IOT-ENABLED ENERGY CONSUMPTION MONITORING AND ANALYSIS FOR DOMESTIC APPLIANCES

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This report is submitted in partial fulfilment of the requirements for the degree of Bachelor of Electronic Engineering with Honours

Faculty of Electronics and Computer Technology and Engineering
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APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Bachelor of Electronic Engineering with Honours.

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DEDICATION

I wholeheartedly dedicate this thesis to my parents, family, friends, supervisor and esteemed lecturers. Moreover, I acknowledge the profound influence of our Almighty Allah S.W.T., whose grace and guidance have been the source of strength and resilience during both challenges and triumphs. Their encouragement and guidance have always inspired me along this educational journey.

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ABSTRACT

Rising energy consumption issues, such as high appliance usage, the absence of user-friendly management systems, and inadequate predictive control algorithms, are increasingly affecting every sector of society, remaining challenging and uncontrolled. This thesis aims to address these critical concerns by proposing an IoT-integrated system with manual and automatic modes, leveraging Blynk app integration and employs artificial neural networks to analyse and predict household energy consumption patterns accurately. This project uses SCT-013 and ZMPT101B for energy monitoring, ESP 32 Microcontroller, and environmental sensor (PIR, DHT22, BH1750) for appliance control, this project integrates Blynk for controlling and monitoring, ThingSpeak to save historical data, Arduino IDE, and MATLAB for analysis. The analysis will compare manual and auto mode appliances and evaluating forecasting performance. Results indicate auto mode's higher efficiency through incremental energy consumption analysis, with forecasting effectiveness confirmed by detailed performance and regression plot analysis. In conclusion, this thesis demonstrates the effectiveness of an IoT-based system in enhancing energy management and predicting consumption patterns, significantly improving efficiency of energy consumption usage in various societal sectors.

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ABSTRAK

Peningkatan penggunaan tenaga, termasuk tingginya penggunaan peralatan, ketiadaan sistem pengurusan tenaga yang ramah pengguna, dan kekurangan algoritma kawalan ramalan, memberi impak besar kepada masyarakat. Tesis ini mencadangkan sistem terintegrasi IoT dengan mod manual dan automatik, memanfaatkan integrasi aplikasi Blynk dan rangkaian neural buatan untuk analisis dan ramalan penggunaan tenaga isi rumah. Projek ini menggunakan sensor arus (SCT-013) dan sensor voltan (ZMPT101B) untuk pemantauan tenaga, Mikrokontroler ESP 32, dan sensor persekitaran (PIR, DHT22, BH1750) untuk kawalan peralatan. Sistem ini mengintegrasikan Blynk untuk kawalan dan pemantauan, ThingSpeak untuk penyimpanan data historis, serta Arduino IDE dan MATLAB untuk analisis. Analisis akan membandingkan mod manual dan auto, menilai prestasi ramalan. Hasil kajian menunjukkan mod auto lebih efisien berdasarkan analisis penggunaan tenaga dan keberkesanan ramalan yang didukung oleh analisis plot prestasi dan regresi. Kesimpulan kajian ini membuktikan efektivitas sistem IoT dalam meningkatkan pengurusan tenaga dan meramalkan penggunaan tenaga, meningkatkan kecekapan dalam berbagai sektor masyarakat.

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I would like to express my heartfelt appreciation to my parents, Jamilah Binti Mohammad and Kamisan Bin Gimin for their unwavering support in sending me to UTeM to pursue the course I have aspired to since my school days, namely, the Bachelor of Electronic Engineering. Beyond providing financial assistance, they have consistently offered words of encouragement, aiding me in navigating the challenges and stresses of university life. I am profoundly grateful to my parents for their support, appreciation, and motivation; without them, none of this would have been possible.

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LIST OF SYMBOLS AND ABBREVIATIONS

IoT	:	Internet of Things
PIR	:	Passive Infrared
LCD	:	Liquid-Crystal Display
LAN	:	Local Area Network
PMAS	:	Power Monitoring and Switching
LoRa	:	Long Range
RFID	:	Radio Frequency Identification
ANN	:	Artificial Neural Network
AI	:	Artificial Intelligence
RMSE	:	Root Mean Square Error
MAPE	:	Mean Absolute Percentage Error
CoAP	:	Constrained Application
SVR	:	Support Vector Regression
MLR	:	Multiple Linear Regression
ARIMA	:	Auto Regressive Integrated Moving Average
kNN	:	k Nearest Neighbour
AR	:	Autoregression
GUI	:	Graphical User Interface

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SoC	:	System on Chip
Op-Amp	:	Operational Amplifiers
IDE	:	Integrated Development Environment
kWh	:	Kilowatt-hours
V	:	Voltage
A	:	Current Ampere
MSE	:	Mean Square Error
MAE	:	Mean Absolute Error
NARX	:	Nonlinear Autoregressive Network with Exogenous inputs

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CHAPTER 1

INTRODUCTION

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1.1 Project Background

In response to the escalating challenges posed by high energy usage and the subsequent financial burdens associated with household appliances, the project, titled by "IoT-Enabled Energy Consumption Monitoring and Analysis for Domestic Appliances," venture to introduce an innovative solution.

The main goal is to put in place a system that can independently control and monitor households' energy usage. The project aims to solve the issue of household appliances having a large influence on energy expenditures by developing a system that not only automates appliance operation but also seamlessly interacts with Internet of Things sensors and the Blynk app for real-time control.

The idea adds an advanced layer by using artificial neural networks to thoroughly examine patterns of energy consumption. The process entails thorough research, detailed analysis, and the design of features that facilitate automated hardware control.

Thus, through the integration of IoT sensors and the Blynk app, coupled with sophisticated energy analysis using MATLAB software, the project aspires to deliver a smart, cost-effective, and environmentally conscious solution for the efficient management of home energy.

1.2 Problem Statement

To save the energy consumption of electrical appliances for household, industry, agriculture and so on, the users should know how much power consumption (Watt/Hour) for each appliance they are using. In addition, they can plan their energy consumption for each month. There are several problems that related to the proposed project's study.

Domestic appliances in a house are major contributors to the high rate of energy consumption that then contributes to the higher electricity bills. The paper "The estimation and relationship of domestic electricity consumption and appliances ownership in Malaysia's intermediate city" by Sharif Shofirun Sharif Ali et al., which revealed the investigation that was conducted in Seremban shows total electricity energy consumption was impacted due to the type, number of equipment, and ownership of electrical appliances, could be used to support this claim [1]. This problem remains unsolved if the system design results still lack of an efficient and user-friendly energy management system that can effectively monitor and control energy usage in real-time. As most of the energy management systems rely on manual data collection that could lead to inaccuracies in realizing the consumer energy utilization design, delays and missed opportunities for energy savings [2]. Based on paper "Energy management in power distribution systems: review, classification, limitations and challenges" by Md Shanin Alam et al. state that the use of IoT sensors in energy management systems is said to increase system effectiveness with automation features, allowing utility firms to optimize energy distribution monitoring[3].

Next, most of the energy consumption system also lacks control algorithms and system design that can help house owners to predict energy consumption. Inaccurate estimates of the total system load may have wider repercussions, including transmission congestion issues. These kinds of incidents should be avoided since they could harm the power market's efficiency [4].

1.3 Objectives

This research aims to create an automated system that can effectively manage and control energy consumption in homes. The specific objectives formulated to achieve this aim are as follows:

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i. To develop a manual and automatic switching system for domestic appliances to improve energy usage efficiency.
ii. To integrate the IoT system with Blynk apps to enable homeowners to easily monitor and control their energy consumption.
iii. To analyse household energy consumption patterns using artificial neural network for accurately predict energy consumption.

1.4 Scope of Project

The scope of this thesis is focused on the implementation of an intelligent home automation system using the ESP32 microcontroller, PIR motion, DHT22 temperature, and BH1750 light intensity sensors, coupled with current and voltage sensors for precise energy consumption monitoring. The details of the scope of project are as follows:

i. The ESP32 microcontroller are employed in this project to implement IoT-based hardware and software functions.

ii. PIR motion sensors, SCT-013 sensor, ZMPT101B sensor, DHT22 temperature sensors, and BH1750 light intensity modules are utilized to detect human presence, temperature, and light intensity, enabling the control of domestic appliances.

iii. For efficient monitoring of energy consumption, current and voltage sensors are selected to measure the flow of current and voltage at each appliance.

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iv. The software integrated into this project includes Blynk and ThingSpeak for controlling and monitoring appliance energy consumption, Arduino IDE for hardware programming, and MATLAB for the application of artificial neural networks in predictive analysis.

v. The project's features and functions involve manual and automatic switching of domestic appliances based on temperature and light intensity, coupled with IoT-enabled energy consumption monitoring. The analysis involved the performance of forecasting and domestic appliances with manual and automatic switching usage.

1.5 Chapter Outline

The project aims to create a smart system that helps appliances use energy wisely, reducing costs, and giving a practical, eco-friendly way to manage home energy. All the details about this project were defined in every chapter of this report as shown below:

CHAPTER 1: This chapter provides a concise overview of the project. A special thanks to those who assisted in its execution is expressed in the acknowledgment section. Following that, the chapter covers the background of the project, problem statement, objectives, project scope, and an outline for the entire project.

CHAPTER 2: This chapter explores articles and sources tied to the project, shaping its understanding. The literature review provides a background for the project, offering insights into its details.

CHAPTER 3: This chapter focuses on the research methodology employed in this project, explaining the specific approach used. It also outlines the important materials chosen for developing the hardware. Additionally, it delves into the theory and practical application of the artificial neural network within the context of this project.

CHAPTER 4: This chapter deals with the results and discussion. It will highlight the results obtained in the development of a manual and automatic switching system for domestic appliances. Besides, it also discusses methods used in integrating the IoT system with Blynk apps. All the obtained results are briefly explained in this section.

CHAPTER 5: The last chapter will describe the conclusion and future recommendation of the project. This encompasses summarizing the project, highlighting the findings, and proposing suggestions for future improvements.

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CHAPTER 2

BACKGROUND STUDY

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2.1 Chapter Overview

This chapter conducts a thorough literature review, analysing and comparing prior relevant studies. It aims to gather data related to controlling, monitoring, and forecasting energy consumption in domestic appliances. Academic literature from journals and reputable websites was used. The chapter is divided into sections covering IoT-Based Controlling, Energy Consumption Monitoring, and Forecasting Analysis, including a comparison with the proposed project.

2.2 IoT Based Controlling and Energy Consumption Monitoring System

The combination of Internet of Things (IoT)-based control systems and energy consumption monitoring has emerged as a potential solution in response to increasing concerns about environmental damage and worldwide energy constraints. There are many methods based on controlling and monitoring energy consumption systems that has been developed such as a power consumption monitoring system using telegrams and LCDs to prevent overconsumption and safeguard electronic devices [5]. There are various methods reviewed in subtopic below.

The paper title “An IoT-Based Smart Home Automation System” presents a flexible and cost-effective smart home automation system based on ESP8266 processors and Raspberry Pi boards. The qToggle system provides a range of features including automation, control, monitoring, and security. Furthermore, it has the potential for ongoing development and improvement.

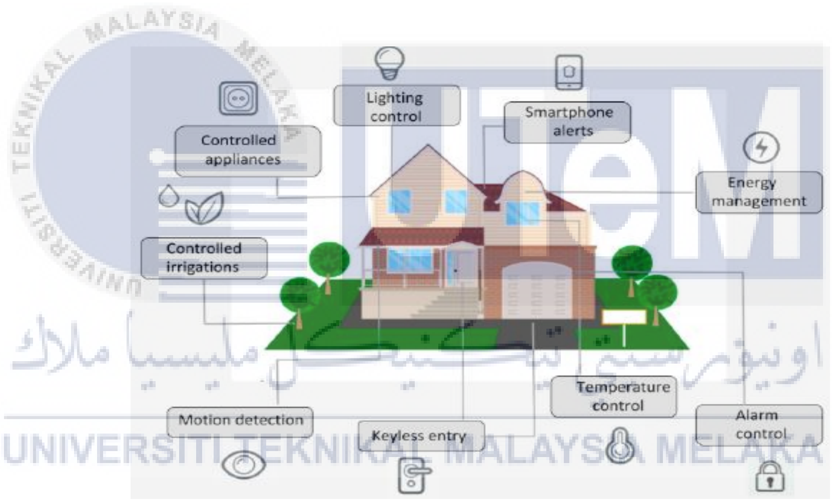

Figure 2.1: Feature of the Proposed System [6]

According to [6], The qToggle system enhances home energy efficiency through automation and monitoring. It turns off lights and devices when not in use, manages indoor temperatures to save on heating and cooling costs, and provides detailed energy consumption data. This helps homeowners identify areas to reduce consumption. Additionally, it can integrate with renewable energy sources like solar panels to reduce expenses and environmental impact.

The study in the next paper introduces a smart electricity monitoring and control system based on the Internet of Things (IoT), which utilises usage data. The system employs current and voltage sensors for the purpose of calculation and transmits data wirelessly using ZigBee and Ethernet protocols. The data that has been gathered is transmitted via WiFi router to the local area network (LAN), and the system is managed and supervised from a remote location. This system is divided into two sections which are receiver section and transmitter section. The receiver section shown in figure 2.2 below is responsible for collecting data from the transmitter section and sending it to the cloud storage using Thing-speak.

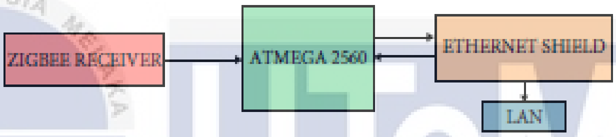

Figure 2.2: Receiver Section of the Proposed System [7]

The suggested system offers an effective methodology for monitoring power consumption in residential buildings and assisting users in managing their power and energy utilisation. The system has the capability to discern the energy use of individual appliances and offer immediate feedback to the user. The transmitter section shown in figure 2.3 below is tasked with the measurement of current and voltage of the appliances, followed by the transmission of the data to the receiver section through the use of ZigBee and Ethernet technologies.

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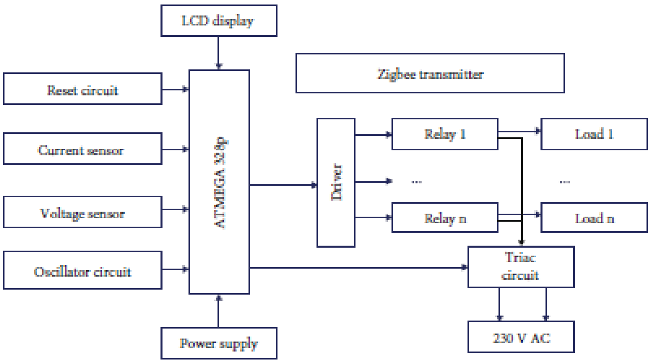

Figure 2.3: Transmitter Section of the Proposed System [7]

The system under consideration has been built and developed with the inclusion of Arduino UNO, a liquid crystal display (LCD), an ACS712 current sensor module, relays, and AC sources. The data is stored in cloud storage utilising Thing-speak, while a mobile application called Virtuino retrieves the data for the purpose of visualising it through graphical and numerical displays. The suggested system demonstrates a reduction in current errors for the hairdryer appliance, with a rate of 0.6%, compared to the present Power Monitoring and Switching (PMAS) system which exhibits a higher rate of 7.8% current mistakes. The project introduces a user-friendly system designed for monitoring and regulating the power usage of household appliances through the utilisation of mobile applications [7].

The article title “Smart Monitoring and Controlling of Appliances Using LoRa Based IoT System” thoroughly explains the system's architecture, including its hardware and software components. It consists of a central hub that connects to various sensors and appliances, enabling remote control via a mobile app. LoRa technology allows long-range wireless communication with minimal battery usage.

The operational procedure involves connecting sensors and appliances to a central hub, which can be controlled through the mobile app. The app provides real-time information on sensor and appliance status, allowing users to control them using virtual switches. The system consists of two parts: the sender end, connecting users' mobile phones to an ESP32 module, and the receiver end, linked to multiple sensors and home appliances.

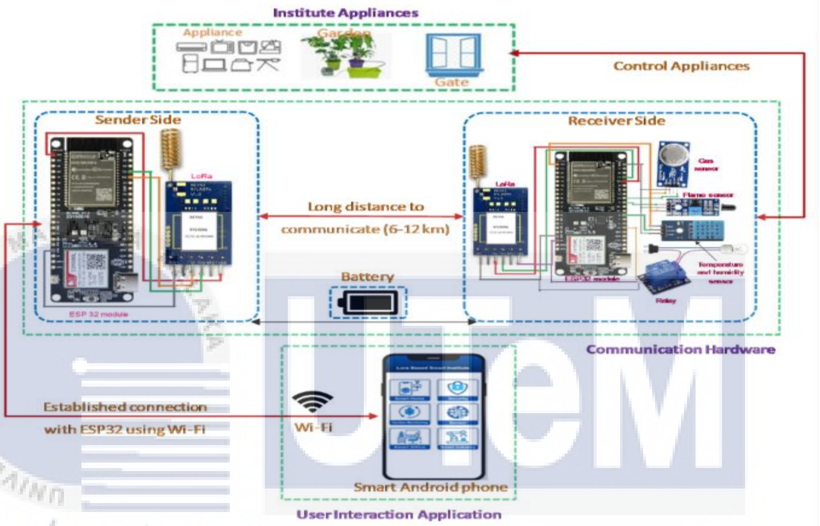

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Figure 2.4: Architecture of the Proposed Project [8]

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The paper additionally investigates the outcomes of the system's performance assessment, revealing its capability to successfully monitor and gather temperature and humidity data within a residential setting at distances of up to 12 kilometres. The system exhibited a detection accuracy of 90% for fire and a control accuracy of 92.33% for managing the switching functionality of appliances[8].

In general, this article offers significant insights related to the utilisation of LoRa technology in the development of intelligent home automation systems. The system's affordability and extensive range render it a compelling choice for the surveillance and regulation of appliances inside residential, institutional, and industrial settings.

The system in paper [9], consists of three subsystems, each with three Arduinos and one ESP32. The first subsystem controls temperature and humidity, sending data to ThingSpeak IoT and Blynk Software. The second subsystem uses RFID and a solenoid door lock for security. The third subsystem uses ESP32 and the Blynk App to manage irrigation and indoor lighting.[9].

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Figure 2.5: Thingspeak Dashboard of the Proposed Project [9]

This paper outlines the methodology employed to implement the system and provides an account of the study's conclusions. The system underwent satisfactory testing, and the proprietor was promptly alerted to an unauthorised entry into the premises. The system offers homeowners a comprehensive smart home infrastructure that promotes security, safety, and comfort, hence increasing home automation capabilities and including additional functionalities like remote house surveillance and environmental control.

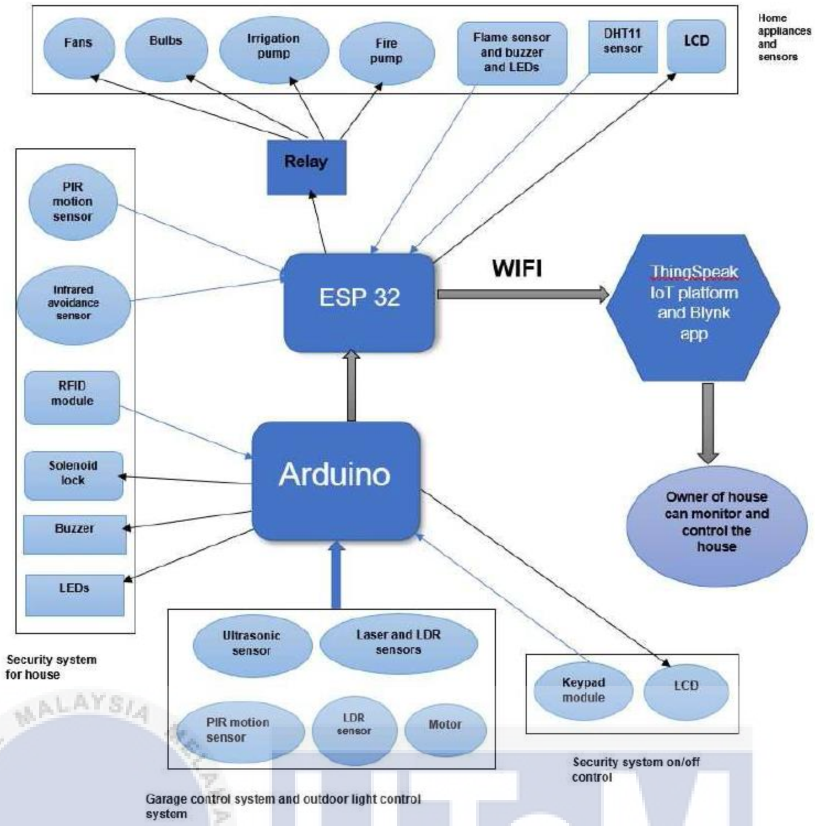

Figure 2.6: Proposed Project System Design [9]

The study additionally examines prior research on home automation and its various uses, while also presenting the Internet of Things (IoT) architecture employed inside the system. The system has been specifically engineered to incorporate additional functionalities through the utilisation of the Internet of Things (IoT) platform. As an integral component of this project, an innovative application for mobile devices has been developed. This article provides a thorough and effective approach to managing and engaging with domestic devices through the utilisation of Internet of Things (IoT) platforms as well remote oversight, and mobile applications. As a result, residences are enhanced in terms of security, safety, and convenience.

The paper, "IoT Based Home Automation System Using ThingSpeak," proposes a solution for remote appliance control via an Android app, aiming to save energy. It employs IoT and cloud technology, with an emphasis on user-friendliness. Real-time energy data helps users monitor and reduce consumption. The system's architecture includes an Android app, ThingSpeak Cloud, Raspberry Pi, Arduino Uno, and sensors. The Raspberry Pi acts as a bridge between ThingSpeak and Arduino. The system successfully reduces energy use, aligning with its goal of energy efficiency, as confirmed by empirical findings.[10].

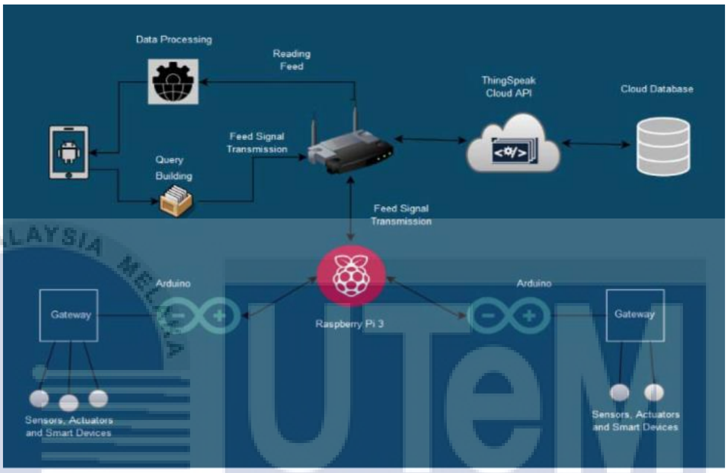

Figure 2.7: Proposed System Architecture [10]

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If implemented widely in residential and industrial sectors, the proposed system can greatly cut energy use. The study's future direction includes using fuzzy algorithms for electric energy management, traffic lights, and street lighting to further reduce energy consumption. Overall, the study provides an effective solution for improving energy efficiency in home automation using IoT technology and cloud services. The system empowers users with information to make informed energy-saving decisions and prioritizes energy efficiency.

Next, by referring to [11], introduces an IoT-based system for monitoring and controlling building energy using LoRa modulation and MQTT protocol. The system measures voltage, current, power, energy, and electricity consumption in a single-phase power line. It consists of two sensor modules, a microcontroller, LoRa-WiFi communication, and a gateway. Sensors provide power data to a unique energy monitoring system, including sensors, a microcontroller with LoRa interface, Arduino Uno, Dragino LoRa Shield, ACS712 current sensor, ZMPT101B voltage sensor, and a relay. The Dragino LoRa Gateway LG01-N transmits data to the IoT cloud server via MQTT, using subscribe and publish techniques.[11].

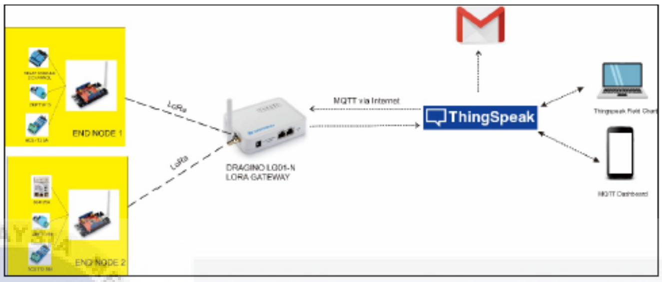

Figure 2.8: Proposed Project System Architecture [11]

The system is meant to optimize energy usage by employing a system for energy management. The free and open-source ThingSpeak platforms is utilised for visualisation of data and device control for savings. The system delivers dependable data effortlessly and is proved to perform successfully. The voltage, current, and power accuracy errors in the end nodes are 1.24%, 2.60%, as well as 3.13%, respectively. The system is an inexpensive IoT gadget that can help smart energy management.

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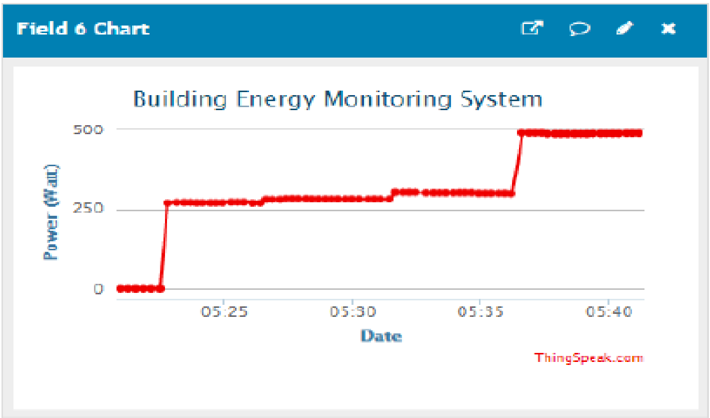

Figure 2.9: Wattage Data from Thingspeak of Proposed System [11]

In conclusion, this study offers a low-power, wide-area network system for monitoring and regulating building energy use utilising LoRa modulation and MQTT protocol. The technology is designed to optimize energy usage and generate trustworthy data seamlessly. The system is a low-cost IoT gadget that can help smart energy management. The system may be used to collect data to help effective energy management and can be utilised for in-depth analysis.

2.3 Forecasting Analysis for Energy Consumption

Accurate energy consumption prediction is crucial due to growing global energy demand and the need for sustainable resource management. This approach is applied across various industries, like predicting energy use in wheat production in India using an Artificial Neural Network (ANN) model [12]. Forecasting is widely used for efficient energy control and monitoring. According to [12], the ANN model with specific parameters yields the best results. The next section reviews different methods and outcomes in forecasting.

The research in "Electricity Consumption Forecast Based on Neural Networks" examines factors influencing electricity consumption in Nur-Sultan, Kazakhstan. Data from 2018 and 2019 is used to study the effects of lighting and temperature on power usage. The study reveals a consistent pattern of higher demand on weekends, similar to Saturdays and Sundays. It suggests that lighting in industrial and private spaces significantly contributes to energy consumption fluctuations due to lighting usage patterns.[13].

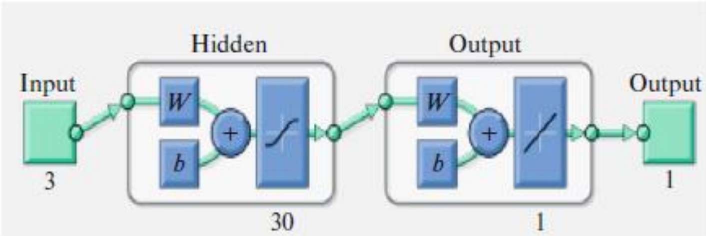

Figure 2.10: Network Structure of Proposed Project [13]

The report reviews energy use forecasting methods, noting around 150 approaches, with 20-30 commonly used. They categorise them based on method formalization, action principles, and information acquisition. The report focuses on classical methods, such as linear regression and weather-dependent load partitioning.

In the experimental findings section, the authors give an overview of the accuracy of several forecasting models for power consumption in Nur-Sultan. The study reveals that the model using linear regression and the model splitting the load into fundamental and weather-dependent components produce the best accurate projections. The authors also remark that the accuracy of the projections varies on the time horizon, having shorter time horizons producing more accurate forecasts. The study suggests that the provided models may be utilised to enhance the accuracy of energy consumption projections in Nur-Sultan and other comparable locations.

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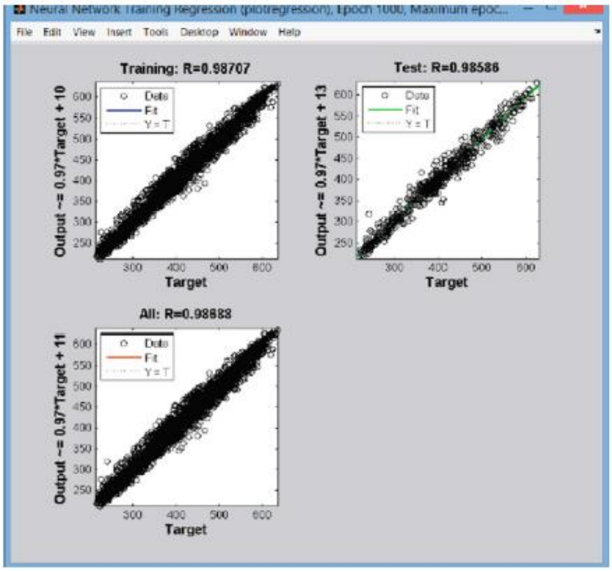

Figure 2.11: Proposed Project Regression Graph of Forecasting [13]

Next, the present article in [14] introduces a research investigation into the utilization of machine learning models for the purpose of predicting and scheduling energy usage in smart buildings. The researchers choose to employ Artificial Neural Networks (ANN) in conjunction with Genetic Algorithms for the purpose of forecasting the energy consumption of various appliances within a building. The model has been implemented using the Python programming language and subsequently integrated with LabVIEW to explore the possibility of incorporating it into the NI CompactRIO platform. The models developed by the authors are implemented in a practical smart building testbed called MiGrid. This testbed is designed to establish a comprehensive platform that integrates smart buildings with energy from renewable sources storage and generation[14].

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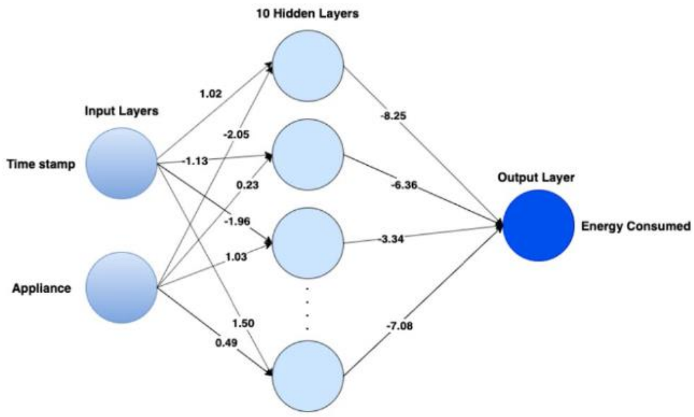

Figure 2.12: Network Model of Presented Project [14]

The authors tested their models to evaluate their effectiveness and compared them with existing models. They found their models more accurate and efficient but noted limitations like needing a lot of training data and difficulties in long-term energy usage predictions. They suggest future research could improve these aspects by using advanced machine learning techniques and incorporating additional data sources.

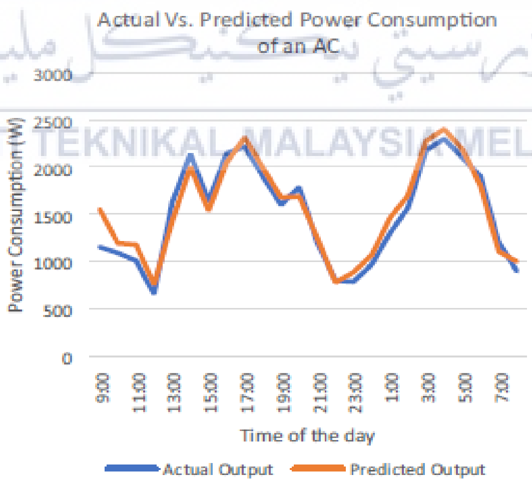

Figure 2.13: Actual versus Predicted Output of Proposed System [14]

In conclusion, this research introduces a promising method to predict and manage energy use in smart buildings using machine learning. The authors provide real-world evidence of their models' effectiveness and highlight areas for future research. These findings benefit researchers and practitioners in the energy-efficient smart building domain, facilitating the development of more accurate machine learning models for energy prediction and scheduling.

According to [15], study explores electricity usage and predictions using artificial neural networks, analysing differences in power use between weekdays and weekends across seasons. It highlights the key role of temperature in electricity consumption and considers time-related factors like time of day and year. The authors also provide a dataset of electricity use and average temperature for further research. [15].

Table 2.1: Pre-processed Dataset of Proposed Project [15]

	Year	Month	Day	Hour	Load	Temp	DOW
0	2004	1	1	1	16853	46	4
1	2004	1	1	2	16450	46	4
2	2004	1	1	3	16517	45	4
3	2004	1	1	4	16873	41	4
4	2004	1	1	5	17064	39	4
5	2004	1	1	6	17727	35	4

The next section focuses on creating a neural network-based model for short and medium-term load prediction. The model is trained with historical data and tested for various timeframes: one day, one week, one month, and six months ahead. The model performs well with a mean square error below 1 (refer to Table 2.2). To enhance it, factors like holidays, rainfall, and wind speed can be considered. Long-term forecasting may also include economic factors in the region.

Table 2.2: MSE and MAPE Scores of Proposed Project [15]

Prediction Period	MSE	MAPE
Day-ahead	0.23741	0.00277
Week-ahead	0.17118	0.00195
Month-ahead	0.21155	0.00172
6 Months-ahead	0.26577	0.00199

In summary, this study offers significant contributions to the examination of historical load patterns and the impact of the surrounding temperature on load. The researchers have devised a neural network-based prediction model for short-term and medium-term load forecasting. This model has demonstrated strong performance, exhibiting a mean square error of less than 1.

The study in [16] explores load forecasting using ANN-based models, essential for effective energy management. Accurate predictions inform decisions regarding power procurement, load switching, and infrastructure expansion. Research highlights drawbacks in short-term load forecasting and promotes AI benefits [16].

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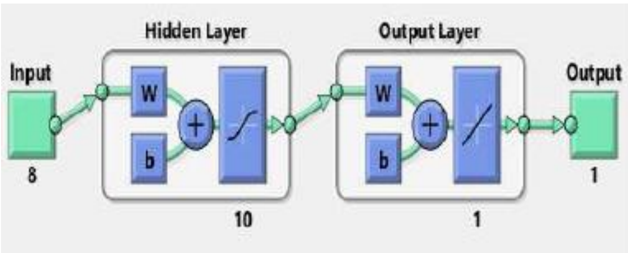

Figure 2.14: Proposed Project Neural Network Architecture [16]

This study's approach involves using historical data and MATLAB simulations to create an Artificial Neural Network (ANN) load forecasting model. The model's performance is assessed using RMSE and MAPE, revealing high accuracy in forecasting, as indicated in Table 2.3.

Table 2.3: Load Forecast Summary of Proposed Project [16]

Testing days	MAPE (%)	RMSE (kWh/day)
Monday	0.118	128.156
Tuesday	0.454	141.246
Wednesday	0.368	163.428
Thursday	0.256	113.274
Friday	0.217	105.442
Saturday	0.131	79.146
Sunday	0.183	153.63

The research additionally examines the possibility of enhancing load forecasting accuracy by the inclusion of additional meteorological variables, such as speed of the wind, relative humidity, precipitation, season, and consumer type, as inputs to the artificial neural network (ANN) model.

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This paper offers a thorough examination of load forecasting through the utilisation of artificial neural network (ANN) based models. It offers significant insights into the possibility of artificial intelligence (AI) tools in enhancing the accuracy of short-term load forecasting. The findings of the forecasting analysis demonstrate encouraging outcomes regarding the efficacy of Artificial Neural Network (ANN) models in forecasting load.

2.4 Comparative Analysis of Proposed Technique and Reviewed Technique

Table 2.4: Comparative Analysis of Reviewed and Proposed Controlling and Energy Consumption Monitoring System

Authors	Methods Used	Controlling Method	Monitoring Method	Limitation	Results
C. Stolojescu-Crisan, C. Crisan, and B. P. Butunoi, 2021[6]	qToggle system	Using qToggle	qToggle	*NA	proposed qToggle system is flexible
M. K. Hasan, M. M. Ahmed, B. Pandey, H. Gohel, S. Islam, and I. F. Khalid, 2021[7]	Power Monitoring and Switching (PMAS) system	Using ZigBee	ThingSpeak	No voltage sensor	0.6% current errors for hairdryer and 7.8% current errors for existing PMAS
Nur-A-Alam, M. Ahsan, M. A. Based, J. Haider, and E. M. G. Rodrigues, 2021[8]	LoRa modulation and MQTT protocol	Using MQTT Protocol	Using MQTT Protocol	*NA	Repeated calibrations result to error minimisation
F. Alsuhaym, T. Al-Hadhrami, F. Saeed, and K. Awuson-David, 2021[9]	Configuration of ThingSpeak	Using mobile application	mobile application and ThingSpeak	Continuous power supply	System connected and disconnected device compared
M. H. Miraz et al., 2019[10]	Wireless network communication with LoRa	Using mobile application	*NS	Low coverage of LoRa	Efficient environmental data
A. Ramelan, F. Adriyanto, B. A. C. Hermanu, M. H. Ibrahim, J. S. Saputro, and O. Setiawan, 2021[11]	Constrained Application (CoAP) and MQTT Protocol	ZigBee	ThingSpeak	*NA	High performance of smart home system
Proposed System	**Integration of Sensors, Blynk and ThingSpeak**	**Using Blynk and Sensors**	**Blynk and ThingSpeak**	**Appliances limited**	**Real-Time data recorded**

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Table 2.5: Comparative Analysis of Reviewed and Proposed Forecasting Analysis for Energy Consumption

Authors	Forecasting Method	Analysis Method	Results
A. B. Uakhitova, 2022[13]	• Artificial Neural Network (ANN) • Support Vector Regression (SVR) • Multiple Linear Regression (MLR) • Auto Regressive Integrated Moving Average (ARIMA) • k Nearest Neighbour (kNN)	Statistical methods: Multiple Linear Regression (MLR), Auto Regressive Integrated Moving Average (ARIMA), k Nearest Neighbour (kNN)	SVR techniques is generally better than statistics for short-term load forecasting.
S. Bourhnane, M. R. Abid, R. Lghoul, K. Zine-Dine, N. Elkamoun, and D. Benhaddou, 2020[14]	Artificial Neural Network (ANN)	Historical load trends and effects of ambient temperature	The prediction model performed well with a mean square error less than 1.
SCAD College of Engineering and Technology and Institute of Electrical and Electronics Engineers, 2019[15]	Autoregression (AR) model	Autoregression integrated moving average (ARIMA) model	The ANN model showed the highest accuracy among all tested prediction methods.
A. A. Khan, A. F. Minai, L. Devi, Q. Alam, and R. K. Pachauri, 2021[16]	Artificial Neural Network (ANN)	Analysis of modern methods for forecasting electricity consumption	The network almost perfectly approximates the function.
Proposed System	**NARX Open-Loop Model**	**Analysis of appliances manual and automode with forecasting performance evaluation**	**Prediction performed well with evidence of performance evaluation, and manual and auto mode appliances energy consumption compared**

*NS = NOT SPECIFIED

*NA = NOT APPLIED

CHAPTER 3

METHODOLOGY

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3.1 Chapter Overview

The methodology encompasses various interconnected concepts, such as model, approach, and procedure. Typically, it establishes the method in which research has been carried out and highlights the approaches that have been utilised. This chapter concentrates on the implementation of the project, including the theory of behind IoT-Enabled Energy Consumption Monitoring and Analysis for Domestic Appliances and the step-by-step process of constructing the system, including both the software and hardware parts.

3.2 Project Flowchart

The flowchart shown in Figure 3.1 illustrates the development of the proposed system process. It begins with the first objective, which is the development of the controlling features. It starts with a comprehensive literature review and the selection of essential components such as microcontrollers, sensors, and appliances. Next, the step proceeds to construct the circuit diagram, wiring, and program the device. Then, the Blynk application integrates with the device to control the appliances. If any issues are encountered, the process will return to the development stage to troubleshoot the problem. In contrast, if the system functioned well, the step would proceed to the second objective, which is the development of monitoring features.

As for the second objective, it begins with a determination of parameters related to environmental and energy consumption sensors for monitoring and prediction. After that, the next stage is integrating the ESP32 with IoT Platform to monitor and save the historical data of temperature, light intensity, and energy consumption data for future processes of forecasting. This process involved the Graphical User Interface (GUI) layout design process for both applications (Blynk and ThingSpeak). Then, the process proceeds to develop a hardware prototype for data collection. If hardware and software implementation does not cause any issues, it will proceed to analysis, which is the third objective. However, the process will return to the software integration to troubleshoot the issue.

Finally, the analysis process begins with the embedded artificial neural network on MATLAB to predict data on energy consumption. This process involved training the model by using temperature, light intensity, and energy consumption data as targets to forecast. After the prediction output is generated, the analysis of the project will involve the analysis of forecasting performance and both manual and automatic switching energy consumption usage.

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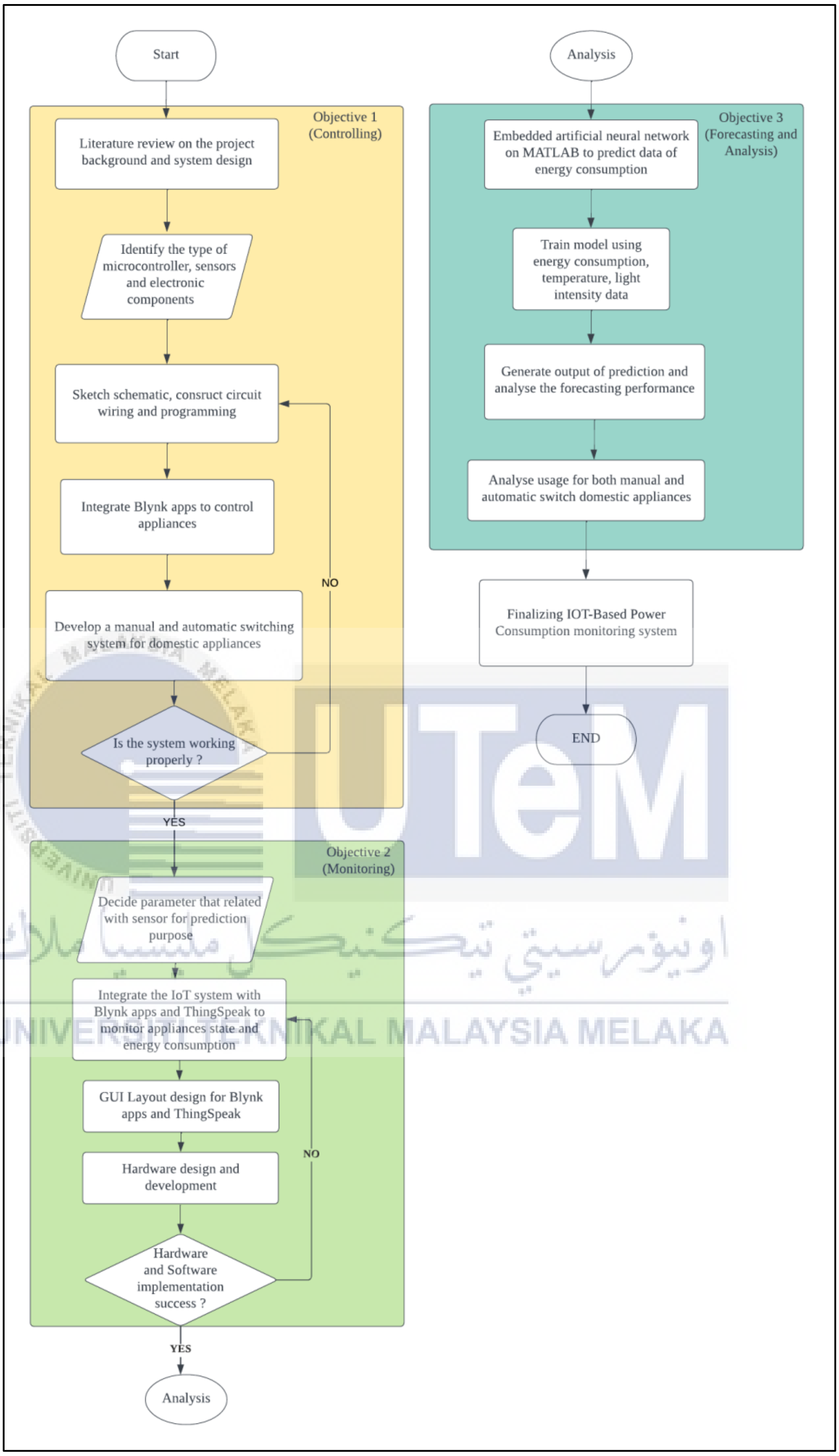

Figure 3.1: Project Process Flow Diagram

3.3 Main Components

In order to develop the IoT-Enabled Energy Consumption Monitoring and Domestic Appliances Analysis, variations of electronic components are needed to construct the devices such as ESP32, Relay, Environmental Sensor (PIR, DHT22 and BH1750) and Energy Consumption Sensor (SCT-013 and ZMPT101B). All sensor data will be transmitted to the ESP32 to display and save the historical data in the IoT platform. The relay will receive data from ESP32 to control the appliances.

3.3.1 ESP 32 Microcontroller

ESP32 is powerful SoC (System on Chip) microcontroller with integrated Wi-Fi 802.11 b/g/n, dual mode Bluetooth version 4.2 and variety of peripherals [17]. The NodeMCU ESP32 serves as the main control unit of the system as shown in Figure 3.2. It is a low-cost and low-power device that integrates Wi-Fi and Bluetooth connectivity. This microcontroller widely used in various application of project and studies related to Energy Consumption Monitoring [18]–[20].

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Figure 3.2: NodeMCU ESP32 Microcontroller

3.3.2 Relay

A relay is a switch that is controlled electrically as depicted in Figure 3.3. It is made up of a group of input terminals that can accept a single or many control signals, as well as a group of contact terminals that are used for operations. It is possible for the switch to have any number of contacts in a variety of contact forms, such as make contacts, break contacts, or combinations of the two. A regular switch is what used to manually close or open a circuit.

Figure 3.3: Relay Switch

3.3.3 Environmental Sensor

Environmental sensors, including the Passive Infrared (PIR) sensor, DHT22 temperature and humidity sensor, and BH1750 light intensity sensor, play a fundamental role in capturing critical data for the system. Together, these sensors provide a full suite of sensors that improve the system's environmental awareness and enable smart decision-making for the best possible user experience and energy conservation.

3.3.3.1 PIR Sensor

The Passive Infrared (PIR) sensor as shown in Figure 3.4 functions as a motion detection device in the system. A PIR-based motion detector is used to sense movement of people, animals, or other objects [21]. This sensor signals the system when motion is detected by detecting fluctuations in the infrared radiation generated by warm objects, such as humans.

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Figure 3.4: PIR Sensor

3.3.3.2 DHT22 Sensor

The DHT22 sensor serves as a vital component in the system. The sensor depicted in Figure 3.5 monitors the air's humidity and the current temperature of its surroundings. Temperature is one of the most monitored items in many industrial and commercial applications. [22] Establishing a pleasant and regulated atmosphere depends on its capacity to deliver accurate measurements of various environmental parameters.

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Figure 3.5: DHT22 Sensor

3.3.3.3 BH1750 Sensor

BH1750 sensor in Figure 3.6 acts as a light intensity detector. This sensor monitors the amount of surrounding ambient light. It allows the system to adjust and make judgements based on the available lighting circumstances by gathering accurate data on light levels. This sensor has four component that was connected in the circuit which are ADC circuit, photosensitive diode, a crystal oscillator, and an Op-Amp (Operational Amplifiers). [23]

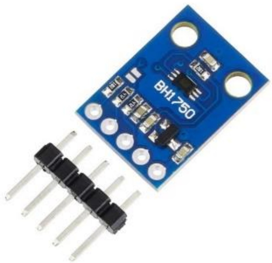

Figure 3.6: BH1750 Sensor

3.3.4 Energy Consumption Sensor

The Energy Consumption Sensor is a key component of the system and plays a vital function in giving vital information about how electrical appliances are used. This sensor plays a crucial role in tracking and measuring the voltage and current flow at each connected device, which adds to a thorough knowledge of the patterns of energy use. The details of this essential element will be covered in more detail in the following explanation.

3.3.4.1 SCT-013 Current Sensor

An essential part of the system, the SCT-013 Current Sensor in Figure 3.7 is used to measure the electric current passing through a conductor. Without requiring direct electrical contact, this sensor measures and detects current using the electromagnetic induction concept. The SCT-013-030 is an inductive, split-core, ferrite current transformer which supports primary currents from 0 to 30 amperes, with equivalent output signal voltage from 0 to 1 volt. [24]

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Figure 3.7: SCT-013 Current Sensor

3.3.4.2 ZMPT101B Voltage Sensor

The ZMPT101B in Figure 3.8 voltage sensor is a significant component within the system, specifically designed to measure the voltage in electrical circuits. It makes use of electromagnetic induction principles, allows voltage to be measured and detected without direct electrical contact.

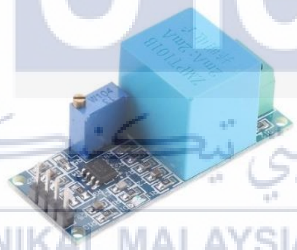

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Figure 3.8: ZMPT101B Voltage Sensor

3.4 IoT Platform and Software

The software and applications related to IoT, and analytical graph development were needed for this proposed project. This section will briefly explain the software that is used in this project. The combination of Arduino IDE Platform, Blynk Platform, ThingSpeak Platform and MATLAB Platform makes this project more efficient. It helps to get the features of controlling domestic appliances, monitoring environmental and energy consumption, and forecasting future energy consumption. The sub-section below explains all three-software mentioned above.

3.4.1 Arduino IDE Platform

The platform to construct and upload the program code to ESP32 is needed to program every configuration in the proposed system. The Arduino Integrated Development Environment (IDE) platform is used for this task. This software can be downloaded from the Arduino Website and is an accessible source. The language used in this software is one type of C++ language, making it a user-friendly platform with many features.

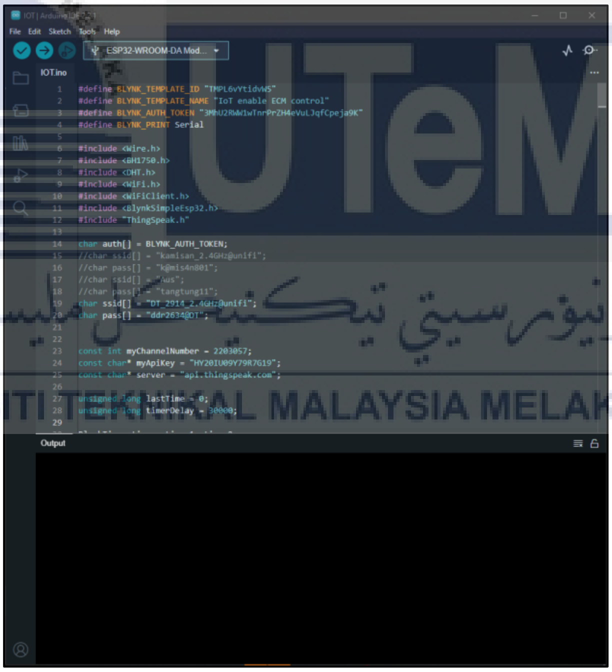

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Figure 3.9: Arduino IDE GUI

3.4.2 Blynk Platform

Blynk is an application for mobile and desktop that used to be the Internet of Things (IoT) platform for controlling, monitoring, and saving historical data from microcontrollers. Based on [25], Blynk uses drag-and-drop features to apply widgets for monitoring and controlling. This application can be downloaded from the Apps Store for iOS users and the Play Store for Android users. It has three plans: the free plan, the maker, and the pro plan. This IoT platform widely used as an application for smart home and smart energy consumption meter [26]–[30].

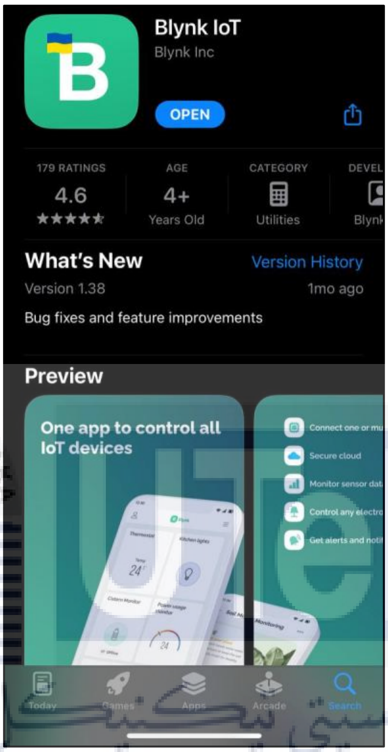

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Figure 3.10: Blynk IoT Application in Apps Store for iOS User

3.4.3 ThingSpeak Platform

One Internet of Things (IoT) platform commonly used for collecting, analysing, and visualising the historical data of sensors and other devices is called ThingSpeak. This platform is an open-source website created by MathWorks and offers a cloud-based infrastructure to capture real-time data quickly. In order to use this platform, users can set up channels and fields. Then, the data will be saved and accessible via APIs for additional processing. By referring to [31], this IoT platform has huge community of users that can support and sharing anything related to this platform.

Figure 3.11: ThingSpeak Platform GUI

3.4.4 MATLAB Platform

In engineering, science and other fields related to analytical graph visualisation with mathematical computation, MATLAB is a programming language commonly used for that task. The ability to handle complex numerical operations makes using it more accessible for individuals or organisations.

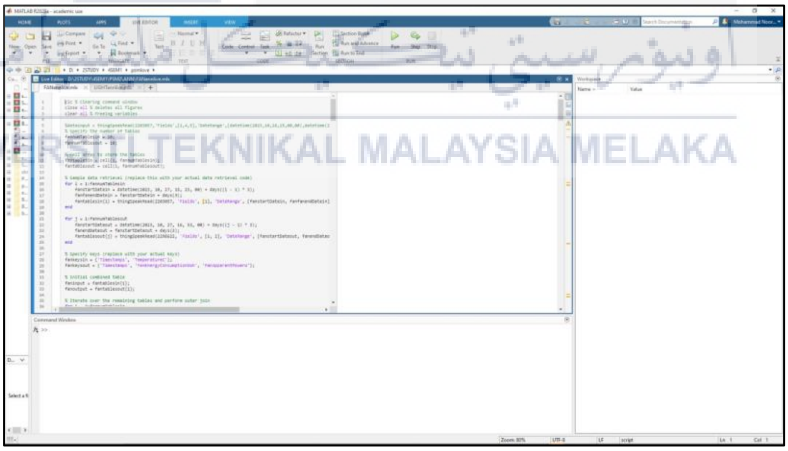

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Figure 3.12: MATLAB Software Live Editor View

3.5 Project Operation Development

This proposed system combines three different features: controlling domestic appliances, monitoring environmental and energy consumption, and forecasting future energy consumption. As for the controlling part of the system, it will control the appliances using two different switches: Manual Switch (Human Control) and Auto Switch (Sensor Control). The monitoring part of this system will integrate the sensor data with the IoT platform. The collected data will be used to forecast future energy consumption. All three features operation will be explained in the subtopic below.

3.5.1 Overall Operation of Proposed System

The overall operation of this proposed system will be explained based on Figure 3.13, which shows the interconnection between hardware and software. This sub-topic will briefly discuss the conceptual design with the block diagram of the overall system. This project uses two devices that use ESP32 microcontrollers: first device, which is used for controlling domestic appliances and environmental monitoring, and second device, which is used for energy consumption monitoring.

The ESP32 in the first device which is used to controlling domestic appliances and displaying environmental data shows in Figure 3.13 will receive the data of PIR, DHT22 and BH1750 that sense the presence of user, temperature, and lux intensity of room. Then, the data will be transmitted to the IoT Platform (ThingSpeak and Blynk) for environmental monitoring part in this system. MATLAB will read the data from ThingSpeak for the forecasting process.

The relay will make the appliances switch on or switch off. The appliance state will depend on the system mode. If the system mode is manual, the appliances will refer to the Blynk virtual pin. However, if the system mode is automatic, the appliance state will refer to the environmental sensor.

As for the second device, the current and voltage data from appliances will be transmitted to the ESP32. The mathematical operation to calculate the energy consumption per hour (kWh) will be configured in the Arduino IDE program code. Then, the energy consumption data will be transmitted to Blynk for user monitoring and ThingSpeak for historical data saving for the forecasting process in MATLAB.

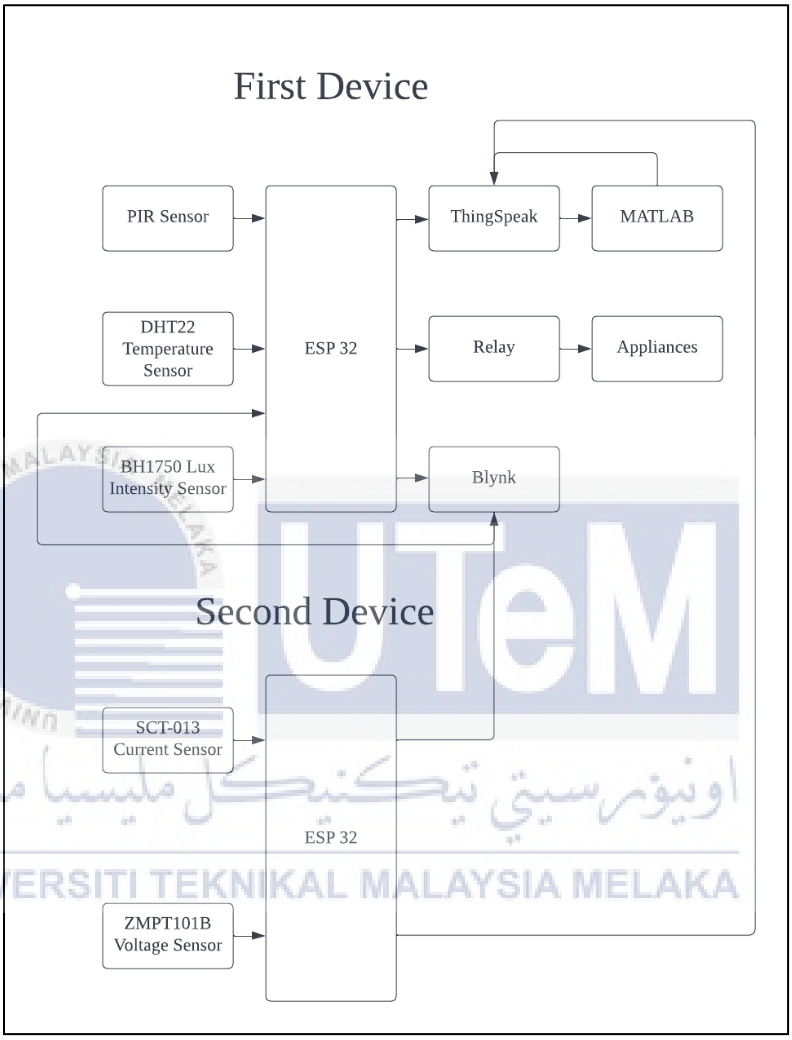

Figure 3.13: System's Conceptual Design of Overall System

3.5.1.1 Operation of Appliances Controlling

The appliance has two modes: manual and automatic. In manual, users turn things on and off with a virtual switch. In automatic, sensors control it. The flowchart in Figure 3.14 shows two parts, controlling fans and lights. If the virtual switch is HIGH, the fan or light turns on. If it is LOW, they turn off. So, whether the fan or light is on or off depends on the virtual switch being HIGH or LOW.

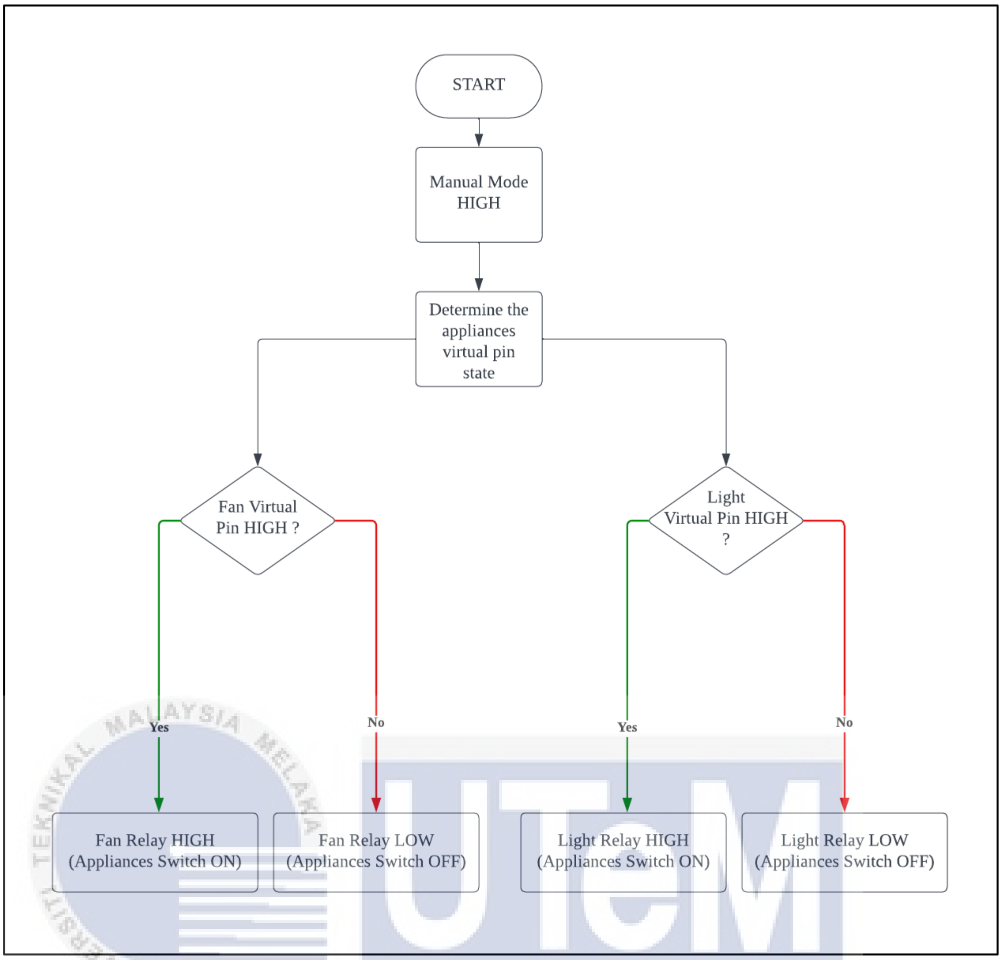

Figure 3.14: Appliances Manual Mode Control Flowchart

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Figure 3.15 illustrates the automatic mode's flowchart for controlling appliances based on environmental factors. When manual mode activated (set to HIGH), the system starts by assessing environmental data. If the PIR (Passive Infrared Sensor) is active (HIGH), it checks the temperature and light intensity. If the PIR is inactive, it reevaluates the environment. Two specific conditions are considered, if the temperature exceeds 27°C, the fan is activated. When light intensity falls below 10 LUX, the lights turn on. If the PIR continues to detect movement, appliances stay on; without movement, they switch off. Thus, the PIR's detection status affect the appliance control path.

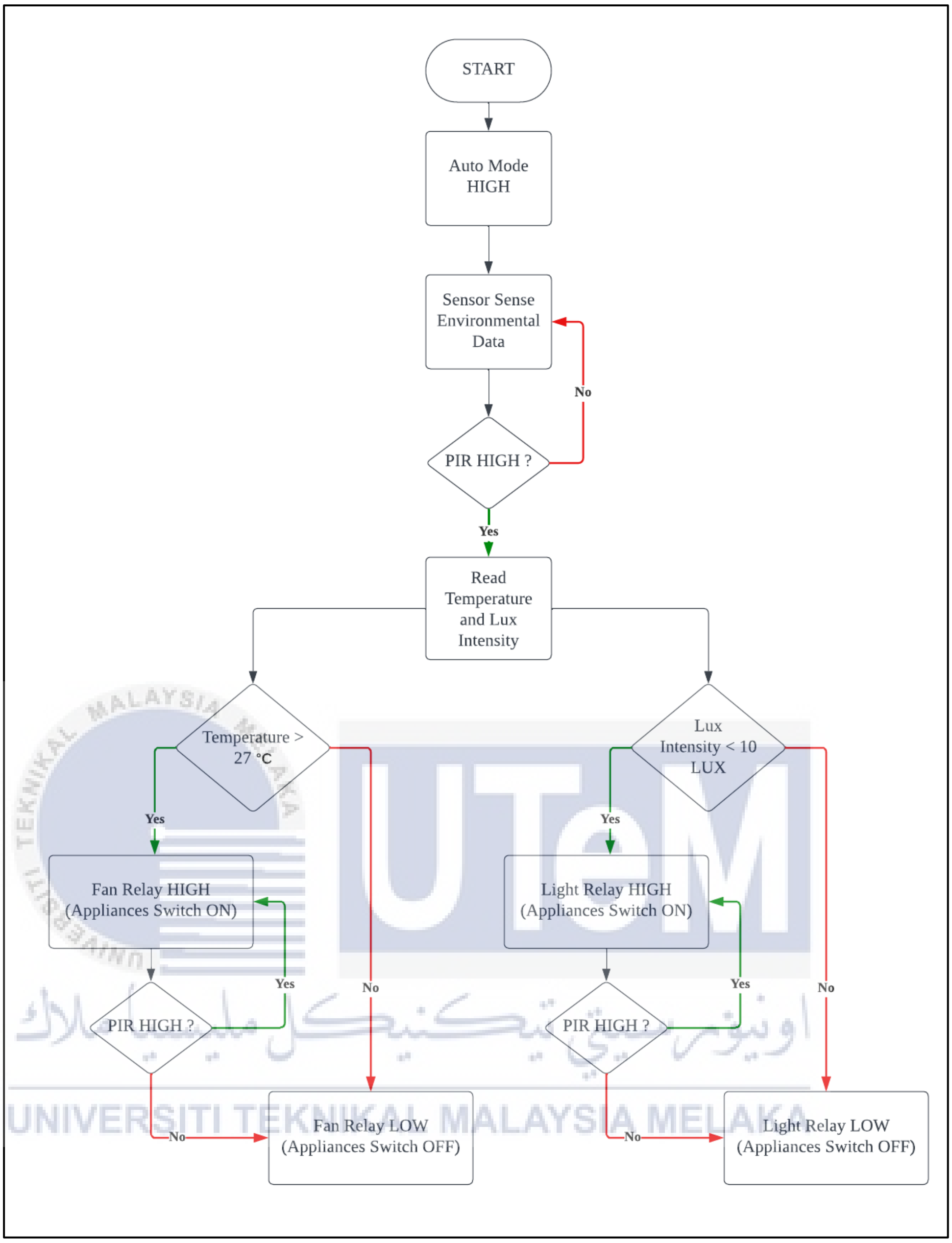

Figure 3.15: Appliances Auto Mode Control Flowchart

3.5.1.2 Operation of Environmental and Energy Consumption Monitoring

Figure 3.16 presents a flowchart explaining how environmental data is gathered and transmitted to IoT platforms, specifically Blynk and ThingSpeak. The procedure starts with collecting temperature, occupancy, and light level data. The DHT22 sensor measures temperature in Celsius. Occupancy is detected by the PIR sensor, and the BH1750 sensor gauges light intensity in LUX, indicating brightness levels. This information, encompassing temperature, occupancy, and brightness, is then transmit to both Blynk and ThingSpeak, demonstrating the integration of sensor data with IoT platforms.

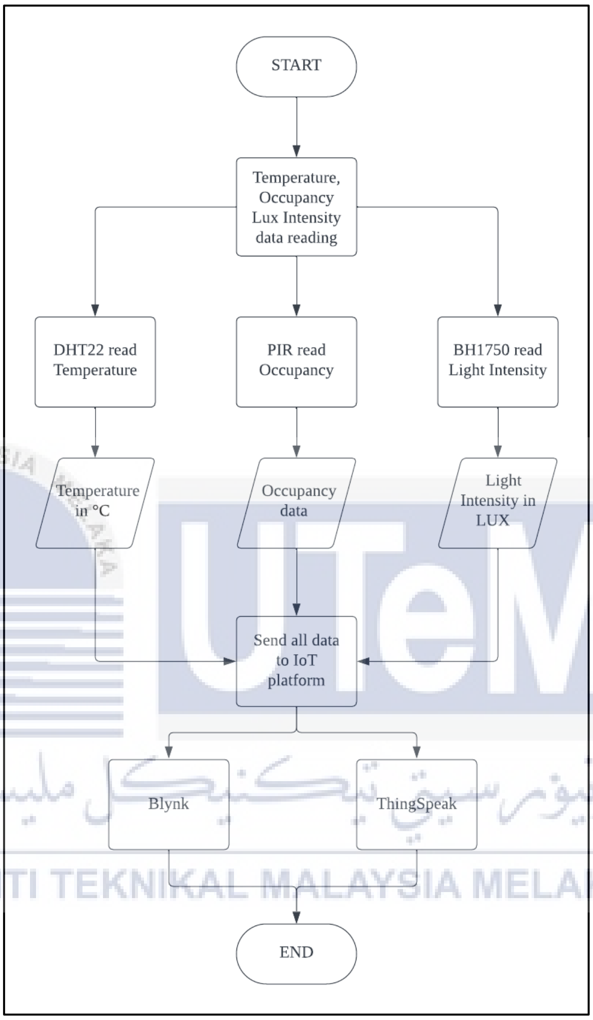

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Figure 3.16: Environmental Data Monitoring Flowchart

The Energy Consumption Monitoring Flowchart as depicted in Figure 3.17 outlines the process of measuring and monitoring energy consumption. The process starts with the collection of voltage and current data, which is then being used to calculate energy consumption in kilowatt-hours (kWh). Voltage is measured in volts (V) and current is measured in amperes (A). Then, the collected data, including energy consumption, is then sent to Blynk and ThingSpeak for further analysis or monitoring.

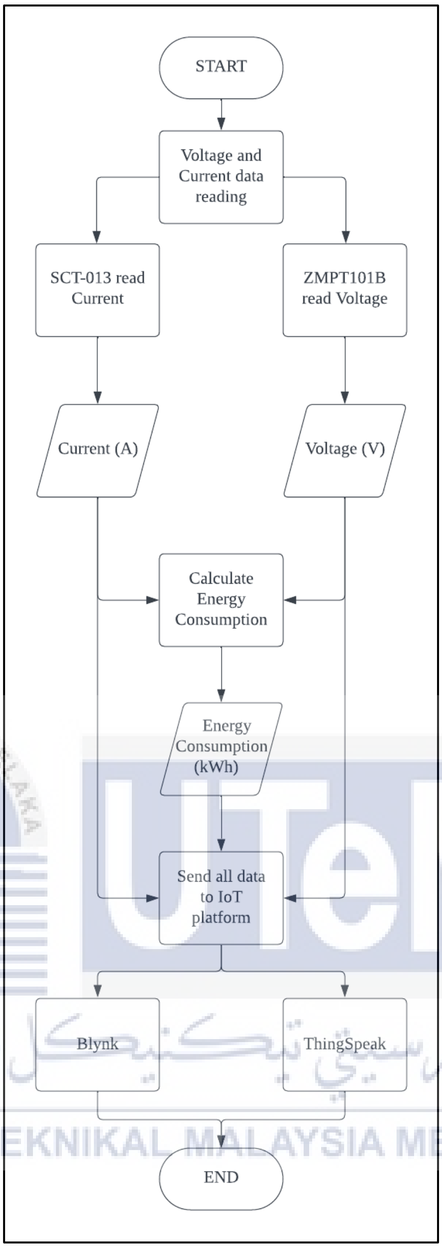

Figure 3.17: Energy Consumption Monitoring Flowchart

3.5.1.3 Operation of Forecasting

Figure 3.18 displays a flowchart describing a step-by-step process to analyse environmental and energy usage data for forecasting. It starts by collecting real-time data from ThingSpeak, an IoT platform. This raw data goes through a pre-processing phase to clean and structure it. The next step involves using this refined data to train a predictive model.

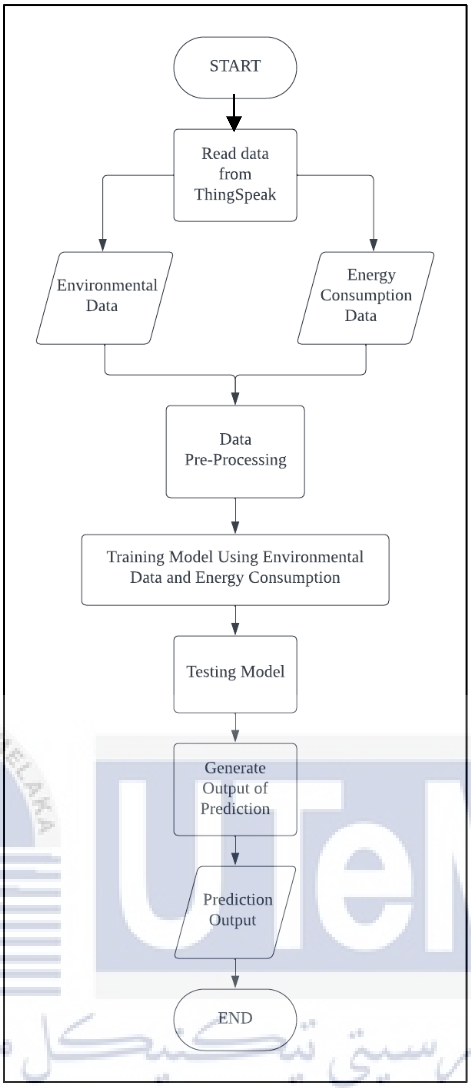

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Figure 3.18: Forecasting Flowchart

3.5.2 Project Implementation Procedure

This subtopic will include a brief explanation of this project procedure. It involves Hardware Preparation, which will focus on constructing and configuring hardware components; Software Implementation, which will explain the installation and procedure to use the software, and Hardware and Software Implementation, which will discuss the integration of both hardware and software for this system.

3.5.2.1 Hardware Preparation

As for hardware preparation, it consists of two preparations of hardware, which are the first device and the second device of this system; both systems are shown in Figure 3.13. The subtopic below explains how the preparation was done.

3.5.2.1.1 First Device Preparation

The first device, aimed at collecting environmental data for monitoring and controlling appliances, begins its setup with Arduino IDE programming. Key steps include assigning ESP32 pins for each sensor, downloading required libraries, connecting sensors and relays to ESP32 GPIOs, aligning these with the Arduino code, compiling and uploading the program, testing sensors and their output, and confirming the relay effectiveness in both HIGH and LOW states.

3.5.2.1.2 Second Device Preparation

The second device follows similar steps to the first, but with additional testing and calibration for the SCT-013 and ZMPT101B sensors. Serial monitors and a multimeter are used to check for errors. If found, the SCT-013 is calibrated via the Arduino IDE for accuracy. The ZMPT101B's calibration involves adjusting its connected variable resistor, vital for optimizing performance and precision.

3.5.2.2 Software Implementation

There are multiple software platforms have been used in this project which are Blynk and ThingSpeak as the IoT platform, Arduino IDE as the hardware setup and MATLAB software as the forecasting implementation. Thus, the process involved will be discussed in this subtopic. The full codes for every software used are presented in the appendix.

3.5.2.2.1 Blynk

Blynk application is very powerful IoT platform which allows users to easily create mobile applications to control and monitor hardware projects. The Blynk Console is a central hub for managing devices, templates, datastreams, and application settings. First and foremost, users need to add and configure the IoT devices used in the Blynk Console. After logging in, navigate to the "Devices" section and click on "New Device" as shown in Figure 3.19.

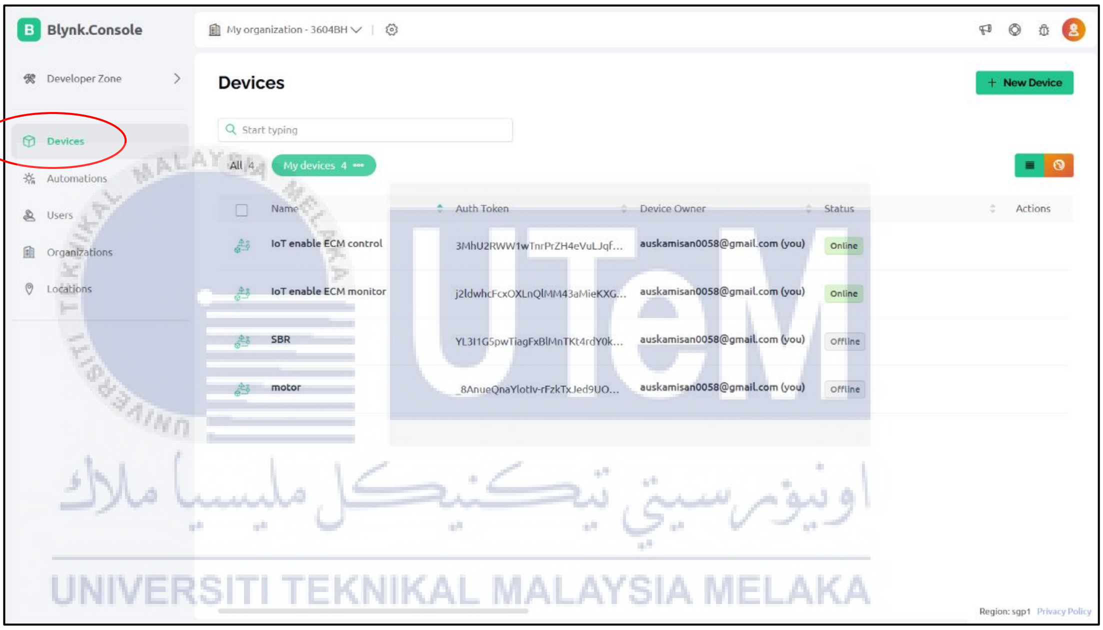

Figure 3.19: Devices section in Blynk Console

To choose the hardware type, authentication method, and connection type, which is Wi-Fi, simply follow the prompts. User will obtain authentication credentials, such as an Auth Token, when the device is connected. These credentials are needed to link the hardware to the Blynk platform. Based on Figure 3.20 select a template from the "Templates" section that created for the project.

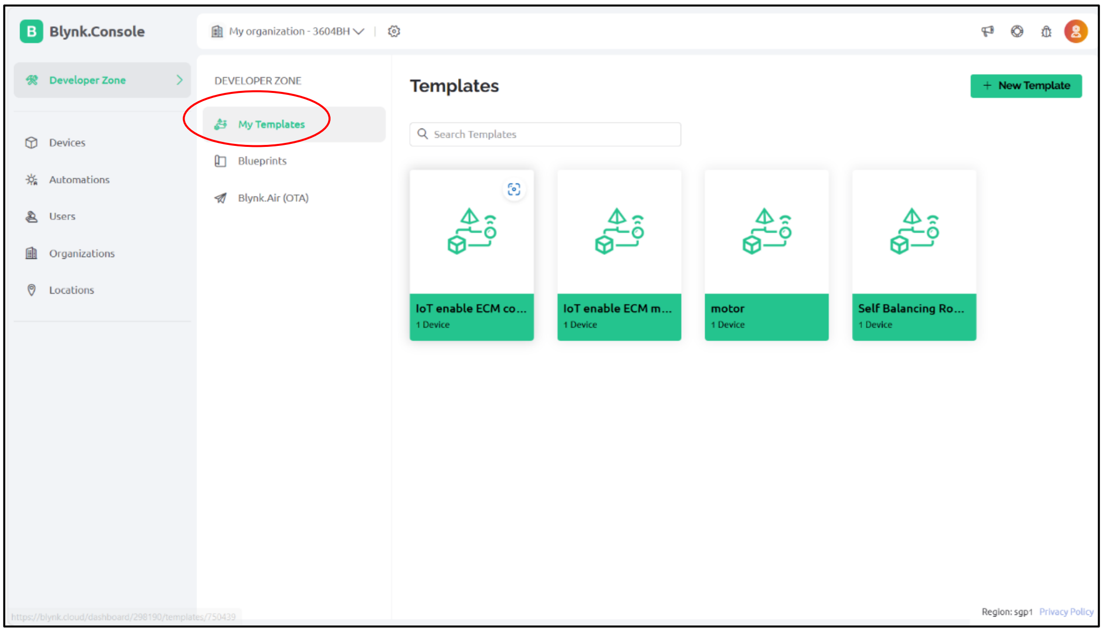

Figure 3.20: Template layout in Blynk Console

Furthermore, when the device and template are configured, the next step is to set up datastreams to easily communicate between the hardware and the Blynk app. For linking virtual pins to certain hardware pins on the device, navigate to the "Datastreams" section and create them. This can be seen in Figure 3.21. Transmitting data is accomplished by use of these virtual pins. Then, set up each virtual pin according to the system's specifications by selecting the direction (input or output) and data type.

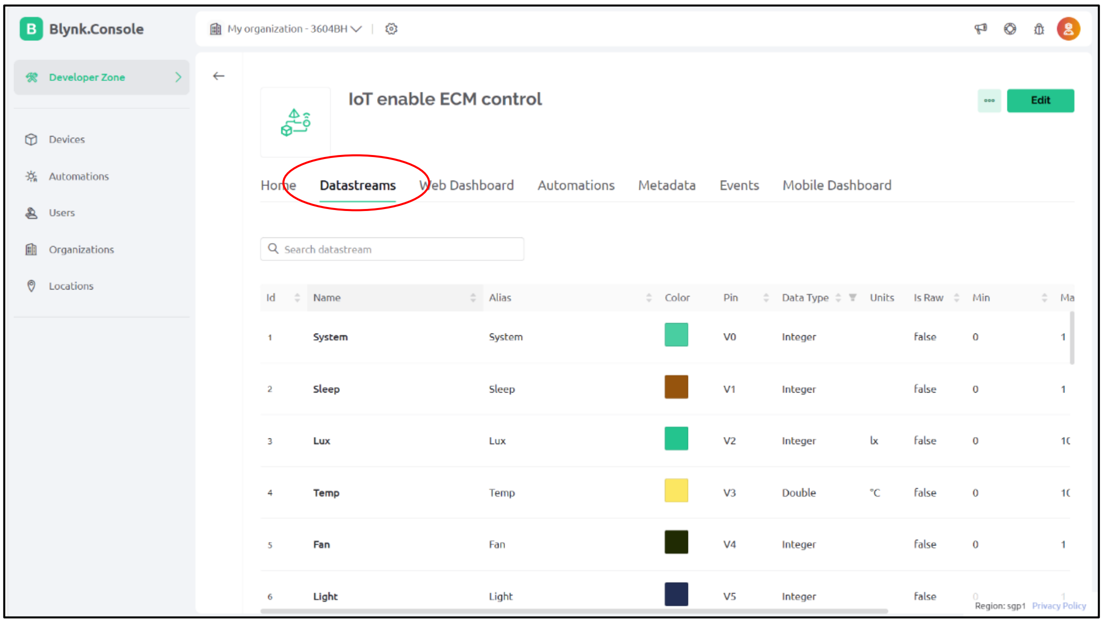

Figure 3.21: Datastreams section in Blynk Console

In the final step, users can personalize their mobile app in Blynk's "Applications" section. Here, they can adjust the application look and functionality by adding and modifying GUI, defining the interface design and theme. Widgets are linked to previously generated virtual pins to connect the app with the hardware. Once the app settings are saved, the device is set to initiate the project, allowing the Blynk app to access and control the system.

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3.5.2.2.2 ThingSpeak

ThingSpeak is an IoT platform that allows user to collect and analyse data from any devices. In this project, this platform is used to collect environmental data, manual and auto data as well as collect the energy consumption data. To get started, go to the ThingSpeak website as depicted in Figure 3.22 and sign up for a new account. This account will be used to manage the IoT projects and data of the system. Then, use the created username and password to access ThingSpeak after creating an account.

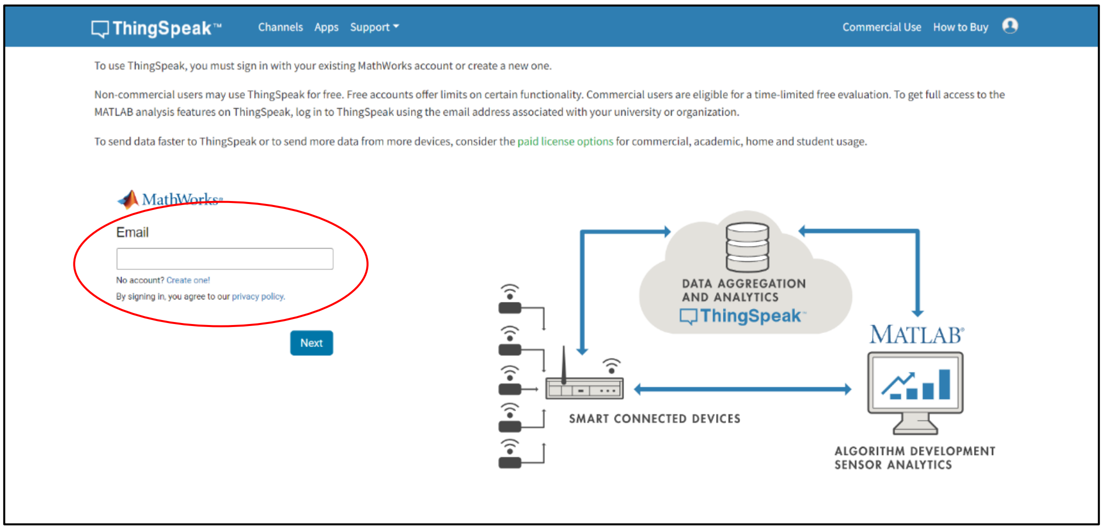

Figure 3.22: Log in page for ThingSpeak platform

Channels are where the device data is stored and organized. In the "Channels" tab, click on "My Channels" and then "New Channel" as shown in Figure 3.23. Provide a name, description, and indicate the number of fields based on the types of data that want to be collected. Each field can represent a different type of sensor data.

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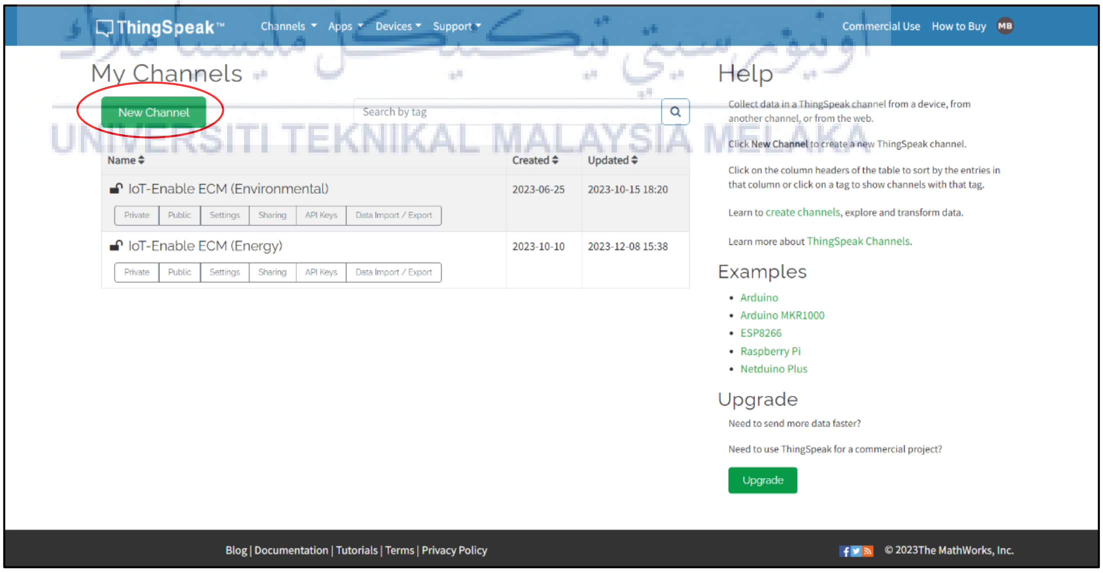

Figure 3.23: Channels in ThingSpeak

Next, open the Arduino IDE and ensure the ThingSpeak library is installed. This library simplifies the process of interacting with ThingSpeak. Import the library in the

Arduino sketch and define Wi-Fi credentials (SSID and password), as well as ThingSpeak channel information, including the Write API Key as shown in Figure 3.24. Use the given credentials to connect the ESP32 to WiFi in the setup() method. In the loop() function, read data from sensors and use the ThingSpeak library to send that data to the ThingSpeak channel.

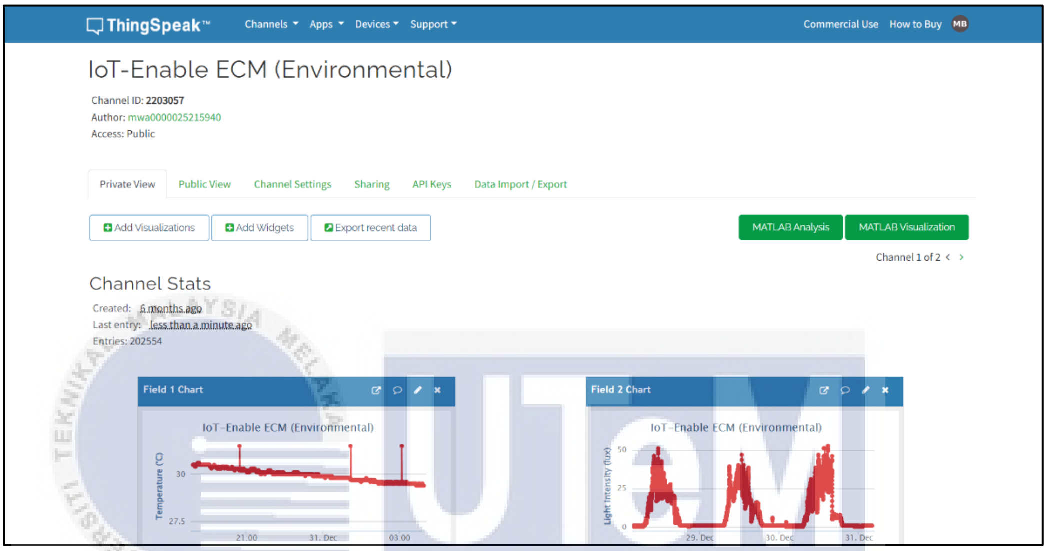

Figure 3.24: Channel created in ThingSpeak

Once data is entering the ThingSpeak channel, observe it on the ThingSpeak website. Open the channel and select the "Apps" option. Here, add visualizations and widgets to represent data in different formats. These visualizations provide a way to easily interpret the information sent by the ESP32 in Arduino IDE. Upon receipt of data from the ESP32, observe and evaluate it in real time on the ThingSpeak website. This includes checking the raw data, visualizations, and any widgets added. Therefore, ThingSpeak provides a user-friendly interface for monitoring and understanding the information collected by the IoT project.

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3.5.2.2.3 MATLAB

As for the MATLAB software, the process forecasting begins by installing MATLAB on the computer or laptop. The installation instructions are provided by MATLAB to ease user to do the installation procedure. Then, the process continues by opening MATLAB and create a new Live Script as shown in Figure 3.25. Live Scripts allow user to combine code, text, and visualizations in a single interactive document.

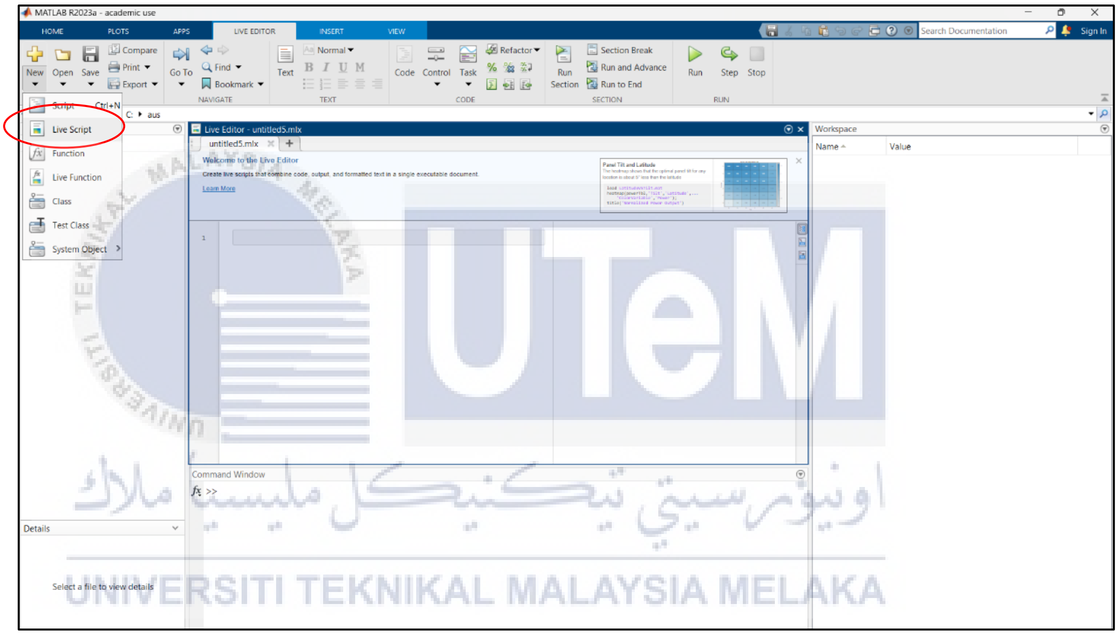

Figure 3.25: Live Script function at the Toolbar

In the Live Script, use the "apps" command to open the Neural Net Time Series app as depicted in Figure 3.26. This app provides a graphical user interface for designing and training neural networks for time series data.

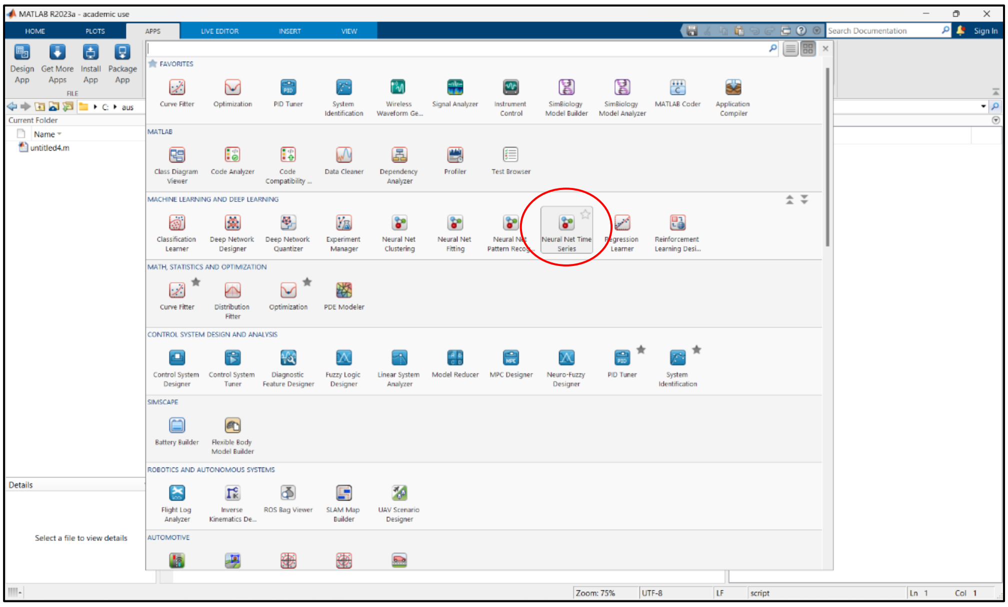

Figure 3.26: Neural Net Time Series app

Then, select network type. Within the Neural Net Time Series app, choose the NARX network type. Figure 3.27 shows the NARX networks that are suitable for modelling time series data with exogenous inputs. In this system, NARX are used to forecast energy consumption using environmental data.

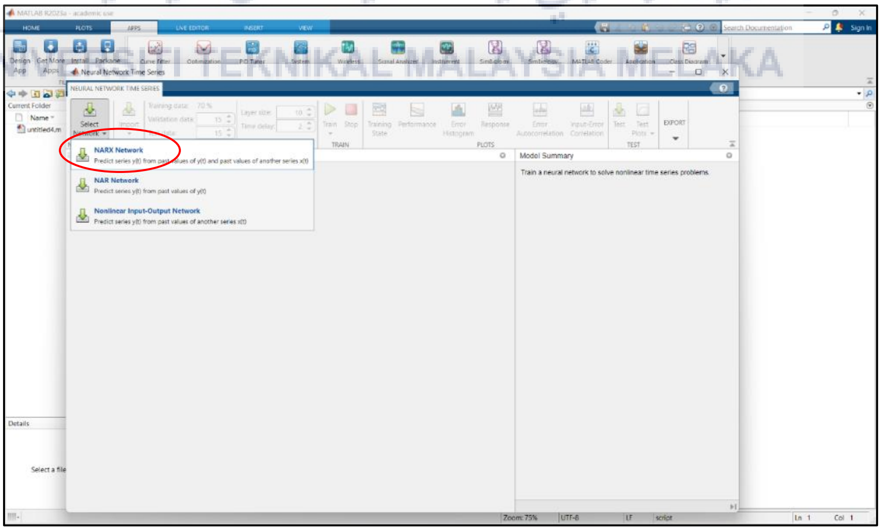

Figure 3.27: NARX network type

After that, use the "import data" as shown in Figure 3.28 functionality to bring in the time series data. In this case, it will show the environmental data as predictors and energy consumption data as the response variable.

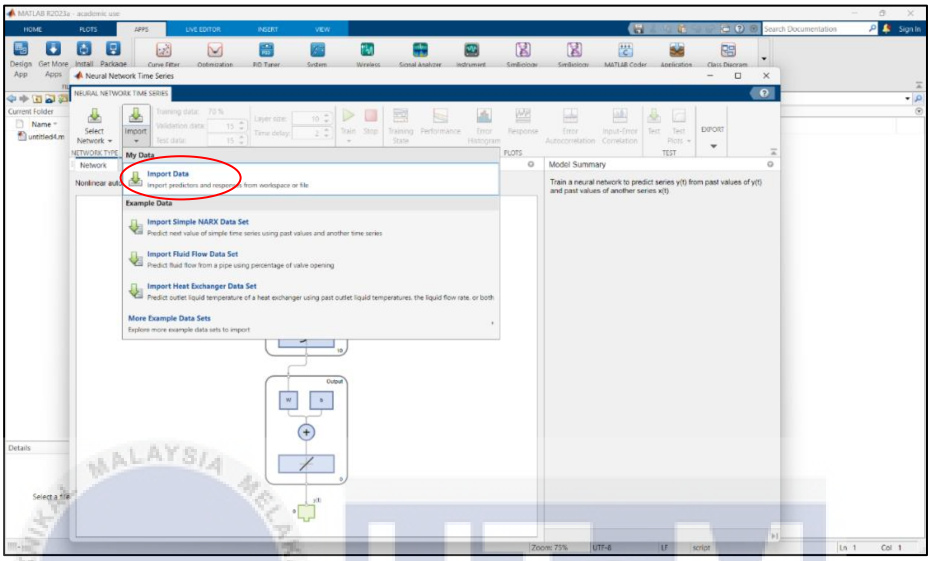

Figure 3.28: Import data function for NARX network type

The predictors and response need to be set up by specify the predictors and the response variable as depicted in Figure 3.29.

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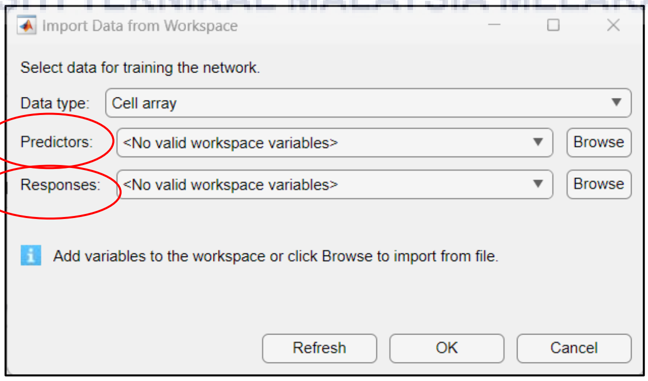

Figure 3.29: Specify the Predictors and Responses for NARX network type

The next step is to determine the NARX network's architecture, specifying the hidden layers and neurons. Select the Levenberg-Marquardt algorithm for efficient training, as illustrated in Figure 3.30.

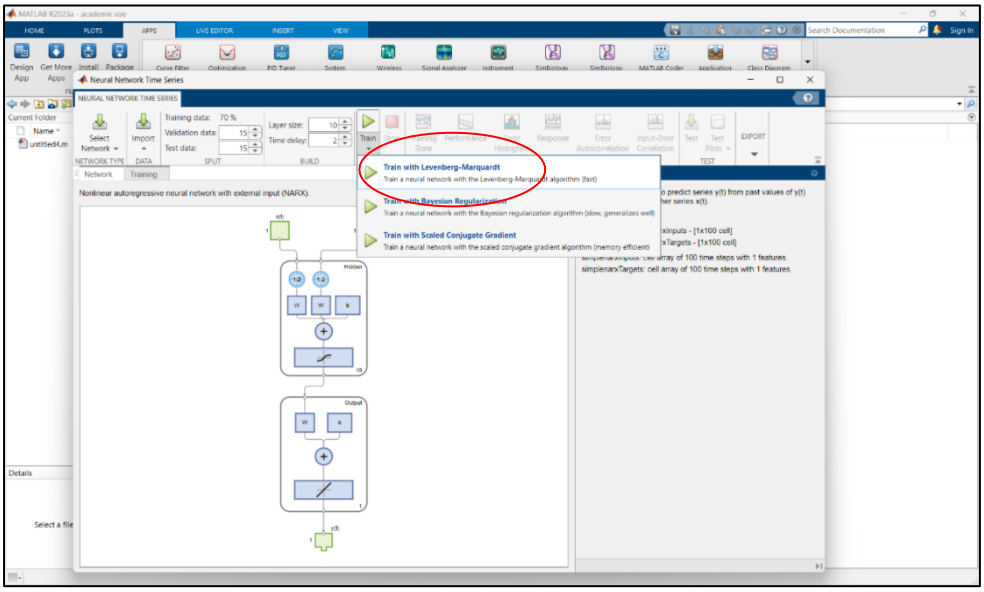

Figure 3.30: Levenberg-Marquardt optimization algorithm

After obtaining a satisfactory model, use the app to generate MATLAB code that represents the configured neural network and training process. Export the generated code to use it in other MATLAB scripts or applications as shown in Figure 3.31.

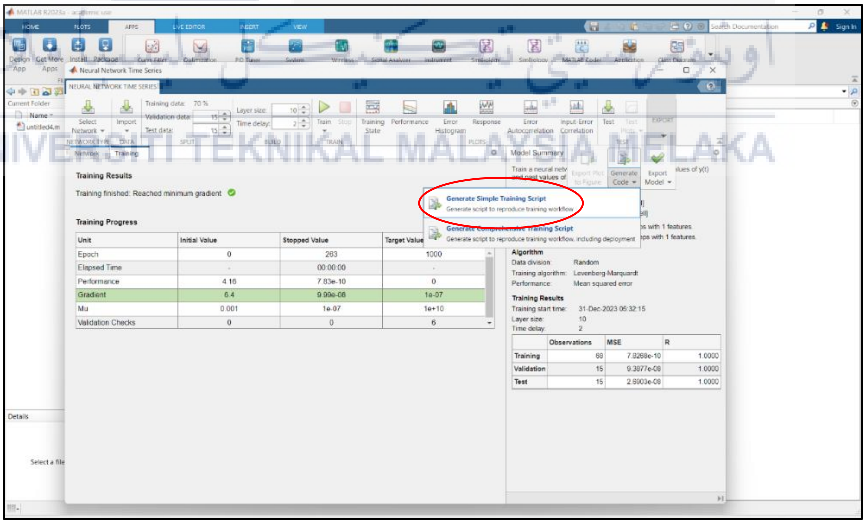

Figure 3.31: Generate simple training script function

Last but not least, execute the modified script to train the NARX network using the data obtained from ThingSpeak to train the new model. Figure 3.32 shows the generated code for training NARX network.

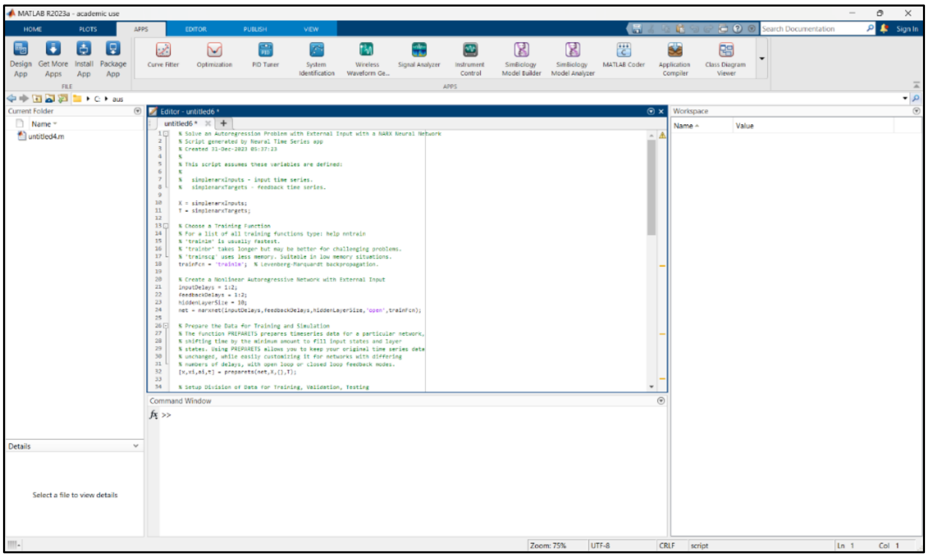

Figure 3.32: Generated code to train NARX network

In summary, installing the software, building a NARX neural network using the Neural Net Time Series app, importing and configuring data, training the model using the Levenberg-Marquardt algorithm, and iteratively improving the model's performance are the steps involved in time series forecasting in MATLAB.

3.5.2.3 Hardware and Software Integration

As previously mentioned, the project involved developing hardware and software independently. Right now, their integration is the main concern. First, hardware components are connected to the ESP32 microcontroller. This involves wiring sensors to collect data on energy and the environment. Software was created in the Arduino IDE to read, process, and become prepared for the communication of this data.

For integration with the Blynk server, a Blynk account was created. The Blynk "virtualWrite" command is used to send environmental and energy data to the Blynk app. This step involves assigning virtual pins in the Blynk project to display the data. A loop structure in the code continuously updates the Blynk app with new sensor readings.

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Additionally, the ESP32 was able to send data to ThingSpeak by configuring the ThingSpeak platform by including the WRITE API Key and channel ID into the code. Environmental and energy data were initially managed by different devices, which resulted in several dashboards and channels on ThingSpeak and Blynk. ThingSpeak data is also used by MATLAB for forecasting and analysis. To sum up, a two-way communication among the hardware, IoT platforms, and data analysis tools is essential to the system's completeness.

3.6 Project Parameter of Analysis

This project consists of two analyses, which include the comparison of manual and automatic appliances' energy consumption and forecasting performance evaluation. Both analyses began with collecting historical data on appliance mode, environmental, and energy consumption data to get a thorough insight into the performance and efficiency of the system.

3.6.1 Comparison of Manual and Automatic Appliances Energy Consumption

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The energy consumption of manual and automatic appliances was compared and analysed using one-month data obtained from ThingSpeak. Examining and contrasting the incremental energy usage trends of manual and automated appliances was part of the comparison. The dataset from ThingSpeak provided insights into how these two types of appliances performed over the course of a month.

Through close examination of the data, any significant distinctions, or patterns in the energy consumption between the manual and automatic modes of operation might be found. The information provided by this comparison research is helpful in comprehending the effectiveness and resource management of both automatic and manual appliances.

3.6.2 Forecasting Performance Evaluation

As for neural network model performance, three plots will be the evaluation reference which is a performance plot related to Mean Square Error (MSE) for training, validation, and testing dataset, regression plot, which consist of training, validation, testing, and combination of all dataset plot, and generalisation performance of open-loop model (One-Step Ahead Prediction).

The analysis parameter for the performance plot will be the convergence, overfitting, and underfitting that will be visualised through the plot. As for the regression plot, linearity, deviation, data consistency, data distribution, outliers, and R-value of the data plot in the regression line will be the parameters to be analysed in the regression plot analysis. Finally, the NARX open-loop model will be analysed based on the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) between both Actual and Predicted data plot.

3.7 Chapter Summary

In summary, the project implementation technique has been described. The project and the system flowchart are described in a whole, together with the components selected to develop this system. The hardware and software integration were thoroughly described. In addition, a detailed explanation of the analysis parameter is provided in relation to the analysis approach.

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CHAPTER 4

RESULTS AND DISCUSSION

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4.1 Chapter Introduction

This section evaluates the outcomes of the previously proposed system, integrating control, monitoring, and prediction on two devices. One device manages appliances and environmental data, while the other tracks energy use. Historical data aids in forecasting. Additionally, the chapter covers essential programming configurations, assesses forecast accuracy, and compares manual and automatic mode usage.

4.2 Hardware Implementation

This topic will show the results of hardware integration with the sensor and relay, and the development of proper prototype for the data collection process. The subsection below shows all of the hardware implementation result.

4.2.1 Distribution Box

Figure 4.1 shows a distribution box for the proposed system, housing both devices' connections. It includes the First Device ESP32 connected to a Relay, and the Second Device ESP32 linked to an Energy Consumption Sensor. A SCT-013 Bridge Circuit regulates current to the sensor from the ESP32.

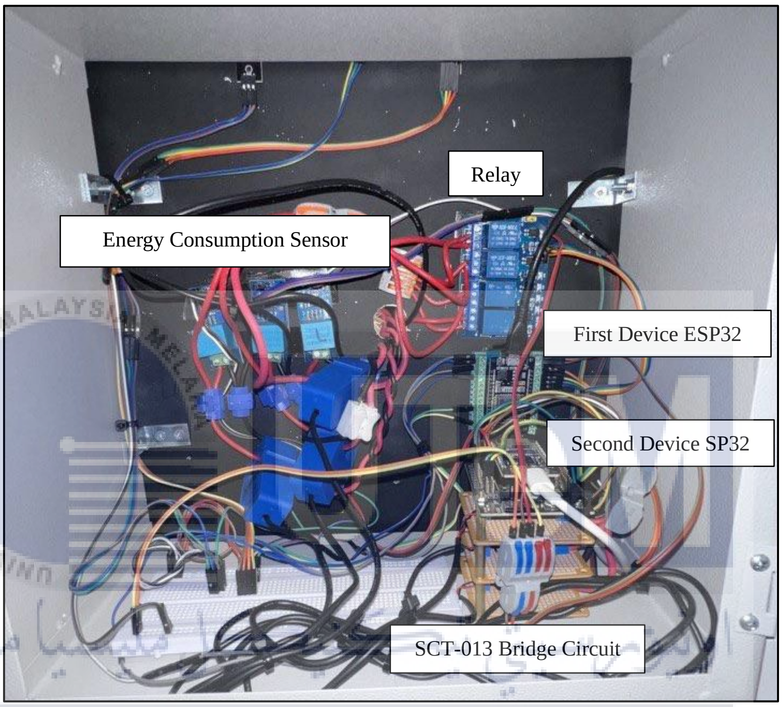

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Figure 4.1: Circuit Connection in Distribution Box

Next, Figure 4.2 shows the sensor placement on top of the distribution box. All environmental sensors are placed on a surface open to the environment to capture efficient data. The environmental sensor in the figure below consists of a DHT22 temperature sensor, a PIR motion sensor, and a BH1750 light intensity sensor. All of these sensors connected to the First Device ESP32.

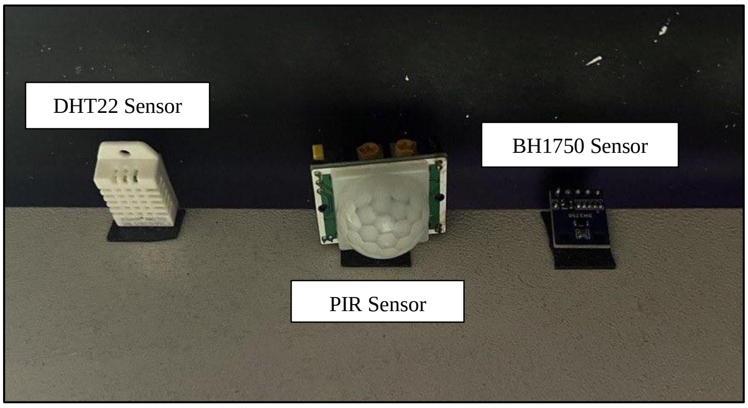

Figure 4.2: Sensor Placement on Top of the Distribution Box

4.2.2 Prototype Development

As for the data collection and experiment of this proposed system, the prototype design has been developed to make it easier to use daily. The setup shown in Figure 4.3.

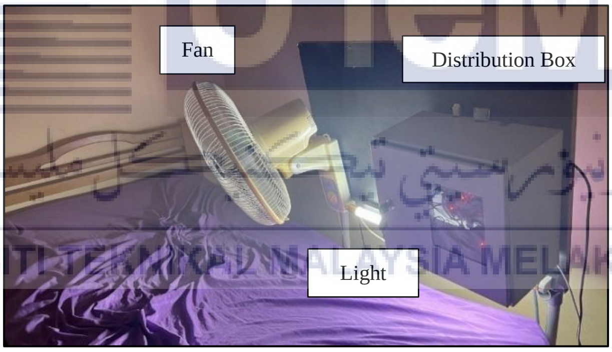

Figure 4.3: Prototype Set Up

4.3 Software Implementation

As for the software implementation, there are variation of software and platform that used in this project such as Arduino IDE to setup device hardware, Blynk for appliances controlling and environmental monitoring, ThingSpeak for monitoring and saving historical data, and MATLAB to forecast energy consumption. In below subtopic, each software and platform configuration code and Graphical User Interface (GUI) layout page will be display and discussed.

4.3.1 Blynk Platform

Figures 4.4 and 4.5 display GUI layouts for two Blynk Platform devices. Figure 4.4 reveals a device handling appliances and environmental monitoring. It features a switch for mode selection, an icon button for appliance states, temperature, and lux intensity monitoring using labeled value widgets, and a WebPage Image Button for ThingSpeak access.

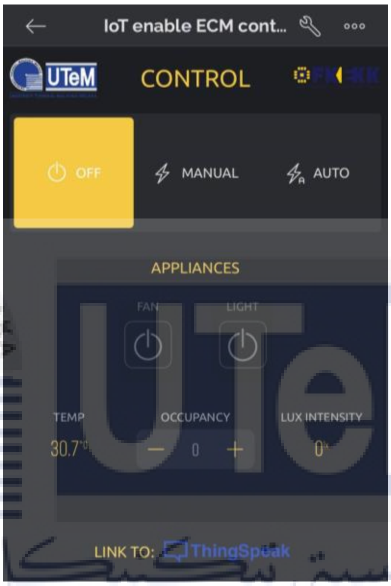

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Figure 4.4: First Device Blynk GUI Layout

As for second device which is for energy consumption monitoring, Blynk GUI layout for it shows in Figure 4.5. This device GUI consists of Gauge widget for energy consumption display, Labeled Value widget to display Vrms, Irms and Apparent Power, and LED to display the appliances state. User also can go to the ThingSpeak channel for this device by clicking the WebPage Image Button in this layout.

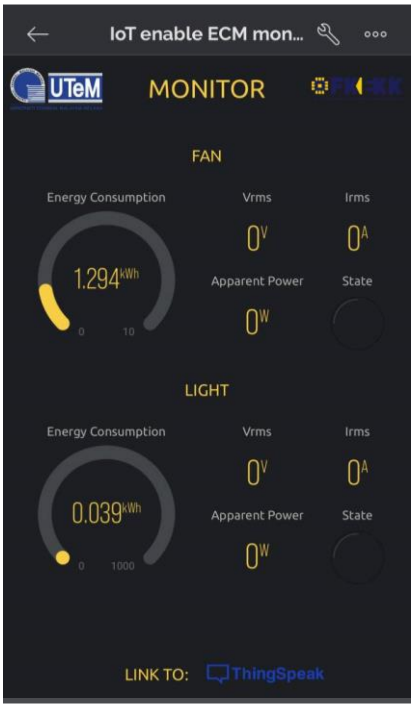

Figure 4.5: Second Device Blynk GUI Layout

4.3.2 ThingSpeak Platform

In the ThingSpeak implementation, two distinct channels were developed for the two previously discussed devices. Figure 4.6 displays environmental data and control mode monitoring for the first device, while Figure 4.7 shows energy consumption monitoring for the second device. Figure 4.6 presents temperature and lux intensity data in the first two fields, along with manual and auto control modes in the third and fourth fields.

Figure 4.6: Environmental and Controlling Monitoring Device ThingSpeak Private View

Figure 4.7 shows the API Keys for this channel. In order to write or read data for this channel, API Keys is required. Different channels will have different channel ID and API Keys. To read data from the channel, Read API Keys could be used. In contrast, Write API Keys could be used to write the data in the channel. As for MATLAB, it will use this API Keys to read the data to proceed the training neural network process.

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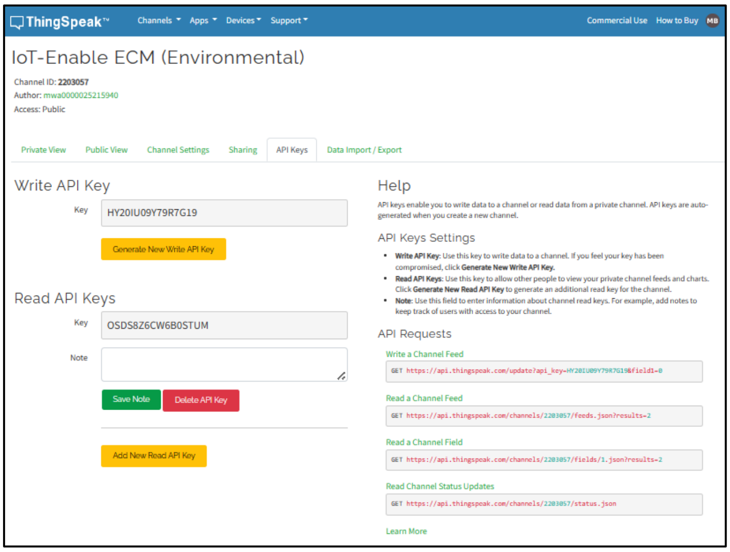

Figure 4.7: API Keys for Environmental and Controlling Monitoring Device ThingSpeak Channel

As for the energy consumption monitoring device ThingSpeak channel, it has four different field using the Numeric Display widget. First field was energy consumption (kWh) for fan, second field was fan apparent power (W), third field for light energy consumption (kWh), and fourth field for light apparent power (W).

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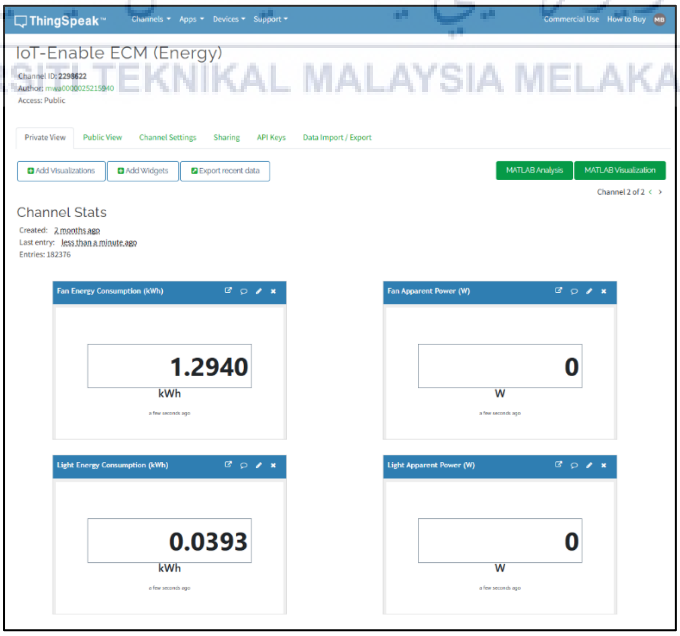

Figure 4.8: Energy Consumption Monitoring Device ThingSpeak Private View

As for API Keys for energy consumption monitoring devices, the function also same with the environmental device but has different value of API Keys. This is because both are from different channel.

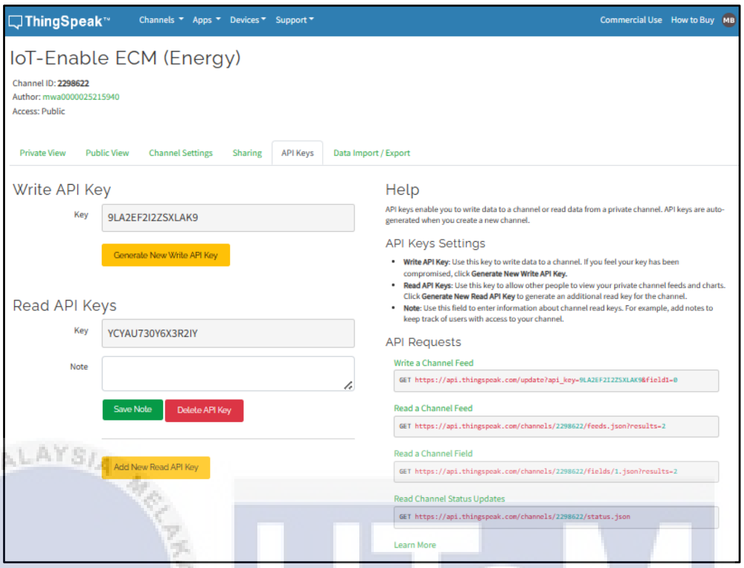

Figure 4.9: API Keys for Energy Consumption Monitoring Device ThingSpeak Channel

4.3.3 MATLAB Platform

In this project, MATLAB is used as an appliance's mode analysis, forecasting neural network model development and GUI development of forecasting application.

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Figure 4.10 shows a MATLAB app interface for energy forecasting, divided into "FAN" and "LIGHT" panels. Each panel has fields for inputting current conditions and energy consumption (kWh for the fan, lux for light). Users can get next-hour energy consumption predictions by pressing "FORECAST," with results displayed in each panel's designated field.

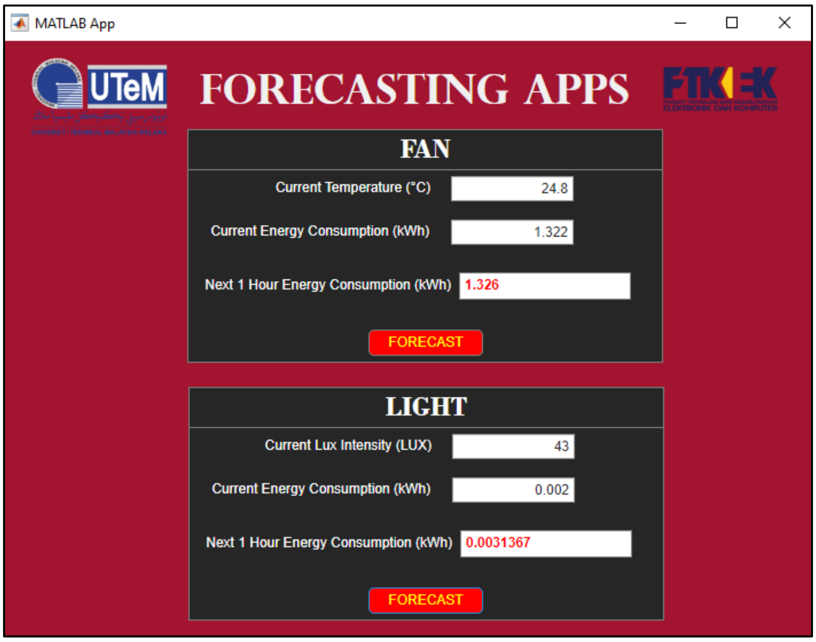

Figure 4.10: MATLAB App GUI for Forecasting

4.4 Analysis Result

The analysis involved using data collected from October 27, 2023, to November 27, 2023, spanning 30 days. For forecasting performance evaluation, testing data from December 2, 2023, to January 1, 2024, was used to compare with model predictions. The analysis included comparing manual and auto mode appliance energy consumption, as well as assessing the NARX open loop model's forecasting performance (One Step Ahead Prediction Model).

4.4.1 Comparison of Manual and Automatic Switching Energy Consumption

Table 4.1 outlines the operational conditions for an automated system controlling appliances for both fan and light based on sensor data. It indicates when the light and fan turn on or off based on temperature and light intensity with the presence of motion. This table specifies the behaviour of the automatic system and enables a direct comparison with energy usage under manual control, where user preference determines appliance states without sensor input. In manual mode, if virtual pin HIGH than appliances will turn on, in contrast when virtual pin LOW, then appliances will turn off. It is crucial to compare the energy consumption analysis of manual and automatic switching.

Table 4.1: Automatic Appliances Mode Operation Table

Sensor	Threshold	PIR Motion State	Fan State	Light State
DHT22 Temperature Sensor	A < 27 °C	0	0	[redacted]
	A < 27 °C	1	0	[redacted]
	A > 27 °C	0	0	[redacted]
	A > 27 °C	1	1	[redacted]
BH1750 Lux Sensor	B < 10 lux	0	[redacted]	0
	B < 10 lux	1	[redacted]	1
	B > 10 lux	0	[redacted]	0
	B > 10 lux	1	[redacted]	0

As for Figure 4.11, the graph indicates the comparison of incremental energy consumption by both manual and auto mode. As for manual mode, the incremental of energy consumption is 1.8862 kWh whereas the auto mode is 0.16884 kWh. Therefore, the increase in incremental energy consumption for manual mode shows that more energy is wasted. Therefore, the analysis shown that the auto mode is more energy efficient compared to the manual mode.

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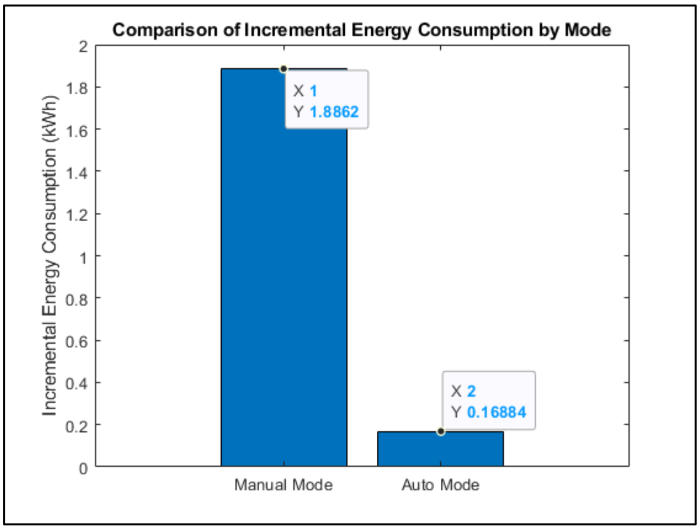

Figure 4.11: Incremental of Energy Consumption Comparison Between Manual Mode and Auto Mode

4.4.2 Forecasting Performance

The analysis of forecasting performance begins with the NARX open loop model (Figure 4.12), which appears after training. This figure illustrates the interconnection of exogenous input (x(t)) and target (y(t)) before the hidden layer, followed by the one-step-ahead output (y(t+1)). In this setup, past target values (y(t-1)) are used during training. For predictions, the input is updated with current energy consumption and environmental data, generating one-step-ahead energy consumption. This process can continue for the desired time steps.

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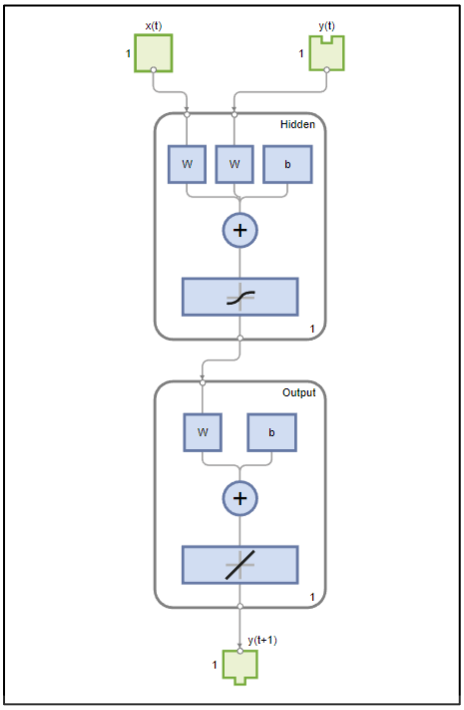

Figure 4.12: NARX Open Loop Model

4.4.2.1 Performance Plot Analysis

In artificial neural network, performance plot analysis is needed to determine the model robustness and training progress evaluation in term of Mean Squared Error (MSE) with the number of epochs. In the performance plot shows in Figure 4.13 and Figure 4.14, the plot consists of Train (blue), Validation (green), Test (red) and Best (dotted line) plot. Train plot will give the information of the MSE for the training dataset across epochs. The MSE of training plot normally decreasing indicating that the model is learning from the training data. But it needs to prevent from being too low because it leads to overfitting. As for Validation plot, it represents how well the model generate the unseen data. Validation MSE should decrease along with training MSE. It considers overfitting if validation MSE increasing while training MSE decreasing. As for test plot, it will indicate to the performance of model to the unseen data. The dotted line with circle is the plot named best which indicates to the point which has best performance on validation set. On this analysis it looks into the convergence, overfitting and underfitting performance.

As for convergence, it is the term used to describe the point at which a model's performance stop improving. Convergence considers late if the best validation performance occurs at near 1000 epoch. Next, overfitting is when a model learns the training set too well until it learns data noise and outliers. Underfitting occurs where a model performs poorly on both training and validation datasets because a model is too simple to capture the underlying trend in the data.

As for Figure 4.13, MSE for three plot is decreasing and stabilizing starting from epochs 8 until 14 and the best validation performance is marked at epoch 8. This is a sign of early convergence. As for the overfitting analysis, train MSE is not significantly lower and the validation plot not increasing while training, so the model does not consider overfitting. Finally, all three-plot decreasing and not in high value demonstrates that the model not underfitting. So, the model for Figure 4.13 is learning effectively during the training process, there is no significant sign of overfitting or underfitting.

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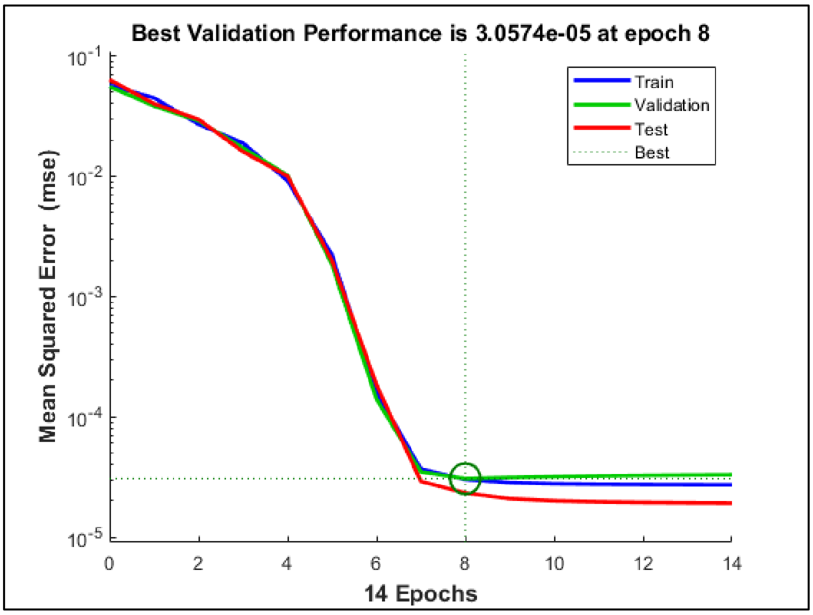

Figure 4.13: Fan Neural Network Performance Plot

Figure 4.14 which is the model performance for light energy consumption forecasting still shows a sign of early convergence because around epochs 20 until 25 the train and validation plot stable and all three plot is decreasing, and the best validation performance is at epoch 36. By referring to training, validation, and test MSE, training MSE is lower than the validation and testing MSE but it just a small range between it and all the plot at low MSE. Therefore, the So, it is no sign of overfitting and underfitting are not shown.

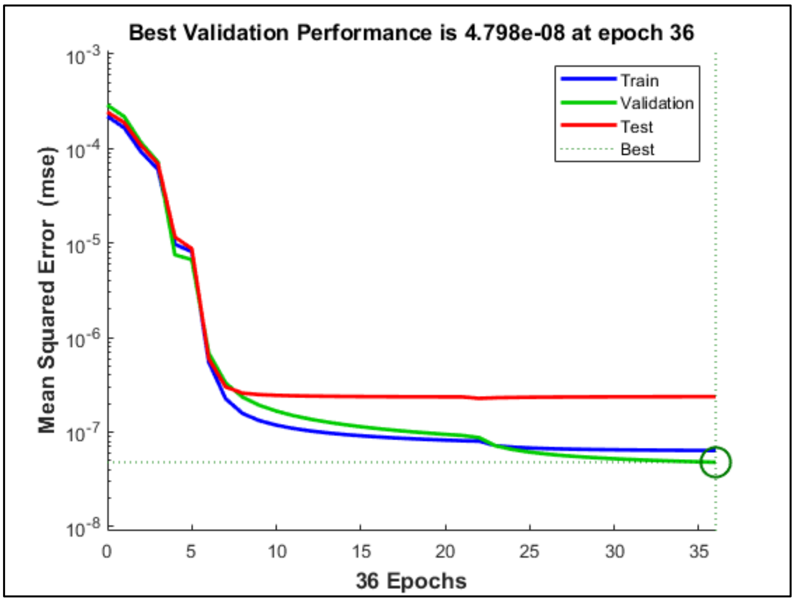

Figure 4.14: Light Neural Network Performance Plot

In conclusion, each model demonstrates good convergence without a sign of overfitting and underfitting, as indicated by the MSE trends and the best validation performance epochs.

4.4.2.2 Regression Plot Analysis

From Figure 4.15 and Figure 4.16, it illustrates the fan and light neural network model regression plot that consists of four components. As for training data regression, it compares the predicted outputs with the actual targets for the training data. In contrast, for validation data regression, it shows the relationship between the predicted outputs and actual targets in which the good fit on the validation data is important to verify that the model is not overfitting. Test data regression compares predictions with actual targets for the test data which is similar to validation plot. All data regression will altogether combine all the other three components. It gives the overall view of how well the model performs across all the data.

As for the analysis process, Figure 4.15 shows regression plots for the neural network model for the fan. The linearity is indicated by the closeness of data points to the fit line (Y=T), which, in this figure, shows a very high level of linearity. The low deviation of data points from the fit line shown in this figure indicates that this model has high prediction accuracy. All data points stay in the line of best fit, demonstrating the consistency of data points across training, validation, and test sets. The distribution of points is tight and linear, with no visible outliers. For every dataset, the correlation measurement (R-value) is near to 1, indicating an excellent prediction performance.

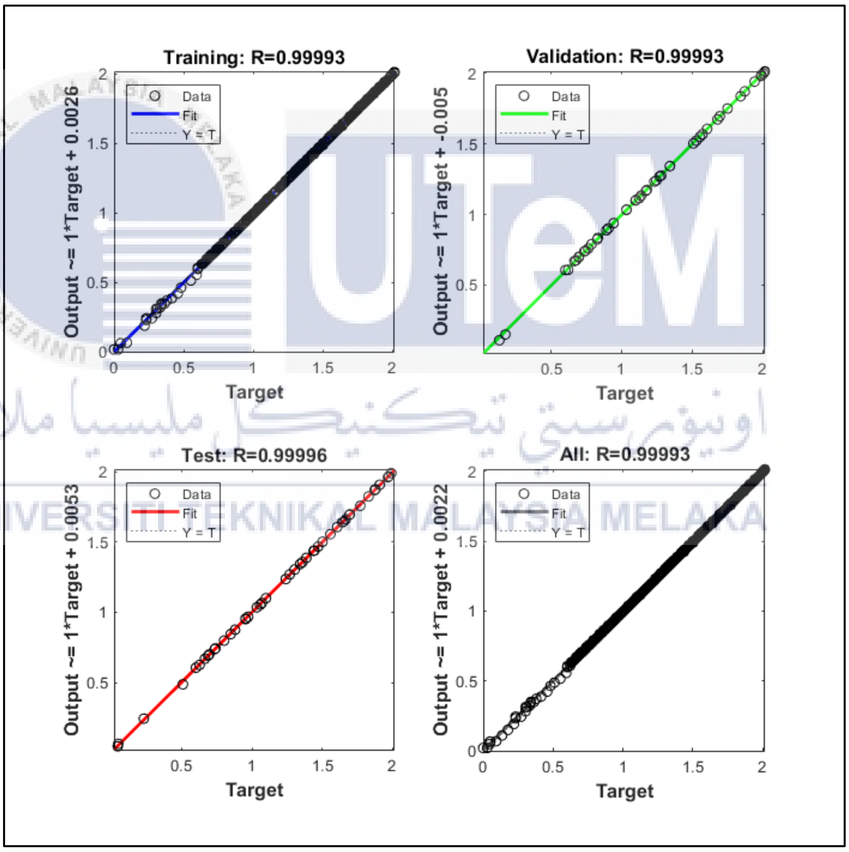

Figure 4.15: Fan Neural Network Model Regression

Regression graphs for a different neural network model (light) with a similar analysis are shown in Figure 4.16. The linearity of this figure is high because the points closely track the Y=T line. A slight deviation occurred in the test set, but it is minimal.

The consistency is maintained across each dataset, and the distribution of points shows a strong correlation without significant outliers. The model in this figure prediction output and actual values have an almost perfect correlation, as indicated by the R-values, which are very near to 1.

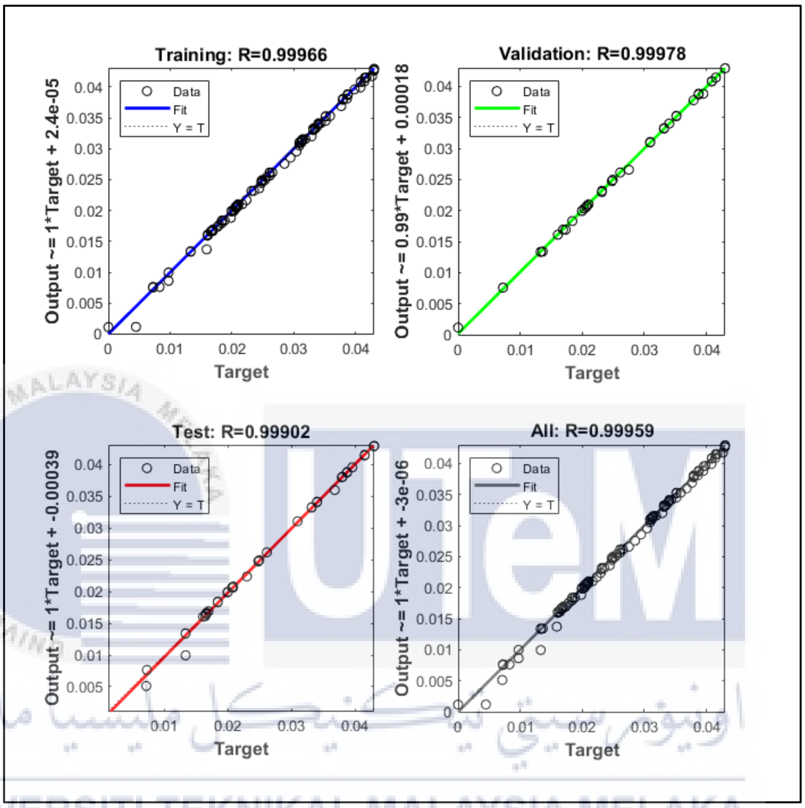

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Figure 4.16: Light Neural Network Model Regression

In conclusion, the models demonstrate excellent performance in predicting the target variable, as evidenced by their high linearity, low deviation, consistency of data points across different data sets, tight point distribution with free of outliers, and R-values nearing 1. The R-value that high in both figures also demonstrate how well the models have captured the actual input and target data relationship, leading to accurate predictions.

4.4.2.3 Model Testing

Figure 4.17 and Figure 4.18 shows the forecasting energy consumption for Fan and Light from the date 2nd December until 1st January. The plot shows the actual and predicted line which is blue and red line respectively. The Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are two metrics used to evaluate the performance of regression models.

Based on Figure 4.17, There are two markers indicating specific points on Jan01 at 14:00 (actual value) and Jan01 at 15:00 (predicted value), showing very close values between predicted (1.29518) and actual (1.29398) energy consumptions. The MAE = 0.0068978 kWh and RMSE = 0.0086227 kWh considered as low value in overall dataset error.

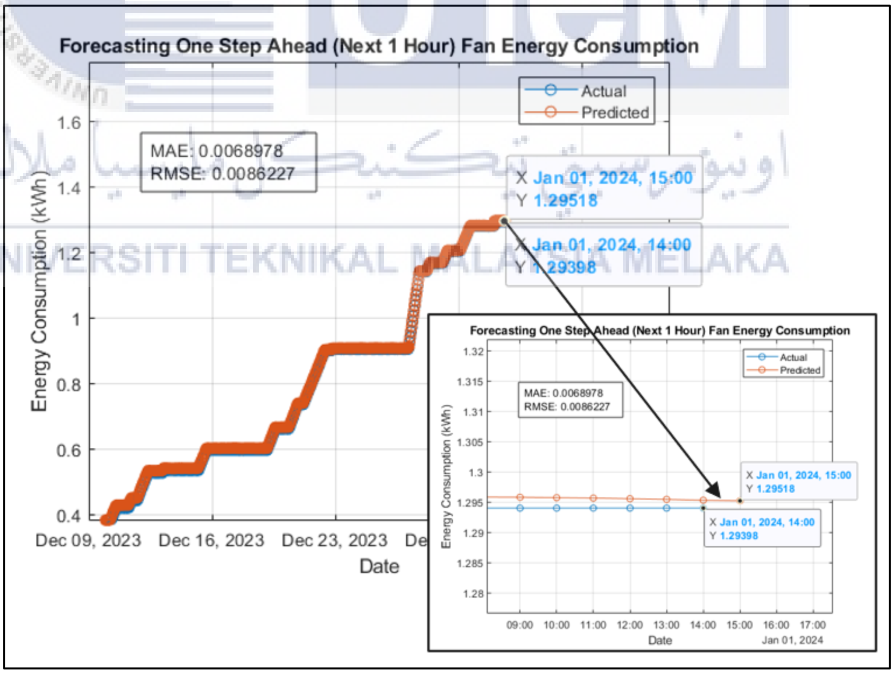

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Figure 4.17: Actual Energy Consumption vs Predicted Plot for Fan

As for Figure 4.18, it shows the forecasting energy consumption for light. From the observations, the value of MAE = 0 00021029 and RMSE = 0.00042346 that also consider as low value. Both MAE and RMSE in each figure suggests high accuracy in prediction because low MAE indicates the average prediction error is small and low RMSE shows that there is no significant error in the prediction.

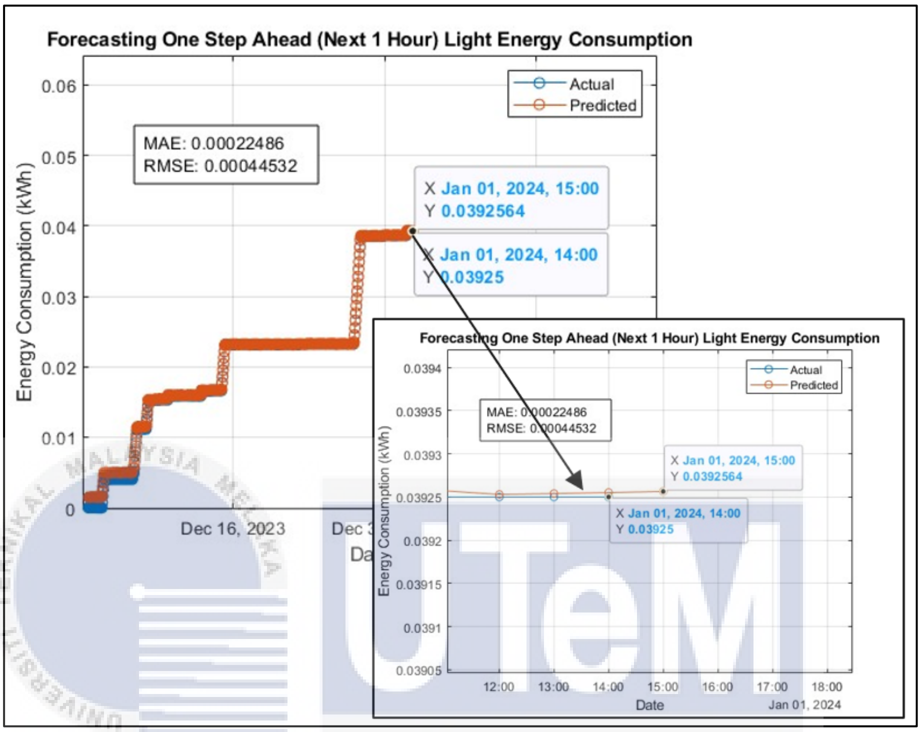

Figure 4.18: Actual Energy Consumption vs Predicted Plot for Light

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4.5 Chapter Summary

This chapter comprehensively covers the implementation of the recommended system, providing detailed discussions on the assembly and configuration of both the hardware and software components. It extensively delves into the system interfaces and functionalities, offering thorough explanations. Thus, this section presents the analysis results and forecasting performance evaluations for model that being used in this system. The project aligns with several sustainable development goals (SDGs) set by the World Health Organization (WHO), including SDG 7 which are Affordable and Clean Energy, by promoting the use of clean and renewable energy sources and optimizing energy consumption. Next, by using innovative technologies such as machine learning and automation, the project contributes to SDG 9 which are related to Industry, Innovation, and Infrastructure. Finally, by reducing greenhouse gas emissions and promoting sustainable living, the project contributes to SDG 13 which represent climate action.

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CHAPTER 5

CONCLUSION AND FUTURE WORKS

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5.1 Chapter Introduction

This section outlines the contributions the project will make to society and ends with a summary of the project's goals. It describes the difficulties and constraints that occurred throughout the project with the intention of offering solutions that might improve the system's functionality in future initiatives.

5.2 Project Achievement

The current system allows users to monitor energy consumption forecasting but lacks the capability for users to actively control or intervene based on the forecasted information. Without control capabilities, users may miss out on the opportunity to actively manage their energy consumption based on forecasted data. For instance, if the forecast predicts a spike in energy usage, users might want the option to adjust settings or schedules to mitigate potential issues. Thus, the solution is to integrate features that allow users to take proactive actions based on forecasted data. Enable users to set automated responses triggered by forecasted events. For example, if a high-energy consumption period is predicted, users could automate the temporary shutdown of non-essential appliances.

Next, the current system relies on stable Wi-Fi connections, potentially limiting its usability in urban areas where network stability can vary. Urban environments often have crowded Wi-Fi channels, leading to interference and signal fluctuations. This can result in intermittent connectivity issues for IoT devices dependent on a stable Wi-Fi connection. In urban areas, network downtimes due to maintenance, technical issues, or high usage may occur. This could disrupt the system's functionality and compromise real-time monitoring and control capabilities. As a solution, design the system to have limited functionality even in the absence of a stable Wi-Fi connection. Users should still be able to access basic functionalities and receive data updates when the connection is restored.

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5.3 Project Problem and Limitation

The current system allows users to monitor energy consumption forecasting but lacks the capability for users to actively control or intervene based on the forecasted information. Without control capabilities, users may miss out on the opportunity to actively manage their energy consumption based on forecasted data. For instance, if the forecast predicts a spike in energy usage, users might want the option to adjust settings or schedules to mitigate potential issues. Thus, the solution is to integrate features that allow users to take proactive actions based on forecasted data. Enable users to set automated responses triggered by forecasted events. For example, if a high-energy consumption period is predicted, users could automate the temporary shutdown of non-essential appliances.

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5.4 Future Work and Recommendations

Despite the project's success, there are areas for improvement and future development:

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1. User-friendly for forecasting – Improve user interface for energy forecasting by offering clear graphs, charts, and infographics for easy understanding of complex energy consumption patterns.

2. Develop a personalized software – Enable users to customise profiles with preferred temperature, light levels, energy goals, and app layout for personalised energy management.

3. Make all features in one device only – Create a central hub combining ESP32, sensors, and monitoring for fewer devices and improved system minimalist.

5.5 Conclusion

In a nutshell, experimental comparison reveals manual mode appliances have higher energy consumption in kWh compared to more efficient automatic mode. it encourages the use of automatic settings. This can lead to reduced energy bills for consumers and lower environmental impact due to decreased energy consumption. Next, successful in integration of Blynk in controlling appliances and monitoring environmental and energy data has enhanced efficiency, convenience, and informed decision-making, leading to energy savings and environmental sustainability. Finally, the development of the NARX model for one step-ahead energy consumption forecasting has a perfect prediction for the new data with the evidence of the deep insight into performance and regression plot analysis.

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