadblocks, and make necessary adjustments. Based on our team's Kanban board, the project manager (Ming Sheng) will identify tasks that are potentially dragging team progress, and allocate additional team member(s) to help with the particular tasks or swap the task owner appropriately. If it is realised that certain low-priority tasks are not manageable within the current sprint, Ming Sheng will move them to the subsequent sprint(s) if required. These Agile ceremonies offer real-time insights into our project status, allowing us to adapt swiftly to changing requirements.

To maintain a tight grip on project timelines and adhere to planned milestones, we utilise **Clockify** time tracking software to monitor the time that every team member spent on specific tasks and user stories, ensuring that we stay within the allocated time frames for each sprint. Clockify helps us to accurately gauge our team progress, assess our team's efficiency, and identify areas for improvement. If a task is approaching its deadline but far from completion, we can flexibly reassign it to a different member who has a track record of completing similar tasks quickly, based on the time tracking history. This helps us to meet deadlines more efficiently.

Additionally, regular communication with our project supervisor is integral to our monitoring and control mechanisms. Our team schedules **weekly online meetings** with Dr. Lim via Zoom, to update him on our project progress, discuss challenges that we face, and seek his guidance or clarifications. These updates serve as a check and balance system to ensure that our project aligns with the objectives and is executed according to the predefined plan, to successfully achieve our milestones. Our team actively requests Dr. Lim's feedback and asks questions during the weekly meetings or through our **team communication channel in Microsoft Teams**, and then incorporates his insights into our Agile practices, fostering a collaborative environment that drives our project forward with clarity and clear direction.

Our team also utilises **Google Calendar reminders** as a proactive control mechanism. The team's Google Calendar is built based on our Gantt chart. The project manager (Ming Sheng) will set up automated reminders to alert team members of impending deliverables or sprint closures two days before each deadline, enabling us to make final adjustments and verifications before project milestones are reached. This ensures our project remains on schedule and reinforces individual team members' responsibility in completing their tasks.

#### 3.4.3.3 Review and Audit Mechanisms

In our versioning control process, we will utilise four individual branches along with a single main branch in the team's **GitHub**. Every team member can push their contributions on the NILM model's code implementation to our own branches. However, before code is merged into the main branch, it undergoes a quality assurance review by the quality assurance (Wai Qi) to ensure it meets high-quality standards and is bug-free. Once approved by Wai Qi, the member's code will be merged into the main branch, allowing every team member to access the latest code implementation. Additionally, the versioning control system provides us with the capability to retrieve previous code versions via Git history. Whenever necessary, we will utilise the rollback mechanism in GitHub to quickly correct errors or bugs introduced in the later version of code, maintaining our code quality.

As for quality assurance, our team will follow a rigorous process of **testing and code review** to ensure the reliability and performance of our work. The quality assurance (Wai Qi) is delegated to develop and execute comprehensive test cases, with a keen focus on coverage and specific evaluation metrics selected (i.e. accuracy, F-score, and M-FScore). Each test case is supported by detailed documentation so our project supervisor can review our code thoroughly.

Furthermore, we utilise a team's shared **Google Drive** as our central repository for all written documents related to our project and assignments. It allows us to retrieve relevant information when needed, which can be seamlessly incorporated into our new assignments or tasks. For instance, the contents for Resource Requirements and External Design sections in this project proposal are retrieved from our previous Initial Design document. We always make sure that our Google Drive is well-organised, with a folder dedicated to a specific sprint. Also, we will consistently update our Google Drive by uploading the latest information and necessary documents for efficient project management. Examples are spreadsheets (e.g. team evaluation forms), PDFs (e.g. assignment specifications, marking rubrics, finalised assignment documents), Word documents (e.g. meeting minutes, agendas, assignment write-ups), resources provided by MIMOS Berhad, etc. A screenshot of our team's Google Drive is shown in Figure 8.9.

For training, we actively **review tutorials** provided by MIMOS Berhad to enhance our understanding of our NILM project, especially regarding preprocessing and implementation. Moreover, we invest in **additional research** by exploring recent works on NILM (e.g. online research papers). These approaches are instrumental in filling our knowledge gaps, especially in the field of electrical signal processing, an area where none of our team members had prior experience.

## 3.5 Schedule and Resource Requirements

### 3.5.1 Schedule

Our team's NILM project is scheduled from 10th August 2023 to 14th January 2024, comprising approximately 21 weeks, excluding 1 week of break in between the identified period due to preparation for final examinations. During Semester 2 2023 of Monash University Malaysia, our team focused on **project management-related tasks** and there are four sprints planned for this semester. After the final examinations, our team will commence our **project execution** phase until the end of Summer 2023-2024 Semester, where two sprints are planned. During the project execution phase, our main goals are to develop, train and fine-tune our NILM model so it achieves satisfactory performance in disaggregating energy consumption patterns and classifying the electrical appliances used (i.e. at least 0.80 M-FScore for our developed NILM model) before the final software product is handed over to MIMOS Berhad. As an Agile team, we will continue to refine our model if time permits, to continuously improve our model's M-FScore.

Our team utilises Work Breakdown Structure (WBS), Gantt chart and Kanban board to facilitate our project schedule management processes effectively.

- ***Work Breakdown Structure (WBS):***
  We develop a WBS to provide us with a clear hierarchical view of tasks, subtasks and deliverables, ensuring that our project is systematically organised and completed [44]. Essentially, our team breaks down the NILM project into seven major phases, where the first four are involved during the NILM project management planning stage; the latter three are involved during the NILM project execution stage. From the collection of deliverables in each major phase, we deconstruct each phase into multiple elements corresponding to their relevant deliverables, so called work packages. With the WBS created, the project manager (Ming Sheng) can better estimate the feasible duration needed for each task completion and set the deadlines accordingly during every sprint planning phase, ensuring that all tasks are manageable and approachable. Our team's WBS is shown in Figure 8.10.

- ***Gantt chart:***
  The work packages in WBS are decomposed into appropriate activities and subsequently documented in Gantt chart, where our team's project tasks, estimated durations, and dependencies are visually presented in a timeline [45], via **Microsoft Excel**. We present our Gantt chart to our stakeholders (Dr. Lim and the teaching team) for review purposes, so they can understand our project's timeline and ensure our tasks are always completed on time. Since we adopted Agile methodology, we need to sequence our work in the correct order to ensure that prerequisite tasks are accomplished before subsequent tasks can start, to meet deadlines. This can be achieved by depicting clear task dependencies in our team's Gantt chart. Additionally, Gantt chart is useful for our team to track task deadlines directly, ensuring we meet project milestones [45].

  Our team's Gantt chart is shown in Figure 8.11. For example, it can be observed that both Task 5.8 and 5.9 depend on Task 5.3, as code review and unit testing must only start until the backend development starts; Task 5.3 and 5.4 cannot finish until Task 5.9 – unit testing finishes. We acknowledge that such a longer sprint (Sprint 5) may be tougher to adapt to changes and feedback, but we are confident in navigating this due to Wai Qi and Kai Jie's past Industry-Based Learning experience. Their familiarity with Agile working culture enhances our adaptability. Also, our NILM project requires substantial research and development, making longer sprint advantageous for more thorough analysis and problem-solving.

- ***Kanban Board:***
  Our team also utilises **Jira** software for developing our Kanban board to track team progress and optimise workflow. To keep our entire team updated with the current team progress, every team member must regularly update the team's Kanban board once a particular user story or assigned task has been accomplished, by simply moving the designated task(s) into the "Done" column. The project manager (Ming Sheng) is responsible for monitoring the status of individual tasks daily, to identify bottlenecks and to address delays in team progress quickly. The team's Kanban board also helps us in prioritising more important tasks and maintaining a well-organised team schedule. A screenshot of our team's Kanban board is shown in Figure 8.12.

### 3.5.2 Resource Requirements

The estimates of total resources needed to accomplish our project are properly documented in this section, which is divided into four categories as shown below.

#### 3.5.2.1 Numbers and Roles of Personnel Required

Our team comprises four members, particularly project manager (Ming Sheng), quality assurance (Wai Qi), and two technical leads (Martin and Kai Jie). Each team member is required to work on this NILM team project for a minimum of **20 hours per week** during the project management planning phase; **40 hours per week** during the project execution phase as all of our team members will only be taking one single unit (i.e. FIT3162/64) during the Summer 2023-2024 Semester. Thus, we can highly focus on executing our NILM project.

During the project execution phase, the **project manager** will focus on documentation-related tasks; **quality assurance** will focus on preparing and executing test cases, checking the code correctness and clarity, and testing the NILM model; **technical leads** will focus on processing electrical signals in NILM, developing the NILM model, and fine-tuning the model to improve its performance. If necessary, the project manager and quality assurance will also help technical leads to further preprocess data and develop the model or GUI to enhance team progress and reduce their workloads, as both Ming Sheng and Wai Qi are also well-equipped with the essential technical knowledge and skill sets for the NILM model and frontend development. Table 8.20 in Appendix shows the estimated effort and tentative number of personnel required for different activities. However, since we are adopting Agile methodology, we will dynamically adjust the number of personnel required where appropriate and needed.

#### 3.5.2.2 Hardware specifications

Table 8.21 in Appendix shows the **hardware specifications** required for our project. Due to the limitations of our team's currently best available laptop, **Google Cloud A2 Virtual Machine (VM)** services are chosen to be acquired by our team, with a minimum hourly rate of **USD$0.87**.

#### 3.5.2.3 Software specifications

Table 8.22 in Appendix shows the **software specifications** required for our project, Table 8.23 in Appendix is designated for showing the **software libraries** to be used as our primary tools in data preprocessing and model implementation, and Table 8.24 in Appendix is designated for depicting the **project management tools** required for our project.

# Chapter 4

# External Design

## 4.1 User Interface

The project's core is its model, showcased through a minimalistic GUI designed for testing and demonstrating performance, refer to Figure 4.1 for its visual representation. The UI emphasises data import/export, adapting to various formats. Users can import datasets through the "**Import Datasets**" component on the top left of the UI and export NILM results through the "**Export data**" component on the right of "**Overall Energy Consumption**" conveniently. The UI's "Overall Energy Consumption" component visualizes disaggregated information with real-time charts, depicting appliance energy patterns, and includes a concise summary of identified appliances and their energy usage in the "**Identification of Appliances**" component.

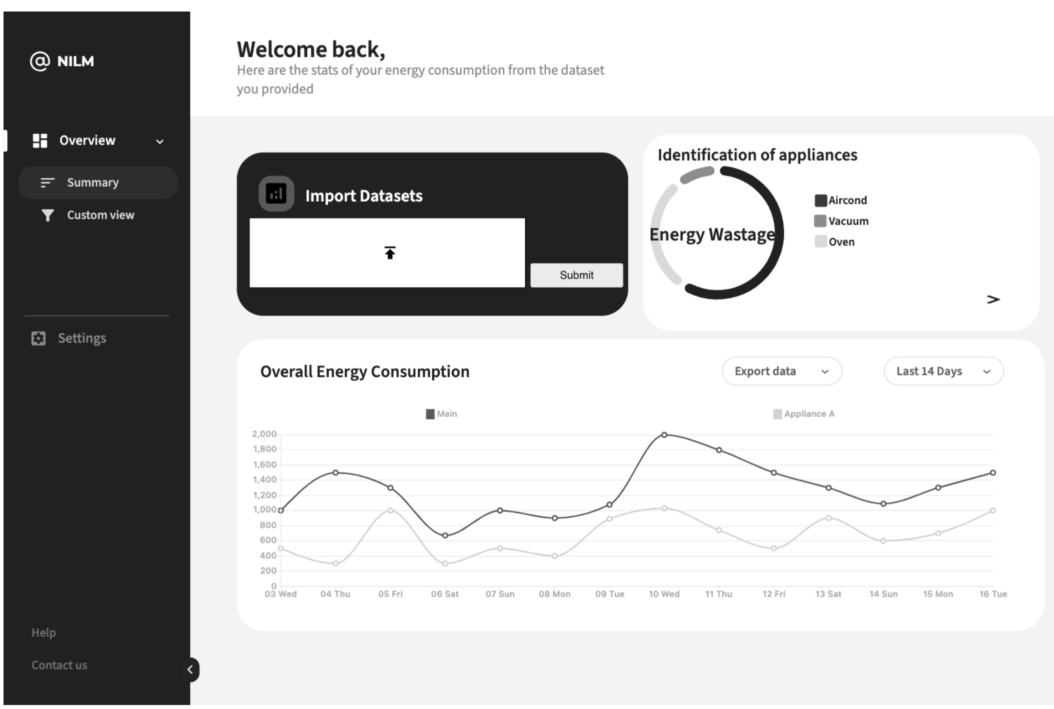


Figure 4.1: Mock UI diagram

## 4.2 Datasets

The datasets essential for both training and testing our NILM model comprise three key fields, which are **Timestamp**, **Apparent (VA)**, and **Active (W)**. These fields contain indispensable information for conducting a thorough analysis and interpretation of energy consumption patterns. "Timestamp" field represents the temporal dimension of the data, indicating the **time** each record was registered by the centralised meter. On the other hand, the Apparent (VA) and Active (W) fields delve into the energy characteristics. "Apparent (VA)" represents the apparent power, encapsulating the **total power flow**, encompassing both real and reactive power components. However, it's crucial to emphasise that not all of this power is necessarily absorbed and utilised for practical work. The portion of power absorbed and used by the load is known as active power, always equal to or less than the apparent power [46]. "Active (W)" denotes the active power, specifically pinpointing the **actual power consumed** by the appliance to perform useful work. These fields form the foundation for NILM analyses, enabling the extraction of meaningful patterns and behaviours related to energy consumption from the provided dataset. Moreover, we have these datasets that recorded the overall energy consumption, known as the main datasets, as well as datasets specific to the energy consumption of various appliances. These categorised datasets provide information on air conditioners, dryers, fridges, kettles, ovens, vacuums, washing machines, and water heaters.

## 4.3 Data Source

This project involves the utilisation of two datasets, namely those obtained from **MIMOS Berhad** and **UK-Dale**.

MIMOS stands as a strategic agency operating under the purview of the Ministry of Science, Technology, and Innovation (MOSTI). As a leading innovation centre specialising in Semiconductors, Microelectronics, and ICT technologies, MIMOS plays a pivotal role in fostering Malaysia's socio-economic growth. The organisation contributes significantly by developing patentable technology platforms, innovative products, and effective solutions that contribute to the advancement of the nation's technological landscape [47].

UK-Dale, short for UK Domestic Appliance-Level Electricity, is a valuable open-access dataset from the UK, created to facilitate research in the field of energy disaggregation algorithms [48].

## 4.4 Performance

The performance of our NILM model is crucial for real-time analysis and user interaction. Our main goal is to optimise processing and training speed for prompt responses to user queries, with a target response time of within **2 seconds**, though Google suggests maintaining a response time within 1.3 seconds for a good responsive user experience [49], considering the time constraints we anticipate in completing the project. Performance testing will assess the model's handling of large datasets, complex algorithms, and user interactions, including UI response time and model training speed. Continuous monitoring and optimisation will ensure a seamless and responsive user experience within our NILM system.

# Chapter 5

# Methodology

## 5.1 Programming Language

We have chosen **Python** as the primary programming language for both data pre-processing and model development, primarily because of its robust deep learning ecosystem, strong community support, widespread popularity, high-level nature, and versatile capabilities. This decision is in line with the expertise and familiarity of our entire team.

## 5.2 Visualisation Tools

In our pursuit of effective data analysis and visualisation, we have chosen **Matplotlib** and **Seaborn** libraries as our primary visualisation tools. Both libraries are known as powerful and versatile visualisation tools in Python.

- ***Matplotlib:***
  Generates visualizations to illustrate energy consumption patterns, aiding users and researchers in understanding long-term energy usage. Annotation features enhance analysis and interpretation of power signal plots, facilitating the identification of specific appliances.

- ***Seaborn:***
  Improves plot aesthetics, valuable for exploring variable relationships, detecting patterns, and gaining insights into statistical characteristics of energy consumption data.

## 5.3 Database System

**PostgreSQL** is a robust open-source relational database management system (RDBMS) that can be used for data processing and management in the context of NILM. In NILM, managing time-series data is crucial for recording energy consumption over time. PostgreSQL's expertise in **handling time-series data** makes it ideal for organizing chronological records related to energy usage. It efficiently stores structured data, including details about appliances, energy usage patterns, and metadata, creating a robust repository for diverse information in NILM.

## 5.4 Version Control System

In our software development, **Git** is our chosen version control system. Git provides a robust framework for efficiently tracking changes, ensuring seamless collaboration among team members, and keeping everyone synchronised with the latest updates. This collaborative aspect is particularly valuable as it allows multiple developers to independently contribute to the same project concurrently, with Git ensuring the smooth merging of these contributions.

## 5.5 Programming Language Environment

**Jupyter Notebook** has been selected as the primary development environment for our project. The choice of Jupyter Notebook provides our team with a high degree of flexibility and control over the development environment. By using Jupyter Notebook, we have the freedom to perform various configurations, install packages, integrate different tools, and customise the environment according to the specific requirements of our NILM tasks.

## 5.6 Frontend Framework

Utilising **Angular** to develop a web-based application integrated with NILM introduces a powerful and dynamic framework for constructing a responsive and user-friendly frontend. Angular's bidirectional data binding ensures real-time synchronisation between the user interface and the underlying model, facilitating the real-time presentation of dynamic information on energy consumption and load profiles.

## 5.7 Data Collection

Our project relies on **data provided by MIMOS Berhad**, MIMOS has generously supplied datasets sourced from their centralised meters. Additionally, we plan to supplement our dataset with the inclusion of the **UK-Dale dataset**, sourced from online repositories. As part of our project's future plans if time permits, we intend to further enrich our dataset collection by gathering real-world datasets from households in Malaysia. A sample of one of the datasets is shown in Figure 5.1.

| | Timestamp | Apparent (VA) | Active (W) |
|---|---|---|---|
| **0** | 2022-11-07 16:01:27 | 0.05 | 0.01 |
| **1** | 2022-11-07 16:01:28 | 0.00 | 0.00 |
| **2** | 2022-11-07 16:01:29 | 0.00 | 0.00 |
| **3** | 2022-11-07 16:01:30 | 0.00 | 0.00 |
| **4** | 2022-11-07 16:01:31 | 0.00 | 0.00 |

Figure 5.1: Sample of datasets provided by MIMOS Berhad

## 5.8 Data Preprocessing

In the context of NILM, where the aim is to disaggregate overall energy consumption into individual appliance-level usage, the significance of adept data preprocessing cannot be emphasised enough. The subsequent paragraphs delineate essential stages in the data preprocessing pipeline, custom-tailored to meet the distinctive requirements of NILM applications.

### 5.8.1 Cleaning and Handling Missing Values

Handling missing or incomplete data is of utmost importance to ensure the accuracy of subsequent analyses. Methods such as imputation or removal of records with missing values are employed to address these gaps in the dataset. Certain timestamps exhibit **missing or unavailable data records** for "Type" == "main," while records for other appliance types are present during these periods. Our working assumption is that this issue is likely attributed to the absence of CSV files in the "main" subfolder within the dataset provided by MIMOS Berhad. Given this, we opted against imputing or generating data values for "Type" == "main" at these timestamps to avoid potential data authenticity concerns. Consequently, we decided to straightforwardly **remove** the records associated with these instances.

### 5.8.2 Dataset Aggregation and Temporal Enhancement

To improve the precision of temporal information within the dataset, we address the limitation posed by the comprehensive "Timestamp" column, which amalgamates both date and time details for each record. Extracting such information at a more granular level, we introduce **new columns**, specifically "Year", "Month", "Day", "Hour", "Minute", and "Second". This process involves retrieving corresponding values from the existing "Timestamp" column, enabling a **detailed breakdown of temporal aspects**. To ensure a consistent application of this modification across all records in the various CSV files within the primary directory "Data", we generated a new dataframe by concatenating data from all available CSV files. This consolidated dataframe not only facilitates the incorporation of new temporal columns but also ensures a standardised implementation of this enhancement throughout the entire dataset.

### 5.8.3 Handling Temporal Misalignments

Addressing temporal misalignments in data ensures that the timestamps across various data sources are synchronised, providing a consistent timeline for analysis. Notably, the "Timestamp" column in the provided datasets does not exhibit a continuous sequence of time/date values, with **certain intervals being unavailable**. To address this, the dataframe is **partitioned** into multiple separate dataframes, each containing a continuous sequence of date/time data values in the "Timestamp" column. In simpler terms, each distinct dataframe comprises records from different time sessions, separated by intervals with unavailable "Timestamp" data. This approach is deemed acceptable as there is **no practical relationship** between one session and another.

### 5.8.4 Handling Outliers

The identification of outliers, which could signal measurement errors or unusual appliance behaviour, requires careful attention. We have detected potential outliers that are characterised by **unusually high or low values** in both the "Apparent (VA)" and "Active (W)" columns, categorised by appliance types. Despite these anomalies compared to mean values, a decision has been made to **not remove or pre-process** these potential outliers. This choice stems from the recognition that they might provide **essential features** for understanding the energy consumption pattern as well as unveil signs of undesirable **energy wastage**. However, it is important to acknowledge the presence of these potential outliers, maintaining awareness of their impact on the dataset.

### 5.8.5 Data Splitting for Model Evaluation

To precisely evaluate our NILM model after the necessary preprocessing, we will partition the datasets into **training** and **testing** sets. The training data will constitute **80%**, while the testing data will comprise **20%** of the total. This segregation ensures that the model undergoes training on one set and is subsequently tested on an independent set. This approach allows for a thorough assessment of our model's generalisation capabilities.

## 5.9 Algorithm Explanation

**Hidden Markov Models (HMMs)** have been widely used in the domain of NILM, notably in the context of event-based approaches as it stands out as a precise algorithm for simulating load performance states, capturing a set of states at a particular time [50]. This model has demonstrated significant utility in learning probabilistic representations of time series data. Within an HMM, historical information is encapsulated in a single discrete variable—referred to as the hidden state [51]. The intrinsic sequential pattern of appliance power consumption events has been used by researchers to model and identify electrical appliances in houses [52]. The capabilities of HMM in load monitoring, as highlighted in the document [53], extend to effectively handling transient loads, which are brief fluctuations in electrical signals associated with the switching on or off of appliances, and simultaneously identifying multiple appliances.

The model that we are going to use is the **Factorial Hidden Markov Model**, also known as **FHMM**. FHMM was employed to address the NILM problem, demonstrating its effectiveness in successfully disaggregating residential load data, particularly when dealing with low sampling rates [54]. An FHMM model comprises multiple chains of HMM. Therefore, FHMM doesn't provide direct outputs for the observations of individual hidden Markov chains, instead, it outputs the summation of observations from each Markov chain, as a result, the model parameters are obtained by consolidating the parameters of each single-layer HMM model. In the context of the NILM problem, the total active or reactive power serves as the observation sequence, and the states and power consumption of each appliance remain unknown. Consequently, each appliance can be conceptualised as a HMM, where the operational state of an appliance constitutes a Markov chain. Aggregating the power of each appliance produces the total power, making it aptly represented as a FHMM composed of multiple HMMs. In this FHMM, the observation sequence is the power consumption. Once all the parameters for the FHMM model are acquired, the hidden states can be decoded using the Viterbi algorithm applied to the aggregated power consumption sequence. It's important to note that the hidden working state sequence obtained through the Viterbi algorithm does not represent the actual working states of each appliance; rather, it denotes the combined hidden state of the FHMM model. To obtain the actual power consumption of each appliance, a power mapping process is adopted, which is illustrated by equations below [55]:

$$AS_t(j) = \lfloor \frac{CZ_t * \prod_{i=1}^{j} WS(i)}{\prod_{i=1}^{N} WS(i)} \rfloor \mod WS(J)$$

$$RP_t(j) = \mu(j)[AS_t(j)], j \in 1, 2, ..., N$$

Here, N represents the number of appliances, $CZ_t$ signifies the combined working state obtained from the FHMM model at time t. $WS(i)$ denotes the number of working states for appliance i, $AS_t(j)$ represents the actual working state of appliance j at time t, and $RP_t(j)$ is the corresponding real power consumption [55].

The pseudocode for the power mapping process is presented in Figure 5.2.

```
Input: μ: the power consumption of each appliance
       CZ: the combined hidden state obtained by FHMM model
Output: RP: the real power consumption of each appliance at each time
for t, z in enumerate(CZ) do
    for i in N do
        AS_t(i) ← Eq.19
        RP_t(i) ← μ(i)[AS_t(i)]
    end
end
return RP
```

Figure 5.2: Power mapping process [55]

The frameworks of HMM and FHMM, illustrated in Figures 5.3 and 5.4 below, are described as follows, where $S_t$ represents the hidden state of HMM at time t, and $Y_t$ is the observation value of the model at time t [56]. Notably, in FHMM, the observed values are influenced by the states of all the HMMs. Building upon the FHMM description, the load disaggregation problem can be characterised as follows: Given the active power and reactive power data $\{Y_1, \ldots, Y_T\}$ of the total load and the HMM parameters for each equipment at a specific time period t, the objective is to determine the states $\{S_1, \ldots, S_T\}$ of each equipment. After estimating the states, the power consumption data for each load is separated from the total power data, and the Viterbi algorithm is utilised to address this specific problem.

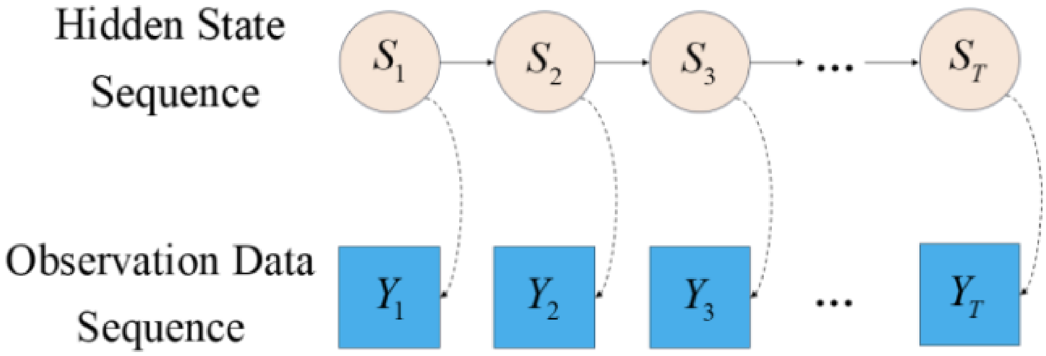


Figure 5.3: Working principle of a single HMM [56]

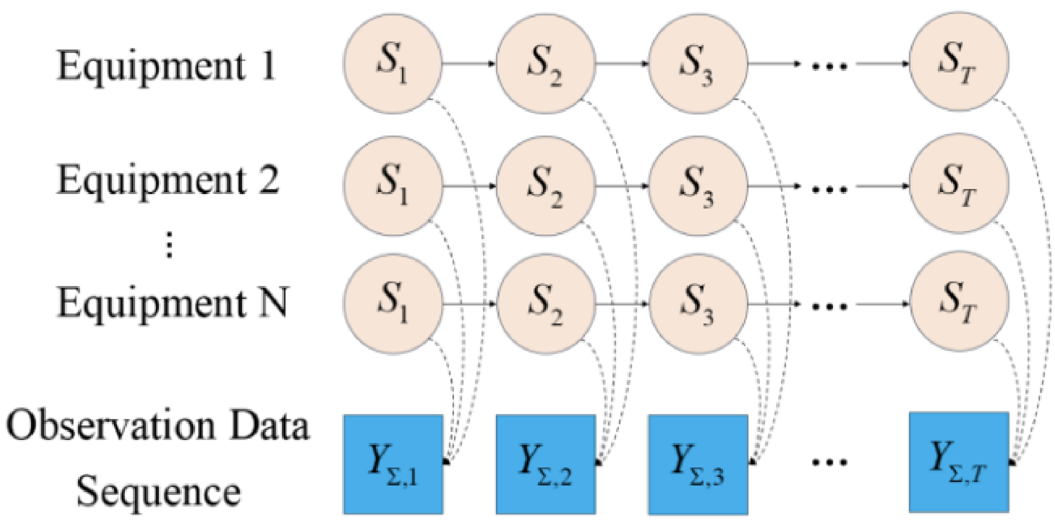


Figure 5.4: Working principle of FHMM composed of multiple HMMs [56]

## 5.10 Data Flow Diagram

### 5.10.1 Level 0 Data Flow Diagram

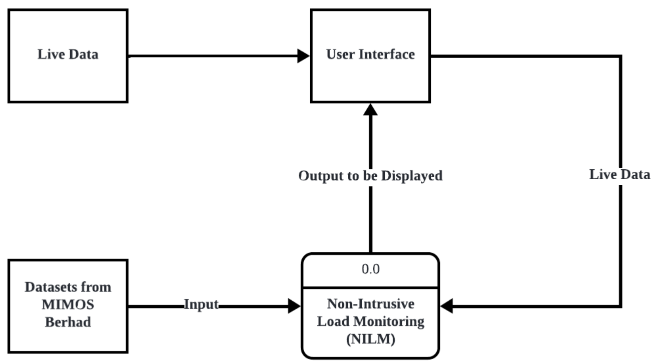


Figure 5.5: Level 0 Data Flow Diagram

In the Level 0 Data Flow Diagram, we provide a broad overview of NILM. The **Datasets sourced from MIMOS Berhad** will serve as input for training the NILM model, and the results generated by the model will be showcased in the **UI**. External users can seamlessly import their **Live Data** into the UI, establishing integration with the NILM model. This integration allows for the presentation of real-time data outputs on the UI for external users.

### 5.10.2 Level 1 Data Flow Diagram

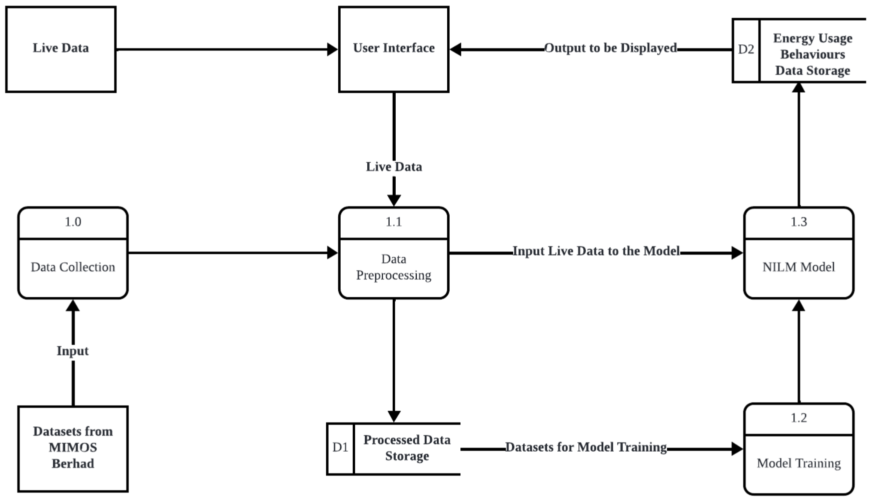


Figure 5.6: Level 1 Data Flow Diagram

The Level 1 Data Flow Diagram provides a detailed breakdown of the system into four core processes which are **Data Collection**, **Data Preprocessing**, **Model Training**, and NILM **Model Execution**. The data collection process involves gathering data from both users and MIMOS Berhad. Subsequently, the collected data undergoes preprocessing, where it is refined and stored in a dedicated preprocessed data storage. The model training process entails training the model using the preprocessed data to generate relevant outputs. Finally, the NILM model execution process involves applying the finalised NILM model to live data for real-time analysis.

### 5.10.3 Level 2 Data Flow Diagram

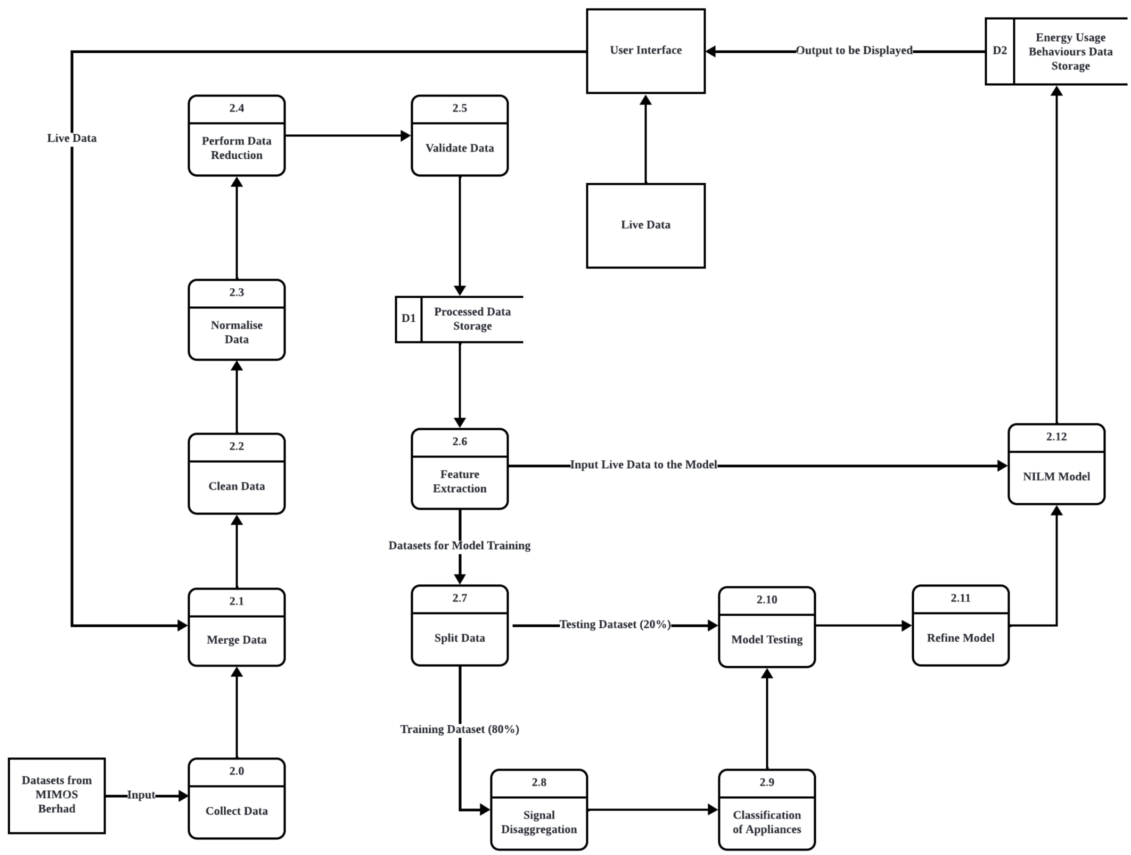


Figure 5.7: Level 2 Data Flow Diagram

In the Level 2 Data Flow Diagram, **Data Preprocessing** and **Model Training** are detailed sub-processes. The data undergoes systematic transformation, including **Merging**, **Cleaning**, **Normalisation**, and **Reduction**, preparing it for the NILM model. A deliberate separation into **Training and Testing Datasets** ensures robust evaluation. Signal processing extracts features for appliance classification. Iterative refinements address accuracy issues. Real-world datasets with established NILM models contribute directly, bypassing certain steps. The model output, offering insights into appliance usage, is stored and visually represented on a dedicated UI.

## 5.11 Model Evaluation

The chosen performance metrics for evaluating our NILM model include **accuracy**, **F-score**, and **modified F-score (M-FScore)**. Our goal is a minimum accuracy of **90%**, with anything exceeding 70% considered excellent [57]. For F-score and M-FScore, the target is a minimum of **0.80**, as an F1 score of 0.70 or higher is generally satisfactory [58]. These metrics assess the model's effectiveness in correctly identifying and categorizing appliance usage patterns, with a high F-score indicating a well-balanced precision and recall.

# Chapter 6

# Test Planning

## 6.1 Introduction

Our NILM project is an **Agile-driven endeavour** aimed at the development of a resilient system for monitoring and disaggregating energy consumption data within both residential and commercial settings. Our Agile approach mandates that **test planning** be an **ongoing and adaptive process**, designed to remain flexible and responsive to changes in project requirements and priorities [59].

The primary objectives of our test planning are threefold: to ascertain that the system **aligns with the project scope** and effectively **fulfils specified requirements**, to validate the **quality of our NILM model and the user interface (UI)**, and to **implement quality assurance and quality control measures** throughout the development process. This encompasses **unit testing**, **integration testing**, **system testing**, and **user acceptance testing** to evaluate the entire NILM system for functionality, performance, and alignment with user expectations.

## 6.2 Test Scope

### 6.2.1 Model Testing

In model testing, our primary goal is to **validate the accuracy and reliability of our NILM model**. This validation involves confirming the model's ability to accurately identify appliances in use, learn and optimise usage behaviours, and detect unwanted energy wastage. Additionally, the model's proficiency in processing and analysing provided meter readings will be thoroughly examined. This process includes collecting, cleaning, and filtering data before it is utilised to train the model. Furthermore, we will evaluate the insights provided by the model, ensuring that they offer meaningful and relevant information about energy usage patterns. This encompasses the identification of appliances and emerging usage trends. Finally, we will assess the real-time data processing capabilities of the model to ensure timely insights are delivered in response to changing energy consumption patterns.

### 6.2.2 GUI Testing

In GUI testing, our primary objective is to **create a user-friendly interface** that enables users to interact effectively with the NILM system. One critical focus area is the validation of user input. We aim to ensure that the UI allows users to input meter readings conveniently and accurately. Moreover, we will assess the overall user experience and usability of the interface, including the ease of navigation, clarity of energy insights presentation, and UI responsiveness. Cross-device and cross-browser compatibility will be a priority, ensuring that the UI functions correctly and appears as expected on various devices and web browsers. Additionally, security features, such as data protection measures, will be rigorously evaluated to safeguard user data and maintain the interface's integrity. Through this comprehensive testing, we aim to provide a dependable UI that aligns with user expectations and ensures data security.

## 6.3 Test Methods

In this section, we explore our testing strategies within the defined test scope, adhering to an agile methodology that emphasises iterative and adaptive testing approaches. Our testing phases include **unit testing**, **integration testing**, **system testing**, and **user acceptance testing**. The overarching goal is to guarantee the system's reliability and flexibility as we strive to create an efficient solution for energy monitoring and load disaggregation.

### 6.3.1 Unit Testing

Unit testing is a critical phase that **focuses on the examination of individual units** or **isolated components** within our system. The primary objectives here are to confirm that each unit functions as intended and complies with the defined requirements. This approach also aids in evaluating whether specific sections of code within our model or UI are delivering the anticipated performance.

### 6.3.2 Integration Testing

Integration testing within our NILM project is designed to rigorously **assess the collaborative performance of interconnected components**. Our primary goals are to confirm that the UI seamlessly communicates with the data processing and analysis components, and that data flows fluidly. For instance, this entails verifying that energy consumption data collected are accurately transmitted to our data processing modules and subsequently analysed for energy disaggregation and appliance identification. These tests are essential to ensure that our NILM system functions reliably, accurately disaggregates energy usage, and successfully manages the complex data interplay crucial for effective energy monitoring. For real user scenarios, integration testing would involve verifying that our UI effectively captures user inputs, passes them to the system for analysis, and returns accurate and meaningful results or recommendations.

### 6.3.3 System Testing

Upon the completion of our NILM system and UI, the system testing phase serves several critical purposes. It seeks to comprehensively **evaluate the overall functionality of the entire NILM system**, ensuring that it operates reliably and effectively under varying conditions. This entails assessing the system's performance, responsiveness, and the **seamless flow of data through all system components**, from data capture to analysis and appliance identification. Real-world energy consumption data will be sourced and used to validate the system's accuracy in presenting the correct output, an essential element in our testing strategy.

### 6.3.4 User Acceptance Testing

The final stage of our Agile test planning process is User Acceptance Testing (UAT). The primary objectives are to **validate that the system meets end-users' expectations** and **aligns with the project scope and objectives**. End-users and project stakeholders actively participate in user acceptance testing, executing a predefined set of test cases to evaluate the system's readiness for production.

Any issues identified during acceptance testing will be documented and resolved before the final system release to ensure that it meets the desired quality and functionality expectations.

## 6.4 Test Cases

Examples of test cases for our model and web application can be found in Appendix (Tables 8.25, 8.26, 8.27, 8.28, and 8.29). Table 8.25 outlines the test scope of our software, while Tables 8.26, 8.27, 8.28, and 8.29 outline the testing processes to be conducted to verify that all outcomes align with our requirements.

# Chapter 7

# Conclusion

In conclusion, the untapped potential of the NILM market in Malaysia offers a compelling opportunity for innovation. With the objective of bridging this gap, our team has set forth a detailed project proposal to introduce a state-of-the-art NILM system tailored to the Malaysian context. Utilising the **event-based FHMM model**, which has proven efficacy with low-frequency data, combined with the robustness of the **Viterbi algorithm** and **power mapping algorithm**, we aim to provide a comprehensive solution for energy disaggregation. A mock GUI, which has been conceptually designed in this proposal, will serve as the foundation during our GUI implementation phase, presenting a clear and user-friendly interface to showcase our model's capabilities. This proposal also outlines the test plan for evaluating our NILM model's performance, robustness and GUI usability, with comprehensive test cases crafted based on this fundamental guideline. It ensures our project's alignment with the highest benchmarks of quality, reliability, and user-centricity.

Recognising the multifaceted challenges of pioneering projects, our project management strategies embrace the **Agile methodology**. This approach ensures that our team remains adaptive, addressing any unforeseen challenges promptly and iteratively. To optimise our workflow and ensure timely deliverables, we have incorporated tools such as the WBS, Gantt chart, and Kanban board. These tools, paired with consistent sprint meetings, will provide both structure and flexibility, guaranteeing that every project phase is executed seamlessly and is in alignment with our objectives.

The guiding light in our project remains our project supervisor, Dr. Lim. His rich experience and unparalleled guidance have been instrumental in channelling our efforts in the right direction, leveraging the best of available resources and expertise.

In essence, our NILM project represents a pioneering effort in Malaysia's energy management landscape. The successful implementation of our project has the potential to make a significant impact on Malaysian households, leading to more efficient energy usage, cost savings, and a reduced environmental footprint.

# Chapter 8

# Appendix

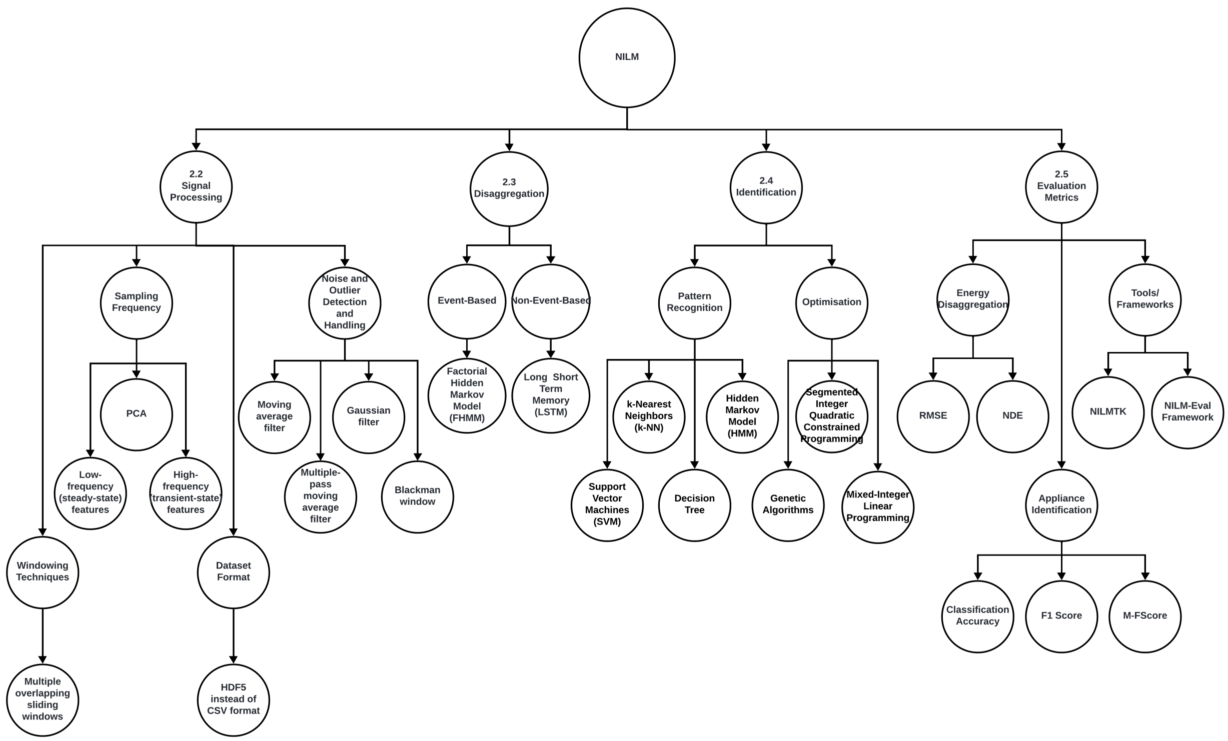


Figure 8.1: Structure of literature review

| Low frequency (0Hz to 100Hz) | High frequency (2kHz to 20kHz) |
|---|---|
| • Reactive power<br>• Active power<br>• Apparent power | • Transient energy<br>• Harmonic spectrum |

Table 8.1: Feature categorisation based on sampling frequency

<table>
<tr><th>Filtering Technique</th><th>Pros</th><th>Cons</th></tr>
<tr><td>Moving average filter</td><td>• Minimise random noise while sharpest step response is preserved<br>• High computational speed due to the use of recursive algorithm<br>• Good performance in time domain</td><td>• Bad performance in frequency domain</td></tr>
<tr><td>Multiple-pass moving average filter</td><td rowspan="3">• Better performance in frequency domain</td><td rowspan="3">• Longer computational time<br>• Slower computational process<br>• Bad performance in time domain</td></tr>
<tr><td>Gaussian filter</td></tr>
<tr><td>Blackman window</td></tr>
</table>

Table 8.2: Comparative Analysis of Different Filter Types [13]

**Non-Intrusive Load Monitoring (NILM) Synthesis Table**

| Title | Year | Venue | Citation | Author | Keywords | Contribution / Impact | Dataset | Evaluation | Gap/Future Work/ Limitation | Hyperlink |
|---|---|---|---|---|---|---|---|---|---|---|
| Non-Intrusive Load Monitoring (NILM) using Deep Neural Networks: A Review | 2023 | Electrical Engineering and Systems Science | 37 | - Mohammad Irani Azad<br>- Roozbeh Rajabi<br>- Abouzar Estebsari | - Smart Grids<br>- NILM<br>- Deep Learning<br>- Energy Management<br>- Event-Based Non-Intrusive Detection<br>- CNN | - Compared the results of different deep learning-based NILM methods with other existing NILM algorithms<br>i) Some deep learning-based method outperformed existing NILM algorithms<br>ii) Deep Neural Network<br>- Pros: High accuracy, can handle complex appliances behavior, can identity multiple appliances simultaneously<br>- Cons: Required a large amount of training data, can be computationally expensive, limited interpretability | - REDD<br>- BLUED<br>- UK-DALE<br>- REFIT<br>- AMPds2 | - Accuracy<br>- Precision<br>- Recall<br>- F-Score<br>- MAE<br>- Proportion of energy correctly allocated (PECA) metrics | - Neutral NILM required time and computational resources to train the neural network and generate the models need a large amount of appliance-level data whereas on-line NILM technique may generate appliance models using aggregate data without the necessity for appliance-level sub-metered data | https://arxiv.org/abs/2306.05017 |
| Non-Intrusive Appliances Load Monitoring (NILM) for Energy Conservation in Household with Low Sampling Rate | 2016 | Procedia Computer Science | 5 | - Somchai Biansoongnern<br>- Boonyang Plungklang | - 3 points method | - Presented a design and construction of measuring system to measure the power consumption of air conditioners and refrigerators in household without installing anything directly to the appliances<br>- Used 3 points method to monitor data to detect any change of power signal that obtained a 1 Hz sampling rate of active power from energy meter<br>- Real time information can be achieved | | - Accuracy | | https://www.sciencedirect.com/science/article/pii/S1877050916303854 |
| Intelligent home energy management using Internet of Things platform based on NILM technique | 2023 | Sustainable Energy, Grids and Networks | 19 | - R. Ramadan<br>- Qi Huang<br>- Olusola Bamisile<br>- Amr S. Zalhaf | - NILM<br>- FHMM algorithm<br>- Disaggregation algorithm<br>- time series | - Used NILM technique to improve the energy efficiency in smart homes - Factorial Hidden Markov Model (FHMM) is used as a NILM technique to achieve high prediction accuracy & enhance energy management.<br>- Compared predicted and actual values of power consumption of the appliances. This result is then compared with other methods.<br>- Twitter is used as one of the ThingSpeak applications to send the information about each appliance data output from load disaggregation to the customer.<br>- Provided a comprehensive analysis of customer behavior in relation to energy consumption. | - REDD | - RMSE | | https://www.sciencedirect.com/science/article/pii/S2352467722000959 |
| NILM applications: Literature review of learning approaches, recent developments and challenges | 2022 | Energy and Buildings | 42 | - Georgios-Fotios Angelis<br>- Christos Timplalexis<br>- Stelios Krinidis<br>- Dimosthenis Ioannidis<br>- Dimitrios Tzovaras | - Load disaggregation<br>- Machine learning<br>- Deep learning | - Provided an analytical overview of widely used datasets for energy disaggregation, including characteristics such as sampling rates, measurement duration, and the types of buildings (residential, commercial, or industrial) represented in the datasets.<br>- Presented various feature extraction and pre-processing techniques used in the energy disaggregation domain. These techniques are crucial for processing energy consumption data efficiently.<br>- Offered an up-to-date overview of existing NILM approaches, with a particular focus on machine learning and deep learning methods. Discussed the latest developments in this field.<br>- Discussed the evaluation methods employed in NILM algorithms.<br>- Discussed the potential applications and implications of NILM for both consumers and utility companies. | - REDD<br>- UK-DALE<br>- AMPds/2<br>- REFIT<br>- Dataport<br>- ECO<br>- ENERTALK<br>- iAWE<br>- BLUED<br>- PLAID<br>- DRED<br>- SynD<br>- Georges Hebrail UCI | - Energy-based F-score<br>- MAE<br>- RMSE<br>- Total Energy Correctly Assigned (TECA)<br>- Energy Accuracy (EA)<br>- | | https://www.sciencedirect.com/science/article/pii/S0378778822001220 |

Figure 8.2: Screenshot of our synthesis table

| **Aspect** | **Event-based Approach (FHMM)** | **Non-Event-based Approach (LSTM)** |
|---|---|---|
| Disaggregation Accuracy | High accuracy when detecting distinct energy events tied to appliance state changes | Demonstrated high accuracy, especially when properly tuned |
| Real-time Disaggregation | Capable of real-time detection and classification with continuous electrical activity monitoring | Can provide real-time results, but high computational requirements might introduce some delays |
| Temporal Resolution | Excellent in capturing instant appliance state changes | Excels due to its capability to handle time-series data and capture temporal patterns |
| Overlapping/Simultaneous Events | Challenges arise when multiple appliances change states simultaneously | Designed to manage overlapping data due to its ability to process sequential data, thus handling simultaneous appliance operations better |
| Complexity | Moderate complexity. Requires mechanisms for event detection, classification, and state sequence determination | High complexity stemming from its deep learning architecture. It requires considerable fine-tuning and optimisation |
| Training Data Requirement | Supervised requires labelled data. Unsupervised can function without, but might employ the Expectation-Maximisation algorithm | Heavily dependent on a significant amount of quality training data for effective learning |
| Appliance Signature Variability | Might face challenges if appliances have variable signatures not distinctly recognisable in event detection | Can adapt to varied signatures given proper training and data. With sufficient epochs and data diversity, LSTMs can accommodate variability in appliance signatures |

Table 8.3: Summary of energy disaggregation, where **green represents pros and red represents cons**

| **Milestone** | **Description** |
|---|---|
| Project Kickoff | Establish team roles and responsibilities while clearly defining the primary objectives |
| Business Case Study on NILM | Immerse into NILM's core concepts to acquire a foundational understanding |
| Project Management Planning | Design a strategic roadmap for project execution with a keen focus on agile methodologies and iterative processes |
| Data Preprocessing and Analysis | Standardise datasets to the HDF5 format, rectify any discrepancies, and unearth crucial insights from the cleansed dataset |
| NILM Model Architecture Design | Sketch the foundational architecture for the NILM model in alignment with project aspirations. Also, finalise the required hardware, software, and libraries |
| NILM Model Implementation Phase | Develop and train the model using the MIMOS Berhad dataset to achieve optimal performance |
| GUI Development | Construct an intuitive GUI that provides a seamless interface with the NILM model |
| NILM Model Evaluation | Gauge the model's efficacy in disaggregating electrical energy signals, and make necessary refinements to enhance performance |
| NILM Model Integration and Testing | Flawlessly integrate the NILM model with the GUI, ensuring fluidity in interaction and precision in data visualisation |
| Project Documentation | Document methodologies, tools, results, and all processes related to the NILM project |

Table 8.4: Milestones in our project

| **Project Deliverables** | **Description** |
|---|---|
| Business Case Study | An analytical document that evaluates the feasibility and different aspects of the NILM project |
| Mind Map and Project Management Planning | Visual representation (Mind Map) outlining project objectives, strategies, and planning techniques |
| Project Concept and Design | Initial blueprints and designs conceptualising the direction and approach of the project |
| Data Analysis Report | Detailed report capturing insights, patterns, and inferences drawn from the datasets |
| Project Scope Statement | Clear articulation of the project's boundaries, objectives, deliverables, and stakeholders |
| Requirement Traceability Matrix (RTM) | A document that maps and traces user requirements with test cases |
| Gantt Chart | Visual timeline representation of the project's schedule, showing task durations and dependencies |
| Work Breakdown Structure (WBS) | Hierarchical decomposition of the project into phases, deliverables, and work packages |
| Stakeholder Analysis Matrix | A matrix identifying project stakeholders, their interests, and strategies for engagement |
| Communication Matrix | Table outlining communication methods, frequency, and stakeholders involved |
| Risk Register | Detailed list of identified risks with their impacts, probabilities, and mitigation strategies |
| Required Resources | List of all resources (i.e., human, technical) necessary for the successful completion of the project |
| Project Proposal | Comprehensive document presenting the project's objectives, methodologies, and expected outcomes for stakeholders' approval |

Table 8.5: Project deliverables

| **Product Deliverables** | **Description** |
|---|---|
| NILM model source code | Codebase for the developed Non-Intrusive Load Monitoring model |
| Visualisation of user's data | Tools and features enabling users to visualise their energy consumption data |
| Interactive Graphical User Interface (GUI) | User-friendly interface facilitating interaction with the NILM model and data visualisations |
| Test plan and test cases | Detailed documentation outlining the testing strategy, scenarios, and specific test cases for the product |
| Code documentation for NILM model | Comprehensive documentation elucidating the structure, functionality, and usage of the NILM model's code |
| Documentation for GUI | Detailed guide and reference material detailing the functionality, features, and best practices for using the interactive GUI |

Table 8.6: Product deliverables

| Category | In-Scope | Out-of-Scope | Limitations | Assumptions |
|---|---|---|---|---|
| Data Collection and Analysis | • Utilisation of datasets provided by MIMOS Berhad for preprocessing, training, and analysis ensures insights into specific consumption patterns of Malaysia.<br>• Evaluation of the trained NILM model on both MIMOS Berhad's datasets and the UK-Dale datasets to ensure the model's broad applicability.<br>• Conversion of MIMOS Berhad's datasets into the HDF5 format for efficient data processing and compatibility with UK-Dale datasets. | • Using datasets from other sources aside from MIMOS Berhad and UK-Dale.<br>• Training the NILM model using UK-Dale datasets. | • Limited data from MIMOS Berhad, covering only seven days of partial recordings (roughly 100,000 rows). | • The datasets from MIMOS Berhad and UK-Dale are both reliable and representative of their respective regions. |
| Model Development and GUI | • Building, training, and optimising an event-based NILM model using low-frequency sampling data (Active and Apparent data) from MIMOS Berhad, which offers potential in real-time analysis and quick energy disaggregation.<br>• Designing an offline, interactive GUI for local usage allows users to input main reading data and retrieve energy insights, ensuring data safety and a consistent user experience. | • Non-event -based NILM model approaches.<br>• Online deployment of the GUI and its integration with central household meters.<br>• Direct appliance-level tracking of energy usage. | • The event-based NILM might not capture all energy consumption patterns, with potential accuracy not reaching the desired 90% threshold.<br>• Offline-only GUI accessibility.<br>• Pytorch library could impose specific limitations.<br>• Requirement of robust computational resources. | • Electrical appliances maintain consistent energy consumption.<br>• Essential resources will remain accessible. |

Table 8.7: Project scope (Part 1)

| Category | In-Scope | Out-of-Scope | Limitations | Assumptions |
|---|---|---|---|---|
| Appliances and Energy Types | • Focusing on distinct appliance types as highlighted in the MIMOS datasets allows for an in-depth and accurate analysis. | • Appliances not specified in the MIMOS datasets.<br>• Other forms of energy consumption like gas and water, as the primary interest lies in electrical energy consumption. | • The model might not generalise well for appliances outside of the MIMOS dataset. | • Selected appliances and energy forms are pertinent to the project's objectives. |
| Project Compliance and External Collaboration | • Regular collaboration with MIMOS Berhad and Dr. Lim ensures the project remains on course and meets its set objectives. | • Broad deployment across all Malaysian households or other regions, as the focus is on development. | • Advanced features or improvements may be deferred due to project deadlines. | • Steady support from stakeholders is expected. |

Table 8.8: Project scope (Part 2)

| ID | Requirements | Assumption(s) and/or Customer Need(s) | Category | FR/NFR | Source | Status |
|---|---|---|---|---|---|---|
| 001 | Data cleaning for MIMOS Berhad dataset | The dataset initially had some data-related issues such as inconsistencies or missing values | Quality | FR | Project Supervisor | Completed |
| 002 | Process and analyse datasets obtained from MIMOS Berhad | Accurate and reliable datasets obtained after data preprocessing | Service | FR | Project Supervisor | Open |
| 003 | Convert the available datasets into HDF5 format | Standardised HDF5 format ensures compatibility and efficient signal processing | Quality | FR | Project Supervisor | Open |
| 004 | Leverage low sampling rate (low-frequency) data | Effective signal processing despite low sampling rates | Performance | FR | MIMOS Berhad | Open |
| 005 | Develop, train, and fine-tune the NILM model | Availability of sufficient computational resources (i.e. power, speed and memory) | Performance | FR | Project Supervisor | Open |
| 006 | GUI allowing user input of centralised meter reading data | Users know the correct format of data to input | Service | FR | Project Supervisor | Open |
| 007 | Visual representation tools for user data and model performance | Users can have a comprehensive understanding of their energy consumption behaviors from the visualization | Quality | FR | Project Supervisor | Open |
| 008 | Evaluate model performance on different datasets | The model can accurately identify appliances in different datasets | Performance | FR | Project Supervisor | Open |

Table 8.9: Requirement Traceability Matrix (Part 1), with ”FR” signifying functional and ”NFR” indicating non-functional requirements.

| ID | Requirements | Assumption(s) and/or Customer Need(s) | Category | FR/NFR | Source | Status |
|---|---|---|---|---|---|---|
| 009 | Trained NILM model achieves a minimum accuracy of 90% | High accuracy in disaggregating energy consumption patterns and identifying the electrical appliances | Performance | NFR | Project Supervisor | Open |
| 010 | Adequate documentation of the NILM model's code | Ensure readability, promote reproducibility and ease of future maintenance | Quality | NFR | Project Supervisor | Open |
| 011 | GUI works seamlessly on local machines | GUI is optimised for local use without dependency on internet access | Service | FR | Project Supervisor | Open |
| 012 | Testing of the developed GUI | Ensure the GUI works efficiently and is free of bugs. The GUI contains all detailed information required by users, and it is readable | Quality | FR | Project Supervisor | Open |
| 013 | The GUI should be user friendly | Users can get used to the developed dashboard without a training or user guide | Quality | NFR | Project Supervisor | Open |
| 014 | The GUI/model should be able to display the results within 2 seconds after the user has inputted the aggregated main meter readings | Users desire to get their results rapidly without any latency | Performance | NFR | Project Supervisor | Open |

Table 8.10: Requirement Traceability Matrix (Part 2), with "FR" signifying functional and "NFR" indicating non-functional requirements

| ReqID | User Story | Acceptance Criteria |
|---|---|---|
| 001 | As a developer, I want to process and analyse datasets to extract relevant insights | The datasets are processed without errors and generate analytical outputs pertinent to energy consumption patterns |
| 002 | As a developer, I want datasets converted to the HDF5 format for efficient data access and processing | The datasets are converted to the HDF5 format without data loss, and the conversion results in demonstrable performance improvements during data access |
| 003 | As a user, I want the model to provide accurate energy disaggregation for each electrical appliance | The NILM model demonstrates an accuracy rate of 90% or higher in disaggregating energy usage by appliance in validation tests |
| 004 | As a user, I want an interactive GUI to input main reading data and view energy consumption insights | The GUI provides a user-friendly interface for data input and displays energy consumption insights based on the provided readings |
| 005 | As a user, I want intuitive visualisation tools to grasp my energy consumption patterns | The system provides visualisations that effectively represent energy consumption patterns, ensuring they are easily interpretable |
| 006 | As a developer, I want to benchmark the model's performance across different datasets for broader insights | The benchmarking results evaluate and contrast model performance over different datasets, showing our model performance in Malaysia vs other countries |
| 007 | As a user, I expect a reliable and tested GUI | The GUI operates without crashes or critical bugs in multiple test scenarios |
| 008 | As a user, I want an interface that is easy to navigate without extensive guidance | The GUI design is intuitive, and users can navigate its features without requiring detailed instructions |
| 009 | As a user, I want immediate feedback upon entering my main readings | Upon inputting the main readings, the system generates and displays insights within 2 seconds |

Table 8.11: Product User Acceptance Criteria

| Role | Team Member |
|---|---|
| Project Manager | Chong Ming Sheng |
| Technical Lead | Martin Ung Chee Hong |
| Technical Lead | Wang Kai Jie |
| Quality Assurance | Pang Wai Qi |

Table 8.12: Project organisation

| Role | Primary Responsibilities |
| --- | --- |
| Project Manager | - Define project scope and approvals<br>- Develop project plans<br>- Coordinate team and allocate resources<br>- Monitoring & Controlling: Track progress, manage changes, report status<br>- Manage team budget |
| Quality Assurance | - Create Quality Assurance plan<br>- Develop test cases and scripts<br>- Execute test cases, document results, log defects<br>- Provide reports on testing status and defects |
| Technical Lead | - Design software architecture and select technologies<br>- Ensure code meets standard<br>- Assist team members with technical challenges<br>- Ensure components of the project work together |

Table 8.13: Project responsibilities

| **Tasks/Activities** | **Ming Sheng (PM)** | **Martin (TL)** | **Kai Jie (TL)** | **Wai Qi (QA)** | **Dr. Lim (PS)** |
|---|---|---|---|---|---|
| Define project scope and objectives | A | R | R | C | C |
| Create a project timeline (Gantt chart) | R | R | C | C | I |
| Track project progress | A | R | C | C | I |
| Risk assessment and mitigation | R | A | R | C | C |
| Stakeholder communication | R | A | C | C | C |
| Data acquisition and preprocessing | R | A | C | R | C |
| Convert datasets into HDF5 format | A | C | R | C | I |
| Research & design model architecture | C | R | R | A | C |
| Model training and testing | A | R | R | R | C |
| Model performance evaluation on different datasets | R | C | A | R | I |
| GUI development & refinement | C | C | R | R | C |
| Version Control & Code Review | R | R | A | C | I |
| Test Plan & test cases | C | R | R | A | I |
| Testing | C | R | R | A | I |
| Presentation | A | R | R | R | C |
| Project Proposal Writing | A | R | R | R | C |
| Documentation | A | R | R | C | C |

Table 8.14: RACI Matrix, where **RACI** where **R** denotes Responsible (who does the work), **A** denotes Accountable (who makes the decision and ensures completion), where **C** denotes Consulted (who provides input, needs to be consulted before a decision or action), and **I** denotes Informed (who needs to be informed after a decision or action). **PM** denotes Project Manager; **TL** denotes Technical Lead; **QA** denotes Quality Assurance; **PS** denotes Project Supervisor.

| Strengths | Weaknesses |
|---|---|
| • Both Kai Jie and Wai Qi have rich experience and technical knowledge in real-life industrial projects, such as frontend development, since they have IBL experience<br>• All team members have sufficient practical knowledge on Machine Learning, as we have previously taken/are currently taking FIT1043 and FIT3181 units<br>• All team members have strong interests in the NILM project, and thus we are highly motivated to learn new things throughout the entire project Highly responsive and reachable project supervisor (Dr. Lim)<br>• Project supervisor (Dr. Lim) is highly professional and experienced in industrial projects | • Ineffective communication between team members, as Martin and Ming Sheng will be working remotely in Sarawak during the during the upcoming Summer 2023-2024 Semester of Monash University Malaysia<br>• Team members underestimate the workloads required for the NILM project execution phase<br>• All team members are new to the field of electricity, which is what the NILM project is about<br>• Martin and Ming Sheng are lacking real-life industrial project experience, and thus are unfamiliar with frontend and backend development or integration |
| **Opportunities** | **Threats** |
| • Our NILM project draws attention from external organisations, signalling potential sponsorships<br>• Our team receives additional datasets from MIMOS Berhad, which can substantially improve the project's depth and model performance<br>• Innovative methodologies used in our NILM model offer significant potentials for publication | • Insufficient time for NILM project execution as the duration of the mentioned Summer semester is only about six weeks<br>• Limited computational resources as the Google Cloud A2 Virtual Machine services might become unavailable<br>• Our developed NILM model might run into overfitting or underfitting issues, potentially causing low model performance<br>• Sudden changes in NILM project's scopes or stakeholders' requirements might cause re-alignments in the project trajectory |

Table 8.15: SWOT Analysis

| No. | Rank | Risk | Description | Category | Root Cause | Triggers | Potential Responses | Risk Owner | Probability (1-10) | Impact (1-10) | Status | Score |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | Project Delays | Due to the compressed timeframe of the summer semester and the complexity of the novel deep learning approach, there's a risk of not completing the project within the | Project Management | Novelty in approach and limited duration of the summer semester. | Extended feedback loops, unexpected technical challenges, or lack of necessary resources. | Prioritize crucial tasks, additional work hours, or secure extra resources. | Ming Sheng (PM) | 9 | 10 | Open | 90 |
| 2 | 11 | Communication Barriers | Given that Ming Sheng (PM) and Martin (TL) will be working remotely (in Sarawak), potential communication challenges might arise due to reliance on online platforms. | Project Management | The shift to a remote work setting and reliance on virtual platforms. | Unstable internet connections, misunderstandings, or differing cultures. | Establish a robust communication protocol, use dependable platforms, and conduct regular check-ins. | Martin (TL) | 3 | 8 | Open | 24 |
| 3 | 12 | Supervisor Unavailability | The project supervisor, Dr. Lim, may not be frequently available for consultations due to his teaching commitments. | Project Management | Supervisor's teaching schedule (FIT 3134 Entrepreneurship) overlaps with consultation hours. | Unresponsive periods from the supervisor or scheduling conflicts. | Set predetermined consultation timings and have a secondary point of contact for | Ming Sheng (PM) | 3 | 6 | Open | 18 |
| 4 | 3 | Model Overfitting | The model, if overly optimized on a specific dataset, might not perform well on unfamiliar data. | Technical | Focusing extensively on training without adequate validation. | Poor model performance on unfamiliar datasets or negative feedback on the model's versatility. | Employ diverse datasets for training and validation, introduce regularization techniques, and carry out rigorous | Kai Jie (TL) | 6 | 10 | Open | 60 |
| 5 | 4 | Resource Limitations | The anticipated computational resources, such as the A100 GPUs, may not be available, which can impede optimal model training. | Technical | High demand for specific resources and potential unavailable during execution phase | Denied resource bookings or unforeseen hardware (members' laptop) malfunctions. | Seek alternative computational resources, refine the model for less resource-intensive training. | Ming Sheng (PM) | 7 | 8 | Open | 56 |
| 6 | 6 | Member Non-commitment | Given the hybrid nature of the summer semester, there's a risk of team members not being fully engaged, affecting the project's progression. | Project Management | The hybrid mode of the semester and potential for decreased in-person interactions. | Delays in task completion, unresponsiveness, or low-quality outputs. | Regular team meetings, clearly defined responsibilities, and performance | Martin (TL) | 5 | 9 | Open | 45 |
| 7 | 2 | Inadequate Model Performance | The team, being relatively new to deep learning, might not be able to train the model to surpass existing benchmarks. | Technical | Limited experience in the field of deep learning. | Model performance metrics not meeting expectations or receiving sub-par feedback. | Continuous research, attending relevant workshops or trainings online, and iterative model | Kai Jie (TL) | 9 | 8 | Open | 72 |
| 8 | 7 | Unforeseen Personal Events | Unexpected personal events like illnesses or accidents can disrupt the team's workflow. | Project Management | Unpredictable personal life events. | Notice of hospitalization, long unexplained absences, or sudden drop in productivity. | Backup plans for every role, task reallocation, or extension requests if needed. | Ming Sheng (PM) | 8 | 5 | Open | 40 |
| 9 | 8 | Insufficient Testing | Due to tight schedules, testing phases might get compressed leading to inadequate coverage. | Technical | Rushed project phases or overlooked testing scenarios. | Unexpected outputs during runtime or increased bug reports post-release. | Allocate dedicated time for testing, employ automated tests, and make user of Gantt chart | Wai Qi (QA) | 6 | 5 | Open | 30 |
| 10 | 5 | Team Conflicts | Differing opinions might lead to conflicts, affecting team harmony and project progression. | Project Management | Varied viewpoints and strong individual convictions. | Heated team discussions, noticeable group divides, or delayed decision-making. | Conflict resolution sessions, team-building exercises, or mediation through an | Martin (TL) | 10 | 5 | Open | 50 |
| 11 | 10 | Workload Underestimation | Team members might underestimate their workloads, leading to rushed tasks and subpar outputs. | Project Management | Overconfidence or lack of clarity in task complexities. | Missed deadlines, low-quality deliverables, or increased stress levels among team members. | Regular workload reviews, peer-checks, and realistic task | Kai Jie (TL) | 3 | 8 | Open | 24 |
| 12 | 13 | Scope Alterations | The project supervisor might suggest changes in scope or requirements to better align with real-world applications. | Project Management | Continuous refinement and desire to maintain relevance. | Frequent feedback rounds suggesting major changes or redefinitions of project boundaries. | Regular check-ins with the supervisor, flexibility in approach, and iterative | Ming Sheng (PM) | 2 | 8 | Open | 16 |
| 13 | 15 | Acquisition of Sponsorships | External organizations have expressed interest in sponsoring the project beyond our initial expectations. | Positive | The project's innovative nature and its significance in the energy sector have garnered attention. | External organizations becoming aware of the project's successes, referrals from other stakeholders, presentations at conferences. | Engage in formal discussions, evaluate terms of sponsorship, ensure alignment with project goals, and allocate additional funds | Ming Sheng (PM) | 1 | 2 | Open | 2 |
| 14 | 9 | Publication of Research Findings | There exists a significant opportunity to publish the findings and methodologies of the NILM project in reputable journals or conferences. | Positive | Innovative methodologies and successful results achieved by the NILM project. | Positive feedback on research, encouragement from stakeholders, or interest from publishers/reviewers. | Initiate drafting of papers, collaboration with industry experts for co-authorship, seek high-impact journals or conferences for | Ming Sheng (PM) | 4 | 7 | Open | 28 |
| 15 | 14 | Provision of Enhanced Dataset by MIMOS Berhad | MIMOS might provide additional or more comprehensive datasets to enhance the depth and accuracy of the project. | Positive | Collaborative partnership with MIMOS and the success of initial datasets. | Positive results from initial datasets, strengthened relationship with MIMOS, formal requests or discussions. | Positive results from initial datasets, strengthened relationship with MIMOS, formal requests or | Wai Qi (QA) | 2 | 6 | Open | 12 |

Figure 8.3: Risk Register

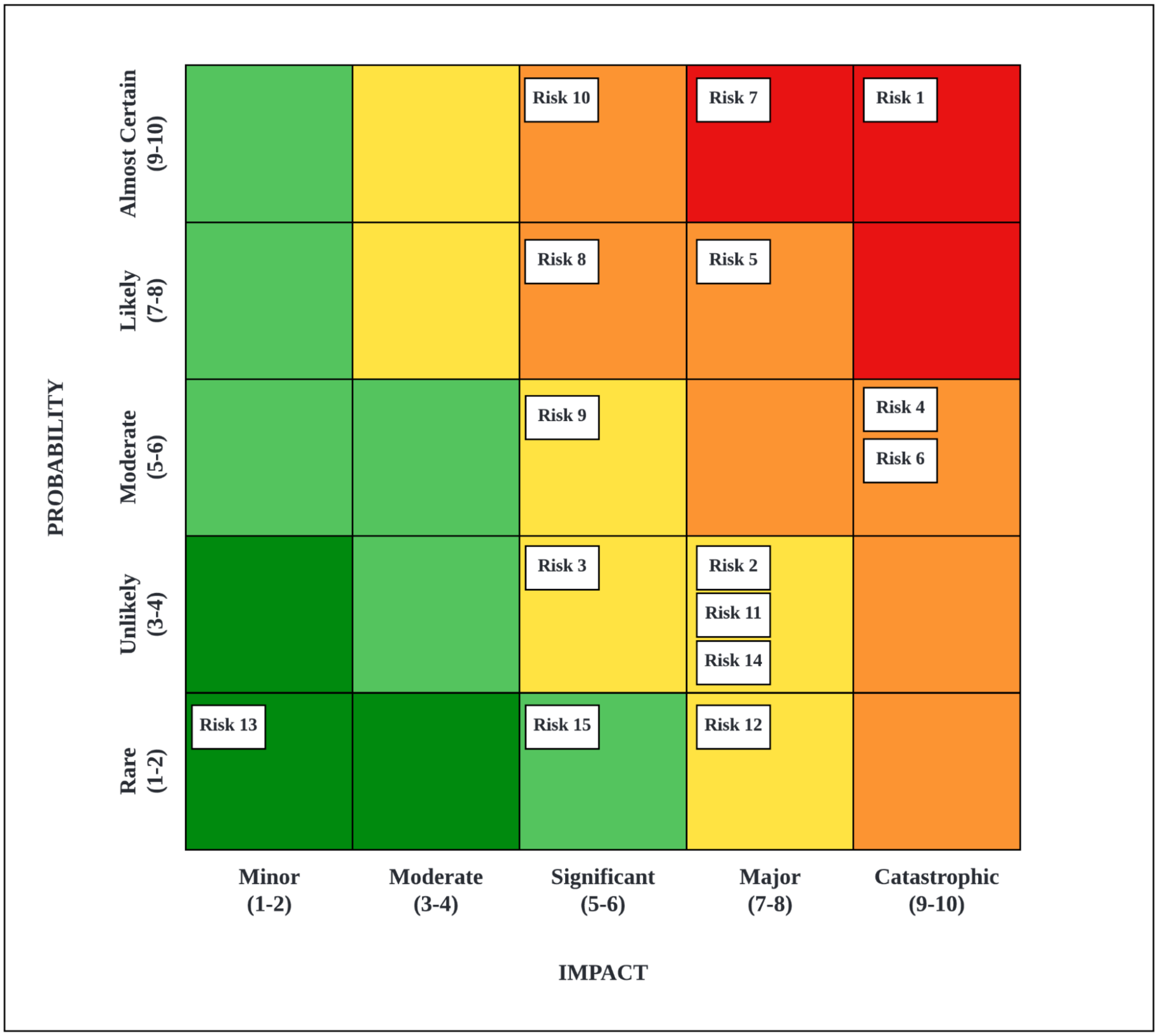


Figure 8.4: Probability/Impact Matrix

| Stakeholder | Interest | Impact | Contribution | Risk | Management Strategy |
|---|---|---|---|---|---|
| MIMOS Berhad | **High**<br>- Ensures our project aligns with their collaborative goals and objectives<br>- Invested in the research outcomes and successful implementation of the NILM model | **High**<br>- Has the utmost authority to make decisions that may have direct control over all project aspects | - Provide dataset and resources such as source code samples and tutorials | - Requirements may change over time<br>- Dataset may contain certain data issues | - Establish regular communication channels to align project goals<br>- Site visit to the company and interview with the project lead(s)<br>- Have contingency plans for data-related risks |
| Project supervisor | **High**<br>- Project's success reflects Dr. Lim's guidance and expertise<br>- Ensures the project aligns with academic, research and industry standards | **High**<br>- Has decision-making authority over the project guidance and academic aspects | - Provide guidance and expertise<br>- Provide feedback and areas for improvement<br>- Help track team progress | - Potential changes in the project scope<br>- Ineffective communication<br>- Sometimes may be unavailable | - Seek guidance and feedback only when necessary<br>- Compile the questions and structure them well, and then ask the questions at one time<br>- Maintain regular updates and reviews to ensure our project aligns with academic, research and industrial expectations |
| Teaching team | **High**<br>- Focus on students' learning and adherence to academic guidelines and learning outcomes | **High**<br>- Has the authority to change and update assignment specifications, deadlines, or teaching periods that may affect our project's day-to-day activities | - Provide academic support | - Possible conflicts between project schedules and academic commitments<br>- Assignment deadlines may change | - Communicate with the teaching team clearly about academic requirements and scheduling flexibility, so that we can balance the academic commitments (e.g. documentation-related tasks) and project's execution-related work |

Table 8.16: Stakeholder Analysis Matrix (Part 1)

| Stakeholder | Interest | Impact | Contribution | Risk | Management Strategy |
|---|---|---|---|---|---|
| Team members | **High**<br>- Project's success impacts our contributions and learning experience. Ensure smooth project run and completion by deadline. Final product should achieve industrial standards and high performance in evaluation metrics. Project must meet requirements for a High Distinction grade. | **High**<br>- Team member commitment directly influences project progress and quality. | - Work proactively on tasks. Provide documentation for project management. Implement NILM model. Conduct code review and testing. Fine-tune the developed model. | - Ineffective communication. Low commitment levels. Unavailability at times. Lack of technical knowledge during execution. | - Regular stand-up meetings. Support for team members. Task assignment based on roles, ability, and availability. Update Kanban board. Task owner changes by project manager if necessary to ensure on-time completion. |

Table 8.17: Stakeholder Analysis Matrix (Part 2)

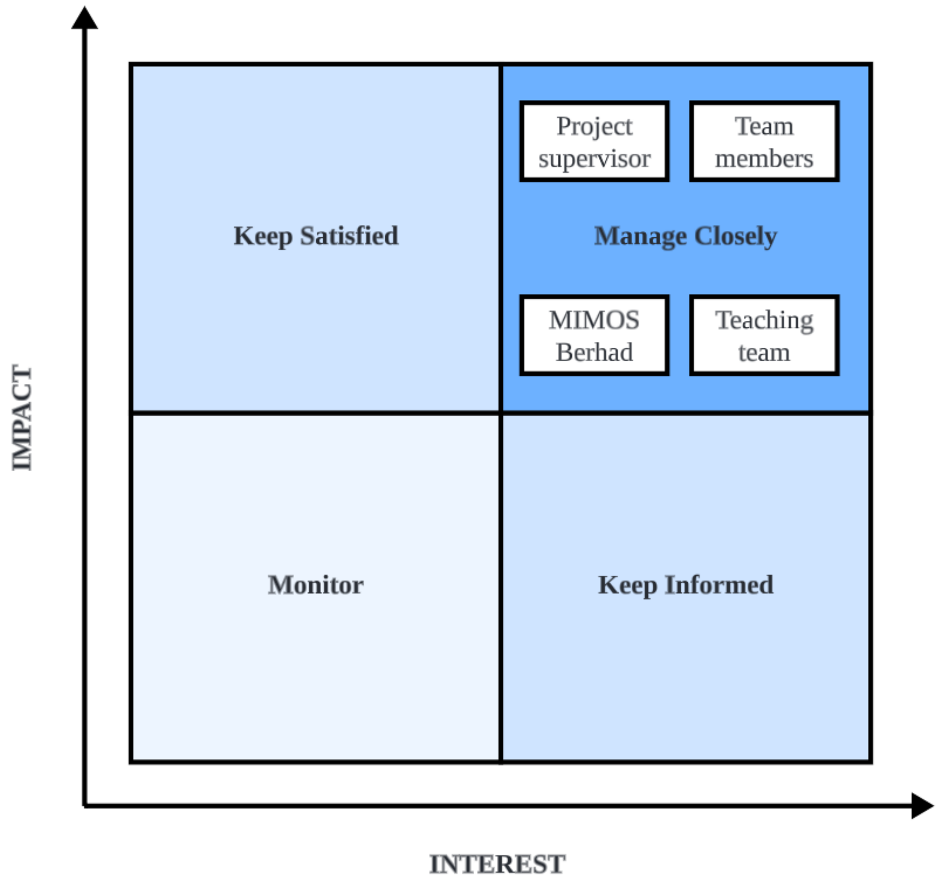


Figure 8.5: Stakeholder Management Matrix

| Communication | Objective | Medium | Frequency | Audience | Owner | Deliverables | Report Format |
|---|---|---|---|---|---|---|---|
| Sprint planning | - Define the scope and goals for the upcoming sprint<br>- Gather all deliverables for the upcoming sprint in a checklist<br>- Assign tasks among team members and set feasible deadlines | Physical | Start of each sprint | - MDS23 team members | Project manager (Ming Sheng) | -Formal meeting agendas and minutes<br>- Updated Kanban board<br>- Updated product backlog | Google Docs in Google Drive |
| Sprint stand-up | - Update the team on individual tasks and progress<br>- Identify roadblocks and suggest mitigations to address them<br>- Project Manager (Ming Sheng) can change task owner where necessary | Zoom | Weekly | - MDS23 team members | Project manager (Ming Sheng) | - Updated Kanban board if necessary<br>- Short and informal meeting minutes | Short text messages via WhatsApp |
| Sprint review | - Completed work is showcased to stakeholders<br>- Get feedback and areas for improvement from stakeholders<br>- Ensure the project aligns with stakeholders' requirements | Microsoft Teams | End of each sprint | - MDS23 team members<br>- Stakeholders i.e., project supervisor (Dr. Lim) and teaching team | Project manager (Ming Sheng) | - Feedback from stakeholders<br>- Formal meeting minutes | Google Docs in Google Drive |

Table 8.18: Communication Matrix (Part 1)

| Communication | Objective | Medium | Frequency | Audience | Owner | Deliverables | Report Format |
|---|---|---|---|---|---|---|---|
| Sprint retrospective | - Team reflection on current sprint's performance<br>- Identify what went well, what did not, and what to improve<br>- Ensure continuous improvement in progress and collaboration | Zoom | End of each sprint | - MDS23 team members | Project manager (Ming Sheng) | - Formal meeting minutes<br>- Team evaluation and feedback form | Google Docs in Google Drive |
| Team discussion | - Discuss project-related tasks and challenges<br>- Exchange ideas and feedback within the team<br>- Promote effective communication | Physical | Weekly | - MDS23 team members | Project manager (Ming Sheng) | - None. Verbal discussions only | None |
| Meeting with project supervisor | - Seek guidance and feedback from supervisor<br>- Update on progress and review work | Microsoft Teams | Weekly | - MDS23 team members<br>- Project supervisor (Dr. Lim) | Project supervisor (Dr. Lim) | - Meeting agendas and minutes<br>- Meeting recordings | Google Docs in Google Drive<br>- MP4 file in Google Drive |
| Workshop and tutorial | - Seek clarifications and enhance skills<br>- Knowledge enhancement in project management | Physical | Weekly | - MDS23 team members<br>- Teaching team (Ms. Kamalahshunee) | Teaching team (Ms. Kamalah-shunee) | - Notes about the lecture contents | Microsoft Word or Google Docs |

Table 8.19: Communication Matrix (Part 2)

# MEETING AGENDA

**FIT3163 MDS23 Sprint Planning Meeting**

**Sprint No.:** 4
**Date:** 16th October 2023 (Monday)
**Time:** 2pm - 5pm
**Location:** The Hive (Begonia Room), Monash University Malaysia

**Prepared by:** Chong Ming Sheng

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**Meeting Objectives:**

1. Implement sprint planning.
2. Discuss the structure and content of the mind map required by our project supervisor.
3. Allocate tasks to each team member for the mind map.
4. Allocate tasks to each team member for the project proposal.

**Agenda Items:**

1. Recap the contents of the synthesis table.
2. Discuss and refine the main sections needed for the mind map.
3. Draft out the appropriate contents for each main section of the mind map.
4. Allocate tasks to team members, where each member works on one main section of the mind map.
5. Review the specifications of project proposal assignment.
6. Discuss about the appropriate contents or deliverables required for every section of the project proposal.
7. Allocate tasks to team members for the project proposal.
8. Update Kanban Board.
9. Update Risk Register.

Figure 8.6: Sprint planning meeting agenda

## MEETING MINUTES

**FIT3163 MDS23 Sprint Planning Meeting**

**Sprint No.:** 4
**Date:** 16th October 2023
**Time:** 2pm - 5pm
**Location:** The Hive (Begonia Room), Monash University Malaysia
**Attendees:**

1. Chong Ming Sheng
2. Martin Ung Chee Hong
3. Pang Wai Qi
4. Wang Kai Jie

**Absentees:** -

**Chairperson:** Chong Ming Sheng
**Minutes Taker:** Martin Ung Chee Hong

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**Agenda Items:**

1. Recap the contents of the synthesis table.
2. Discuss and refine the main sections needed for the mind map.
3. Draft out the appropriate contents for each main section of the mind map.
4. Allocate tasks to team members, where each member works on one main section of the mind map.
5. Review the specifications of project proposal assignment.
6. Discuss about the appropriate contents or deliverables required for every section of the project proposal.
7. Allocate tasks to team members for the project proposal.
8. Update Kanban Board.
9. Update Risk Register.

| Agenda Item | Proceedings | Status / Deadline |
|---|---|---|
| 1 | All team members review the entries in the synthesis table and list down all the important or relevant points that are appropriate for the development of the mind map required by our project supervisor. The mind map can then guide us to develop write-ups for the literature review part of our project proposal. | Completed |
| 2 | All team members discuss the main sections to be included in the mind map. Eventually, the main sections identified are:<br>• Signal Processing<br>• Disaggregation<br>• Appliance Identification<br>• Evaluation Metrics | Completed |
| 3 | From all the important points listed down in Agenda Item 1, we organise and categorise them into the four main sections identified above. We also put some detailed information next to | Completed |

Figure 8.7: Sprint planning meeting minute (Part 1)

| | | |
|---|---|---|
| | certain nodes where necessary, serving as reminders about what to be further discussed in the particular node when working on the literature review part of the project proposal. | |
| 4 | Each team member is responsible for working on each main section of the mind map.<br>• **Ming Sheng:** Signal processing<br>• **Martin:** Disaggregation<br>• **Kai Jie:** Appliance identification<br>• **Wai Qi:** Evaluation metrics<br><br>We will let our project supervisor, Dr. Lim Wern Han, review our mind map upon completion and request for his feedback on 20th October 2023 (Friday). | 20th October 2023 (Friday) |
| 5 | All team members read through the project proposal assignment specification again. Wai Qi and Kai Jie show us their notes taken during the workshop when the lecturer explained about the specifications in detail. Every member gets a clear understanding about what to be included in each section of the project proposal. | Completed |
| 6 | All team members list down all the deliverables required for different sections of the project proposal in a checklist. | Completed |
| 7 | Each team member is responsible for working on specific parts of the project proposal as documented below, but it is subject to changes based on our availability and progress.<br>• **Ming Sheng:** Literature review (signal processing), management process, schedule and resource requirements<br>• **Martin:** Literature review (disaggregation), project overview, project scope, project organisation<br>• **Kai Jie:** Literature review (appliance identification), external design, methodology<br>• **Wai Qi:** Literature review (evaluation metrics & introduction & conclusion), NILM project background information, test planning, conclusion of project proposal | 25th October 2023 (Wednesday) |
| 8 | Project manager (Ming Sheng) updates team's Kanban Board. | Completed |
| 9 | All team members brainstorm and list down the potential risks related to this sprint, suggesting who to take the responsibility and what is the mitigation to be actioned to mitigate each risk. They are well-documented and team's Risk Register is updated. | Completed |

**Sprint Stand Up Meeting:**
The sprint stand up meeting is scheduled every Friday for this sprint, from 10:00am to 10:30am via Zoom.

**Regular Team Discussion Meeting:**
The regular team discussion meeting is scheduled every Monday and Friday for this sprint, from 10:00am to 4:00pm, at The Hive (Begonia Room), Monash University Malaysia.

Figure 8.8: Sprint planning meeting minute (Part 2)

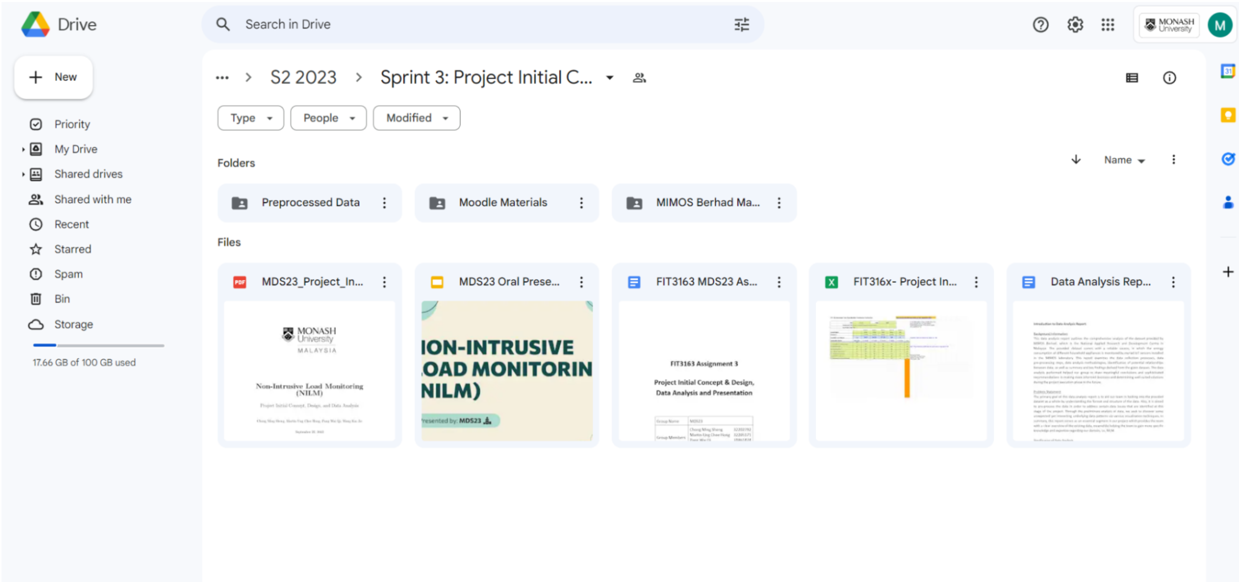


Figure 8.9: Team MDS23's shared Google Drive

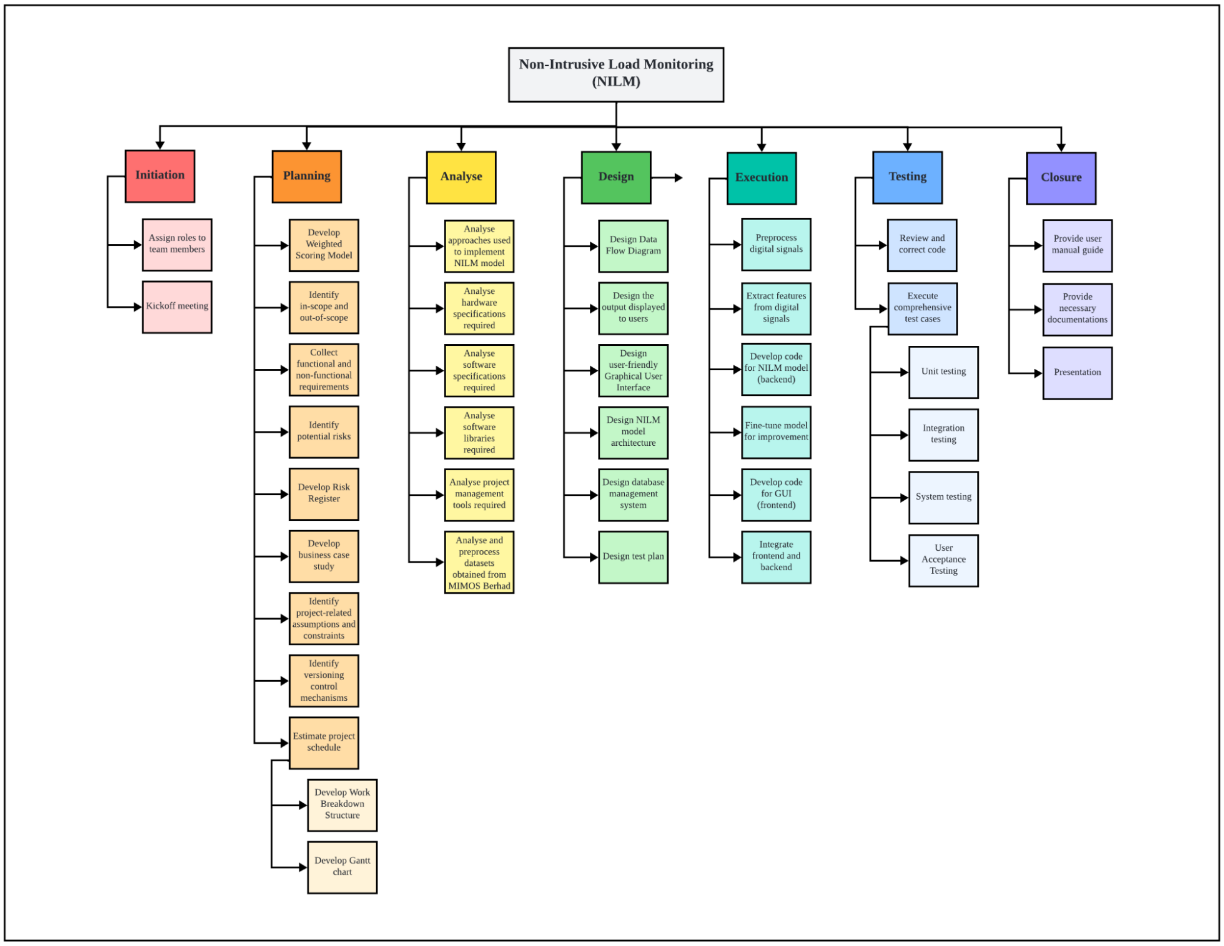


Figure 8.10: Work Breakdown Structure

| TASK | DESCRIPTION | PROGRESS | START | END |
|---|---|---|---|---|
| **Sprint 5: Execution** | | | | |
| 5.1 | Preprocess digital signals | 0% | 11/13/23 | 11/18/23 |
| 5.2 | Extract features from digital signals | 0% | 11/19/23 | 11/24/23 |
| 5.3 | Develop code for NILM model (backend) | 0% | 11/25/23 | 12/13/23 |
| 5.4 | Develop code for GUI (frontend) | 0% | 11/25/23 | 12/4/23 |
| 5.5 | Train and fine-tune developed NILM model (backend) | 0% | 12/14/23 | 12/16/23 |
| 5.6 | Integrate frontend and backend frameworks | 0% | 12/17/23 | 12/21/23 |
| 5.7 | Prepare comprehensive test cases | 0% | 11/25/23 | 11/29/23 |
| 5.8 | Review and correct code (bugfix) | 0% | 11/30/23 | 12/31/23 |
| 5.9 | Unit testing | 0% | 11/30/23 | 12/13/23 |
| 5.10 | Integration testing | 0% | 12/22/23 | 12/26/23 |
| 5.11 | System testing | 0% | 12/22/23 | 12/26/23 |
| 5.12 | User Acceptance Testing (UAT) | 0% | 12/27/23 | 12/31/23 |
| 5.13 | Refine NILM model based on UAT | 0% | 12/27/23 | 12/31/23 |
| **Sprint 6: Closure** | | | | |
| 6.1 | Document the methodologies, analysis, results and findings | 0% | 1/1/24 | 1/7/24 |
| 6.2 | Provide clear code documentation | 0% | 1/1/24 | 1/7/24 |
| 6.3 | Create clear user manual guide based on user feedback in UAT | 0% | 1/1/24 | 1/5/24 |
| 6.4 | Give presentation to stakeholders | 0% | 1/8/24 | 1/11/24 |
| 6.5 | Project finalisation and wrap up | 0% | 1/12/24 | 1/13/24 |
| 6.6 | Hand over final product deliverables to stakeholders | 0% | 1/14/24 | 1/14/24 |

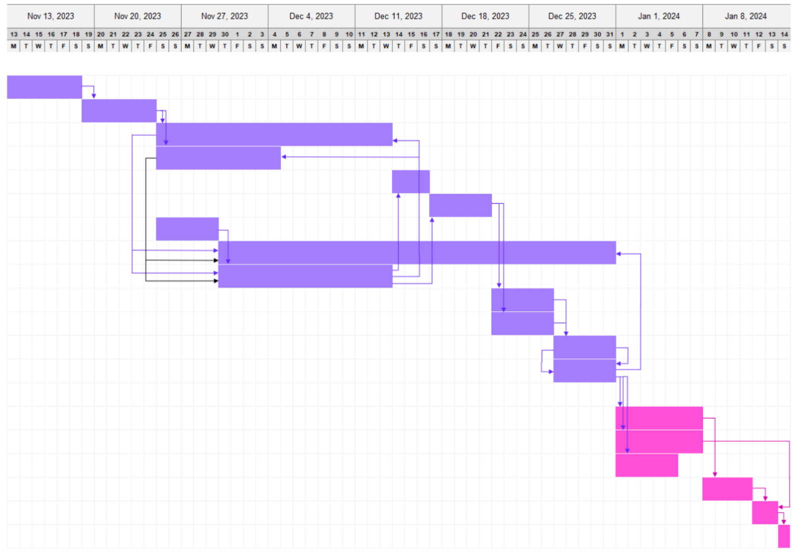


Figure 8.11: Gantt chart

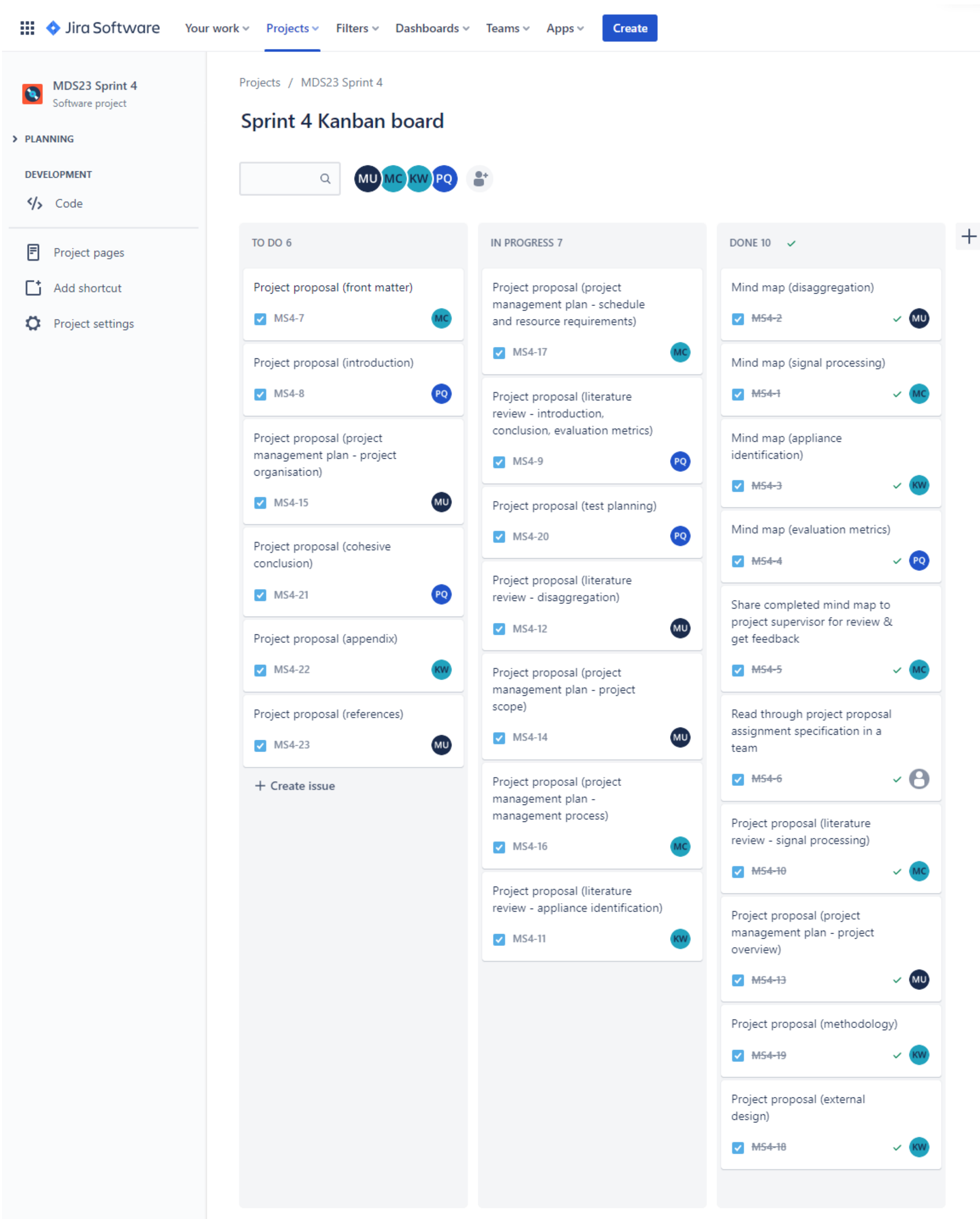


Figure 8.12: Kanban board

| Activities | Estimated Effort (Story Points) | Number of Personnel Required |
|---|---|---|
| Data preprocessing to solve data-related issues | 8 | 2+2 |
| Convert dataset obtained from MIMOS Berhad into standard HDF5 format | 1 | 1 |
| Research and design model architecture | 8 | 2+2 |
| Test plan and test cases creation | 5 | 1+1 |
| NILM model development | 13 | 2+2 |
| NILM model fine-tuning | 5 | 2 |
| NILM model performance evaluation | 3 | 1 |
| NILM model testing | 2 | 1 |
| GUI development and refinement | 13 | 2+2 |
| Code review and correction | 13 | 1+3 |

Table 8.20: Number and roles of personnel required, where the number after the "+" symbol denotes the additional personnel(s) required for the particular activities as human resources backup.

| | |
|---|---|
| **Central Processing Unit (CPU)** | Intel Cascade Lake |
| **CPU architecture** | x86 |
| **Virtual CPUs (vCPUs)** | 12 to 96 cores (Based on the configuration chosen) |
| **Random-Access Memory (RAM) Storage** | 85 to 1360 GB |
| **Graphics Processing Unit (GPU)** | NVIDIA A100 GPUs (Up to 16 GPUs) (Each have 6912 CUDA cores.19.5 teraflops of FP32 performance and 1.6TB/s of graphics memory bandwidth.) |
| **Physical Storage Capacity** | Maximum 3 TB of Local SSD |

Table 8.21: Hardware specifications

| | |
|---|---|
| **Programming Language** | Python 3.11 |
| **Database System** | PostgreSQL |
| **Prototyping and Experimental Platform** | Jupyter Notebook 7.0.6 |
| **Debugger** | Debugger Visual Studio Code built-in debugger |
| **Operating System** | Windows 11 |
| **Package and Environment Manager** | Anaconda 2.3.1 |

Table 8.22: Software specifications

| | |
|---|---|
| **Deep Learning Framework** | PyTorch 2.0.1 |
| **NILM toolkit libraries** | NILMTK 0.4.3 |
| **Data visualisation tools** | Matplotlib 3.7.2 |
| **Numerical computing library** | Numpy 1.25.0 |
| **Machine learning library** | Scikit-learn 1.3.0 |
| **Data analysis and manipulation tools** | Pandas 2.1.0 |
| **Advanced Visualisation tools** | Seaborn 0.12.2 |
| **Graphical User Interface (GUI)** | Angular 7.2.11 with Node.js 21.0.0 |

Table 8.23: External software libraries

| | |
|---|---|
| **Version Control System** | Git |
| **Online Communication Channel** | WhatsApp & Microsoft Teams |
| **Project Planning Platform** | Jira |
| **Time Tracking** | Clockify |
| **Documents Sharing Platform** | Google Drive & Microsoft Teams |
| **Reference Management Tool** | Overleaf |
| **Document Processing/Text Editing Software** | Overleaf |

Table 8.24: Project management tools

| ID | Test Description | Testing Stages |
|---|---|---|
| 1 | Check if our NILM model can correctly identify appliances in use, given aggregated energy usage. | Unit Testing<br>Integration Testing |
| 2 | Check if our NILM model can learn energy usage behaviour and correctly estimate energy usage of each appliance, given aggregated energy usage. | Unit Testing<br>Integration Testing |
| 3 | Check if our NILM model can identify energy wastage by recognising appliances that exhibit inefficiency, consuming more energy than expected, given aggregated energy usage. | Unit Testing<br>Integration Testing |
| 4 | Check our NILM model's performance with different datasets. | Unit Testing<br>Integration Testing<br>System Testing |
| 5 | Check if our web application can take in input from users and pass them to our model accurately. | Unit Testing<br>Integration Testing<br>System Testing<br>User Acceptance Testing |
| 6 | Check if our web application can display output (predicted energy usage of appliances) accurately. | Unit Testing<br>Integration Testing<br>System Testing<br>User Acceptance Testing |
| 7 | Check if our web application is user-friendly and its content is easy to understand. | User Acceptance Testing |
| 8 | Check our web application's response time under real-world load conditions to ensure it is adequately fast (i.e. within 2 seconds). | Unit Testing<br>Integration Testing<br>System Testing<br>User Acceptance Testing |

Table 8.25: Test scope

| ID | Requirements | Test Methods | Test Procedures | Expected Outcome | Actual Outcome |
|---|---|---|---|---|---|
| 1 | Data cleaning for MIMOS Berhad dataset | Check data cleaning process and data quality criteria | 1. Perform the data cleaning process on the MIMOS Berhad datasets, including handling missing values, outliers, and inconsistencies.<br>2. Verify that the cleaned dataset meets the defined data quality criteria, which may include completeness, correctness, and consistency. | The MIMOS Berhad dataset is cleaned effectively, and the cleaned dataset complies with the specified data quality criteria. | |
| 2 | Process and analyse datasets obtained from MIMOS Berhad | Check data processing, analysis techniques, and insights extracted from the data | 1. Use data processing techniques to preprocess the datasets obtained from MIMOS Berhad.<br>2. Apply data analysis techniques to extract useful insights from the processed data.<br>3. Verify that the processed data is suitable for further modelling and decision-making. | The datasets obtained from MIMOS Berhad are effectively processed, and valuable insights are derived for informed decision-making. | |
| 3 | Convert the available datasets into HDF5 format | Check data format conversion process and file integrity after conversion | 1. Convert the available datasets into HDF5 format using NILMTK.<br>2. Verify the integrity of the resulting HDF5 files to ensure they are not corrupted during the conversion process.<br>3. Ensure that the conversion process does not result in data loss. | The datasets are successfully converted into HDF5 format without data loss, and the resulting HDF5 files are valid. | |
| 4 | Leverage low sampling rate (low-frequency) data | Check identification of low-frequency data and effectiveness of statistical methods | 1. Identify low-frequency data within the dataset.<br>2. Implement statistical methods or models to leverage the low-frequency data for analysis and modelling.<br>3. Confirm that the model effectively utilises the low-frequency data to enhance the project's objectives. | Our model successfully identifies and leverages low-frequency data for analysis and modelling purposes. | |

Table 8.26: Test cases (Part 1)

| ID | Requirements | Test Methods | Test Procedures | Expected Outcome | Actual Outcome |
|---|---|---|---|---|---|
| 5 | Develop, train, and fine-tune the NILM model | Check model development and training process, as well as hyperparameter tuning | 1. Develop the NILM model as per project requirements.<br>2. Train the model on the prepared datasets.<br>3. Fine-tune the model using appropriate techniques.<br>4. Monitor the model's performance during training and tuning. | The NILM model is successfully developed, trained, and fine-tuned to meet performance criteria. | |
| 6 | GUI allowing user input of centralised meter reading data | Check user interface functionality, data input validation, user experience, and usability | 1. Open the GUI and navigate to the input section.<br>2. Check if users can input centralised meter reading data.<br>3. Validate that the input data is correctly processed and stored.<br>4. Test the GUI's responsiveness and user-friendliness. | The GUI allows users to input meter reading data, performs data validation, and provides a positive user experience. | |
| 7 | Visual representation tools for user data and model performance | Check data visualisation components, data integration with visual tools, and real-time updates | 1. Input the centralised meter reading data and check the output visualisation components.<br>2. Check if our web application correctly displays energy consumption behaviours.<br>3. Verify that visualisations are updated in real-time. | The visual tools (e.g. charts) effectively display energy consumption behaviours, with real-time updates where required. | |
| 8 | Evaluate model performance on different datasets | Check model performance metrics, dataset variations, and model adaptability | 1. Use different datasets to assess the NILM model's performance.<br>2. Compare the model's performance metrics across the datasets.<br>3. Evaluate the model's ability to adapt to varying data sources. | Our NILM model performs consistently well on different datasets, showcasing adaptability. | |

Table 8.27: Test cases (Part 2)

| ID | Requirements | Test Methods | Test Procedures | Expected Outcome | Actual Outcome |
|---|---|---|---|---|---|
| 9 | Trained NILM model achieves a minimum M-FScore of 0.80 and accuracy of 90% | Check model accuracy and validation | 1. Measure the accuracy of the trained NILM model using a validation dataset (e.g., UK-Dale, REDD, etc.).<br>2. Ensure that the model's M-FScore and accuracy are at least 0.80 and 90%, respectively, as per the requirement. | The trained NILM model achieves a minimum M-FScore of 0.80 and accuracy of 90% on the validation dataset. | |
| 10 | Adequate documentation of the NILM model's code | Check code documentation completeness, code commenting, and clarity | 1. Review the codebase of our NILM model.<br>2. Check if it contains comprehensive documentation, including explanations of functions, classes, and variables.<br>3. Verify that code comments are clear and informative. | The NILM model's code is well-documented, making it easy for developers and maintainers to understand and work with. | |
| 11 | GUI works seamlessly on local machines | Check GUI installation and setup, as well as functionality across different operating systems | 1. Install and set up the GUI on a local machine.<br>2. Test the GUI's functionality on different operating systems (e.g., Windows, macOS, Linux). We will dockerise our web application to ensure portability across devices/environments. | The GUI can be unpacked and run smoothly on various local machines and operating systems. | |
| 12 | Testing of the developed GUI | Check GUI functionality, user interface components, and responsiveness | 1. Thoroughly test all features and functionalities of the GUI.<br>2. Verify that user interface components (buttons, forms, etc.) work as expected.<br>3. Evaluate the GUI's responsiveness to user actions and data input. | The GUI is thoroughly tested and functions as intended, with a responsive user interface. | |

Table 8.28: Test cases (Part 3)

| ID | Requirements | Test Methods | Test Procedures | Expected Outcome | Actual Outcome |
|---|---|---|---|---|---|
| 13 | The GUI should be user friendly | Check user interface design, ease of use, user feedback, and user acceptance testing | 1. Conduct user acceptance testing with target users to gather feedback on the GUI's design and ease of use.<br>2. Evaluate the user interface for intuitive navigation and clear instructions. | The GUI is user-friendly based on user feedback and user acceptance testing results. | |
| 14 | The GUI/model should be able to display the results within 2 seconds after the user has inputted the aggregated main meter readings | Check response time and performance under various load scenarios | 1. Input aggregated main meter readings into the GUI.<br>2. Measure the time taken for the GUI/model to process and display results.<br>3. Test performance under different load scenarios to ensure timely responses. | The GUI/model outputs result within 2 seconds after the user inputs data, even under varying loads. | |

Table 8.29: Test cases (Part 4)

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