Internet of Things (IoT) based Adaptive Energy Management System for Smart Homes

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Abstract

Internet of things enhances the flexibility of measurements under different environments, the development of advanced wireless sensors and communication networks on the smart grid infrastructure would be essential for energy efficiency systems. It makes deployment of a smart home concept easy and realistic. The smart home concept allows residents to control, monitor and manage their energy consumption with minimal wastage. The scheduling of energy usage enables forecasting techniques to be essential for smart homes. This thesis presents a self-learning home management system based on machine learning techniques and energy management system for smart homes.

Home energy management system, demand side management system, supply side management system, and power notification system are the major components of the proposed self-learning home management system. The proposed system has various functions including price forecasting, price clustering, power forecasting alert, power consumption alert, and smart energy theft system to enhance the capabilities of the self-learning home management system. These functions were developed and implemented through the use of computational and machine learning technologies. In order to validate the proposed system, real-time power consumption data were collected from a Singapore smart home and a realistic experimental case study was carried out. The case study had proven that the developed system performing well and increased energy awareness to the residents. This proposed system also showcases its customizable ability according to different types of environments as compared to traditional smart home models.

Forecasting systems for the electricity market generation have become one of the foremost research topics in the power industry. It is essential to have a forecasting system that can accurately predict electricity generation for planning and operation in the electricity market. This thesis also proposed a novel system called multi prediction system and it is developed based on long short term memory and gated recurrent unit models. This proposed system is able to predict the electricity market generation with high accuracy.

Multi Prediction System is based on four stages which include a data collecting and pre-processing module, a multi-input feature model, multi forecast model and mean absolute percentage error. The data collecting and pre-processing module preprocess the real-time data using a window method. Multi-input feature model uses single input feeding method, double input feeding method and multiple feeding method for features input to the multi forecast model. Multi forecast model integrates long short term memory and gated recurrent unit variations such as regression model, regression with time steps model, memory between batches model and stacked model to predict the future generation of electricity. The mean absolute percentage error calculation was utilized to evaluate the accuracy of the prediction. The proposed system achieved high accuracy results to demonstrate its performance.

Table of Contents

Nomenclature

Acronyms / Abbreviations

AA Application Agents

AC Air Conditioner

ACL Agent Communication Language

AI Artificial Intelligence

AMI Advanced Metering Infrastructure

AMS Agent Management Service

ANN Artificial Neural Network

APE Absolute Percentage Error

ARIMA Auto Regressive Integrated Moving Average

BH Bathroom Heater

BI Business Intelligence

BS Battery Storage

CMA Control and Monitoring Agent

CR	Continuous Relaxation
DAQ	National Instruments Data Acquisition
DC	Desktop Computer
DCM	Data Collection Module
DF	Directory Facilitator
DIFM	Double Input Feeding Method
DSM	Demand Side Management
ED	Economic Dispatch
EDP	Electric Dispensing Pot
EMC	Energy Market Company
EMS	Energy Management System
EV	Electric Vehicles
F	Fridge
FIPA	Foundation for Intelligent Physical Agents
FLC	Fuzzy Logic Controller
FRTU	Feeder Remote Terminal Unit
GRU	Gated Recurrent Unit
HD	House Demand
HDB	Housing and Development Board

$HEMS$ Home Energy Management System

IA Information Agent

IB Incandescent Bulbs

ICT Information & Communications Technology

IoT Internet of Things

IR Iron

$LSTM$ Long Short Term Memory

LT Laptop

$MAPE$ Mean Absolute Percentage Error

MAS Multi-Agent System

$MBBM$ Memory Between Batches Model

MFM Multiple Feeding Method

MG Main Grid

$MILP$ Mixed Integer Linear Programming

MLP Multi-Layer Perceptron

$NSGA-II$ Non-Dominated Sorting Genetic Algorithm-II

OA Optimization Agent

PC Price Clustering

PCA Power Consumption Alert

PCA Principal Component Analysis

PF Price Forecasting

PFA Power Forecasting Alert

PNS Power Notification System

POMDP Partially Observable Markov-Decision Process

PV PhotoVoltaics

QoE Quality of Experience

RC Rice Cooker

RE Renewable Energy

RES Renewable Energy System

RM Regression Model

RMSE Root Mean Squared Error

RNN Recurrent Neural Network

RTSM Regression with Time Steps Model

S Speaker

SCADA Supervisory Control and Data Acquisition

SD Smart Devices

SETS Smart Energy Theft System

SF Standing Fan

SHMS	Self-learning Home Management System
SIFM	Single Input Feeding Method
SM	Stacked Model
SMA	Simple Moving Average
SP	Singapore Power
SSM	Supply Side Management
SVM	Support Vector Machine
TF	Tower Fan
TLWM	Top Loading Washing Machine
TV	LED Television
UC	Unit Commitment
VC	Vacuum Cleaner
WTGs	Wind turbine Generators

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Overview

In modern days, electricity is one of the most important sources of energy as it is used to power electronic devices like mobile phones, computers, and light bulbs. As electricity is mostly generated by burning fossil fuels, the increasing electrical consumption exacerbates environmental problems such as climate change and global warming. By optimizing the distribution and usage of electricity, it could prevent the worsening of existing environmental issues.

The three main processes of the power industry are generation, transmission, and distribution. Power generation is often done within a power plant in order to supply the power grid with electricity [1]. Transmission of electricity describes a process whereby electricity is either step-down from a high voltage to a lower voltage or vice versa when it is passed through a substation. Finally, the electricity is then distributed to end-users such as industrial, commercial, and residential consumers. This whole process makes up the electrical power grid [2]. Currently, the electrical power grid is evolving into an innovative upgrade named "Smart Grid".

Smart grid plays an important role in delivering electricity from suppliers to industrial commercial, and residential sectors in a reliable, efficient, and secure manner [3]. It represents an innovative delivery method from supply to demand by using the power grid system. One of its biggest strength is the two-way communication that leads to better reliability and energy efficiency [4]. Other capabilities include sensing grid situation, power monitoring, control and management of electricity generations, transmission and distribution in the power grid [5].

Another benefit of the smart grid is the integration of renewable energy from sources like solar, wind, tidal, and wave energy [6]. These energy integrations have become essential due to environmental protection, energy conservation, and emission reduction for a "greener" environment [7]. The increased use of renewable sources requires major redevelopments for electrical systems for a stable, secure, and reliable operation in the grid. Upcoming technologies like the Internet of Things (IoT) enhances the flexibility of measurements in different environments. Thus, the development of advanced technologies to leverage on the smart grid infrastructure will be essential for energy efficient systems. In this thesis, two major parts of the project had been developed and implemented:

- Multi Prediction System
- Self-learning Home Management System (SHMS)

The motivations of the implemented systems are explained in the following sections.

1.1.1 Multi Prediction System

During the last few years, electricity generation forecasting has been a popular topic in the power industry due to the advancement of technology. The role of electricity generation forecasting facilitates the operations of the power generation companies, electricity market, and contestable consumer. Hence, electricity forecasting plays a crucial role in the power market as it is beneficial to economical and operational activities.

Electricity forecasting has attracted different fields of prediction tools such as statistics and deep learning machines. These methods focus on relevant data features to forecast electricity price or demand within a time frame [8]. Current trends mainly focus on forecasting electricity prices. Companies are particularly interested due to economical reasons. To provide for the end consumer's needs, the forecast of electricity generation plays a fundamental role in determining the electricity demand [9, 10]. Thus, the ability to forecast electricity generation is essentially beneficial to power supply companies. These companies will be able to plan more efficiently without sacrificing additional productivity for excessive preparations [11, 12].

Forecasting electricity generations have reached a significant improvement in performance due to the restructuring of industries. Forecasting approaches [13, 14] such as Auto Regressive Integrated Moving Average (ARIMA), regression analysis, fuzzy logic, genetic algorithm, and Artificial Neural Network (ANN), the most popular option, which backpropagation neural network was commonly used for electricity forecasting [15, 16]. In recent times, Recurrent Neural Network (RNN) was used as one of the forecasting tools for the electricity market. However, a variation of RNN such as Long Short Term Memory (LSTM) has yet to be widely used for electricity generation prediction [17].

This project proposes a novel idea of Multi Prediction System for Electricity Generation Forecast. This forecasting system is more accurate compared to previous methods. As the electricity generation information in the electricity market is time series data, various advantageous predictive LSTM and GRU models such as Regression Model (RM), Regression with Time Steps Model (RTSM), Memory Between Batches Model (MBBM), and Stacked Model (SM) were utilised for more accurate predictions. Compared to most forecasting approaches in time series electricity data, its ability to retain relevant information and link it with the latest data point proves to be beneficial. The simulations of Multi-Layer Perceptron (MLP), standard RNN, standard LSTM, standard GRU, and Multi Prediction System were benchmarked against each other to find the highest accuracy system based on Mean Absolute Percentage Error (MAPE).

1.1.2 Self-learning Home Management System (SHMS)

In recent years, the Internet of Things (IoT) has been widely recognised as an important component for smart homes [18]. It allows smart homes to monitor, control, and manage the house environment according to the home owner's lifestyle. Most research in smart homes focuses on the establishment of communication infrastructure, the speed of communication, data transmission reliability, cyber security, and enhanced hardware development [19–23]. It has also sparked the future research on IoT systems for next-generation smart homes [24]. Thus, Home Energy Management System (HEMS) in smart homes is emerging as a hot research topic in most countries [25].

Integrating Home Energy Management System (HEMS) into smart homes will help to achieve higher efficiency of distribution with sustainable energy. This system has a realistic design and is well-developed with the use of Information & Communications Technology (ICT)-enabled collaborative technical for smart homes in Singapore. Smart homes are a part of the smart grid fundamental concept of a modern electrical power grid that leads to a more reliable, efficient, and decentralised environment. This will increase the efficiency of electricity usage [26]. HEMS has often included supply and demand side management system to facilitate electricity distributions.

Supply Side Management (SSM) system manages the electricity supplies from different power sources in the energy management system. This process has been improved based on the type of supply as well as the infrastructure network for distribution. Another intelligent management system that manages energy demand in the electrical system is known as

Demand Side Management (DSM) system. DSM methods include load shifting, demand response, and demand scheduling [27]. By leveraging the electricity market "Peak" and "Off-Peak" hours, planning and operations became an important process for companies [28]. Due to lower rates for "Off-Peak" hours, many companies expenditure can be reduced by operating during these periods. However, it is still vulnerable to malicious behaviour such as energy theft.

Energy theft has been a rising issue for various countries around the world. Despite this, only a few preventive energy theft methods were created to combat the issue [29–31]. Zhou, Y. et al. proposed a dynamic programming algorithm for leveraging probabilistic detection of energy theft in the smart home [30]. This proposed method requires the deployment of Feeder Remote Terminal Unit (FRTU) on top of a smart meter which incurs high costs for consumers. Additionally, it works only under the assumption that a smart meter is available. Hence, a new energy theft system will enhance the security of energy transmission. However, these systems require a reliable communication network that can transmit information efficiently.

Several researchers [32–34] have shown that most industrial companies are interested in agents for various applications such as scheduling, resourcing, strategic planning, control, and real-time planning. One of the solutions provided by S. D. J. McArthur, et al., [35] was the implementation of Multi-Agent System (MAS) [36]. Integrating MAS into the smart home system allows for flexible modifications to the agent's behaviour when there are changes in the environment. MAS network management, control, parallel program design, and computer communication were well-known to be strong in an ununiformed environment such as in a smart home [37].

MAS is an intelligent agent-based communication system that has proven itself to be capable to be implemented in a smart grid. This system comprises multiple agents or intelligent agents to interact regardless of the environment. An agent is a hardware or software entity that can respond differently upon changes in an environment.

The implementation of MAS in HEMS for smart homes allows fast data transfer between agents for computational speed. It enables house owners to be aware of the amount of electricity used through smart meters and to configure the settings to their comfort. Supervisory Control and Data Acquisition (SCADA), with optimising functions, is often referred to as "advanced applications" that provides the monitoring and controlling functions. However, the self-learning algorithms of data usage were not mentioned in past studies for smart homes concept.

Machine learning is known to be a fascinating technique for smart homes [38]. Its functionality for self-decision making can be incorporated into smart home energy management systems. Machine learning uses data to learn behavioural patterns to offer optimised solutions [39]. The customised solution, accommodating to different environment and situation, offers HEMS to be a self-learning system.

This project proposes a novel smart home system called Self-learning Home Management System (SHMS). This model is proposed using a multi-agent system communication network. It includes rule-based classifier techniques in the supply and demand side management system with machine learning functions in HEMS.

1.2 Research Gap

Based on literature reviews from various papers, there are multiple research gaps that had been identified. For energy management system, multiple works only used the simple rule-based classifier and this works only when certain conditions are met. Thus, there is a need to develop a flexible energy management system. This can be solved by integrating machine learning into the energy management system to create a more adaptive system. As machine learning algorithms can self-learn and adjust to different situations. By using machine learning, energy distribution can be optimised based on the electricity market and end consumers' energy usage.

Another issue is the integration of renewable energy sources, various past works have not considered the constraints, notably the unpredictability of resources, of the renewable energy sources in the energy management system. Therefore, it is one of the important considerations in the system. Detecting energy theft is essential to prevent energy stealing. However, many energy management systems have not included this function in its systems. High accuracy forecasting system for electricity generation is required to plan and schedule the electricity usage. Lastly, a reliable and efficient industrial standard communications channel is needed to facilitate the communication between systems. These points are further elaborated in section 2.2

1.3 Main Objective

The main objective of this project is to design and develop an internet of things based adaptive Energy Management System (EMS) for smart homes. A Home Energy Management System (HEMS) was redesigned by understanding smart homes in Singapore. With the help of existing Internet of Things (IoT), data collection devices in the smart homes were implemented to analyse the home environment. The design and development for monitoring of energy theft were benchmarked against existing methods in the market for smart homes. Multi-Agent System (MAS) communication channels based on industrial standards were also considered. The design and development of MAS are integral to its performance. Furthermore, the forecasting system for the electricity generation was developed and tested against conventional methods to prove its performance.

From this research, it allows smart homes to be more economical, efficient, and is able to solve problems independently. Consumers will be more aware of their power usage as they are able to monitor their energy consumption. Hence, this avoids overloading and unnecessary uses of electrical appliances.

1.4 Dissertation Outline

The rest of this dissertation is organised as follows.

1. Chapter 2 provides a literature review of the research that includes a review of the proposed systems and its background information.

2. Chapter 3 provides the algorithms and methodologies of the multi prediction system and Self-learning Home Management System (SHMS).

3. Chapter 4 provides the simulation and results for the multi prediction system and SHMS.

4. Chapter 5 concludes the research and future works of this dissertation.

Chapter 2

Literature Review

This chapter provides the necessary literature for information about smart home, Home Energy Management System (HEMS), machine learning, Multi-Agent System (MAS), Internet of Things (IoT), and electricity market. In general, the smart home's information provides the available technology, tool, and algorithm to build an energy efficient system. The importance of these resources and how they work independently would be discussed later in the thesis.

This literature review discusses past research and their contributions to the individual experiment or work. The past research will identify the research gaps to provide the research motivations section on the current works.

2.1 Smart Home

Smart home is one of the important entity in the smart grid [40]. In the research studies by Independent Electricity System Operator [41], it defines the term "Smart Grid" as a contemporary electricity system that uses users' sensors, communications, automation, monitors, and computers to improve the security, reliability, extensibility, safety, and efficiency of the electricity system. Smart grid is made possible by two-way communication technology and computer processing. The two-way communication technology has enhanced reliability and is energy efficient, hence being used in other industries for decades. It has the capability of sensing grid situations, measure power, and control appliances with two-way communication to electricity generations, transmission and distribution of the power grid. This concept of the intelligent power grid is to perform independent adaptations of its elements for optimal electricity consumption [42].

As part of the smart grid, smart home is commonly termed as a household that has a system capable of communicating between systems through a connected network. An overview of the smart home is shown in Fig. 2.1.

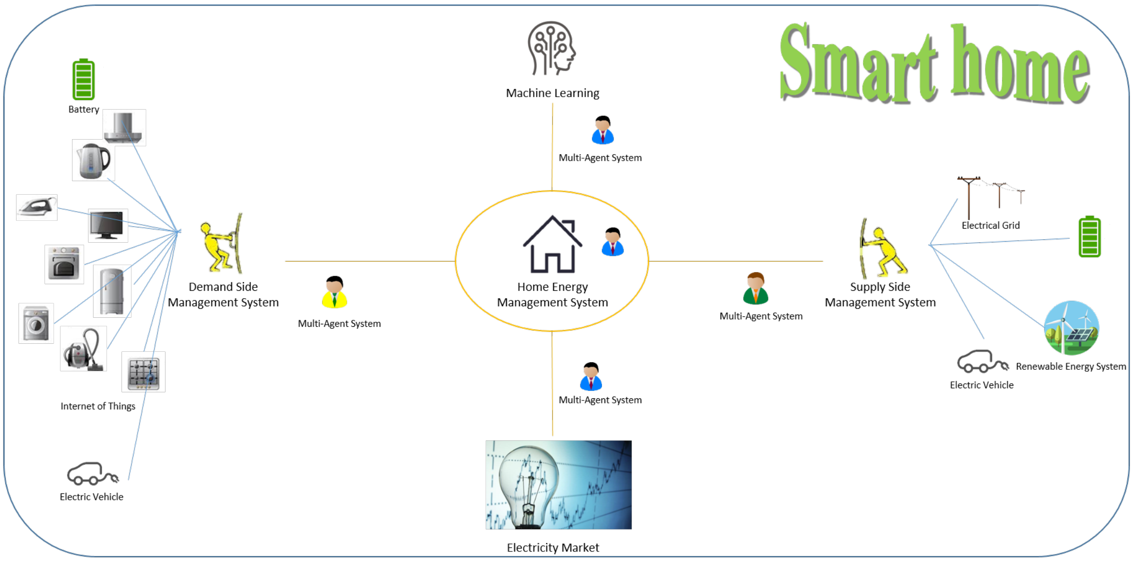

Fig. 2.1 Interactions between IoT devices

In a smart home, a smart meter is responsible for providing energy for the system to run and for the interface between houses. The smart meter will be replacing the traditional electromechanical meter, which operates digitally, allowing the complex transfer of information between houses and the energy provider [43]. The smart meter is capable of receiving signals from the energy provider in order to aid in balancing the household demand. It reduces energy cost and receives more detailed information on the level of energy consumption.

On the other hand, a smart appliance allows access and control via an automated management system. Such appliances can react to signals received from the smart meter and thus prevent the use of energy during the peak periods. Ramchurn et al. [44] argue that the smart grid provides substantial new challenges for research in agent intelligence as these technologies require algorithms and mechanisms that can solve problems involving a large number of highly heterogeneous actors. It was also mentioned in the same article that virtual power plants, DSM, energy prosumers, electric vehicles, and self-healing networks are some strategic components that warrant attention in smart home research.

The new generation of devices can be differentiated via the three characteristics [45]:

- Instrumented: Devices can provide detailed information, control over their operation, and also information about the surrounding environment in which they operate.
- Interconnected: Devices are capable of communicating, interacting with people, systems, and other devices. This involves the collection of information and control of devices throughout the network.
- Intelligent: Devices are capable of making decisions based on data collected and optimise for better outcomes.

Current smart appliances and their communication technology are heterogeneous among different vendors, due to the standardisation in the early phases. In this scenario of heterogeneous devices and protocols, it is essential to take on a standards-based view of the new smart home. This will avoid multiple maintenance efforts for easier management system [46]. In general, smart homes [47] consist of: Sensors to detect surroundings; Controllers for devices; Programming units for the system; Interface network for communications; Smart meters to monitor energy consumption and user behaviour.

One of the challenges for the smart home vision is the need to incorporate a large number of networking protocols and technologies, entity interfaces, and a range of applications and services already set up in the home today. An example could be installing a solar system to generate renewable energy.

Corno, F. and Razzak, F. [48] proposed an intelligent energy optimisation for user intelligible goals in smart home environments. It tackles from the point of view of the utility provider and consumers through suitable local energy management systems to minimise power consumption. The boolean formalisation of the Domotic Effects modelling framework was the approach to satisfy user requirements and find satisfactory power results while respecting timing constraints. However, many home appliances were not considered for this experiment as it focuses mostly on areas of the home.

There are issues other than the enhancement of a smart home. An example could be the consumer's lifestyle, if the consumer can use his appliances during off-peak time then it would help to reduce the electricity expenses.

Smart home's has software and hardware components such as Home Energy Management System (HEMS), machine learning, Multi-Agent System (MAS), Internet of Things (IoT), and electricity market. These components are further elaborated in the following sections.

2.1.1 Home Energy Management System (HEMS)

Smart homes can be developed through the implementation of the Internet of Things (IoT) and smart meters [49–53]. In order to monitor and control the Advanced Metering Infrastructure (AMI), Home Energy Management System (HEMS) becomes an essential integration to the system infrastructure [54, 55].

HEMS is a software system designed for smart homes to monitor, control, and optimise the electricity generation, transmission and distribution in smart grids. A smart meter is an important part of HEMS that provides the monitor and control functions. The "advanced applications" is a part of HEMS which provides the optimisation function. For example, HEMS enables users to conveniently dictate the smart appliances within the home by using mobile devices.

More applications have been implemented into smart homes with HEMS, one of the upcoming trends is integrating Electric Vehicles (EV) as a sustainable moving battery into smart homes. In the coming years, a large-scale implementation of electric vehicles that changes the energy requirements of transport from common fossil fuels to electricity from the implementation of smart homes. Due to the EV battery limited capacity, faster-charging rates for EV battery will be required for HEMS in smart homes [56].

Lin, Y. H. and Tsai, M. S. [57] proposed an advanced HEMS facilitated by a non-intrusive load monitoring (NILM) technique with an automated Non-Dominated Sorting Genetic Algorithm-II (NSGA-II)-based multi-objective in-home power scheduling mechanism. The method was implemented in a real-life house environment in Taiwan for data acquisition and control of the load. However, it requires major restructuring of the electrical wiring using National Instruments Data Acquisition (DAQ) devices within the household and the experiment was implemented using only specific household appliances.

Wu, Z. et al. [58] proposed Fuzzy Logic Controller (FLC), Continuous Relaxation (CR), and Mixed Integer Linear Programming (MILP) control for the rolling optimization by the HEMS. The three approaches aim to control and monitor heating, task-specific and energy storage devices based on computational resource, cost optimization, and practical implementation. All three approaches can optimise energy consumption close to ideal cost at the expense of higher computation time. The proposed strategies are embedded into HEMS for local cost optimisation of the managed devices.

Joo, I.Y. and Choi, D.H. [59] proposed a distributed optimization algorithm for scheduling the energy consumption of multiple smart homes with distributed energy resources. The approach uses a distributed two-level HEMS optimisation algorithm to minimize the total electricity cost for multiple households with distributed energy resources while maintaining the thermal comfort level. The proposed distribution algorithm manages to perform almost equivalently with a centralised algorithm based on electricity cost and the consumer's comfort level.

In this thesis, more advanced and developed HEMS further analyses the data collected and to make its own decision for smart homes to operate in the most cost-effective and energy-efficient method based on the user's schedule. Supply and demand side management systems are included to facilitate the information in HEMS.

2.1.1.1 Supply Side Management (SSM)

Supply Side Management (SSM) is a method of optimising electrical supplies from various power sources in HEMS [39]. SSM is known as generation scheduling in energy management systems. It schedules the generation of power from different generation units over a period of time while considering the constraints of the systems. Objective functions of SSM include costs of associated energy productions, start-up and shut-down decisions, and lastly, predicted profits. This results in large-scale nonlinear optimisation problems. SSM problems can be divided into two sub-problems: Unit Commitment (UC) and Economic Dispatch (ED). UC problem decides the ON or OFF statuses of generators over a scheduled period while the ED problem identifies the operating power levels of generators based on the operating costs.

The modern power grid consists of multiple power generators, increasing the generation units over time to meet increasing electricity demand. This problem could result in additional reconstruction time due to changes in the physical infrastructure. As such, improvement of SSM problem-solving capabilities would play a significant role in HEMS to result in a significant change in the system [60, 61].

One of the key issues for future energy distribution systems, smart homes, and smart devices would be intelligent management of energy distribution. The problem could be tackled from the supply sources on how electricity should be distributed. This would help to improve electrical efficiency by developing an optimal algorithm for the system so that electricity can be used in an efficient manner for HEMS [62].

As mentioned by Schweppe et al., the reasons why electricity demands should be accommodative to supply conditions [63]. It was known that in order to have a long-term contract of cheaper production, the demand for electricity must be lower to achieve an effectual grid at lower pricing. Thus, a better balance between supply and demand would result in an efficient power grid.

Kahrobaee, S. et al. [64] proposed an optimum sizing of distributed generation and storage capacity in smart households. It involves developing an electricity management system based on stochastic variables such as wind speed, electricity rates, and load. Then, a three-stage hybrid stochastic method based on Monte Carlo simulation and particle swarm optimisation is proposed to determine the optimum size of the wind generation-battery system. Although this is a good simulation for determining the size of storage capacity in smart homes, the inclusion of other renewable energy was not part of this experiment.

Renewable Energy System (RES) is an important part of the smart home that reduces carbonisation. The use of RES is encouraged by various countries to decarbonise the traditional power generators. This results in the increasing use of pollutant-free energy sources such as wind, tidal, and solar to produce distributed power for the grid with immense pace.

Solar Energy: PhotoVoltaics (PV) system uses solar cells to convert the sun's solar radiation to generate electrical energy [65]. Due to the dependence on direct sunlight, it is the most efficient in the morning and afternoon when the sun is up. It is usually on rooftops, walls or grounds mounted with a solar tracker to follow the sun. PV system can either be grid-tied or connected to a battery system.

Wind Energy: Wind turbine generators (WTGs) are powered by windmills and they are usually operated by electricity companies. Windmills are generally located in places with strong wind regardless of land or sea. The effective use of wind energy is essentially based on the wind's direction and speed, which is also a major drawback. Thus, power generation by the wind is dependent on the environmental conditions, hence the amount of wind power generation can fluctuate over time [66].

Tidal Energy: Tidal energy is a type of renewable energy that relies on tidal waves to produce electricity. It can be produced every day, which makes it an effective resource for electricity generation. Tidal energy is an attractive type of renewable energy not affected by outdoor weather conditions which are an advantage compared to solar or wind energy [67]. Furthermore, the tides are easily predictable. Generation of electricity from tidal energy can be harnessed by installing tidal barrages, tidal impoundments, and tidal stream turbines [68].

The world's renewable energy contributes 19% to the current electricity usage, of which hydroelectric energy produces 16%, making productions from wind and photovoltaic energy relatively modest [69]. The implementation of RES to supply smart home suggests that many improved initiatives can be done.

Pilloni, V. et al. proposed a Quality of Experience (QoE) aware smart home energy management including renewable energy [70]. The approach aims to reduce electricity cost while maintaining QoE perceived by the users with two algorithms based on time of use tariffs, taking account the user habits, and whenever renewable energy sources are installed.

Javaid, N. et al. proposed an intelligent load management system with renewable energy integration for smart homes [71]. The approach uses binary particle swarm optimization, cuckoo search, and genetic algorithm to build an evolutionary algorithms-based demand side management model for rescheduling the appliances of residential users. The proposed method significantly reduced the high peaks and electricity bill for residential users.

Melhem, F. Y. proposed the optimization and energy management in the smart home considering photovoltaic, wind, and battery storage system with integration of electric vehicles [72]. The approach uses a mixed integer linear programming model to optimise the energy consumption and production with the integration of battery storage systems, renewable energy resources, and electric vehicles. the proposed method achieved significant energy cost savings and show the global optimum solution through the design of experiments with the Taguchi method for three case studies.

RES is not able to replace existing electrical grids as it has been established and used for ages due to its reliability. Renewable energy sources are unpredictable due to the environment or weather, thus leading to flexible operations to facilitate reliable integration and development. For advanced control and monitoring to be practical, RES involves certain criteria such as reliability, efficiency, development of algorithms. Thus, the availability of equipment or tools would be crucial for the research of such technology [73].

Although RES technology is not able to cope with the demand for electricity consumption these days. However, integrating it with the existing power grid has shown that it is able to change the system to a certain extent [74]. Battery storage system is essential to store power when necessary and can be used during an emergency or peak periods. Off-grid battery storage systems traditionally used rechargeable batteries as a medium to store excessive electricity. However, the drawback of such a system would be the need for maintenance which incurs extra cost. Grid-tied systems, allow excessive electricity to be sent back to the transmission grid and use the grid as a storage mechanism.

2.1.1.2 Demand Side Management (DSM)

Demand-Side Management (DSM) is designed to reduce electricity consumption and provide highly efficient distribution of electricity to consumers [75]. Consumers' electricity bills could be greatly reduced if electricity is used more during off-peak hours rather than peak hours due to cheaper electricity tariff prices. For this purpose, DSM helps to reduce consumer electricity cost and increase the efficiency of electricity usage. Hence, it plays a key role in the HEMS.

Chen, X. et al.proposed an uncertainty-aware household appliance scheduling considering dynamic electricity pricing in the smart home [76]. The approach introduces a new demand side management technique to arrange the household appliances for the operation to reduce monetary expenses based on the time-varying model with the considerations of intermittent renewable generation and uncertainties in household appliance operation time. The proposed method reduces up to 41% monetary expenses as compared to operations in traditional home scenario.

Di Giorgio, A. and Pimpinella, L. proposed an event-driven smart home controller enabling consumer economic saving and automated demand side management [77]. The approach introduced the design of a smart home controller strategy to provide efficient management of electrical energy in a domestic environment. The proposed formulation optimises the overload management and economic saving through the time of use tariff and DSM.

Khalid, A. et al. proposed towards dynamic coordination among home appliances using multi-objective energy optimization for demand side management in smart buildings [78]. The approach is employing a load shifting strategy of demand side management for optimising the energy consumption patterns in a smart home. It aims to minimise electricity cost and peak to average ratio while preserving the user comfort through the coordination between home appliances.

The existing approaches to reduce electricity demand have been limited to either directly controlling the devices used by the consumers (i.e., automatically switching off high load devices such as air conditioners at peak times), or by providing customers with tariffs that prevent peak time use of electricity due to the wholesale electricity market [79]. Thus, with the disposition of smart meters, it is possible to make an immediate calculation on the amount of electricity consumption, providing every home, every commercial and industrial consumer with the capability to spontaneously reduce the load in response to signals from the grid [80].

The key challenge of implementing Artificial Intelligence (AI) [44] in DSM is the decision-making design for the heterogeneous device. AI learns to adjust to real-time prices and electricity consumption based on predictions of future supply and demand. It was well-known that lower demand results in cheaper production and longer long-term contracts, thus leading to a more effectual grid at lower prices.

2.1.2 Machine Learning

Machine learning is an application of Artificial Intelligence (AI) that gives the machine the ability to learn and improve by itself through historical data without definite programming [81]. This technique allows the computer to learn automatically without the intervention of humans. It focuses on the development of its own self-learning algorithm through data inputs. The learning process begins with an observation of the patterns of the database on the instruction given. It makes better decisions after identifying the patterns of the data. Fig. 2.2 shows the processes of supervised and unsupervised learning.

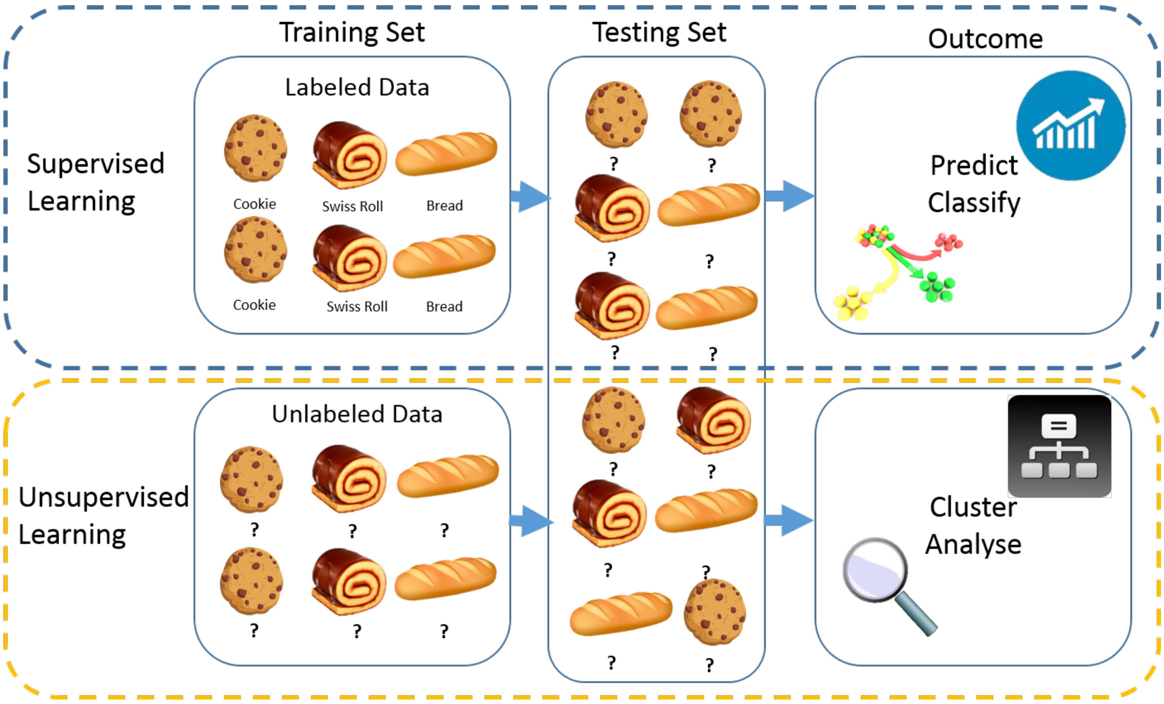

Fig. 2.2 Agent interaction diagram

Machine learning algorithms have certain categories such as the following:

- Supervised machine learning algorithms: It applies the learnt algorithm using labelled historical data to predict the incoming new data [82]. It trains from a known training dataset to produce the learning algorithm and tests the testing dataset with the correct or intended data for accuracy. This procedure allows modification and adjustments to the model if the results are unsatisfactory.

- Unsupervised machine learning algorithms: In contrary to supervised machine learning algorithms, it applies the learnt algorithm to unlabelled or unclassified data [83]. This system does not have an accuracy check, but it can label the data according to the patterns and infer its own solutions.

- Semi-supervised machine learning algorithms: It is a hybrid mixture of supervised and unsupervised learning. As it uses both labelled and unlabelled data for training and testing [84]. Typically, the quantity of labelled data will be smaller than unlabelled data. This will decrease the additional resources to label the data.

- Reinforcement machine learning algorithms: It is a learning method that learns from its own mistakes during the process [85]. This reinforcement learning allows machines and software agents to determine the ideal behaviour based on the objective to maximise its own performance. This simple reward feedback is essential for agents to learn the best action required.

In addition, machine learning enables analysis of high quantities of data. Although it delivers reasonably accurate results in a short time frame, it may require more time and relevant information to train the algorithm properly [86]. By combining machine learning with other platforms can potentially be more effective in a deep understanding of data patterns. Due to current technology, building high-performance computer systems are becoming inexpensive. This trend allows AI to emerge as potential solutions for various smart home problems.

Mandal, P. et al. proposed using RNN in price forecasting for day-ahead electricity market [87]. It shows different methods with RNN for the prediction accuracy. However, it lacks the comparison of any other methods that validate the improved accuracy.

Taylor, J. W., and McSharry, P. E. evaluate different forecasting methods that include ARIMA, ANN, double seasonal Holt-Winters method and Principal Component Analysis (PCA) for power systems electricity demand [88]. The extensive experimental result shows double seasonal Holt-Winters method as the most successful model. However, many other machine learning techniques were not included for evaluation.

Hoiles, W. and Krishnamurthy, V. evaluate a non-parametric test to detect if the demand behaviour of consumers is consistent with time-of-day electricity tariff initiatives [89]. It included the test on various forecasting algorithm, but the method is only for the detection of consumers that participate in time-of-use electricity pricing initiatives that do not require the utility function of the consumers to be known.

Shrivastava, N. A., and Panigrahi, B. K. proposed a novel approach for the generation of prediction intervals using a differential evolution-based multi-objective approach [90]. It focuses on optimising Support Vector Machine (SVM) to predict the electricity demands and prices. However, in comparison with other machine learning methods has not been studied. This shows the lack of forecasting systems that are developed for electricity generation forecast.

The implementation of AI into smart homes will improve home automation technologies for energy efficiency and residential user's level of convenience. Thus, integrating energy management system and AI brings HEMS nearer to become energy efficient smart home.

2.1.3 Multi-Agent System (MAS)

Multi-Agent System (MAS) is a distributed computational intelligence technique, which involves two or more intelligent agents [35]. In such a system, there is no overall system goal, but there are goals for individual agents. Till now, MAS is extensively used in modelling approach which can be either hardware or software system [91].

A research was done by Wooldridge [92], a computer system which is also known as a software agent is found in some environments that are capable of autonomous action to achieve its designed objectives. A software agent is viewed as sovereign software which is capable of operating without user involvement and having the ability to communicate, monitor, and understand the environment in which it inserted [93]. The difference between conventional software and software agents is the issue of autonomy, where an agent is goal orientated compared to conventional software which is not goal orientated. Another significant difference is that software agents are situated in a particular environment and able to interact continuously with the environment through perceptions and actions [92].

As mentioned in Hayes studies, intelligent agents should be capable of performing the following functions: recognizing dynamic conditions in their environment; response to conditions in their environment; assess perceptions, solve problems, trace inferences, and decide on what actions to take [93]. Software agents can do many activities such as: being able to search for information on the network, manage schedules, negotiate simple intentions, etc. However, to achieve this, it would require a high degree of knowledge as its programming is complex.

MAS is applied in the industry through market simulation, network and automation control, condition monitoring, and power system restoration [94].

There are a few essential characteristics that an agent should abide. Several characteristics of an agent are briefly explained:

- Social ability: Interactions with other intelligent agents are essential, where this implies more than simply passing data between software and hardware entities. Additionally, the ability to negotiate and interact cooperatively. This is commonly strengthened by Agent Communication Language (ACL).

- Reactivity: This characteristic enables the agent to react immediately for changes caused by the environment and leap in with regard to the specified function designed to it.

- Pro-activeness: This characteristic enables the agent to parade a goal-directed behaviour. The agent changes its behaviour in order to achieve the designated goals.

Foundation for Intelligent Physical Agents' (FIPA) sets several standards to be used by MAS developers [95]. The FIPA structure is shown in Fig.2.3.

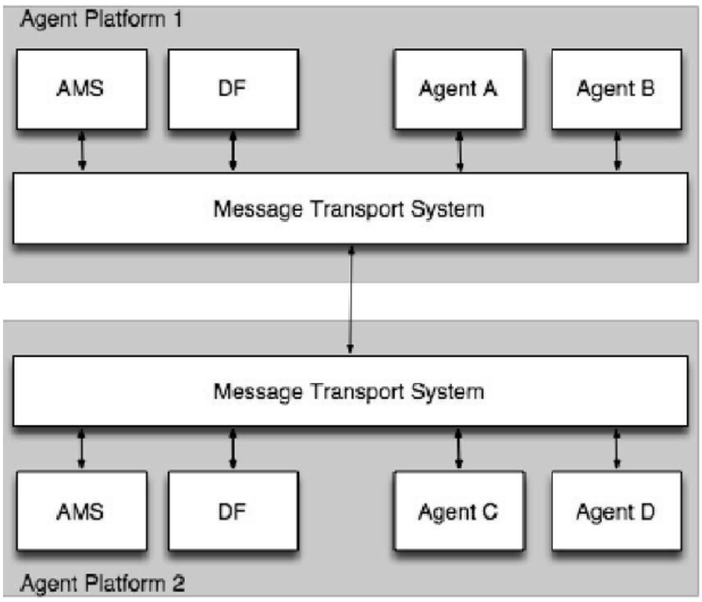

Fig. 2.3 Standards set by FIPA

These standards aim to support interoperability between agent-based systems developed by different establishments. It impacts on not only methods for inter-agent communication, but also on the fundamental architecture that a MAS should instrument [91]. As shown in

Fig. 2.3, each agent consists of two utility agents: Agent Management Service (AMS) agent, a compulsory agent, and a Directory Facilitator (DF) agent, an agent that is not necessarily required, in the platform. In both agent platforms, AMS is an agent that is in control of maintaining various agents to be registered with the MAS. On the contrary, DF supports various agents and services that various agents can offer to the system. The presence of DF enables agents to search for respective agents that aid in providing services to fulfil its own goals [91]. Fig. 2.4 shows an example of the agent interaction diagram.

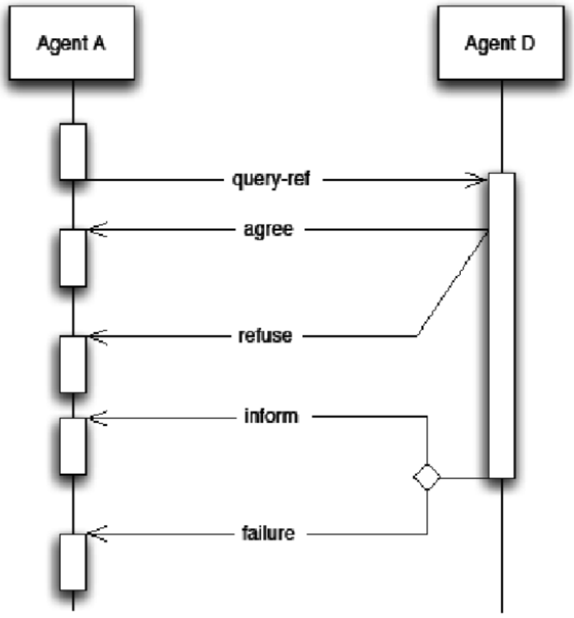

Fig. 2.4 Agent interaction diagram

2.1.4 Internet of Things (IoT)

Internet of Things (IoT) is a wireless network integrated with physical objects such as devices, vehicles, buildings, and other electronics systems [96]. IoT implementation enables objects in obtaining, analysing, processing, controlling, and feeding back the information remotely across the network by computer-based systems [97]. As such, it enables users to have total control via phones or over the internet. Fig. 2.5 shows the interaction between IoT devices.

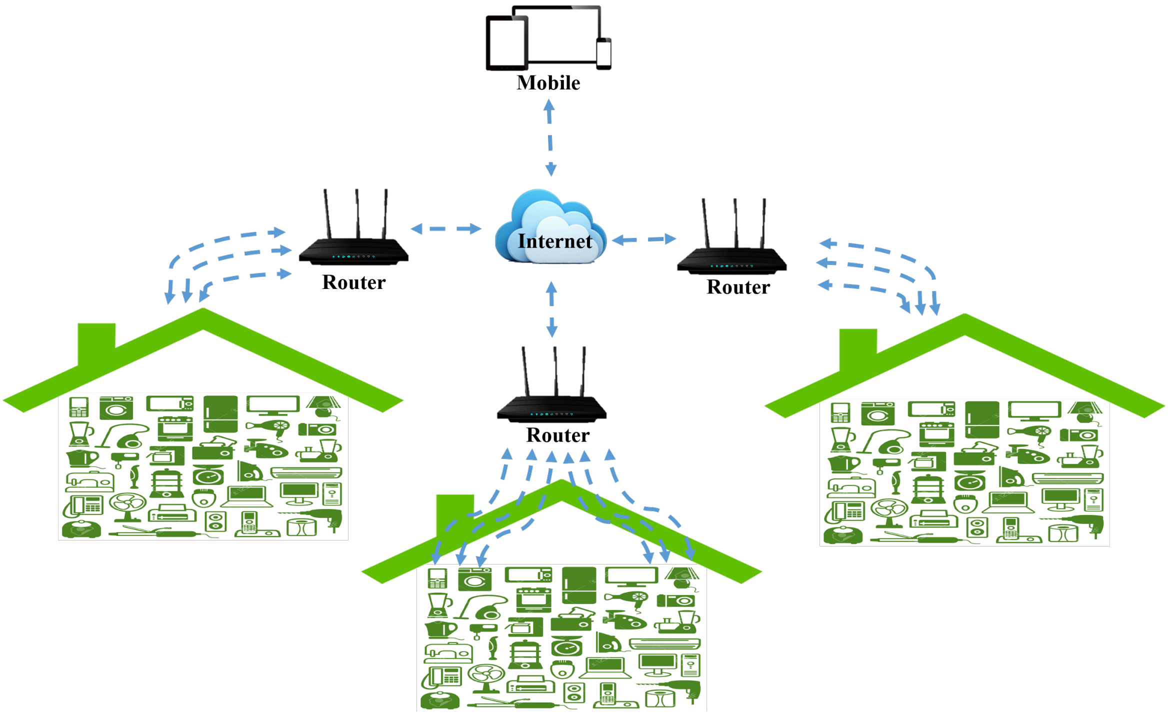

Fig. 2.5 Interactions between IoT devices

This technology becomes a general class of cyber-physical system which incorporates various technologies such as smart grids, smart buildings, and smart homes and has been successfully implemented.

Pan, J. et al. proposed an IoT framework with smart location-based automated and networked energy control [98]. The approach uses cloud-computing technologies and smart-phone platform to enable multiscale energy proportionality including organisational, building, and user level energy proportionality. The vision for the work will provide significant economic benefits and huge social benefits in terms of global sustainability.

Al-Ali, A.R. et al. proposed a smart home energy management system that utilises off-the-shelf Big Data analytics and Business Intelligence (BI) software packages to improve managing energy consumption and meeting consumer demand. The approach uses data analytic tools and scalable storage to aid different stakeholders with their respective level of privileges.

Barker, S. et al. [99] present several techniques that enable reliable and high-resolution monitoring of existing low-bandwidth power line communication networks for energy monitoring. The implementation of intelligent polling and event detection methods reduces the bandwidth requirements and undetected power events in a real-world Insteon network.

Industrialisation development of IoT in the smart home industry vigorously promotes the practical applications of IoT [100]. An example of the IoT system is shown in Fig. 2.6.

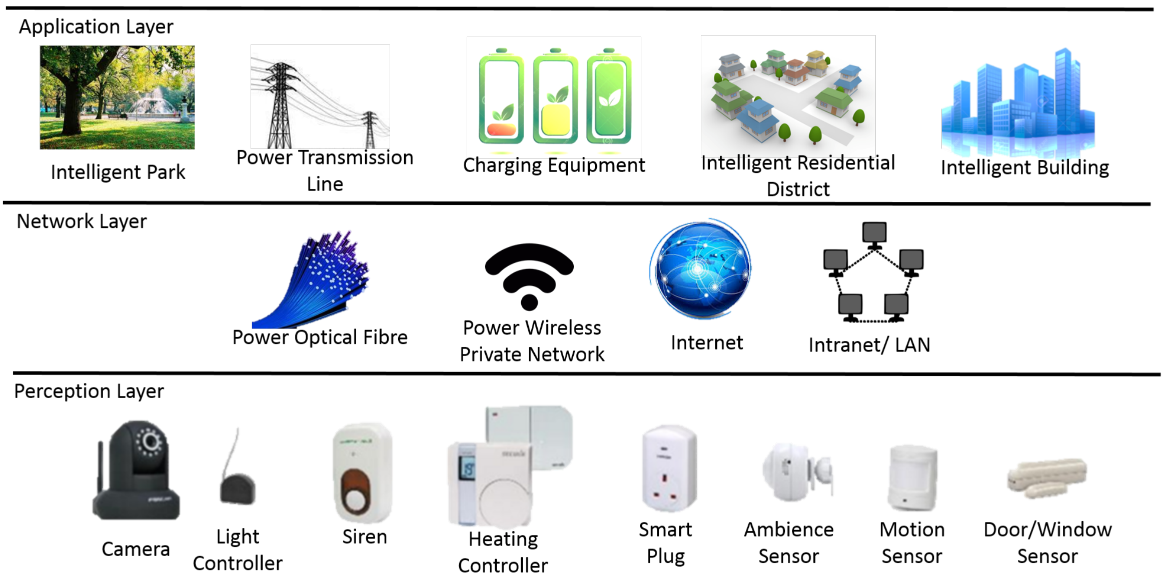

Fig. 2.6 IoT architecture

The IoT system architecture of a smart home is divided into three layers [101]:

1. Perception layer: Identifying and gathering data or information in the smart home using smart devices.

2. Network layer: Maps the gathered information and transmit it to the application layer through various networks such as the power optical fibre network, internet, and local area network.

3. Application layer: Processes the information from the network layer, monitors, and troubleshoots all aspects of the smart home in real time according to the information received. It also organises resource and establishes communication with the end users.

The three layers of the system in a smart home is to collect information on the electric power, electric power transmission, and processing respectively.

Integrating sensing and actuation systems with connection to the internet could optimise energy consumption as real-time communication to utility supply company results in an effective balance of power generations and energy usage. IoT devices offer users the option of remotely monitoring and controlling their devices via cloud-based interface or scheduling function. Smart home with IoT capability could improve the efficiency, reliability, intelligent, security, convenience, economics, sustainability of production, and distribution of electricity [102]. However, there will also be negative implications such as energy theft.

2.1.4.1 Energy Theft

Energy theft has become a serious issue in the smart home community [103]. It has been a rising issue for various countries around the world that cause massive losses exceeding billions of dollars. Despite this, only a few preventive energy theft methods are created to combat the issue.

Liu, Y. and Hu, S. proposed a detection technique that has an average detection accuracy of 92.55% [31]. This proposed detection technique integrated Bollinger-bands-based detection with the Partially Observable Markov-Decision Process (POMDP). However, it does not reflect on all conditions of a house environment. Firstly the house demand data has consistent energy consumption throughout the entire twenty-four hours. It does not include any energy consumption for the particular hour. Another condition of the Bollinger Band method, the deviation can only be in a consistent range of energy usage. However, if the range of energy usage became too large, the Bollinger Band method could not be used because of its deviation.

Nowadays, a smart meter will be placed at the end of every distribution network to record power consumption and generate energy reports remotely. An example of the home distribution network is shown in Fig.2.7.

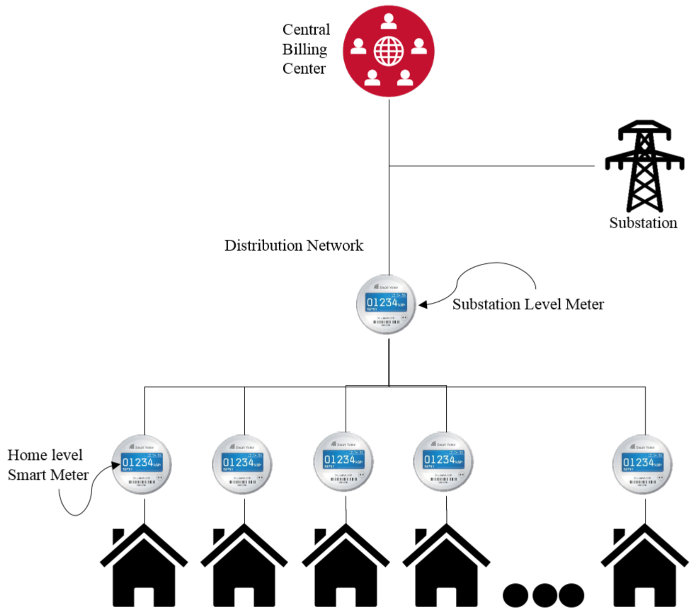

Fig. 2.7 Home distribution network

Energy theft methods involve hacking smart home's IoT devices and most commonly direct hooking on other household's electricity supplies. Thus, attackers can reduce their own electricity usage by manipulating other households through tampering and hacking to increase their electricity usage as the aggregate bill for all customers in the community remains the same [29]. Fig.2.8 shows an example of an energy theft scenario.

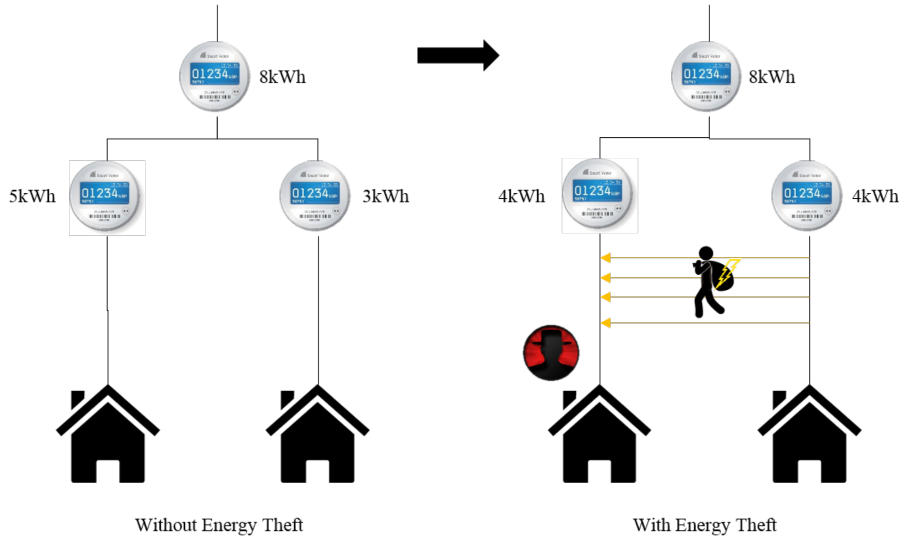

Fig. 2.8 Energy theft situation

The example shows that through energy theft, the higher consumption household can reduce their own power consumption by tapping into another household. It increases the electricity bills for the other household victim while reducing the energy theft culprit bills.

2.1.5 Electricity Market

The electricity market regulates the price of electricity transmitted to the smart home. An electricity market is a system that bids to buy, sell or trade electricity by electric suppliers [104]. The bid and offer prices are based on the supply and demand principles. Long-term power purchase contracts are usually given due to the complications on the grid connections. Electricity market contributes to this system as consumers are paying for these services through the power grid electricity usage, thus the price of electricity would play a major role in this thesis.

Chen, X. et al. [105] proposed an uncertainty-aware household appliance scheduling considering dynamic electricity pricing in the smart home. An energy efficient scheduling algorithm is proposed to arrange the household appliances for operation such that the monetary expense of a customer is minimised based on the electricity market's time-varying pricing model. The proposed appliance operation scheduling algorithm also accelerates the generation of the desired operation schedule by paralleling the computing process. However, it lacks the studies of energy consumption and how it will affect consumer's behaviour as it focuses on monetary expenses.

Pedrasa, M. A. A. et al. proposed a coordinated scheduling of residential distributed energy resources to optimise smart home energy services [106]. The approach uses particle swarm optimisation to enhance decision support tools through scheduling of distributed energy resources and optimise residential consumers' acquisition of electrical energy services.

Hansen, T. M. et al. proposed a POMDP approach to residential home energy management [107]. The method uses one myopic approach and two non-myopic POMDP approaches to minimise household electricity bill in real-time pricing market. One of the non-myopic POMDP shows promise for home energy management due to the cost savings advantage over several months.

An example of the electricity market structure is shown in Fig. 2.9.

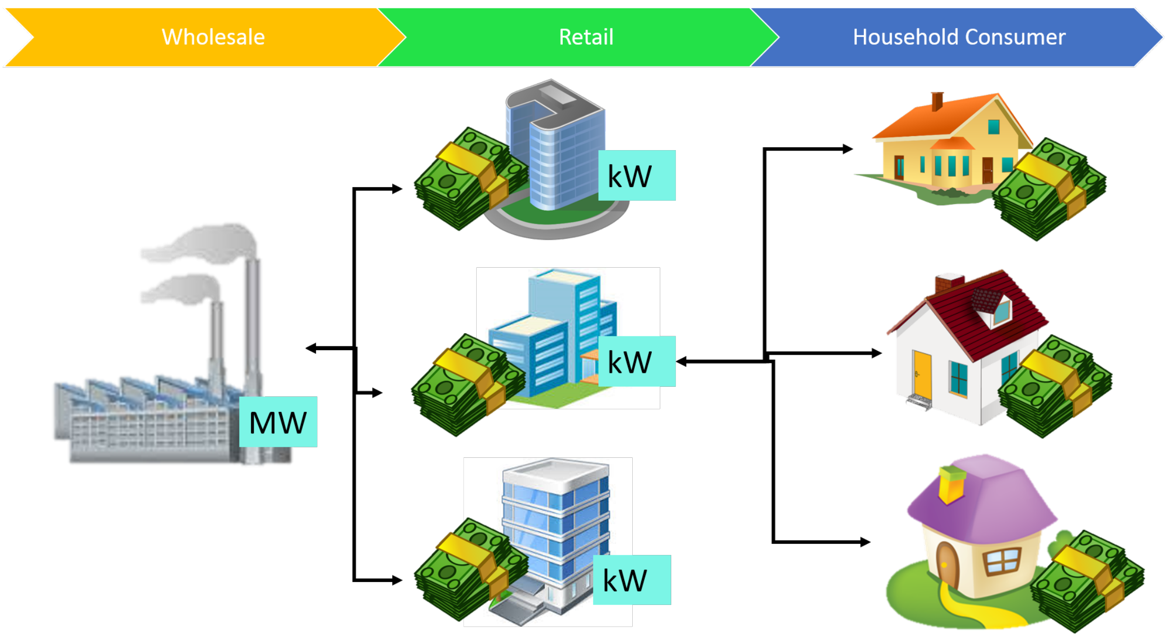

Fig. 2.9 Electricity Market Structure

In electricity markets, the importance of accurate forecasting is essential for the planning and operations of utility companies [108]. Overestimation of electricity generation will lead to supplying excessive energy and adds unnecessary operational cost. Underestimation results in the sudden deployment of additional peak capacity and purchases of necessity at a higher cost for additional generations [109]. As a result of this hostile trade-off, it was reported that an estimated 1% forecast error increased the operating cost of a UK power utility by £10 million in 1985 [110]. This problem results in research for a more accurate forecast system, it will increase the reliability of the power supply and delivery system while saving a substantial amount of operational and maintenance costs. Hence, it is a key requirement for the planning, economic, and secure operation of future power systems to smart homes.

There are a few advantages for accurate electricity generation forecasting [111–115]:

- Minimise the risks for the utility company.
- Understanding the future long-term electricity generation helps the company to plan and make economically viable decisions in regard to the future generation and transmission investments.
- Helps to determine the required resources such as fuels required to operate the generating plants as well as other resources that are needed to ensure uninterrupted and yet economical generation and distribution of the power to the consumers. This is important for short, medium, and long-term planning.
- The electricity generation forecasting helps in planning the future in terms of the size, location, and type of the future generating plant. By determining areas or regions with high or growing demand, the utilities will most likely generate the power near the load. This minimises the transmission and distribution infrastructures as well as the associated losses.

- Helps in deciding and planning for maintenance of the power systems. By understanding the generation, the utility operators understand when to carry out the maintenance and ensure that it has a minimum impact on the consumers. For example, they may decide to do maintenance for residential areas during the day when most people are at work and generation is very low.

- Maximum utilisation of power generating plants. The forecasting avoids under or over generations.

2.2 Research Motivations

The research studies suggest that an IoT based adaptive EMS for smart home will be highly desirable in the smart home community. The potential system should be a "Plug and Play" concept for existing infrastructures and be constantly updated to customise the algorithm for each individual smart home. Another consideration of the system will be energy theft, it will require an energy monitoring system that alerts the users when energy theft occurs. As electricity market plays an important part in the operational scheduling of smart homes, accurate forecasting system for the electricity market's generation should be in place. It should not involve expensive equipment and non-flexible infrastructure that will incur a high cost for manual labour works. This concept should include AI for the communication channels and decision-making process within the system. It will involve AI for the self-learning algorithms to customise beneficially based on the behaviours in each smart home.

Chapter 3

Projects' Proposal and Algorithms

The first section shares the algorithms implemented in multi prediction system and Self-Learning Home Management System (SHMS).

The second section provides multi prediction system information about data collecting and pre-processing module, multi-input feature model, and multi forecast model: Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU). The functions and algorithms will be further explained and discussed in this section. The project in the second section provides the prediction method performance evaluation for the methodology in section three.

The third section provides the design of the proposed self-learning home management system and explanations of each function in the system. The explanations include machine learning algorithms, k-means algorithm, decision-making system algorithms, Supply Side Management (SSM) system, Demand Side Management (DSM) system, Power Notification System (PNS), and Multi-Agent System (MAS) for the SHMS.

3.1 Algorithms

This section shares the algorithms used in multi prediction system and Self-Learning Home Management System (SHMS). Detail explanation of the algorithms will be explained in the following sections.

3.1.1 Machine Learning Algorithms

This section shares the details of machine learning algorithms implemented in multi prediction system and Power Notification System (PNS).

3.1.1.1 Multi-Layer Perceptron (MLP)

Neural networks or often term as Artificial Neural Networks (ANN) represents a variety of deep learning technologies. ANN is inspired by the biological neural networks of the brain to solve difficult computations without task-specific programming. Its ability to adapt without redesigning the system to changing inputs gained popularity in industries that require computation work. A class of feed-forward ANN called Multi-Layer Perceptron (MLP) develops robust algorithms and data structures to solve difficult computational problems [116]. Fig.3.1 shows a typical MLP network.

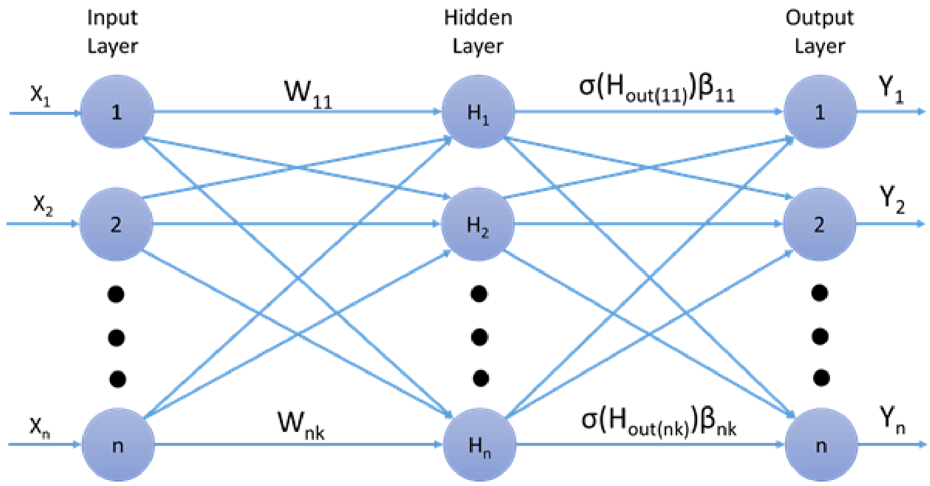

Fig. 3.1 MLP network

The MLP formulations [117] are defined as:

$$H_{(out(nk))} = \sum_{i=1}^{n} \sum_{j=1}^{n=k} (X_n.W_{nk}) \tag{3.1}$$

$$Y_n = \sigma(\sum_{i=1}^{n} \sum_{j=1}^{n=k} (H_{(out(nk))}.\beta_{nk})) \tag{3.2}$$

where, X_n : Input data, Y_n : Prediction outputs, $H_{(out(nk))}$: Hidden layer outputs, W_{nk} : Input-to-hidden layer weights, β_{nk} : Hidden-to-output layer weights, and σ : Activation function.

The best set of results in the network are found by using the hidden layer function. MLP prediction capability of learning from training data (Inputs) and producing the testing data are according to the user-defined output in a multi-layered or hierarchical design of the network. A supervised learning technique called backpropagation is often used for training the network in MLP. The MLP backpropagation equations are defined as follows:

$$E_n = \frac{(T_n - Y_n)^2}{2} \tag{3.3}$$

$$E_{total} = \sum_{i=1}^{n} \frac{(T_n - Y_n)^2}{2} \tag{3.4}$$

$$W_n = (T_n - Y_n)^2 \tag{3.5}$$

$$W_{(n+1)k} = W_{nk} - \eta \frac{\partial E_{total}}{\partial W_{nk}} \tag{3.6}$$

where, E_n : Square errors, E_{total} : Total square errors, T_n : Targeted values, and η : Learning rate. The backpropagation algorithm reduces the error rate by updating the weights using equation (3.6). Therefore, the better accuracy of achieving T_n will occur for MLP after multiple iterations.

Due to its popular ability to compute and solve difficult problems, many varieties of MLP were developed to optimise for different types of computational issues [118].

3.1.1.2 Recurrent Neural Network (RNN)

A class of ANN called Hopfield network or otherwise known as Recurrent Neural Network (RNN) was designed to learn patterns from data sequences such as text, images, and numerical time data [119]. It is a powerful type of ANN that had been used for industries involved in speech recognition, handwriting recognition, text to speech synthesis, and machine translation [120–123]. Fig. 3.2 illustrates an RNN network with loops that allow information to be preserved in the next process.

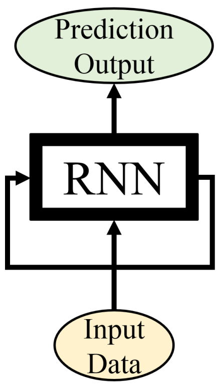

Fig. 3.2 Recurrent Neural Network (RNN)

Fig. 3.3 shows the complete sequence of the RNN full network (unfolded). For example, if there is a sequence of three numerical values, the network unfolds itself into a three-layer neural network that supports a layer for each numerical value.

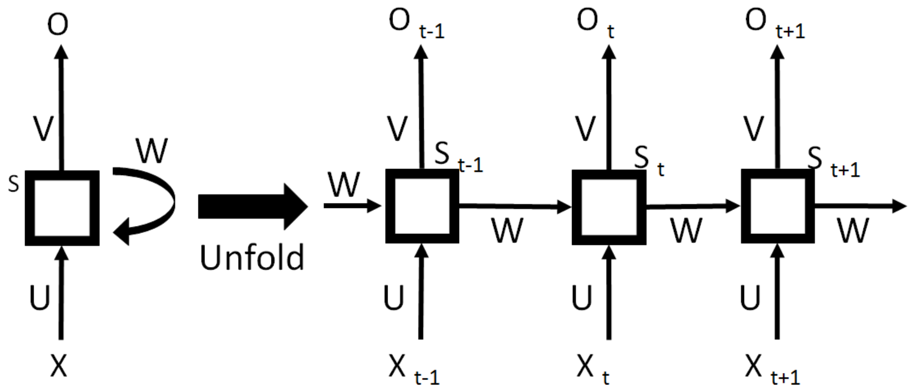

Fig. 3.3 Recurrent neural network and unfolding sequence diagram

The RNN computational equations [124] are defined as:

$$s_t = \sigma(s_{t-1}.W_{t-1} + x_t.U_t + b) \tag{3.7}$$

$$o_t = s_t.V_t \tag{3.8}$$

where, t : Time step, x_t : Input data, o_t : Predicted output, s_t : Hidden state, U_t : Input-to-hidden weights, W_{t-1} : Hidden-to-hidden weights, V_t : Hidden-to-output weights, b : Bias value, and σ : Activation function.

Hidden state s_t is considered the "memory" of the network; the hidden state captures information about the situation in all previous time steps that represents the main feature of RNN. o_t is the output predicted solely based on the current memory at time step t. RNN weights U, V, W are consistent throughout the process, unlike traditional ANN where it is different at each layer. It reduces the number of features required to be learnt by repeating the same task at each time step but with different input values. RNN like MLP also utilises a unique backpropagation algorithm in its network. The backpropagation equations for RNN are defined as follows:

$$E_t = -T_t \ log \ o_t \tag{3.9}$$

$$\delta_{V_t} = \frac{\partial E_t}{\partial V_t} = \frac{\partial E_t}{\partial o_t}.\frac{\partial o_t}{\partial V_t} \tag{3.10}$$

$$\delta_{W_t} = \frac{\partial E_t}{\partial W_t} = \sum_{k=0}^{t} \frac{\partial E_t}{\partial o_t}.\frac{\partial o_{t+1}}{\partial s_t}.(\prod_{j=k+1}^{t} \frac{\partial s_j}{\partial s_{j-1}}).\frac{\partial s_k}{\partial W_t} \tag{3.11}$$

$$\delta_{U_t} = \frac{\partial E_t}{\partial U_t} = \sum_{k=0}^{t} \frac{\partial E_t}{\partial o_t}.\frac{\partial o_{t+1}}{\partial x_t}.(\prod_{j=k+1}^{t} \frac{\partial x_j}{\partial x_{j-1}}).\frac{\partial x_k}{\partial U_t} \tag{3.12}$$

$$Weights(V,W,U)_{t+1} = Weights(V,W,U)_t - \eta \delta_{(V,W,U)_t} \tag{3.13}$$

where, E_t : Cross entropy loss, T_t :Targeted value, δ_{V_t} : Gradient of weight V_t, δ_{W_t} : Gradient of weight W_t, δ_{U_t} : Gradient of weight U_t, and η : Learning rate.

Equation (3.13) updates the weights at the next RNN iteration cycle. The RNN weights U, V, W are computed from the gradients in equations (3.10), (3.11), and (3.12).

3.1.1.3 Long Short Term Memory (LSTM)

The appeal of RNN is the ability to connect previous relevant information for the currently assigned task. RNN is able to learn and utilise past information if the gap between the relevant information and the latest computational point that it requires is small [125]. However, if the gap is big, RNN is unable to link the required information for the latest learning process. An example is shown in Fig 3.4.

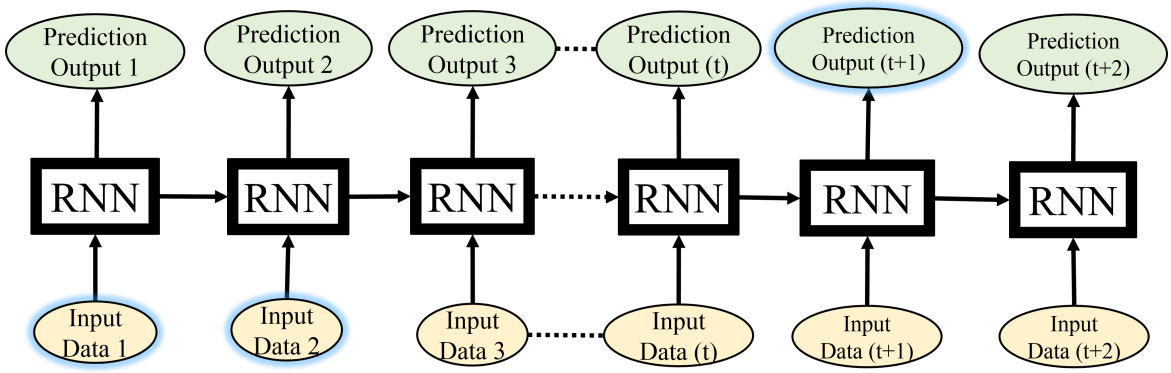

Fig. 3.4 Long Recurrent Neural Network

This issue prompt to create a system for long-term dependency issues, thus an alternative type of RNN called Long Short Term Memory (LSTM) was developed. Hochreiter & Schmidhuber [126] introduced the system that is later popularised and enhanced by people in different industries as it works positively on many distinct problems. Fig. 3.5 shows the interaction of each LSTM block in the network.

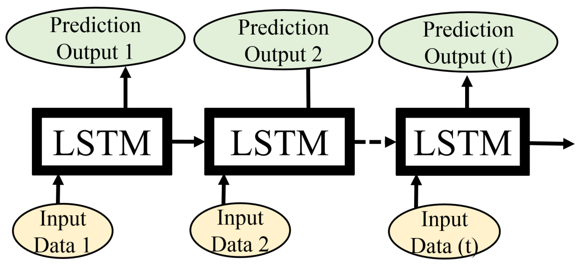

Fig. 3.5 LSTM network

Fig. 3.6 shows the design details of the LSTM block [125]. In Fig. 3.6, each line carries an entire vector, from the output of one node to the inputs of the others. The grey circles represent pointwise operations, similar to vector addition, while the orange boxes are learned neural network layers. Lines (vector transfer) denote content going to different locations.

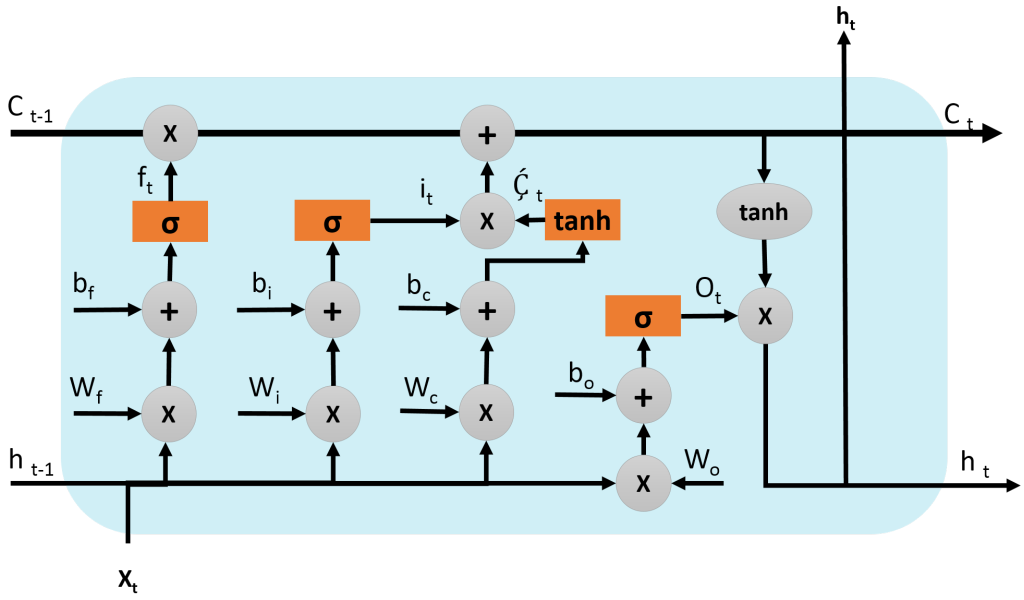

Fig. 3.6 LSTM block

LSTM block computational formulas [127, 128] are defined as:

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{3.14}$$

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{3.15}$$

$$\acute{\text{Ç}}_t = tanh(W_c.[h_{t-1}, x_t] + b_c) \tag{3.16}$$

$$C_t = f_t.C_{t-1} + i_t.\acute{\text{Ç}}_t \tag{3.17}$$

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \tag{3.18}$$

$$h_t = o_t.tanh(C_t) \tag{3.19}$$

where, t : Time step, x_t : Input value, h_t : Output value, o_t : Output gate, f_t : Forget gate, i_t : Input gate, C_t : Cell state, $\acute{\text{Ç}}_t$: Candidate value, W_o : Output gate weights, W_i : Input gate weights, W_f : Forget gate weights, W_c : Cell state weights, b_o : Output gate bias value, b_i

: Input gate bias value, b_f : Forget gate bias value, b_c : Cell state bias value, and σ : Gate state.

There are three gates in the block that manage the block state and output:

- Forget Gate f_t: Computes and decides the information to process back in the block.
- Input Gate i_t: Computes and decides the input values to update the memory state.
- Output Gate o_t: Computes and decides the output based on the input and memory state.

Each block represents a mini-state machine, where gates have weights that are learned during the training process [129]. The backward components, which is widely known as the backpropagation algorithm, for LSTM are defined as follows [130, 131]:

Note, the following representations are defined for simplicity.

$$Gates_t = \begin{bmatrix} \acute{Ç}_t \\ i_t \\ f_t \\ o_t \end{bmatrix}, W_t = \begin{bmatrix} W_c \\ W_i \\ W_f \\ W_o \end{bmatrix}, b_t = \begin{bmatrix} b_c \\ b_i \\ b_f \\ b_o \end{bmatrix}$$

$$E_t = \frac{(T_t - h_t)^2}{2} \tag{3.20}$$

$$\partial_x E_t = T_t - h_t \tag{3.21}$$

$$\delta h_t = \partial_x E_t + \Delta h_t \tag{3.22}$$

$$\delta C_t = \delta h_t . o_t . (1 - tanh^2(C_t) + \delta C_{t+1} . f_{t+1}) \tag{3.23}$$

$$\delta \acute{Ç}_t = \delta C_t . i_t . (1 - \acute{Ç}_t^2) \tag{3.24}$$

$$\delta i_t = \delta C_t . \acute{Ç}_t . i_t . (1 - i_t) \tag{3.25}$$

$$\delta f_t = \delta C_t.\delta C_{t-1}.f_t.(1-f_t) \tag{3.26}$$

$$\delta o_t = \delta h_t.tanh(\delta C_t).o_t.(1-o_t) \tag{3.27}$$

$$\Delta h_{t-1} = \delta x_t = W_t^T.\delta Gates_t \tag{3.28}$$

$$\delta W_t = \sum_{i=0}^{t} \delta Gates_i.x_i \tag{3.29}$$

$$\delta b_t = \sum_{i=0}^{t} \delta Gates_{i+1} \tag{3.30}$$

$$[W_{t+1}, b_{t+1}] = [W_t, b_t] - \eta.\delta[W_t, b_t] \tag{3.31}$$

where, E_t : Square error, T_t : Targeted value, and η : Learning rate. Equations (3.23) $\sim$ (3.27) are derivations from the initial algorithms of LSTM. Equations (3.29) and (3.30) calculate the gradients of the weights. Equation (3.31) updates the weights or bias for the next LSTM network iteration. This allows the development of large LSTM to address complex sequence problems and achieve optimal results.

3.1.1.4 Gated Recurrent Unit (GRU)

Another variation of the LSTM is the Gated Recurrent Unit (GRU) that was introduced by Cho, et al. [128]. This system combines the input and output gate to create a single update gate. The hidden and cell state were merged to make a simplified model compared to a standard LSTM model. Fig. 3.7 shows the design details of the GRU model [125].

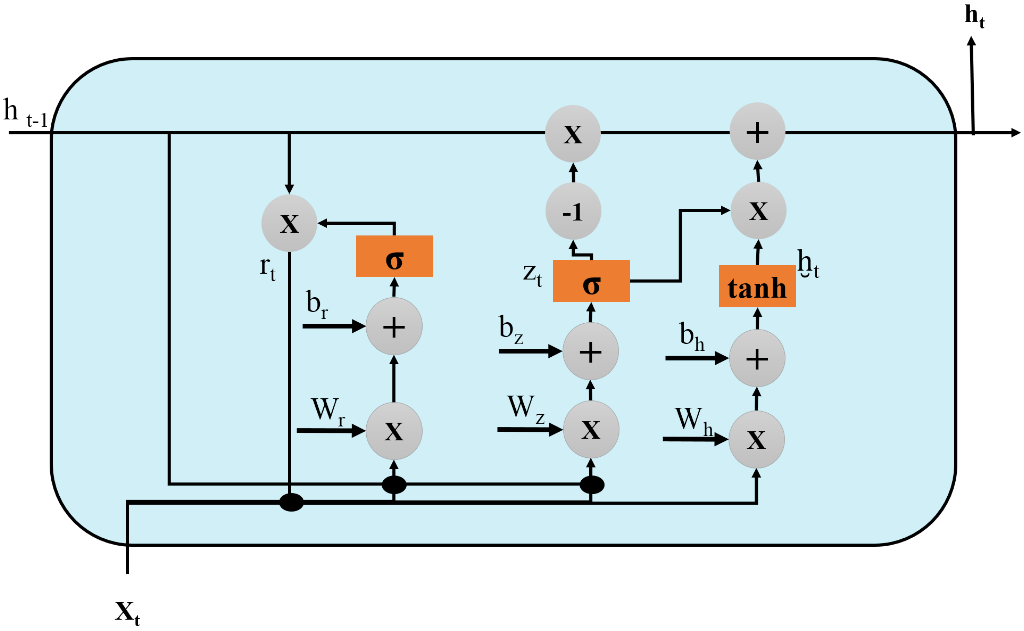

Fig. 3.7 GRU block

GRU was derived from LSTM which results in similar equations:

$$z_t = \sigma(W_z.[h_{t-1}, x_t] + b_z) \tag{3.32}$$

$$r_t = \sigma(W_r.[h_{t-1}, x_t] + b_r) \tag{3.33}$$

$$\underset{\sim}{h}_t = tanh(W_h.[r_t.h_{t-1}, x_t] + b_h) \tag{3.34}$$

$$h_t = (1 - z_t).h_{t-1} + z_t.\underset{\sim}{h}_t \tag{3.35}$$

where, t : Time step, x_t : Input value, h_t : Output value, r_t : Reset gate, z_t : Update gate, $\underset{\sim}{h}_t$: Candidate value, W_r : Reset gate weights, W_z : Update gate weights, W_h : Candidate gate weights, b_z : Update gate bias value, b_r : Reset gate bias value, b_h : Candidate bias value, and σ : Gate state.

The reset gate r_t determines the new input and previous memory combination. The update gate z_t determines the amount of previous memory kept. The idea of using a gating mechanism like GRU similar to LSTM with the same objective to solve long-term dependencies issues. The key differences are:

- GRU has two gates while LSTM has three.
- GRU does not have an output gate and internal memory.
- GRU trains faster due to lesser parameters.

The backward components, simplified from LSTM, for GRU are defined as follows [130, 132]:

Note, the following representations are defined for simplicity.

$$Gates_t = \begin{bmatrix} r_t \\ z_t \\ \underset{\sim}{h}_t \end{bmatrix}, W_t = \begin{bmatrix} W_r \\ W_z \\ W_h \end{bmatrix}, b_t = \begin{bmatrix} b_r \\ b_z \\ b_h \end{bmatrix}$$

$$\delta z_t = \delta h_t.(\underset{\sim}{h}_t - h_{t-1}).z_t.(1 - z_t) \tag{3.36}$$

$$\delta \underset{\sim}{h}_t = \delta h_t.z_t.(1 - \underset{\sim}{h}_t^2) \tag{3.37}$$

$$\delta r_t = \delta h_t.z_t.h_{t-1}.(1 - tanh^2(r_t)).r_t.(1 - r_t) \tag{3.38}$$

Equations (3.20) $\sim$ (3.22) and (3.28) $\sim$ (3.31) are implemented for both LSTM and GRU backward components algorithm. The difference is the equations (3.36) $\sim$ (3.38) that are derivations from the initial GRU algorithms. GRU and LSTM models had solved the long-term dependencies issues, but the side effects of both systems are not yet fully explored [129].

3.1.1.5 Hidden Layer Formula

The number of nodes in the hidden layer for multi-model prediction system[133] :

$$n_h = \frac{(n_i + n_o)}{2} + \sqrt{n_t} \tag{3.39}$$

where, n_h : Number of nodes in the hidden layer, n_i : Number of nodes in the input layer, n_0 : Number of nodes in the output layer, and n_t : Number of nodes in the training sets.

3.1.1.6 Power Accumulator

Power accumulator for PFA and SETS:

$$PA_{(n)} = \sum_{i=1}^{n} x_i \tag{3.40}$$

where, $PA_{(n)}$: Power Accumulator value for n data point, n : Number of data points, and x : The value of the data point in the list.

3.1.1.7 Mean Absolute Percentage Error (MAPE)

The MAPE for multi-model prediction system and SETS:

$$MAPE_n = \frac{100}{n} \sum_{i=1}^{n} |\frac{A_i - F_i}{A_i}|, where\ A_i \neq 0 \tag{3.41}$$

where, $MAPE_n$: MAPE value for n data point, n : Number of data, A_i : Actual output data, and F_i : Forecast output data.

3.1.1.8 Absolute Percentage Error (APE)

The APE for multi-model prediction system and SETS:

$$APE_n = 100(|\frac{A_n - F_n}{A_n}|), where\ A_n \neq 0 \tag{3.42}$$

where, APE_n : Absolute Percentage Error for n and n : datapoints.

3.1.1.9 Root Mean Squared Error (RMSE)

The RMSE of the training and testing data for multi prediction system. The error loss using RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3.43}$$

Where, n : Number of data, y_i : Original output data, and $\hat{y}_i$: Predicted output data.

3.1.2 K-Means Algorithm

K-means algorithm is an unsupervised technique that was first introduced by MaxQueen in 1967 [134] to solve complex clustering issues. It classifies the group of data sets through a user-defined cluster number. K-means algorithm had been used widely for different types of unsupervised applications [135]. K-means algorithm starts by initialising k centroids to each different clusters. The centroids could be initialised in multiple ways:

- Dynamically chosen: Initialised by referencing from the first few data sets.
- Randomly chosen: Initial centroids are randomly placed.
- Choosing from upper and lower bounds: Initial centroids are chosen from the highest and lowest within the data range.

However, the randomly chosen method is often used in the traditional k-means algorithm. The next step takes each point from the given data sets and referenced it to the nearest centroid. This process is enhanced via conducting an early grouping of the data points and the centroids. The k centroids will proceed to be recalculated with the same sets of data points and the centroids will be shifted back to the closest data. This updating process will continue to repeat until the k centroids have reached stability within the data range.

The advantages of k-means are robust, fast, and able to obtain optimal results from well-separated datasets. However, the disadvantages are unresolvable overlapping of data, the specification of cluster centroids number, randomised chosen centroids may not lead to optimised results, incapable of handling outliers, and noisy data.

K-means algorithm is relatively an efficient and reliable method. However, the final results are sensitive to the initialising defined by the users. The general idea of the k-means clustering algorithm, which was often referred to as Lloyd's algorithm, is represented in Fig. 3.8 [136–138].

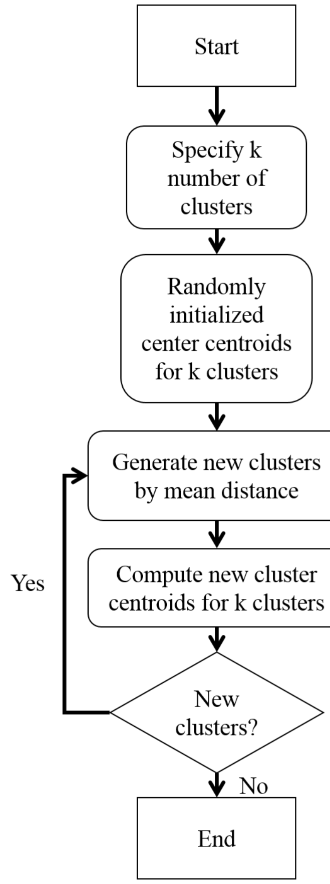

Fig. 3.8 K-Means Algorithm

K-means algorithms are defined as:

$$J = argmin \sum_{i=1}^{K} \sum_{j=1} ||x_j^{(i)} - \mu_i||^2 \tag{3.44}$$

$$x_j^{(i)} = \{x_j : ||x_j - \mu_i||^2 \leq ||x_j - \mu_i||^2\} \tag{3.45}$$

$$\mu_i = 1/|x_j^{(i)}| \sum_{j=1} x_j^{(i)} \tag{3.46}$$

where, K : Number of clusters initialised, J : Final K centroids, i^{th} : Index of the cluster, $x_j^{(i)}$: i^{th} cluster data point, μ_i : Distance of the data points from their respective cluster centroid, and $x_j^{(i)} - \mu_i{}^2$: Squared Euclidean distance measures between the cluster's data point and i^{th} cluster centroid μ_i.

Due to the k-means random initialisation of centroids, it requires an algorithm for the centroids to be initialised and placed in a better location of the cluster. The math equations for the initialisation are defined as:

$$P_{avg} = (\sum_{i=1}^{n} x_i)/n \tag{3.47}$$

$$P_{lavg} = (\sum_{i=1}^{n} (x_i : P_{avg} > x_i))/|n_{low}| \tag{3.48}$$

$$P_{havg} = (\sum_{i=1}^{n} (x_i : P_{avg} < x_i))/|n_{high}| \tag{3.49}$$

where, n : Number of data, x_i : Data points power, P_{avg} : Average power of the entire dataset, P_{lavg} : Average power from data points less than P_{avg}, P_{havg} : Average power from data points more than P_{avg}, n_{low} : Number of data from data points less than P_{avg}, and n_{high} : Number of data from data points more than P_{avg}.

These formulas are used for initialising the k centroids coordinate where P_{havg} for the higher boundary, P_{lavg} for the lower boundary, and P_{avg} for the middle boundary of the data set. This centroid initialisation method ensures the clustering of the centroids are well separated and solves the random initialisation problem in k-means.

The mean distance between data points and i_{th} cluster centroids are needed to understand the k-means final centroids. The algorithm of the mean distance between the data points and cluster centroids are defined as:

$$P_d = ((\sum_{j=1}^{n_i} (x_j - \mu_i))/n_i) \tag{3.50}$$

where, n_i : Number of data in the i_{th} cluster, μ_i : i_{th} cluster centroid, x_j : Data point value, and P_d : Distance mean.

Fig.3.9 shows the flowchart for the initialisation algorithm integrated with the k-means process sequences.

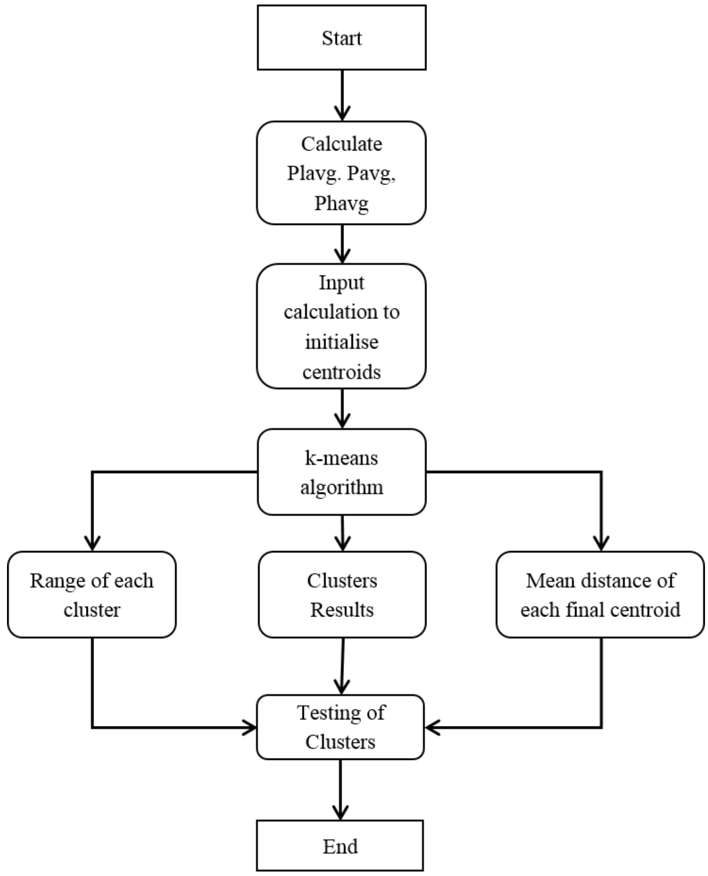

Fig. 3.9 Flowchart of the initialisation algorithm integrated with the k-means

The following steps have taken place:

1. Calculate the coordinates of the data collected using equations (3.47), (3.48), and (3.49).
2. Input the calculated centroid's coordinate into the initialising procedure.
3. Using the process as shown in Fig. 3.8 and the equations (3.44), (3.45), and (3.46).
4. Retrieving the range of cluster's coordinates from the final clusters.
5. Using equation (3.50), retrieve the mean distance from centroids to data point from the final clusters.
6. Test the resulted final clusters using random values within the range of the datasets.

Its function indicates to users on their power consumption in three levels: low, average, and high.

3.1.3 Decision Making System Algorithms

This section explains the algorithms implemented in the decision-making system.

3.1.3.1 Simple Moving Average (SMA)

The SMA for the SETS:

$$SMA_{(n)} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3.51}$$

where, $SMA_{(n)}$: SMA value for n hour, n : The number of hours for SMA, and x : The variable for the hour in the list.

3.1.3.2 Maximum SMA Difference Algorithm

The Maximum SMA difference algorithm for SETS:

$$\begin{aligned} SMA_{(md)} = \max_{i \in n} f(|SMA_{(i)} - SMA_{(i-1)}|), \\ where\ n \neq 0 \end{aligned} \tag{3.52}$$

where, $SMA_{(md)}$: Maximum of the SMA difference between two sequential $SMA_{(n)}$.

3.1.3.3 Maximum Wattage

The maximum wattage for SETS:

$$P_{(md)} = \max_{i \in n} f(|P_{(i)}|) \tag{3.53}$$

where, $P_{(md)}$: The maximum power from the list of measurement.

3.1.3.4 State of prediction

The state of prediction algorithm for SETS:

$$sp_{(n)} = \begin{cases} 0, & \text{if } APE_n \leq MAPE_n \\ 1, & \text{otherwise} \end{cases} \tag{3.54}$$

where, $sp_{(n)}$: State of prediction model decision-making condition.

3.1.3.5 State of hours

The state of hours algorithm for SETS:

$$s_{h(n)} = \begin{cases} 0, & \text{if } (SMA_n - SMA_{n-1}) \leq \frac{3}{4}SMA_{(md)}, \\ 1, & \text{otherwise} \end{cases} \tag{3.55}$$

where, $s_{h(n)}$: State of hours algorithm decision-making condition. Equation (3.55) is inspired by the Bollinger Bands algorithm [139]. $\frac{3}{4}$ represents the upper band of the equation for detecting the anomaly.

3.1.3.6 State of energy theft

The state of energy theft algorithm for SETS:

$$sets_{(n)} = \begin{cases} 0, & \text{if } \frac{3}{4}P_{(md)} \leq P_n \leq P_{(md)} \\ 1, & \text{otherwise} \end{cases} \tag{3.56}$$

where, $sets_{(n)}$: State of energy theft algorithm decision-making condition.

3.2 Multi Prediction System

This section proposes a novel idea of the multi prediction system for electricity generation forecast. The proposed forecasting system is more accurate compared to traditional machine learning methods. As the electricity market generation is a time series data, various advantageous predictive LSTM and GRU models such as Regression Model (RM), Regression with Time Steps Model (RTSM), Memory Between Batches Model (MBBM), and Stacked Model (SM) were used for accurate predictions. Compared to most forecasting approaches in time series electricity data, multi prediction system ability to retain relevant information and link it with the latest data point proves to be beneficial. The simulations of Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN), standard Long Short Term Memory (LSTM), standard Gated Recurrent Unit (GRU), and multi prediction system were benchmarked against each other to find highest accuracy system based on Mean Absolute Percentage Error (MAPE).

Fig. 3.10 shows the overall design of the proposed multi prediction system. Multi prediction system is designed for predicting electricity generation. It collects information from real-time electricity generation data to predict the future generation and pick the most accurate predictions.

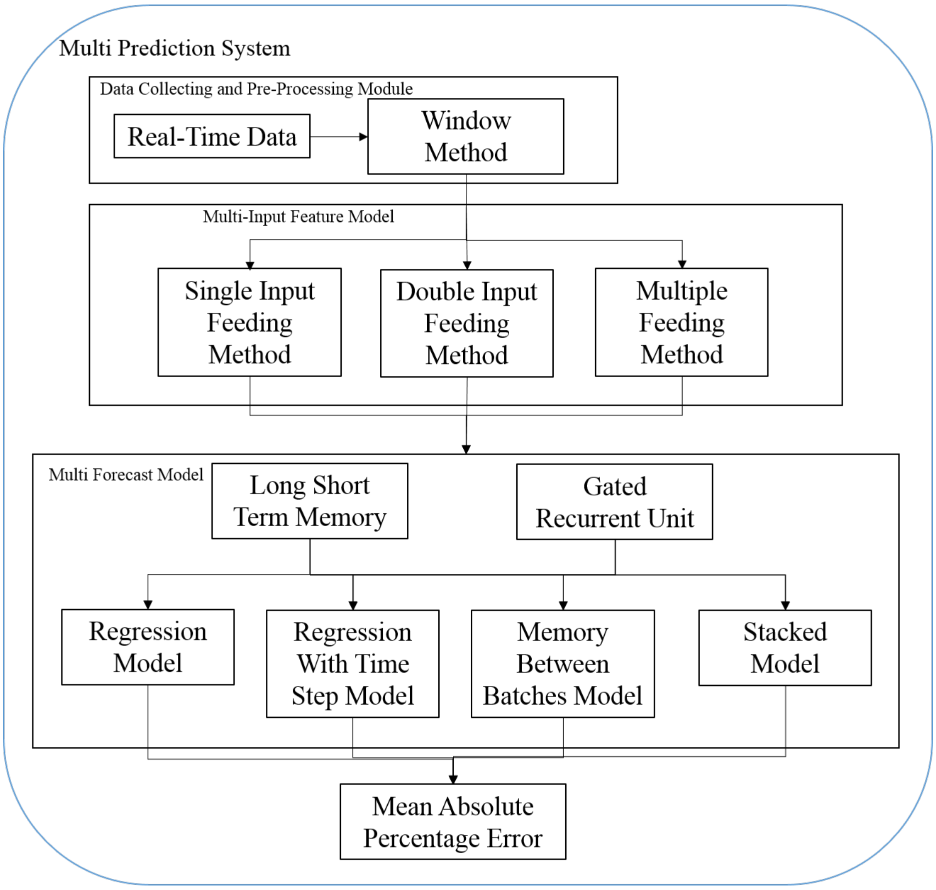

Fig. 3.10 Overall Multi Prediction System architecture

The overall architecture comprises the following modules:

- Data Collecting and Pre-Processing Module
- Multi-Input Feature Model
- Multi Forecast Model
- Mean Absolute Percentage Error (MAPE)

The data collecting and pre-processing module collect and pre-process the real-time data with a window method for multi prediction system.

The multi-input feature model function has the number of features as an input for multi forecast model to have different accuracy results. It includes different input methods such as

Single Input Feeding Method (SIFM), Double Input Feeding Method (DIFM), and Multiple Feeding Method (MFM).

The multi forecast model function is predicting future electricity generations. It comprises different LSTM and GRU variations such as Regression Model (RM), Regression with Time Step Model (RTSM), Memory Between Batches Model (MBBM), and Stacked Model (SM). These methods will go through MAPE to determine the final accuracy of the multi forecast model.

3.2.1 Data Collecting and Pre-Processing Module

3.2.1.1 Data Collecting and Pre-Processing Module: Real-Time Data

Real-time data will be taken from Energy Market Company (EMC) historical data for power generations by the electricity market in Singapore [140]. There are 48 periods each day which amounts to 30 minutes per period in the electricity generation for demand and each row of the data represents a period.

The collected data are pre-processed by using:

$$X1_t + X2_t = Y_t \tag{3.57}$$

Where, t : Time step, $X1_t$: Combined-cycle gas turbine/cogeneration/trigeneration power, $X2_t$: Steam turbine generation power, and Y_t : Actual total generation power.

$X1_t$, $X2_t$, and Y_t are used for predicting the next time step prediction output Y_{t+1}.

3.2.1.2 Data Collecting and Pre-Processing Module: Window Method

Window method is a way of updating a sequence of value with the next time step, t, of the data, X, within a determined size of features. Examples of window method with a window size of 4 are shown in Fig. 3.11.

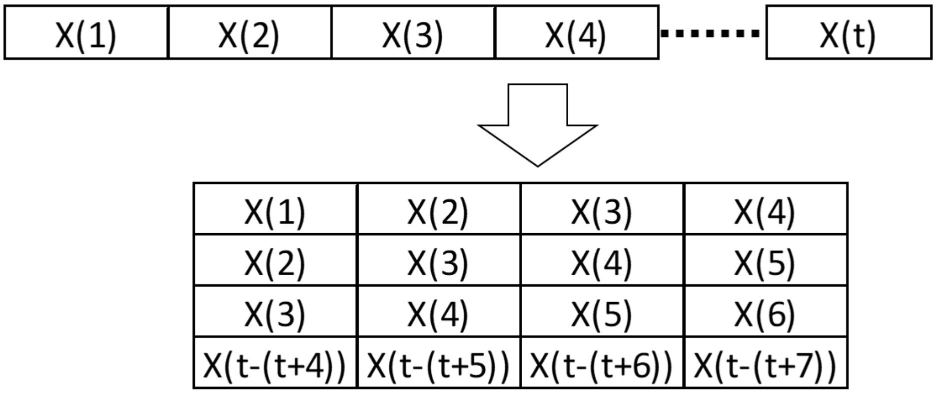

Fig. 3.11 Window Method with a window size of 4

3.2.2 Multi-Input Feature Model

Multi-input feature model process the features input to multi forecast model for different forecasting results. By using different methods, the possibility of distinct computation process results in accuracy differences. Thus, these methods will be tested to identify the most accurate prediction by the given data.

There are three methods for implementing the multi-input feature model:

1. Single Input Feeding Method (SIFM)

2. Double Input Feeding Method (DIFM)

3. Multiple Feeding Method (MFM)

These methods are further elaborated in the following sections.

3.2.2.1 Single Input Feeding Method (SIFM)

Using a single input feature to determine the output accuracy results. An example is shown in Fig.3.12.

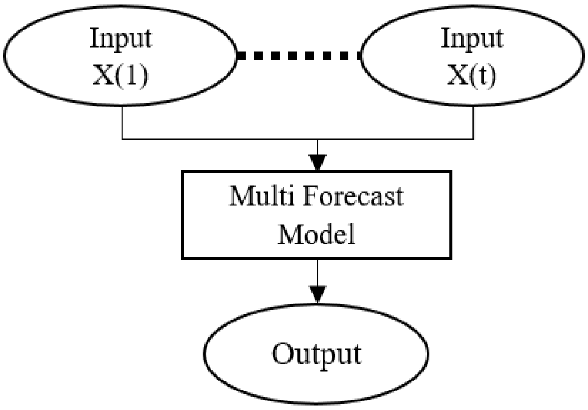

Fig. 3.12 SIFM block diagram

3.2.2.2 Double Input Feeding Method (DIFM)

Using two input features to determine the output accuracy results. It is a method that computes two input individually and predicts the two output values to have the final output. An example is shown in Fig.3.13.

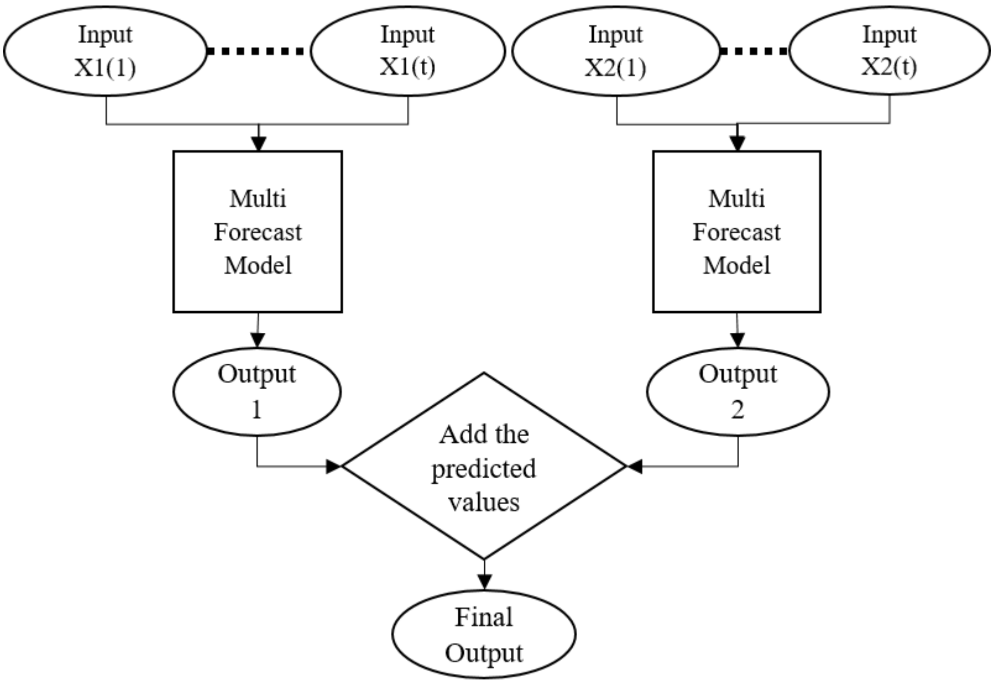

Fig. 3.13 DIFM block diagram

3.2.2.3 Multiple Feeding Method (MFM)

Using multiple input features to determine the output accuracy results. It is a method that computes multiple input features to get the output. An example is shown in Fig.3.14.

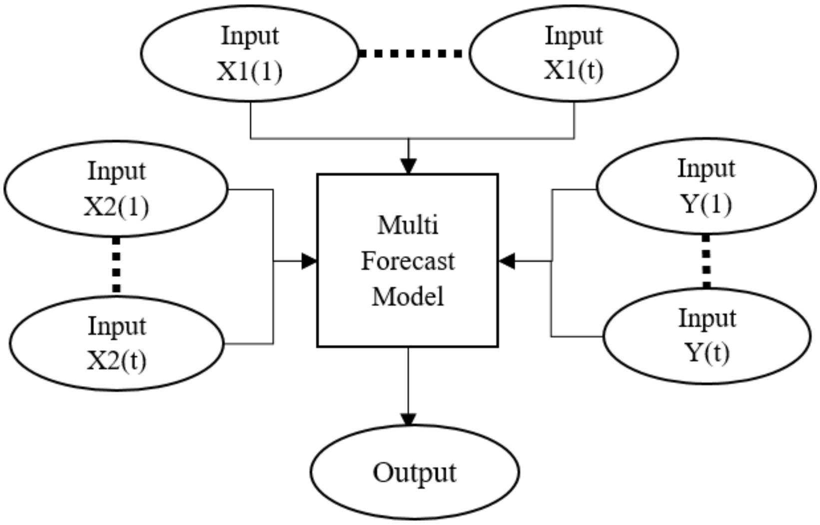

Fig. 3.14 MFM block diagram

3.2.3 Multi Forecast Model: Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU)

Multi forecast model uses Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) variations to forecast future electricity generation. The background information and formula are found in section 3.1.1.3 and 3.1.1.4. Multi forecast model integrates the following LSTM and GRU variation models:

1. Regression Model (RM)

2. Regression with Time Steps Model (RTSM)

3. Memory Between Batches Model (MBBM)

4. Stacked Model (SM)

These models are further elaborated in the following sections.

3.2.3.1 Regression Model (RM)

Fig. 3.15 shows the sequence averages of all the time step outputs by LSTM or GRU to the average pooling resulting in h. h_t will be fed to a logistic regression layer whose target is the input sequence associated with the class label.

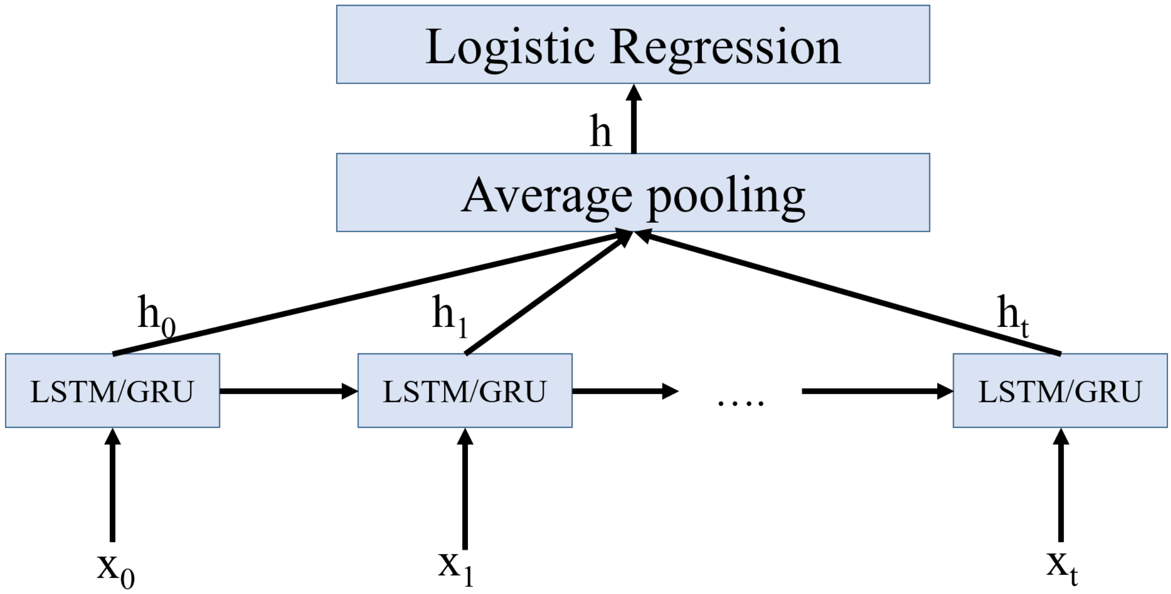

Fig. 3.15 RM block diagram

The logistic regression formula was represented as such:

$$\sigma = 1/(1+e^{-h}) \tag{3.58}$$

3.2.3.2 Regression with Time Steps Model (RTSM)

RTSM relabels the data with an additional feature called time steps sequence. It will increase the accuracy of the prediction model [141]. An example was shown in Fig. 3.16.

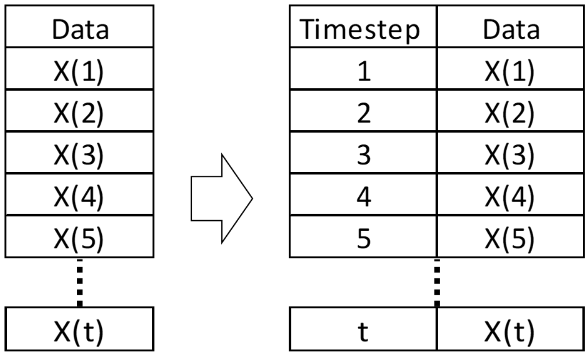

Fig. 3.16 RTSM diagram

3.2.3.3 Memory Between Batches Model (MBBM)

The output states of each batch will be reused as initial states in the next batch. Fig. 3.17 shows an example of MBBM.

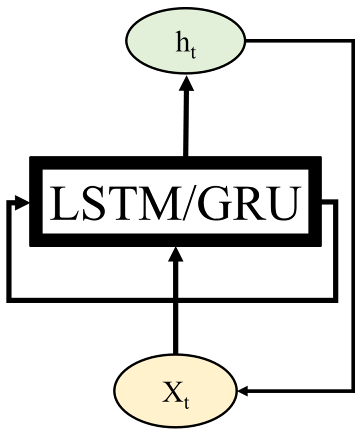

Fig. 3.17 MBBM block diagram

3.2.3.4 Stacked Model (SM)

By stacking numerous LSTM or GRU layers on top of each other, it makes the model capable of learning higher-level temporal representations. The last layer of the LSTM or GRU layers returns the last step in its output sequence which results in dropping the temporal dimension. Fig. 3.18 shows an example of the SM.

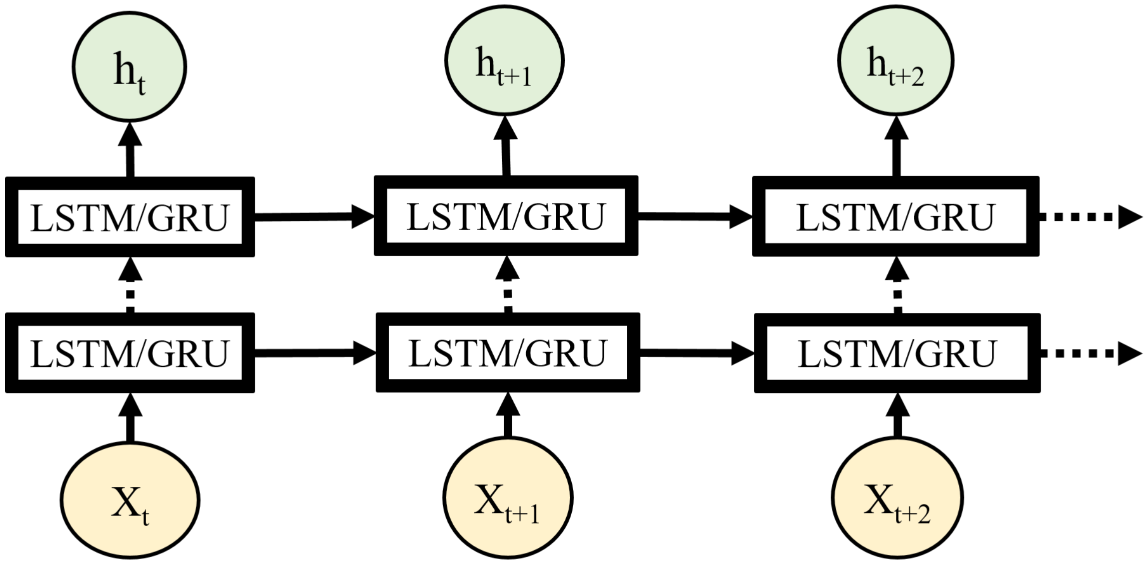

Fig. 3.18 SM block diagram

3.3 Self-learning Home Management System (SHMS)

A novel smart home system called Self-learning Home Management System (SHMS) is proposed in this section. 'Self-learning' implies that energy optimisation does not require any human intervention due to machine learning. This model uses the multi-agent system communication network and rule-based classifier techniques in the supply and demand side management systems. Additionally, several machine learning functions were included in the home energy management system. Fig.3.19 shows the architecture of the proposed system.

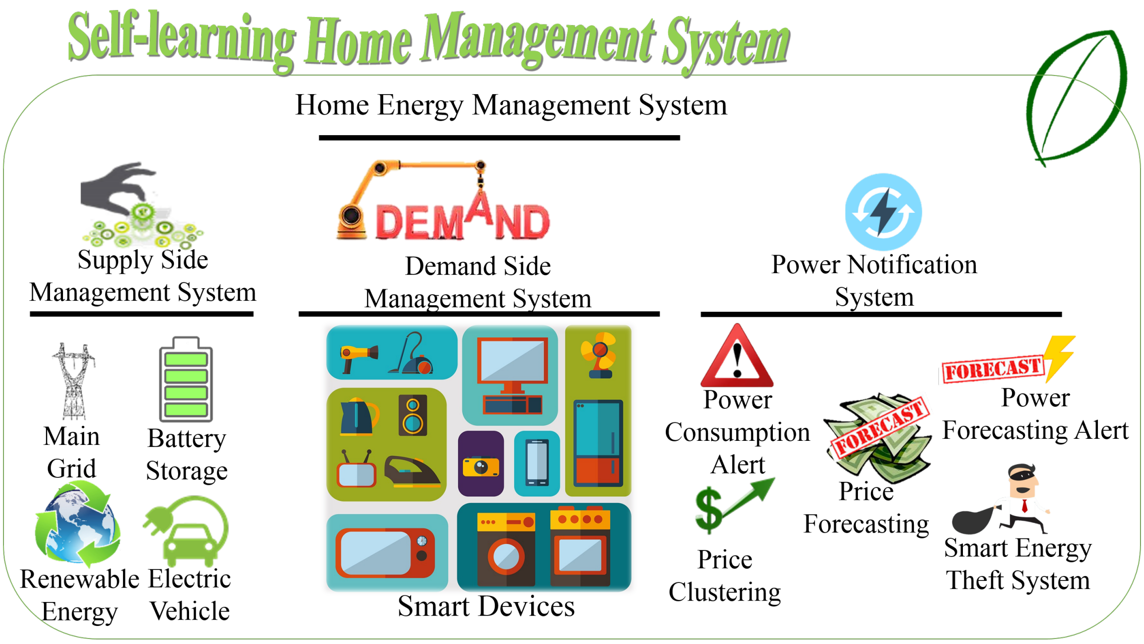

Fig. 3.19 Proposed SHMS architecture

The Home Energy Management System (HEMS) optimises residential household units by consumers' comfort, electricity cost and reduce overloading of the power supply. SHMS uses HEMS as the main decision maker in the system with the following components:

1. Supply Side Management (SSM) System

2. Demand Side Management (DSM) System

3. Power Notification System (PNS)

SSM and DSM use the rule-based classifier to manage the respective supply and demand sources available such as renewable energy, battery storage, main grid, electric vehicle, and smart devices. PNS has various functions such as Power Consumption Alert (PCA), Power Forecasting Alert (PFA), Price Consumption (PC), Price Forecasting (PF), and Smart Energy Theft System (SETS) using different algorithms. PFA and PF use the machine learning algorithm for predicting power consumption and price. PCA and PC classify the different range of price and power usage using K-means algorithms. SETS uses the machine learning and decision-making system algorithms for detecting energy theft.

The DSM system controls the demand of the SHMS architecture while SSM system controls the power supply. The HEMS will activate the DSM and SSM based on the user-defined process where it can be more economical or energy efficient. With machine learning functionality in PNS, these components build the capability of residential household energy optimisation through electrical distribution optimal algorithms.

3.3.1 Supply Side Management (SSM) System

Supply Side Management (SSM) system optimises the supply of HEMS by using components such as Renewable Energy (RE), Battery Storage (BS), Main Grid (MG), and Electric Vehicle (EV). RE is the power generated from renewable sources, BS stores power when emergency power is needed, MG is the power supply from the grid, and EV supplies when there is an emergency or when required.

The major factors in the flowchart are the House Demand (HD) and the renewable energy sources which define the supply process. The HEMS activation is user-defined, this will occur if the user prefers using the energy from the BS and EV battery to supply the demand. When the demand still exceeds the supply, an option for the users to activate the DSM process will be presented or the demand to be directly supplied by the MG. This has been enhanced from W.Li, et al., [142] for SHMS. Fig.3.20 shows the flowchart for the SSM system. Table 3.1 shows the entities representative in Fig. 3.20.

Table 3.1 Entities representative in Fig. 3.20

Entity	**Representative**
Renewable Energy	RE
House Demand	HD
Electric Vehicle	EV
Battery Storage	BS
Main Grid	MG

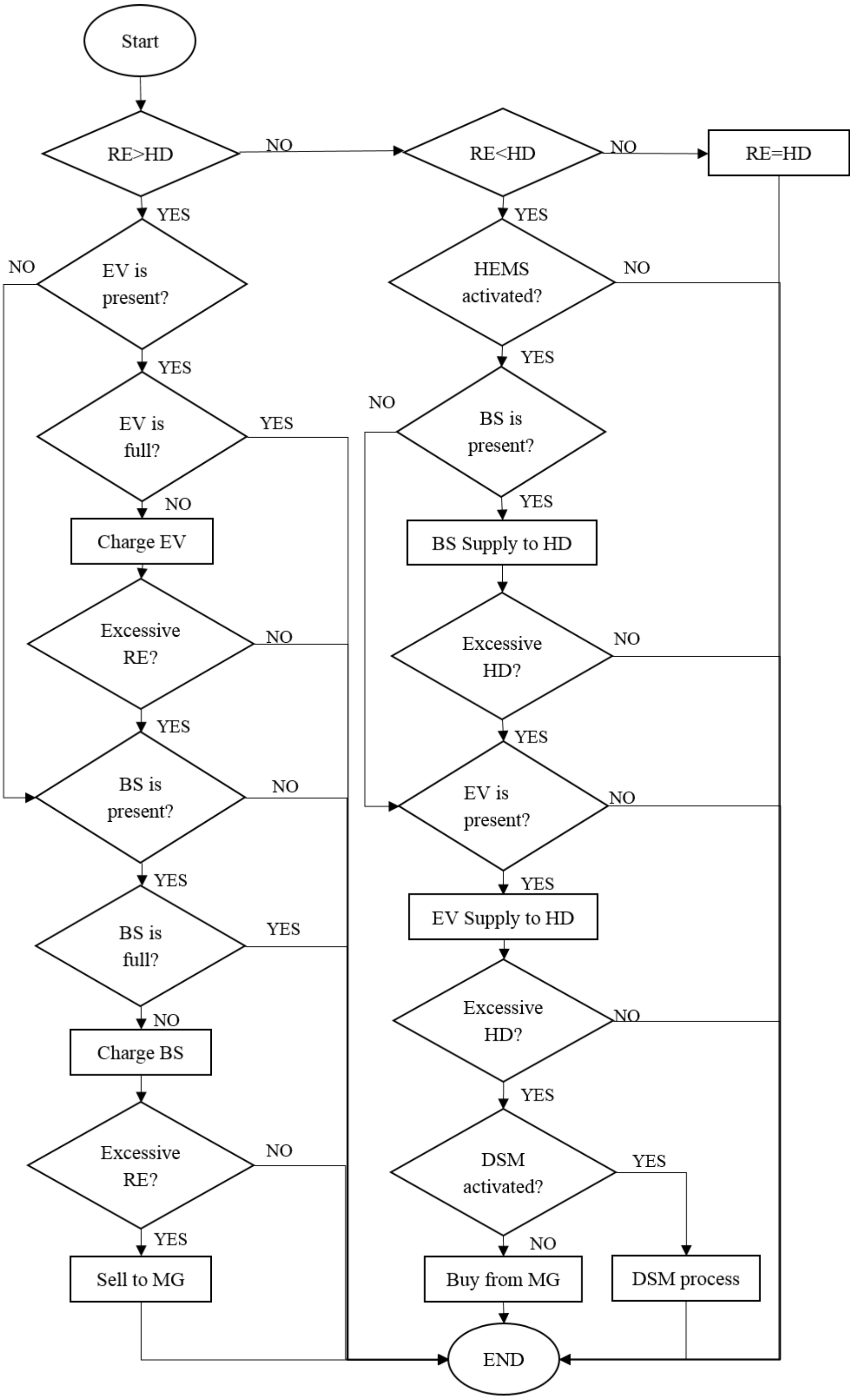

Fig. 3.20 SSM Flowchart

Fig.3.21 shows the flowchart that is designed to facilitate appliances for different hours or period of the day. The appliances are based on whether the switches are turned 'ON' during the different time period in a day and computation of the total demand for that time period. Table 3.2 shows the devices representative in Fig. 3.21.

Table 3.2 Devices representative for Fig. 3.21

Device	**Representative**	**Switches Representative**
Standing Fan	SF	SFS
Tower Fan	TF	TFS
Fridge	F	FS
Rice Cooker	RC	RCS
Electric Dispensing Pot	EDP	EDPS
Bathroom Heater	BH	BHS
Vacuum Cleaner	VC	VCS
Iron	IR	IRS
Air Conditioner	AC	ACS
Speaker	S	SS
Desktop Computer	DC	DCS
Laptop	LT	LTS
LED Television	TV	TVS
Top Loading Washing Machine	TLWM	TLWMS
Incandescent Bulbs	IB	IBS

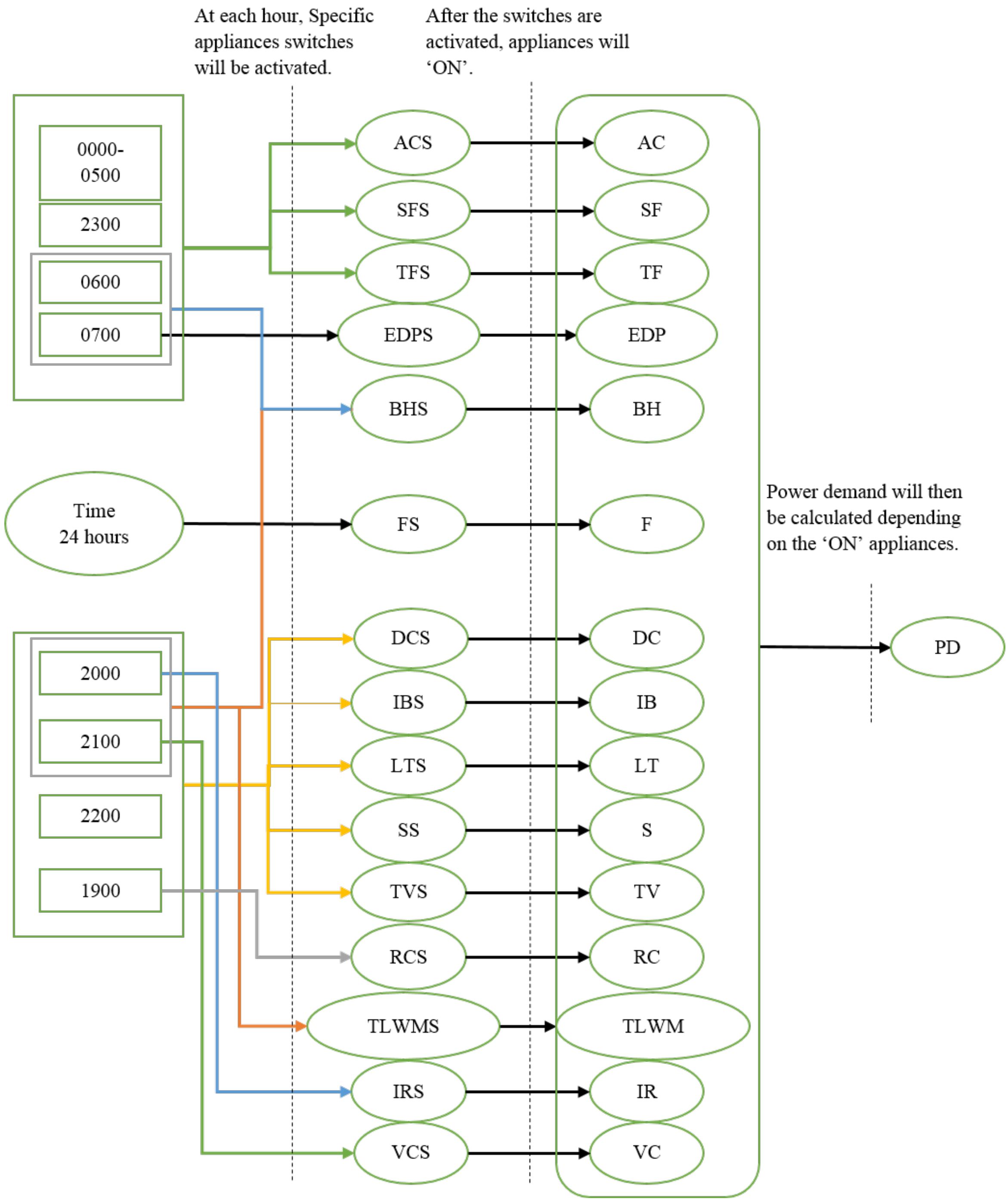

Fig. 3.21 Proposed demand schedule

3.3.2 Demand Side Management (DSM) System

Demand Side Management (DSM) system collects and calculates the total House Demand (HD) from the IoT based smart plugs with home devices (eg. Computer, Television, and etc..) and EV.

Smart plugs data are pre-processed before implementing in the DSM as shown in Fig. 3.22. Pre-processing procedure identifies the consumers' usage behaviour through the number of times the plugs are turned "ON" or "OFF" and the power consumption data. This process generates a priority list in ascending order through the learning from historical data of the user. Thus, its ability to customise each priority list for different users.

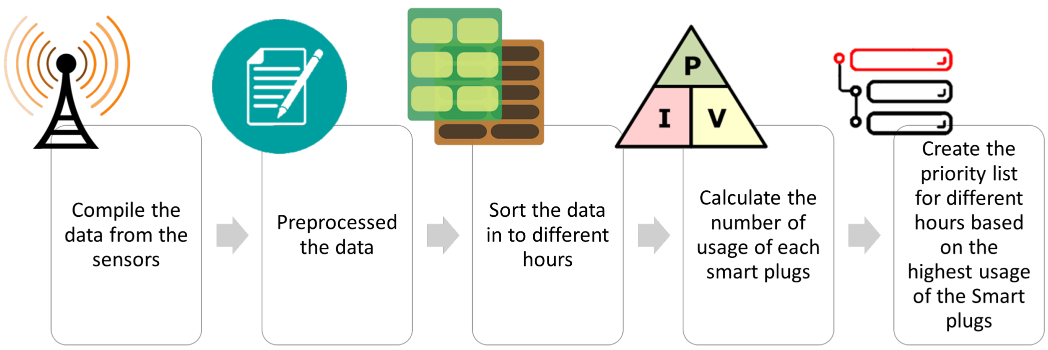

Fig. 3.22 Pre-processing Procedure

Fig. 3.23 shows the DSM system with its priority list selection. Pre-processed data is fed into the DSM system.

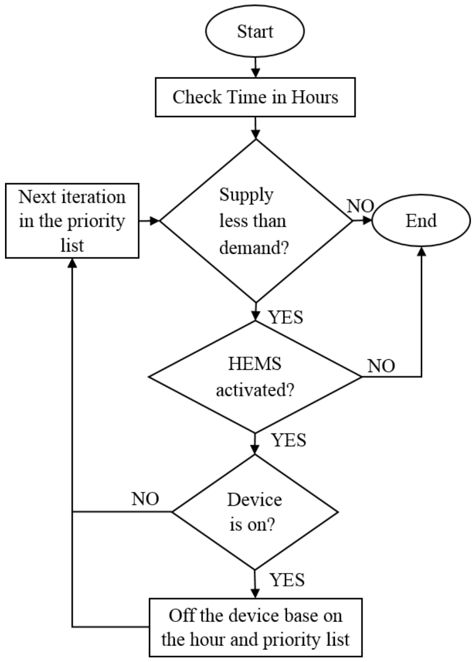

Fig. 3.23 DSM Flowchart

The proposed DSM prioritises the smart plugs by creating a list of smart plugs with the highest usage as the top priority. The lowest priority shall be "OFF" when the power demand exceeds the power supply until the power demand is lower than the power supply.

3.3.3 Power Notification System (PNS)

This section proposes a novel idea of Power Notification System (PNS) for the IoT based smart home. PNS integrates different machine learning methods to analyse energy-related data and notify the house tenants. As a result of a non-intrusive method of data collection, an energy monitoring system is implemented in a real house in Singapore. The data collected includes time series data power consumption from a non-controlled real-life house environment and real electricity prices from Singapore electricity market. This power notification system is more efficient and reliable compared to previous conventional methods.

Fig. 3.24 shows the overall design of the proposed PNS.

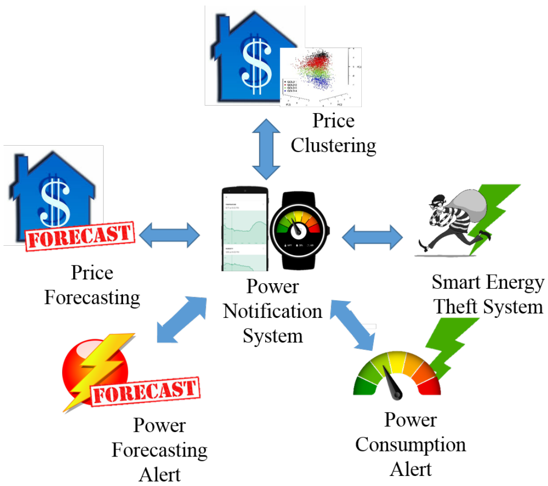

Fig. 3.24 Overall PNS architecture

The proposed PNS is designed as an additional feature for any existing smart home energy management system. PNS is designed for predicting energy, electricity market prices, detecting energy theft, and alerting the consumers.

PNS is designed with the following functions:

- Power Consumption Alert (PCA)
- Power Forecasting Alert (PFA)

- Price Forecasting (PF)
- Price Clustering (PC)
- Smart Energy Theft System (SETS)

Fig. 3.25 shows the details of the proposed PNS.

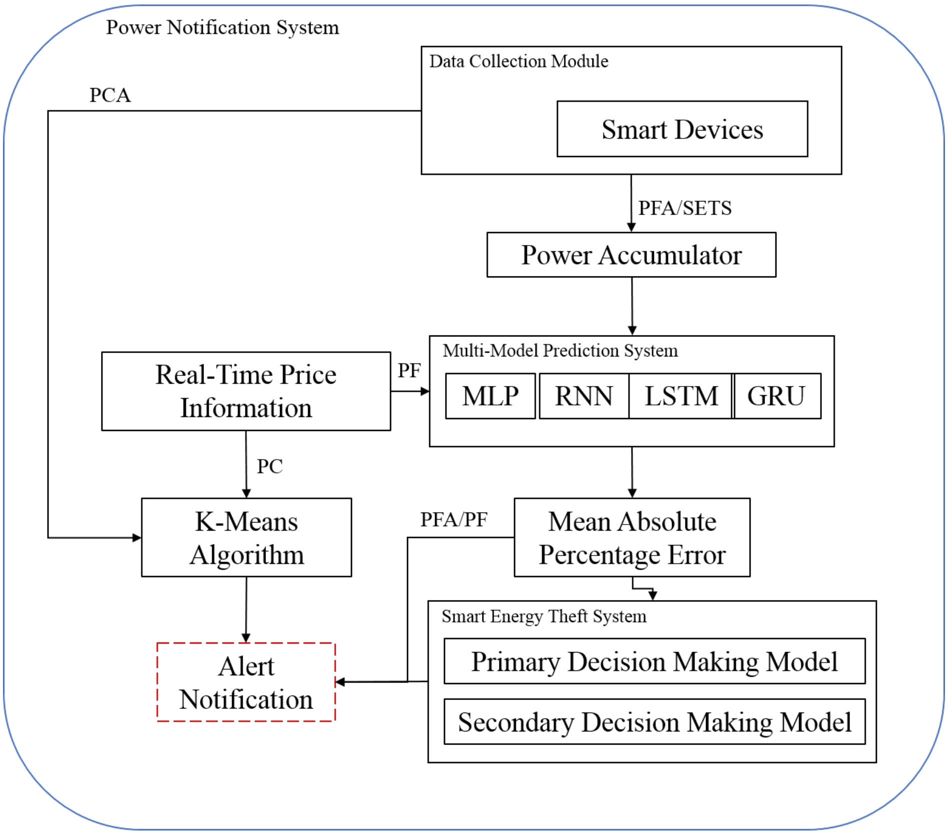

Fig. 3.25 Overall PNS architecture

The overall architecture comprises the following modules:

- Data Collection Module (DCM)
- Real-time price information
- Multi-model prediction system
- SETS

- K-means algorithm
- Power accumulator
- MAPE
- Alert notification

The DCM collects the smart device's data for PNS. Real-time price information collects the price data from the electricity market. Multi-model prediction system consists of different prediction methods such as MLP, RNN, LSTM, and GRU. The prediction methods were chosen to accommodate different level of data length. For example, LSTM will generally have better predictions for long period sequential data compared to RNN which is better for short period sequential data. Thus, making the prediction methods suitable to predict the energy and electricity market price for the smart home as the information are time-series. SETS uses primary and secondary decision models to decide if energy theft has occurred. Power accumulator process the data from DCM for the use of multi-model prediction system. K-means algorithm is used to cluster the smart home power and electricity market price. MAPE determines the prediction accuracy of the multi-model prediction system. The alert notification alerts the consumers based on the different functions of PNS. The entities in Fig. 3.25 communicates information between each entity using Multi-Agent System (MAS).

3.3.3.1 Data Collection Module (DCM)

Data Collection Module (DCM) collates the information from various real-time monitoring smart devices. Data collection module uses a set of smart plugs called Aeon Labs Z-Wave UK Plug-in Switch plus Power Meter and the main controller is a VeraEdge Home Controller. This system is placed on a Singapore smart home for collecting data through a non-invasive method of energy monitoring.

3.3.3.2 Real-Time Price Information

Real-time price information is taken from Energy Market Company (EMC) historical data for power generations by the electricity market in Singapore [143]. There are 48 periods each day which amounts to 30 minutes per period in the electricity generation for demand and each row of the data represents a period.

3.3.3.3 Price Forecasting (PF)

Price Forecasting (PF) predicts the electricity prices in advance with electricity price market data. It is designed with the following steps:

- Step 1: Retrieve the real-time price information.
- Step 2: Using multi-model prediction model to predict the data.
- Step 3: Using MAPE to get the best prediction accuracy model.
- Step 4: Send the results to alert notification.

3.3.3.4 Price Clustering (PC)

Price Clustering (PC) collects and reclassify the electrical prices into "Peak" and "Off-Peak" hours. The price clustering functionality in PNS is designed with the use of the k-means algorithm. The following steps have been taken:

- Step 1: Retrieve the real-time price information.
- Step 2: Using the k-means algorithm to classify the price data.
- Step 3: Send the results to alert notification.

3.3.3.5 Power Forecasting Alert (PFA)

Power Forecasting Alert (PFA) predicts the smart home power in advance with smart devices data. It is designed with the following steps:

- Step 1: Collect and pre-process the DCM information using power accumulator.
- Step 2: Using multi-model prediction model to predict the data.
- Step 3: Using MAPE to get the best prediction accuracy model.
- Step 4: Send the results to alert notification.

3.3.3.6 Power Consumption Alert (PCA)

Power Consumption Alert (PCA) collects and reclassify the smart home power consumption into "High Power", "Average Power", and "Low Power". It is designed with the following steps:

- Step 1: Collect and pre-process the DCM information using power accumulator.
- Step 2: Using the k-means algorithm to classify the power data.
- Step 3: Send the results to alert notification.

3.3.3.7 Proposed Smart Energy Theft System (SETS)

In modern smart homes, smart meters, and the Internet of Things (IoT) have been massively deployed to replace traditional analogue meters. It digitalised the data collection and the meter readings. The data can be wirelessly transmitted that significantly reduces manual works. However, the community of smart home network is vulnerable to energy theft. Energy theft consists of cyber, physical, and data attacks, attack techniques like intercepting communications, bypassing meters to remove loads measurement and alter consumption report have been encountered [144]. Such attacks cannot be effectively detected since the existing techniques require certain devices to be installed to work. This imposes a challenge for energy theft detection systems to be implemented despite the lack of energy monitoring devices.

This section develops an energy detection system called Smart Energy Theft System (SETS) based on machine learning and statistical models. SETS has 3 stages of decision-making modules, the first stage is the prediction model which uses a multi-model prediction system. This multi-model prediction system integrates Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN), Long Short Term Memory (LSTM), and Gated Recurrent Unit (GRU) into a single forecast system. Stage 2 is the primary decision making model that uses the Simple Moving Average (SMA) for filtering abnormally. Stage 3 is the secondary decision making model that makes the final stage of the decision on energy theft. The simulation results demonstrate that the proposed system can successfully detect 99.96% accuracy.

Fig. 3.26 shows the detail design of the proposed SETS. SETS is designed for detecting energy theft and alerting the consumers. It collects information from monitoring devices and analyses the data to detect energy theft.

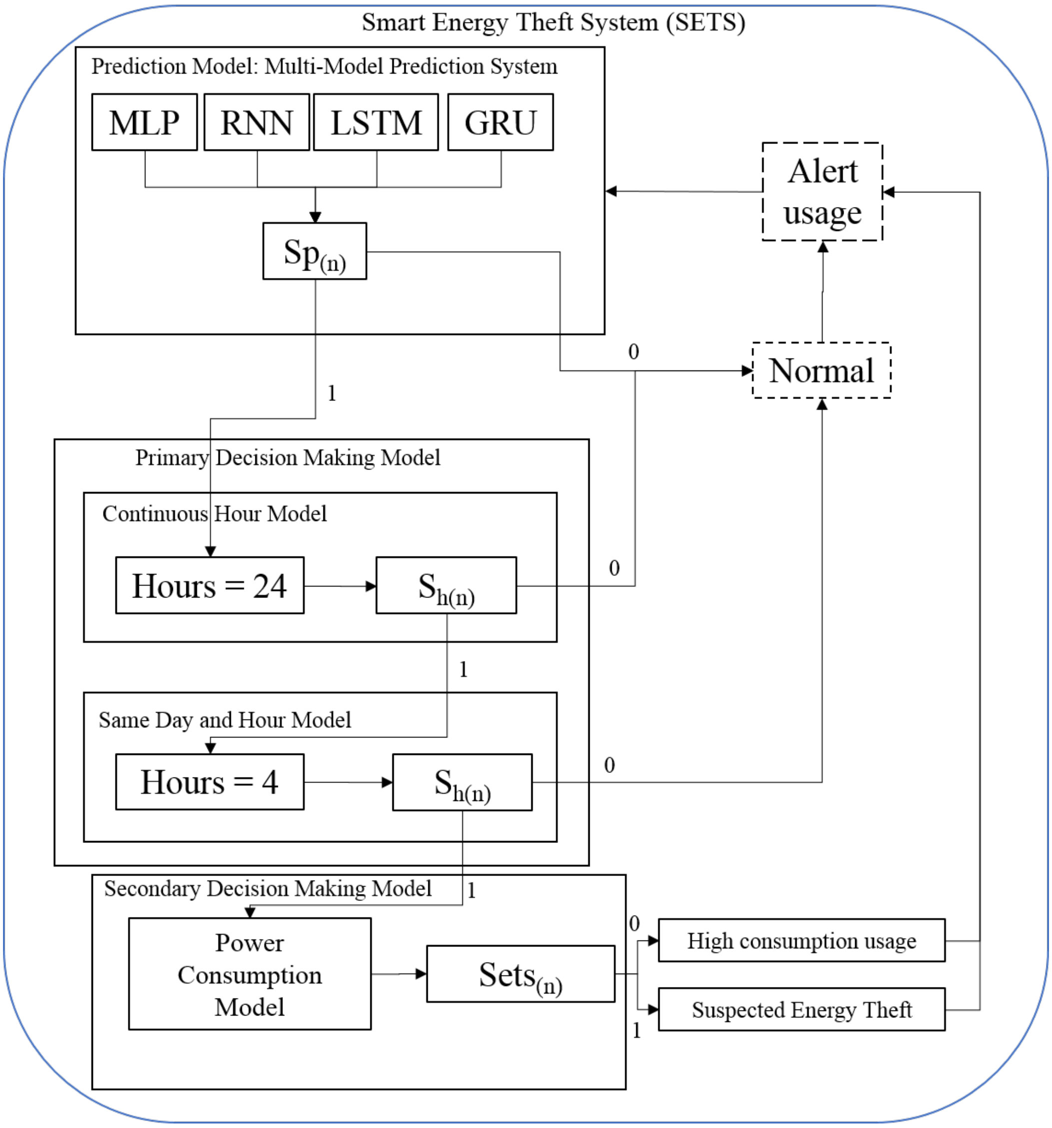

Fig. 3.26 Detail SETS architecture

The overall architecture comprises the following modules:

- Prediction model
- Primary decision making model
- Secondary decision making model

The first stage of SETS is the prediction model. The prediction model uses multi-model forecasting system that comprises different machine learning methods such as MLP, RNN, LSTM, and GRU. It predicts and compares the actual data to detect abnormally.

Second Stage of SETS is the primary decision making model. This stage uses a statistical model called Simple Moving Average (SMA) in the continuous hour model and same day and hour model to filter the abnormally from the first stage. SMA is used to detect abnormally in a time window period, as the time period where data is used must be attuned to the house's latest behaviour.

Third Stage of SETS is the secondary decision making model. This stage filters from the second stage and decides whether energy theft had occurred in the power consumption model. After taking the final decision, the whole process is then repeated for the next incoming data.

3.3.3.7.1 Stage 1: Prediction model: Multi-Model Forecasting System

The prediction model forecast the next 24 hours by using multi-model forecasting system. Measured data is used for predictions and comparison to calculate the accuracy of the various forecasting systems. The following steps have been taken for this stage:

- Step 1: Pre-process the data to accumulative data.
- Step 2: Using prediction model to predict the data.
- Step 3: Using MAPE to dictate the best prediction model.
- Step 4: Use the updated MAPE to compare with APE for every hour.
- Step 5: If $sp_{(n)} = 1$ then go to the next stage, otherwise go to the next iteration.

3.3.3.7.2 Stage 2: Primary Decision Making Model

This stage uses SMA to determine energy theft predictions. The following steps have been taken for this stage:

- Stage 2.1: Continuous hour model:
  - Step 1: Calculate SMA using 24 hours period.
  - Step 2: Find the difference between the SMA calculation for the last hour and the current hour after 25 hours of measured data.
  - Step 3: Use the Maximum SMA difference algorithm and proceed to the state of hours algorithm.
  - Step 4: If $s_{h(n)} = 1$ then start the same day and hour model, otherwise go to the next iteration.
- Stage 2.2: Same day and hour model:
  - Step 1: Rearrange the data according to the day and hour.
  - Step 2: Calculate SMA using 4 hours of data from the same day and hour from different dates.
  - Step 3: Find the difference between the SMA calculation for the last point and the current point after 5 points of measured data.
  - Step 4: Use the Maximum SMA difference algorithm and proceed to the state of hours algorithm.
  - Step 5: If $s_{h(n)} = 1$ then go to the next stage, otherwise go to the next iteration.

3.3.3.7.3 Stage 3: Secondary Decision Making model

This stage uses the user's history to find the occasional maximum power usages. The following steps have been taken for this stage:

- Step 1: Find the Maximum watt and proceed to the state of energy theft algorithm.
- Step 2: If $sets_{(n)} = 1$ then possible energy theft, otherwise unexpected high consumption usage from consumers.

- Step 3: Proceed to the next iteration.

After all the stages are completed, it will move to the next period and repeat the process from stage 1. However, SETS requires at least 5 weeks of data, Where Stage 2.2 requires 5 points of measured data are needed to calculate Equation 3.52, at every hour in order for the system to learn from the historical data. This learning process will be constantly updated for real-time monitoring and it can increase its accuracy with more data coming in.

3.3.4 Multi-Agent System (MAS) for SHMS

As shown in Fig.3.27, in a MAS-based SHMS architecture, agents are represented by either a hardware or software entity that is responsible for learning the environmental conditions, states, situations, and habits of the owners in order to respond appropriately [145].

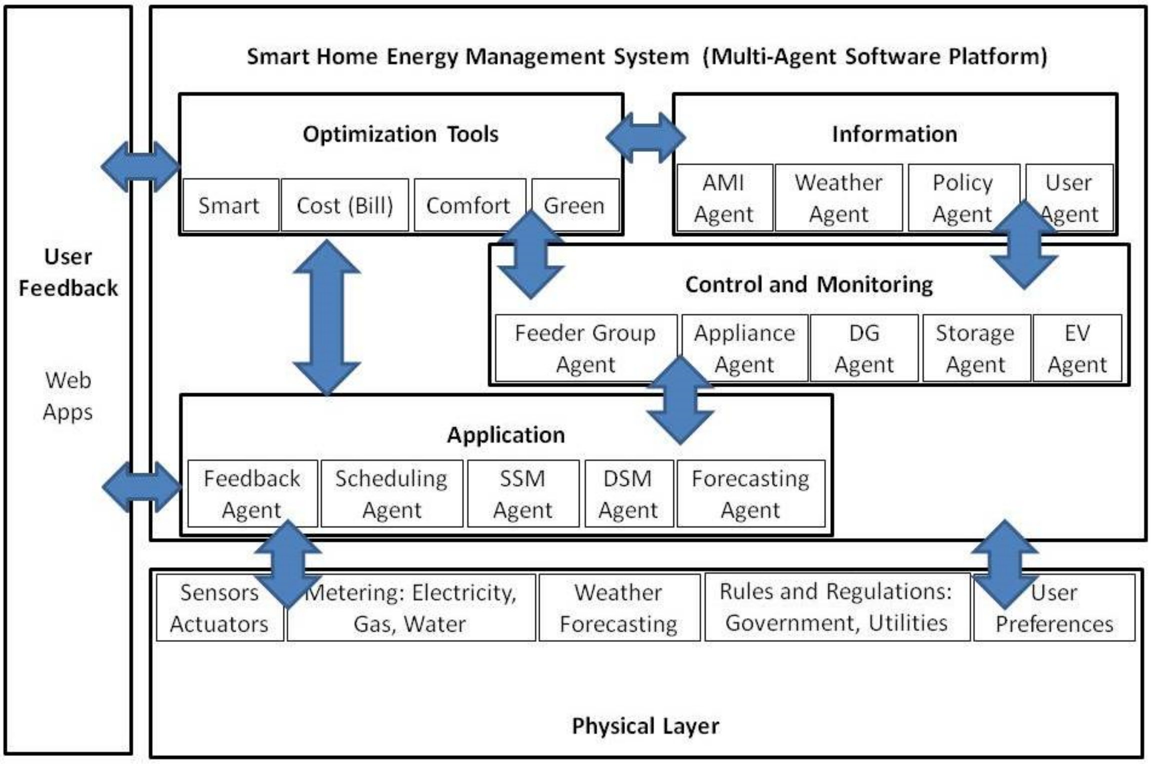

Fig. 3.27 A MAS architecture for SHMS

The following main agent groups are known to be involved in the architecture for smart home energy management and its optimisation.

1. Control and Monitoring Agent (CMA)

   Agents are responsible for direct monitoring or control of sensors and actuators. These control and monitoring agents can be seen from Fig.3.27:

- Feeder Group Agents (FGA): Monitor consumption of energy in a group of loads in a household dissemination system. As shown in Fig.3.27, it monitors device performance as well as the home automation system.
- Device Agents (DA): Controls (on/off switches) or monitor load or generation devices (i.e. washing machines).

2. Information Agent (IA)

   This agent stores and retrieves relevant data that are considered to be leading factors in operations of home devices. The information agent group encompasses the following agents:

   - Policy agent: Handle the tariff system and government policies on energy.
   - User agent: In control of user inputs as well as acknowledging the preferred environmental conditions, habits and situations of the user.
   - AMI agent: Switches measurements from the smart metering system and external signals from utilities, companies, or/and third parties.
   - Weather agent: Keep track of temperature changes, irradiation, humidity, and even wind speed data.

3. Application Agents (AA)

   This agent encompasses the following agents:

   - Feedback agents: Providing information to the customer viewed or home display.
   - Forecasting agent: Forecasts load used, amount of energy generated, and price calculation.
   - Scheduling agents: Search for ideal time allocation of shiftable loads.

4. Optimization Agent (OA)

   This agent observes and coordinates activities of all distributed agents involved. It handles optimisation problems and set the overall control strategy for the household based on the user's preferences. It is done via broadcasting messages to all agents involved to attain system optimisation.

Fig.3.28 shows the overall Multi-Agent System (MAS) network design. Self-learning Home Management System (SHMS) uses the Home Energy Management System (HEMS) as a catalyst for the MAS network.

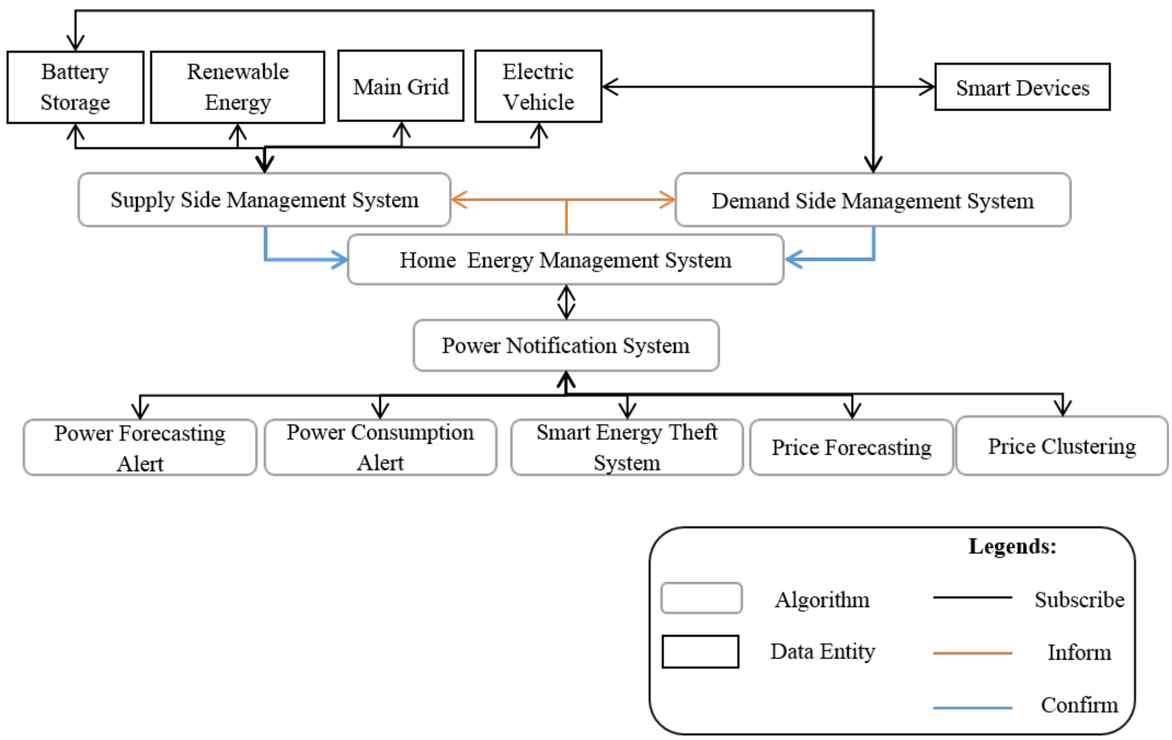

Fig. 3.28 Overall SHMS architecture

Table 3.3 shows the agent representative in the SHMS MAS network.

Table 3.3 Agent representative in SHMS's MAS network

Names	**Representative**	**Agent Representative**
Power Notification System	PNS	PNSAgent
Power Forecasting Alert	PFA	PFAAgent
Power Consumption Alert	PCA	PCAAgent
Smart Energy Theft System	SETS	SETSAgent
Price Forecasting	PF	PFAgent
Price Clustering	PC	PCAgent
Renewable Energy	RE	REAgent
Main Grid	MG	MGAgent
Electric Vehicle	EV	EVAgent
Battery Storage	BS	BSAgent
Smart Devices	SD	SDAgent
Supply Side Management System	SSM	SSMAgent
Demand Side Management System	DSM	DSMAgent
Home Energy Management System	HEMS	HEMSAgent

The HEMS agent collects the information from the supply and demand side management systems to compute the data. Fig.3.29 shows the design of the HEMS agent communication.

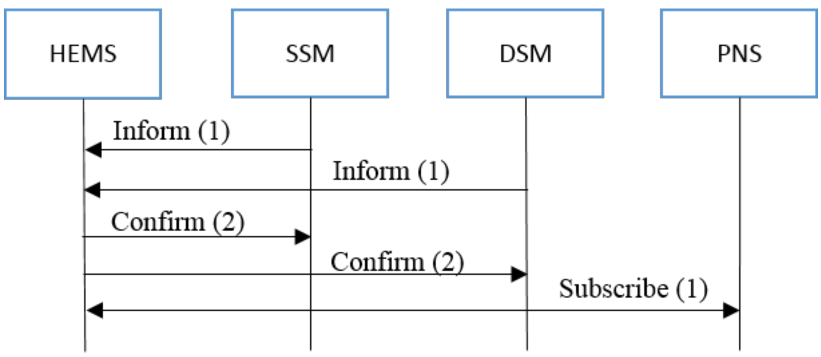

Fig. 3.29 HEMS MAS communication

The HEMS MAS network is designed by the following components:

Fig.3.30 shows the design of the SSM agent communication.

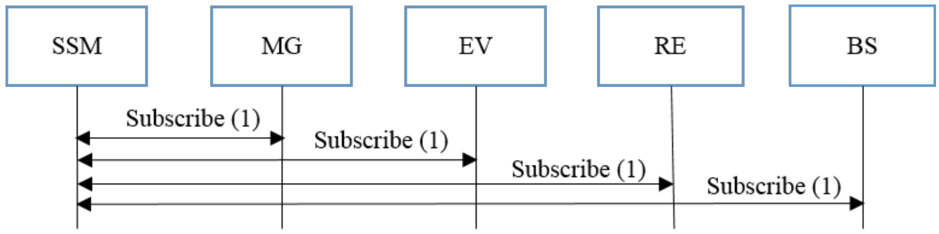

Fig. 3.30 SSM MAS communication

1. SSM system agent: Receive data from the home supply sources and inform the HEMS agent.

    (a) RE agent: Sends the total harvested electricity data to SSM agent.

    (b) MG agent: Sends the total house supply grid data to SSM agent.

    (c) EV agent: Sends the total electric vehicle's electricity supply data to SSM agent.

    (d) BS agent: Sends the total battery storage's electricity data to SSM agent.

Fig.3.31 shows the design of the DSM agent communication.

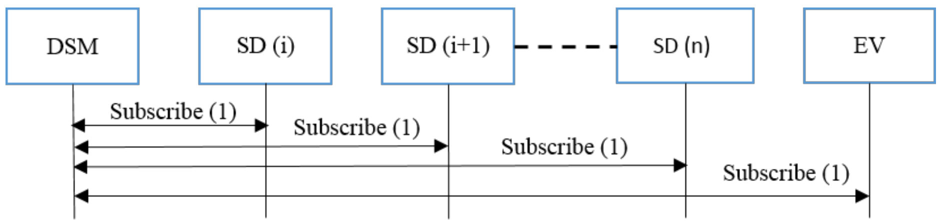

Fig. 3.31 DSM MAS communication

2. DSM system: Receive data from the home supply sources and inform the HEMS agent.

    (a) SD agent: Sends the smart devices electricity demand data to the DSM agent.

    (b) EV agent: Sends the total electric vehicle electricity demand data to DSM agent.

Fig.3.32 shows the design of the PNS agent communication.

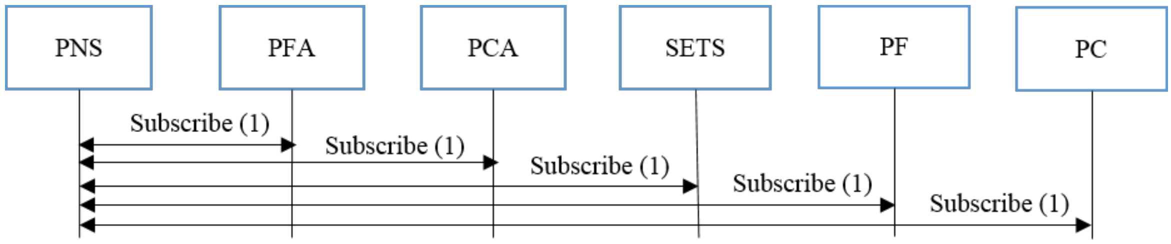

Fig. 3.32 PNS MAS communication

3. PNS agent: Continuously update the notifications to HEMS agent.

    (a) PCA agent: Continuously update the power classification to PNS agent.

    (b) PFA agent: Continuously update the power forecast to PNS agent.

    (c) PF agent: Continuously update the electricity price forecast to PNS agent.

    (d) PC agent: Continuously update the electricity price classification to PNS agent.

    (e) SETS agent: Continuously update the notifications to power notification system agent.

The system components play a part in developing the communication system on the smart home level.

Chapter 4

Simulation Studies and Results

The simulation studies and results share the simulations' result for the multi prediction system and Self-learning Home Management System (SHMS).

The first section provides the original data plots, simulation results, and discussion for multi prediction system. It also includes the overall summary of the multi prediction system. The simulations' result was used to support the justification of the proposed methodology in section three.

The second section provides the simulation results for the supply side management system, demand side management system, power notification system, and multi-agent system. Details of the information and data used will be explained as well. A summary of each system at the end of each subsection. Subsequently, SHMS would be summarised at the end of this chapter.

4.1 Multi Prediction System

The simulation studies were carried out using multi prediction system. The systems have the following standard parameters throughout to ensure consistency of the different type of neural networks:

- Hidden layer of four blocks/neurons
- Batch size of 1
- Epochs (System iteration) of 50 and 100
- Training data of 75% (9 months)
- Testing data of 25% (3 months)

Epochs 50 and 100 were chosen to check if there are any overfitting situations for the simulation studies. For the multi prediction system, the window size was 48. These systems were using Keras library in Python language [146] for the simulation studies.

4.1.1 Original Data Plots

The power generated data was taken from EMC [140] to represent the original power generation that was used to train and test the various systems. Fig. 4.1, Fig. 4.2, and Fig. 4.3 show the original data plots.

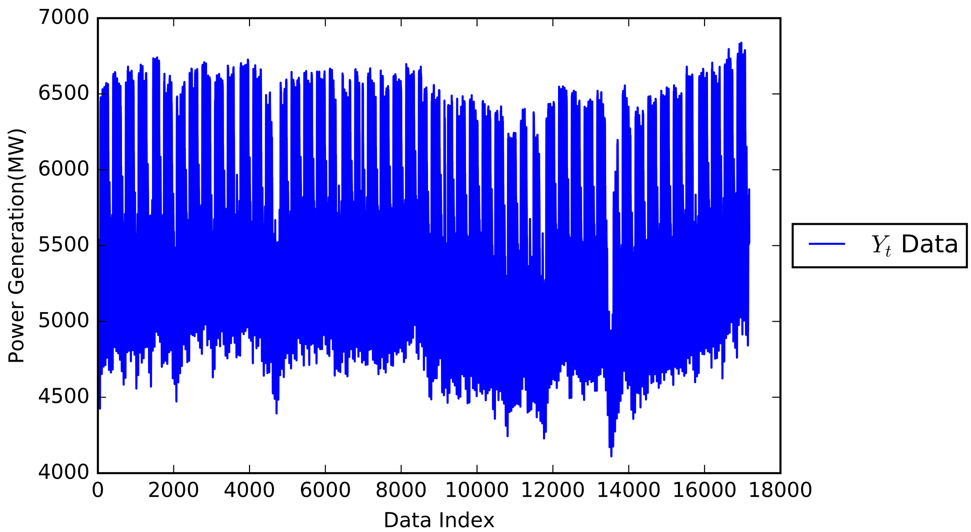

Fig. 4.1 Plot of actual total generation Y_t data graph

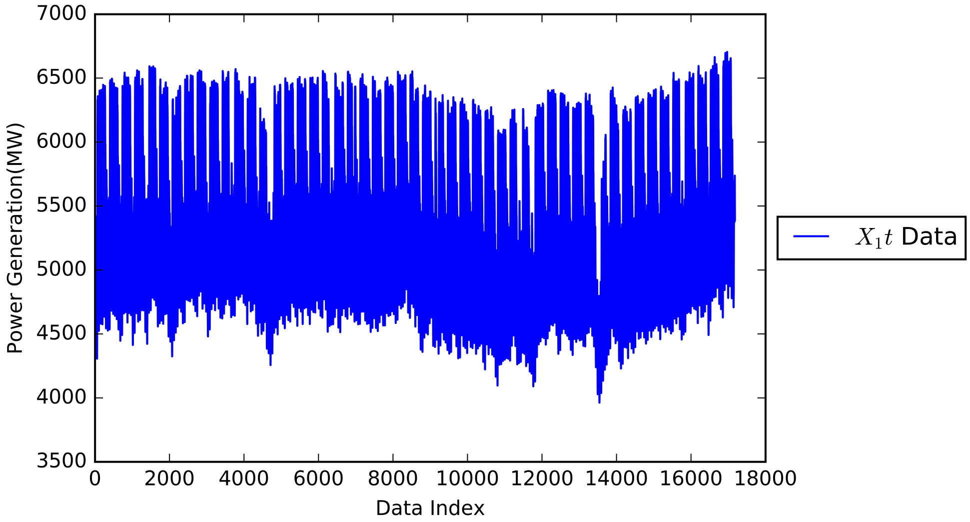

Fig. 4.2 Plot of Combined-cycle gas turbine/ cogeneration/ trigeneration $X1_t$ data graph

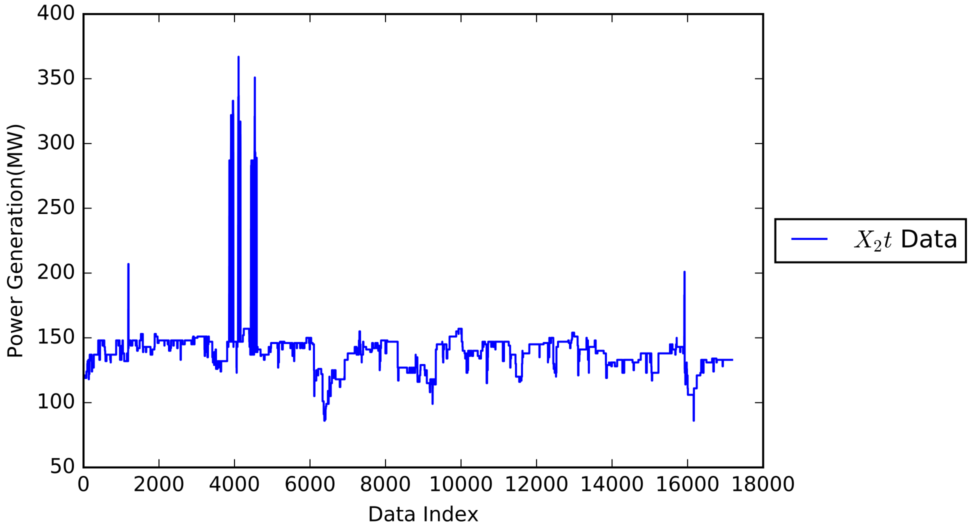

Fig. 4.3 Plot of Steam turbine generation $X2_t$ data graph

4.1.2 Simulation Results

This section shows the simulation results for multi prediction system. It was simulated to demonstrate its performance for the system. Simulation studies include the following integrated models of multi forecast model:

- Regression Model (RM)
- Regression with Time Step Model (RTSM)
- Memory Between Batches Model (MBBM)
- Stacked Model (SM)

4.1.2.1 RMSE on Training and Testing data

This section shows the Root Mean Squared Error (RMSE) of the training and testing data

The error loss using RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4.1}$$

Where, n: Number of data, y_i: Original output data, and $\hat{y}_i$: Predicted output data.

4.1.2.1.1 Standard System

Table 4.1 shows the RMSE results from the training and testing procedure for the standard system.

Table 4.1 Training and testing data RMSE value

Multi-Input Feature Model		**RMSE Score**	**Epochs**	**Standard System**			
				MLP	**RNN**	**LSTM**	**GRU**
Single Input Feeding Method		Train:	50	97.22	105.77	101	96.46
		Test:		96.29	105.38	99.92	**95.51**
Double Input Feeding Method	Output 1	Train:		97.11	97.7	100.95	96.31
		Test:		96.33	97.38	100.03	**95.52**
	Output 2	Train:		3.95	3.99	3.88	3.82
		Test:		1.96	1.9	1.7	**1.68**
Multiple Feeding Method		Train:		104.06	96.96	97.36	97.62
		Test:		103.59	**96.23**	96.4	96.93
Single Input Feeding Method		Train:	100	98.89	97.27	96.84	96.75
		Test:		98.01	96.86	95.86	**95.8**
Double Input Feeding Method	Output 1	Train:		98.84	97.15	96.5	96.66
		Test:		98.1	96.94	**95.68**	95.85
	Output 2	Train:		3.82	3.85	4.13	4.13
		Test:		**1.66**	1.69	2.21	1.77
Multiple Feeding Method		Train:		97.28	97.72	96.82	96.51
		Test:		96.19	97.61	96.23	**95.74**

Table 4.1 results indicated by bold were the lowest RMSE for the test scores in the different computed system. For 50 and 100 epochs, most of the lower test scores were generated by GRU. The reason could be due to long term sequential data advantage to GRU algorithm.

4.1.2.1.2 LSTM System

Table 4.2 RMSE results obtained from the training and testing procedure were collated into a table for various LSTM system.

Table 4.2 Training and testing data RMSE value

<table>
<tr><th colspan="2" rowspan="2">Multi-Input Feature Model</th><th rowspan="2">RMSE Score</th><th rowspan="2">Epochs</th><th colspan="4">LSTM System</th></tr>
<tr><th>RM</th><th>RTSM</th><th>MBBM</th><th>SM</th></tr>
<tr><td colspan="2" rowspan="2">Single Input Feeding Method</td><td>Train:</td><td rowspan="8">50</td><td>26.67</td><td>30.53</td><td>75.44</td><td>109.12</td></tr>
<tr><td>Test:</td><td>29.89</td><td>31.79</td><td>84.45</td><td>111.6</td></tr>
<tr><td rowspan="4">Double Input Feeding Method</td><td rowspan="2">Output 1</td><td>Train:</td><td>30.69</td><td>27.58</td><td>36.08</td><td>52.47</td></tr>
<tr><td>Test:</td><td>32.38</td><td>29.14</td><td>38.56</td><td>65.5</td></tr>
<tr><td rowspan="2">Output 2</td><td>Train:</td><td>2.7</td><td>3.52</td><td>6.65</td><td>6.2</td></tr>
<tr><td>Test:</td><td>1.85</td><td>2.78</td><td>5.69</td><td>5.33</td></tr>
<tr><td colspan="2" rowspan="2">Multiple Feeding Method</td><td>Train:</td><td>19.42</td><td>1.89</td><td>27.08</td><td>13.58</td></tr>
<tr><td>Test:</td><td>21.44</td><td>2.31</td><td>28.34</td><td>14.92</td></tr>
<tr><td colspan="2" rowspan="2">Single Input Feeding Method</td><td>Train:</td><td rowspan="8">100</td><td>30.8</td><td>26.56</td><td>33.22</td><td>61.17</td></tr>
<tr><td>Test:</td><td>33.4</td><td>27.79</td><td>35.36</td><td>66.89</td></tr>
<tr><td rowspan="4">Double Input Feeding Method</td><td rowspan="2">Output 1</td><td>Train:</td><td>20.96</td><td>28.06</td><td>38.25</td><td>53.35</td></tr>
<tr><td>Test:</td><td>24.02</td><td>29.2</td><td>40.67</td><td>64.65</td></tr>
<tr><td rowspan="2">Output 2</td><td>Train:</td><td>2.68</td><td>2.64</td><td>7.28</td><td>6.09</td></tr>
<tr><td>Test:</td><td>1.78</td><td>1.89</td><td>8.11</td><td>6.48</td></tr>
<tr><td colspan="2" rowspan="2">Multiple Feeding Method</td><td>Train:</td><td>5.63</td><td>2.14</td><td>13.46</td><td>16.78</td></tr>
<tr><td>Test:</td><td>11.3</td><td>2.07</td><td>14.48</td><td>14.62</td></tr>
</table>

Table 4.2 results indicated by bold has the lowest RMSE for the test scores in the different LSTM system section. For 50 and 100 epochs, most of the lower test scores were generated by RM and RTSM. The reason could be due to RM and RTSM creates time step labels that

improve the LSTM algorithm which is meant for long term sequential data. These indicators have further experimented with different methods of implementation with the LSTM system.

4.1.2.1.3 GRU System

Table 4.3 shows the RMSE results from the training and testing procedure for GRU system.

Table 4.3 Training and testing data RMSE value

Multi-Input Feature Model		**RMSE Score**	**Epochs**	**GRU System**			
				RM	**RTSM**	**MBBM**	**SM**
Single Input Feeding Method		Train:	50	29.16	29.87	42.95	74.19
		Test:		31.73	**30.95**	49.18	98.91
Double Input Feeding Method	Output 1	Train:		31.81	29.96	4.79	65.25
		Test:		34.39	31.01	**2.94**	168.05
	Output 2	Train:		2.94	2.8	47.13	9.5
		Test:		1.9	**1.86**	56.4	10.12
Multiple Feeding Method		Train:		8.78	3.29	21.75	55.7
		Test:		9.7	**3.12**	19.95	93.13
Single Input Feeding Method		Train:	100	23.03	28.09	67.47	119.32
		Test:		**26.29**	30.09	73.9	95.07
Double Input Feeding Method	Output 1	Train:		20.6	28.13	9.55	55.89
		Test:		24.23	29.9	**15.52**	62.57
	Output 2	Train:		2.6	3.1	106.68	16.86
		Test:		**1.72**	2.34	110.68	18.78
Multiple Feeding Method		Train:		6.2	6.94	14.75	48.16
		Test:		10.27	**6.46**	12.96	56.32

Table 4.3 results indicated by bold has the lowest RMSE for the test scores in different GRU system. For 50 epochs, most of the lower test scores were generated by RTSM and RM has the lowest score for the 100 epochs. The reason could be due to RM and RTSM creates time step labels that improve the LSTM algorithm which is meant for long term sequential data.

4.1.2.1.4 Comparison of RMSE results

Table 4.17 shows the results for the optimised RMSE values. It shows the summary table of the best RMSE results of the different forecasting systems.

Table 4.4 Best RMSE results from different systems

Multi-Input Feature Model		**Epochs**	**Standard System**	**LSTM System**	**GRU System**
Single Input Feeding Method		50	95.51	**29.89**	30.95
		100	95.8	27.79	**26.29**
Double Input Feeding Method	Output 1	50	95.52	29.14	**2.94**
		100	95.85	24.02	**15.52**
	Output 2	50	**1.68**	1.85	1.86
		100	**1.66**	1.78	1.72
Multiple Feeding Method		50	96.23	**2.31**	3.12
		100	95.74	**2.07**	6.46

Table 4.4 results indicated by bold has the lowest RMSE for the test scores. Most of the lower test scores were generated by LSTM and GRU system. This gave an indicative measurement on which system will provide better accuracy. It validates the potential of the multi prediction system.

4.1.2.2 LSTM: Regression Model (RM)

Table 4.5 shows the percentage results from the training and testing data for LSTM RM.

Table 4.5 Percentage error results of RM

RM system	**SIFM**	**DIFM**	**MFM**	**SIFM**	**DIFM**	**MFM**
Epochs	**50**			**100**		
MAPE(%)	0.4116	0.4652	0.3192	0.4753	0.3226	0.1012
MAX(%)	3.0224	3.205	2.0745	3.6875	3.3631	3.9135
Min(%)	0.000008	0.000007	0.0003	0.00009	0.00009	0.00005

Table 4.5 shows the results with the lowest MAPE value for 50 epochs was 0.3192% and 0.1012% for 100 epochs. LSTM RM system with MFM method in 100 epochs was shown to be the optimised combination. Fig. 4.4 shows the plot of the 100 epochs LSTM RM with MFM method prediction results.

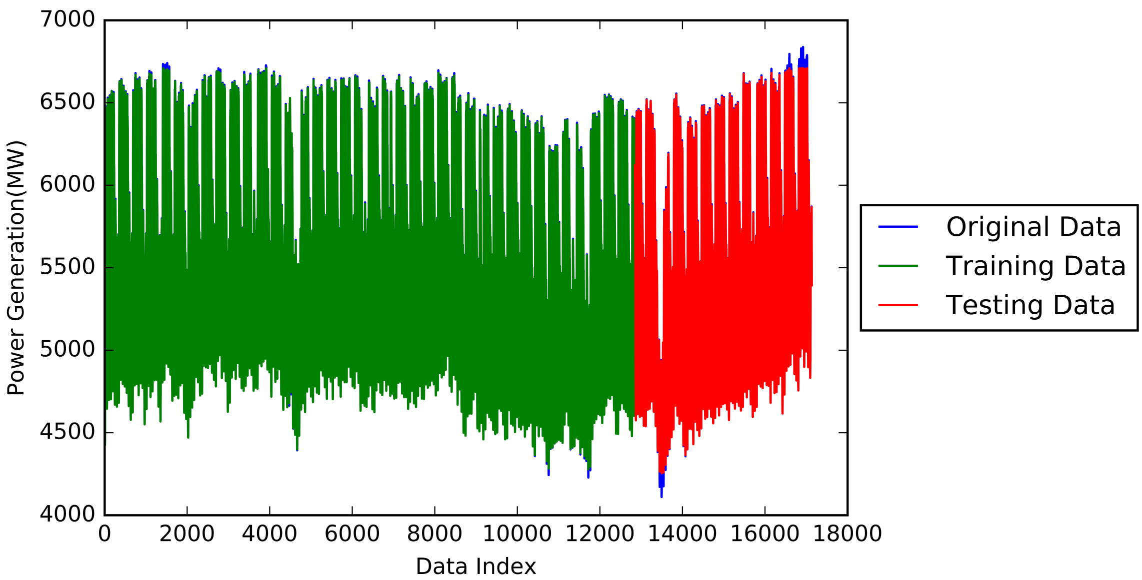

Fig. 4.4 LSTM RM: 100 epochs MFM

4.1.2.3 LSTM: Regression with Time Steps Model (RTSM)

Table 4.6 shows the percentage results from the training and testing data for LSTM RTSM.

Table 4.6 Percentage error results of RTSM

RTSM system	**SIFM**	**DIFM**	**MFM**	**SIFM**	**DIFM**	**MFM**
Epochs	**50**			**100**		
MAPE(%)	0.4416	0.4009	0.0298	0.3665	0.41473	0.0294
MAX(%)	3.7033	3.4519	0.7063	3.1209	3.3851	0.3233
Min(%)	0.0002	0.0001	0.000008	0.0001	0.00006	0

Table 4.6 shows the results with the lowest MAPE value for 50 epochs was 0.0298% and 0.0294% for 100 epochs. LSTM RTSM system with MFM method in 100 epochs was shown to be the optimised combination. Fig. 4.5 shows the plot of the 100 epochs LSTM RTSM with MFM method prediction results.

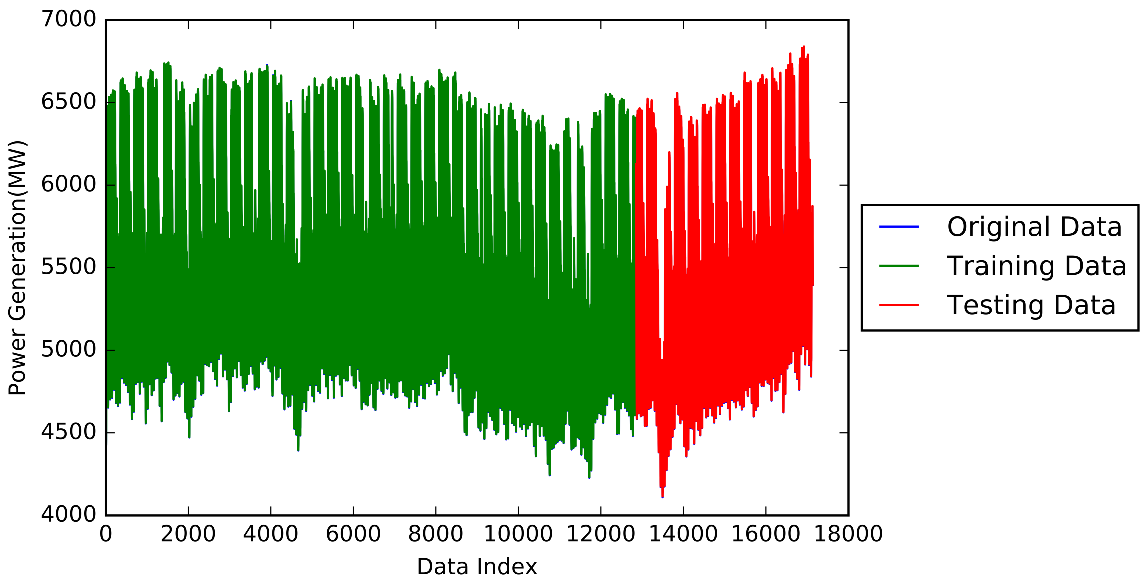

Fig. 4.5 LSTM RTSM: 100 epochs MFM

4.1.2.4 LSTM: Memory Between Batches Model (MBBM)

Table 4.7 shows the percentage results from the training and testing data for LSTM MBBM.

Table 4.7 Percentage error results of MBBM

MBBM system	**SIFM**	**DIFM**	**MFM**	**SIFM**	**DIFM**	**MFM**
Epochs	**50**			**100**		
MAPE(%)	1.1305	0.547	0.2753	0.4885	0.5532	0.19
MAX(%)	7.0283	3.8256	3.6602	3.761	3.6901	0.8286
Min(%)	0.0009	0.0011	0.00004	0.0002	0.000002	0.0001

Table 4.7 shows the results with the lowest MAPE value for 50 epochs was 0.2753% and 0.19% for 100 epochs. LSTM MBBM system with MFM method in 100 epochs was shown to be the optimised combination. Fig. 4.6 shows the plot of the 100 epochs LSTM MBBM with MFM method prediction results.

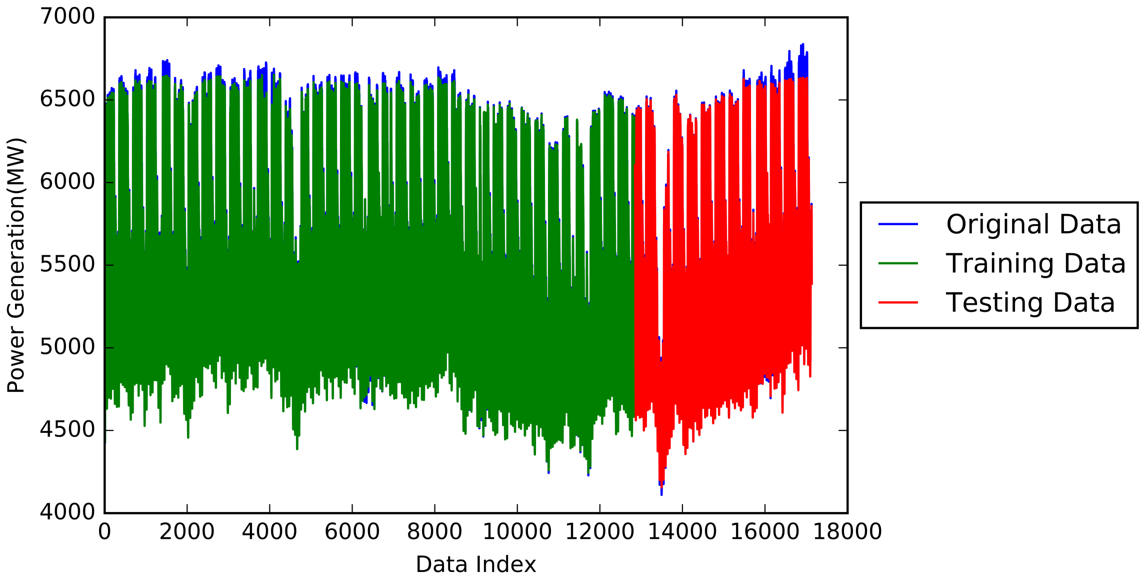

Fig. 4.6 LSTM MBBM: 100 epochs MFM

4.1.2.5 LSTM: Stacked Model (SM)

Table 4.8 shows the percentage results from the training and testing data for LSTM SM.

Table 4.8 Percentage error results of SM

SM system	**SIFM**	**DIFM**	**MFM**	**SIFM**	**DIFM**	**MFM**
Epochs		**50**			**100**	
MAPE(%)	1.3324	0.7932	0.473	0.9444	0.8677	0.2299
MAX(%)	8.578	5.3171	4.6155	6.0083	8.0928	1.6526
Min(%)	0.00003	0.0002	0.00048	0.00003	0.00005	0.00002

Table 4.8 shows the results with the lowest MAPE value for 50 epochs was 0.473% and 0.2299% for 100 epochs. LSTM SM system with MFM method in 100 epochs was shown to be the optimised combination. Fig. 4.7 shows the plot of the 100 epochs LSTM SM with MFM method prediction results.

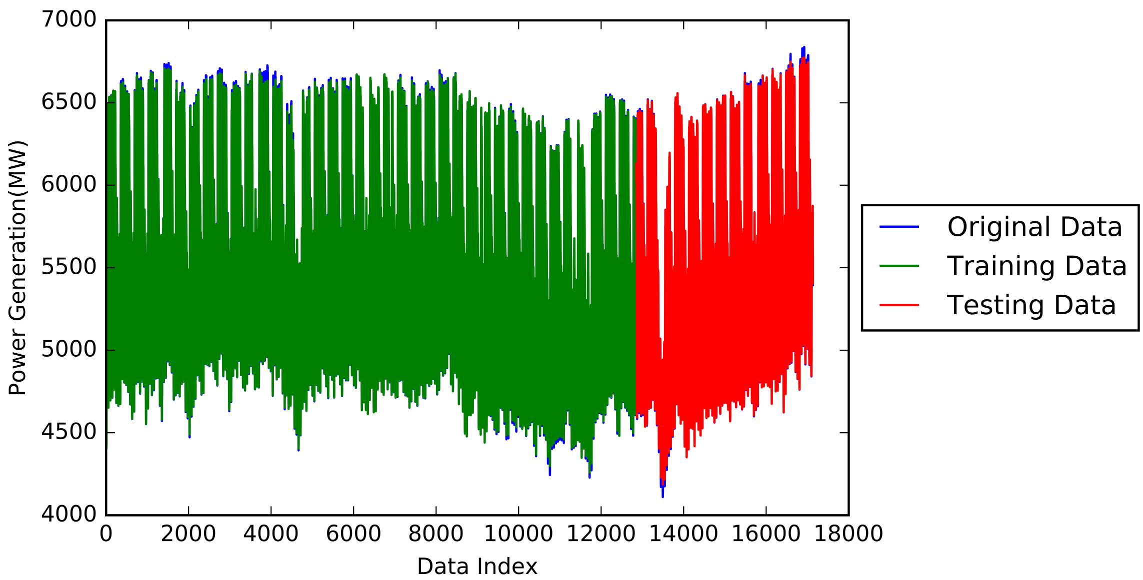

Fig. 4.7 LSTM SM: 100 epochs MFM

4.1.2.6 GRU: Regression Model (RM)

Table 4.9 shows the percentage results from the training and testing data for GRU RM.

Table 4.9 Percentage error results of RM

RM system	**SIFM**	**DIFM**	**MFM**	**SIFM**	**DIFM**	**MFM**
Epochs	**50**			**100**		
MAPE(%)	0.4649	0.4953	0.1181	0.3538	0.3120	0.1083
MAX(%)	3.5873	3.6151	1.4843	3.1487	3.5068	1.9485
Min(%)	0.00021	0.00036	0.00007	0.00016	0.00004	0.00008

Table 4.9 shows the results with the lowest MAPE value for 50 epochs was 0.1181% and for 100 epochs was 0.1083%. GRU RM system with MFM method in 100 epochs was shown to be the optimised combination. Fig. 4.8 shows the plot of the 100 epochs GRU RM with MFM method prediction results.

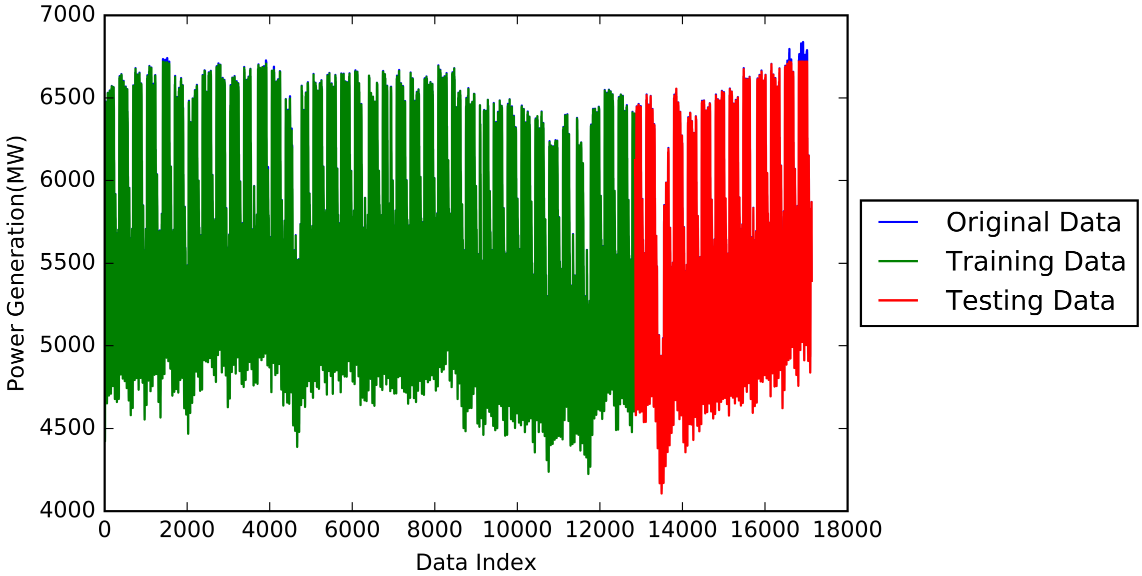

Fig. 4.8 GRU RM: 100 epochs MFM

4.1.2.7 GRU: Regression with Time Steps Model (RTSM)

Table 4.10 shows the percentage results from the training and testing data for GRU RTSM.

Table 4.10 Percentage error results of RTSM

RTSM system	**SIFM**	**DIFM**	**MFM**	**SIFM**	**DIFM**	**MFM**
Epochs	**50**			**100**		
MAPE(%)	0.4139	0.4155	0.0477	0.4058	0.4057	0.1077
MAX(%)	3.331	3.4241	0.235	3.6335	3.6626	0.5161
Min(%)	0.0004	0.00007	0.00001	0.0005	0.0003	0.00132

Table 4.10 shows the results with the lowest MAPE value for 50 epochs was 0.0477% and for 100 epochs was 0.1077%. GRU RTSM system with MFM method in 50 epochs was shown to be the optimised combination. Fig. 4.9 shows the plot of the 50 epochs GRU RTSM with MFM method prediction results.

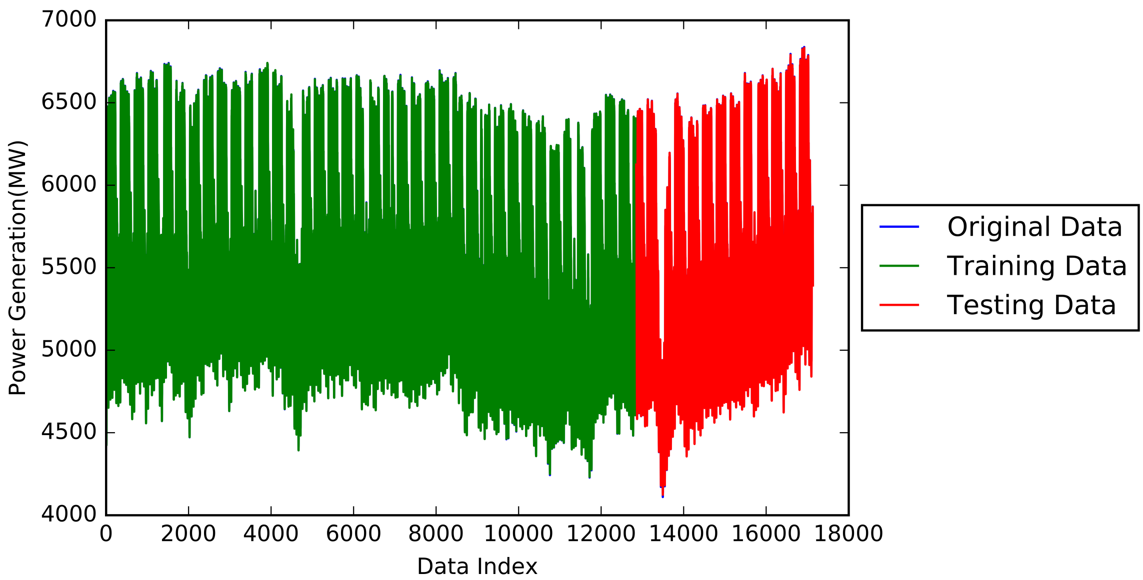

Fig. 4.9 GRU RTSM: 50 epochs MFM

4.1.2.8 GRU: Memory Between Batches Model (MBBM)

Table 4.11 shows the percentage results from the training and testing data for GRU MBBM.

Table 4.11 Percentage error results of MBBM

MBBM system	**SIFM**	**DIFM**	**MFM**	**SIFM**	**DIFM**	**MFM**
Epochs	**50**			**100**		
MAPE(%)	0.6624	0.766	0.3036	1.0809	1.467	0.2109
MAX(%)	4.6371	5.6524	1.7427	5.8835	6.5384	0.7765
Min(%)	0.00006	0.00045	0.00006	0.00002	0.0006	0.00007

Table 4.11 shows the results with the lowest MAPE value for 50 epochs was 0.3036% and for 100 epochs was 0.2109%. GRU MBBM system with MFM method in 100 epochs was shown to be the optimised combination. Fig. 4.10 shows the plot of the 100 epochs GRU MBBM with MFM method prediction results.

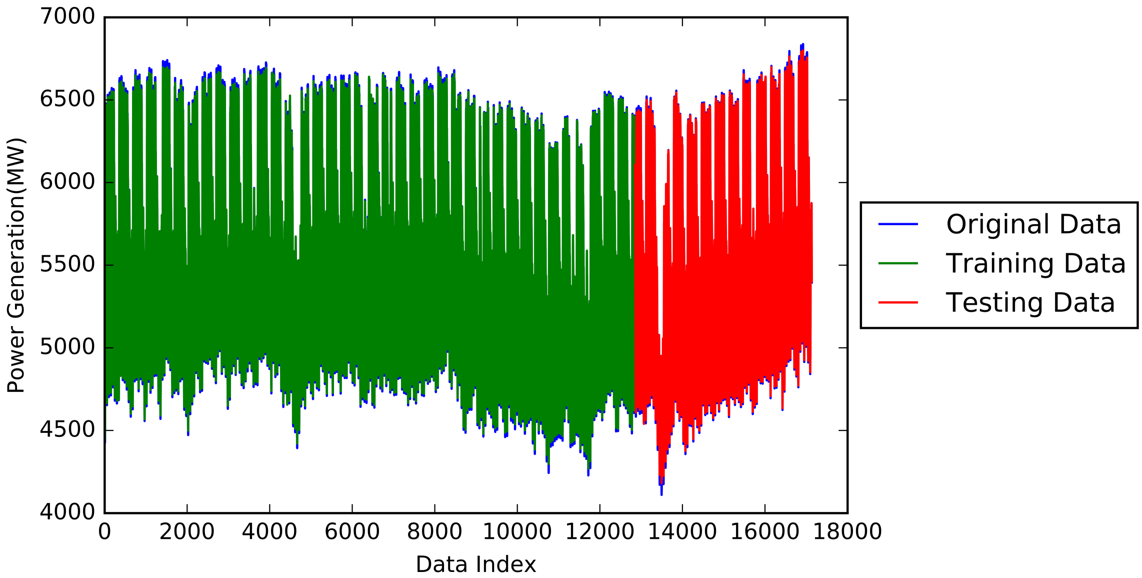

Fig. 4.10 GRU MBBM: 100 epochs MFM

4.1.2.9 GRU: Stacked Model (SM)

Table 4.12 shows the percentage results from the training and testing data for GRU SM.

Table 4.12 Percentage error results of SM

SM system	**SIFM**	**DIFM**	**MFM**	**SIFM**	**DIFM**	**MFM**
Epochs	**50**			**100**		
MAPE(%)	1.5978	2.9055	1.5345	1.3758	1.1164	0.947
MAX(%)	5.6262	9.5328	4.8746	6.4143	6.3706	6.384
Min(%)	0.00272	0.06286	0.00093	0.00098	0.00087	0.00021

Table 4.12 shows the results with the lowest MAPE value for 50 epochs was 1.5345% and for 100 epochs was 0.947%. GRU SM system with MFM method in 100 epochs was shown to be the optimised combination. Fig. 4.11 shows the plot of the 100 epochs GRU SM with MFM method prediction results.

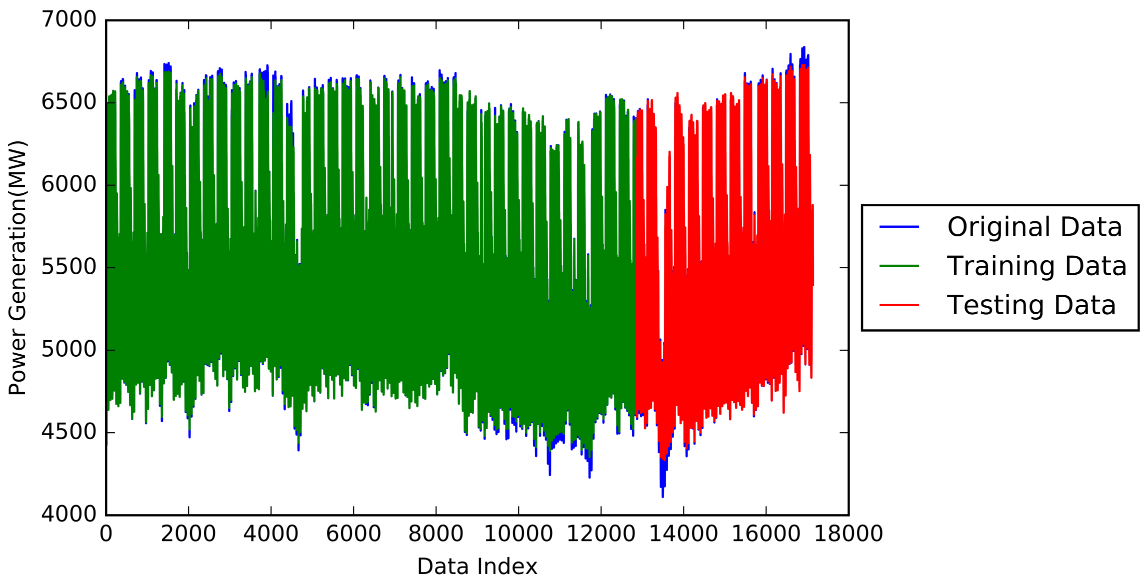

Fig. 4.11 GRU SM: 100 epochs MFM

4.1.3 Discussion

This section discusses the performance of the multi prediction system. The performance of the multi prediction system was benchmarked with Standard Multi-Layer Perceptron (MLP), Recurrent Neural network (RNN), and Long Short Term Memory (LSTM). The evaluation of the multi prediction system was done using the simulated results.

4.1.3.1 Standard Multi-Layer Perceptron (MLP)

Table 4.13 shows the percentage results from the training and testing data for MLP system.

Table 4.13 Percentage error results of MLP

MLP system	**SIFM**	**DIFM**	**MFM**	**SIFM**	**DIFM**	**MFM**
Epochs	**50**			**100**		
MAPE(%)	1.3519	1.3586	0.7113	1.4139	1.416	0.2059
MAX(%)	5.6773	5.657	0.9043	5.5013	5.4972	0.5044
Min(%)	0.0006	0.0002	0.4277	0.00015	0.0006	0.0098

Table 4.13 shows the results with the lowest MAPE value for 50 epochs is 0.7113% and for 100 epochs is 0.2059%. MLP system with MFM method in 100 epochs was shown to be the optimised combination. Fig. 4.12 shows the plot of the 100 epochs MLP with MFM method prediction results.

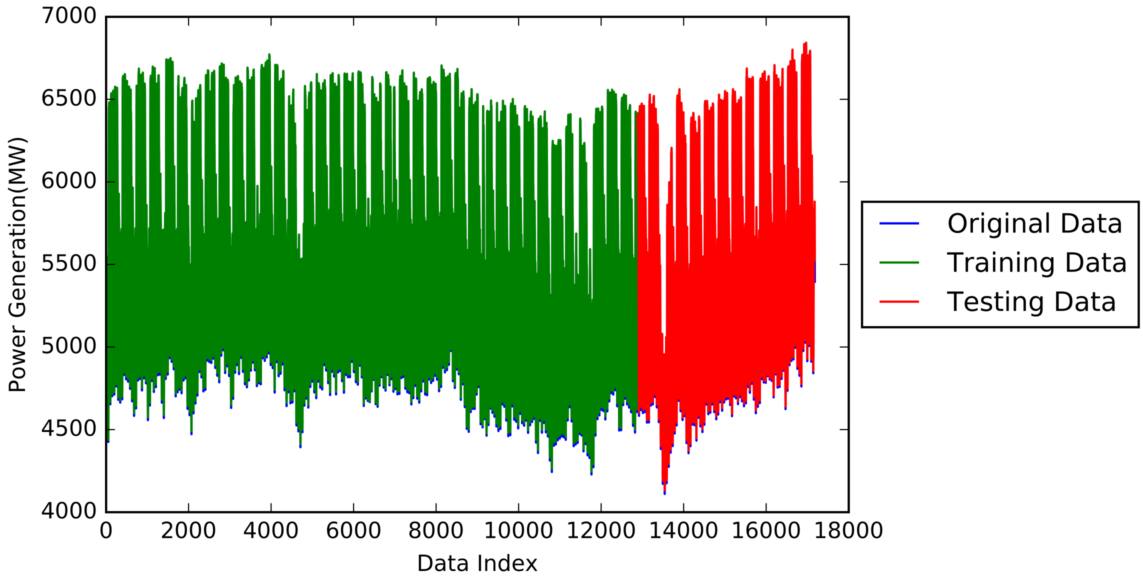

Fig. 4.12 MLP: 100 epochs MFM

4.1.3.2 Standard Recurrent Neural network (RNN)

Table 4.14 shows the percentage results from the training and testing data for RNN System.

Table 4.14 Percentage error results of RNN

RNN system	**SIFM**	**DIFM**	**MFM**	**SIFM**	**DIFM**	**MFM**
Epochs	**50**			**100**		
MAPE(%)	1.6059	1.3982	0.1677	1.3704	1.3713	0.3136
MAX(%)	5.7412	5.6232	2.0779	5.8223	5.8245	3.41
Min(%)	0.0016	0.001	0.0001	0	0.0002	0.00003

Table 4.14 shows the results with the lowest MAPE value for 50 epochs is 0.1677% and for 100 epochs is 0.3136%. RNN system with MFM method in 50 epochs was shown to be the optimised combination. Fig. 4.13 shows the plot of the 50 epochs RNN with MFM method prediction results.

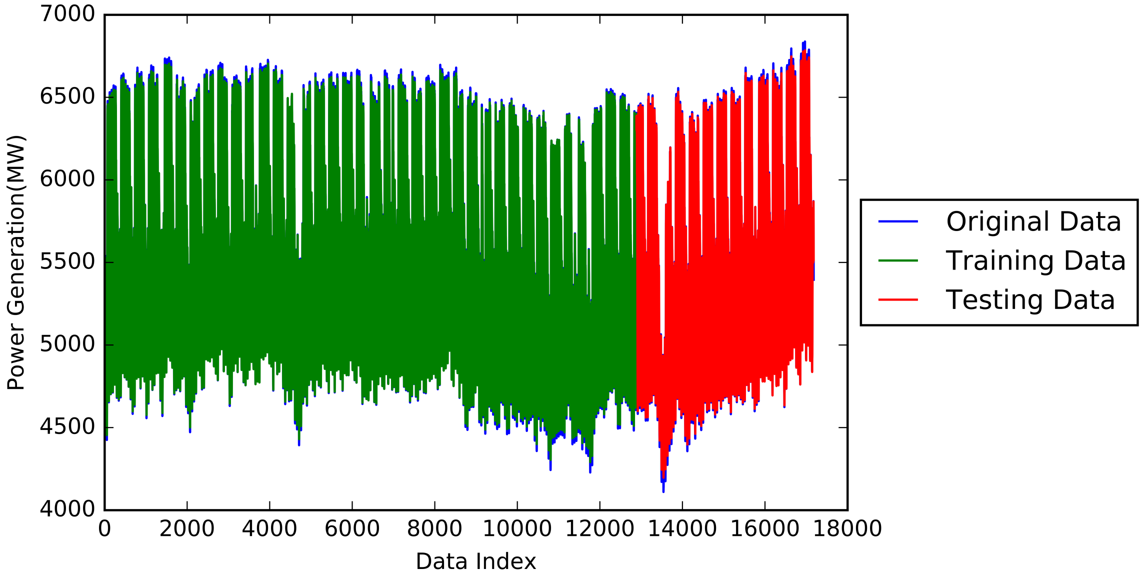

Fig. 4.13 RNN: 50 epochs MFM

4.1.3.3 Standard Long Short Term Memory (LSTM)

Table 4.15 shows the percentage results from the training and testing data for standard LSTM system.

Table 4.15 Percentage error results of LSTM

LSTM system	**SIFM**	**DIFM**	**MFM**	**SIFM**	**DIFM**	**MFM**
Epochs	**50**			**100**		
MAPE(%)	1.3171	1.3181	0.2697	1.2929	1.2933	0.115
MAX(%)	6.4324	6.4422	1.4077	6.0699	6.0534	0.3818
Min(%)	0.0006	0.0007	0.00004	0.000008	0.0002	0.00009

Table 4.15 shows the results with the lowest MAPE value for 50 epochs was 0.2697% and 0.115% for 100 epochs. LSTM system with MFM method in 100 epochs was shown to

be the optimised combination. Fig. 4.14 shows the plot of the 100 epochs LSTM with MFM method prediction results.

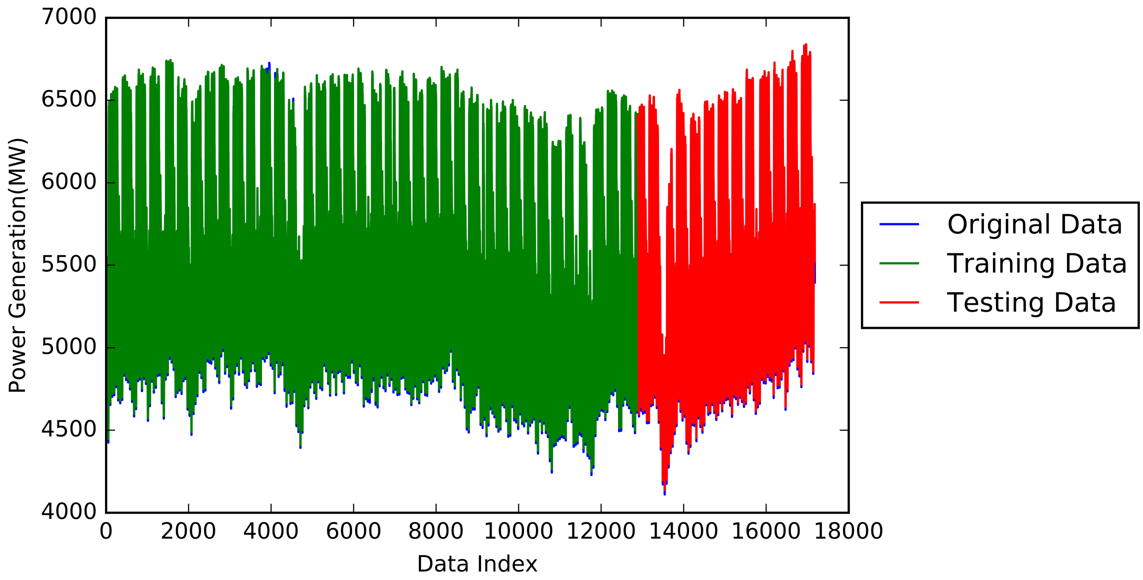

Fig. 4.14 LSTM: 100 epochs MFM

4.1.3.4 Standard Gated Recurrent Unit (GRU)

Table 4.16 shows the percentage results from the training and testing data for standard GRU system.

Table 4.16 Percentage error results of GRU

GRU system	**SIFM**	**DIFM**	**MFM**	**SIFM**	**DIFM**	**MFM**
Epochs	**50**			**100**		
MAPE(%)	1.3102	1.3102	0.2913	1.2908	1.291	0.1606
MAX(%)	5.946	5.9523	0.8549	6.1358	6.1409	2.069
Min(%)	0.0003	0.0002	0.0001	0.00006	0.0004	0.00008

Table 4.16 shows the results with the lowest MAPE value for 50 epochs was 0.2913% and for 100 epochs was 0.1606%. GRU system with MFM method in 100 epochs was shown to be the optimised combination. Fig. 4.15 shows the plot of the 100 epochs GRU with MFM method prediction results.

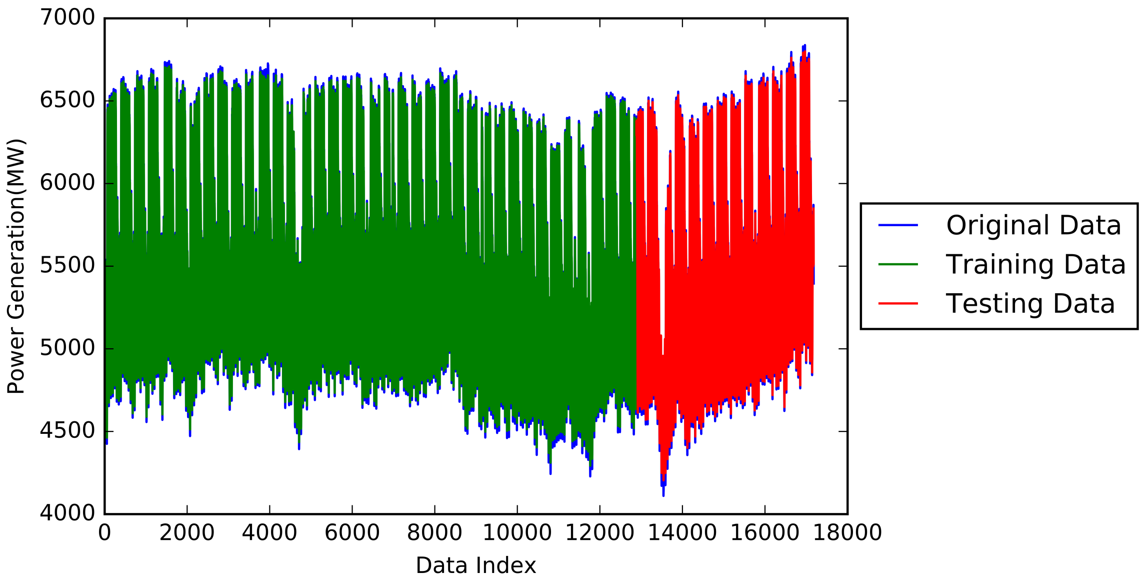

Fig. 4.15 GRU: 100 epochs MFM

4.1.3.5 Comparison of simulated MAPE results

Table 4.17 shows the results of the optimised MAPE values. It shows the summary table of the best MAPE results of the different forecasting systems.

Table 4.17 Best MAPE results

Forecasting Systems	**Best Results (%)**	
	50 epochs	**100 epochs**
MLP	0.7113	0.2059
RNN	0.1677	0.3136
LSTM	0.2697	0.115
GRU	0.2913	0.1606
LSTM: RM	0.3192	0.1012
LSTM: RTSM	0.0298	0.0294
LSTM: MBBM	0.2753	0.19
LSTM: SM	0.473	0.2299
GRU: RM	0.1181	0.1083
GRU: RTSM	0.0477	0.1077
GRU: MBBM	0.3036	0.2109
GRU: SM	1.5345	0.947

By comparing the results based on lower MAPE, LSTM RTSM system has the lowest MAPE value of 0.0298% using 50 epochs and 0.0294% using 100 epochs. The final result could be due to the RTSM creation of time step labels that improve LSTM algorithm's advantages for long-term sequential data.

Although the RNN system has better results than most multi prediction system models in the 50 epochs simulation, its result for 100 epochs was the worst among the forecasting systems. The likely explanation for the scenario is due to the RNN algorithm's advantages for short-term sequential data and disadvantages for long-term sequential data. Additionally, GRU RTSM 50 epochs MAPE result is lower than the 100 epoch MAPE result. The likely reason for this scenario is caused by overfitting where the increased number of epochs fit extremely well to the trained data.

The simulation results validate the advantage of the multi prediction system in large designed forecast systems. Furthermore, by comparing both results at the end, LSTM RTSM using MFM proves to be the most optimal system for the time series data of electricity market generation.

4.2 Overall Summary

In this thesis, an innovative multi prediction system is proposed for electricity generation forecast. A multi-input feature model consists of three different features input method for the forecasting systems such as Single Input Feeding Method (SIFM), Double Input Feeding Method (DIFM), and Multiple Feeding Method (MFM) as part of the multi prediction system. Multi prediction system includes the multi forecast model which integrates Regression Model (RM), Regression with Time Steps Model (RTSM), Memory Between Batches Model (MBBM), and Stacked Model (SM) to predict future electricity generation. Multi prediction system uses Mean Absolute Percentage Error (MAPE) to determine the prediction accuracy. It presents a finding of the most optimised forecasting system such as RTSM using MFM narrows down the scope on further improvement in this system for future electricity market generation forecast. With proper use of this novel prediction system, better accuracy for electricity generation forecast could be achieved for electricity markets.

4.3 Self-learning Home Management System (SHMS)

4.3.1 Supply Side Management (SSM) System

This section includes the experimental information, simulations, results, and discussions for the Supply Side Management (SSM) system. It provides information about the data retrieved from electric vehicles, household appliances, electricity tariff, and photovoltaics system in Singapore. The following sections provide the experimental data used in the simulation study.

4.3.1.1 Electric Vehicles (EV)

Most EVs require high charging rates as an EV battery capacity with 32 kWh needs to be stationed and charged for a minimum amount of hours [147]. Thus, making charging rates constraints an important factor in this study. Table 4.18 shows the type of chargers available in Singapore.

Table 4.18 Chargers for Electric Vehicle (EV) in Singapore

Types of Charging	**Electrical Power**	**Recharging Time**
Public Normal Charger	3 kW	7-8 hours
Residential Normal Charger		
Quick Charger	30-50 kW	30-45 min

Public normal chargers are usually installed or available at shopping malls, HDB car parks, and charging stations while residential normal chargers are found in private properties. Both types of chargers have long charging time of 7 to 8 hours compared to quick chargers. Quick chargers are usually installed or available at certain shopping malls and charging stations. It has a faster charging time of 30 to 45 minutes as it supplies more electrical power.

The charging information will be used to realistically simulate the charging process with the considered constraints.

For EVs or hybrid cars, charging stations are needed to recharge the batteries for the vehicles. There are currently 71 charging stations by Bosch in Singapore and consumers have to pay SGD$180 a month for unlimited charging [148]. The information gathered will create a realistic home energy management system customised for Singapore smart homes.

4.3.1.2 Household appliances and Electricity Tariff

Table 4.19 shows the data of various appliances for most Singaporean's household during different time period [149].

Table 4.19 Singapore Appliances Data

Equipment	**Representative**	**Switches Representative**	**Power (W/H)**	**Hours**	**Hours Turned 'On' (24Hr)**
Standing Fan	SF	SFS	55	9	0-7,23
Tower Fan	TF	TFS	40	9	0-7,23
Fridge	F	FS	300	24	0-24
Rice Cooker	RC	RCS	820	1	19
Electric Dispensing Pot	EDP	EDPS	800	1	7
Bathroom Heater	BH	BHS	1500	4	6,7,20,21
Vacuum Cleaner	VC	VCS	1600	1	21
Iron	IR	IRS	2200	1	20
Air Conditioner	AC	ACS	1400	9	0-7,23
Speaker	S	SS	45	4	19-22
Desktop Computer	DC	DCS	620	4	19-22
Laptop	LT	LTS	65	4	19-22
LED Television	TV	TVS	230	4	19-22
Top Loading Washing Machine	TLWM	TLWMS	400	2	20-21
Incandescent Bulbs	IB	IBS	60	4	19-22

The total cost for the day is based on SGD$0.2035 per kilowatts with reference to Singapore Power (SP) as residential consumers in Singapore are all provided by the same electricity company [150].

4.3.1.3 PhotoVoltaics (PV) system

Table 4.20 shows the information for the Housing and Development Board (HDB) buildings in Singapore that is currently installed with PhotoVoltaics (PV) system [151].

Table 4.20 Solar Panel Buildings in Singapore

Singapore Solar Panel information	**Capacity (Wp)**	**Estimated energy output (kWh / yr)**	**Estimated energy output (kWh / day)**	**PV Yield (kWh)**
7 residential blocks and a Multi-Storey Car Park (MSCP)	73000	80,300	220	9.17

4.3.1.4 Simulation and Results

Table 4.21 shows the settings of parameter values throughout the simulations.

Table 4.21 SSM: Fixed Parameters in Simulation

Parameters	Power (kW)
Full PV Battery Storage capacity	74
PV Battery Storage charging/discharging rate	3
Full EV Battery Storage capacity	32
EV Battery Storage charging/discharging rate	3

Fig.4.16 shows the SSM MAS ACL messages of SHMS. SSM communicates with BS, EV, MG, and RE to collect the available electricity supply information. "SUBSCRIBE" message was used to keep connecting to the SSM at all times.

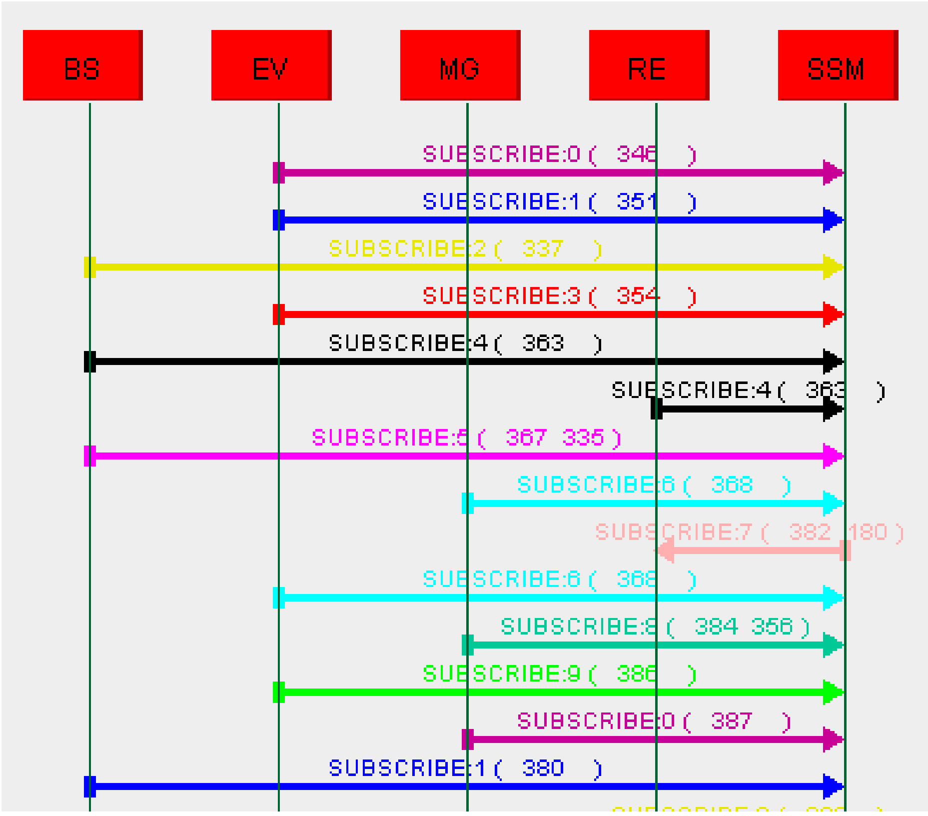

Fig. 4.16 SSM MAS ACL messages

Fig.4.17 shows the SSM MAS communication of SHMS. The MAS communication shows the created agents' information such as sender, receiver, content, and reply.

```
BS: I receive message.
(SUBSCRIBE
 :sender  ( agent-identifier :name SSM@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc ))
 :receiver  (set ( agent-identifier :name BS@192.168.1.61:1099/JADE ) )
 :content  "Subscription"
)
SSM: I receive message.
(SUBSCRIBE
 :sender  ( agent-identifier :name MG@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc ))
 :receiver  (set ( agent-identifier :name SSM@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc )) )
 :content  "Subscription"
 :reply-with  SSM@192.168.1.61:1099/JADE1513663344428 )
EV: I receive message.
(SUBSCRIBE
 :sender  ( agent-identifier :name SSM@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc ))
 :receiver  (set ( agent-identifier :name EV@192.168.1.61:1099/JADE ) )
 :content  "Subscription"
)
MG: I receive message.
(SUBSCRIBE
 :sender  ( agent-identifier :name SSM@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc ))
 :receiver  (set ( agent-identifier :name MG@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc )) )
 :content  "Subscription"
 :reply-with  MG@192.168.1.61:1099/JADE1513663345288  :in-reply-to  SSM@192.168.1.61:1099/JADE1513663344428 )
```

Fig. 4.17 SSM MAS communication

Fig. 4.18 shows the power demand for each hour of the proposed SSM system. The power demand simulation was based on the appliances shown in Table 4.19 to display the power demand for each hour.

```
Demand (kW)= 1.795 , Hour (24Hr)= 0 Demand (kW)= 0.3 , Hour (24Hr)= 12
----------------------------------- -----------------------------------
Demand (kW)= 1.795 , Hour (24Hr)= 1 Demand (kW)= 0.3 , Hour (24Hr)= 13
----------------------------------- -----------------------------------
Demand (kW)= 1.795 , Hour (24Hr)= 2 Demand (kW)= 0.3 , Hour (24Hr)= 14
----------------------------------- -----------------------------------
Demand (kW)= 1.795 , Hour (24Hr)= 3 Demand (kW)= 0.3 , Hour (24Hr)= 15
----------------------------------- -----------------------------------
Demand (kW)= 1.795 , Hour (24Hr)= 4 Demand (kW)= 0.3 , Hour (24Hr)= 16
----------------------------------- -----------------------------------
Demand (kW)= 1.795 , Hour (24Hr)= 5 Demand (kW)= 0.3 , Hour (24Hr)= 17
----------------------------------- -----------------------------------
Demand (kW)= 3.295 , Hour (24Hr)= 6 Demand (kW)= 0.3 , Hour (24Hr)= 18
----------------------------------- -----------------------------------
Demand (kW)= 4.095 , Hour (24Hr)= 7 Demand (kW)= 2.14 , Hour (24Hr)= 19
----------------------------------- -----------------------------------
Demand (kW)= 0.3 , Hour (24Hr)= 8   Demand (kW)= 5.42 , Hour (24Hr)= 20
----------------------------------- -----------------------------------
Demand (kW)= 0.3 , Hour (24Hr)= 9   Demand (kW)= 4.82 , Hour (24Hr)= 21
----------------------------------- -----------------------------------
Demand (kW)= 0.3 , Hour (24Hr)= 10  Demand (kW)= 1.32 , Hour (24Hr)= 22
----------------------------------- -----------------------------------
Demand (kW)= 0.3 , Hour (24Hr)= 11  Demand (kW)= 1.795 , Hour (24Hr)= 23
----------------------------------- -----------------------------------
```

Fig. 4.18 Power demand for the different time period

Table 4.22 shows the simulation results for SSM system.

Table 4.22 SSM: Simulation Results

Time(Hours)	Total Power Demand(kW)	Total Power Supply(kW)	Initial PV Battery Storage capacity(kW)	Initial EV Battery Storage capacity(kW)	Power buy(+)/sell(-) from/ back to Main Grid(kW)	After Simulation, Balanced PV Battery Storage capacity(kW)	After Simulation, Balanced EV Battery Storage capacity(kW)	Money earned when Power sold back to Grid(Profit)(SGD$)	Money spent when Power bought from Grid(Loss)(SGD$)
0	1.795	2	1	1	0	1	1.205	0	0
1	1.795	2	1	1.205	0	1	1.41	0	0
2	1.795	2	1	1.41	0	1	1.615	0	0
3	1.795	2	1	1.615	0	1	1.82	0	0
4	1.795	2	1	1.82	0	1	2.025	0	0
5	1.795	2	1	2.025	0	1	2.23	0	0
6	3.295	2	1	2.23	0	0	1.935	0	0
7	4.095	2	0	1.935	0.16	0	0	0	0.03
8	0.3	2	0	0	0	0	1.7	0	0
9	0.3	2	0	1.7	0	0	3.4	0	0
10	0.3	2	0	3.4	0	0	5.1	0	0
11	0.3	2	0	5.1	0	0	6.8	0	0
12	0.3	2	0	6.8	0	0	8.5	0	0
13	0.3	2	0	8.5	0	0	10.2	0	0
14	0.3	2	0	10.2	0	0	11.9	0	0
15	0.3	2	0	11.9	0	0	13.6	0	0
16	0.3	2	0	13.6	0	0	15.3	0	0
17	0.3	2	0	15.3	0	0	17	0	0
18	0.3	2	0	17	0	0	18.7	0	0
19	2.14	2	0	18.7	0	0	18.56	0	0
20	5.42	2	0	18.56	0.42	0	15.56	0	0.09
21	4.82	2	0	15.56	0	0	12.74	0	0
22	1.32	2	0	12.74	0	0	13.42	0	0
23	1.795	2	0	13.42	0	0	13.625	0	0

In the simulation, the supply is more than demand as shown in Time 0-5, 8-18, and 22-23, thus the excessive power supplies were stored in the EV battery storage. On the other hand, the demand is more than supply as shown in Time 6-7 and 19-21, thus the excessive power demand uses power from the PV battery storage first, then from the EV battery storage, and lastly buying from the main grid to supply the rest of the power demand. Fig.4.19 shows the calculation results in the simulation.

```
-----------------------------------------------------------------
Demand for this Hour in (kW)= 1.795 ||Hour of the day (24Hr)= 23
-----------------------------------------------------------------
Power Distribution
-----------------------------------------------------------------
Total Power Demand(W)= 1.795
Total Power Supply(W)= 2.0
-----------------------------------------------------------------
PV system Battery Storage Status
-----------------------------------------------------------------
Initial PV Battery Storage capacity(W)= 68.3
Full PV Battery Storage capacity(W)= 74.0
PV Battery Storage charging/discharging rate(W)= 3.0
-----------------------------------------------------------------
Electrical Vehicle(EV) Battery Storage Status
-----------------------------------------------------------------
Initial EV Battery Storage capacity(W)= 32.0
Full EV Battery Storage capacity(W)= 32.0
EV Battery Storage charging/discharging rate(W)= 3.0
-----------------------------------------------------------------
Power Redistribution
-----------------------------------------------------------------
Power buy(+)/sell(-) from/back to Main Grid (W)= 0.0
-----------------------------------------------------------------
Balanced Power in Batteries After Simulation
-----------------------------------------------------------------
After Simulation, Balanced PV Battery Storage capacity(W)= 68.505
After Simulation, Balanced EV Battery Storage capacity(W)= 32.0
-----------------------------------------------------------------
Money earned when Power sold back to Grid(Profit)= $0.00
Money spent when Power bought from Grid(Loss)= $0.00
---------------------------END OF THIS PERIOD--------------------
```

Fig. 4.19 SSM: Calculation results

4.3.1.5 Summary

Supply Side Management (SSM) system was designed and developed based on consumer comfort, electricity efficiency, and the electricity cost of a household. The SSM system's results ensure the utilisation of the available energy resources were efficiently distributed and used for the simulated house environment. This general concept of a home energy management system allows consumers to enjoy the highest comfort level with optimised overall power efficiency and electricity bills with the internet of things based on home appliances.

4.3.2 Demand Side Management (DSM) System

4.3.2.1 Experimental Setup

Fig.4.20 shows a schematic design drawing of the house being used for case studies.

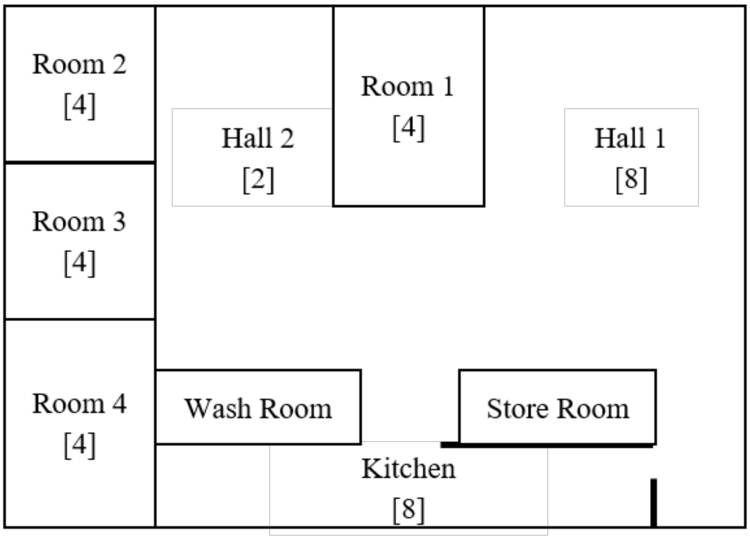

Fig. 4.20 Diagram of Experimental Home

For this experiment, a house was used for case studies of the proposed Self-learning Home Management System (SHMS). Fig.4.20 shows the number of Z-Wave UK Plug-in Switch plus Power Meter used for each section of the house. The IoT based smart plug system was installed in this area for power usage monitoring, data analysis, and optimisation suggestion to the home users.

Table 4.23 shows all the smart plugs' location in the smart home.

Table 4.23 Summary of smart plugs

Plug Names	Representatives	Devices	Agent Representatives	Plug Status
Room 1 (R1)				
Plug Room 1-1	PR11	Iron	PR11Agent	On
Plug Room 1-2	PR12	Mounted Fan	PR12Agent	On
Plug Room 1-3	PR13	Phone Charger	PR13Agent	On
Plug Room 1-4	PR14	MISC	PR14Agent	Off
Room 2 (R2)				
Plug Room 2-1	PR21	Multi-plug: TV, stereo system	PR21Agent	On
Plug Room 2-2	PR22	Multi-plug: Fan, MP3 charger, MISC, Apple Charger, Laptop Charger	PR22Agent	On
Plug Room 2-3	PR23	MISC	PR23Agent	Off
Plug Room 2-4	PR24	MISC	PR24Agent	Off
Room 3 (R3)				
Plug Room 3-1	PR31	TV, stereo system, shaver, dvd player	PR31Agent	On
Plug Room 3-2	PR32	Fan	PR32Agent	On
Plug Room 3-3	PR33	Multi-plug: Phone Charger, Laptop Charger, 2x MISC	PR33Agent	On
Plug Room 3-4	PR34	MISC	PR34Agent	Off
Room 4 (R4)				
Plug Room 4-1	PR41	MISC	PR41Agent	Off
Plug Room 4-2	PR42	MISC	PR42Agent	Off
Plug Room 4-3	PR43	Multi-plug: Hairdryer, 3x MISC	PR43Agent	On
Plug Room 4-4	PR44	Multi-plug: Fan, 3 x Phone charger, MISC	PR44Agent	On
Hall 1 (H1)				
Plug Hall 1-1	PH11	Printer	PH11Agent	On
Plug Hall 1-2	PH12	Laptop	PH12Agent	On
Plug Hall 1-3	PH13	Multi-plug: MIO cable TV Box, Singtel Modem, Starhub Cable TV Box, TV Power, 3x MISC	PH13Agent	On
Plug Hall 1-4	PH14	Multi-plug: Prayer Lamp, Vera Power, MISC, Singtel Optical Network Terminal	PH14Agent	On
Plug Hall 1-5	PH15	Phone charger x2, MISC	PH15Agent	On
Plug Hall 1-6	PH16	Fan	PH16Agent	On
Plug Hall 1-7	PH17	MISC	PH17Agent	Off
Plug Hall 1-8	PH18	MISC	PH18Agent	Off
Hall 2 (H2)				
Plug Hall 2-1	PH21	MISC	PH21Agent	Off
Plug Hall 2-2	PH22	Multi-plug: Tower Far, Vacuum Cleaner, 4 x MISC	PH22Agent	On
Kitchen (K)				
Plug Kitchen 1-1	PK11	Fridge	PK11Agent	On
Plug Kitchen 1-2	PK12	MISC	PK12Agent	Off
Plug Kitchen 1-3	PK13	Kettle	PK13Agent	On
Plug Kitchen 1-4	PK14	Kettle (Tayomi)	PK14Agent	On
Plug Kitchen 1-5	PK15	Steamer (SATO)	PK15Agent	On
Plug Kitchen 1-6	PK16	MISC	PK16Agent	Off
Plug Kitchen 1-7	PK17	Door Bell	PK17Agent	On
Plug Kitchen 1-8	PK18	Washing Machine	PK18Agent	On

Table 4.23 shows the devices implemented in the house:

1. 34 x Z-Wave UK Plug-in Switch plus Power Meter

2. 1 x Z-Wave VeraEdge Smart Gateway

Z-Wave UK Plug-in Switch plus Power Meter gather and save energy data from devices in the IoT based smart home. At the same time, it helps to reduce electricity consumption by setting up a system to control the devices "ON/OFF" button within the time range.

Z-Wave VeraEdge Smart Gateway collates the data from Z-Wave UK Plug-in Switch plus Power Meter in order to study the trend of the house occupant's behaviour. By placing the smart plugs on various sections of the house, it studies the frequency pattern of the occupant's switches "ON" and "OFF" to use the smart plugs. The data recorded also shows how much power was used in a Singapore home and what could be done to reduce electricity consumption and cost for homeowners.

This housing unit was used by Singapore housing development board as a test bed. Water heaters and lights measurements were excluded due to obscure wiring by the licensed electrical worker and intrusive retrofitting. These would not affect the overall study of reducing the electricity consumption without disruption of consumer's habits.

Data collection of the time stamp and power consumption were implemented between 10 December 2016 to 2 April 2017, all power sockets were plugged with smart plugs. This allows understanding of consumer’s behaviour on energy consumption through a 24 hours energy reading and control on the devices when necessary due to unforeseeable circumstances. Data collected was used for system design simulation to further optimise electricity consumption with regard to home owner’s habit.

4.3.2.2 Simulation and Results

Fig.4.21 shows the DSM MAS ACL messages of SHMS. DSM communicates with SD to collect the electricity demand information. "SUBSCRIBE" message was used to keep connecting to the DSM at all times.

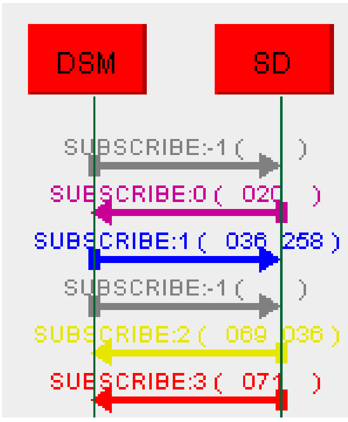

Fig. 4.21 DSM MAS ACL messages

Fig.4.22 shows the DSM MAS communication of SHMS. The MAS communication shows the created agents information such as sender, receiver, content, and reply.

```
DSM: I receive message.
(SUBSCRIBE
 :sender  ( agent-identifier :name SD@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc ))
 :receiver  (set ( agent-identifier :name DSM@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc )) )
 :content  "Subscription"
 :reply-with  DSM@192.168.1.61:1099/JADE1513663286680  :in-reply-to  SD@192.168.1.61:1099/JADE1513663286680 )
SD: I receive message.
(SUBSCRIBE
 :sender  ( agent-identifier :name DSM@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc ))
 :receiver  (set ( agent-identifier :name SD@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc )) )
 :content  "Subscription"
 :reply-with  SD@192.168.1.61:1099/JADE1513663287093  :in-reply-to  DSM@192.168.1.61:1099/JADE1513663286679 )
```

Fig. 4.22 DSM MAS communication

Fig.4.23 shows the priority list for DSM calculations. This priority list was based on Fig. 3.22 and the data from Table 4.23. It enables DSM to switch devices "OFF" based on the priority of this list.

Period/Priority List	0	1	2	3	4	19	20	21	22	23
1	PK11	PK11	PK11	PK11	PK11	PK11	PK11	PK11	PK11	PK11
2	PR21	PR13	PR44	PR44	PR44	PK15	PR31	PR31	PR21	PR21
3	PR34	PR44	PR13	PK13	PH15	PR21	PR21	PR21	PR31	PR34
4	PR14	PR21	PK13	PH22	PK13	PK13	PK18	PR11	PR11	PR13
30	PR24	PR24	PR23	PR24	PR24	PR24	PR24	PR33	PR33	PR33
31	PR33	PR33	PR24	PR33	PR33	PR41	PR41	PR41	PR41	PR41
32	PR41	PR41	PR33	PR41	PR41	PR42	PR42	PR42	PR42	PR42
33	PR42	PR42	PR41	PR42	PR42	PR43	PR43	PR43	PR43	PR43
34	PR43	PR43	PR42	PR43	PR43	PR44	PR44	PR44	PR44	PR44

Fig. 4.23 DSM: Priority list

Fig.4.24 shows the priority list for DSM calculations. This result was implemented using Fig. 3.23 methodology and the data from Table 4.23.

```
Hour 0
-------------------
Fixed Supply: 505
Initial Demand: 1720
Device Off: PR43, Demand of Device:511.05
Priority: 33
Final Demand: 1208.95
-------------------
-------------------
Fixed Supply: 505
Initial Demand: 1208.95
Device Off: PR42, Demand of Device:200.88
Priority: 32
Final Demand: 1008.07
-------------------
-------------------
Fixed Supply: 505
Initial Demand: 1008.07
Device Off: PR41, Demand of Device:198.75
Priority: 31
Final Demand: 809.32
-------------------
```

(a) DSM: Simulation results for the 1st hour

```
-------------------
Hour 19
-------------------
Fixed Supply: 582
Initial Demand: 1009
Device Off: PR44, Demand of Device:531.55
Priority: 33
Final Demand: 477.45
-------------------
-------------------
Fixed Supply: 582
Device On: PR43
Priority: 32
Demand: 477.45
-------------------
-------------------
Fixed Supply: 582
Device On: PR42
Priority: 31
Demand: 477.45
-------------------
```

(b) DSM: Simulation results for the 19th hour

Fig. 4.24 DSM: Simulation results

Fig.4.24 includes information such as fixed supply, initial or final demand, device off or on, demand of device, and priority. Fixed supply is the supplied value to be achieved in that period. "Device On" or "Device Off" represents the device being turned on or off during that period. Priority is the importance of the device based on the priority list in Fig.4.23.

Fig. 4.24a shows that the devices are being turned off based on the initial total demand and the fixed supply value. The devices keep turning off to decrease the demand until the value reaches an equal or lesser amount than the targeted fixed supply.

However, Fig. 4.24b shows that the system stops turning off devices after the demand is lesser than the targeted fixed supply. Additionally, the priority of devices are different in the two figures and follows the priority list in Fig.4.23. Hence, these simulations validate the DSM design for SHMS.

4.3.2.3 Summary

The development of the proposed Demand Side Management (DSM) System was carried out to accommodate the different level of consumers' comfort. It aims to optimise efficiency and cost savings of the homes. The DSM system's results have achieved the optimal use of energy efficiency and energy bills

From the smart grid research point of view, this provides a flexible decentralised control and management system for the residential electrical power system. The SSM and DSM softwares provide a potential solution to the smart nation concept by further enhancing the smart grid technique that benefits the entire power grid. It decreases the overloading of the electricity generators in the power grid due to its optimizing power redistribution capability and the help of renewable energy sources.

4.3.3 Power Notification System (PNS)

This section includes the experimental information, simulations, results, and discussions for the Power Notification System (PNS).

4.3.3.1 Experiment Setup and Data Collection

The Aeon Labs Z-Wave UK Plug-in Switch plus Power Meter was installed on every available energy consumption devices in the experimental house as shown in 4.20 and 4.23. Subsequently, the data was collected through a centralised smart device called VeraEdge Home Controller. Fig. 4.25 shows the data collected between 10-12-2016 to 02-04-2017 from the experimental house.

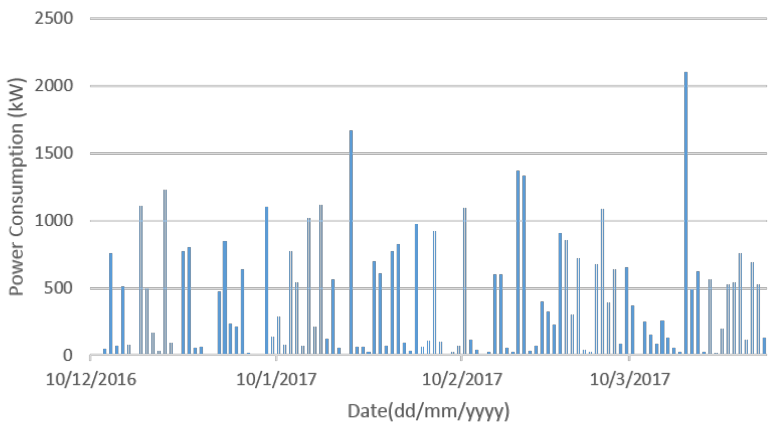

Fig. 4.25 Experimental house data

Fig. 4.26 shows the data collected between 10-12-2016 to 02-04-2017 from the electricity market.

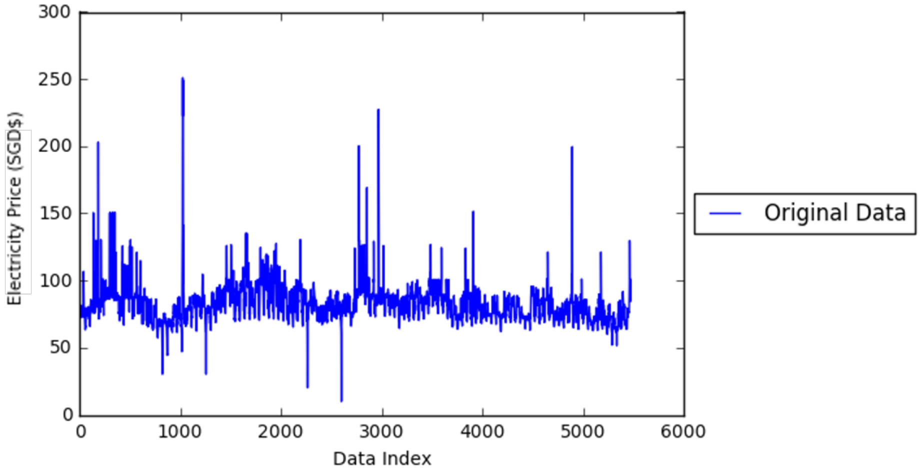

Fig. 4.26 Experimental house data

The simulation studies for the proposed multi-model prediction system consist of the following standard parameters throughout to ensure consistency of the different types of neural networks:

- Hidden layer based on equation (3.39)
- Batch size of 1
- Epoch (System iteration) of 100
- Training data of 75% (3 months)
- Testing data of 25% (1 month)

The system was done by using Keras library in Python language [152].

4.3.3.2 Multi-Agent System (MAS)

Fig.4.27 shows the PNS MAS ACL messages of SHMS. PNS communicates with PF, PC, PFA, PCA, and SETS to collect the electricity demand information. "SUBSCRIBE" message was used to keep connecting to the PNS at all times.

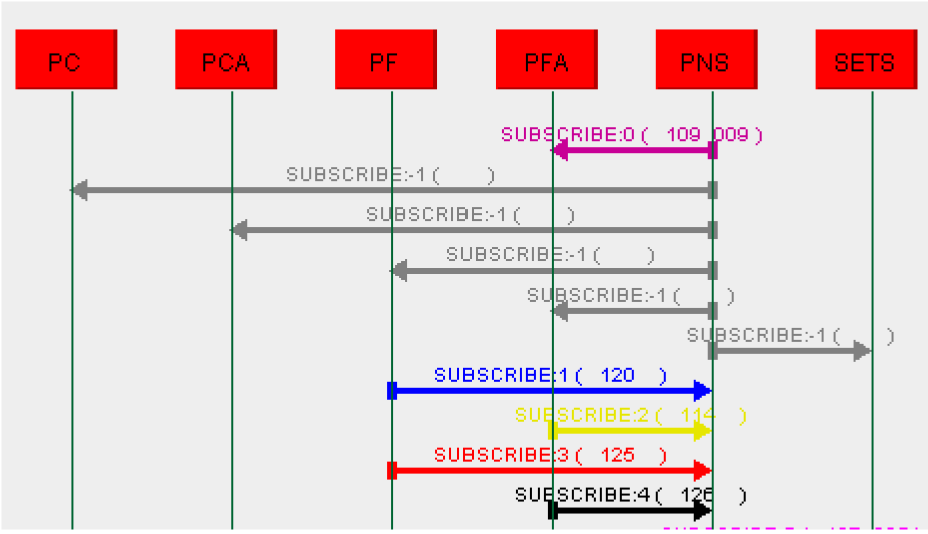

Fig. 4.27 PNS MAS ACL messages

Fig.4.28 shows the PNS MAS communication of SHMS. The MAS communication shows the created agents information such as sender, receiver, content, and reply.

```
PNS: I receive message.
(SUBSCRIBE
 :sender  ( agent-identifier :name SETS@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc ))
 :receiver  (set ( agent-identifier :name PNS@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc )) )
 :content  "Subscription"
 :reply-with  PNS@192.168.1.61:1099/JADE1520421677563 )
SETS: I receive message.
(SUBSCRIBE
 :sender  ( agent-identifier :name PNS@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc ))
 :receiver  (set ( agent-identifier :name SETS@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc )) )
 :content  "Subscription"
 :reply-with  SETS@192.168.1.61:1099/JADE1520421678224  :in-reply-to  PNS@192.168.1.61:1099/JADE1520421677563 )
PC: I receive message.
(SUBSCRIBE
 :sender  ( agent-identifier :name PNS@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc ))
 :receiver  (set ( agent-identifier :name PC@192.168.1.61:1099/JADE ) )
 :content  "Subscription"
)
```

Fig. 4.28 PNS MAS communication

4.3.3.3 Price Forecasting (PF)

This section shows the prediction results for PF in SHMS. Fig.4.29, 4.30, 4.31, and 4.32 shows the respective prediction results for MLP, RNN, LSTM, and GRU in PF. It presents the results in ”Original Data”, ”Training Data”, and ”Testing Data” in blue, green, and red respectively. Multi-model prediction model uses historical electricity prices and predicts the incoming electricity prices.

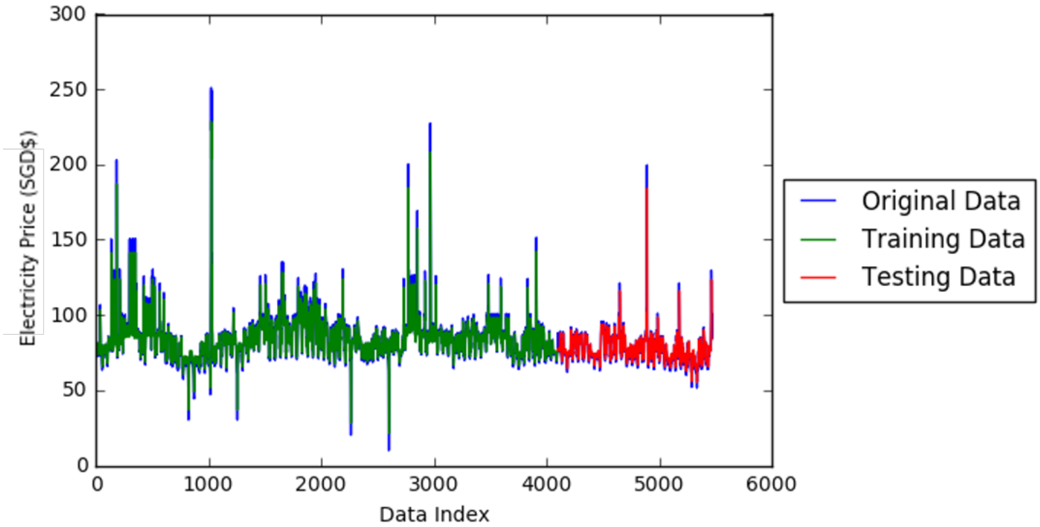

Fig. 4.29 PF: MLP prediction result

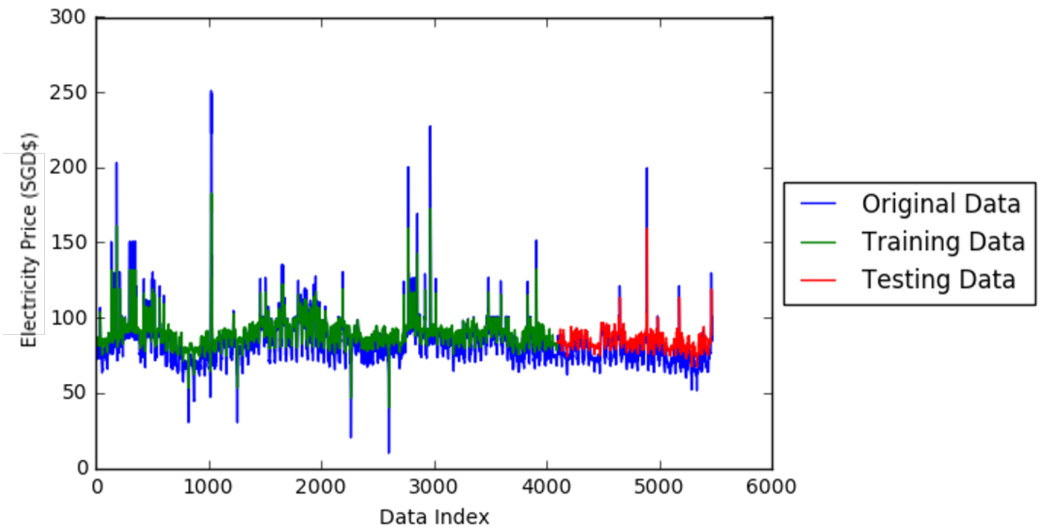

Fig. 4.30 PF: RNN prediction result

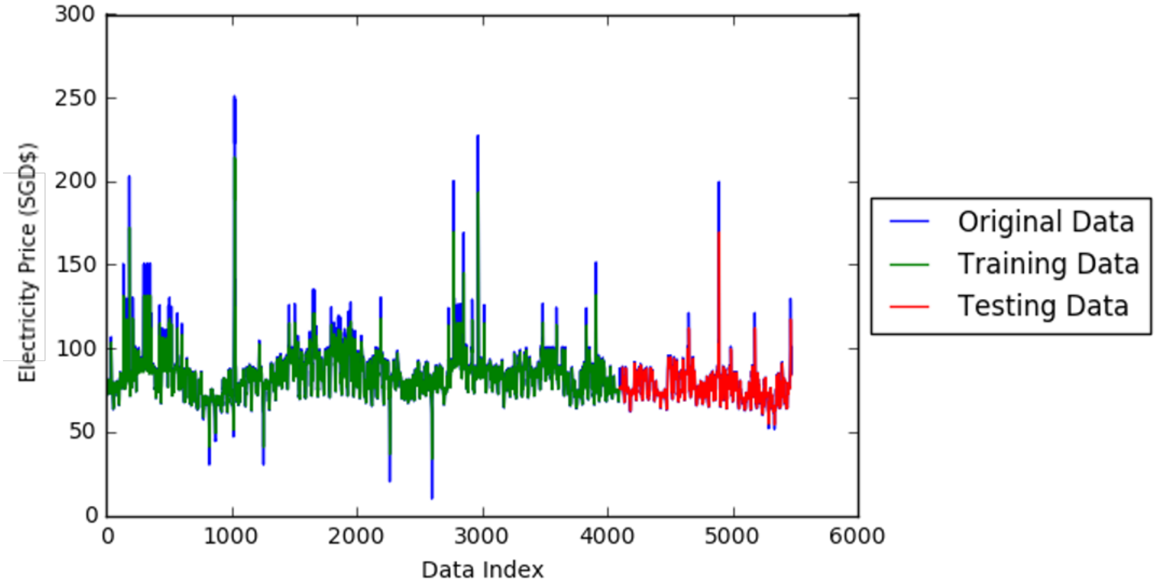

Fig. 4.31 PF: LSTM prediction result

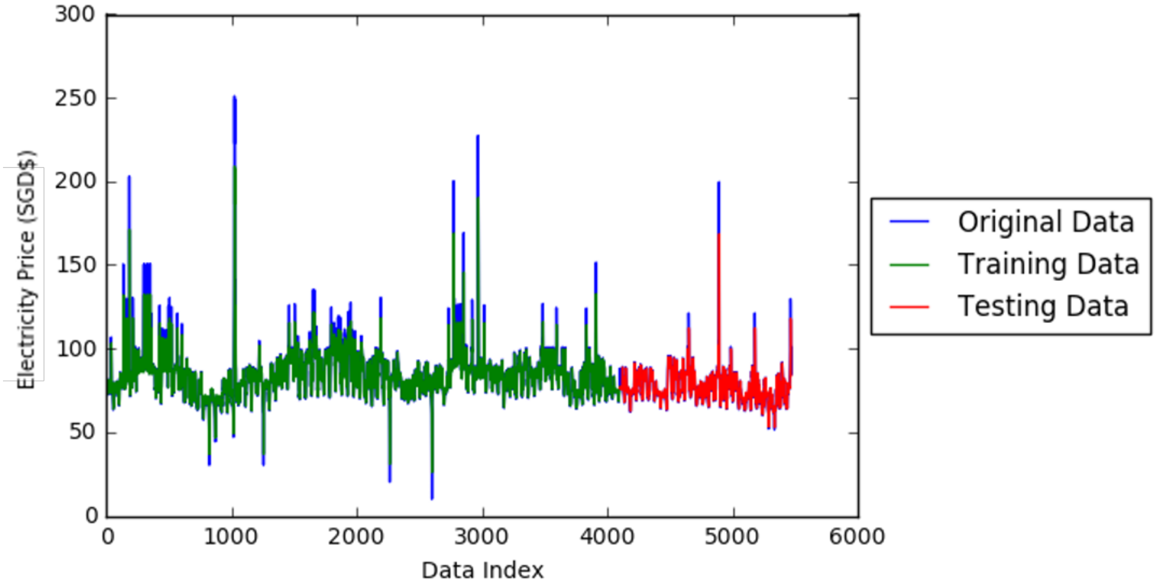

Fig. 4.32 PF: GRU prediction result

Table 4.24 shows the MAPE results for multi-model prediction model in PF. k-fold cross-validation of 10 iterations had been implemented for the presented results. It shows the training and testing MAPE results of the different prediction models in the multi-model prediction model. The best testing MAPE result was 2.72% using LSTM. However, the best training result was 3.79% by GRU. The likely reason, why LSTM produced better testing results, was the LSTM algorithm is meant for long-term sequential data. Although GRU was also meant for long-term sequential data, as it was designed to run for lesser computation power, the compromisation of the original LSTM algorithm affected GRU accuracy.

Table 4.24 PF: Multi-model prediction model MAPE results

Prediction models	**MLP**	**RNN**	**LSTM**	**GRU**
MAPE(%)-Train	4.09	8.90	3.80	3.79
MAPE(%)-Test	3.22	10.80	2.72	2.80

4.3.3.4 Price Clustering (PC)

This section shows the PC simulation results for SHMS. Fig. 4.33 shows the final centroids and clusters results in PC. This differentiates the range of "Off-Peak" and "Peak" prices for every period.

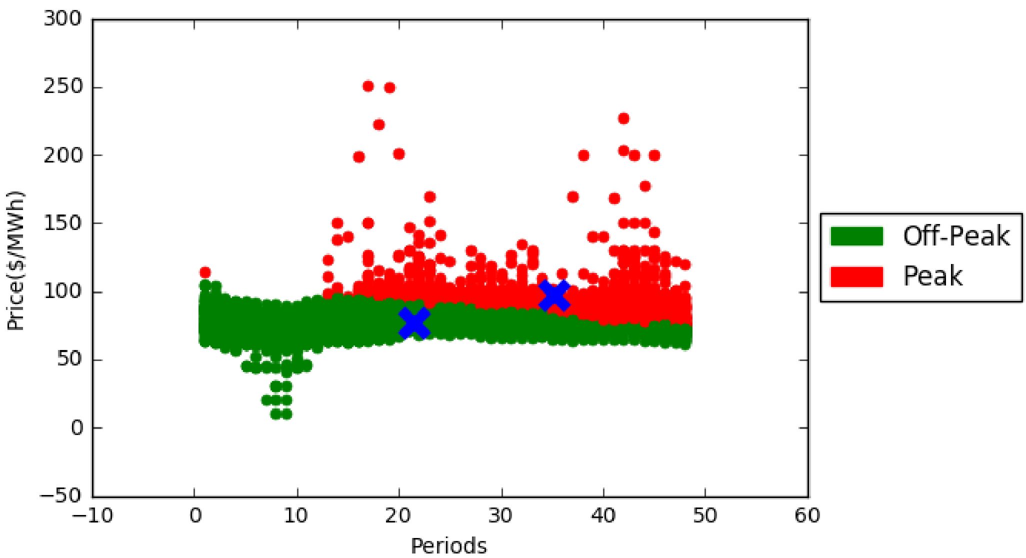

Fig. 4.33 PC: Final Centroids and Clusters

Fig.4.34 shows the testing of the clusters' results in PC. This testing verifies the range of "Peak" and "Off-Peak" values from the model.

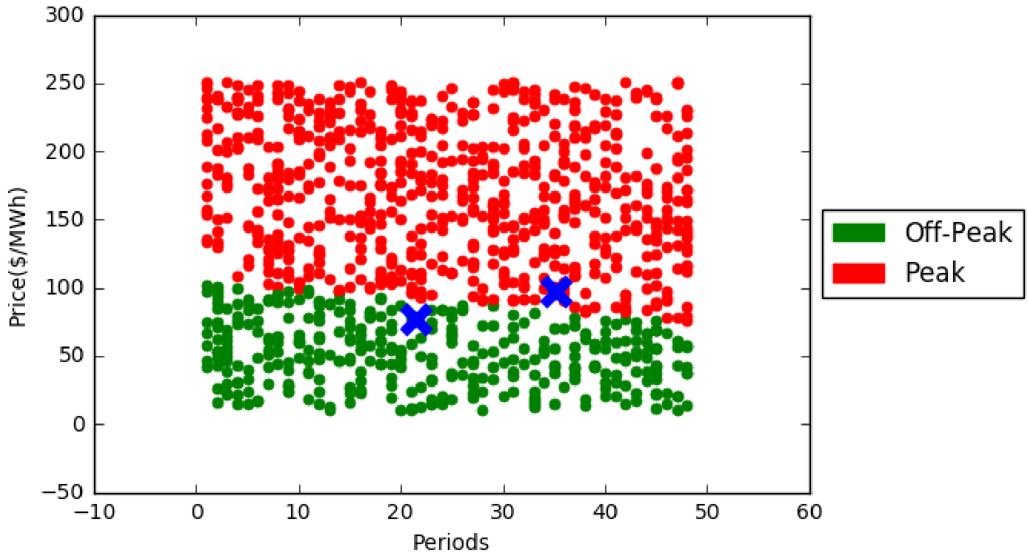

Fig. 4.34 PC: Testing of Result's Cluster

4.3.3.5 Power Forecasting Alert (PFA)

This section shows the prediction results for PFA in SHMS.

Fig.4.35, 4.36, 4.37, and 4.38 show the prediction results for MLP, RNN, LSTM, and GRU in PFA. Multi-model prediction model uses the historical electricity consumption and predicts the future electricity consumption.

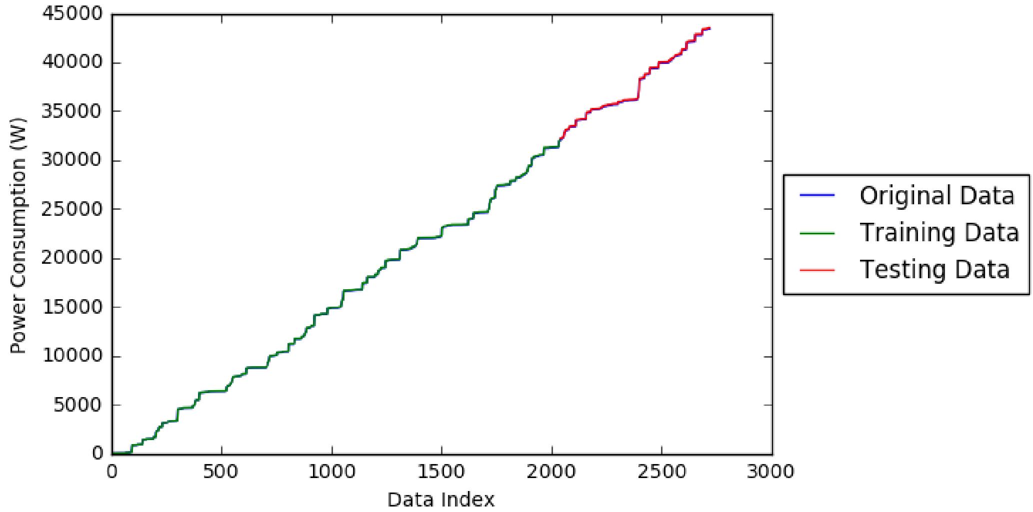

Fig. 4.35 PFA: MLP prediction result

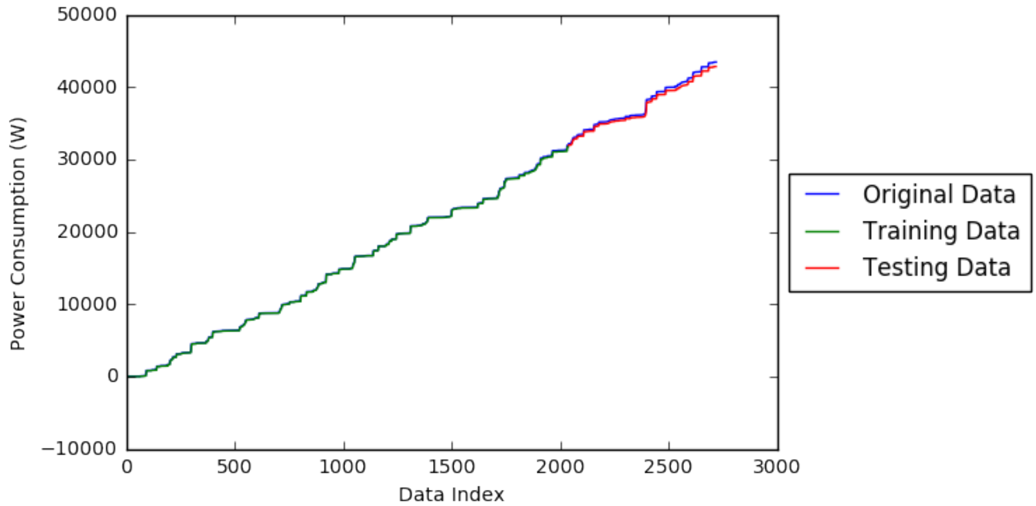

Fig. 4.36 PFA: RNN prediction result

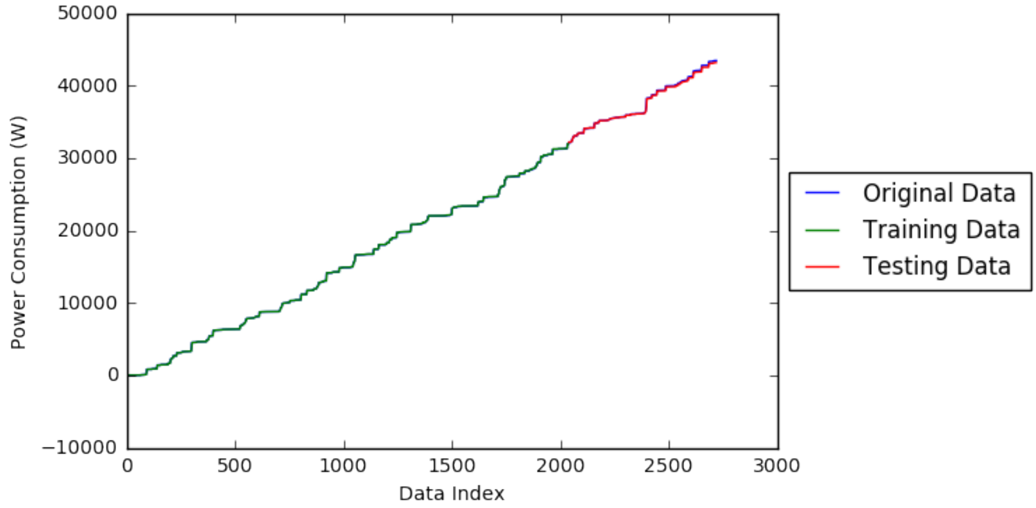

Fig. 4.37 PFA: LSTM prediction result

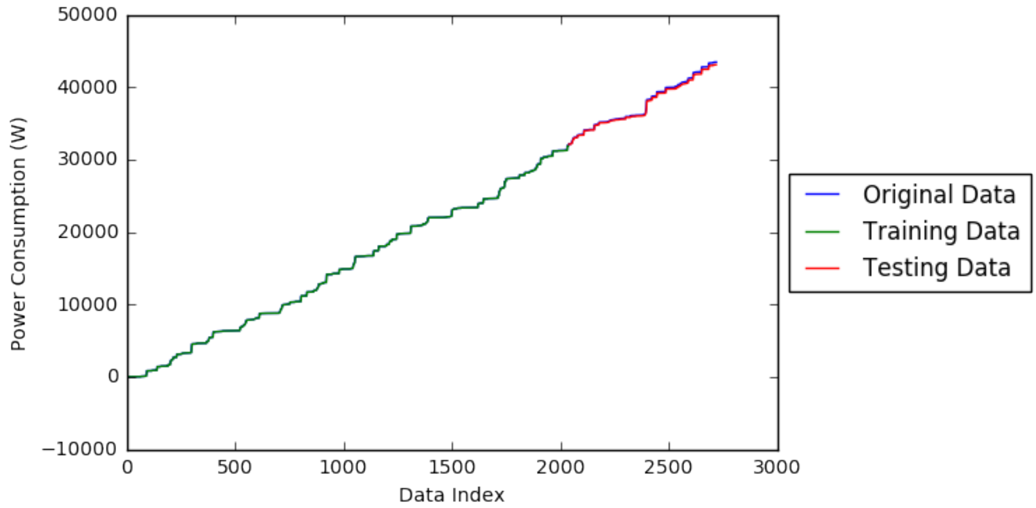

Fig. 4.38 PFA: GRU prediction result

Table 4.25 shows the MAPE results for multi-model prediction model in PFA. k-fold cross-validation of 10 iterations had been implemented for the presented results. It shows the training and testing MAPE results of the different prediction models in the multi-model prediction model. The best testing MAPE result was 0.24% using LSTM. However, the best training result was 0.74% by MLP. The likely reason, why LSTM produced better testing results, was the LSTM algorithm is meant for long-term sequential data. However, the better training results shown by MLP indicated that it manages to find the correlation of the features faster.

Table 4.25 PFA: Multi-model prediction model MAPE results

Prediction models	**MLP**	**RNN**	**LSTM**	**GRU**
MAPE(%)-Train	0.74	17.19	2.14	4.07
MAPE(%)-Test	0.25	1.00	0.24	0.46

4.3.3.6 Power Consumption Alert (PCA)

This section shows the PCA simulation results for PNS. Fig.4.39 shows the final centroids and clusters result in PCA. This differentiates the range of "Low", "Average", and "High" power consumptions for every period.

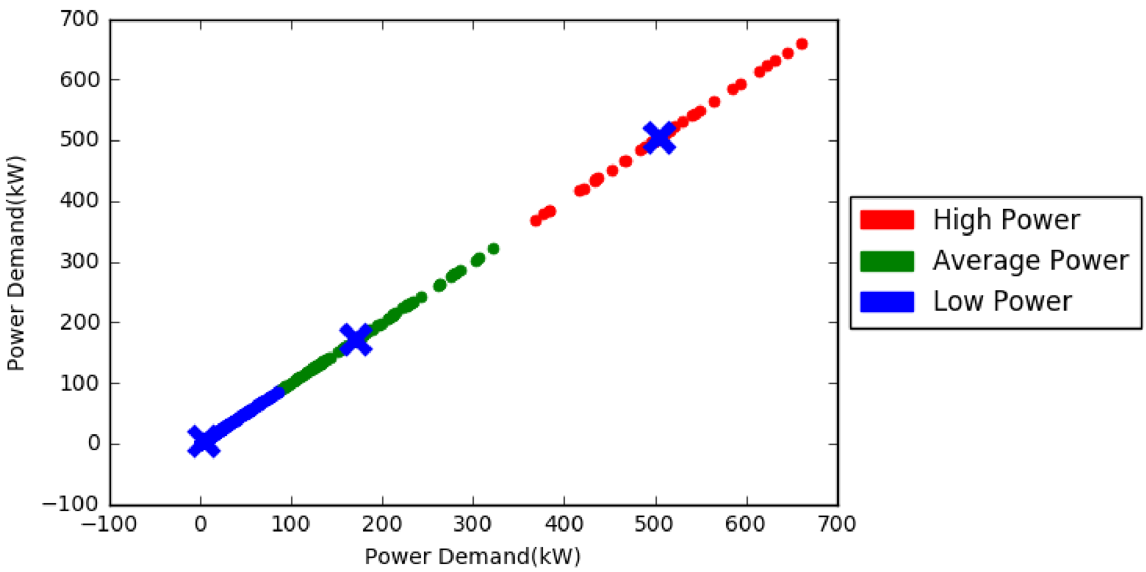

Fig. 4.39 PCA: Final Centroids and Clusters

Fig.4.40 shows the testing of the resulted clusters results in PCA. This testing verifies the range of "Low", "Average", and "High" values from the model.

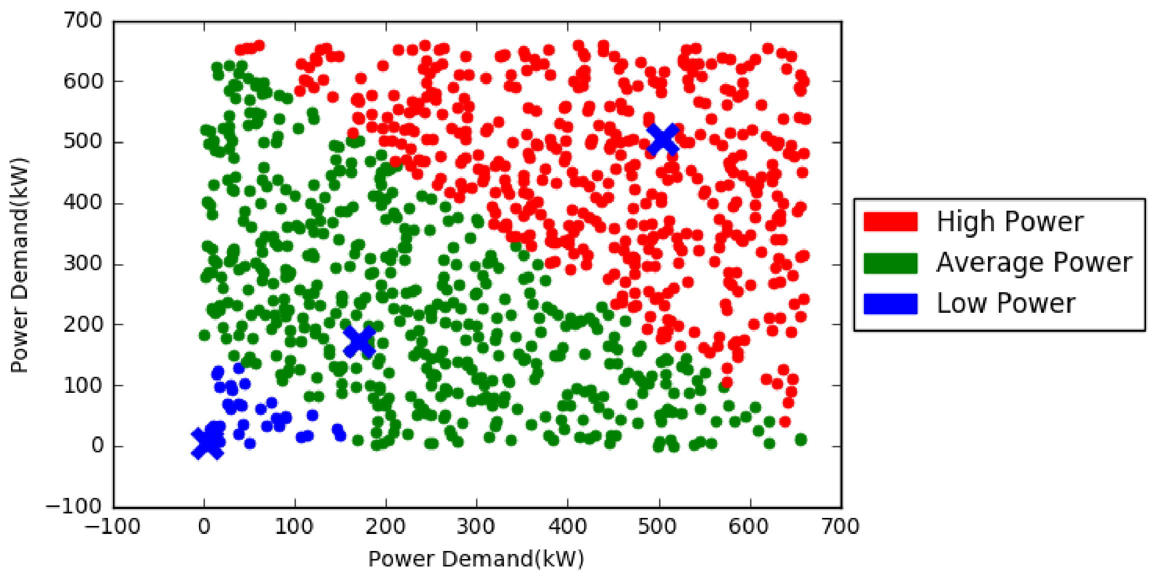

Fig. 4.40 PCA: Testing of Result's Cluster

4.3.3.7 Smart Energy Theft System (SETS)

This section shows the SETS simulation results in SHMS. SETS was tested by randomly stealing energy on 50 different periods.

Fig. 4.41, 4.42, 4.43, and 4.44 show the respective prediction results for MLP, RNN, LSTM, and GRU in SETS.

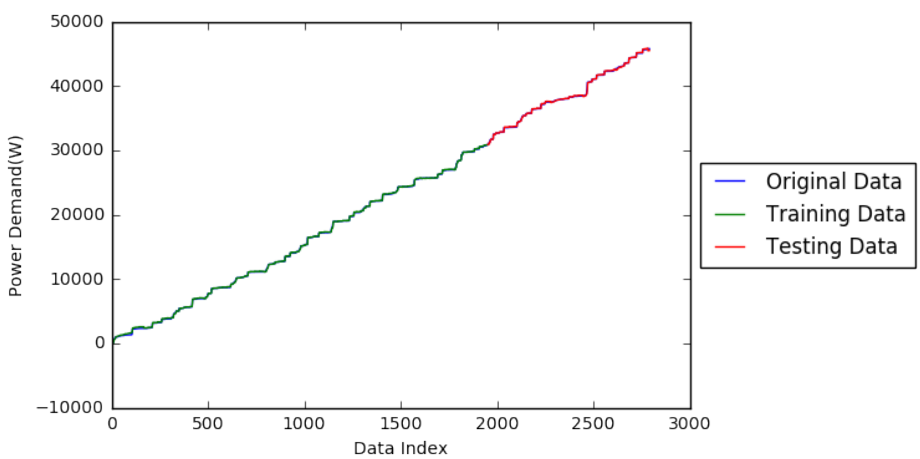

Fig. 4.41 SETS: MLP prediction result

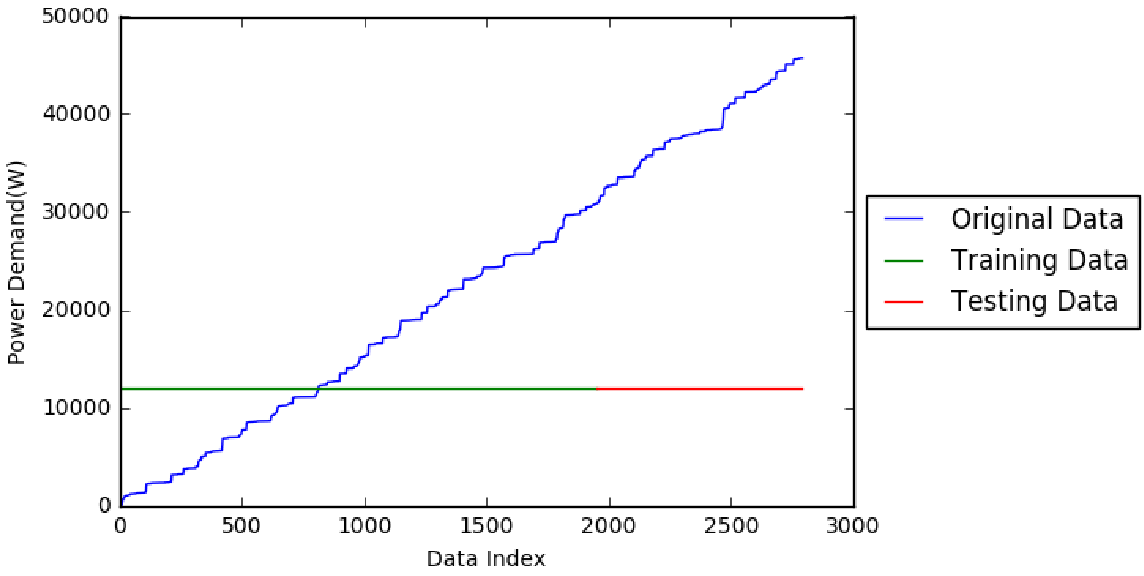

Fig. 4.42 SETS: RNN prediction result

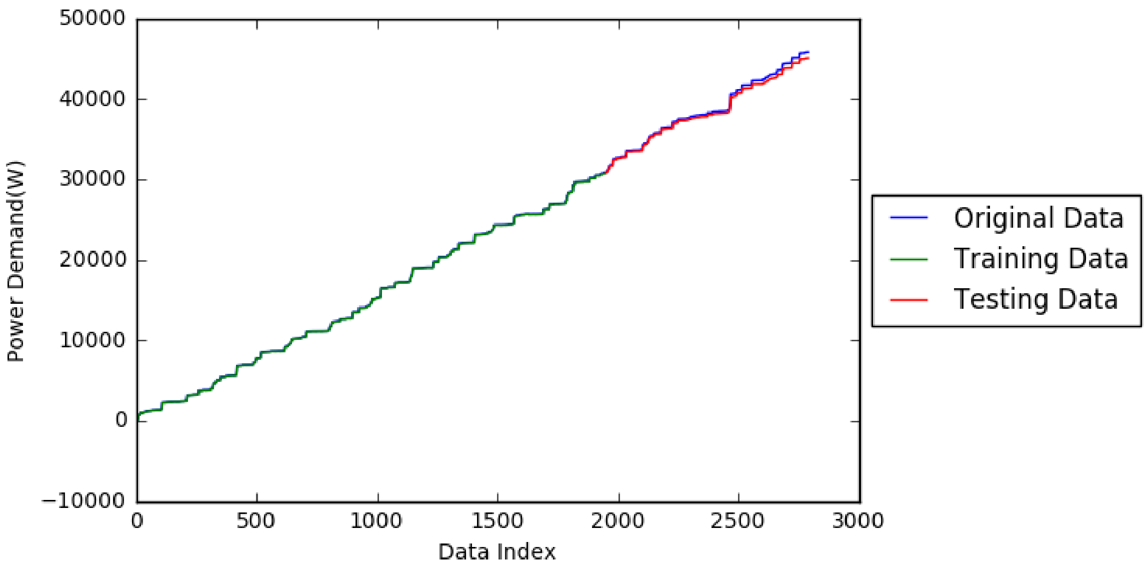

Fig. 4.43 SETS: LSTM prediction result

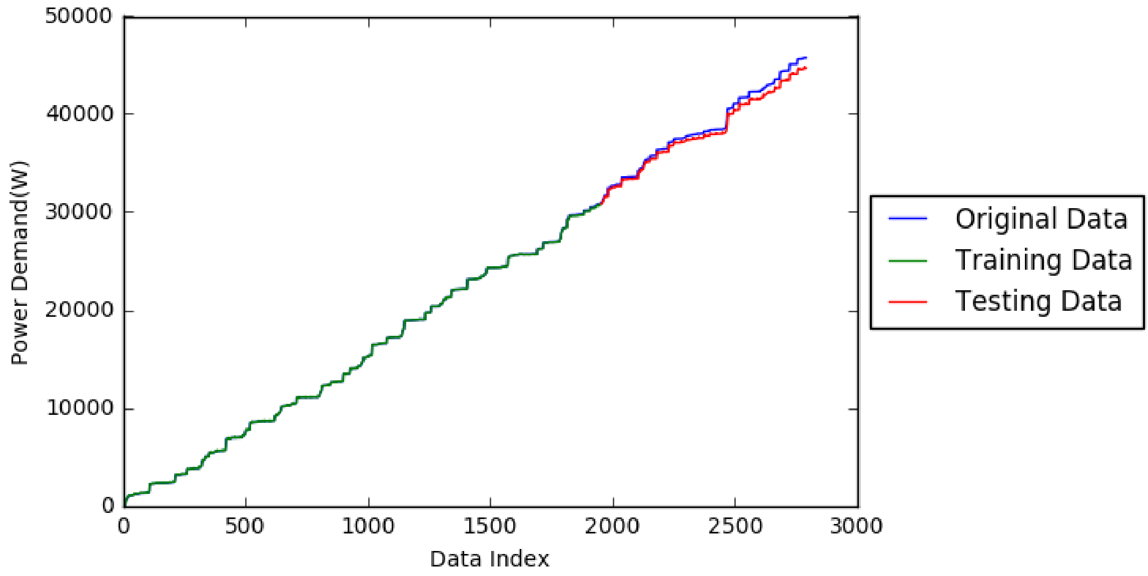

Fig. 4.44 SETS: GRU prediction result

Table 4.26 shows the MAPE results for stage 1 in SETS. k-fold cross-validation of 10 iterations had been implemented for the presented results. The best MAPE testing result was 0.18% using MLP. However, the best MAPE training result was 5.48% using LSTM. The likely reason, why MLP has better testing results, was the event of power accumulation does not have a pattern that relies on historical usages. Fig. 4.42 shows the worst results among the rest could be caused by RNN algorithm of retaining short time-frame information where there is no reliance on past usages.

Table 4.26 SETS: Stage 1 MAPE results

Prediction models	**MLP**	**RNN**	**LSTM**	**GRU**
MAPE(%)-Train	33.99	2353.23	5.48	11.20
MAPE(%)-Test	0.18	68.83	0.81	1.32

Fig. 4.45 shows the stage 2 alert system for SETS. These results were obtained after the data processed through stage 2 in SETS.

```
Normal Usage:'5/3/2017 22:00'
Normal Usage:'12/3/2017 22:00'
Possible Sudden High consumption usage:'19/3/2017 22:00'
Normal Usage:'26/3/2017 22:00'
Normal Usage:'18/12/2016 23:00'
Normal Usage:'25/12/2016 23:00'
```

Fig. 4.45 SETS: Stage 2 alert notifications

In Fig.4.45, the alert notifications were made after processing through stage 2. It filters the abnormally from stage 1 and proceeded to stage 3 if it is not able to make a decision.

Fig.4.46 shows the final alert result for SETS. These results were obtained after the data processed through stage 3 in SETS.

```
Normal Usage:'22/12/2016 13:00'
Normal Usage:'29/12/2016 13:00'
Possible Energy Theft:'5/1/2017 13:00'
Possible Sudden High consumption usage:'12/1/2017 13:00'
Normal Usage:'19/1/2017 13:00'
Normal Usage:'26/1/2017 13:00'
```

Fig. 4.46 SETS: Stage 3 alert notifications

In Fig.4.46, the final alert notifications were made from processing stage 2 and using stage 3 algorithms. The ground truth data were simulated attacks on top of the original data collection. The results were obtained after randomly stealing the energy of 50 different periods. The final result was produced after doing the entire process 10 times with random stealing and k-fold cross validation of 10 iterations each time. This results in 99.92% accuracy of classifications using SETS. Further analysis of the result can be found in W.Li, et al., [153] for energy theft detection.

4.3.3.8 Summary

This section develops an alert notification system called Power Notification System (PNS) based on machine learning methods and statistical algorithms. PNS consist of various functions such as Price Forecasting (PF), Price Clustering (PC), Power Forecasting Alert

(PFA), Power Consumption Alert (PCA), and Smart Energy Theft System (SETS). It uses information from Data Collection Module (DCM) and Real-Time Price Information for PNS. The PNS functions use power accumulator, Multi-model prediction system, Mean Absolute Percentage Error (MAPE), and K-Means algorithm as part of its system. Multi-model prediction system integrates Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN), Long Short Term Memory (LSTM), and Gated Recurrent Unit (GRU) into a single forecast system for predictions. SETS includes the primary and secondary decision models to detect and make the decision on energy theft. The simulation results demonstrate the proposed system capability through real data from the IoT based smart home in Singapore and the electricity market.

4.3.4 Implementation of Overall Multi-Agent System (MAS)

This section includes the experimental information, simulations, results and discussions for the overall Multi-Agent System (MAS).

Fig.4.47 shows MAS network of SHMS. The network was designed based on Fig. 3.28 using networkx [154].

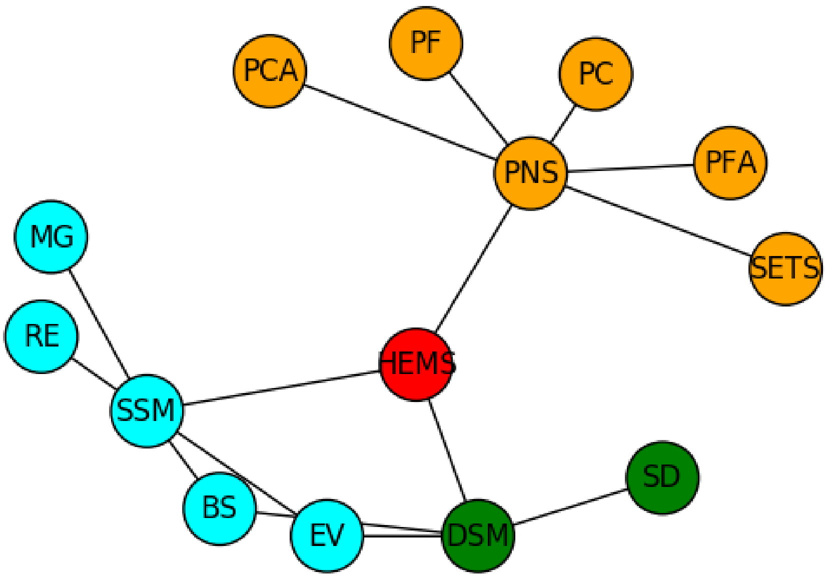

Fig. 4.47 SHMS MAS network

Fig.4.48 shows MAS communication of SHMS. The MAS communication shows the created agents' identities, connections and IP addresses.

```
PNS Connections:
tcp://localhost:1000/10 connecting to tcp://localhost:1000/2
tcp://localhost:1000/10 connected to deviceProxy('tcp://localhost:1000/2')
tcp://localhost:1000/10 Received Data
PNS Connections:
tcp://localhost:1000/10 connecting to tcp://localhost:1000/4
tcp://localhost:1000/10 connected to deviceProxy('tcp://localhost:1000/4')
tcp://localhost:1000/10 Received Data
DSM Connections:
tcp://localhost:1000/11 connecting to tcp://localhost:1000/5
tcp://localhost:1000/11 connected to deviceProxy('tcp://localhost:1000/5')
tcp://localhost:1000/11 Received Data
SSM Connections:
tcp://localhost:1000/12 connecting to tcp://localhost:1000/6
tcp://localhost:1000/12 connected to deviceProxy('tcp://localhost:1000/6')
tcp://localhost:1000/12 Received Data
```

Fig. 4.48 SHMS MAS communication

Fig.4.49 shows the HEMS MAS ACL messages of SHMS. The ACL messages consist of "SUBSCRIBE", "INFORM" and "CONFIRM". PNS "SUBSCRIBE" to HEMS for exchanging information at all times. SSM and DSM "INFORM" HEMS when new information comes in, HEMS will "CONFIRM" the received information. Subsequently, SSM and DSM will acknowledge the message by replying with a "CONFIRM".

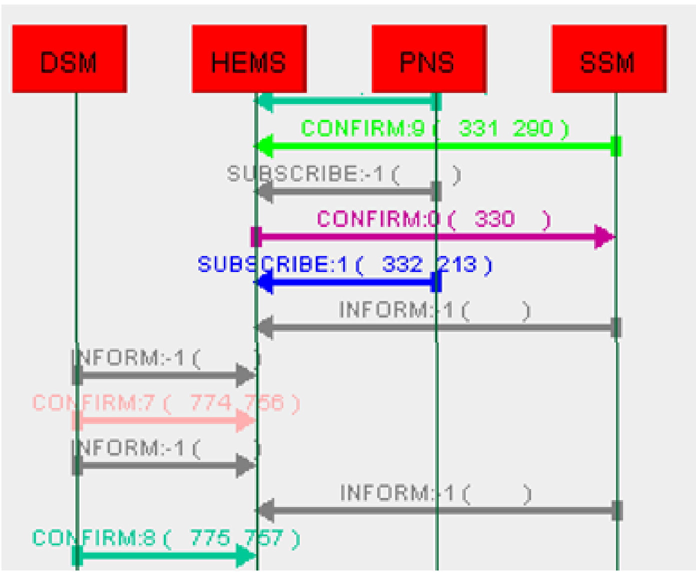

Fig. 4.49 HEMS MAS ACL messages

Fig.4.50 shows the HEMS MAS communication of SHMS. The MAS communication shows the created agents information such as sender, receiver, content and reply.

```
HEMS: I receive message.
(INFORM
 :sender  ( agent-identifier :name SSM@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc ))
 :receiver  (set ( agent-identifier :name HEMS@192.168.1.61:1099/JADE ) )
 :content  "Send me the data?"
)
SSM: I receive message.
(CONFIRM
 :sender  ( agent-identifier :name HEMS@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc ))
 :receiver  (set ( agent-identifier :name SSM@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc )) )
 :content  "Alright!"
 :reply-with  SSM@192.168.1.61:1099/JADE1513664792339 )
HEMS: I receive message.
(SUBSCRIBE
 :sender  ( agent-identifier :name PNS@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc ))
 :receiver  (set ( agent-identifier :name HEMS@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc )) )
 :content  "Subscription"
 :reply-with  HEMS@192.168.1.61:1099/JADE1513664790027  :in-reply-to  PNS@192.168.1.61:1099/JADE1513664790027 )
PNS: I receive message.
(SUBSCRIBE
 :sender  ( agent-identifier :name HEMS@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc ))
 :receiver  (set ( agent-identifier :name PNS@192.168.1.61:1099/JADE  :addresses (sequence http://192.168.1.61:7778/acc )) )
 :content  "Subscription"
 :reply-with  PNS@192.168.1.61:1099/JADE1513664792340  :in-reply-to  HEMS@192.168.1.61:1099/JADE1513664790027 )
```

Fig. 4.50 HEMS MAS communication

4.3.4.1 Summary

A proposed Multi-Agent System (MAS) for Self-learning Home Management System (SHMS) was developed for the interactive communication channel between devices, management systems and energy sources information. It enhances the reliability of the communication system within the network. Additionally, MAS digitalises the data communication and improve the efficiency of the communication network.

4.4 Overall Summary

Self-learning Home Management System (SHMS) was developed on a Multi-Agent System (MAS) platform, the communications and interactions among agents were implemented on the Internet of Things (IoT) principles. Intelligent agents and their interaction play an important part in the efficient operation of the smart home. Real simulations based on internet of things based smart home in Singapore shows the SHMS concept capability in using a Demand Side Management (DSM) system, Supply Side Management (SSM) system and

Home Energy Management System (HEMS) to make adaptive and intelligent decision-based. In addition, the functionalities use computational and machine learning techniques in Power Notification System (PNS) enhance the capability of the proposed system. PNS consist of various functions such as Price Forecasting (PF), Price Clustering (PC), Power Forecasting Alert (PFA), Power Consumption Alert (PCA) and Smart Energy Theft System (SETS).

Ultimately, it demonstrates the potential of a more reliable, adaptive, optimised, and predictive energy management system. This system can be further implemented into commercial and industrial sectors as an additional "Plug & Play" function to existing infrastructure.

Chapter 5

Conclusion and Future Works

5.1 Overall Conclusion

This thesis presents an internet of things based adaptive energy management system for smart homes called Self-Learning Home Management System (SHMS). The thesis includes an accurate forecasting system for electricity generation called multi prediction system. A FIPA compliant multi-agent system was designed and developed for SHMS. It integrates machine learning and agent-based system for self-learning algorithms to customise the decision making based on the household behaviours for each individual smart home. The proposed system was developed and simulation studies show the desired capabilities for a smart home. These results were simulated based on a real smart home environment in Singapore. Thus, the simulated results show the practicality of the proposed system.

Additionally, the multi prediction system was designed and developed using various machine learning techniques for accurate prediction of electricity generation. It was developed to accurately predict the electricity generation that benefits the planning and operation in a smart home with dynamic electricity pricing. Different algorithms were developed to improve the accuracy of the electricity generation prediction for Singapore electricity market.

The simulation studies show the high accuracy of the system using Singapore electricity market data for practicality. Hence, supporting the proposed methods in SHMS.

These proposed systems further enhance the smart grid community through a "Plug and Play" concept. The novelty of the proposed system improves the functionality of the smart home in a reliable and energy efficient way. This research shows the potential of exploring artificial intelligence to customise each smart home behaviour and the additional beneficial functions for the smart grid. The contributions of this novel research are listed as follows:

- Adaptive energy management system for smart homes.
  Integrate artificial intelligence into the smart home energy system to classify and predict energy consumption automatically for different home's environment.

- Non-intrusive IoT based energy analytic system.
  Implement different IoT devices to the homes without affecting the house owners and using the data produced by the IoT devices to analyse the household behaviours.

- Energy theft detection for smart homes.
  Detect energy theft through the usage of artificial intelligence with energy monitoring IoT devices in smart homes.

These contributions will benefit the IoT based smart home community in terms of energy analytics. It visualises, classifies, and predicts the energy consumptions and electricity prices through the IoT and industrial standard multi-agent system for smart homes. Furthermore, it prevents energy stealing from predators. The proposed system also adapts to different smart home' environment without major reconstructions of the system, thus able to implement it directly to smart homes. The proposed IoT based energy management system should be useful for researchers in the academic and industry to further study in this area of research.

5.2 Future Research Works

This thesis presents an internet of things based adaptive energy management system for smart homes. Thus, research for further implementations on commercial and industrial sectors should be explored. Additionally, this proposed system uses just a small part of artificial intelligence methods to implement. This shows the potential of using more machine learning techniques to further develop the system and extend it to other sectors.

As the field of machine learning for smart home energy management system is relatively new, it provides several new aspects into smart homes. Some recommendations for future works are as follows:

- Further insight is required to expand this research with other machine learning techniques.
- To overcome the challenges of using Multi-Agent System: Overlapping decisions, interoperability and robustness of the system.
- More variety of smart devices are needed for monitoring of smart home behaviours.
- Fast transmission and large storage space will be essential for machine learning techniques to be in place.
- Research on planning and operation strategies for optimal distribution.
- Research on the higher accuracy of energy theft detection and preventive measures.
- Adaptive to future renewable sources within the grid.
- Advanced decentralised algorithms are needed for decision making in each individual smart devices.
- Fault analysis will be essential for a bigger scale grid level.

In addition, it is important to identify the key technical problems and challenges for the development of an IoT based adaptive energy management system effectively within the field, and how to overcome them. The challenges include industry standards, reliability, and cyber security of the system. Therefore, future research is also necessary to focus on these areas.

Appendix A

List of Publications

A.1 Journals

[1] W. Li, T. Logenthiran, V. T. Phan, and W. L. Woo, “A Novel Smart Energy Theft System (SETS) for IoT based Smart Home,” *IEEE Internet of Things Journal,* 2019, In press.

[2] W. Li, C. H. Ng, T. Logenthiran, V.-T. Phan, and W. L. Woo, "Smart Grid Distribution Management System (SGDMS) for optimized electricity bills," in *Journal of Power and Energy Engineering,* vol. 6, no. 08, p.49, 2018.

[3] W. Li, T. Logenthiran, V. T. Phan, and W. L. Woo, “Implemented iot based self-learning home management system (shms) for singapore,” *IEEE Internet of Things Journal,* pp. 1–1, 2018.

[4] W. Li, T. Logenthiran, V.-T. Phan, and W. L. Woo, “Housing development building management system (hdbms) for optimized electricity bills,” *Transactions on Environment and Electrical Engineering,* vol. 2, no. 2, pp. 64–71, 2017.

[5] W. Li, T. Logenthiran, V.-T. Phan, and W. L. Woo, “Multi-GRU Prediction System for Electricity Generation’s Planning and Operation,” *IET Generation, Transmission & Distribution,* 2018, In press.

A.2 Conferences

[6] W. Li, C. H. Ng, T. Logenthiran, V.-T. Phan, and W. L. Woo, "Smart Grid Distribution Management System (SGDMS) for optimized electricity bills," in *Transportation Electrification Conference and Expo (ITEC), 2018 IEEE.* IEEE, 2018, pp. 212-216.

[7] W. Li, T. Logenthiran, V.-T. Phan, and W. L. Woo, “Power Alert System using K-Means for Smart Home,” in *Innovative Smart Grid Technologies-Asia (ISGT ASIA), 2018 IEEE.* IEEE, 2018, pp. 722-727.

[8] W. Li, T. Logenthiran, V.-T. Phan, and W. L. Woo, “Proposed Optimised Smart Grid System using Multi-Agent System,” in *Innovative Smart Grid Technologies-Asia (ISGT ASIA), 2018 IEEE.* IEEE, 2018, pp. 528-533.

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A.3 Awards

[13] Student Travel Scholarship from IEEE Transportation Electrification Conference and Expo, Long Beach, California, USA.

[14] IEEE PES Student Travel Grant Award from IEEE PES ISGT - Asia, Bangkok, Thailand, 2015

[15] Conference Support Grant Award from IEEE PES Singapore Chapter, 2015

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