DESIGN AND DEVELOPMENT OF SMART AIR-CONDITIONING CONTROLLER FOR ACHIEVING ENERGY SAVING

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A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Electrical and Electronic Engineering with Honours

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DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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APPROVAL FOR SUBMISSION

I certify that this project report entitled **"Design and Development of Smart Air Conditioning Controller for Achieving Energy Saving"** was prepared by **Joshua Wee Khui Ren** has met the required standard for submission in partial fulfilment of the requirements for the award of Bachelor of Electrical and Electronic Engineering with Honours at Universiti Tunku Abdul Rahman.

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ABSTRACT

This project focuses on the design and development of a Smart Air Conditioning Controller (SACC) using a Fuzzy Logic (FL) algorithm as its decision-making engine. The primary goal of the SACC is to control air conditioning (AC) systems for energy savings without compromising user comfort. Three versions of the FL algorithm were developed, each with different input parameters, fuzzy sets, and rules, showing progressive improvement. The third version achieved 19.85% energy savings and maintained 63.21% more time in the thermal comfort zone, outperforming the baseline 24°C control scheme. The SACC also integrates Internet-of-Things (IoT) features, enabling remote monitoring and control, voice command for monitoring and control, and additional functionalities like automation, Over-the-Air (OTA) enabled, and Wi-Fi provisioning. Developed at a low cost, below RM 200, the SACC offers a plug-and-play solution, making it suitable for residential split-air conditioners. This project contributes to energy efficiency and decarbonization efforts by providing an affordable, user-friendly controller that balances energy savings with thermal comfort.

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LIST OF SYMBOLS / ABBREVIATIONS

ABC	Artificial Bee Colony
AC	air-conditioner
API	Application Programming Interface
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineer
CO2	carbon dioxide gas
DQL	Deep Q-Learning
FL	Fuzzy Logic
GA	Genetic Algorithm
GHG	greenhouse gas
IDE	Integrated Development Environment
IOS	iPhone Operating System
IoT	Internet of Things
IR	Infrared
MBC	Model-Based Control
mm	millimeter
MOO	Multi-Objective Optimization
MPC	Model-Predictive Control
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
OTA	Over-The-Air
PID	Proportional-Integral-Derivative
PMV	Predicted Mean Vote
PPM	Parts Per Million
PSA	Particle Swarm Optimization
SACC	Smart Air-Conditioner Controller
ST	Suruhanjaya Tenaga
SSID	Service Set Identifier
UTAR	Tunku Abdul Rahman University
WHO	World Health Organization

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CHAPTER 1

INTRODUCTION

1.1 General Introduction

Climate change is a serious issue and it needs to be addressed before it is too late. It causes various problems such as the rise in global temperature, melting of ice glacier, unpredictable weather patterns and etc (Koca, Bhuiyan and Mayorga, 2020). One of the contributors of climate change is the greenhouse gases (GHG). GHG traps heat which causes the heat unable escape the Earth's atmosphere. Carbon dioxide gas (CO2) is an example of GHG gases. Therefore, one way to tackle the issue of climate change is through decarbonization. Decarbonization is a method to reduce the CO2 gases that are release to the Earth's atmosphere. There are many ways to do it, for example, through the use of clean energy to replace fossil fuels, replacement of fossil fuel vehicles with electric vehicles and reduction of energy consumption.

Reduction of energy consumption in buildings can be a good option as a decarbonization method to tackle the climate change issue. The energy consumption in buildings accounts for 20 % of the total energy worldwide (Sun, et al., 2013). For residential building, air conditioner (AC) is one of the main contributors of energy consumption as it accounts for 45 % of the residential building's energy consumption. In Malaysia, 48 % of the country's total electricity generation is consumed by the building sector, which includes residential (Aqilah, et al., 2021). Besides that, this value is going to increase, as through urbanization, more people in Malaysia are going to install AC in their residential building to tackle the hot weather conditions. Therefore, one way to address the issue of climate change is to reduce the energy consumption of AC.

To reduce the energy consumption of AC is to make the AC energy efficient. There are two technical routes to achieve it (Shao, et al., 2023). One way is to improve the hardware technology of the AC such as the compressor, coil, fans, refrigerants and etc. By improving the hardware, the AC will be more energy efficient which reduces the energy consumption. Another way is to improve the software technology of the AC. The software technology refers to the control algorithm that controls the operation of the AC. By improving the control algorithm, the AC will operate more efficiently. The software route has some advantages over the hardware route. First, the structure of the AC does not need any necessary changes. Since only the control algorithm needs to be improved, no major changes are needed for the AC itself. This means that the existing AC unit can operate more energy efficient with just the upgraded control algorithm. Second, energy saving of AC can be achieved with lower investment. Upgrading the control algorithm typically requires lower upfront costs compared to hardware changes. This is because the software approach requires less investment in purchasing new equipment. Third, ease of implementation. The control algorithm can be an external unit to the existing AC unit. This external unit can be easily deployed and installed with the existing AC unit. Compared to hardware route, it is simpler and faster.

There are already existing control algorithms used in AC such as the ON/OFF control, Hysteresis control and Proportional-Integral-Derivative (PID) control. These traditional control techniques can help achieve energy saving of AC. However, they become ineffective when the system becomes complex. Besides that, these control algorithms are unable to account for user comfortability. This is because they can only handle one objective which is to save energy. Therefore, they will do their best in achieving the objective while neglecting other objectives such as occupant comfortability. One way to tackle it is to maintain the temperature set point at 24 °C. Based on Suruhanjaya Tenaga (ST) guidelines, setting the temperature set point at 24 °C can help save energy without compromising user comfort. However, various study has shown that advanced control algorithms can achieve higher energy saving than this method without compromising user comfort. Besides that, setting it at constant 24 °C may feel cold for some people after some time which causes them to set above 24 °C. Once setting above 24 °C, people may feel hot at set back to 24 °C and the cycle repeats. Therefore, it is better to go for advanced control algorithms approach that can automatically set the optimum temperature for the users then maintaining at 24 °C to tackle the climate change issue.

There are several advanced control algorithms for AC currently in research phase. Some advanced control algorithms require the modelling of the system that the AC controls, some require data for training of the control algorithm, some required high computing resources. Examples of the advanced control algorithms are the model-based control (MBC) algorithms, data-driven control algorithms and multi-objective optimization (MOO) control algorithms and fuzzy logic (FL) algorithm. Each has their own advantages and disadvantages which will be discussed in the literature review section.

In this paper, FL is proposed as the control algorithm to regulate the air conditioning system. It is capable of addressing both energy saving and user comfort simultaneously. Unlike other control algorithms, fuzzy logic is relatively simple to implement as it does not require complex system modeling, training of data nor high computation resources. The fuzzy logic controller is designed to adjust the AC temperature dynamically based on multiple inputs, such as carbon dioxide concentration, occupancy detection, Predicted Mean Vote (PMV), temperature and power consumption, ensuring efficient energy usage while maintaining thermal comfort for the occupants. The prototype is developed and tested in a real environment to validate its performance, with a focus on tropical countries like Malaysia, where only cooling operation is considered.

1.2 Importance of the Study

This paper develops a real controller with FL algorithm as the brain and is tested in real environment. In this paper, data is collected real-time for the analysis of the controller in terms of energy saving and user comfortability. The main purpose of this paper is to shed light on the feasibility of the FL algorithm in controlling the AC. By demonstrating the feasibility, the study paves the way for widespread implementation of the AC controller with FL algorithm as the decision-making engine.

Another purpose of this paper is to develop a protype that can easily be integrated with the existing AC unit. With minimal to no modifications on the existing AC unit, the controller with FL algorithm is capable of controlling the AC unit, effectively functioning as an external unit to the AC. With this plug-and play characteristic, people will be encouraged to buy the product due to ease of installation. This will help contribute to the global decarbonization efforts to tackle the climate change challenge. Additionally, users can benefit from lower energy bills due to increase in AC energy efficiency. Moreover, by verifying FL algorithm, this protype can be further be developed or modified to hybrid with other control algorithms to handle more complex system. In other words, this study will help in the advancement of research in FL control algorithm for AC.

1.3 Problem Statement

Traditional control algorithms are single-optimization algorithms capable of handling one objective at a time. The main objective is typically to reduce the energy consumption of the AC system, making the AC system energy efficient. However, other objectives such as occupant comfort are neglected. Besides that, when the system becomes complex, the traditional control algorithms can lack in precision and accuracy, unable to control the AC properly for energy saving. Advanced control algorithms have the upper hand over traditional control algorithms as they are capable of handling multiple objectives and complex system. However, some advanced control algorithms are difficult to be implemented. This is because they lack in the aspect of practicality, cost effectiveness and portability. Besides accuracy and having the capability to handle complex system, a viable control algorithm has to be practical, affordable and portable in order to be attract the common people to purchase it, especially in the residential sector.

FL algorithm is capable of managing multiple constraints while efficiently controlling an AC system by utilizing linguistic rules. It is well-suited for handling complex systems and offers a simpler design and development process compared to other advanced control algorithms. However, for FL to effectively regulate the AC, careful fine-tuning of the input parameters and fuzzy rules is essential. Despite its potential, the practicality of implementing FL for AC control remains a critical question. Therefore, developing and testing a prototype with FL as the decision-making engine is necessary to validate its effectiveness and feasibility in real-world applications.

1.4 Aim and Objectives

The aim of this study is to design and develop a smart AC controller with FL algorithm as the decision-making engine to achieve energy saving without compromising user comfort. The objectives of the study are as follows:

1. To design and develop a FL controller algorithm that can achieve energy saving without compromising user comfort.
2. To design and develop a smart AC controller.
3. To compare the performance of the developed FL controller algorithm with the 24 degree baseline scheme.

1.5 Scope and Limitation of the Study

The scope of the study focuses on the design and development of the smart air conditioning system with FL algorithm as the decision-making engine. This includes the development of both the monitoring and control systems to intelligently manage the operation of the AC. Besides that, the scope includes ensuring compatibility and ease of integration with the existing AC units commonly found in residential sector. The developed prototype functions as an external unit that can be seamlessly integrated with different AC models. Moreover, the study aims to evaluate the feasibility of the developed smart AC controller in achieving energy saving without compromising user comfort. This involves real-time monitoring and assessment of energy consumption and user satisfaction metrics. The study seeks to verify the applicability of FL based control algorithms in real-world settings.

The developed smart AC controller has limitations in terms of features, performance and scalability. The developed system is not fully optimized due to the limited resource and time given for the duration of the study. Besides that, the evaluation of the developed system is limited by the sample size and diversity of the test environments. The prototype is tested in a controlled cabin environment in a tropical country for a certain duration. Therefore, the findings of the study have limitations in generalizing to different building types and geographic regions. Moreover, since the evaluation period is in limited duration, the results does not capture the long-term performance and effectiveness of the smart AC controller.

1.6 Contribution of the Study

The research on the development of a fuzzy logic-based smart air conditioning controller (SACC) offers a cost-effective solution for enhancing energy efficiency without requiring significant hardware upgrades. By deploying the SACC prototype with IoT monitoring systems in a controlled environment, the study emphasizes the benefits of utilizing fuzzy logic algorithms to optimize energy consumption while maintaining thermal comfort. The analysis of control strategies, using real-time data, highlights the effectiveness of fuzzy logic in balancing multiple objectives, such as energy savings and occupant comfort. The study's findings provide valuable insights into the potential of fuzzy logic for residential air conditioning systems and lay a foundation for future implementations in larger-scale applications, focusing on affordability, scalability, and ease of integration with existing AC units.

1.7 Outline of the Report

The report is organized into five chapters. Chapter 1 provides a general introduction to the project, emphasizing its significance, and presenting the problem statement, aims and objectives, scope, limitations, and contributions of the study. Chapter 2 delves into various control algorithms for air conditioning systems, highlighting their advantages and disadvantages, while comparing their suitability for energy saving and thermal comfort optimization. Chapter 3 focuses on the design and development of the FL algorithm, as well as the SACC prototype, including the hardware and software components. Additional features of the SACC are also discussed. Chapter 4 presents and analyses the performance of the FL algorithm in terms of energy savings and thermal comfort. Furthermore, it explores refined versions of the FL algorithm, assessing their improvements in both areas. Additional evaluations, such as the battery life and cost-effectiveness of the SACC, are also covered in this chapter. Finally, Chapter 5 concludes the study with a summary of findings and provides recommendations for future improvements to the SACC's performance.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Energy efficient AC plays a main role in the decarbonization efforts to tackle the climate change issue. With energy efficient AC, AC consumes less energy which reduces the emission of CO2 gas. Improving the control algorithm that controls the AC is one way for the AC to operate more efficiently in terms of energy. Although it is important for AC to operate efficiently, the user comfort must not be compromised. Both energy saving and thermal comfort of user are important factors to be considered when designing and developing a control algorithm. There are existing control algorithms out there in used to control the AC and various advanced control algorithms currently in research. This section reviewed on the advantages and disadvantages of the existing control algorithms and advanced control algorithms.

2.2 Traditional Control Algorithms

The ACs in buildings are currently using traditional control algorithms for their operation. These control algorithms are categorized as single-optimization methods. Their only objective is to properly operate the AC for energy saving. They are simple and cheap to be implemented, making them an attractive solution for AC energy saving. These traditional control algorithms work effectively when the controlled system is simple. However, when the building complexity increases, these control algorithms tend to struggle to operate the AC for energy saving. Besides that, since they are single-optimization methods, the thermal comfort of the occupants may be compromised. Examples of the traditional control algorithms are the ON/OFF control, Hysteresis control, Thermostat-based control and PID control.

2.2.1 ON/OFF Control

As its name stated, ON/OFF control is a binary control that consists of two types of signals which are ON (1) and OFF (0) (Mirinejad, et al., 2008). The actuating parameter of the ON/OFF controller is the temperature. The controller monitors and compares two parameters which are the system temperature and the temperature setpoint. When the system temperature exceeded the temperature setpoint, the ON/OFF controller will send the signal to the AC to be turn on. The AC turns on and cools down the environment. On the other hand, when the system temperature is below the temperature set point, the controller signals the AC to turn off. This allows the AC to save energy.

The operation of the ON/OFF controller is the simplest compared to the other traditional control algorithms. However, due to the nature of the ON/OFF control algorithm, the AC is frequently being turned on and off because of the fluctuation of the environment temperature (Ryniecki, Wawrzyniak and Pilarska, 2015). The frequent on and off cycles of the AC unit leads to an overall inefficiency in energy saving, unable to fulfill its purpose as an energy saving controller. Moreover, this phenomenon leads to large temperature swings which may cause discomfort of the occupants. It also reduces of service life of the air conditioning equipment due to wear and tear. Therefore, the ON/OFF controller is rarely used in AC control even though it is cheap and easy to be implemented.

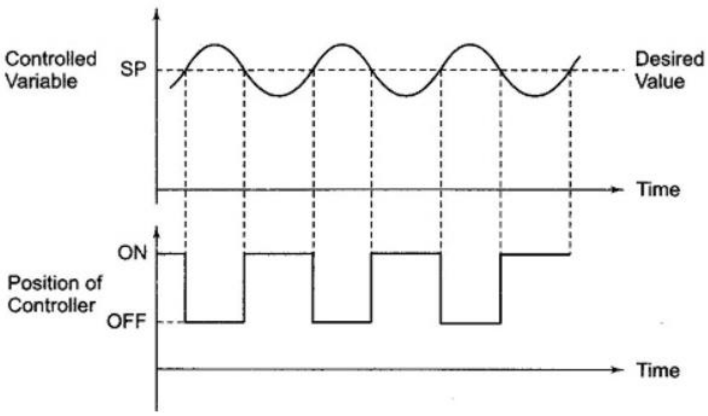

Figure 2.1: Characteristics of ON/OFF control
(EEEGUIDE.COM, n.d.)

2.2.2 Hysteresis Control

Hysteresis control is very similar to ON/OFF control. It is also considered as a binary control as it operates on the basis of ON (1) and OFF (0). However, a slight modification on this controller allows it to address the problem posed by the ON/OFF controller (Fayazbakhsh, Bahgeri and Bahrami, 2015). As mentioned before, the ON/OFF controller causes the AC unit to frequently turn on and off. Hysteresis controller solves the problem by introducing two fixed temperature setpoints instead of a fixed temperature setpoint. For example, 23 °C and 26 °C as the two fixed temperature setpoints. The Hysteresis controller monitors and compares the system temperature with the two fixed temperature setpoints. The AC is initially turn off. When the system temperature reaches the 23 °C set point, the controller will not turn on the AC. The controller only turns on the AC when the system temperature exceeds 26 °C to cool the environment. When the environment cools down and drops below 26 °C, the controller does not turn off the AC. The controller only signals the AC to turn off when the system temperature drops below 23 °C.

Due to the nature of the Hysteresis controller, the AC is being turned on and off less frequently. The two fixed temperature setpoint introduces a deadband. This deadband essentially maintains the AC at its current state. Therefore, there is no immediate switching of the state of the AC when it reaches one of the temperatures set points, ensuring smoother operation of the AC. Less switching means high energy efficiency of the hysteresis controller compared to ON/OFF controller, greater occupant comfort and reduce wear and tear of the air conditioning components. The Hysteresis controller is better than the ON/OFF controller in every aspect. All being said, Hysteresis controller has difficulty in controlling the AC when the system becomes complex.

Since the Hysteresis controller relies on the deadband to effectively reduce the frequent switching of the AC, there is a problem in determining the optimum deadband. If the deadband is too wide, the precision of the controller in achieving the energy saving of the AC is reduced. If deadband is too narrow, the Hysteresis controller will operate like the ON/OFF controller. Even though if the deadband is properly selected by trial-and-error method, the non-linearity and dynamic of the system will cause the controller to struggle to maintain the optimal performance due to the fixed deadband limits (Al-Azba, et al., 2020). In other words, because of the nature of the working principle of the hysteresis controller, it has limited adaptability to the dynamic environment which affects its ability in achieving greater energy saving and thermal comfort of the occupant.

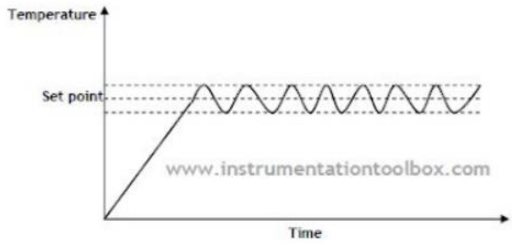

Figure 2.2: Characteristics of Hysteresis control (instrumentationtoolbox.com, n.d.)

2.2.3 Thermostat-Based Control

Thermostat-based control is the most commonly used controller for AC. Most advanced control algorithms work on the base principle of this controller. The Thermostat-based control compares the two parameters which are the system temperature and the temperature setpoint (Jain, 2018). The goal is to maintain the system temperature as close to the temperature setpoint. When the system temperature is lower than the temperature setpoint, the AC works lesser. This means that the AC operates at a lower power. On the other hand, when the system temperature is higher than the temperature setpoint, the AC works harder to cool the environment. This means that the AC operates at a higher power. Besides that, based on the thermostat-based controller, the AC operates at a different power level depending on the temperature difference between the system temperature and the temperature setpoint. The higher the difference, the higher the operating power and vice versa.

Due to nature of the thermostat-based control, the flexibility of the AC to work at different operating power based on the temperature difference between the system temperature and the temperature setpoint allows it to achieve better energy saving when compared to ON/OFF controller and Hysteresis controller. Besides that, since it is not a binary controller, there is no occurrence of AC being turn on and off, thus reducing the wear and tear of the mechanical components of the AC and better occupant's thermal comfort. Essentially, the thermostat-based control is more superior to the ON/OFF controller and the Hysteresis controller in terms of energy saving and occupant's comfort.

Note that the temperature setpoint is set manually by the user. In tropical countries, a higher temperature setpoint will achieve a better energy saving. This is because tropical countries have hot climates. Hence, the AC works lesser to maintain the difference between system temperature and the high temperature setpoint. However, this will compromise the user comfort as the occupant will feel hot and uncomfortable. Likewise, a lower temperature setpoint might improve the occupant comfort but consumes more energy. Therefore, it is important to choose the right temperature setpoint that will both achieve a considerable energy saving and user comfort. Study has shown that choosing the temperature setpoint to be 24 °C can optimally save energy while maintaining user satisfaction. However, various study has shown that advanced control algorithms can save more energy without compromising user comfort. Hence, it is better to go for the advanced control algorithm approach if it is feasible to be implemented in terms of simplicity, cost effectiveness, energy saving and thermal comfort.

2.2.4 Proportional-Integrative-Derivative Control

The PID control can be considered as an advanced control algorithm when compared amongst the other traditional control algorithms. This control algorithm is widely used in split inverter air conditioner. It usually works as a feedback controller to the main controller such as the thermostat-based control. The PID controller feedbacks the main controller to reduce the temperature difference between the system temperature and desired temperature. The difference between the system temperature and desired temperature is called as error (Yamakawa, et al., 2011). Each element in the PID controller works to reduce the error as much as possible.

The proportional element of the PID controller works proportionally to the size of the error. The higher the error, the greater the output of the proportional element of the PID controller to reduce the error. However, with proportional element alone, there will always be a minor difference between the system temperature and the target temperature. This difference is called as the steady-state error. The integrative element of the PID controller help eliminates this error. It works by accumulating the steady-state error over time and adjust the output of the controller according to the size of the accumulated steady-state error. Higher accumulated steady-state error means greater output of the integral element of the PID controller and vice versa. As for the derivative element, it handles the sudden disturbances to the system. Disturbances to the system causes fluctuations in the system temperature. Fluctuations in the system temperature can be reflected by the rate of change of error. The derivative element of the PID controller reacts to the rate of change of error. Higher rate of change of error indicates greater disturbances. The output of the derivative element of the PID controller will be greater to counter the greater disturbances. This help reduce the fluctuations of the system temperature caused by the disturbances, stabilizing the system.

Due to the nature of the PID controller, it requires careful tuning of the proportional, integral and derivative element of the controller to ensure it works at its best performance (Nausation, 2011). The tuning of PID controller can be time-consuming, labor-intensive and vary depending on the system characteristics. Even if the parameters are tuned correctly, they may not be optimal across all scenarios due to the dynamicity and non-linearity of the system. Hence, the PID controller struggles to adapt to changing environmental conditions. This will also affect the performance of the PID controller in energy saving. However, due to its simplicity and cost-effectiveness aspect, the PID controller is a well-established technology, and it is widely used to control AC. Therefore, the advanced control algorithms that are in research mostly paired it with the PID controller to improve the overall performance of the controller in terms of energy saving and thermal comfort.

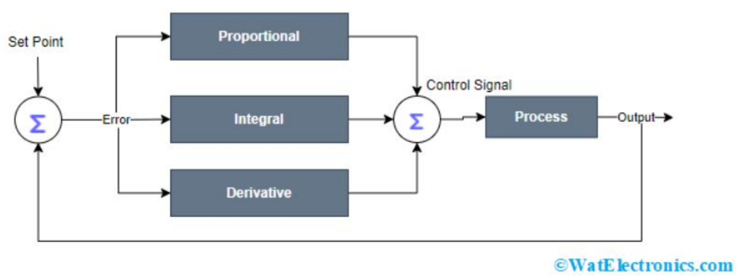

Figure 2.3: PID Block Diagram

(WatElectronics, 2022)

2.3 Advanced Control Algorithms

The system that the AC is controlling is typically non-linear and dynamic. Traditional algorithms fail to handle the non-linearity and dynamicity of the system due to their algorithms' working principle. Hence, they are unable to adapt to the changing of the system's conditions. This leads to the energy inefficient of the AC. On the other hand, advanced control algorithms are able to overcome this challenge. Advanced control algorithms utilize various advance techniques to form the control algorithm to control the AC so that it can handle the non-linearity and dynamicity of the environment. Example of the advanced techniques are the modeling techniques, data-driven techniques, multi-objective optimization techniques and linguistic techniques. These techniques can be used individually or combined to form the control algorithm to handle complex systems.

2.3.1 Model-Based Control Algorithm

MBC algorithms refer to control algorithms that are formed from models. These models are able to reflect the non-linearity and dynamicity of the system. The models can be formed from mathematical models or through software. With the model of the system, the control algorithm uses it to compute the predicted behavior of the system. Behavior of the system refers to the indoor temperature, humidity, air flow and etc. It then compares the predicted behavior with the actual observed behavior of the system. Suitable outputs such as temperature setpoint and fan speed are generated from the control algorithm to meet the desired behavior of the system. The MBC controllers can anticipate and respond to the disturbances to the system in real time which enables them to adapt to varying system conditions, maintaining the optimal performance of AC in energy saving and occupant's comfort.

In the paper by Bohara, et al. (2023), they did an experimental study on the Model Predictive Control (MPC) control algorithm to control a residential split air conditioner. The model of the system, in this case, a residential sleeping room, is modeled using the EnergyPlus software. Instead of predicted behavior, MPC controller computes future behavior of the system for a specific time horizon. It then outputs the optimal AC temperature setpoints to obtain the desired future behavior of the system. The study has shown that the MPC controller saves around 7% of energy as compared to the thermostat-based control at constant 24 °C. Besides that, the MPC controller gives better thermal comfort, 42 % better than the thermostat-based control at constant 24 °C. In another paper by Boodi, et al. (2019), they also use MPC control algorithm to achieve thermal comfort and energy optimization in a container building. They were able to achieve a reduction of 31% reduction in energy usage compared to the traditional control algorithms. However, since MPC is a MBC algorithm, the designed controller is specific to the building type. Therefore, the MPC controller's performance might degrade with different building type. For another building type, the model has to remodeled for accurate performance of the AC. There is no generalized modelling approach, thus additional investments are needed for targeted modelling. Besides that, due to the nature of MPC, if the system is too complex, the model reflects the complexity. The more complex the model, the higher the computational power which can be difficult to build and perform on controllers.

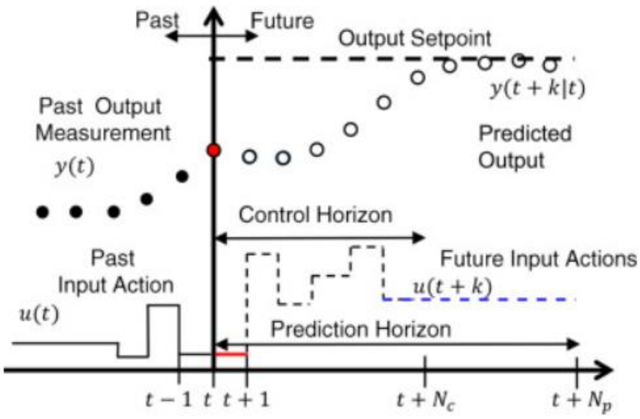

Figure 2.4: MPC Scheme

(Bohara et al., 2023)

2.3.2 Data-Driven Control Algorithm

As its names implies, data-driven control algorithms are formed using data. As compared to MBC algorithms, data-driven control algorithms do not need to rely on system modelling. Instead, the control algorithms are trained with datasets to understand the system behavior. These datasets can include the weather patterns, occupancy pattern, indoor and outdoor temperature, fan speeds and etc. A data-trained control algorithm is able to extract the patterns between the input and output relationships of the datasets that it was trained with. The correlation between the inputs and outputs enables the controller to understand the system behavior. With that, the controller is able to output the relevant signals to control the AC for energy saving and occupant's comfort.

In the paper by Ku, et al. (2015), they utilized a trained control algorithm to accurately output the temperature setpoint for AC control of a split-type air conditioner in a room. The datasets used to train the control algorithm are the Predicted Mean Vote (PMV) value, clothing insulation of the occupants, metabolism rate of the occupants and mean radiant temperature. The study has shown that the trained control algorithm can achieve a 37.3% of energy saving as compared to the conventional control algorithm (fixed temperature setting at 26 °C). It is also able to maintain the thermal comfort in the room for the whole experimental period. Besides that, the paper by Yu, et al. (2021), they use a control algorithm called Deep Q-Learning (DQL) for the AC to control the classroom environment. DQL is also trained with data to learn to make decisions. It has shown that this method is able to save energy of up to 43% without comprising thermal comfort of the occupants as compared to the conventional control algorithm (fixed temperature setting at 25 °C).

For data-driven control algorithms to work properly, they have to be well-trained. For them to be well-trained, the training data needs to be in good quality and amount. Therefore, in situations where data are scare or unreliable, the data-driven control algorithms may struggle to generalize well to the environment's behavior. This means that they can control a specific environment properly when they are trained with the data specific to that environment, but fail to perform when given a new environment. Hence the AC performance might not be optimized for energy saving and thermal comfort for the new environment. Moreover, instead of learning the patterns and correlations from the data, the data-driven control algorithms may memorize the patterns of the data instead. Memorization of data by the control algorithms is the effect of poor training and it also leads to poor generalization to the system.

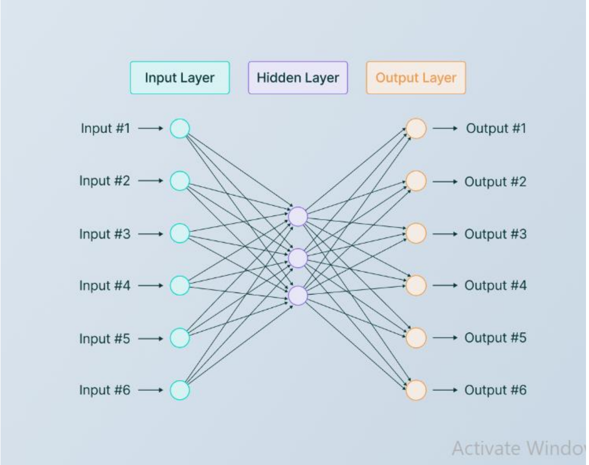

Figure 2.5: Data Driven Algorithm Structure
(Baheti, 2021)

2.3.3 Multi-Objective Optimization Control Algorithm

Multi-objective optimization (MOO) control algorithms are control algorithms that are able to handle multiple objectives. Note that MBC and data-driven control algorithms are also able to handle multiple objectives. Evolutionary control algorithms are part of MOO control algorithms used to control AC. Example of these are Genetic Algorithms (GA), Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) algorithm. Unlike MBC algorithms, MOO algorithms do not need any modelling of the system. They also do not need any datasets for training. These algorithms are able to find the best solution from a pool of solutions. They do that by evolving the pool of solutions and evaluate the quality of each of the solutions in the pool. Solutions that are not good in quality are eliminated, the ones that are good quality are remained and evolved. The process is done iteratively until the best quality of solutions remain in the pool. In AC control context, the pool of solutions can be the temperature setpoint, fan speed, compressor speed and etc. These solutions are evaluated by a function. The function can include the calculations of the energy consumption of AC and thermal comfort of the occupant. Solutions that give lower energy consumption and high thermal comfort are good quality solutions, and those that are the opposite are bad quality solutions. The bad quality ones are eliminated whereas the good quality ones are evolved through operators. The process is done iteratively until the best quality of temperature setpoints, fan speeds, compressor speeds and etc are obtained. The MOO controller then uses these values to control the AC for maximum energy saving without compromising user comfort.

In the paper by Khorram, et al. (2019), they proposed the PSO control algorithm to optimize the AC energy consumption based on CO2 concentration level. The set of solutions are the period to turn on and turn off the AC. The evaluation function for the solutions includes the calculation of CO2 concentration level and the required AC power reduction. A constraint is included to limit the AC power reduction to handle the user comfort aspect. The best set of solutions are obtained through PSO and the AC is turned on and off according to the periods. Results have shown that the PSO is able to effectively reduce the energy consumption of the AC without compromising user comfort. In another paper by Ullah and Kim (2017), they are able to achieve 27.32 % and 31.42 % of reduction of energy consumption in a lab using PSO and GA respectively when compared to their baseline scheme. The results also shown that PSO and GA are able to increase the user comfort by 10% compared to their baseline scheme. Ruiz, et al. (2021) proposed an advanced GA control algorithm called NSGA-II to control the AC. The simulation results shown that NSGA-II is able to effectively reduce more power consumption of AC while having a better user comfort index as compared to the GA.

Compared to MBC algorithm and data-driven control algorithm, MOO control algorithm is simpler to be implemented. However, as system becomes more complex, it might be difficult for MOO algorithm to find the best set of solutions from the pool of solutions. Due to the difficulty for the MOO algorithm to converge, the optimal set of solutions might not be found, and this will degrade the performance of AC in energy saving and thermal comfort. This can be solved by choosing good operators for the evolution process and having larger number of iterations. However, larger number of iterations increases computational burden and cost. Besides this, MOO algorithms cannot be embedded into microcontrollers as of now. Therefore, plug-and-play characteristics cannot be implemented as a personal computer is required for MOO algorithm to connect with the microcontroller for controlling the AC.

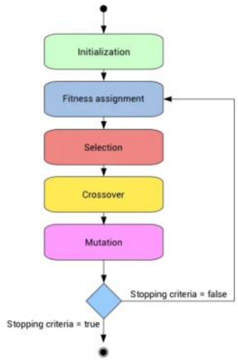

Figure 2.6: General Structure of GA

(Gómez, 2023)

2.3.4 Fuzzy Logic Algorithm

FL algorithm has the ability to handle uncertainty and approximate reasoning. In the context of AC control, FL provides a framework for dealing with imprecise inputs and creating flexible, adaptive control systems. The process starts with fuzzification, which converts crisp input values such as temperature and humidity into fuzzy values by mapping them to linguistic terms like "cool" or "warm" using membership functions. These membership functions could be triangular, trapezoidal, or Gaussian, depending on the system's requirements. After fuzzification, the fuzzy inference system processes the inputs using a set of if-then rules. There are two main types of inference systems which are the Mamdani and Sugeno methods. Mamdani inference is more common in control systems like ACs because it provides intuitive linguistic rules and outputs that are easier to interpret. It uses a min-max approach for aggregation and implication, combining the fuzzy outputs from multiple rules to form a final fuzzy set. Finally, the defuzzification process translates the fuzzy output back into a crisp value, typically using methods like centroid defuzzification. For an AC system, this would result in an exact output, such as the new temperature setpoint or fan speed, based on the fuzzy logic engine’s decisions. The flexibility of fuzzy logic allows for improved control, enabling the system to maintain energy efficiency while optimizing user comfort.

In the paper by Attia, Rezeka and Saleh (2015), they were able to develop a FL controller to control the air conditioning system. Instead of temperature setpoint as the output of the controller, the controller controls the percentage of chilled and hot water flow rates for summer and hot water and steam flow rates at winter. With this FL, they were able to demonstrate the efficient operation of the air-conditioning system in terms of energy saving and user comfort when controlled by FL as compared to PID control. In the paper by Belman- Flores, et al. (2019), they presented a FL control system for domestic refrigerator, designed to optimize temperature and reduce energy consumption. The results showed a 3% of energy saving by minimizing compressor starts, highlighting the potential for enhanced efficiency through more real-time data integration into the FL system.

Compared to other advanced control algorithms, FL control algorithm is simpler to be implemented as it does not require system modeling, training of data nor high computational resources. Besides that, FL control algorithm can be embedded into microcontroller. This allows the FL control algorithm to control the AC in real-time without the need of extensive setup and laboratory intensive work. Due to this, a controller can be easily built with the FL control algorithm as the decision-making engine to control the AC, working as an external unit. However, for FL to operate properly, the membership functions for the inputs and outputs as well as the fuzzy rules have to be properly defined or else it can lead to suboptimal control performance.

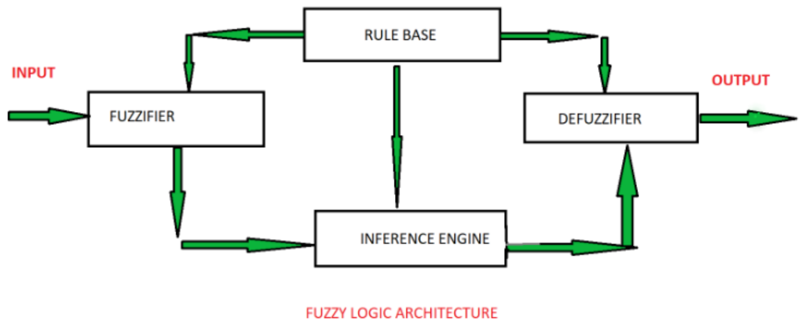

Figure 2.7: Fuzzy Logic Architecture
(GeeksforGeeks, 2023)

Category	ON/OFF Control	Hysteresis Control	Thermostat-based Control	PID Control	Model-Based Control (MBC)	Data-Driven Control	Mutiple Objective Optimization (MOO) Control	Fuzzy Logic (FL) Control
System Modelling	✗	✗	✗	✗	✓	✗	✗	✗
Training of Data	✗	✗	✗	✗	✗	✓	✗	✗
High Computational Resource	✗	✗	✗	✗	✓	✓	✓	✗
Adaptability	✗	✗	✗	✗	✓	✓	✓	✓
Handling Complexity	✗	✗	✗	✗	✓	✓	✓	✓
Ease of Implementation	✓	✓	✓	✓	✗	✗	✗	✓

Figure 2.8: Summary of Comparisons of the Control Algorithms

CHAPTER 3

METHODOLOGY

3.1 Design and Development of Fuzzy Logic (FL) Control Algorithm

The controller algorithm is developed using FL. There are a total of five inputs and one output. The five inputs for the controller algorithm are the indoor carbon dioxide concentration, indoor occupancy, predicted mean vote (PMV), indoor temperature and power consumption of the AC itself. These inputs are feed into the FL algorithm. The FL algorithm consists of the fuzzification process, inference system and defuzzification process to produce the output which is the AC temperature to control the AC. The inference system used is the Mamdani inference system.

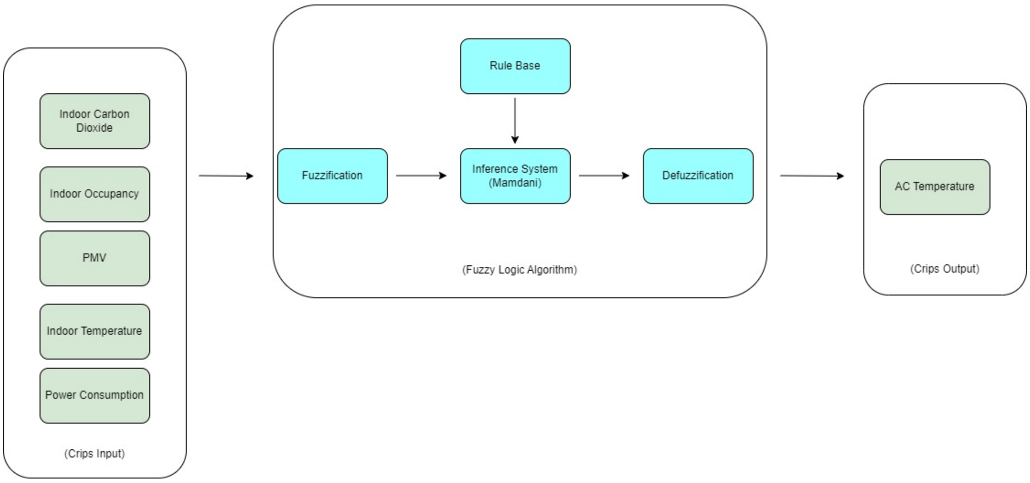

Figure 3.1: Fuzzy Logic Algorithm for AC controller

The indoor carbon dioxide concentration input parameter functioned as a parameter to indirectly measures the number of occupancies in the controlled area. If there is high occupancy level, the indoor carbon dioxide concentration is high and vice versa (Areif-Ang et al., 2018). Lower occupancy may require less cooling, saving energy, while higher occupancy levels may necessitate more cooling to maintain comfort. Therefore, the carbon dioxide concentration functions to indirectly monitor the occupancy in the controlled area to effectively adjust the AC set temperature for energy saving and occupancy comfort.

The indoor occupancy detection input parameter functioned as a complimentary parameter to the indoor carbon dioxide concentration. Unlike indoor carbon dioxide concentration, indoor occupancy detection directly detects whether there is presence of occupancy or not (Yes or No). By combining both the indoor occupancy detection and indoor carbon dioxide concentration, the AC set temperature can be better adjusted to cater for the energy saving and occupancy comfort.

The PMV input parameter functioned as a parameter to directly measures the occupancy thermal comfort. PMV is a standard thermal comfort model used by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) (Dyvia and Arif, 2019). The PMV parameter aims to directly monitors thermal comfort of the occupancy and adjusts the AC set temperature to maintain the thermal comfort. This parameter focuses on the thermal comfort aspect.

For the power consumption input parameter, it directly monitors the ON/OFF operation of the air compressor of the AC. It functions to adjust the AC set temperature to a higher value whenever it detects the air compressor of the AC in ON state. This is to aim to reduce the workload of the air compressor, saving energy. This parameter focuses on the energy saving aspect.

The indoor temperature input parameter is a parameter that compliments the power consumption parameter. Whenever the air compressor of the AC turns on, the AC set temperature will be set to a value depending on the indoor temperature. This is to aim to reduce the workload of the air compressor while ensuring that the user comfort is not compromised.

3.1.1 Fuzzy Logic (Fuzzification)

Fuzzification is a part of the FL algorithm that convert the crips values into corresponding fuzzy sets for fuzzy inference process. The crips inputs which are the indoor carbon dioxide concentration, indoor occupancy detection, PMV, power consumption and indoor temperature are mapped onto the defined fuzzy sets through membership functions.

For the indoor carbon dioxide concentration, the range defined is from 300 to 1000 parts per million (ppm) as this range is categorized as normal CO2 concentration level (Wisconsin Department of Health Services, 2018). Five membership functions are used to categorize this range. These membership functions are of triangular membership function and trapezoidal membership function. The range are segregated into five different fuzzy sets which are low, slightly low, normal, slightly high and high. Below Figure 3.2 shows the membership functions for the indoor carbon dioxide concentration.

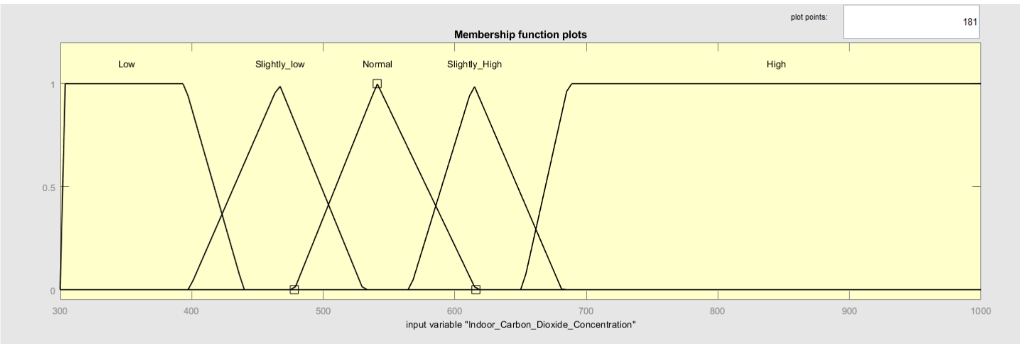

Figure 3.2: Membership Functions for Indoor Carbon Dioxide Concentration

The membership functions for the input variable, indoor occupancy detection, define two fuzzy sets: No Detection and Detection. The No Detection set represents situations where no occupant is detected within the monitored area, corresponding to a membership value of 1.0 when the input variable is 0. On the other hand, the Detection set represents the presence of an occupant in the area. This set is characterized by a membership value of 1.0 when the input variable is 1, which reflects full occupancy detection. Below Figure 3.3 shows the membership functions for the indoor occupancy detection

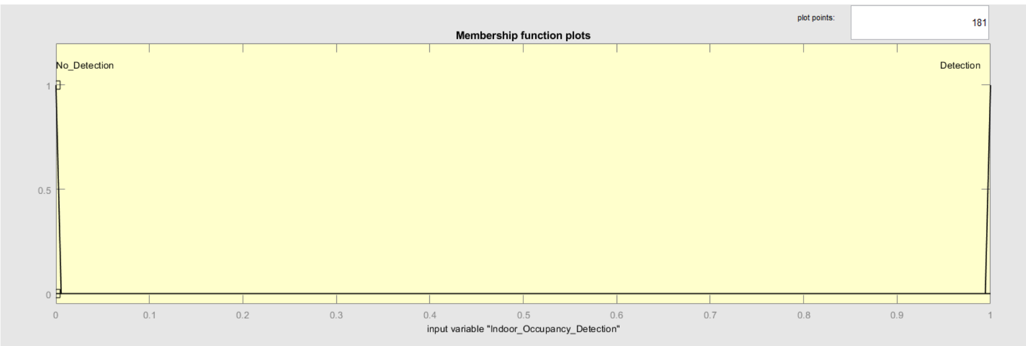

Figure 3.3: Membership Functions for Indoor Occupancy Detection

For the PMV, the defined range is from -2 to 2. The range of -2 to 2 is chosen instead of -3 to 3 for the PMV as it focuses on more commonly experienced thermal comfort levels, excluding extreme conditions that are less relevant in typical indoor environments. Five membership functions are used to categorize this range. The membership functions used are the triangular and trapezoidal membership functions. The range are segregated into five different fuzzy sets which are cold, moderately cold, slightly code, neutral and hot. Below Figure 3.4 shows the membership functions for the PMV.

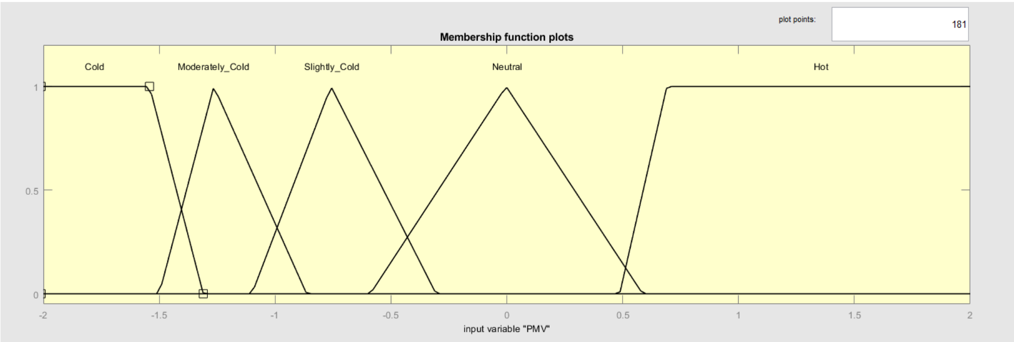

Figure 3.4: Membership Functions for PMV

The power consumption of the AC has two fuzzy sets. These two fuzzy sets are the Low fuzzy set and High fuzzy set. When the air compressor of the AC turns on, the power consumption is typically above 1 kW but always below 2 kW. Therefore, within this range, it belongs to the High fuzzy set with membership value of 1.0. On the other hand, when the air compressor of the AC turns off, the power consumption is below 1 kW. Therefore, anything below 1 kW belongs to the Low fuzzy set with membership value of 1.0. Sigmoid membership functions are used to give a smooth transition from low to high and vice versa. Below Figure 3.5 shows the membership functions for the power consumption of AC.

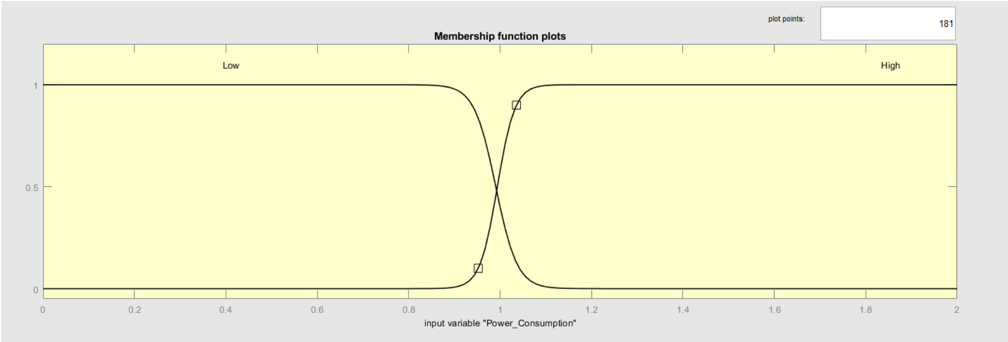

Figure 3.5: Membership Functions for Power Consumption of AC

For the indoor temperature, it has a defined range of 18 °C to 30 °C. This range is chosen as the indoor temperature of the test area is within this range. Five fuzzy sets are used to define this range. The trapezoidal and triangular membership functions are used for the fuzzy sets. The five fuzzy sets are the cold set, slightly cold set, normal set, slightly hot set and hot set. Below Figure 3.6 shows the membership functions for the indoor temperature.

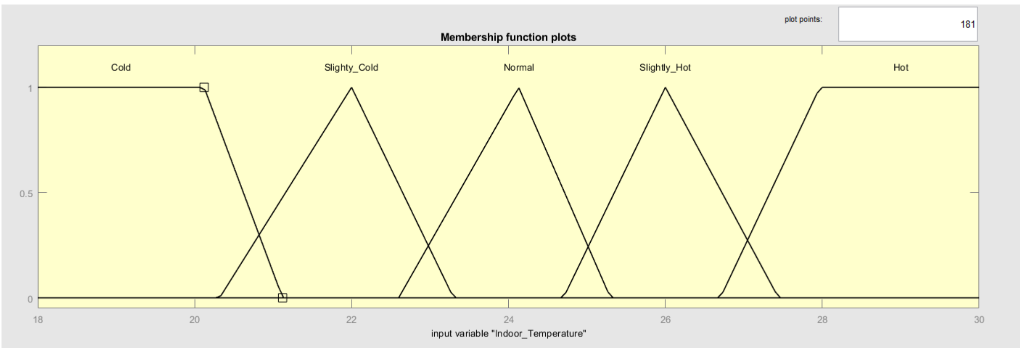

Figure 3.6: Membership Functions for Indoor Temperature

3.1.2 Fuzzy Logic (Defuzzification)

Defuzzification is the process of converting fuzzy outputs into crips values that can be used in the real-world after undergoing the inference process. There is only one output which is the AC set temperature. After going through the inference process whereby multiple fuzzy outputs of AC set temperature is produced, these fuzzy outputs will undergo defuzzification using centroid method to produce a single crips value for controlling the AC.

The AC set temperature has a defined range of 21 °C to 28 °C. Although it has a range of 21 °C to 28 °C, the possible AC temperature range to control the AC is only from 22 °C to 27 °C. The range of 22°C to 27°C is selected as this is the typical range common users set. Five fuzzy sets are defined within this range which are the low set, slightly low set, medium set, slightly high set and high set. Below Figure 3.7 shows the membership functions for the AC set temperature.

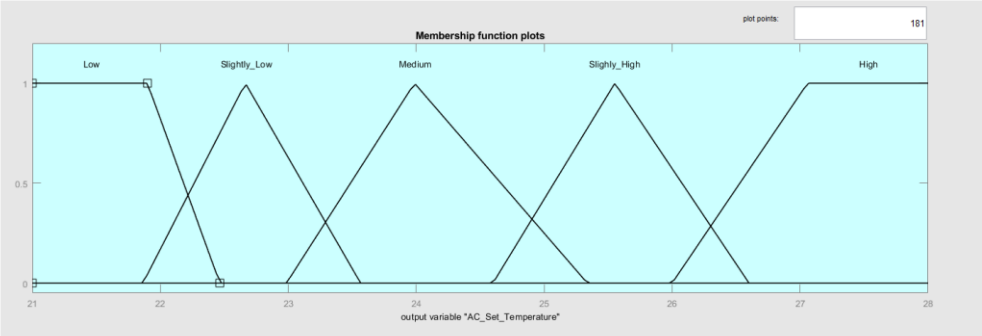

Figure 3.7: Membership Functions for AC Set Temperature

3.1.3 **Fuzzy Logic (Inference System)**

Rule No.	Indoor CO2 Concentration	Indoor Occupancy Detection	PMV Status	Power Consumption	Indoor Temperature	AC Set Temperature
1	Low	No Detection	Cold	-	-	High
2	Low	No Detection	Moderately Cold	-	-	High
3	Low	No Detection	Slightly Cold	-	-	High
4	Low	No Detection	Neutral	-	-	Slightly High
5	Low	No Detection	Hot	-	-	Slightly High
6	Low	Detection	Cold	-	-	High
7	Low	Detection	Moderately Cold	-	-	High
8	Low	Detection	Slightly Cold	-	-	Slightly High
9	Low	Detection	Neutral	-	-	Slightly High
10	Low	Detection	Hot	-	-	Slightly High
11	Slightly Low	No Detection	Cold	-	-	High
12	Slightly Low	No Detection	Moderately Cold	-	-	Slightly High
13	Slightly Low	No Detection	Slightly Cold	-	-	Slightly High
14	Slightly Low	No Detection	Neutral	-	-	Slightly High
15	Slightly Low	No Detection	Hot	-	-	Slightly High
16	Slightly Low	Detection	Cold	-	-	High
17	Slightly Low	Detection	Moderately Cold	-	-	Slightly High
18	Slightly Low	Detection	Slightly Cold	-	-	Slightly High
19	Slightly Low	Detection	Neutral	-	-	Medium
20	Slightly Low	Detection	Hot	-	-	Medium
21	Normal	No Detection	Cold	-	-	Slightly High
22	Normal	No Detection	Moderately Cold	-	-	Slightly High
23	Normal	No Detection	Slightly Cold	-	-	Slightly High
24	Normal	No Detection	Neutral	-	-	Medium
25	Normal	No Detection	Hot	-	-	Medium
26	Normal	Detection	Cold	-	-	Slightly High
27	Normal	Detection	Moderately Cold	-	-	Slightly High
28	Normal	Detection	Slightly Cold	-	-	Medium
29	Normal	Detection	Neutral	-	-	Medium
30	Normal	Detection	Hot	-	-	Medium
31	Slightly High	No Detection	Cold	-	-	Slightly High
32	Slightly High	No Detection	Moderately Cold	-	-	Slightly High
33	Slightly High	No Detection	Slightly Cold	-	-	Medium
34	Slightly High	No Detection	Neutral	-	-	Medium
35	Slightly High	No Detection	Hot	-	-	Medium
36	Slightly High	Detection	Cold	-	-	Slightly High
37	Slightly High	Detection	Moderately Cold	-	-	Medium
38	Slightly High	Detection	Slightly Cold	-	-	Medium
39	Slightly High	Detection	Neutral	-	-	Medium
40	Slightly High	Detection	Hot	-	-	Low
41	High	No Detection	Cold	-	-	Slightly High
42	High	No Detection	Moderately Cold	-	-	Medium
43	High	No Detection	Slightly Cold	-	-	Medium
44	High	No Detection	Neutral	-	-	Medium
45	High	No Detection	Hot	-	-	Medium
46	High	Detection	Cold	-	-	Slightly High
47	High	Detection	Moderately Cold	-	-	Medium
48	High	Detection	Slightly Cold	-	-	Medium
49	High	Detection	Neutral	-	-	Low
50	High	Detection	Hot	-	-	Low
51	-	-	-	High	Cold	Slightly Low
52	-	-	-	High	Slightly Cold	Medium
53	-	-	-	High	Normal	Slightly High
54	-	-	-	High	Slightly Hot	High
55	-	-	-	High	Hot	High

Figure 3.8: Fuzzy Rules for Inference Process

There is a total of fifty-five fuzzy rules. The first 50 rule, from rule 1 to rule 50, the AC set temperature is determined by different combinations of fuzzy sets from different input parameters such as the indoor carbon dioxide, indoor occupancy detection and PMV. There is a total of 50 rules from these combinations because there are 5 fuzzy sets from indoor carbon dioxide, 2 fuzzy sets from indoor occupancy detection and 5 fuzzy sets from PMV. By multiplying them together, 50 possible combinations are available. The rules are set such that to conserve energy whenever possible and providing comfort whenever necessary.

From rule 51 to rule 55, these five rules are set such that to save energy. Whenever, the power consumption is high, while considering rules from 1 to 50, the AC set temperature is set to a higher degree depending on the indoor temperature. This is to reduce the workload of the AC compressor to save energy.

The fuzzy logic algorithm operates based on the Mamdani inference system. The fifty-five combinations of rules are formed using the AND method. Hence, for Mamdani inference system, the minimum operator is used for the AND method to determine the rule strength during the rule evaluation process. As for the aggregation process, Mamdani inference system uses the maximum operator. Aggregation is a process that combines all the same fuzzy output sets after the rule evaluation process into a single fuzzy output set for defuzzification.

3.2 Design and Development of Smart Air-Conditioner Controller (SACC)

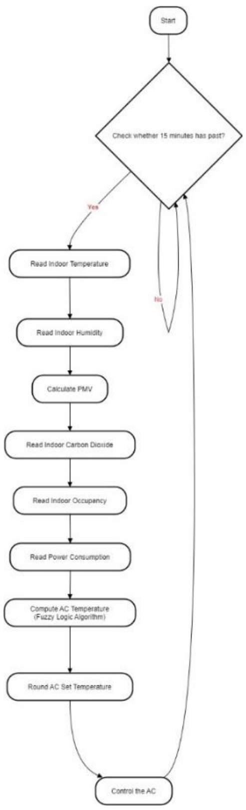

Figure 3.9: Main Algorithm Flow of Smart AC Controller

Above Figure 3.9 shows the main algorithm flow of the Smart AC Controller (SACC). The FL algorithm is designed using MATLAB software and converted into C ++ program. This C++ program is programmed into the ESP32 microcontroller for real-time controlling of the AC. The SACC controls the AC temperature for every 15 minutes. For every 15 minutes, the SAAC takes in the indoor temperature, indoor humidity to compute the PMV. After that, it measures the indoor carbon dioxide concentration, checks the indoor occupancy and measures the power consumption. All these input parameters are then feed into the FL algorithm to produce the crips output of AC set temperature. The AC set temperature is then round up to nearest integer for controlling the AC.

The MH-Z19C carbon dioxide sensor is used to measure the indoor carbon dioxide concentration. The MH-Z19C is a low-cost CO2 sensor and has an effective range of 400 – 5000 ppm, which is sufficient enough for the measuring of CO2. For the indoor occupancy, HLK-LD2410C, millimeter Wave (mmWave) radar sensor is used. This sensor has the capability to detect non-movement unlike other sensors like PIR and microwave radar which only detects motion.

The PMV parameter takes in six inputs. These inputs are the indoor temperature, indoor mean radiant temperature, indoor humidity, air velocity, metabolic rate and clothing insulation. The indoor mean radiant temperature is influenced by the temperatures of surrounding surfaces. According to Alegría-Sala, et al. (2024), this parameter is difficult to measure and is normally assumed to be the same as the indoor temperature as the surface temperatures do not vary significantly from the indoor temperature. For the air velocity, it is assumed to be 0.11 m/s. This value comes from (Designingbuildings.co.uk, 2016) whereby 0.11 m/s can be used as an assumption for internal air velocity for simple heat transfer calculation. The metabolic rate is defined as a constant 1.1. 1.1 directly translates to the metabolic rate for typing. As the test area consists of subjects that are in postgraduate degree, they are mostly with their laptop doing their research. Hence 1.1 is a suitable value to be chosen as the metabolic rate. For the clothing insulation, it is set as a constant 0.31. The clothing insulation of 0.31

is the sum of clothing insulation of T-shirt, thin trousers, men’s underwear, ankle socks and shoes. This combination is the usual combination worn by the subjects in the test area. For the indoor temperature and indoor humidity parameter to calculate the PMV, DHT22 is used. DHT 22 is a low-cost sensor that can measure both temperature and humidity at an accurate accuracy.

The power consumption of the AC is taken from a smart energy meter (ADW300) which is already installed in the test area. The values are collected and stored at an IoT platform called Blynk. The microcontroller is connected to Blynk for assessing the power consumption data to compute the AC output temperature using the FL algorithm. Infrared (IR) transmitter is used to send the IR signal of the computed AC temperature value to control the AC.

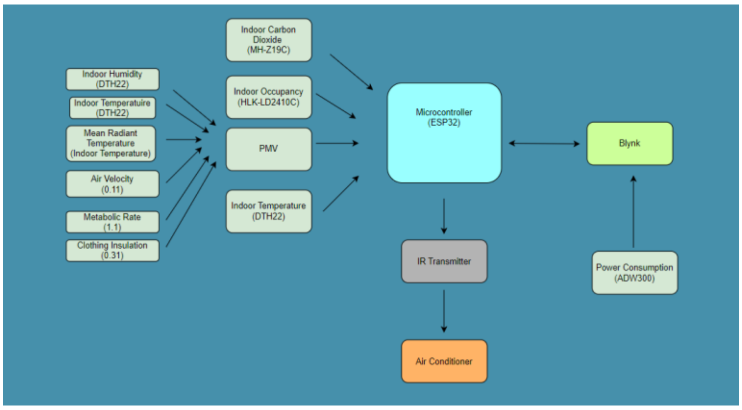

Figure 3.10: Block Diagram of Smart AC Controller

3.3 Prototype Development of Smart Air-Conditioner Controller (SACC)

Below Figure 3.11 and Figure 3.12 shows the schematic diagram and the prototype of the SACC. Besides the aforementioned components used to obtain the input parameters of the FL algorithm, some other components are used to improve the quality of life of the SACC.

An OLED display is used as a user interface of the SACC to display essential information such as the indoor temperature status, indoor humidity status, PMV status, indoor CO2 status, indoor occupancy status, power consumption status and AC temperature status. Besides this, the OLED also displays the online status of the SACC, AC power status, AC control mode status and energy consumption of the AC.

The online status of the SACC shows whether the SACC is connected to the Blynk IoT platform or not. The AC power status indicates whether the AC is ON or OFF state. For the AC control mode status, it indicates whether the AC is in automatic mode or manual mode. In automatic mode, the SACC is running on FL algorithm to control the AC temperature. On the other hand, FL algorithm is deactivated on manual mode. User can manually adjust the AC temperature via the Blynk IoT platform when manual mode is initiated.

Four physical push buttons are used as the physical user control panel for the SACC. These four push buttons are the SACC power push button, AC power push button, AC control mode push button and Wi-Fi configuration push button. The SACC power push button is to power ON/OFF the microcontroller. The AC power push button is to power ON/OFF the AC. AC control mode push button is to change the operating mode of the AC, either automatic or manual. As for the Wi-Fi configuration push button, when pressed, it allows user to connect to the any available Wi-Fi networks by inputting the Service Set Identifier (SSID) and password of the Wi-Fi network through a portal using mobile phone.

The power supply of the SACC can be either through power socket connection or using power bank. As the SACC is a plug-and-play device, it works as an external unit to control the AC. Hence, no retrofitting of the AC is needed.

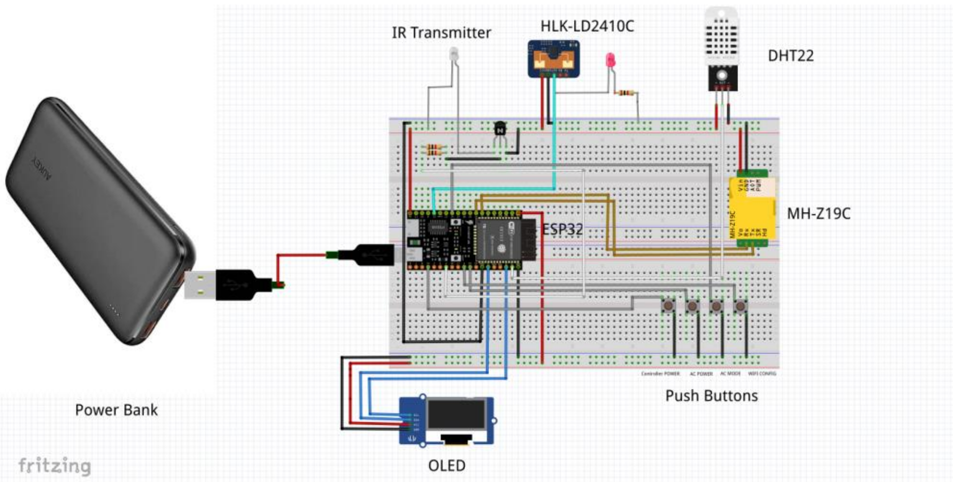

Figure 3.11: Schematic Diagram of Smart AC Controller

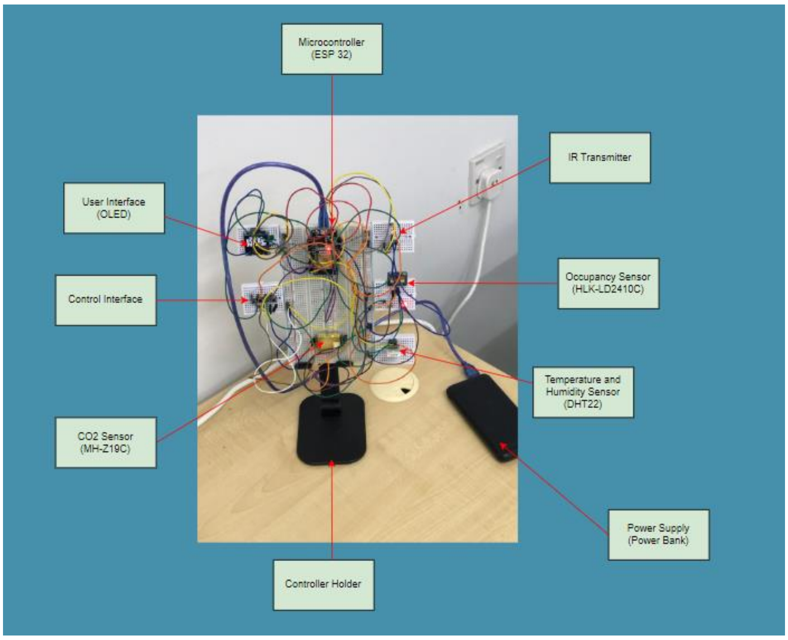

Figure 3.12: Smart AC Controller Prototype

Figure 3.13: OLED display of Smart AC Controller

3.4 Software Applications for Smart Air-Conditioner Controller (SACC)

The HLK-LD2410C, mmWave radar sensor that is used for indoor occupancy detection can be remotely calibrated using Bluetooth connection via the HLK Radar Calibration Tool application. Among the relevant parameters that can be calibrated are the detection range, static energy thresholds and motion energy thresholds.

The detection range for the mmWave radar sensor is set to maximum six meters for the test area. For the static and motion energy thresholds, they are set based on trial-and-error method. The setting of the thresholds for the static and motion energy are similar whereby higher thresholds are set for nearer distances (gate 1 to gate 4, 0m to 2.25m) and lower thresholds are set for further distances (gate 5 to gate 9, 3m to 6m). This means that for nearer distances, the mmWave radar sensor is less sensitive to prevent false positives. On the other hand, for further distances, the mmWave radar sensor is more sensitive such that little to no movement is able to trigger the mmWave radar sensor as long there is a presence of person.

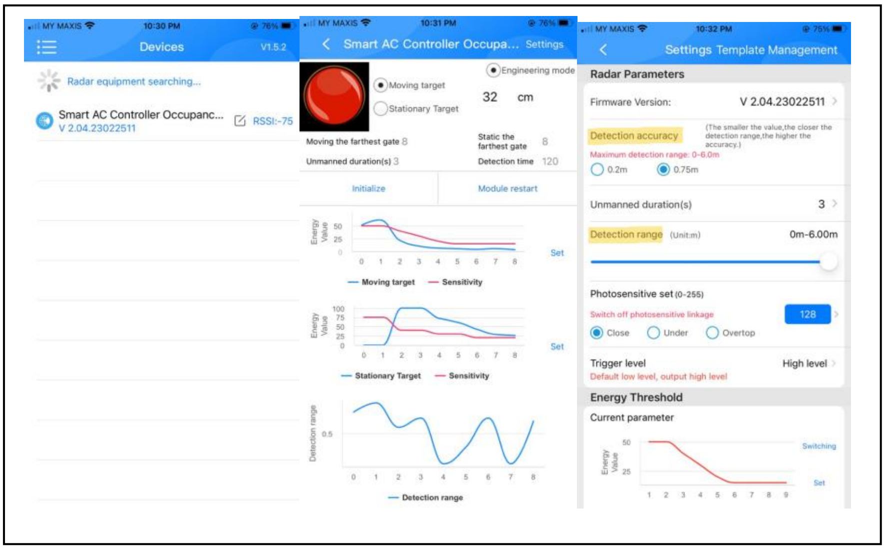

Figure 3.14: HLK Radar Calibration Tool

Figure 3.15: Static and Motion Energy Threshold Calibration

The power consumption of the AC is tapped from the existing installed energy meter in the test area. Node-RED software is used to obtain the energy consumption and power consumption from the energy meter. Before the readings are passed to Blynk platform, they are properly formatted. Below Figure 3.16 shows the Node-RED software to obtain the power consumption and energy consumption from the meter.

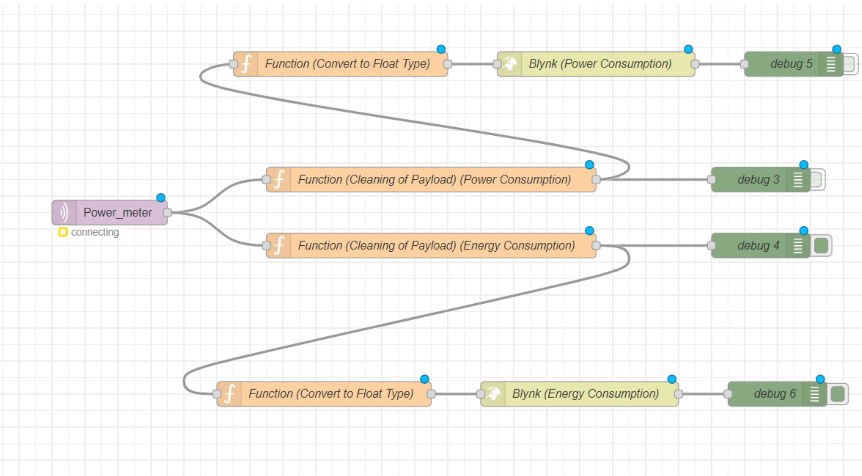

Figure 3.16: Node-RED software application

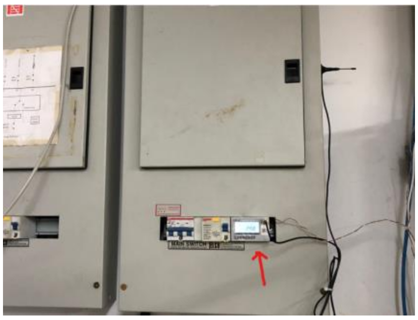

Figure 3.17: Existing installation of the Energy Meter

The SACC is connected to the Blynk IoT platform to allow users to control the SACC remotely. Users are able to remotely power ON/OFF the AC, switch between automatic mode and manual mode and manually control the AC temperature if manual mode is initiated. Besides that, the SACC also allows users to view essential information remotely such as the AC power control status, AC control mode status, AC temperature status, indoor temperature status and etc. Users are able to do this via their personal computer or their mobile phone.

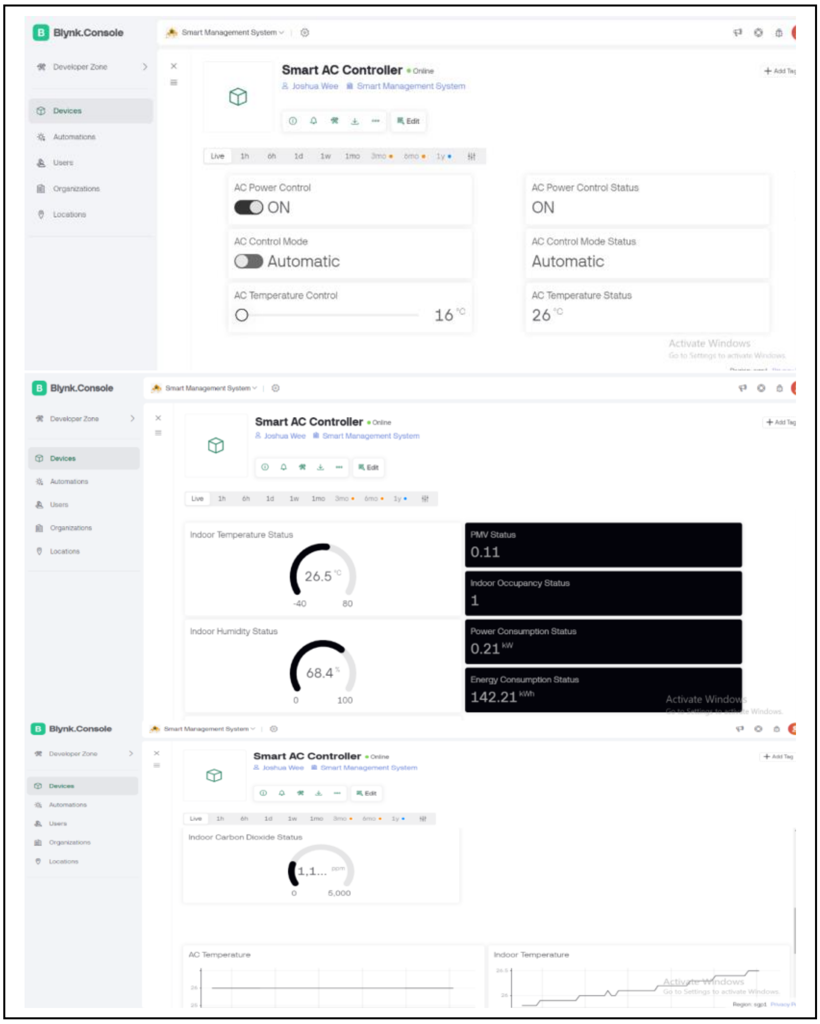

Figure 3.18: Blynk Web Dashboard

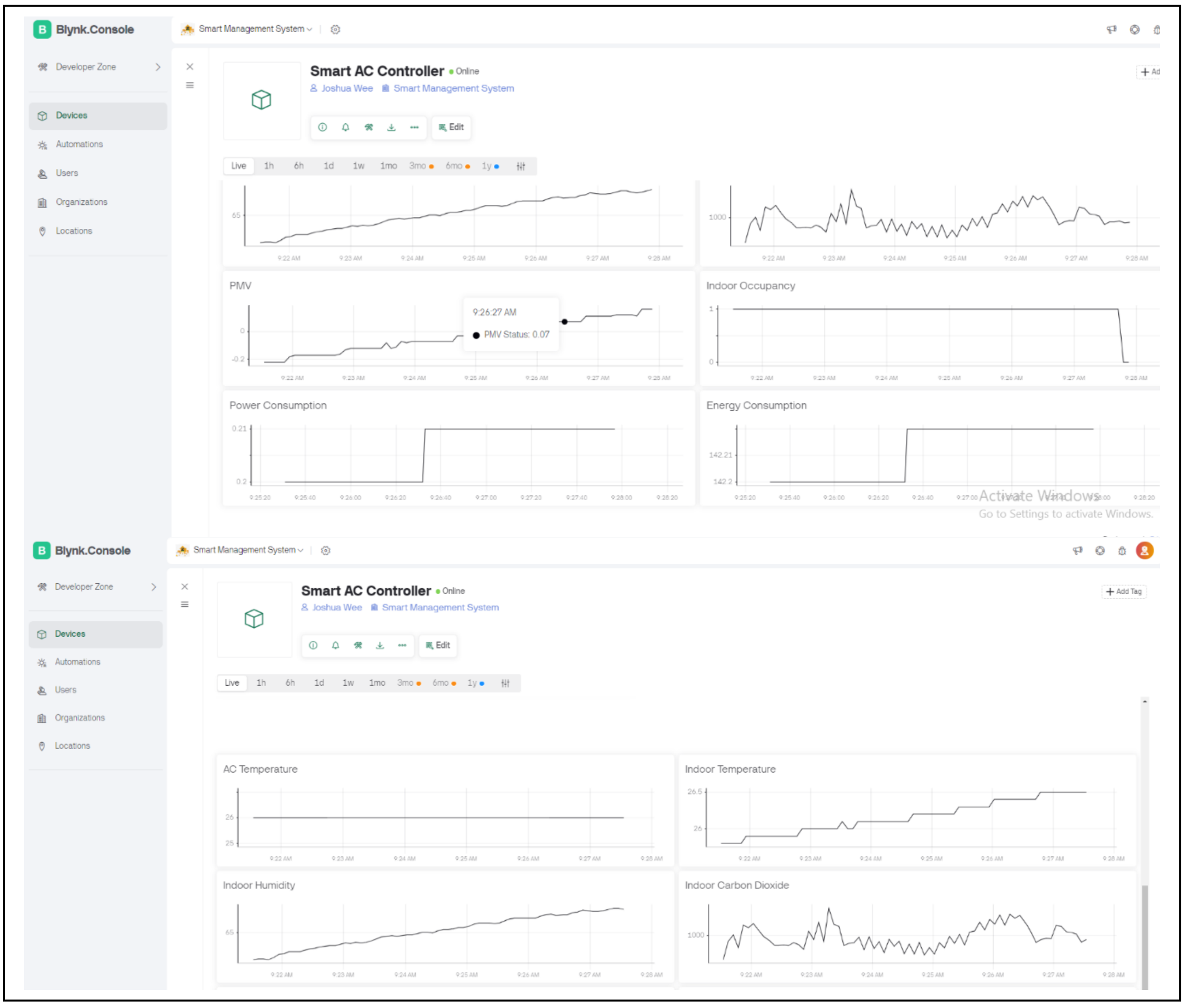

Figure 3.19: Blynk Web Dashboard (Graph)

Figure 3.20: Blynk Mobile Dashboard

3.5 Other Features for Smart Air-Conditioner Controller (SACC)

To further enhance the SACC, making it smarter, the SACC is developed such that it can be controlled via voice command. With this feature, the users can control the AC remotely via voice control to power ON/OFF the AC, changing the operation mode and setting the AC temperature. Environment information such as the indoor carbon dioxide and indoor temperature can also be monitored using voice command.

This can be done due to the Blynk RESTFUL Application Programming Interface (API). This API allows other third-party applications to access Blynk. With this API, IOS shortcuts can be used to access Blynk remotely, which in turns accessing the SACC as the SACC connects to Blynk. Hence, when utilising Siri voice command feature from Iphone Operating System (IOS), the IOS shortcuts can be triggered, which indirectly triggers Blynk, allowing users to control the SACC.

Figure 3.21: IOS shortcuts

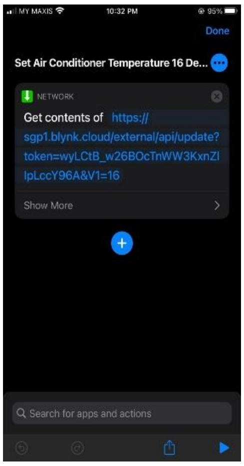

Figure 3.22: Blynk API

Besides voice command feature, the SACC also has the automation feature. This feature is a complimentary feature of the SACC. It allows the AC to turn ON/OFF automatically at a specified time. For example, the AC turns on every 8:00 AM and turns off every 6:00 PM. Besides that, for further energy saving, the AC can be controlled such that at 12:00 PM, it will check whether there are occupants in the area through the mmWave radar sensor and set the AC temperature to a higher degree if there is no one around the area. Below Figure 3.23 shows the types of automations available for the SACC.

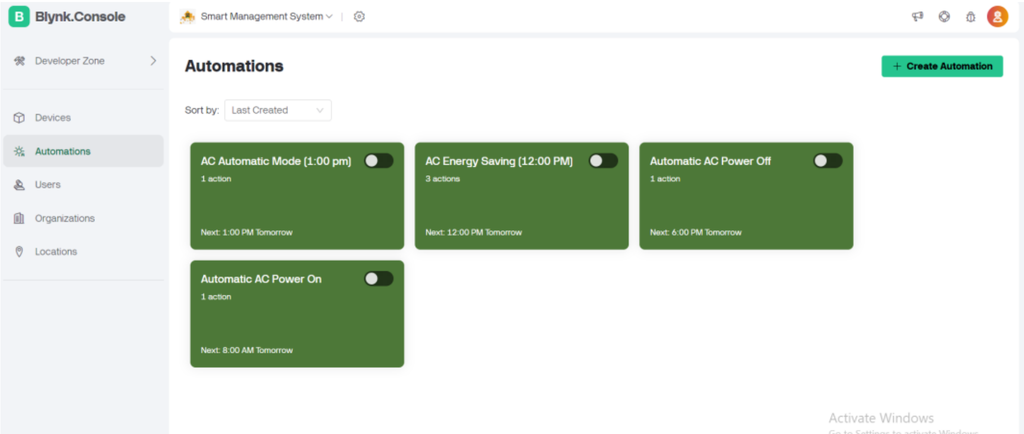

Figure 3.23: Automations for Smart AC Controller

When updating the firmware is needed for the SACC to fix bugs or to implement new features, one way is to connect the microcontroller to a personal computer via cable and update it through an Integrated Development

Environment (IDE). However, this type of way is complex for the common users and introduces inconveniences. Therefore, Over-The-Air (OTA) update feature is enabled for the SACC. With OTA, common users can update the firmware of the SACC with ease via Blynk platform.

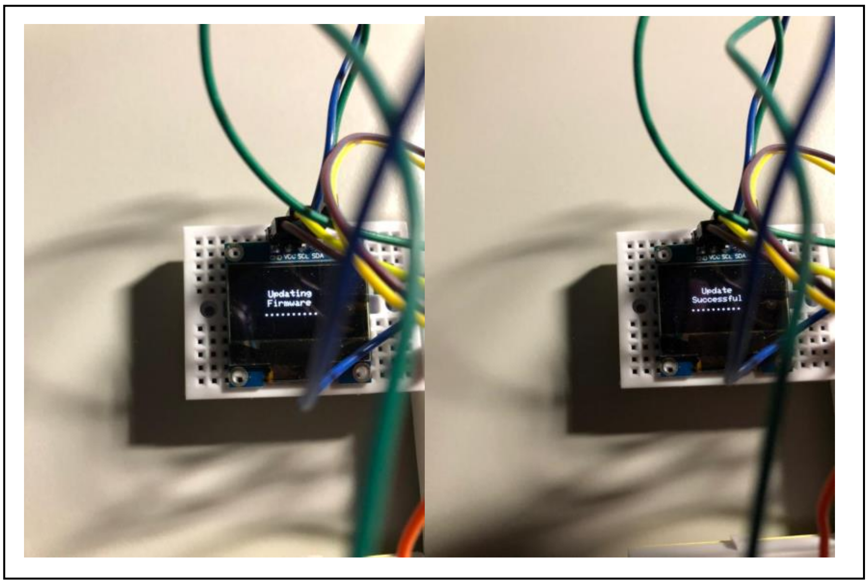

Figure 3.24: OLED display during OTA update

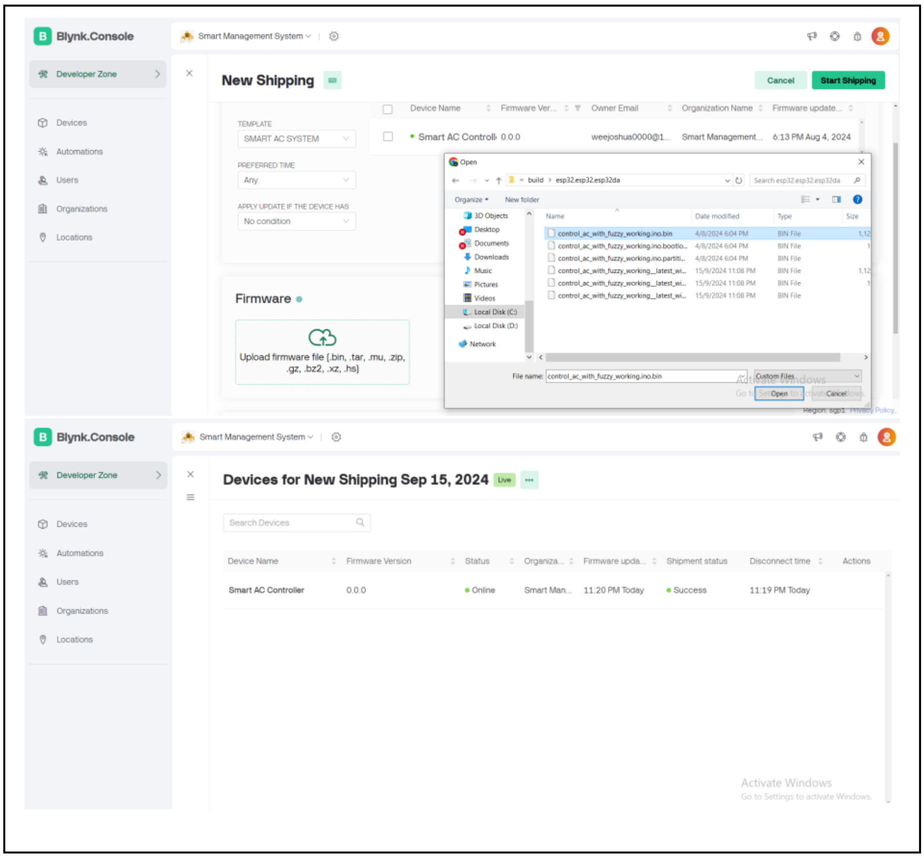

Figure 3.25: Smart AC Controller OTA Update

To complement the Wi-Fi connectivity feature, Wi-Fi provisioning is provided for the SACC. This means that the device can be configured to connect to any available Wi-Fi by providing the service set identifier (SSID) and password. This provides flexibility to the SACC as the SSID, and password are not hard coded into the microcontroller. A push button is used to enable the Wi-Fi provisioning feature. Below Figure 3.26 shows the Wi-Fi provisioning process for the SACC.

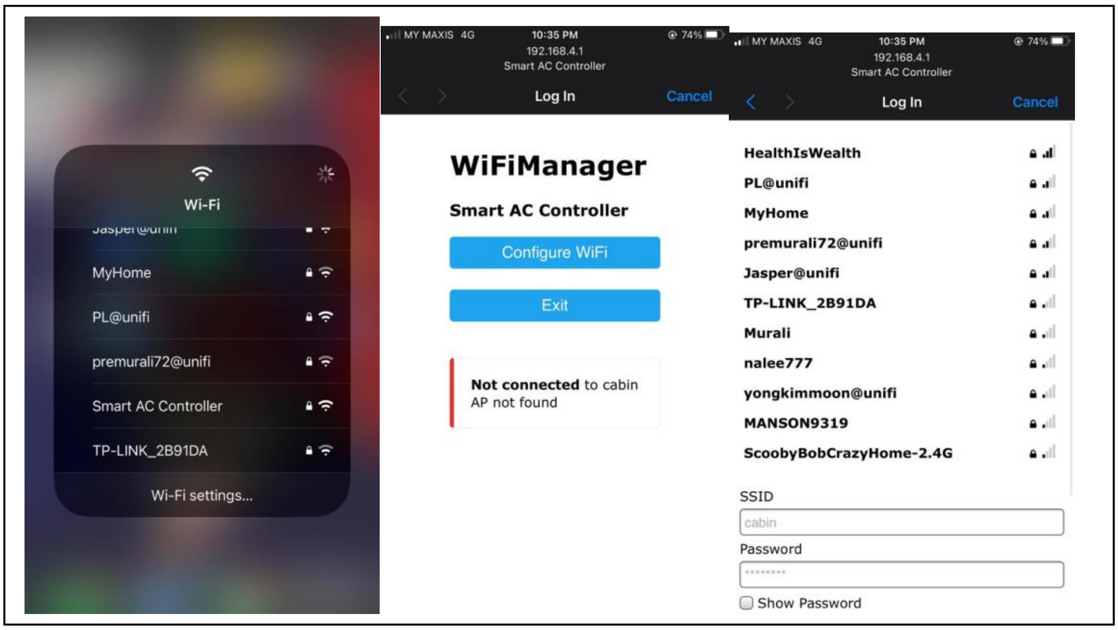

Figure 3.26: Wi-Fi Provisioning Process for SACC

3.6 Deployment of Smart Air-Conditioner Controller (SACC)

The SACC was deployed in one of the cabins located at the KA block of Tunku Abdul Rahman University (UTAR). It was used to control a non-inverter, 3-star rating, split-air conditioner. The performance of the FL algorithm of the SACC was compared with the baseline scheme. The baseline scheme is the constant 24 °C temperature setpoint AC control.

The performance of the FL algorithm of the SACC was compared with the 24 °C baseline scheme on the aspect of energy consumption and thermal comfort. Energy consumption readings were obtained from the digital energy meter through Blynk IoT platform. As for the thermal comfort, it was evaluated through the PMV thermal comfort model. The PMV algorithm was programmed into the ESP32 microcontroller and calculated in real-time. PMV readings was stored in Blynk IoT platform for the evaluation of the thermal comfort performance for SACC and 24 °C baseline scheme.

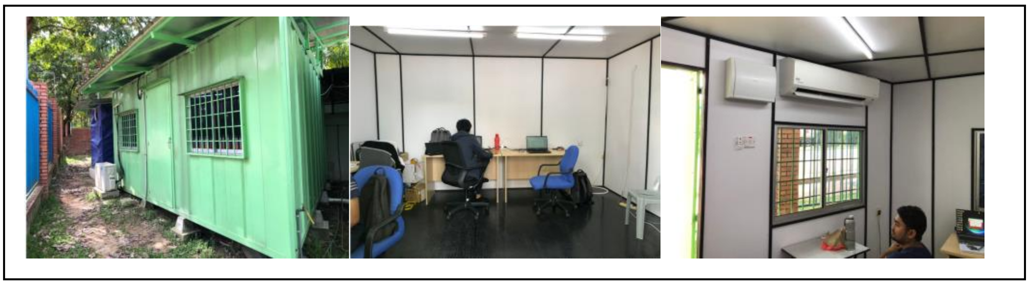

Figure 3.27: Test area

Table 3.1 Formula Used for Evaluation Parameters

Evaluation Parameters	**Formula**
Energy Saving	$\frac{\lvert Fuzzy\ Logic - Constant\ 24\ °C \rvert}{Constant\ 24\ °C}\ x\ 100\ \%$
Average Thermal Comfort Difference	$\lvert Fuzzy\ Logic - Constant\ 24\ °C \rvert$
Average Outdoor Temperature Difference & Average Outdoor Humidity Difference	$\frac{\lvert Fuzzy\ Logic - Constant\ 24\ °C \rvert}{\frac{Fuzzy\ Logic + Constant\ 24\ °C}{2}}\ x\ 100\ \%$

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Results and Analysis of SACC [Fuzzy Logic Ver 1]

The SACC and constant 24 °C baseline scheme were both run for 5 days each from 9:00 am till 5:00 pm to collect the energy consumption and PMV data for the evaluation of energy saving and thermal comfort aspect of the SACC. By comparing the 5 days of SACC and 5 days of constant 24 °C, SACC was able to save an average of 5.65 %. Below Figure 4.1 shows the comparison of energy consumption between the SACC and 24 °C baseline scheme

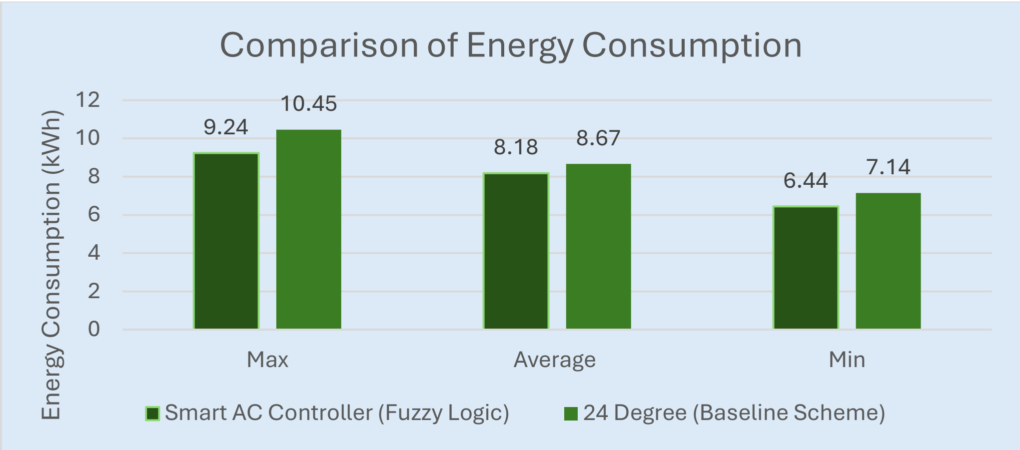

Figure 4.1: Comparison of Energy Consumption Between SACC and Constant 24 °C

During the 5 days of running the SACC and 24 °C, it was raining for the majority of the time for the days running the 24 °C. This can be seen by the average outdoor temperature difference of 3.42 % and average outdoor humidity difference of 6.78 % shown in Figure 4.2 and Figure 4.3 respectively. An average outdoor temperature difference of 3.42 % indicates that the days running the SACC was hotter whereas an average outdoor humidity difference of 6.78 % indicates that the days running the 24 °C was raining. The SACC may have higher energy savings if the weather conditions of the days are the similar.

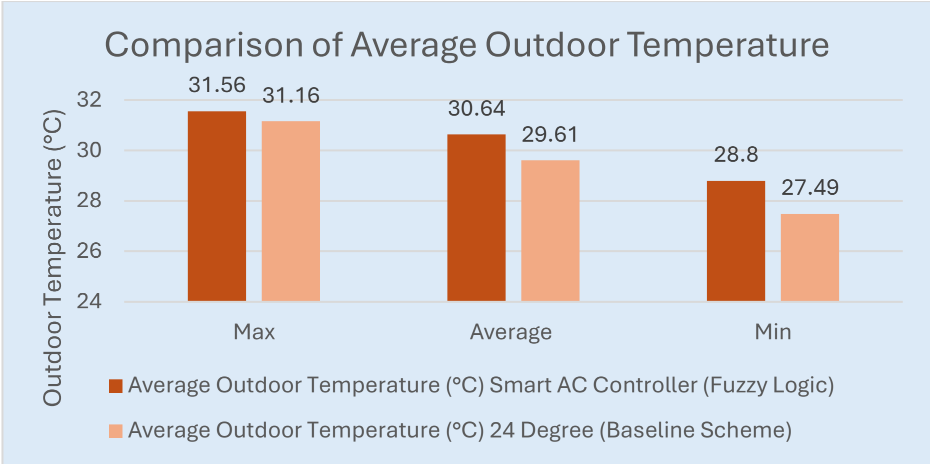

Figure 4.2: Comparison of Average Outdoor Temperature Between SACC and Constant 24 °C

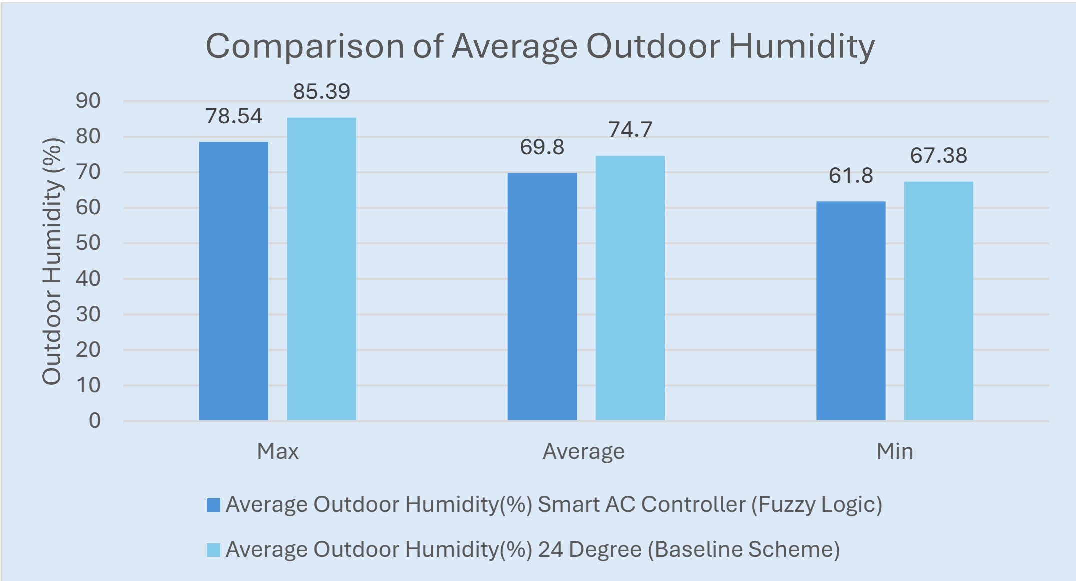

Figure 4.3: Comparison of Average Outdoor Humidity Between SACC and Constant 24 °C

For the thermal comfort aspect, within the 5 days of running the SACC, SACC was able to maintain a maximum of 59.03 %, minimum of 27.09 % and an average of 44.83 % in the thermal comfort zone. This is equivalent to a maximum of 4.72 thermal comfort hours, minimum of 2.17 thermal comfort hours and an average of 3.59 thermal comfort hours. When compared with the 24 °C, the SACC was able to maintain longer thermal comfort hours, an average of 26.45 % more. Below Figure 4.4 shows the comparison of thermal comfort between the SACC and 24 °C baseline scheme

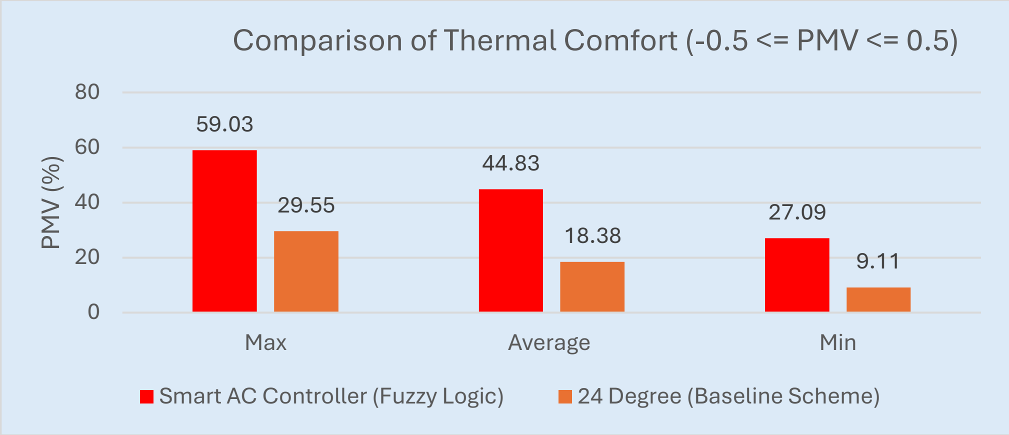

Figure 4.4: Comparison of Thermal Comfort Between SACC and Constant 24 °C

The SACC outperformed the constant 24 °C in both the energy saving and thermal comfort aspect. However, for the thermal comfort aspect, maintaining an average of 44.83 % in the thermal comfort zone for the SACC was suboptimal. By enlarging the thermal comfort zone by a small margin, between -0.5 and 0.5 to between -0.75 and 0.5, the thermal comfort hours increased from 44.83 % to 73.21 % for the SACC. This means that majority of the time during the running of the SACC, the PMV was slightly out of the thermal comfort zone, skew to the cold zone.

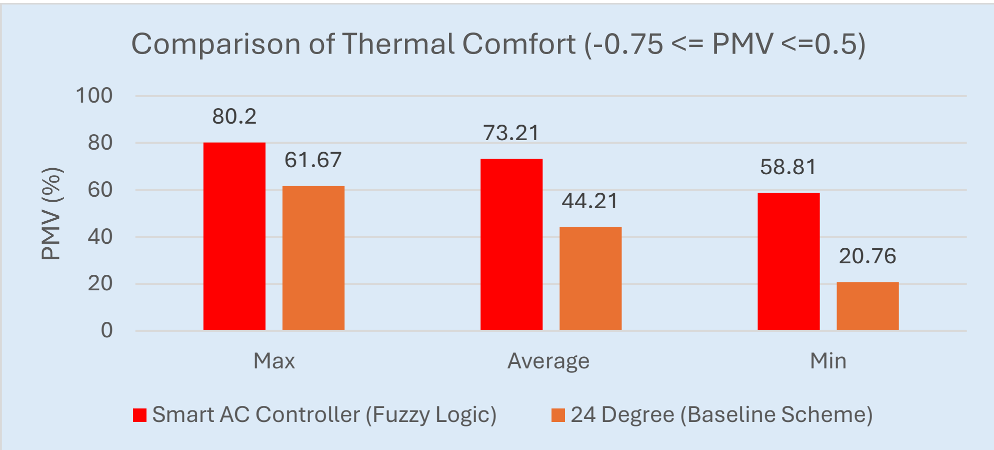

Figure 4.5: Comparison of Extended Thermal Comfort Zone Between SACC and Constant 24 °C

The reason behind the low thermal comfort hours of the SACC was due to the tuning flaw of the FL algorithm. When defining the fuzzy sets for the indoor carbon dioxide concentration, for the High fuzzy set, it was defined for the range of 650 ppm to 1000 ppm. As for the rules defined, when indoor carbon dioxide concentration is in High fuzzy set, the AC set temperature is in Medium and Low fuzzy sets. During the 5 days of running the SACC, the average indoor carbon dioxide concentration for each of the days were 725, 605, 653, 769 and 691 ppm. Due to this, for the majority time during the running of the SACC, the AC set temperature was in the medium to low range. This affects the overall PMV performance and energy saving performance of the SACC.

During the 5 days of running of the SACC, it was discovered that the indoor CO2 concentration maintained between the aforementioned range. This was because the number of occupancies in the test area remained the same which was 3 persons. Besides that, there was no frequent in and out movement by the occupancies. Below Figure 4.6 shows the average indoor CO2 level for each of the 5 days during the running of the SACC.

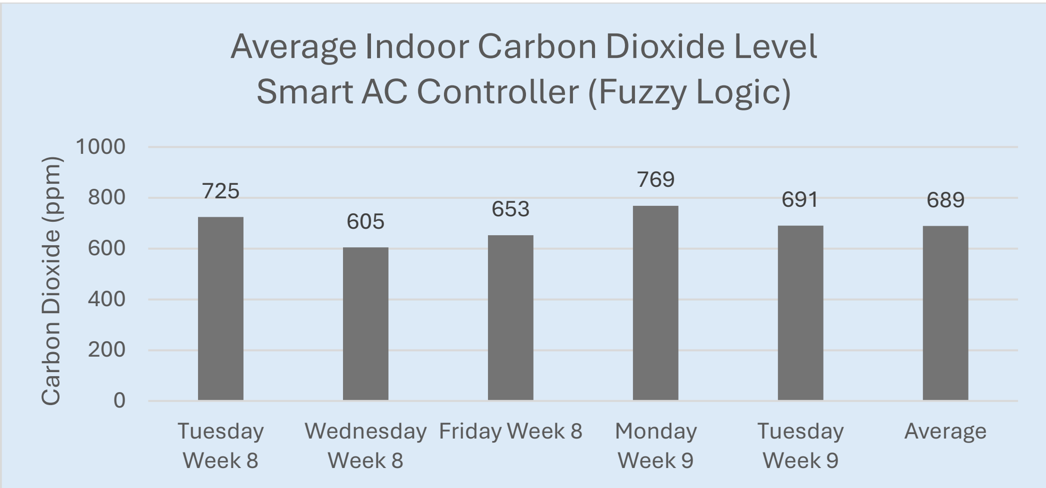

Figure 4.6: Average Indoor CO2 level [Smart AC Controller (Fuzzy Logic)]

Below Figure 4.7 shows the indoor occupancy status for one of the days when SACC was controlling the AC. Based on the Figure 4.7, there was presence of occupants for the majority of time. For the mmWave radar sensor to not detect anyone, all the occupants must leave the test area which rarely happens. Due to this, only the fuzzy rules that are defined with “Detection” for indoor occupancy detection are being triggered. There was no opportunity for the “No Detection” rules to be triggered, thus limiting the SACC in saving more energy.

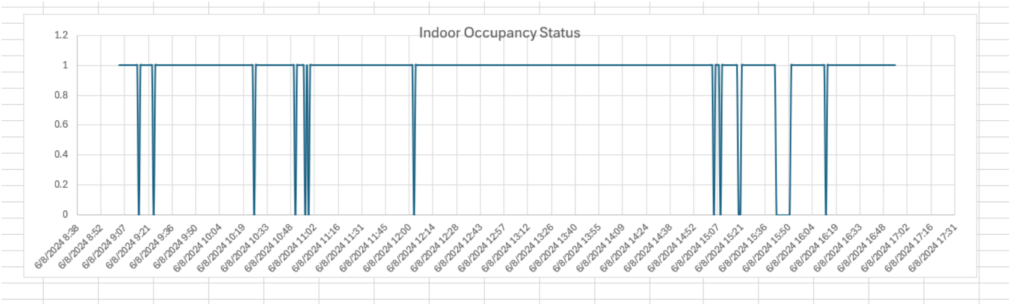

Figure 4.7: Indoor Occupancy Status [Smart AC Controller (Fuzzy Logic)]

Energy Saving (%)	Average Thermal Comfort Difference (%) (-0.5=<PMV<=0.5)	Average Thermal Comfort Difference (%) (-0.75=<PMV<=0.5)	Average Outdoor Temperature Difference (%)	Average Outdoor Humidity Difference (%)
5.65	26.45 (High Side)	29 (High Side)	3.42 (Hide Side)	6.78 (Low Side)

Figure 4.8: Overall Comparison Between SACC and 24 °C

4.2 Design and Development of Refined Fuzzy Logic (FL) [Fuzzy Logic Ver 2]

A refined version of FL algorithm (Fuzzy Logic Ver 2) was developed for the SACC with the intention of improving the energy saving and thermal comfort. Instead of taking in 5 input parameters, only 3 input parameters were feed into the FL algorithm which were the PMV, indoor temperature and power consumption of AC. The indoor CO2 concentration and indoor occupancy detection were removed as the condition of the test area did not allow these two input parameters to vary. Below Figure 4.9 shows the refined version of the FL algorithm.

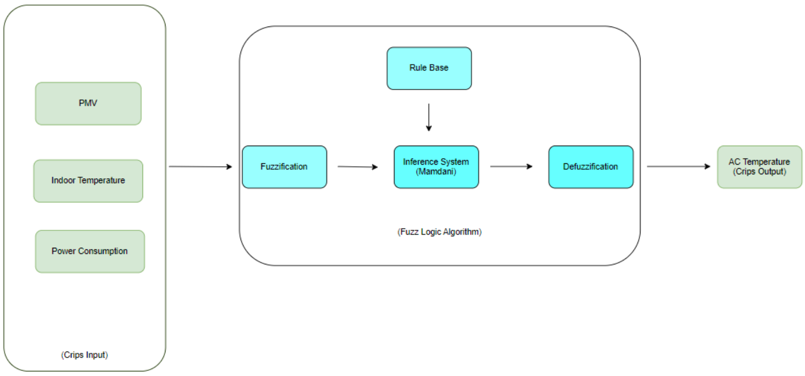

Figure 4.9: Refined Version of FL Algorithm (Fuzzy Logic Ver 2)

As both the indoor CO2 concentration and indoor occupancy detection were removed in the refined version of FL algorithm, the number of fuzzy rules were changed. A total of 10 rules were developed, whereby rule 1 to rule 5 were responsible for the thermal comfort aspect and rule 6 to rule 10 were responsible for the energy saving aspect. Rule 6 to rule 10 remained the same as previous FL algorithm. As for the membership functions and fuzzy sets for the inputs and output and the type of inference system, these remained the same. Below Figure 4.10 shows the fuzzy rules for the refined version of FL algorithm.

Rule No.	PMV Status	Power Consumption	Indoor Temperature	AC Set Temperature
1	Cold	-	-	High
2	Moderately Cold	-	-	Slightly High
3	Slightly Cold	-	-	Medium
4	Neutral	-	-	Slightly Low
5	Hot	-	-	Low
6	-	High	Cold	Slightly Low
7	-	High	Slightly Cold	Medium
8	-	High	Normal	Slightly High
9	-	High	Slightly Hot	High
10	-	High	Hot	High

Figure 4.10: Fuzzy Rules for Refined Version of FL algorithm (Fuzzy Logic Ver 2)

4.2.1 Results and Analysis of SACC [Fuzzy Logic Ver 2]

The SACC with the refined version of FL algorithm was tested for 3 days, each day from 9:00 am till 5:00pm. For fair comparisons, the results were compared with three of the days from the 24 °C testing that had similar weather conditions with the days of running the refined version of FL algorithm, with an average outdoor temperature difference of 1.53 % and an average outdoor humidity difference of 1.27 %. For the energy consumption, the refined version of SACC had an average energy consumption of 8.38 kWh whereas the 24 °C has an average energy consumption of 9.64 kWh. For this, the SACC has an improved energy saving of 13.07 %.

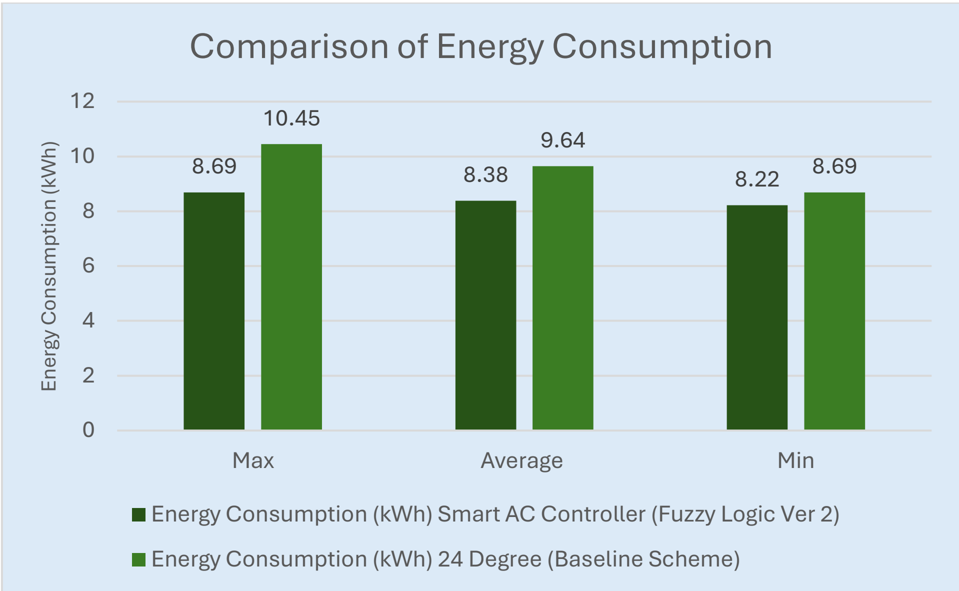

Figure 4.11: Comparison of Energy Consumption Between Refined SACC and Constant 24 °C

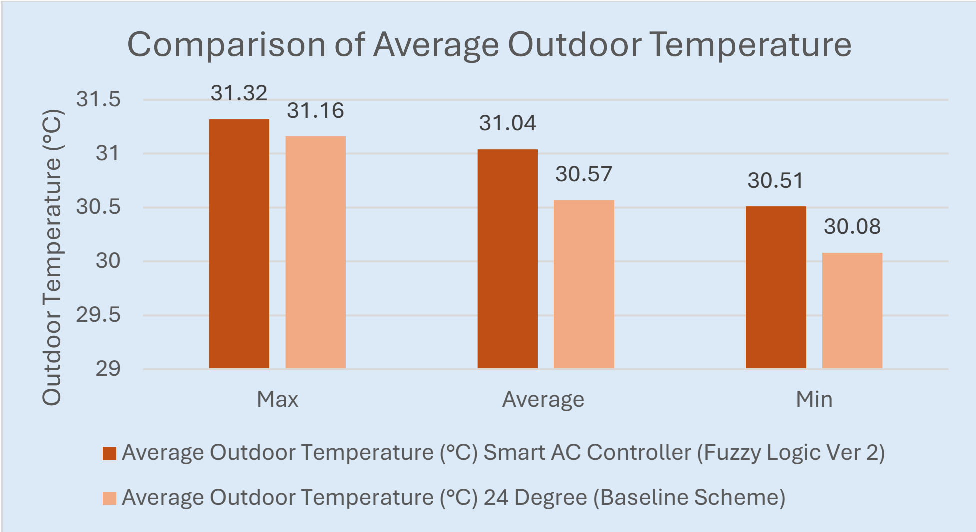

Figure 4.12: Comparison of Average Outdoor Temperature Between Refined SACC and Constant 24 °C

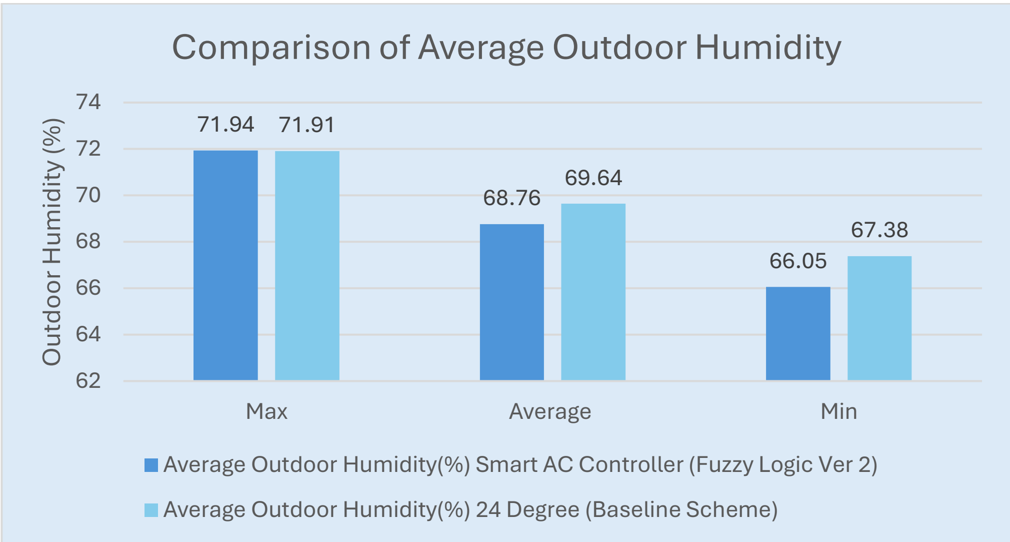

Figure 4.13: Comparison of Average Outdoor Humidity Between Refined SACC and Constant 24 °C

For the thermal comfort aspect, within the 3 days of running the refined SACC, the refined SACC was able to maintain an average of 46.55 % in the thermal comfort zone. This is equivalent to an average of 3.72 thermal comfort hours which is slightly better than the previous FL algorithm. When compared with the 24 °C, the refined SACC was able to maintain longer thermal comfort hours, an average of 33.28 % more. Below Figure 4.14 shows the comparison of thermal comfort between the refined SACC and 24 °C baseline scheme

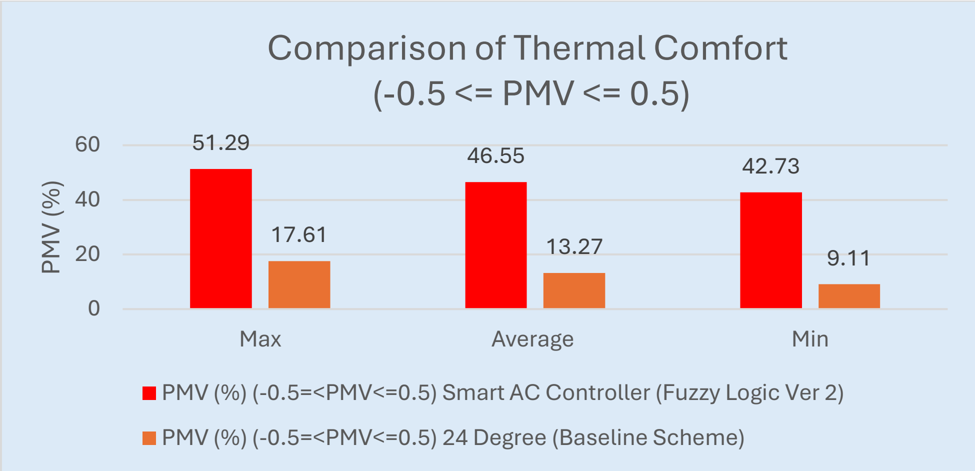

Figure 4.14: Comparison of Thermal Comfort Between Refined SACC and Constant 24 °C

The refined SACC outperformed the constant 24 °C in both the energy saving and thermal comfort aspect and has better performance than the previous FL algorithm. However, for the thermal comfort aspect, maintaining an average of 46.55 % in the thermal comfort zone for the refined SACC was still suboptimal. By enlarging the thermal comfort zone by a small margin, between -0.5 and 0.5 to between -0.75 and 0.5, the thermal comfort hours increased from 46.55 % to 80.34 % for the refined SACC. This means that majority of the time during the running of the SACC, the PMV was slightly out of the thermal comfort zone, skew to the cold zone.

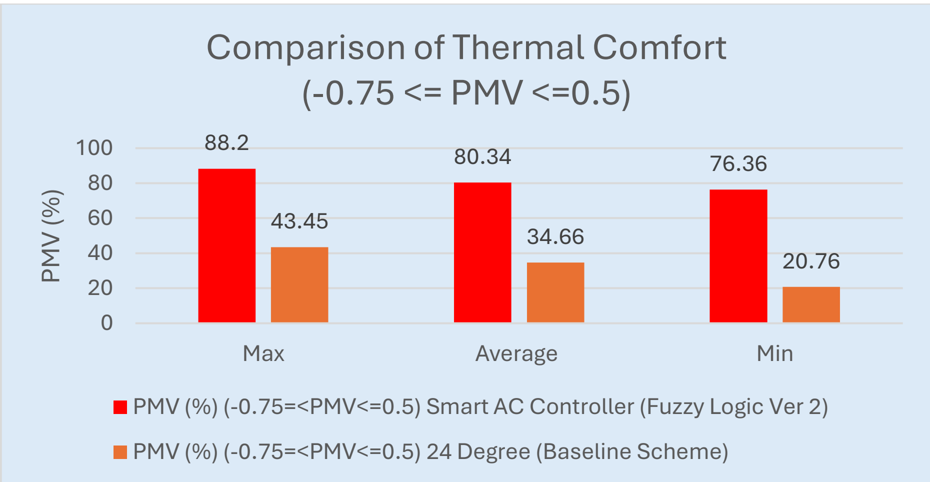

Figure 4.15: Comparison of Extended Thermal Comfort Zone Between Refined SACC and Constant 24 °C

Below Figure 4.16 shows the relationship between the PMV and AC Set Temperature. By looking at the first box, whenever the PMV goes slightly beyond 0.2, the AC set temperature drops to 23 °C. This causes the PMV to exceed beyond -0.5. By focusing on the second box, when PMV exceeds beyond -0.5, the AC set temperature increases to 25 °C to bring the PMV back into the comfort zone. However, the PMV still falls out of the comfort zone, skew to the cold zone. These are due to the flaws in the refined FL algorithm. The flaws are in the defined fuzzy sets for the PMV and the defined fuzzy rules for the refined FL algorithm.

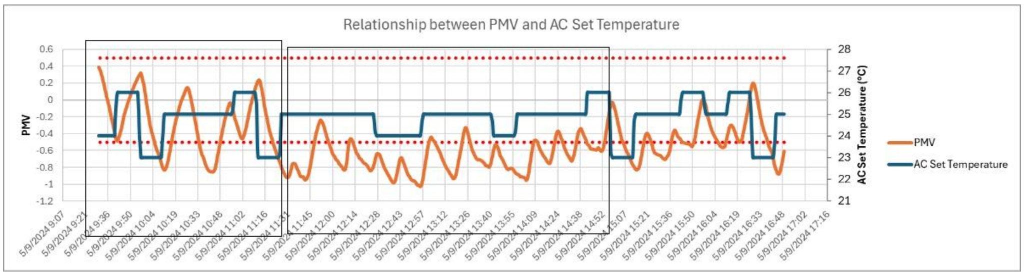

Figure 4.16: Relationship between PMV and AC Set Temperature

Energy Saving (%)	Average Thermal Comfort Difference (%) (-0.5=<PMV<=0.5)	Average Thermal Comfort Difference (%) (-0.75=<PMV<=0.5)	Average Outdoor Temperature Difference (%)	Average Outdoor Humidity Difference (%)
13.07	33.28 (High Side)	45.68 (High Side)	1.53 (High Side)	1.27 (Low Side)

Figure 4.17: Overall Comparison Between Refined SACC and 24 °C

4.3 Design and Development of Further Refined Fuzzy Logic (FL) [Fuzzy Logic Ver 3]

A further refined version of FL algorithm (Fuzzy Logic Ver 3) was developed for the SACC to further improve the energy saving and thermal comfort. In this version, everything remained the same as in the previous refined version except some changes were made in this further refined version on the fuzzy sets of the PMV and the fuzzy rules defined. The fuzzy sets for the PMV were increased from four to a total of seven fuzzy sets. At the hot zone (beyond 0.5), instead of one single fuzzy set to define the range, two additional fuzzy sets namely, slightly hot and moderately hot were introduced. Below Figure 4.18

shows the fuzzy sets for the PMV for the further refined version of FL algorithm.

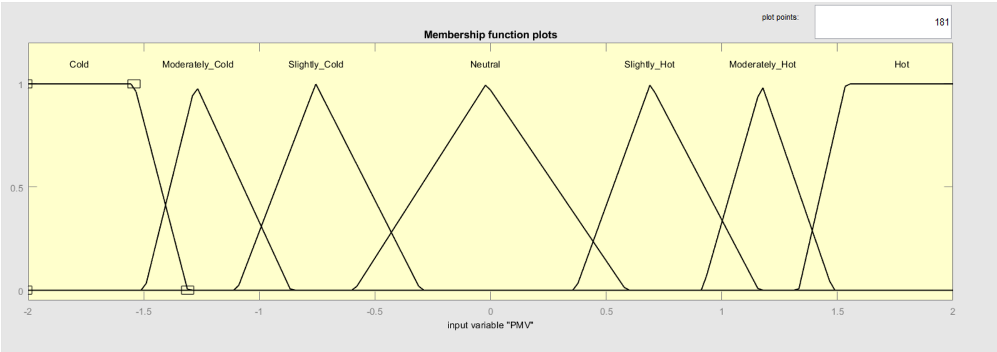

Figure 4.18: New Fuzzy Sets for Further Refined FL Algorithm (Fuzzy Logic Ver 3)

With the new fuzzy sets introduced for the PMV, the fuzzy rules increased from ten to twelve. These new fuzzy rules were developed in an attempt to solve the problem in the previous refined FL algorithm. Now, for the AC set temperature to set at 23 °C or below, the PMV has to go beyond the neutral zone. Besides that, when the PMV goes beyond 0.5 and into the cold side, the AC set temperature is more likely to be set above 25 °C to bring the PMV back to the comfort zone. Note that rule 8 to rule 12 remained the same as previous FL algorithms. Below Figure 4.19 shows the newly defined fuzzy rules for the further refined version of FL algorithm.

Rule No.	PMV Status	Power Consumption	Indoor Temperature	AC Set Temperature
1	Cold	-	-	High
2	Moderately Cold	-	-	High
3	Slightly Cold	-	-	Slightly High
4	Neutral	-	-	Slightly High
5	Slightly Hot	-	-	Medium
6	Moderately Hot	-	-	Medium
7	Hot	-	-	Low
8	-	High	Cold	Slightly Low
9	-	High	Slightly Cold	Medium
10	-	High	Normal	Slightly High
11	-	High	Slightly Hot	High
12	-	High	Hot	High

Figure 4.19: Fuzzy Rules for Further Refined Version of FL algorithm (Fuzzy Logic Ver 3)

4.3.1 Results and Analysis of SACC [Fuzzy Logic Ver 3]

The SACC with the further refined version of FL algorithm was tested for 3 days, each day from 9:00 am till 5:00pm. For fair comparisons, the results were compared with three of the days from the 24 °C testing that had similar weather conditions with the days of running the further refined version of FL algorithm, with an average outdoor temperature difference of 1.9 % and an average outdoor humidity difference of 4.13 %. For the energy consumption, the further refined version of SACC had an average energy consumption of 7.35 kWh whereas the 24 °C has an average energy consumption of 9.17 kWh. For this, the SACC has an improved energy saving of 19.85 %, performing better than the previous versions of FL algorithm.

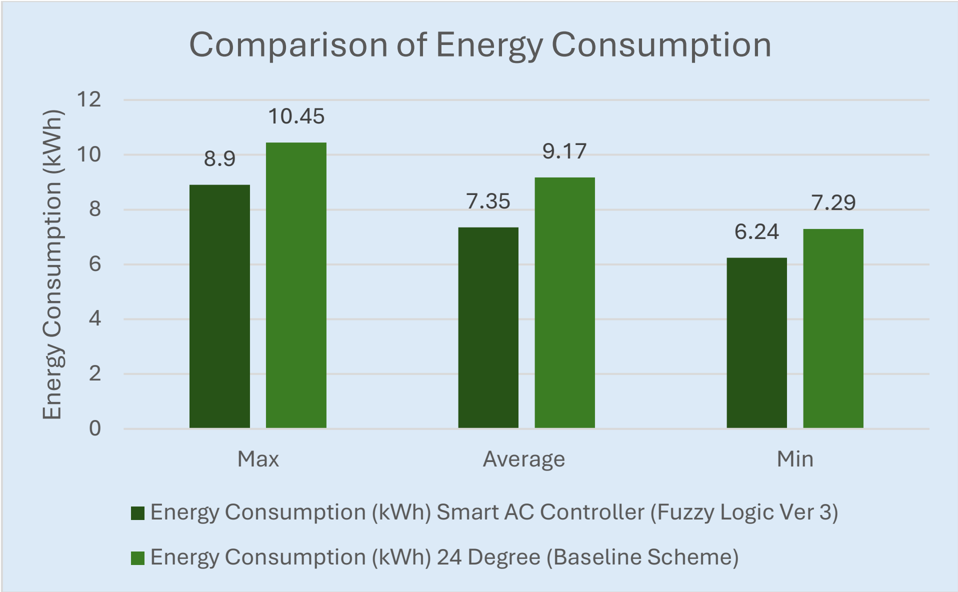

Figure 4.20: Comparison of Energy Consumption Between Further Refined SACC and Constant 24 °C

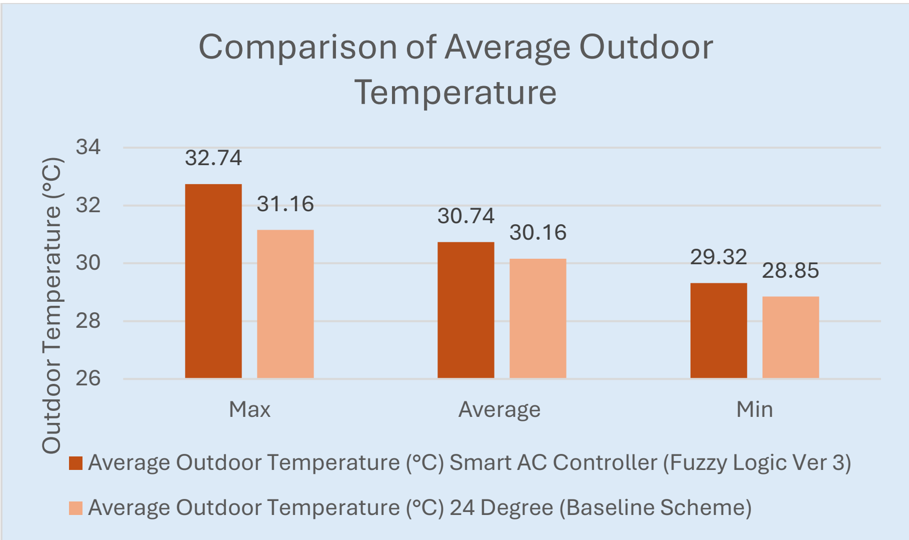

Figure 4.21: Comparison of Average Outdoor Temperature Between Further Refined SACC and Constant 24 °C

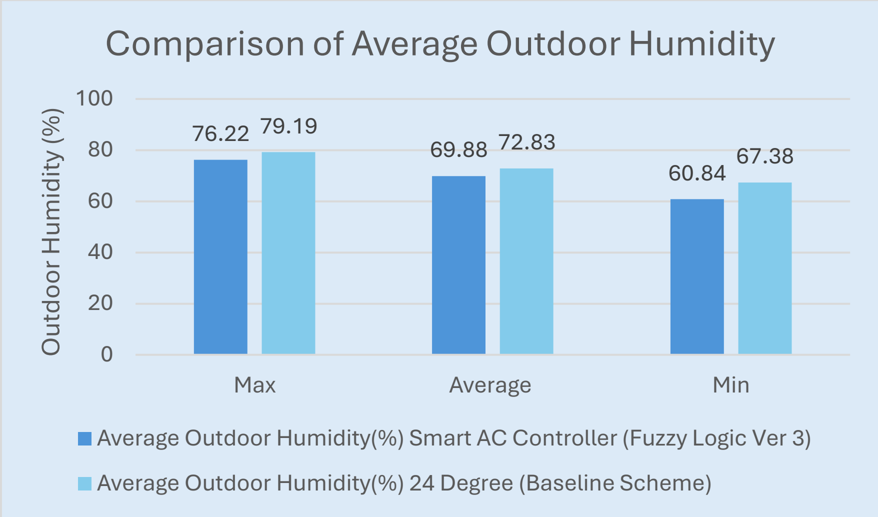

Figure 4.22: Comparison of Average Outdoor Humidity Between Further Refined SACC and Constant 24 °C

For the thermal comfort aspect, within the 3 days of running the further refined SACC, the further refined SACC was able to maintain an average of 80.46 % in the thermal comfort zone. This is equivalent to an average of 6.44 thermal comfort hours which is much better than the previous versions of FL algorithm. When compared with the 24 °C, the refined SACC was able to maintain longer thermal comfort hours, an average of 63.21 % more. Below Figure 4.23 shows the comparison of thermal comfort between the further refined SACC and 24 °C baseline scheme

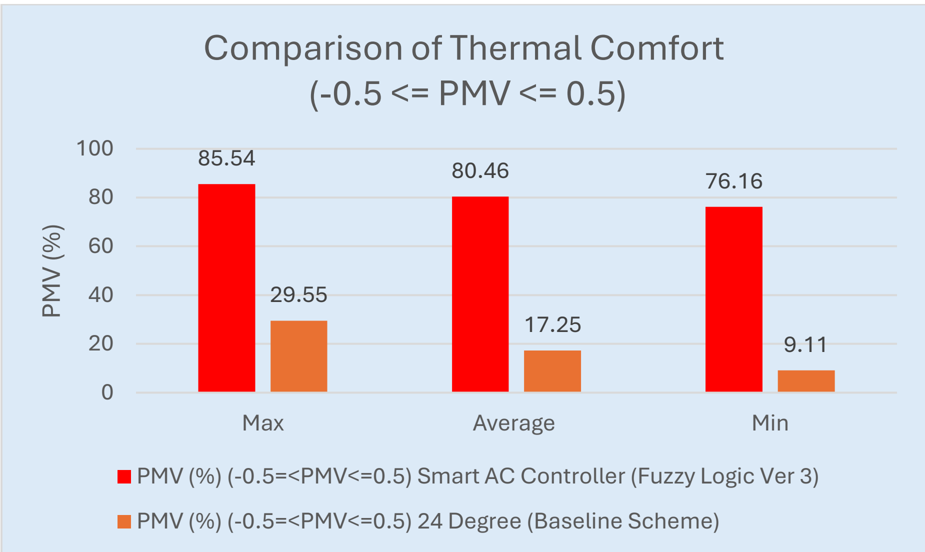

Figure 4.23: Comparison of Thermal Comfort Between Further Refined SACC and Constant 24 °C

The further refined SACC outperforms the constant 24 °C in both the energy saving and thermal comfort aspect and has better performance than the previous versions of FL algorithm. With the modifications made on the FL algorithm, the energy saving of the SACC improved from 5.65% to 19.85 %. As for the thermal comfort aspect, it increased from 26.45 % to 63.21 % more when compared with the 24 °C baseline scheme.

Energy Saving (%)	Average Thermal Comfort (%) (-0.5=<PMV<=0.5)	Average Outdoor Temperature Difference (%)	Average Outdoor Humidity Difference (%)
19.85	63.21 (High Side)	1.9 (High Side)	4.13 (Low Side)

Figure 4.24: Overall Comparison Between Further Refined SACC and 24 °C

4.3.2 Relationship of Input Parameters with the AC Set Temperature [Fuzzy Logic Ver 3]

Below Figure 4.25 shows the further refined FL algorithm effect on the AC Set temperature. By looking at the first box, whenever the power consumption of the AC is ON, the further refined FL algorithm detects it, and the SACC sets the AC set temperature to a higher degree The AC set temperature computed by the further refined FL algorithm considers both the power consumption and PMV in this case. With this, the workload of the AC is reduced, and the power consumption of the AC is OFF. Once the power consumption of the AC is in idle state (OFF), the further refined FL algorithm focuses only on the PMV value, and the SACC sets the AC set temperature to ensure the PMV is in the comfort zone.

In the second box, for this period, the AC set temperature is in constant 26 °C. This is based on the fuzzy rules defined in the further refined FL algorithm. It considers both the power consumption and the PMV value and determines that 26 °C is the suitable temperature to maintain the PMV in the thermal comfort zone and at the same time, reduce the workload of the AC.

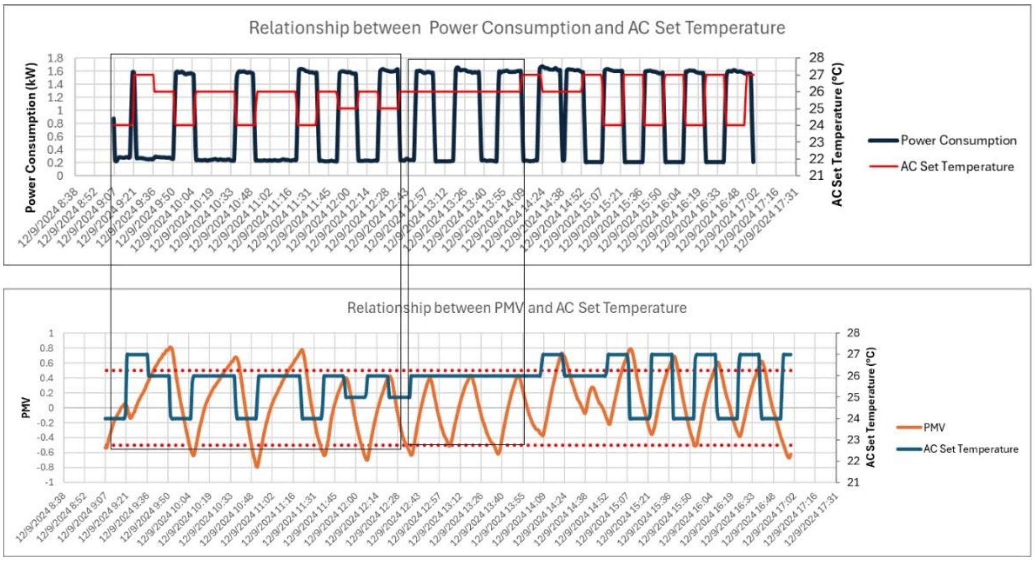

Figure 4.25: Effect of Further Refined FL Algorithm on AC Set Temperature

4.4 Battery Life and Costing of SACC

The SACC operates as an external unit to the AC and requires external power supply for it to run. To be considered a reliable Smart AC Controller, the controller needs to be long-lasting in terms of its battery life. Below Table 4.1 shows a simple battery life evaluation for the SACC when it is powered with a 10000mAh power bank.

Table 4.1: SACC Battery Life Evaluation

Component	Active Mode (mA)
ESP-WROOM-32	~170
DHT22	~1
HLK-LD2410C	~70
MH-Z19C	~85
IR LED	~30
Push Buttons (x4)	-
OLED	~25
Total Current Consumption (mA)	~381
Battery Life (10000mAH)	26 h 14 m

By considering the current consumption of the components used for the SACC, for a 10000mAH power bank, it can last for 26 hours and 14 minutes. This is approximately equivalent to 3 days of continuously 8 hours (9:00 am to 5:00 pm) of operation of the SACC, which tallies with the real-life testing. For controlling residential split-air conditioner, this battery life span is more than enough for the reliable operation of the SACC. Alternatively, the SACC can be powered through power socket with the used of power adapter for it to continuously operate without worrying about battery life span. Even though the mmWave radar sensor and carbon dioxide sensor were not used for the final version of the FL algorithm, they are being considered for the battery life evaluation for further enhancement on the FL algorithm that includes these two components.

Besides battery life, the costing of the SACC is also an important factor in determining whether it is suitable to be commercialized. For the SACC, it costs below RM200 while considering the 10000mAh power bank being used as the power supply. Without considering the 10000mAH power bank, the SACC only costs below RM 150, which considers as low cost and affordable. All the costing of the SACC comes from the hardware components. The software components which are the Blynk IoT platform and IOS shortcut are free of cost. Blynk IoT platform has free subscription plan which was used to develop the necessary features for the SACC. Below Table 4.2 shows the costing of the SACC.

Table 4.2: Costing of the SACC

Components	Quantity	Price (RM)
Physical Components (Main)		
ESP-Wroom-32	1	27.00
mmWave Radar Sensor (HLK-LD2410C)	1	10.02
Temperature Sensor (DHT22)	1	7.90
CO2 Sensor (MH-Z19C)	1	79.27
IR LED	1	0.2
OLED	1	14.90
Push Buttons	4	3.20
Total Cost		142.47
Physical Components (Other)		
Power Bank (10000mAH)	-	50
Cables and Other Accessories	-	5
Total Cost		55
Software Components		
Blynk IoT Platform	-	-
IOS Shortcut	-	-
Total Cost		-
Grand Total		197.47

CHAPTER 5

CONCLUSIONS AND FUTURE WORK AND RECOMMENDATIONS

5.1 Conclusion

A smart air conditioning controller (SACC) was designed and developed in this project. The SACC uses fuzzy Logic (FL) algorithm as its decision-making engine to optimally compute the AC set temperature to control the AC to achieve energy saving without compromising user comfort. In this project, three versions of FL algorithm were designed and developed with different set of input parameters, fuzzy sets and rules defined, each performs better than its predecessor.

By comparing it with the 24 °C baseline scheme, for the first version of FL algorithm, it was able to save 5.65 % of energy and was able to maintain 26.45% more of time in the thermal comfort zone. Second version of FL algorithm was able to save 13.07 % of energy and was able to maintain 33.28 % more of time in the thermal comfort zone. With the third version of FL algorithm, the SACC saves 19.85 % of energy and was able to maintain 63.21 % more of time in the thermal comfort zone. With these results, it demonstrates the feasibility of the FL to be used as a control algorithm to control the AC for energy saving and thermal comfort.

Besides that, the SACC is Internet-of-Things (IoT) enabled. The SACC is developed such that it can be monitored and controlled remotely through IoT platform and voice command. Not only that, features such as automations, Over-the-Air (OTA) update and Wi-Fi provisioning are made available for the SACC. With all these features, the SACC only cost below RM 200.

Last but not least, the SACC is a low-cost and affordable and has plug-and-play characteristic that enabled users to use it wherever they want to control their residential split-air conditioner. This work will benefit the community and environment by offering simple and affordable solution to effectively control the AC in the effort of decarbonization while saving energy cost.

5.2 Future Work and Recommendations

The developed SACC is a prototype to test the feasibility of the FL algorithm in energy saving and thermal comfort. As the feasibility of the FL algorithm is proved, at least for the controlling of a single split-air conditioner unit, the SACC can have a more compact design by switching to Printed Circuit Board (PCB) for the architecture and 3D- printing for the enclosure. With these, there will be no loose connections that might affect the operation of SACC, and the SACC can operate as a complete product to control the AC.

The latest version of FL algorithm only includes PMV, indoor temperature and power consumption of AC as its input. It is recommended to include back the indoor CO2 concentration and indoor occupancy parameters into the FL algorithm if the test area setting allow these two parameters to vary. If the test area setting allows these two parameters to vary, the SACC might further improve on its energy saving and thermal comfort.

As the developed SACC is only capable of controlling a single split-air conditioner unit, for the control of multiple split-air conditioner units, the SACC can be of multiple units. For example, for the controlling of three split-air conditioner units, the SACC can be 3 units, whereby one unit has all the sensors attached to it and able to control one of the ACs, while the other two SACC just comprises of a microcontroller and an IR transmitter to control the other two ACs. The FL algorithm will run on the SACC that has all the sensors attached to it and compute the AC set temperature. The AC set temperature information then can be sent to the two other SACCs via communication protocol such as ESP-NOW to control their respective ACs.

Additionally, as the developed SACC is a single module with all sensors integrated, the accuracy of the sensor readings may be compromised. To ensure more precise measurements for the FL algorithm, particularly when controlling multiple split-air conditioners, it is recommended to deploy the sensors across different locations.

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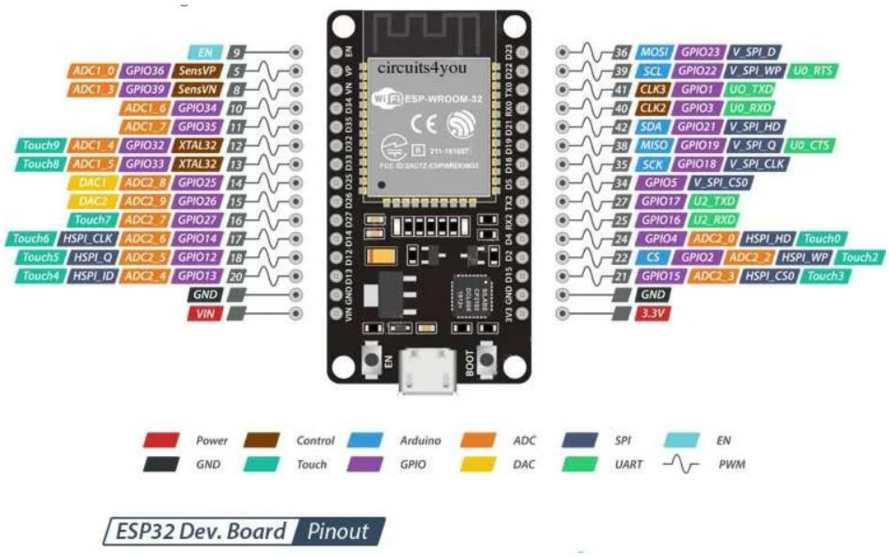
APPENDICES

Appendix A: Pin Layout Diagram of ESP32 (Microcontroller of SACC)



Appendix B: Datasheet of DHT22 (Temperature and Humidity Sensor)

Model	DHT22
Power supply	3.3-6V DC
Output signal	digital signal via single-bus
Sensing element	Polymer capacitor
Operating range	humidity 0-100%RH; temperature -40~80Celsius
Accuracy	humidity +-2%RH(Max +-5%RH); temperature <+-0.5Celsius
Resolution or sensitivity	humidity 0.1%RH; temperature 0.1Celsius
Repeatability	humidity +-1%RH; temperature +-0.2Celsius
Humidity hysteresis	+-0.3%RH
Long-term Stability	+-0.5%RH/year
Sensing period	Average: 2s
Interchangeability	fully interchangeable
Dimensions	small size 14*18*5.5mm; big size 22*28*5mm

Appendix C: Datasheet of HLK-LD2410C (Indoor Occupancy Sensor)

Operating frequency	24GHz~ 24.25GHz Compliant with FCC, CE, non-commission certification standards
Operating Voltage	DC 5V, power supply capacity>200mA
Average operating current	79 mA
Modulation	FMCW
Interface	A GPIO, IO level 3.3V A UART
Target application	Human presence sensor
Detection distance	0.75m ~ 6m, adjustable
Detection angle	±60 °
Distance resolution	0.75m
Sweep Bandwidth	250MHz Compliant with FCC, CE, non-commission certification standards
Ambient temperature	-40 ~ 85℃
Dimensions	7mm x 35 mm

Appendix D: Datasheet of MH-Z19C (Indoor Carbon Dioxide Concentration Sensor)

Product Model	MH-Z19
Target Gas	CO2
Working voltage	3.6 ~ 5.5 V DC
Average current	< 18 mA
Interface level	3.3 V
Measuring range	0 ~ 0.5% VOL optional (refer to Table 2)
Output signal	UART
	PWM
Preheat time	3 min
Reponse Time	T_{90} < 60 s
Working temperature	0 ~ 50 ℃
Working humidity	0 ~ 95% RH (No condensation)
Dimension	33 mm×20 mm×9 mm (L×W×H)
Weight	21 g
Lifespan	> 5 years