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Optimal energy allocation for households in generation-constrained off-grid microgrids

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OPTIMAL ENERGY ALLOCATION FOR HOUSEHOLDS IN GENERATION-CONSTRAINED OFF-GRID MICROGRIDS

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ABSTRACT

For microgrids with limited generation capacity, allocating a daily equal energy budget to each household is one way of ensuring that all households are provided with sufficient energy to be used in a day without compromising the daily operation of the power system. With the same daily energy quota, households are given freedom on how to spend energy according to their preferences and priorities. Issues in this type of energy management scheme include 1) power outage in households that use up all their energy allowance before the scheduled replenishment and 2) unused energy allocation turned to waste from households that are unable to consume the energy allowance. Energy waste in terms of unused energy allocation of some households can be beneficial to other households. The unused energy can be distributed to other households that experience a power outage and need more energy than the allocated. One approach to solving the above issues is to frame the problem as an optimisation problem that aims to minimise the energy wastage and maximise energy availability.

This research proposes an optimal energy allocation for households connected to generation-constrained microgrids. The proposed optimal energy allocation scheme has two main parts. First, the ideal energy utilisation of each household is predicted using a multi-layer perceptron (MLP); secondly, the optimal energy allocations for the households based on their predicted utilisations are derived using Karush-Kuhn-Tucker (KKT) optimality conditions. From the application of the KKT conditions, a methodology for optimal energy allocation that is adaptive to each household is proposed. The approach is optimal as it minimises the energy wastage/deficit while maximising energy availability to households, and adaptive because it uses the household's historical data and demographic information.

To support the development of the MLP-based forecast model, this thesis implemented an energy monitoring system called Philippines Micro-Off-Grids (PMOG) system to gather the actual historical energy usage data in representative households from select villages in Cebu, Philippines which have microgrids with limited generation capacity. In the Philippines, there are 40 million people without access to electricity [Och13] and microgrids are used to provide electricity access to villages that are not accessible by the traditional grid. There are three villages selected with two of them being off-grid communities and one being grid-tied community. The energy data from PMOG system serves as the baseline data for the development of the forecast model and the optimal allocation scheme. A survey is also conducted to gather the household demographic information that affects their daily energy consumption.

This thesis presents an experimental method to determine the best combination of hidden layers and neurons of the neural network along with the input delay window in shaping the input variables that allows

the forecast model to generate the lowest possible root mean squared error (RMSE). Since the optimal energy allocation is dependent on the accuracy of MLP-based load forecast model, the right combination of those design parameters of the neural network together with the delay window used in shaping the inputs is crucial. These parameters are considered as the main factors affecting the performance of the neural network in forecasting.

Experimental results show that as the households' demographic information is included as input variables secondary to the historical energy data and weather information, the performance of the neural network improves significantly. The RMSE decreases from 92 W to 81 W, which represents a 12 % decrease for a neural network with three hidden layers, 20 neurons and seven delays.

Given the limited generation capacity of the microgrid, the objective is to minimise the squared difference between the ideal utilisation of the household (which is estimated by the MLP-based forecast model) and the (calculated) allocated energy. Results from the data from the select villages show an aggregated unused or deficit energy per household (for a day) from the existing equal allocation can be reduced from 0.24 kWh to 0.11 kWh using the proposed dynamic/adaptive allocation, which is about 54 % reduction in unused or deficit energy. For 288 days, a total of 44 % reduction of energy wastage is achieved with the proposed methodology when compared with equal allocation, that is 112 kWh using equal energy allocation, and 62 kWh using the proposed optimal energy allocation.

In summary, the proposed approach of allocating the daily energy allowance of the household which is a hybrid approach using an MLP-based forecast model and KKT optimality conditions minimises the unused energy and enables households to maximise their energy usage without compromising the minimum energy requirement of each household in villages powered by microgrids with limited generation capacity. By incorporating household profiles as inputs to the MLP-based forecast model, prediction accuracy was improved by 12% in terms of RMSE. From my experiments, employing MLP-based forecast model ensures better forecasting performance than other techniques such as Autoregressive Integrated Moving Average (ARIMA), Radial Basis Function Network (RBFN) and Gaussian Process Regression (GPR). The overall average accuracy for the MLP-based forecast model is 91% with the highest accuracy of 93% for House 5 predictions, and the lowest is 91% for House 3.

This approach is expected to work on households with similar profiles connected to any off-grid power systems. Optimising the daily energy quota will enable the village to maximise the usage of the available energy with minimum wastage in terms of unused energy quota. This approach will also lead the village to have a better payment scheme based on their actual usage of electricity.

To the memory of my beloved parents: my mother whose love is eternal and my father who instilled discipline in us. They are the greatest parents I could ever have wished for ...

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D	Number of delays or the window of the inputs considered in reshaping historical energy data, in days
E_g	Generated energy supply by the off-grid power system, kWh
E_i^a	Optimal energy allocation for each household, kWh
E_i	Ideal energy usage as predicted by the ANN-based forecast model, kWh
E_{min}	Daily energy threshold for each household, kWh
E_l	Second smallest amount of energy after E_s using ANN-based forecast model, kWh
E_s	Smallest amount of energy predicted using ANN-based forecast model, kWh
E_s^a	Smallest amount of energy allocated to a household, kWh
$g(x)$	Equality function
$h(x)$	Inequality function
HL	Number of hidden layers of neural network
j	Index of the households separated from households with s or l indices.
l	Index of the household with the second smallest ideal energy demand E_i
L	Langrangian function

$minJ$	Nonlinear optimisation problem
n	Total number of households
N	Number of neurons of neural network
P_n	Number of historical energy data, in days
μ	Complementary slackness
s	Index of the household with the smallest amount of energy ideal energy demand E_i

ACRONYMS

AUC	Area Under Curve
ANOVA	Analysis of Variance
ANN	Artificial Neural Network
ARIMA	AutoRegressive Integrated Moving Average
BEC	Building Energy Consumption
BPN	Backpropagation Neural Network
CBR	Case-Based Reasoning
DG	Distributed Generation units
ECQ	Energy Consumption Quota
EMCS	Energy Management Control System
EMS	Energy Management System
EmS	Energy Monitoring System

ES Exponential Smoothing

FFNN Feedforward Neural Network

HVAC Heating, Ventilation, and Air Conditioning

KKT Karush-Kuhn-Tucker approach

k**-NN** k-Nearest Neighbour (k-NN)

LTLF Long-Term Load Forecasting

MAPE Mean Absolute Percentage Error

MDP Markov Decision Process

MSE Mean Squared Error

MTLF Medium-Term Load Forecasting

MLP Multi-Layer Perceptron

MA Moving Average

PMOGS Philippines Micro-Off-Grid System

RBFN Radial Basis Function Neural Network

RMSE Root Mean Squared Error

STLF Short-Term Load Forecasting

SVM Support Vector Machines

1 INTRODUCTION

Electricity access is one of the problems faced by many developing countries, such as the Philippines. According to the World Bank, there are 1.2 billion people in the world without access to electricity, and most of them are in Asia [DW17]. Areas with no or limited access to electricity are mostly located in rural or remote regions of the countries. In the Philippines, there are approximately 2.3 million households that do not have access to electricity [IRE17]. While conventional electricity providers aim to connect every village and community in the country, they can be restricted by accessibility and geographical locations for some island communities and remote villages. Remote areas where households are dispersed and have meagre income are often less prioritised or left with no access to electricity for years. Microgrid power systems have been utilised to address this issue [IRE17; Int14].

Microgrid power systems can provide electrification to villages or communities where traditional grids are not economically feasible. Microgrid power systems are small-scale versions of a traditional grid which can operate in both grid-tied (on-grid systems) or stand-alone (off-grid systems) modes of operation. Most microgrid power systems use renewable energy resources available locally to the community such as water for mini-hydropower systems, wind for wind turbines, solar energy for solar power systems and biomass or agricultural wastes for biomass power plants [IRE17; HA12; Ene12]. Back-up power sources such as batteries and diesel generators are used in case of system failures [Int14].

1.1 MOTIVATION OF THE RESEARCH

Access to electricity for remote areas in The Philippines has been a great challenge. Remote areas, outside the reach of the traditional grid providers, opt to have an off-grid power system to provide their electricity needs [Ene12; RS16]. In rural communities and villages, off-grid power systems are designed and implemented in order to accommodate the basic electricity needs of each household. In a typical Filipino household, basic electricity needs consist of a television, an electric fan or ceiling fan, lighting bulbs, and a radio [Phi13].

While off-grid power systems are expected to provide the basic electricity needs of each household all the time, they are also expected to do so without having to restrict the amount of energy that can be used by each household [Uni12]. However, most off-grid power systems are operating with restrictions such as load shedding and load shifting, time-based operation and daily energy quota in providing electricity to the consumers because of its limited generation capacity [Ene12]. Load shedding allows the power system to offload some of its load when the threshold for safe operation is breached [Mar+16]. This approach is used to save the power system from system failure due to overloading. The consumers have no control over their electricity access. The power system shed off parts of its distribution whenever necessary [Xu+16]. Load shifting is to defer the operation time of the load when demand is higher than the available energy at the time. Shifting is done based on load priorities [EAR20]. The implementation of load shedding or load shifting as part of the energy management system of microgrids is too costly. This makes it impractical to implement in off-grid power systems. Time-based operation is used when the power system can not operate for 24 hours daily due to technical issues [ARP16]. To save the power system from breakdown, a time-based operation is employed. The system will operate in a specific period in a day. Only at that time, customers will have access to electricity [Mar+13].

Daily energy quota is one of the common energy management scheme employed in off-grid microgrids with limited generation capacity [Sun+16]. Dwellings are given a daily energy quota to be used in a day [ZXT12]. This scheme is employed to ensure that each household will have sufficient energy for their basic electricity needs. The advantage of this approach is that the households control their energy usage, but they can not use any more than to what is being provided. Restrictions on household appliances are applied to maintain the power systems operation and prevent systems failure due to overloading.

For example, consider the Red Cross village located in Daanbantayan, Cebu, Philippines, the village is powered by community-based off-grid solar power systems with an aggregate generation capacity of 119 kW, serve 128 households including a community livelihood centre, and a day-care centre [Han15]. The solar power systems of the village are not capable of supplying the estimated peak power demand of 2 kW for each household without energy usage restrictions to the households and without compromising the operation of the whole off-grid power system. These peak demands are estimated to occur at different times according to household profile. Hence, the energy management system of the solar power systems was then designed to allocate an everyday power allowance to each household equivalent to 0.8 kWh for 24-hour use at their own times, in such a way that the total generation capacity is not exceeded. When the allocated energy is surpassed, the system would automatically cut off the connection of that household from the solar power system, and the energy quota would be restored the subsequent day. The solar power system was designed by Technician without Borders, a French non-government organisation, that helps install and implements the solar power systems in the village [Han15]. Restrictions on the power consumption of each household are imposed to cater to the needs of the whole community while ensuring a steady operation of the off-grid power system. Implementing such restrictions with fixed monthly fees is necessary to provide the basic electricity services to each household.

With an equal amount of energy allocated daily and considering the limited generation capacity of the off-grid power system, two main drawbacks can be highlighted:

1.) Some households use up the allocated daily quota and experience power outage but may require more energy than what is currently provided to them.

2.) Some households do not use all the allocated energy daily and pay the same fixed monthly tariffs as the households that use all their allocated energy.

The two issues above are based on the assumption that all households have equal energy requirements and that the basic electricity needs of the households do not change. This assumption is flawed since the household's electricity needs can vary through time. These variations depend on several factors, such as the household's size, total monthly income, household's head occupation, household's head education, and the number of children who are attending school and staying at home. Furthermore, the fact that some households experience power outage almost every day may indicate that those households require more energy than what is allocated and those households that do not use up all the energy allocation daily might require less energy than the daily quota. All household is required to pay a fixed amount of monthly fees even though their daily energy allocation is not fully utilised. Paying a fixed amount for unused energy is unfair.

Increasing the generation capacity can resolve the issues with the limited energy allocation to each household. However, this approach is only appropriate if the community has the necessary finances to pay the cost of increasing the capacity of the off-grid power systems. Since increasing the generation capacity is not feasible without the necessary finances, one way of resolving the above drawbacks is to adaptively allocate energy to different households based on their expected energy usage so that billing can be based on the actual amount of energy used. The adaptive energy allocation scheme considers not only the basic loads of the households but as well as the individual household profiles. This way, each household would have the freedom to control how they spend their energy without worrying about a shortage, or not using all their energy allocation. The unused allocated energy is considered to be a waste that could have been useful to other households that needs more energy.

All conditions mentioned above are similar to any households in remote areas connected to microgrids which the generation capacity is not designed with the demand of the households but with the available resources for the implementation power systems. In villages such as the Red Cross Village which are built for people who suffers natural calamities, the issues surrounding electricity access are similar [IRE17].

Hence, this research proposes a new method of allocating the daily energy allowance of household in off-grid villages such as the Red Cross village in Daanbantayan, Cebu. Specifically, this research investigates a way of optimising the allocation of energy proportional to the consumption of each household with the following considerations:

1.) Case 1: If the energy allocation is more than the basic needs for a given household, they pay for something they do not use. Therefore, they want an allocation commensurate with their usage.

2.) Case 2: If the allocation is less than the desired utilisation for a given household, they would be dissatisfied with the amount of energy they have, as they would experience a shortage every day. Therefore, they want to have an energy allocation that is within their usage.

3.) The allocations in cases 1 and 2 are not guaranteed to be same.

4.) Energy allocation is constrained within the limited generation capacity of the off-grid power system.

1.2 RESEARCH AIM

Given that there are remote communities that are powered by a limited supply of electricity from an off-grid power system, with no capability of increasing the generation capacity of the power system, this research aims to provide a solution in maximising the energy usage of the available energy from limited supply and satisfy the basic electricity needs of the households.

To achieve this aim, an optimised energy allocation is proposed based on the forecasted energy usage of the households with constraints from the limited generation capacity of the microgrid, and the minimum energy threshold for each household. A Multilayer perceptron (MLP)-based load forecast model is developed that uses the individual household profile along with the historical electricity usage and temperature as its inputs to predict the energy that is likely to be consumed by the household a day-ahead. The proposed optimal energy allocation is limited to a dataset gathered from a village in Daanbantayan, Cebu, Philippines. Amongst the forecast models, the most widely used forecasting model is the Artificial Neural Network (ANN) [BGK15; Dud16; Moo+19]. One of the advantages of neural networks is their ability to generate a general map between inputs and outputs and does not require a priori knowledge that is needed in conventional statistical and econometric modelling. When using a neural network, the input data does not need to satisfy assumptions that are required in other statistical methods. Neural network-based forecast model is known for being robust in handling real-world data.

Load forecasting is essential for efficient energy management operation. When the generation capacity of the system is not capable of providing the desired energy of the households, forecasting the energy consumption is important to ensure maximum usage of the available energy and also to provide the basic electricity needs of the households whilst maintaining a balanced operation of the power systems.

1.3 RESEARCH QUESTIONS

To achieve the above aim in the context of microgrid off-grid power systems, this study investigates the following research questions:

1. Can the household's daily energy consumption be forecast with reasonable accuracy? For this research, optimising the daily energy allowance of each household requires a forecast model that can estimate the next-day energy consumption of the household to minimise the energy wastage in terms of unused/deficit energy. When a household is using a lamp with a 10 W power rating, this lamp consumes 100 Wh energy for ten hours of use. When another household uses an electric fan with a 60 W power rating, this appliance will consume 120 Wh for two hours of use. The forecast model should predict as close as the expected usage of energy of each household to provide the households energy needs as accurate as possible. Since the performance of the load forecast model affects in optimising the daily energy al-

location of each household, a reasonable accuracy in forecasting is desired. The goal is to determine the combinations of network parameters such as the hidden layer HL, and neurons N and delay window D for historical data points that would produce the least root-mean-squared error (RMSE). The aim is to have RMSE that is equal or less than 120 Wh, a 15% tolerance from the current daily energy allocation of the selected village. The tolerance is derived as the minimum allowable error in daily energy allocation of the household. According to the work of Hsiao [Hsi15] and Moriano et al. [Mor+16], 20% or less is an acceptable error difference in load forecasting in terms of RMSE or 10% or less in terms of mean-absolute-per cent error (MAPE) [Mor+16]. Answers to this research question are presented in Chapter 5.

2. Can knowledge of consumer profiles aid in optimal and adaptive energy allocation?

   Economic factors such as type of consumer, price of electricity, and demographic information of the households such as household income and the number of occupancies, are major factors affecting energy consumption [Hsi15; Che17; Har+15]. The performance of the load forecast model can be improved by incorporating consumer profiles as inputs. An MLP-based forecast model is developed with consumer profiles as inputs along with the historical energy usage, and temperature. Integrating the consumer profiles as inputs in the forecast model makes it possible to predict individually the daily energy consumption of the households using an adaptive model for the whole community. Chapter 6 presents how the consumer profiles to aid in achieving an optimal and adaptive energy allocation.

3. Can the energy allocation be optimised to improve energy efficiency under the limited generation capacity?

   Energy efficiency can be improved by providing an optimal and adaptive energy allocation to each household through forecasting using ANN-based forecast model and calculating the optimal daily energy allocation using Karush-Kuhn-Tucker (KKT) conditions given the limited generation capacity of the off-grid power system while ensuring the basic electricity needs of the households. KKT approach is used as the constraints of the optimisation problem meets the requirements of the KKT conditions. In this research, energy efficiency is defined as the adaptive energy allocation to reduce energy wastage by households that use less energy, or to provide more energy to those households that have higher needs. Energy wastage refers to the unused energy allocation of some households that could be redistributed to other households that needs more energy than to what is being provided.

This research aims to allocate each household some energy that is as close as possible to their ideal utilisation. This measure of closeness can be defined by the Euclidean distance (a measure of how far the proposed energy allocation for the household deviates from their actual energy consumption). Consequently, for all households, the aim is to minimise the summation of all Euclidean distances, or equivalently, the squared Euclidean distances, under the constraint that the sum of all allocations do not exceed the total generation capacity of the solar system and each allocation is not less than the energy threshold for all households.

Section 6.2 of Chapter 5 answers this question by comparing the difference between optimal energy allocation and the ideal energy usage as predicted by ANN-based forecast model and the difference between fixed energy allocation and the ideal usage. With the proposed optimal energy allocation, the difference between the optimal energy allocation and the ideal usage of energy is minimised. With optimal allocation, the ideal electricity needs of each household are met, and the usage of the available energy generated by the off-grid system is maximised.

1.4 STRUCTURE OF THE THESIS

This chapter describes the research questions and aim of this research work and presents an overview on the proposed optimal energy allocation to each household that would allow dynamic energy allocations per day based on the forecasted energy consumption.

The rest of the thesis, as shown in Figure 1.1, is structured as follows. Chapter 2 presents the related literature on load forecasting techniques such as Artificial Neural Networks (ANNs), Gaussian Process Regression (GPR) and Autoregressive Integrated Moving Average (ARIMA) in time series. Approaches for optimising the energy allocation in remote communities with off-grid power systems to maximise the usage of generated electricity are also discussed. The gaps in the existing literature on energy allocation are identified and explained in the context of the off-grid communities.

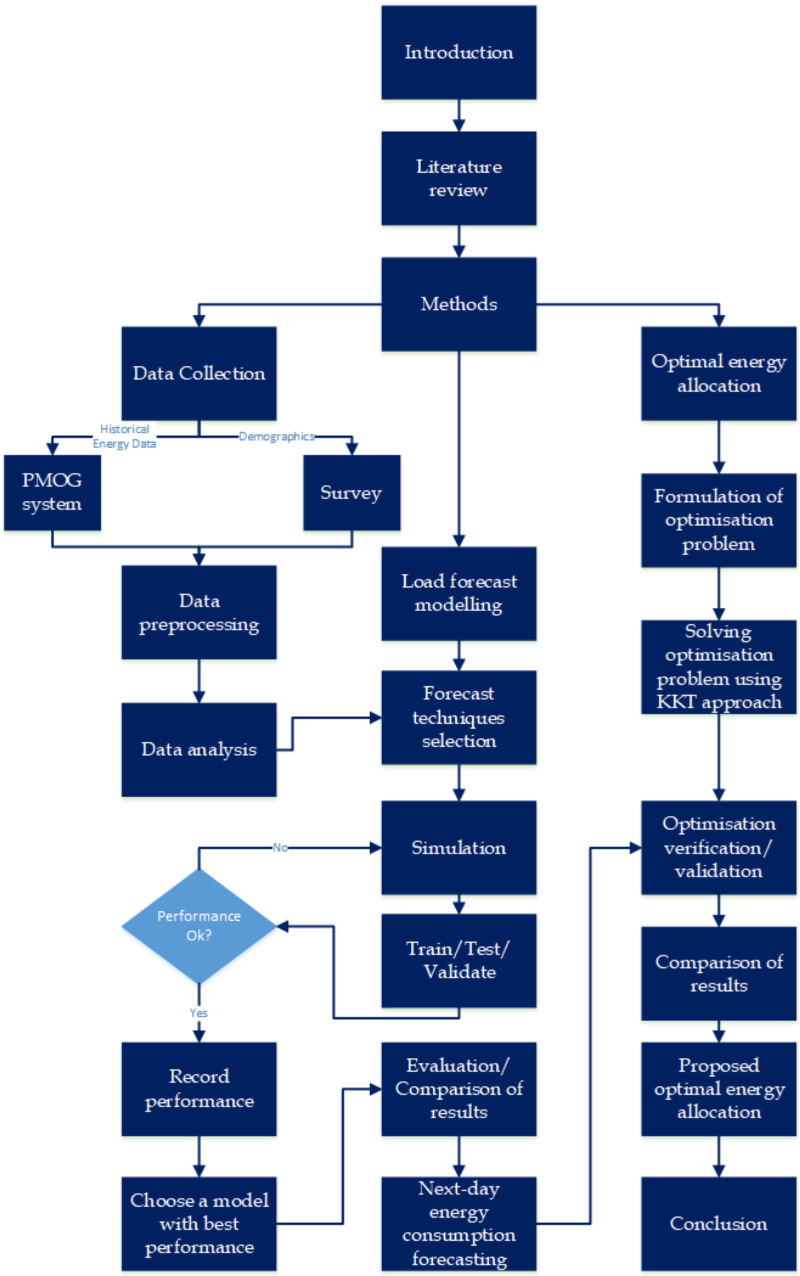


Figure 1.1: Structure of the thesis

Chapter 3 presents the methods used in this research from data gathering to calculating the optimal energy allocation of the households.

Chapter 4 details the design and the deployment of an energy monitoring system which is referred to as Philippine Micro-Off-Grid (PMOG) system. PMOG systems are used to gather the electricity consumption data of the selected households. In this chapter, the survey conducted to collect data about the off-grid communities is also discussed, as well as the design of the survey. The survey questionnaire was evaluated by conducting a pre-survey to check the reliability of the questionnaire. PMOG systems are evaluated by allowing the system to run for almost 2 months before the actual installation in the selected households.

Chapter 5 describes the load prediction model for each household based on the historical electricity usage and the profile of the individual household. In this chapter, the modelling of the MLP-based forecast model and its experimental results are presented. The performance of the forecast model is evaluated in terms of RMSE and MAPE. The results were also compared to the performance of other forecasting techniques such as ARIMA, RBFN, and GPR.

Chapter 6 presents the mathematical solution of the optimisation problem of the proposed optimal energy allocation based on the forecasted energy consumption of each household, as discussed in chapter 5. The methodology for this allocation is presented in this chapter. The results were evaluated by comparing to the other energy allocation scheme as presented in Section 6.2. Analysis of Variance (ANOVA) is used to determine if the means between the proposed optimal energy allocation and the other two techniques (equal allocation and allocation by ratio and proportion) are statistically significant.

Chapter 7 then concludes the work of the thesis and discusses possible directions for future work.

2 LITERATURE REVIEW

This chapter presents the theoretical background for load forecasting and the existing related literature for this work. Energy management systems for microgrids, energy allocation, and load forecasting are the focus of this chapter. Energy allocation is one of the many ways of addressing the limited generation capacity of the microgrids in remote communities. This chapter discusses the current works on different techniques for energy allocation and presents applications of different load forecasting techniques. The chapter also discusses the considerations in selecting the forecasting technique used in this research.

This chapter presents the gap in the literature that this research work is trying to address, and the existing literature on forecasting techniques and optimisation applied in energy management systems that made a good change in improving the performance of a power system.

This chapter discusses the following major topics that are relevant to the work of this thesis:

- Microgrids and its energy management systems
- Challenges in remote communities with generation-constraint microgrids
- Energy allocation schemes
- Load forecasting techniques

Off-grid microgrid systems with limited generation capacity distribute the available energy to the consumers through energy management schemes such as equal energy allocation daily, load shedding, load shifting, or time-based operation [IRE17]. With limited generation capacity, off-grid microgrids may not be able to supply the demand of the consumers [Ene12]. For most of the off-grid power systems, equal daily energy allocation is practical and the simplest to implement among others [Ene12]. However, this approach does not ensure maximum utilisation of the available energy, and with limited daily energy quota or allocation, households experience power outage before replenishment of the quota [Pal16]. On the other hand, some households do not use all the energy given to them daily but pay the same amount as other houses that use all of their allocated energy daily [Pal16]. These issues motivate this research.

2.1 MICROGRID POWER SYSTEMS

A microgrid consists of generation units, such as wind turbines, solar panels, mini-hydro plants, diesel generators, and electricity generators that use biomass, power lines for distribution and transmission, power control systems, and power loads [ZB16]. Microgrids are a compact type of electrical power infrastructure designed to have better efficiency, reliability, and integration of renewable energy sources than the traditional power grid[Kua+16]. A microgrid has two modes of operation: grid-connected or online and islanded or off-line (referred to as off-grid power systems) [KI06; HD14]. When operating in grid-connected mode, the microgrid provides support to the main grid by drawing power from the localised source, and provide the energy demand of the consumers whenever necessary. The main grid provides the deficit power in the microgrid when needed [HB12]. When a crisis occurs, and the main grid operation is interrupted, microgrids supply the power temporarily and operate in isolated mode to maintain the operation of the grid [Zhe+11]. In this operation, the microgrid must operate separately from the main grid and maintain the integrity of the process. The process refers to as the off-line mode of operation of the microgrid [Xu+17]. In an off-line mode of operation, the generated power must be in balance with the demand of the local loads [Oli+14]. Microgrids are typically implemented in areas where a conventional grid is not possible. These areas are usually in remote places far from the urban setting. Although, a microgrid is used as a backup power source to the traditional grid when power crisis occurs, providing electricity to remote areas with renewable energy resources gains more impact than as being an alternative source of energy for the main grid [IRE17].

Microgrids operate permanently in off-line or stand-alone mode when implemented in the remote areas where the conventional grid is not feasible because of economic or technical constraints. These microgrids are commonly referred to as the off-grid power systems that usually use renewable energy (RE) resources, such as water (mini-hydropower), sun (solar power), wind (wind energy), biomass and other RE resources available locally. Localised microgrids can lead to tremendous opportunities to increase power system efficiency, sustainability, and reliability [ZDM12].

For off-grid power systems, maintaining a balanced operation can be difficult, especially when the generation capacity of the system is limited [AR20]. Power systems are required to operate with a reliable operation between the generation and demand side. Power systems are in balanced operation when the generation side generates sufficient energy for the demand of the consumers [MSS20]. Energy management system (EMS) controls the operation of the power systems. The EMS monitors the status of each generation plant, and each consumer connected to the plant. A good EMS can determine the next load or energy consumption of each consumer and generates energy according to the demand [Kip+20].

For an off-grid power system with a limited generation capacity, to meet the demand of the consumers while maintaining proper operation of the power system, energy allocation approaches are deployed such as load shedding [SSP11; Gu+14; Moh+18], daily energy allocation (quota based) [ZXT12; LL18] and time-based operation [Hu+17; Shu+19; Xu17]. Section 2.4 discuss the details about each approach.

Some energy providers employed a smart EMS to control the operation of the system to avoid unnecessary operational cost due to excessive generation of energy over what is demanded by the consumers [LC16].

This research proposes a new scheme of allocating the daily energy allowance of each household connected to the off-grid power systems with a limited generation capacity to avoid the above problems.

2.1.1 *Benefits and challenges of off-grid power systems*

There are several benefits of having off-grid power systems than a conventional grid. As a localised grid, implementation of an off-grid power system is cheaper than a traditional grid as off-grid power system uses renewable energy resources that are available locally like water for a hydropower plant, and sun for the solar plant [IRE18]. Other implementation uses biomass such as rice hay and animal wastes in areas where biomass are abundant. Furthermore, localisation of microgrid can provide jobs to the community [Kir+09].

According to the study of Meng et al. [Men15a], the following are the benefits of having microgrids

1) better power quality and reliability in case of a power outage;
2) economic advantages for microgrids that uses renewable energy (RE) resources, such as the wind and solar energy which have low carbon emission;
3) minimum cost for transmission infrastructure (for localised RE)

These advantages can be classified as economic, environmental, and technical benefits [Rol11].

For remote areas, it is assumed that having access to electricity will lead to an increase in the economic condition of the users [IRE18].

The absence of a reliable energy source or electricity can hinder their economic progress [IRE17]. Access to energy or electricity can give to the people in remote communities a way to meet their basic needs such as home lighting [Int14; IRE17]. Moreover, if the generated power will be used by the farmers for their farm activities and small businesses in the local community to be more productive, economic progress is expected [Man+16].

The challenges include technology transfer to the community, generation capacity, and maintenance of the plant [Sap+18]. Maintaining a reliable operation of the microgrid can be a challenge when there is no available engineer in the community to do the job [BK07; FHC16]. Thus, technical transfer to local people is essential for the sustainability of the power system [Per+12; FHC16]. Issues such as stability of the frequency and voltages of the distribution network can also arise, especially in the islanded mode of operation. This issue is addressed by using a load shedding technique in managing the generation and the demand side [Sap+18]. The work of Schnitzer et al. presented several methods and recommendations based on actual practices employed in off-grid communities for sustaining the operation of off-grid power systems [Sch+14]. According to their study, the sustainability of the off-grid systems implemented in the remote areas can be achieved with good business model and cooperation between the provider, consumer and government that subsidised part of the cost of implementation and operation. This was also highlighted by the work of Frame et al. [Fra+11]. They argue that for the off-grid power system to be sustainable, the community needs to be involved in the design and implementation stages. The community must be educated on how to maintain the power systems on their own. Several case studies were presented to assessed their chosen methods. This comprises their proposed community approach for the sustainability of the power system. Aside from community involvement, another factor that is worthy of attention is the chosen technology to be implemented. Aberilla et al. [Abe+20] emphasised the importance of suitable technology to be installed in the community. Through a series of simulations using Homer, they found out that the house level PV power system combine with wind turbines at the community level with back up batteries is most likely to be a sustainable configuration for off-grid communities. Homer is a software that allows the design of power systems with vast choices of components with real-life characteristics [Abe+20].

The challenges on the implementation of the microgrid systems occur in the off-grid power system in remote areas. According to the study of Schafer et al. [SKN11], these are

1. Installed off-grid power system technology is not suitable to the state of the locality and does not satisfy the user's requirements.

2. Reliability of the power systems is not assured with issues on the implementation.

3. Design and management of the power system are not built with economical financing schemes for the local people.

Other studies such as Ahlborg and Sjostedt [AS15], Miller et al. [Mil+15], and Ulsrud et al. [Uls+15], have mentioned that socio-technical design aspect of the project must be considered to have successful project implementations. Long-term sustainability can be achieved when this design aspect of the project is examined at the planning stage [IRE18; Uls+15].

2.2 ENERGY MANAGEMENT SYSTEM (EMS)

An energy management system (EMS) is considered to be an essential unit of power systems [ZDM12]. EMS is the control unit of the off-grid systems designed to ensure reliable operations 2.1. EMS ensures the balanced operation between the generation units and the demand side by synchronising the operation schedule of the distributed generation (DG) sources while managing the efficient use of the power loads [ZDM12; Shi+15]. EMS has two distinct approaches in managing and controlling the power system operations 2.2: one is called centralised, and the other is decentralised [Oli+14]. In centralised control and management, the system operates based on the information from a controller that determines the actions taken by all units at a time. This approach entails extensive communications between the controller and the controlled units to ensure a balanced operation [Shi+15]. In a decentralised approach, a controller is used to control each unit. This approach requires a local controller that process information from the local unit only and is isolated from other controllers [Gu+14]. A dynamic consensus algorithm-based distributed hierarchical control method ensures an accurate current sharing and voltage restoration for microgrids with distributed generation sources [Men+15]. With consensus algorithm, the DG units share information and communicate in the network. For off-grid microgrids, the EMS can have either of the two controls depending on the available renewable resources.

In planning an off-grid power system, all significant parameters such as the load capacity, the generation capacity, the expected load, the storage size, the distribution networks, and the EMS, must be taken into consideration to secure successful project implementations [SW12; DM13]. Projection of power load is crucial for a thorough power

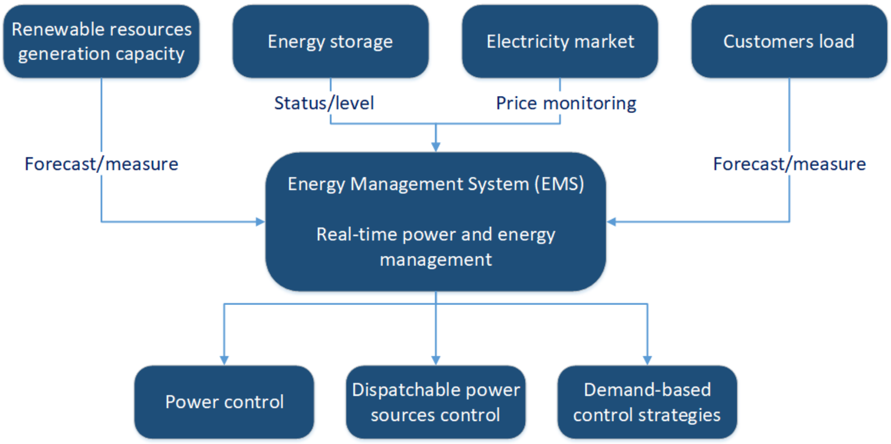


Figure 2.1: Energy management system (EMS) [GG15].
Legend: LC - Local controller

system design. The power load must be appropriately established as well as the projected level of daily energy consumption and the factors that influence the variations of this level through time [KK15].

2.3 SIGNIFICANCE OF OPTIMISING THE USAGE OF THE ELECTRICITY IN OFF-GRID COMMUNITIES

In optimising the distributed generation system, the general objective is to find the timetable and the commitment level for each generator and load to minimise the aggregated operation costs and maximise the power usage [ZDM12]. Aggregated operation cost includes the local generation resources and the cost of energy obtained from the power market for grid-tied microgrids. Several studies, such as Meng et al., [Men15b], Zelazo et al. [ZDM12], Shi et al. [Shi+15], and Meng and Zhao et al. [Men15a] conducts experiments and simulation on how to optimise the operation of the EMS.

Other problems for optimisation of EMS is the scheduling of the local sources to generate energy. To optimise the generation cost, Zakariazadeh et al. [ZJS14] adopts demand response programs that enable them to use the energy resources using the stochastic method efficiently. Various types of demand response were considered and participated in the program that represents consumers from residential, commercial and industrial zones. Meanwhile, the work of Rigo-Mariani et al. [RM+14] proves that having optimal scheduling for the next day minimises the generation cost. The confirmation comes from the results of their investigation for different procedures for the optimal power dispatch of a grid-tied microgrid.

On the other hand, the study of Shi et al. [Shi+15], the design of a distributed EMS for optimum operation of microgrids where emphasised addressing the issues on the distribution network and the

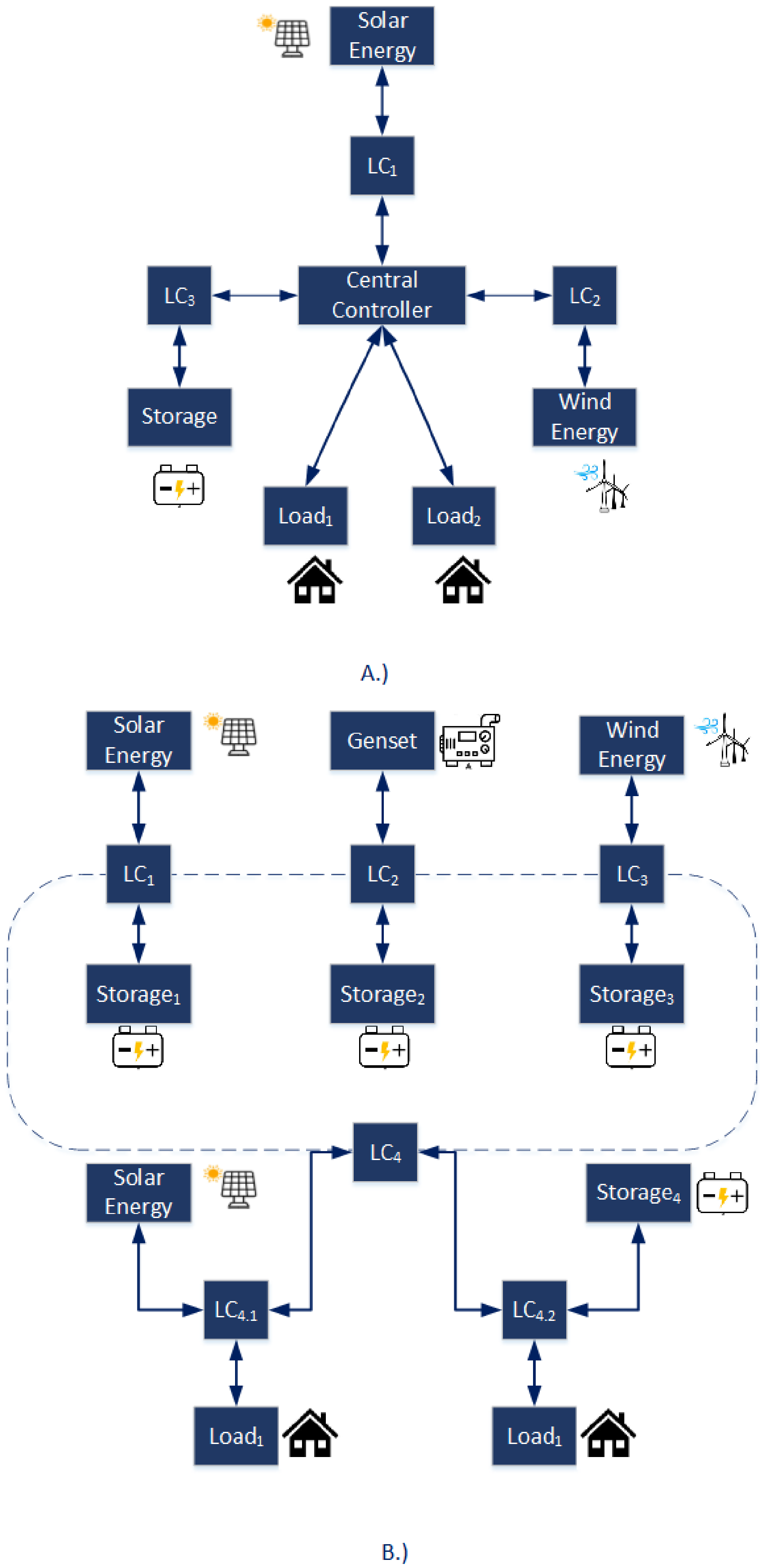


Figure 2.2: Architecture of EMS control A.) centralised and B.) decentralised illustrated by Espín-Sarzosa et al. [EPBN20]
Legend: LC - Local controller

associated constraints. As pointed out in the study of Meng et al. [Men+16], and Nasirian et al. [Nas+14], the problem with most of the existing approaches with regards to the EMS of the microgrids (grid-connected or off-grid), the demand-supply matching algorithm considers the demand to be always equal to the generated supply. All generation sets and loads are assumed to be connected to one single bus distribution line and ignore the power distribution network, power flow, and system operational constraints. When those algorithms are applied, the system may not work correctly [Shi+15]. Other energy optimisation approaches include incentive-based and price-based demand response [Ima+18; Zha+18; PNS15].

For off-grid communities, the generation capacity of the off-grid power systems is often limited [IRE17]. Most often, the generated electricity is distributed according to their basic needs for lightings. The available energy is allocated to each household equally to maintain a reliable power system operation [Shi+15; Gup17]. However, some households need more electricity for other purposes such as entertainment (e.g., television and radio), and comfort (e.g., electric fans). This situation leads to a power shortage for some households. Therefore, to maximise the available generated electricity, optimisation of the electricity utilisation by providing sufficient electricity to households is necessary. That is to ensure that the basic electricity needs of the households are provided. This can be done by predicting load and allocating energy of the households based on their previous electricity usage. With accurate forecasting, wastage in terms of unused energy allocation can be reduced if not eliminated. The remaining energy can now be allocated to the households that need more energy, and this ensures that the generated electricity is used efficiently.

2.3.1 *Generation-constrained off-grid microgrids*

Off-grid microgrids operate off-line and not tied to the traditional grid. The available energy is limited with the installed generation capacity of the power system may it be from solar, hydro, wind or biomass source [Xu+16]. For this research, the off-grid microgrid of interest is the solar power system. For this system, the generation capacity is dictated by the solar panels total capacity of converting the solar source to electricity. The capacity of the off-grid microgrid is not always sufficient to supply the electricity needs of the village; hence the different energy management schemes such as load shedding, load shifting, time-based operation and energy consumption quota are important. The next section presents the details of these approaches.

2.4 ENERGY MANAGEMENT SCHEMES

There are three common energy allocation schemes employed in a microgrid. These are

- load shedding and load shifting,
- time-based operation or scheduling
- energy consumption quota

When the power system is not able to supply the electricity demand of its customers such as households, commercial buildings, hospitals, etc., the available energy should be managed in a way that the basic electricity needs of all customers is served [Kha+18]. Load shedding is used when a threshold of usage of the available energy is breached [Gu+14; D'A+17]. Identifying the critical load is the key to make this approach successful [AAM20]. Load shifting is used when there is a need to defer in time the load operation [EAR20]. Time-based operation is used when the microgrid is only allowed to operate in a specific period of the day due to technical or management issues [Maz+14]. Energy consumption quota is used when the available energy is not sufficient to meet the electricity demands of customers and that they are encouraged to take charge of their energy usage in a day [ZXT12].

2.4.1 *Load shedding and load shifting*

Load shedding is one of the techniques used by the energy providers to address issues of stability of frequency and voltages in the distribution network. The stabilisation is done by shedding some load to ensure that there is a right balance between the generation and consumer end [Sap+18; Bak+17]. Furthermore, the technique is used in a microgrid with limited generation capacity to cater to the demand of the consumer by shedding loads identified as less prioritised [Gu+14]. The process of load shedding involves disconnecting the load from the power system when the energy demands are higher than the available energy.

In load shedding, energy management control is actively monitoring the conditions and status of both the generation and demand side. When a crisis occurs, load shedding commences ensuring the balance of the operation of the power system. Maintaining the stability of the system is one of the crucial processes in operating the microgrid. Multiple crises can occur depending on the current conditions of the microgrid that are caused by either energy sources, distribution network, and control instrumentations.

Traditional load shedding approaches, under frequency load shedding (UFLS) and voltage load shedding (UVLS), are usually designed separately to protect the system independently from frequency and voltage instability, respectively [SSP11]. However, they are not equipped to handle mixed fluctuations from frequency and voltage. This instability, if not addressed properly, would result in power system breakdown [Tan+13]. The inflexibility of the traditional approaches fails to consider the other sources of the instability of the system as they are designed independently and separately implemented, which made strategies unfavourable [SSP11].

To improve the traditional load shedding approaches, the adaptive approach was introduced as presented in the work of Mohamad et al. [Moh+18], Terzija et al. [Ter06], Chin et al. [Chi+08], Hooshmand et al. [HM12], and Santos et al. [San+19]. These research studies employ either machine learning algorithms such as artificial neural networks and a centralised, hierarchical multi-agent scheme that coordinates different stages of the monitoring and decision-making process or a combination of the approaches. However, all these studies have only considered frequency information and not the voltage information in dealing with instability issues in power systems. Kanimozhi et al. [KSB14], and Tamilselvan and Jayabarathi [TJ16] proposed new schemes of improving the stability of the power systems using voltage information combined with genetic algorithm (GA) and artificial neural network (ANN). As the techniques are working separately in dealing with the voltage and frequency instabilities, this motivates other researchers to address the issue by proposing techniques that deal with both the frequency and voltage information as presented in the works of Tang et al. [Tan+13], Hsu et al. [HCC11], and Giroletti et al. [GFS12].

Adopting load shedding help maintains the balance between the generation and demand side of the power systems but this lead to power blackout for some consumers that are off-loaded from the power systems [Xu+16]. Load shedding is good for the generation side of the power system but will have a negative impact on the off-loaded consumers. Load shedding as presented by Xu et al. [Xu+16] was proposed to address the issue with microgrid with limited generation capacity. In order to continue supply power to the critical load of the power system, a dynamic load shedding was proposed. They formulated the load shedding as a stochastic optimisation problem where uncertainties caused by the intermittent power resources and the loads are considered as constraints. They aim to maximise the economic performance of the microgrid considering the limitations of the generation resources. Then they develop a model using a Markov decision process (MDP) to determine the optimal load shedding process. With their approach, they were able to maximise the economic factor of the power system by providing an optimal load shedding strategy for a microgrid with limited generation capacity.

2.4.2 *Time-based operation*

The EMS schedules the availability of the power to the consumers. The operation can be scheduled hourly or daily depending on the availability of the generated energy. This is done to maintain a well-balanced operation of the microgrid. For a traditional grid, scheduling is done to have an optimal system operation. This approach has been addressed extensively in the recent research work in the field as the most efficient means to optimally coordinate the controllable and uncontrollable resources [Ima+18; CMP14; Zha+16; MMS16b; Jia+15; GZ16].

Carpinelli et al. [Car+17] proposed a way of minimising imbalances in low-voltage microgrids by the scheduling of distributed resources. Their work is based on a multi-objective approach that considers the structure of the low-voltage microgrid systems which have inherent imbalances of lines, loads, and generation systems. They formulated their model to be a multi-objective optimisation problem. The objective functions are defined as dependent to power, line current and the positive and negative component of voltages in minimising the imbalance factor, cost of energy, peak shaving, losses, security margin and voltage deviation. The constraints relating to the technical limitations and operation requirements are all considered from the buses (such as load bus, distributed bus, and electric vehicle bus), and the microgrid constraints such as different phase-voltage magnitude, and the line phase-currents. Their experimental results show that using a multi-objective approach for the scheduling of unbalanced microgrids provide advantages in terms of savings and efficiency in system operations.

In most cases, scheduling the operation of microgrid has been a challenge. The work of Mazidi et al. [Maz+14] presents an efficient way of solving the operational scheduling problem of microgrids with different generation sources. The problem was formulated considering the various constraints related to microgrid operations such as allocating the reserve capacity, battery scheduling, and the uncertainty innate to the renewable resources like the wind and solar power generations. A Latin hypercube sampling method was employed to combine and generate the different scenarios relating to the two sources, which in this case were wind and solar power generations. Their results showed that a lower reserve requirement is achievable with the stochastic method they used compared with a conventional deterministic approach.

Mazidi et al. [MMS16a] present an effective and efficient day-ahead scheduling of smart distribution networks by incorporating price-responsive customers in their method. They formulated an optimisation problem to maximise the profit while maintaining the customers' satisfaction. The optimisation considers the hourly sale prices offered to customers, purchase or sale transactions made to the market, a commitment of the distributed generation units, dispatch of battery energy storage systems and the planning of interruptible loads. The models were formulated as a Mixed Integer Linear Programming (MILP) optimisation problem. The model formulation covers both the demand and consumer side that benefits both sides. Mathematical models were formulated for both distribution network and demand response (DR) including price-based and incentive-based DR models. These formulation leads to the objective function to maximise the difference between the profit and cost of operations. Constrains relating to power balance, distribution network, and distributed generation units were considered. The optimisation problem was then solved using Karush-Kuhn-Tucker (KKT) conditions. According to the results of their implementations and case studies, higher profit is achievable while keeping their customers satisfied. Their method even results in the customer's motivation to use energy efficiently and have a reduced electricity bill.

Most of these approaches are focused on the generation side and not on the customers' side in scheduling the operations of the microgrid. Most of these approaches are made for microgrids that are grid-connected and not in stand-alone. There are very few published works addressing the time-based scheduling operation of the off-grid power systems [Mar+13; Mar+16]. Hence, this necessitates us to look into the possible method that can work in any stand-alone microgrid systems that allocate daily energy to each customer to maintain a stable operation.

2.4.3 *Energy consumption quota*

Another popular technique in dealing limited generation capacity of the microgrid is allocating energy consumption quota (ECQ) to each household daily [Sun+16]. This is to maintain a stable operation of the power system. In this setup, all households connected to the power system is given an equal energy allocation daily for a fixed amount of monthly fees. Some use energy quota to encourage energy savings in commercial buildings [ZXT12]. Another application of energy quota is influencing the energy consumption of commercial buildings. By giving them energy quota, commercial buildings will be encouraged to limit their energy consumption within the given quota [Xin+12].

For example, the study of Xin et al. [Xin+12] presented a method on how to calculate the energy consumption quota of different hotels in China as a way of promoting the development of building efficiency. The method covers from data collection to analysis, and calculation of energy consumption data using statistical analysis methods such as the mean index of total energy consumption (MITEC), mean of EUIs, quadratic average method, median, percentile method and mode. For data collection, they used a questionnaire to be field up by the building owners. The data gathered involved the basic building information such as building area, age, number of guestrooms and occupancy rates as well as the energy consumption of the hotels in recent years. The basic building information was considered as factors affecting energy consumption of hotels. Basically, they gathered the information through a questionnaire answered by building owners, and then the energy providers verified the energy consumption. The approach is susceptible to biases as answers, and the verification process is based on the memory of the respondents (owners and energy providers). The study does not mention that the information was verified from the archives of the energy providers. Hence, the validity and reliability of the data may be compromised. However, their study underpins the importance of actual historical energy data for the development of energy consumption quota of the hotels. A correlation was performed to determine the factors affecting building energy consumption (BEC). These factors refer to the basic building information they have gathered. For the analysis of the energy data, they used the statistical analysis, and this approach serves its purpose right for calculating the energy consumption quota of each hotel. This is because there are no constraints involve except for promoting the building efficiency in China. However, for off-grid microgrids with limited generation capacity, this approach may not be adequate to address the constraints.

All three energy management schemes have their advantages and disadvantages, as presented in this section. Regardless of the type of renewable energy resources, these approaches are applicable in ensuring balanced operation of off-grid microgrids. For most cases in off-grid communities, energy daily quota is the most common technique used for its simplicity in implementation [IRE18]. However, this approach can be improved by combining machine learning algorithm such as a neural network to improve the energy management system of the microgrid [ZXT12].

Daily energy allocation is quite popular in off-grid power systems implemented in remote areas [Int14; IRE17; IRE18]. This approach can be improved by incorporating the load forecasting technique that would predict day-ahead daily consumption. By doing this, the energy allocation can be done optimally, and better energy utilisation of the generated energy by the off-grid microgrid with limited generation capacity can be achieved.

2.5 LOAD FORECASTING TECHNIQUES

Forecasting is considered an essential component of any power providers [Gup17]. Forecasting the load helps operation planning which can lead to reducing unnecessary power production. Currently, power providers gather the power usage of their customer to help them predict the next day average power usage [Chi+15]. The accuracy of predicting the power usage of any building or industry has improved a lot since the application of neural network for forecasting as presented in the study of Dudek et al. [Dud16]. With accurate load forecasting, efficient generation scheduling can be achieved [Gup17]. The main objectives of accurate load forecasting can be categorised as

- Scheduling the operation of the generation of the power system
- Securing the reliable operation of the power system

Moreover, the allocation of generation resources, the operational limitations, environmental and equipment constraints can be determined and properly addressed [ESMK11; DM13]. For example, in the case of hydropower generation units, the optimal release of water from the reservoir and the generation scheduling of power systems can be carried out based on the short-term load forecasting (STLF) [RK15]. Load forecasting is also used to ensure power systems operations regardless of the distributed generation units used to generate the power [Maz+14; Dud16; RK15]. Accurate load forecasting is a crucial tool to determine the optimal operational state of the power system [ESMK11; RK15]. Additionally, forecast data can be used to prepare the power system per future load state and corrective actions. All these objectives lead to saving the cost of operation of the power system [FA14; RK15].

Load forecasting is used by the energy provider to ensure stable operations of power systems and to predict the necessary power to be generated to meet the demand [Gup17]. Unnecessary expenditures in generating excessive power can be avoided when an accurate prediction of the load is performed [FA14]. Moreover, accurate load forecasting is a necessary tool to determine the optimal operation of power systems [Sol+15].

Predictors such as historical load data, time information (i.e. year, month, day of the month, and day of the week), and minute-dependent context features (e.g., temperature, humidity, wind speed, UV index, and time index) were identified as factors affecting energy consumption [Hsi15]. These factors are used as the inputs for the backpropagation neural network to predict the household's electricity consumption volume. A strong correlation between weather information and load demand is evident as presented in the paper of Hernandez et al., [Her+12] and Hsiao et al., [Hsi15]. A study claims that incorporating appliance usage patterns for non-intrusive load monitoring improves the performance of load identification and forecasting using non-intrusive load monitoring approach [Wel+17]. A long short-term memory (LSTM) recurrent neural network (RNN) based framework was used to address the issues such as uncertainty and high volatility in load forecasting for an individual household [Kon+17].

Depending on the available data, prediction can be made a day ahead, a week, a month, or even a year [Moo+19]. The prediction can be categorised as follows:

- Short-Term Load Forecasting (STLF)

  SLTF refers to forecasting the load in the range of minutes, hours, days or a week. A short period where the load is specifically determined to provide better accuracy in forecasting [TS16]. Short-term load forecasting is used for reliable and efficient energy management and is influenced by many factors, such as weather, house occupancy and household income [KRF13].

- Medium-Term Load Forecasting (MTLF)

  MTLF refers to forecasting the load in the range of several weeks, months and a year [Gup17]. This is done when the industry wants to know the next week or next month average power usage. The result may not be as accurate as it can be like the STLF, but the results give an idea of how much energy is needed to be generated for the next week/month. Medium-term load forecasting is used for efficient operation and maintenance of the power system [Bor+17].

- Long-Term Load Forecasting (LTLF)

  LTFL, as the name implies, is in the range of years. This can be done when there are lots of data for years (10 to 15 years worth of data) [TS16]. So the prediction is made for the entire year of average power usage. Long-term load forecasting is used for long-term power system planning according to the future energy demand and energy policy of the state [Chao0].

2.5.1 *Time series forecasting*

Analysis of time series can be divided into two essential parts. The first part focuses on the derivation of the structure and the underlying trend of the observed data. The second part emphasises on the fitting of the model to perform future predictions [LLC09].

Time series analysis is used in many applications, such as economic forecasting, yield projections, process and quality control, workload projections, and any other predictions that use history data with inherent correlations, trends, and complexity [PB17; Deb+17].

The general approach in analysing the time series is to divide the time-series into three elements [Dud16; Tay10; Bor+17]:

1. Trend – The general characteristics that the variable exhibits within the considered period without taking into consideration the seasonality and irregularities of the data [Dud16].

2. Seasonality – This refers to the cyclic variations of the variable concerning weather information. The seasonality consists of the effects that are steady and unwavering through time [Tay10].

3. Residual – This is the remaining part of the time series after the above two features are considered. Most of the time, this part of the time series is mostly unexplained. Sometimes, residuals can be large enough to conceal the trends and seasonality of the variable [Bor+17].

Model fitting of the time series is a complex and challenging process.Time series forecasting can be grouped into univariate and multivariate analysis [TMM06]. Univariate time series analysis is a time series forecasting that has a single observation recorded sequentially over time while multivariate time series analysis deals with a group of time series variables that interacts with each other [TMM06].

2.6 FUNDAMENTALS OF ARTIFICIAL NEURAL NETWORKS (ANNS)

ANN-based load forecasting models are used by many energy providers for decades now since the earliest published paper on electric load forecasting using an ANN [Par+91; MS97]. Energy is then generated according to the forecasted energy consumption using the ANN model. Many research works are published to show

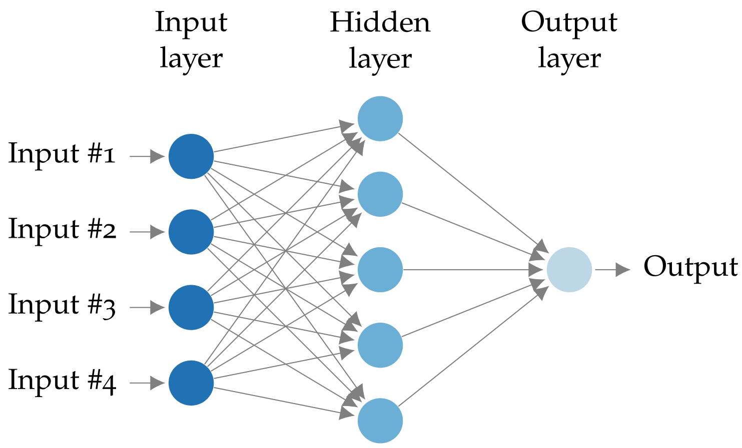
how ANN-based load forecasting models used to resolve issues in the energy management system, particularly the generation side []. However, there are few published research works for forecasting energy consumption for the benefit of consumers (demand side). Since the goal of this research is to provide sufficient energy to the households from a source with limited generation capacity, forecasting the energy consumption of the households is important.

Artificial neural networks (ANN) are modelled after the cognitive learning process and the neurological functions of the human brain. Neural networks are capable of predicting new observations from the existing observations after learning from data. A specific neural network architecture must be designed and built. This includes choosing a specific number of hidden layers, each consisting of a certain number of neurons. The training process commences once the number of hidden layers and neurons are established. An iterative process is applied by the neurons to the number of inputs to adjust the weights of the network to optimally predict the sample data on which the training is performed. After learning from the given existing data set, the neural network is now ready to forecast. In forecasting, the output of the network represents the pattern it has detected from the training data set [LBH15].

Neural networks are considered to be one of the best techniques in load forecasting. One of the desirable features of the neural network is its robustness and flexibility in handling real-world data that have both linear and nonlinear components. It can handle well both the linear and nonlinear aspects of the data in generalising when used as approximators [HSW89]. Good modelled neural network-based forecast model can make a precise prediction of new observation after learning from the existing data. A specific network architecture must be designed specifying the network's hidden layers and neurons. In the training process, the network is learning specific features of the data. The network developed and trained with the existing data can be used to predict new values from the pattern it has detected and learned from the training.

Figure 2.3 shows the basic architecture of neural network. Traditionally, the neural network is fed with an input vector (or matrix depending on the architecture of neural network) V_x and generates the output vector V_y in which the network's topology defines the relationship between them. For multilayer perceptron (MLP)-based model, 3-layer back propagation neural network is widely accepted to generate an estimation of any continuous function with sufficient mid-layer units.

Figure 2.3: The simplest architecture of neural network has an input layer, a hidden layer, and an output layer.



2.6.1 *Back-Propagation Neural Network*

Backpropagation (BP) learning algorithm is used to train the ANN. The BPN learning algorithm uses the gradient descent method to update the weights of the network [LBH15]. The BPN network consists of an input layer, a hidden layer, and an output layer that are connected by synaptic weights.

There are several issues with BPN algorithm that affects the performance of the network while training. These are as follows:

- Local minima – The training algorithm aims to reduce the error to the global minimum value to achieve higher training performance of the network. However, sometimes the network can get stuck in the local minimum even though the weight values keep updating and adjusting. This results in poor performance in training the model. This problem can be avoided by applying a modified error function that harmonises the updates of weights between the hidden layer and the output layer [Bi+05].

- Network paralysis – The weights of the network can be varied and adjusted for large values of output where the derivative of the triggering function is small during the training process. This is to send back the error of the network according to its derivative during the training process. Network paralysis happens when the network comes to a standstill during the training process that may lead to erroneous network output due to poor learning. By using the rectified backpropagation neural network called Morbidity neuron Rectified Backprogation network (MRBP)[JS05]. MRBP identifies and corrects the defective neurons making the network more adaptive and robust that can easily escape from a local minimum.

- Temporal instability – For the training algorithm to learn, the neural network needs to imitate the whole training set without disruptions according to what it has already learned. When a backpropagation training algorithm fails to learn from complex systems, network learning is suffering from temporal instability. This happens when the network fails to remember what it has already learned while trying to learn something new during the training process [RK15]. This issue can be minimised using Self-Partitioning Neural Network (SPNN). SPNN measures the conflict amongst the datasets during the training process and split into smaller groups by partitioning. The partitioning is done in such a way that the conflict between groups is significantly reduced. Reducing the conflict between groups speeds up the training process of the network and decreases the network paralysis and temporal instability [RKS95].
- Generalisation and the over-fitting problem of the neural network – In modelling, the ultimate goal of the training is to minimise the Mean Squared Error (MSE) of the network with its training set. When the output of the network is accurate or close to the target values of the data that are not included during the training, the network is considered to be well generalised. Several factors affect the generalisation of the network. The factors include the quality and size of the data and the architecture and complexity of the neural network [Bas07]. With more complicated models, the possibilities of over-fitting are high. An over-fitted model can describe the training data well but poorly predict when given with new dataset [Cha+16a].

2.6.2 *Issues in designing neural network-based forecasting models*

Unlike other forecasting models such as Auto-Regressive Integrated Moving Average (ARIMA), the selection of parameters, such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC), for a neural network is not straightforward. The approach usually starts with the simplest architecture and gradually explores more complex structures. Kaastraa and Boyd [KB96] presented a design process for ANN-based forecasting. They aim to provide an introductory guide for designing an artificial neural network for forecasting. They presented the 8-steps design procedure of the neural network for forecasting. The steps start from input variables selection until the implementation of the model. The procedure was implemented in forecasting financial and economic series.

Raza and Khosravi [RK15] conducted a systematic literature review of Artificial Intelligence (AI) based on short-term load forecasting techniques to identify, evaluate and analyse the performance of AI-based load forecasting model. They have concluded that the accuracy of ANN-based forecast model is dependent on several parameters such as model architecture, input combination, activation functions and training algorithm of the network and other variables that affect the input of the forecasting model. A technique that can generate a diverse and effective neural network, a group-based chaos genetic algorithm was developed by Chen et al. [Chi+16] to improve the performance of STLF. They also developed an ANN-based nonlinear ensemble of partially connected NN predictors to enhance the accuracy of the STLF further.

In determining the design parameters of the artificial neural network, the procedure become complex for finding the right combinations of the network's hidden layers HL and neurons N, in which a trial and error approach is usually employed.

Palmer et al. [PJS06] also presents a step-by-step methodology in designing ANN-based forecasting for tourism. They point out that there is no definite rule in choosing the number of hidden layers HL and neurons N to build a neural network that generates accurate prediction. They provided a trial and error approach for a specific range of hidden layers HL and observed the effects on the performance of the network. The models were assessed in terms of Root-Mean-Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) for performance accuracy using validation data. According to their experimental results, MLP architecture with eight inputs, one hidden and one output neurons performs best with the most accurate prediction with the validation data. For this research, both RMSE and MAPE is used to evaluate the performance of the proposed MLP-based forecast model.

Hunter el al. [Hun+12] also pointed out the difficulty of the researchers in deciding the proper sizes and architectures when using neural networks. Their work presented a comparative analysis of the performance of 3 neural networks, namely Multilayer Perceptron (MLP), Bridged Multilayer Perceptron (BMLP), and Fully Connected Cascade (FCC). They also presented a detailed comparison of learning algorithms used for training the neural networks. Amongst the learning algorithms they have used, they pointed out that the Levenberg Marquardt (LM) algorithm is the most efficient from their theoretical analysis and experimental results. LM algorithm is used in MatLab neural network toolbox. This research used MatLab neural network toolbox in building the load forecast model that utilises household demographic profile as inputs together with the historical energy data to forecast the next-day energy consumption of the households.

Given the advanced configurations of neural network for load forecasting, MLP, as one of the basic architecture of ANN, is commonly used. This is because MLP allows simple implementation of the network, and it can handle both linear and nonlinear features of real-world data. For this reason, MLP-based forecast model is preferred in forecasting the next-day energy consumption of the households in this research. The details are presented in Chapter 5.

2.7 FACTORS INFLUENCING LOAD FORECAST MODEL PERFORMANCE

In load forecasting, selecting the right inputs is one of the crucial processes. This process is conducted to determine what are the key factors affecting the energy consumption of households, buildings, or any other dwellings[Che17]. In determining factors affecting load forecasting, there are several parameters to be considered. According to the study of Hsiao [Hsi15], behavioural patterns of similarity and difference in electricity consumption are caused by external factors called context factors. These factors are time, weather, calendar days and economic indicator. Aside from historical data, these factors significantly affect load forecasting. The work of Bedir and Kara [BK17] used factor analysis to determine the factors influencing the behaviour of households towards electricity consumption. Then they used these factors in correlation analysis to determine the relationship between the behavioural factors and the household characteristics. These approaches made them identify what the drivers and behavioural profiles that significantly affects the way dutch dwellings consumes electricity are. The factors they identified are household appliances, presence (in terms of frequency of lighting usage in different rooms), household characteristics (this includes the household size, occupants age, monthly household income, education, working schedule), and type of dwellings. According to their results, there is a significant correlation between behavioural factors and electricity consumption. Also, recall from Section 2.4.3 that these factors are similar to the factors considered by the work of Xin et al. [Xin+12] as they determined the factors affecting BEC using the same method, the correlation analysis. Thus, these factors were considered important demographic information in the proposed load forecasting model used in this thesis.

Chae et al. [Cha+16b] use variable important analysis to select key features that affect electricity consumption of commercial buildings. The features include the day type indicator, time-of the day, HVAC set temperature schedules, outdoor air dry-bulb temperature and outdoor humidity as the most critical factors. These factors can be categorised into subgroups such as historical data, economic factor and weather information [Che17].

In the study of Mandal et al. [Man+06], it was pointed out that the performance of the forecast model is improved as the temperature is added as one of the input. Moon et al. [Moo+19] present an ANN-based model that considers factors affecting energy consumption such as calendar data, weather information and historical data.

For every subgroup of the factors affecting load forecasting, each needs corresponding data. Using actual data can achieve more realistic results in load forecasting as opposed to computer-generated data from a formulated function. The work of Hsiao [Hsi15] presents how the data being used for pattern analysis to determine the demand of the household for each trend and daily behaviour patterns of electricity usage from the actual data.

2.8 USER PREFERENCES

Another parameter that needs to be considered in forecasting the household's load in off-grid communities is user preferences. User preferences refer to the household's behaviour related activities that use electricity. Accuracy in load forecasting can be improved when the behavioural-related parameters such as daily frequency of usage of deferrable loads, and non-deferrable are being considered in the modelling and prediction. The studies of Hsiao et al. [Hsi15] and Kong et al. [Kon+17] reported that user behaviour towards energy usage affects the aggregated energy consumption of the consumers. Electricity usage can be determined by studying the behavioural electricity usage patterns of individual households. Behavioural patterns can be determined based on the actual occupant behaviour towards lighting and appliance use [BK17]. Mixed methods approach was used to determine the importance of occupant's behaviour towards electricity usage. Data were collected and analysed to determine the effect of individual comfort and household attributes on occupant's behaviour towards energy [GS+16]. Occupant's behaviour is one of the factors influencing energy usage. A study presented an approach to estimate potential energy savings using behavioural measures. The approach includes the profiling of the occupant's behaviour, then simulate and analyse the individual and integrated impacts on energy usage. The study concluded based on the simulation results that the behaviour measures can save energy significantly, and the main energy savings came from the energy savings on unoccupied rooms [SH17]. Individual residential loads are usually volatile to forecast because of the resident's various activities. An extended short-term memory-based deep learning forecasting framework with appliance consumption sequences has been proposed by Kong et al. [Kon+17] to address the issue.

2.9 RESEARCH DATA

Most of the data used in research can be taken from any repository that is available for the public. For microgrids, there are several data available for public consumption and research purposes, and the most popular ones are from GitHub [Tia18; Bye19], government domain (Department of Energy) and electric company that are available upon request. However, for energy data of households connected to generation-constrained microgrids, there are very few to none data available for public or research use. Also, as pointed out in section 2.4.3, historical data is vital in determining the ECQ of the buildings. Thus, this research developed and deployed an energy monitoring system to gather household data and to study the energy usage of the households. The energy monitoring system is designed to gather specific information from the households about their energy usage. Chapter 4 presents the development and deployment of the system.

Factors affecting energy consumption are also collected. As discussed in section 2.7, demographics of the households is gathered through face-to-face surveys. The survey is used as this is the simplest way of gathering information. Chapter 4 presents the development of the survey questionnaire and the deployment of the survey to the selected villages in Cebu, Philippines.

Using these collected data in the development of the load forecast model (detailed in Chapter 5) will give real-world results that are more reflective of the actual usage of the households. For this research, the data gathered is used for the development of the load forecast model and the proposed optimal energy allocation scheme. The process of gathering the data is presented in Chapter 4.

Chapter 4 presents the gathering and preprocessing of the data from the deployed PMOG systems in the households at the selected remote villages in Cebu, Philippines. The real-world data serves as the baseline data for the development of the MLP-based load forecast model, as discussed in Chapter 5.

2.10 CHAPTER SUMMARY

In this chapter, the importance of energy consumption quota in the context of an off-grid microgrid is presented. Energy consumption quota (ECQ) promotes building efficiency. For households in off-grid communities, it ensures the basic electricity needs of the household while using the available energy efficiently from a generation-constrained microgrid. The actual data from the households or buildings is the key to calculate the ECQ. The method used by Xin et al. [Xin+12] in data collection can be improved by employing actual energy monitoring systems. The approach of calculating the ECQ can be improved by using machine learning and optimisation techniques that can handle defined constraints.

The need for optimising the energy management system of a power system is discussed. Different schemes of the energy management system (EMS), such as load shedding, time-based operation, and energy allocation are presented and how they are being employed to maintain the balanced operation of the power systems (Section 2.4). For off-grid microgrids, energy allocation is commonly used to cater and provide the basic electricity needs of the connected households.

In optimising the operation of the power system, load forecasting is incorporated into the energy management control system (EMCS). MLP-based load forecasting is one of the popular techniques along with ARIMA, GPR and other forecasting techniques such as RBFN. The fundamental architecture of the neural network is presented as well as its robustness in dealing both linear and nonlinear features of data which makes the neural network as a good approximator (Section 2.6). Furthermore, applications of neural networks on load forecasting are discussed.

Finally, factors affecting load forecasting are also presented and discussed (Section 2.7) as well as the importance of gathering an actual energy usage (Section 2.9) for the development of MLP-based forecast model in Chapter (5) and the proposed optimal energy allocation in Chapter (6) for households connected in off-grid microgrids with limited generation capacity.

Within the presented literature, studies about optimal energy allocation in the context of off-grid microgrids are limited. Although there are several studies (Section 2.4) in optimising the energy management system, these approaches are not implemented in an off-grid microgrid with limited generation capacity. In providing an optimal solution for an optimisation problem, real-world research data is crucial. Thus, this thesis focuses on the following areas:

1. In addressing the importance of historical energy data in determining the ECQ, an energy monitoring system (EmS) is developed. PMOG system is built using readily available components and sensors to gather energy data. For this research, gathering real-world data of load consumption from the selected villages that will serve as the baseline data for the load forecasting model. The deployment of the PMOG system to gather historical energy data is discussed in Chapter 4.

2. Development of MLP-based load forecasting model that includes household demographic profile as inputs to achieve better prediction performance of the network. The need for forecasting the next-day energy consumption is crucial in calculating the optimal energy allocation, hence MLP-based load forecast model is proposed. The process of finding the best combination of parameters of the neural network is presented in Chapter 5.

3. An optimal energy allocation based on forecasted load consumption considering the limited generation capacity of the microgrid and maintaining the basic electricity needs of the households. In the context of off-grid power systems, ECQ ensures sufficient energy for the households while maintaining a balanced operation of the power systems and efficiently use the available energy. The analytical approach of allocating daily energy allowance optimally to each household is presented in Chapter 6.

3 METHODS

This chapter describes the methods used in this research for the data gathering as discussed in Chapter 4, developing the forecast model presented in Chapter 5, and optimising the daily energy allocation of the households as shown in Chapter 6. Figure 3.1 shows the flow of work of this research from data gathering to allocating of daily energy quota using the proposed scheme.

3.1 DATA GATHERING

Data gathering is divided into two parts. First is the collection of demographic profile through field survey, and second is the collection of the energy usage using the PMOG system.

As discussed in Section 2.7 and 2.9, real-world data is essential in developing models that would describe the characteristics of the household's energy consumption [Che17]. These data include the factors affecting their energy consumption and drivers of using energy [BK17]. Since data are important in developing the load forecast model, the factors influencing the behaviour of the households towards energy, as identified by surveying the existing literature, are classified as demographic information. A survey is conducted to collect this data.

To do the first part of the data gathering, we need a survey questionnaire. The survey questionnaire serves as a guide while conducting the survey to the participants. The development of the survey and its deployment is discussed in Chapter 4, Section 4.2 and Section 4.4, respectively.

A survey was done with the developed survey questionnaire with the aim of gathering the demographic information of the households. A face-to-face survey was employed as this approach is the most suitable for the selected villages that are located in remote areas. Another approach, such as online survey is not doable as the people in the villages have no access to the Internet.

For the second part of the data gathering, a PMOG system was developed and installed to the selected households of the two villages. PMOG system is an energy monitoring system (EmS) that is designed to gather the energy consumption of the households in two levels – household level and appliance level, using wireless sensors. The

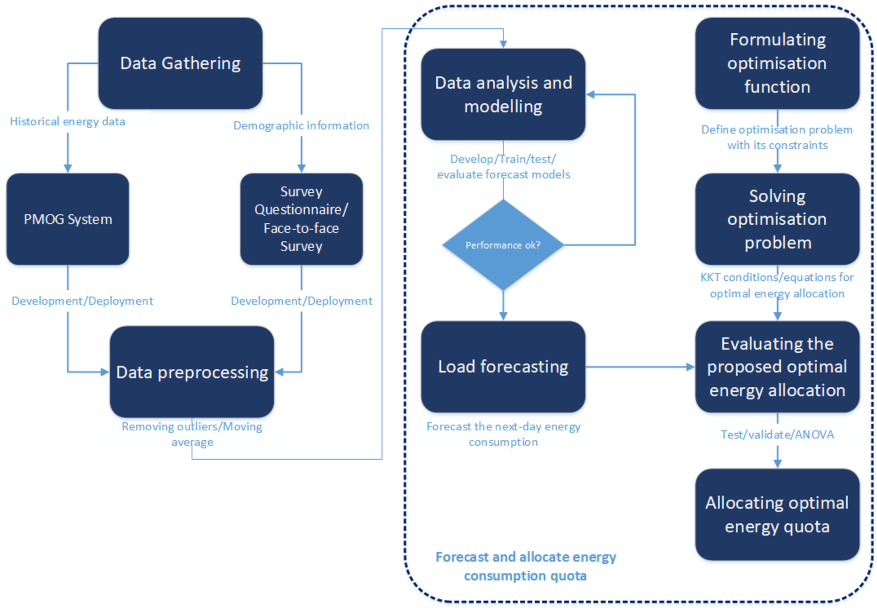


Figure 3.1: Flow of methods used in this research.

development and the deployment of the system are presented in Chapter 4, Section 4.3 and Section 4.4.

For the historical data, energy monitoring systems called Philippines-Micro-Off-Grid (PMOG) systems were installed in the selected households to monitor and gather their electricity usage. PMOG systems were developed and tested in the laboratory before the deployment.

3.1.1 *Evaluation of the survey questionnaire and testing of PMOG system before deployment*

The survey questionnaire was tested by conducting a pre-survey in the laboratory with colleagues act as participants. This is done to ensure that the questionnaire is readable, understandable and each question written serves with a purpose for the research as a whole.

For the PMOG system, the testing was done by allowing the system to run for two months prior to the deployment to test its reliability. The output is being recorded and monitored in the remote server. When data gathering is interrupted, the systems were checked for errors. If code bugs caused the errors, the system code is adjusted to make sure that the error will not happen again if external factors like power blackout cause the interruption, the system will just stop recording. This will appear as blank or N/As in the data for the duration of the blackout. No data or N/As will appear in the records whenever the system is experiencing a blackout or power interruption. Chapter 4, Section 4.3.1 presents the details of the PMOG system flow and operations.

3.2 LOAD FORECAST MODELLING

A Multi-layer Perceptron (MLP) based model is employed for load forecasting in this research. MLP network is used because of its simplicity and straightforward approach in forecasting and can perform best while dealing with the nonlinearities of the data. Four forecasting techniques were considered in the development stage of the forecast model for this research. These four techniques are MLP, ARIMA, RBFN and GPR. Both MLP and RBFN can handle well with nonlinear features of the data, and both ARIMA and GPR are best suitable in handling linearities.

The MLP-based forecast model is developed by using the Matlab tool. Functions are available to use with an option of designing the network by determining the best combinations of the network's layer and neurons, as well as the number of the historical electricity usage of the households. Different simulation and experiments were conducted to determine the right combinations of the networks' hidden layers HL, neurons N, and delay window D. Simulations were conducted to observe the influence of these three parameters in the performance of the network in forecasting. The model is trained using the energy data from PMOG system and demographic information from the survey data. During the training stage of the model, several case scenarios involving a number of inputs for the network were considered—all for the purpose of finding best performance of the model in forecasting in terms of RMSE. The goal is to find the lowest possible RMSE given the inputs and the chosen architecture of the neural network. The process of determining the forecast model includes the input shaping, as discussed in Section 5.1.2.

In the development of the forecast model, the following inputs were considered:

1.) Historical energy data (PMOG data) such as power consumption of the household

2.) Household's temperature (indoor)

3.) Calendar days such as weekdays

4.) Household profiles from the survey data (demographics, and monthly energy tariff)

The steps on how to design a neural network for load forecasting is presented in Chapter 5 as well as the details of the simulation and its results.

The final model with the lowest RMSE is chosen through a grid search where all possible combinations of inputs and neural architectures are considered.

3.2.1 *Evaluation of the loaf forecast model*

The forecast model was validated using k-fold validation with $k = 10$ in all input combinations used to determine the best combinations of the three networks parameters. This is presented in Section 5.1.1 The MLP-based forecast model is evaluated by comparing its performance to three other techniques such as Gaussian Process Regression (GPR), Autoregressive Integrated Moving Average (ARIMA), and Radial Basis Function Network (RBFN) (see Section 5.4). Furthermore, the performance of the proposed load forecast model used in this thesis is compared with two other works that also used neural network-based models in load forecasting as detailed in Chapter 5 Section 5.15.

3.3 OPTIMISING ENERGY ALLOCATION OF THE HOUSEHOLDS

The optimisation of the energy allocation of the households consider in this research takes two-steps process. The first step is the forecasting of the next-day energy consumption based on their historical usage and households profile. The second step is the calculation of the optimal energy allocation, considering the known constraints.

The first step is done using the proposed forecast model developed using MLP that uses the historical energy data and the household profiles. The second step is done by solving the optimisation problem using the Karush-Kuhn-Tucker (KKT) approach, given the constraints of the microgrid generation capacity and the minimum energy level for each household. The optimisation process aims to minimise the difference between the forecasted values and the calculated optimal energy allocation of each household. At the same time, it is ensuring that the total optimal energy allocation does not exceed to the generated energy by the microgrid and that the optimal energy allocation of each household should not be lesser than the minimum energy required by the households. This is to ensure maximum utilisation of the available energy while ensuring that households that need more energy than what is allocated will get sufficient energy. There will be no wasted energy allocation in terms of excess of energy allocation or unused energy allocation. The formulation of the optimisation problem is presented in Chapter 6, Section 6.1

KKT approach is one of the optimisation techniques that is used in solving an optimisation problem that subjects to constraints written in the form of inequalities. The formulated optimisation problem described in Chapter 6 meets the requirements of KKT conditions that involves inequality equation in the optimisation conditions allows us to use the KKT approach. These conditions are the constraints written in the form of equality and inequality. The two constraints meet the requirement of KKT conditions; hence the approach is used to solve the optimisation problem. The details of solving the optimisation problem is presented in Chapter 5, Section 6.1.1.

3.3.1 *Evaluation*

Using the available data from PMOG system, the approach is evaluated by carrying sample calculations on what would be the optimal energy allocation using the proposed method and compared with the other existing methods such as the equal daily allocation and ratio and proportion approach. Chapter 6, Section 6.1.4

Analysis of Variance (ANOVA) is employed to determine the difference between the average energy allocation of each household. This is to show that the difference between each households energy allocation is statistically different. ANOVA is the most common and easy to implement in comparing the averages of the two or more groups to determine whether the difference between the averages are statistically significant. The null hypothesis is tested by comparing the means of the different groups, that is

$$H_0 = \phi_1 = \phi_2 = \phi_3 = \phi_n \tag{3.1}$$

where ϕ is the means and n is the number of groups. The alternate hypothesis H_A is accepted that the group means are statistically different from each other when the result of ANOVA test returns statistically significant.

The proposed optimal energy allocation is validated using the values forecasted by MLP-based forecast model. It is important that the results of the calculation of the optimal energy allocation should meet the stated constraints of the optimisation problem. The detailed validation process is presented in Chapter 6, Section 6.1.4.

In this research, three methods in daily energy allocation are considered together with the proposed optimal energy allocation that uses load forecasting and KKT conditions to be compared using ANOVA. The detailed discussion is presented in Chapter 6, Section 6.2.

3.4 CHAPTER SUMMARY

This chapter presents the methods used in the proposed optimal energy allocation of households connected in off-grid microgrids with limited generation capacity. The methods cover the data gathering to the development of the forecast model and calculating the optimal energy allocation of each household.

In collecting the necessary data for the development of the forecast model and the solving the optimisation problem, a survey questionnaire and PMOG system were developed and deployed. For forecasting the next-day energy consumption of the household, an MLP-based forecast model is proposed that uses both historical energy data and households profiles. A mathematical approach is proposed in determining the optimal energy allocation using KKT approach incorporated with the forecasted values by the MLP-based forecast model.

In this chapter, a two-step process of finding the optimal energy allocation is proposed using MLP-based forecast model and KKT approach.

4

DATA COLLECTION AND PROCESSING

Given this research project is done with the support of British Council, Philippines in partnership with the Department of Science and Technology-Science Education Institute to positively impact the chosen local communities, this chapter presents the selected villages and the data gathered from these villages. The data collected serves as the baseline of this research in the development of the load forecast model presented in Chapter 5 and the optimal energy allocation shown in Chapter 6. The problem this research stated in Chapter 1 is a real-world problem faced by the people in off-grid villages. For this reason, the profiles of the villages are also presented in this chapter.

This chapter also presents how the data collection process using the energy monitoring system called PMOG system and the survey questionnaire. The demographic information collected includes the factors affecting their energy consumption as discussed in Section 2.7 that falls to the three subgroups, namely historical data, economic factor, and weather information. Furthermore, this chapter presents the foundation of the proposed adaptive energy allocation, given the collected data from the selected households.

To perform load forecasting and calculate the optimal daily energy allocation for households connected to generation-constrained microgrids, the following data are needed:

- Historical data such as power usage, weather information such as temperature, and monthly tariff to identify patterns and trends in the usage.
- Demographic information such as the household's total monthly income, education and employment of the household head, total number of household's occupants, number of children, and the number of working members of the household, to understand the influence of socio-economic factors on household consumption.

A survey and PMOG system was deployed to gather demographic and the historical energy data of the households, respectively.

The historical energy data is necessary for the development of the load forecast model, and the proposed scheme for optimally allocating the available energy adaptively while meeting the basic needs of each household. In forecasting the energy usage, the demographic

Table 4.1: Village profiles: The 3 villages have different levels of access to electricity. Village 1's access to electricity is limited to a 5-hour window, Village 2's is constrained with daily energy quota, and Village 3 is connected to the conventional grid.

Village	**Location (Philippines)**	**Electricity service**	**Water service**	**Total HH with electricity**	**Surveyed HH**
Village 1	Pangan-an Island, Cebu	Yes (5-h daily) Off-grid	No	204	152
Village 2	Paypay, Daanbantayan, Cebu	Yes (0.8 kWh daily) Off-grid	Yes (4-h daily)	128	121
Village 3	Aguho, Daanbantayan, Cebu	Yes (unlimited) Grid	Yes	67	50

information of each household is also essential, second to the historical energy data, since it helps the load forecast model to identify the different households according to their profile [Hsi15]. Both historical energy data and the household profile are therefore considered to be essential factors affecting the load forecasting [Gup17]. The monthly tariff can be used as inputs to identify the electricity usage patterns of the households. The corresponding monthly tariffs of each household is reflective of how much electricity they have used for the month. To understand the community's energy usage as a whole, community profile in terms of electricity and water services is presented in the following section.

4.1 OFF-GRID VILLAGES' PROFILES

Three villages were selected in the province of Cebu, Philippines as the communities of interest for this research.

These three off-grid communities are located in remote areas of the province of Cebu that are powered by stand-alone power systems or connected to the traditional grid. Table 4.1 presents the profile of the villages surveyed for this study. The villages were selected according to their electricity access – limited access (off-grid) and unlimited access (traditional grid). A total of 366 sample households (HH) were surveyed, 195 from Village 1 which 152 households are connected to the off-grid power system and 43 of which have no electricity access, 121 from Village 2, and 50 from Village 3.

4.1.1 *Village 1*

Village 1 is a small island located in Pangan-an, Lapu-lapu city, Cebu, Philippines, with a household total of 405 with an average of 5 members for each family (Figure 4.1). Out of 405 households, only 204 households are connected to the off-grid power system (diesel generators) and only 152 of which participated in the survey along with other 43 households that are not connected to the off-grid power system. Diesel generators are scheduled to operate around 6:00 PM to 11:00 PM daily, and the community has electricity access only at this time. In exceptional cases, the power system can operate in day time upon request with corresponding fees for diesel and other operating expenses. The Pangan-an Island Cooperative for Community Development (PICCD) manages the operation of the power system in the village.

The village used to be serviced by an off-grid solar power plant with a generation capacity of 45 kW. The solar plant was composed of 504 solar modules (90 W), 118 lead-acid batteries with 12V 1800AH rating, charge controllers, inverters and a low voltage distribution system. However, the solar plant stopped operating sometime in 2011 on the recommendation of the Department of Energy Visayas Field Office (DOE VFO) after they had conducted an assessment. According to the assessment of the DOE VFO, the solar plant needed full replacement of the battery bank and 150 solar modules that would cost around PHP 6 million before the plant could go back to its regular operation. The management of PICCD decided to purchase diesel generators to continue to provide electricity to the community instead of doing an overhaul of the solar plant because of financial constraint. Without external help, the community cannot implement the recommendation of the DOE FVO as there is no funding available for them to avail and purchase the necessary components and devices for replacement.

Village 1 has no access to potable water supply within the island. Almost all households store rainwater for daily use. Rainwater is used for bathing, washing of clothes, cleaning and other household activities that require water, except for cooking for which they need to use potable water. Some households use rainwater for drinking after boiling and cooling it. The island sources its potable water from the nearest mainland.

4.1.2 *Village 2*

Village 2 is located in Paypay, Daanbantayan, in the southern part of Cebu province (Figure 4.2). In 2013, the super typhoon Yolanda

Figure 4.1: Village 1 is located in a remote island in Lapu-lapu city, Philippines. Houses are typically made of light materials such as bamboos, plywood, and weaved coconut leaves.

devastated several villages, towns, and cities in the Philippines. Many people died, while others lost their homes and livelihoods. Village 2 is located in one of the towns affected severely by the typhoon, and where many people lost their houses. Aside from food and other relief goods, selected survivors of the super typhoon were provided with houses to help them recover faster. The Philippine Red Cross in cooperation with their partners and the local government unit of Daanbantayan, Cebu, built houses in a small community called Red Cross Village for the benefit of a selected few survivors of typhoon Yolanda. The village is composed of 128 households, a daycare centre, and a community livelihood centre. Five mini solar plants service the whole community. Three of the mini solar plants have 33 kW generation capacity, and two have 10 kW that aggregates to 119 kW. With this generation capacity, each household is allocated with 0.8 kWh of energy for daily use (4.1). Each household is installed with energy usage indicator that the households can check the level of their energy usage. The indicator has three levels with different colours. Green for "go" status that means the remaining energy is still high. Orange for "warning" status that the available energy is low and the allocated energy is at a critical level. Red is for "stop" status that means the allocated energy is at an empty level and signifies that the households consume all their allocated energy for the day. Once the red level is breached, the energy management system automatically cut-off the connection of the household to the off-grid power system. The power system is using batteries that serve as energy storage during the day and back-up source during the night. The allocation is done to control the energy usage of the households according to

Figure 4.2: Village 2 is a community whose houses are built by the Red Cross, Philippines in cooperation with the Local Government Unit (LGU) of Daanbantayan, Cebu for the survivors of typhoon Yolanda. The community has an off-grid solar power that allocates 0.80 kWh as the daily energy quota for each household.

the generation capacity of the available solar plants. The remaining energy is then used to supply the community livelihood centre and the daycare centre.

All households are connected to the local water supply that operates 4-hours daily, 2-hours in the morning (randomly selected) that runs between 6:00 AM to 10:00 and 2 hours in the afternoon that runs between 2:00 PM to 6:00 PM.

4.1.3 *Village 3*

Village 3 is located in Aguho, Daanbantayan, Cebu, Philippines (Figure 4.3). The community is composed of 67 households and a community livelihood centre. Out of 67 households, 65 are occupied, and five households are not connected to the grid. The community was built by Human Habitat Philippines, a non-government organisation with the aide of their building partners and the local government. This community is another project of the non-government organisation for typhoon Yolanda survivors of the town.

The community is connected to a local water supply operating 24-hours daily.

4.2 Development of Survey Questionnaire (SQ)

In this study, collected data includes energy usage of households in terms of the number of appliances and frequency of use each day,

Figure 4.3: Village 3 is a community built by Human Philippines in coordination with the help of the LGU of Daanbantayan, Cebu. The community is donated to the survivors of typhoon Yolanda. The community is connected to the conventional grid.

apart from their demographic information. Thus, a personal interview or face-to-face survey with a questionnaire was employed.

Aside from gathering the demographic information of the households, the survey is used to:

1) determine the household energy usage pattern based on the number of appliances and frequency of usage and

2) understand their energy needs in the context of the available services such as water and electricity in their villages.

The questionnaire was designed to have three sections that covered the following profiles of the selected villages: Demographics, Energy, and User-empowerment.

4.2.1 *Profiles*

4.2.1.1 *Demographic Profile*

The Demographic Profile (DP) section includes questions that gather information, such as their:

- role in the family,
- age,
- gender,
- educational attainment,
- house occupancy type,
- occupation,
- number of children in school,

- total number of people living in the household,
- total number of people working, and
- total monthly income of the household.

The demographic information is considered important in determining the different factors that affect the energy consumption of the household. These information were selected based on the works of Hsiao [Hsi15], Chae et al. [Cha+16b], Mandal et al. [Man+06], and Moon et al. [Moo+19] as discussed in Chapter 2.

4.2.1.2 *Energy Consumption Profile*

The Energy Consumption Profile (ECP) section covers information, such as:

- the list of household appliances,
- the frequency of use,
- monthly electric bill, and
- the list of people who stay at home at night and day with their corresponding ages.

An open-ended question was also included in the ECP section to determine whether their electricity usage would change when there is no power interruption or quota for day use.

4.2.1.3 *User-empowerment Profile*

The last part of the questionnaire is the User-empowerment Profile (UEP) section. This section allows the participants to rank ten enumerated items according to their priorities. The 10 items are:

- water,
- sanitation,
- electricity,
- housing,
- roads,
- employment/job,
- community livelihood program,
- health facilities,
- education/school,
- flood/typhoon protection.

These items are considered to be the basic needs of the people according to Maslow's hierarchy of needs [Mas43]. These items also represent the two levels (low and high) of the needs of the people.

Water, sanitation, electricity, housing, and roads represent the low-level needs, and the items represent the high-level needs: employment/job, community livelihood program, health facilities, education/school, and flood/typhoon protection.

In User Empowerment Profile section (UEP), participants awareness level on the impact of their energy use on the environment is also surveyed, as well as their motivation for saving energy. The data from this section is used in comparing the three villages concerning their needs in Section 4.6.2.

The survey questionnaire is attached as appendix A.3 of this thesis.

4.3 DEVELOPMENT OF PMOG SYSTEM

For collecting the energy data of the households, an Energy Monitoring System (EmS) is developed and deployed. The EmS used in this research is based on an existing monitoring system available in the Cogent Laboratory of Coventry University called Cogent-House [Cog15]. The EmS is a modified version of Cogent-House that caters for the requirements of this research, which is to gather the electricity usage of the households in the remote communities powered by an off-grid power system, with limited generation capacity. The Cogent-House system is designed to run individually from a group of sensors communicating with a centralised server, and sending the data by hopping from one local server to another. For this research, the EmS is designed to collect the total household's energy usage using a Current Transformer (CT) jaw sensor of the Current Cost Envi energy monitor, and the appliance energy usage using Individual Appliance Monitors (IAMs). This modified version of the EMS is referred to as the Philippines micro-off-grid (PMOG) system.

Apart from energy usage (house and appliance levels), the PMOG system is enabled to gather environmental data such as the temperature inside the households. The PMOG systems can store and transmit data to a remote server, where it can be accessed and viewed through a web browser. Full details of PMOG system deployment are attached in this thesis as appendix A.4.

4.3.1 *PMOG system flow*

The PMOG system is composed of the Envi energy monitor and IAMs, gateway (Raspberry Pi (RPi), and internet dongle) as shown in Figure 4.4. The PMOG system uses an RPi 2, Model B, with 1 GB RAM and external internet dongle as its local server devices and internet gateway. RPi is installed with a micro Secure Digital (SD) card which serves as the storage unit of the system and the house of the codes. The codes govern the system's operations from logging, storing, sending, and displaying data to the webpage intended for the PMOG (see appendix C for the RPi set up guide). The webpage displays power consumption and temperature of the household for a given date and time. The Current Cost Envi energy monitor and IAMs are both off-the-shelf devices. The Current Cost Envi energy monitor consists of two integral parts: 1) the function display monitor with built-in receiver and 2) the CT jaw sensor with energy transmitter [Cur]. CT jaw sensor is clamped to the electricity mainline of the house to monitor the household level energy consumption without altering the existing electricity circuits connections to contact the probe to the electrical lines physically. The Envi energy monitor gathers data from the generated energy of the microgrid, and the total power usage of the selected households in the community. IAMs monitor the appliance level power consumption of each appliance plugged into it. An external antenna is attached to the 4G modem internet dongle to enhance the signal for data transmission. Sensors and the local server communicate wirelessly through the Envi energy monitor. The Envi display monitor displays all current readings of both CT jaw and IAM sensors. All data recorded in the local server are transmitted to the remote server using the internet dongle. The current clamps and IAMs take power reading every 6 s and the PMOG system stores the data temporarily in the local server and push all the recorded data to the remote server every hour (Figure 4.5). PMOG system gathers electricity reading from the household and appliance level every 6 seconds and update the remote server every hour. The PMOG system was deployed without altering the existing set up of the microgrid on both the generation and utilisation side during installation.

4.4 DEPLOYMENT OF THE SURVEY AND PMOG SYSTEMS

The deployment of both the survey and PMOG system were carried out with the help of the University of San Carlos (USC) in Cebu City, Philippines. The survey and the installation of the PMOG to the selected households were conducted between August – September 2016. This research project has undergone the Ethical approval process of Coventry University.

4.4.1 *Field survey: Household face-to-face interview*

The survey was done in the three remote villages in the Philippines. The survey took 40 – 50 minutes for each respondent. The survey

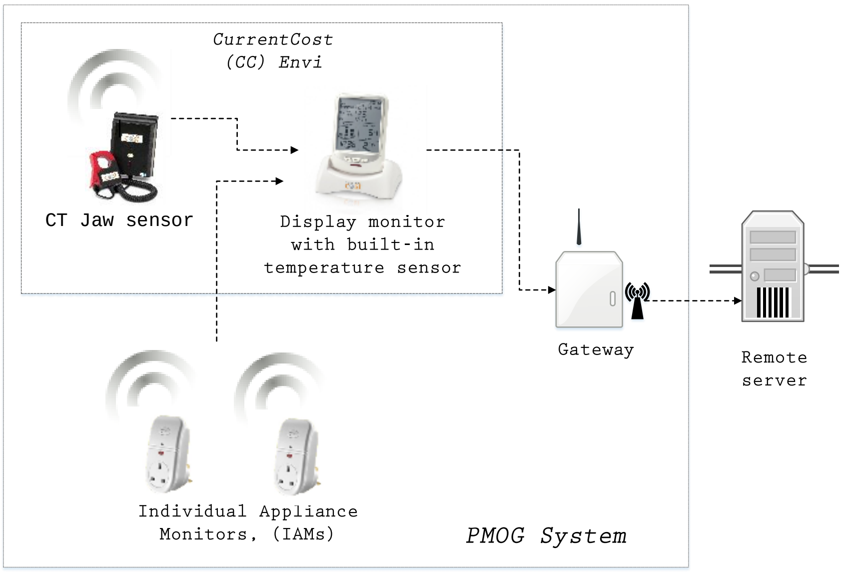


Figure 4.4: PMOG System Architecture. The PMOG system is designed to collect energy data on both household and appliance levels using CT jaw sensor and IAMs, respectively. Energy data is stored locally and pushed through to the remote server.

questionnaire was written in English, so orientation was conducted for the interviewees to familiarise the questions and get acquainted with the local language translations. Orientation was done to ensure that the interviewees knew how to explain the questions from the survey questionnaire to the respondent when needed, as not all respondents were expected to understand English.

All answers were recorded in English or Cebuano – the local dialect, according to the preference of the interviewer.

4.4.2 *PMOG system installation*

There were 10 PMOG systems installed in the selected households and microgrid at the two villages; Village 1 and Village 2. These two villages are both powered by an off-grid power system with limited generation capacity. Each village had 5 PMOG systems, 1 for monitoring the generation side and 4 for the households representing the household profiles as discussed in Section 4.8. The maximum number of IAMs installed in each household is 3 for television, electric fan, and DVD players, respectively. Full details of the installation is shown in Table 4.2.

Households were selected after the survey was done where the demographic information was already gathered. The number of households with the same profile was considered in the selection process. Parameters such as number of appliances, number of occupancies and

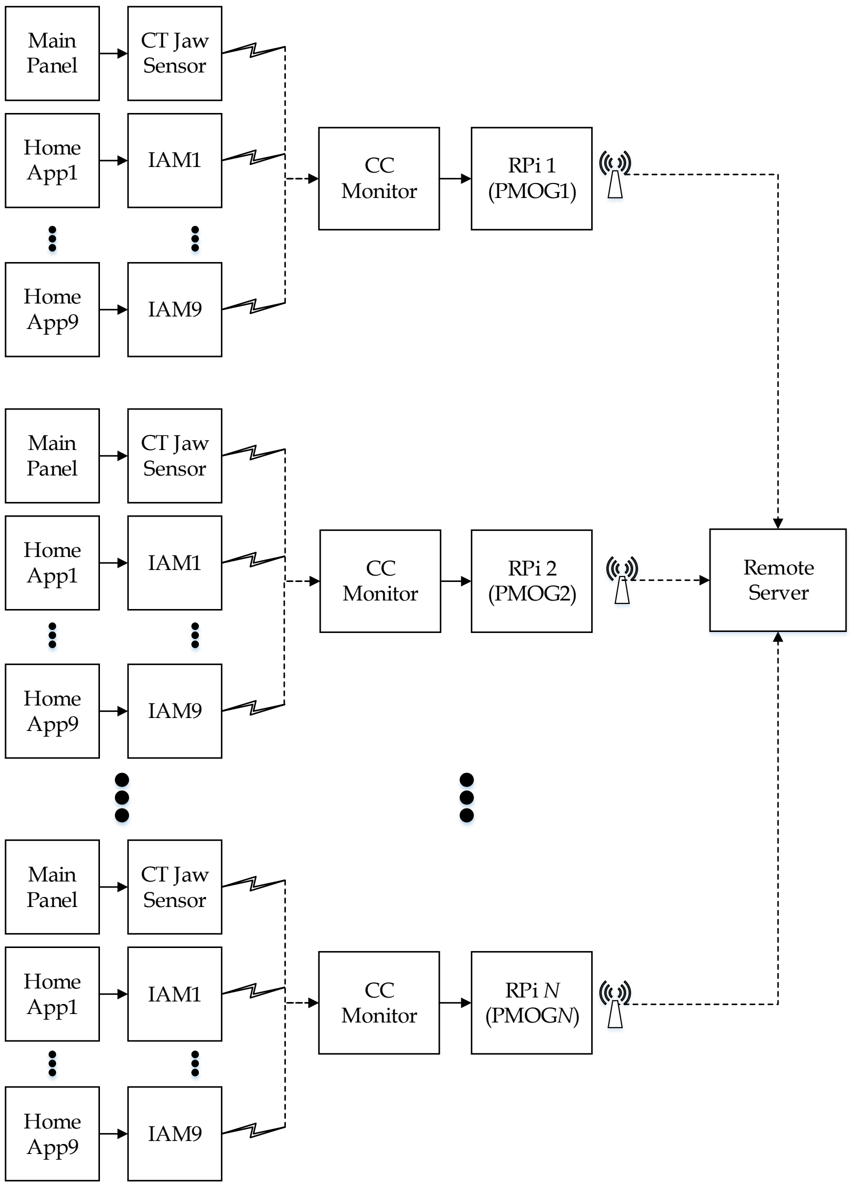


Figure 4.5: PMOG Data Flow. Each household has 1 PMOG system, as shown in Figure 4.4. CT jaw sensors sense the total energy consumption of the households as they are connected to the main panel and communicate with the local server RPi for storage. Each IAM monitors the energy of the assigned appliance into it and sends the data to the local server through wireless transmission.

Figure 4.6: Face-to-face interview with the respondents in one of the villages. Participants are asked to rank and give scores to the 10 items as enumerated in Section 4.2.1.3 according to their priorities.

Table 4.2: Summary of installed PMOG systems in Village 1 and Village 2

Location	Server	Device No.	Dwelling/ Appliance	No. of occupants	Date installed	Monthly Income (PhP)	Monthly bill (PhP)
Village 1	PMOG1	0	Generator		02-Sep-16		
	PMOG2	0	House 1	7	01-Sep-6	10000	270
		1	TV		01-Sep-16	(£164)	(£ 4.5)
	PMOG3	0	House 2	4	02-Sep-16	14000	525
		1	TV		02-Sep-16	(£230)	(£8.6)
		2	Fan		02-Sep-16		
	PMOG4	0	House 3	10	02-Sep-16	17800	800
		1	TV		02-Sep-16	(£292)	(£13.1)
	PMOG5	0	House 4	11	02-Sep-16	6500	560
		1	TV		02-Sep-16	(£107)	(£9.2)
VIillage 2	PMOG6	0	Solar Plant		21-Sep-16		
	PMOG7	0	House 5	3	21-Sep-16	6500	100
		1	Fan		21-Sep-16	(£107)	(£1.6)
		2	TV		21-Sep-16		
		3	DVD player		21-Sep-16		
	PMOG8	0	House 6	9	21-Sep-16	8000	100
		1	TV		21-Sep-16	(£131)	(£1.6)
		2	Fan		21-Sep-16		
		3	DVD player		21-Sep-16		
	PMOG9	0	House 7	5	22-Sep-16	10000	100
		1	TV		22-Sep-16	(£164)	(£1.6)
		2	Fan	5	22-Sep-16		
	PMOG10	0	House 8	4	22-Sep-16	2500	100
		1	TV		22-Sep-16	(£41)	(£1.6)

total household's monthly income were considered in the selection process. The number of households with the same count of those three parameters was tallied. Then a household was selected in each profile to represent them. Figure 4.7 shows the actual PMOG system installed in households. The details of PMOG system installation are attached to this thesis as appendix A.2

The webpage, which is running from the remote server, updates the displayed data every 20 minutes after each hour. When the webpage is not updated, PMOG system may need to be checked to confirm its status.

Figure 4.8 is the actual webpage of the PMOG monitoring system. The webpages display sender, device number, server time for both local and remotes servers, and the readings from IAMs, CT jaw sensors and built-in temperature sensors. Appliances monitored by the IAMS were assigned to a specific channel display in the Envi display monitor in which the devices number is displayed on the webpage. The Envi display monitor can display individual energy consumption of the appliances through IAMs with channel numbers from 1 to 9 with channel 0 reserved for the CT jaw sensor. The transmitted data can be retrieved from the remote server designated to the PMOG system by accessing the server from any computer connected to the internet. The data is in the form of .csv file that can be viewed with Microsoft Excel. It includes the date and time, electricity usage (power (W)), temperature (degree C), device number, and the server number of the nodes.

The technical report of the deployment is available online for public consumption (http://cogentee.coventry.ac.uk/ gene/).

4.5 DATA PROCESSING

From the six seconds interval, the data is preprocessed to convert the raw data into the targeted interval of forecasting, which is a day ahead load forecasting. The data used for this research is collected from September 2016 to December 2018.

The PMOG data is processed to clean the data and eliminate the possible extreme values recorded from the CT jaw sensor (household level monitoring) and the IAMs (appliances level monitoring).

Table 4.3 shows the summary statistics of the energy data from the PMOG system. With 5 hours operation daily for Village 1, the data points are much lesser when compared with Village 2 which households have 24 hours access to electricity depending on their usage of the given energy quota. For households in Village 2, the energy quota can last for 24 hours when used accordingly. Although

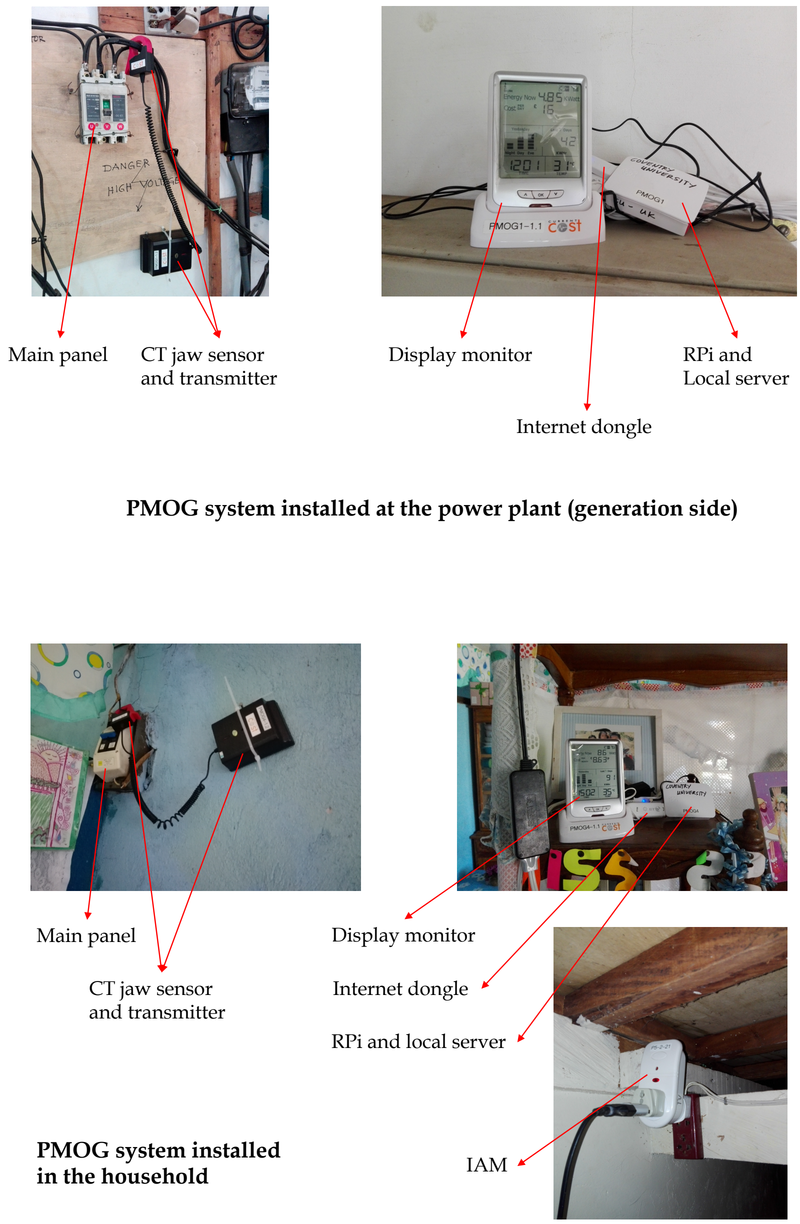
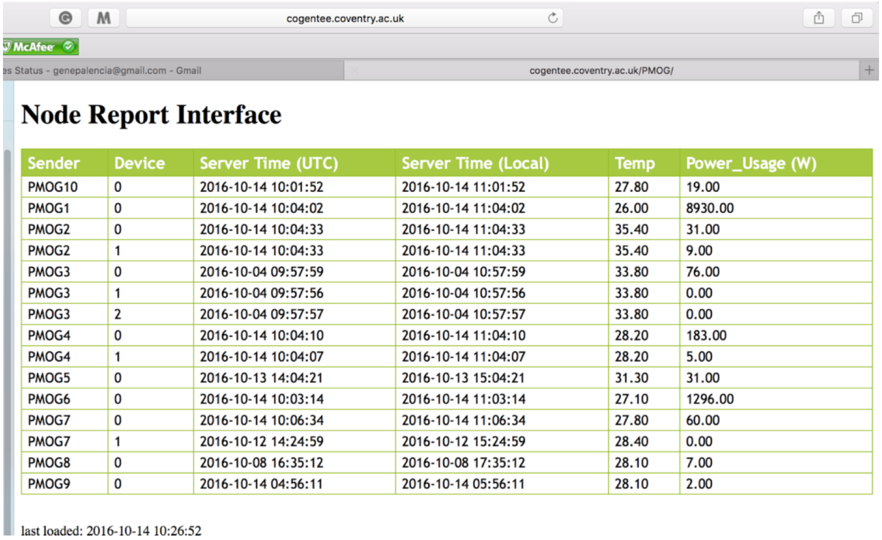


Figure 4.7: PMOG systems deployed in the villages collecting energy data on both the off-grid power systems (generation side) and the households with individual appliance monitors (IAMs).



cogentee.coventry.ac.uk

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Node Report Interface

Sender	Device	Server Time (UTC)	Server Time (Local)	Temp	Power_Usage (W)
PMOG10	0	2016-10-14 10:01:52	2016-10-14 11:01:52	27.80	19.00
PMOG1	0	2016-10-14 10:04:02	2016-10-14 11:04:02	26.00	8930.00
PMOG2	0	2016-10-14 10:04:33	2016-10-14 11:04:33	35.40	31.00
PMOG2	1	2016-10-14 10:04:33	2016-10-14 11:04:33	35.40	9.00
PMOG3	0	2016-10-04 09:57:59	2016-10-04 10:57:59	33.80	76.00
PMOG3	1	2016-10-04 09:57:56	2016-10-04 10:57:56	33.80	0.00
PMOG3	2	2016-10-04 09:57:57	2016-10-04 10:57:57	33.80	0.00
PMOG4	0	2016-10-14 10:04:10	2016-10-14 11:04:10	28.20	183.00
PMOG4	1	2016-10-14 10:04:07	2016-10-14 11:04:07	28.20	5.00
PMOG5	0	2016-10-13 14:04:21	2016-10-13 15:04:21	31.30	31.00
PMOG6	0	2016-10-14 10:03:14	2016-10-14 11:03:14	27.10	1296.00
PMOG7	0	2016-10-14 10:06:34	2016-10-14 11:06:34	27.80	60.00
PMOG7	1	2016-10-12 14:24:59	2016-10-12 15:24:59	28.40	0.00
PMOG8	0	2016-10-08 16:35:12	2016-10-08 17:35:12	28.10	7.00
PMOG9	0	2016-10-14 04:56:11	2016-10-14 05:56:11	28.10	2.00

last loaded: 2016-10-14 10:26:52

Figure 4.8: PMOG system node report interface. The webpage displays the newest transmitted data to the remote server. The data includes the date and time, device number, and PMOG number aside from the main data which are the temperature and power usage of the household.

some households experience power outage as their demand is much higher to what is provided. If households use their energy quota in 5 hours, the number of data points will be similar to that of Village 1. Energy data shows that households from Village 1 have much higher energy usage than households from Village 2, as shown in Table 4.3. This can be attributed to the available energy of each village. Village 1 is not limited to how much electricity they use within the 5 hours operation while Village 2 is limited with the daily quota.

It can be observed that House 3 from village 1 has the highest average power usage of 261.8 W, and House 8 of village 2 has the lowest average power usage of 13.4 W. To confirm that the tabulated average from the PMOG system reflects the expected power usage of each household, reference is made to the survey data. During the survey, the households were asked to list all their appliances and their frequency of use every day or per week. According to our survey data, household 8 has listed a television, and two ceiling fans as their main load aside from 3 light bulbs used during the night. From this list, an average of at least 50 W of electricity usage is expected per day when the television is used. However, from the energy data gathered, the television has not been used since the TV is broken (confirmed with the survey data). This explains why household 8 has an average power usage of 13.4 W instead of the expected average power usage of at least 50 W.

Most of the households have the same electricity load, which include television, electric fan or ceiling fan, light bulbs, and DVD players

Table 4.3: Descriptive summary for the households daily energy usage

Dwelling	Number of data points	Power usage, (W) Mean	SD	Median	MAD	Min	Max	Range	Skew	Kurtosis	Std. Error
Village 1											
House 1	9288	78.2	33.0	93.5	16.6	1.3	146.2	144.9	-1.0	-0.4	0.34
House 2	9116	112.5	29.1	116.8	19.0	0.0	610.2	610.2	-0.1	10.6	0.30
House 3	7667	261.8	67.3	273.6	80.2	0.0	767.3	767.3	0.4	1.6	0.77
House 4	9369	80.5	70.5	75.9	52.2	6.5	718.7	712.2	3.6	19.3	0.73
Village 2											
House 5	68657	55.0	53.6	35.7	43.9	0.0	452.5	452.5	1.2	1.3	0.20
House 6	82514	22.9	32.0	7.6	7.1	1.0	254.5	253.5	1.8	2.0	0.11
House 7	58692	33.0	40.6	14.5	13.1	0.0	378.4	378.4	1.6	1.4	0.17
House 8	61136	13.4	11.3	11.0	10.4	0.0	122.9	122.9	1.9	6.6	0.05

Legend: SD - Standard Deviation, MAD - Median Absolute Deviation

with speakers. Their electricity usage varies in time of use, frequency of use, and availability of the electricity.

The data is processed by eliminating all extreme values or spikes reading of the PMOG system. PMOG reading beyond 1000 W for house level monitoring is suppressed and 200 W for appliance level. The thresholds are approximate values calculated from the total power rating for the available appliances of the households. The elimination of power surges or spikes are done before the daily average of the power usage is performed.

Daily average power consumption is calculated by getting the area under a curve. A trapezoidal method is used to estimate the daily average power usage. The generalised form of the trapezoidal method in getting the area under a curve in integrating a sine function with $N + 1$ evenly spaced points is expressed as

$$\int_p^q f(x)dx = \frac{q-p}{2N} \sum_{n=1}^{N} \Big(f(X_n) + f(X_{n+1}) \Big) \tag{4.1}$$

where the scalar value of $\frac{q-p}{2N}$ is the spacing between each point. The trapezoidal method is readily available as a Matlab function. This function is then used in getting the average power usage per day.

The calculated daily average power consumption is used as the input data of the forecast model in Chapter 4. The aim is to forecast the next day power usage and used it as one of the basis in determining the optimal energy allocation of the household.

4.6 DESCRIPTION OF DATA

The preprocessing of the dataset is done using R tool, free software for computing and one of the popular programming languages used in

Table 4.4: Statistics of households temperature data

Dwelling	Number of data points	Temperature, (°C) Mean	SD	Median	MAD	Min	Max	Range	Skew	Kurtosis	Std. Error
House 1	9288	34.0	5.2	35.9	4.9	21.6	39.4	17.8	-0.6	-1.2	0.05
House 2	9116	35.0	3.7	35.9	4.1	23.9	39.4	15.5	-0.6	-0.8	0.04
House 3	7667	30.2	1.4	30.1	1.1	25.4	39.4	14.0	2.5	13.5	0.02
House 4	9369	35.4	4.0	36.8	3.6	22.8	39.4	16.6	-0.9	-0.5	0.04
House 5	68657	28.8	2.2	28.4	2.1	23.6	37.3	13.7	0.8	0.3	0.01
House 6	82514	28.0	2.6	27.5	2.4	21.9	37.3	15.4	0.8	0.2	0.01
House 7	58692	29.5	1.9	29.5	2.0	24.6	39.4	14.8	0.2	-0.4	0.01
House 8	61136	29.6	2.4	29.3	2.4	23.4	39.4	16.0	0.5	-0.2	0.01

Legend: SD - Standard Deviation, MAD - Median Absolute Deviation

the field of Data Science [Rto]. Tables 4.3 and 4.4 present the statistics of the household's energy consumption and the temperature data. The energy consumption and temperature data of the households were collected from September 2016 to December 2018. For the forecasting model, the dataset was divided into 70:15:15 ratio for training, test, and validation purposes. Both energy consumption and temperature data were used as inputs for the forecast model, as presented in Chapter 5. All data are stored and available for public consumption at Cogentee repository (url: http://cogentee.coventry.ac.uk/ gene/researchdata/) [Pal19].

4.6.1 *Energy data yield*

The average data yield every day is determined to check if the data points collected are adequate to represent the daily energy usage of the households. Figure 4.9 shows the average data yield for each PMOG system installed in selected households at village 1 and village 2. The average yield of the data collected daily is above 80 %, as shown in Table 4.5.

For any system that collects data, missing values are often one of the issues. There are many possible reasons as to why missing values occur. This issue can be attributed to the system's malfunction (i.e. short circuit, system breakdown), interrupted operation (i.e. systems are turned off), loss of contact (i.e. lossy cable), or no internet connection for wireless transmissions. All these are difficult to address within the system itself to avoid all the possible causes of missing data. In this study, to ensure that daily energy usage of the household is represented well by the data points from the PMOG system, daily data points must at least have 80% yield. This is equivalent to 4 hours of electricity usage in a day for Village 1 and 19.2 hours for Village 2. For Village 1, the average daily yield is above 90% and for Village 2 is above 80% as shown in Table 4.5. A data yield of at least 80%

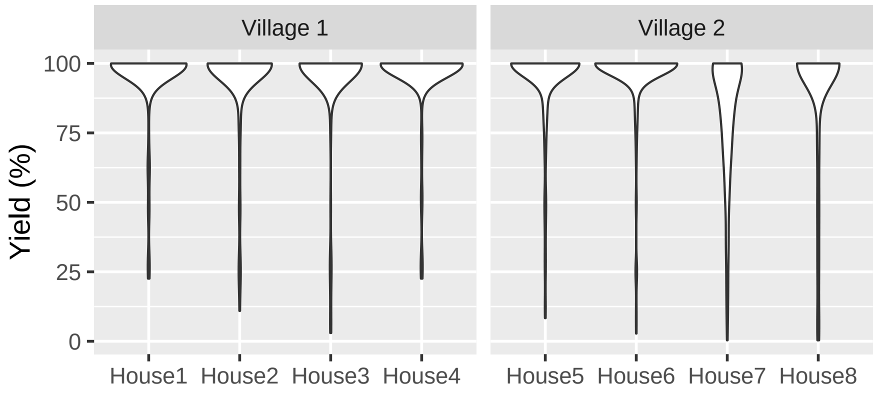


Figure 4.9: PMOG system data yield. The daily yield of the data in % (y-axis) for each household (x-axis). The daily average of yield (%) is above 80% for all PMOG systems installed in the households.

Table 4.5: Daily yield of PMOG systems

Dwelling	N	Daily yield				
		mean	std. dev	min	max	median
House1	307	95.17	14.93	22.55	100.00	100.00
House2	315	94.18	17.33	10.94	100.00	100.00
House3	232	94.94	18.12	2.99	100.00	100.00
House4	314	95.90	14.06	22.55	100.00	100.00
House5	266	94.23	16.40	8.33	100.00	100.00
House6	314	95.81	14.72	2.78	100.00	100.00
House7	263	81.52	23.00	0.35	100.00	89.58
House8	246	89.18	24.97	0.35	100.00	100.00

is considered necessary to build the forecasting model to maintain the integrity of the data as logged by the PMOG system for each household that is monitored.

Figure 4.10 shows the actual electricity usage of one of the households from Village 1 over 5 hours that the off-grid power system is operating. It can be observed that the household immediately uses electricity as soon as the power system is up around 6:00 PM. Power level variations reflect certain changes in electricity usage of the households. From Figure 4.10, the house-level power lever changes as soon as the TV is turned on and off. When the electric fan is turned on, total power usage increase reflecting the power consumption by the fan on house level.

According to the survey data [Pal19], households usually use televisions during dinner time (around 7:00 PM) until the last TV program they like which is generally around 9:30 PM to 10:30 PM daily. This can be observed that the power usage in this hour is high, as shown

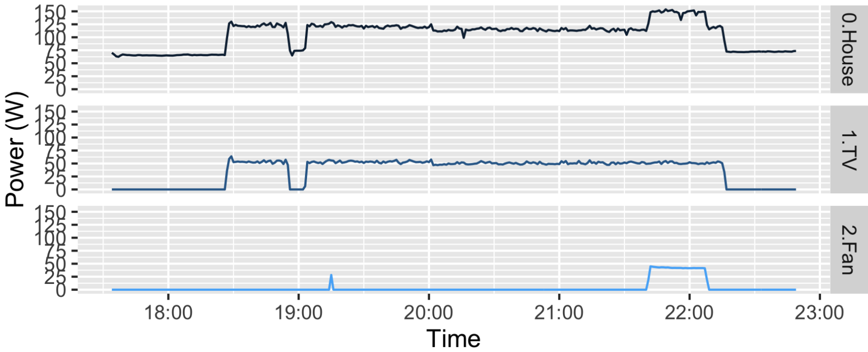


Figure 4.10: Actual electricity usage pattern of house 1 from Village 1. House-level power usage (y-axis) varies as the usage of TV and electric fans change reflecting the power usage of each appliance over time (x-axis). Data: 1 day (5 hours) electricity usage.

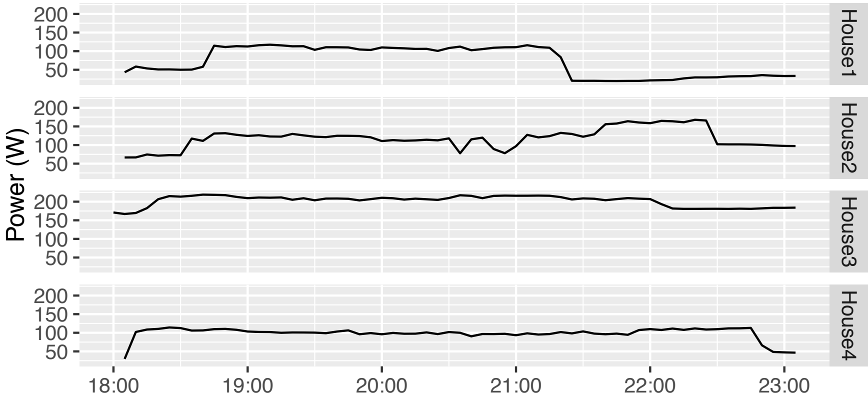


Figure 4.11: Households energy usage pattern. House level power usage (y-axis) of the selected households in village 1 varies in time (x-axis) when the load is changed. Most of the households use electricity as soon as the power system is up. Some households maintain almost the same load throughout the operation of the power system (e.g., House 3); thus very few variations on power usage is reflected.

in Figure 4.10 Otherwise households just use light bulbs, electric fans and phone chargers until the operation cuts down.

Figure 4.11 shows the house-level power usage of the selected households in village 1. The variations in electricity depend on how the household uses their appliances at any time. The house level power usages reflect the general characteristics of the electricity usage of the household. According to our survey, people in village 1 use electricity as much as they can during the operation time of the off-grid system. From figure 4.11, it can be observed that some households register power usage higher than 100 W just before the cut off time. According to the survey data, correspondents used electricity by watching television until the end of operation of the microgrid. This explains the 100 W usage of power right before the cut-off time.

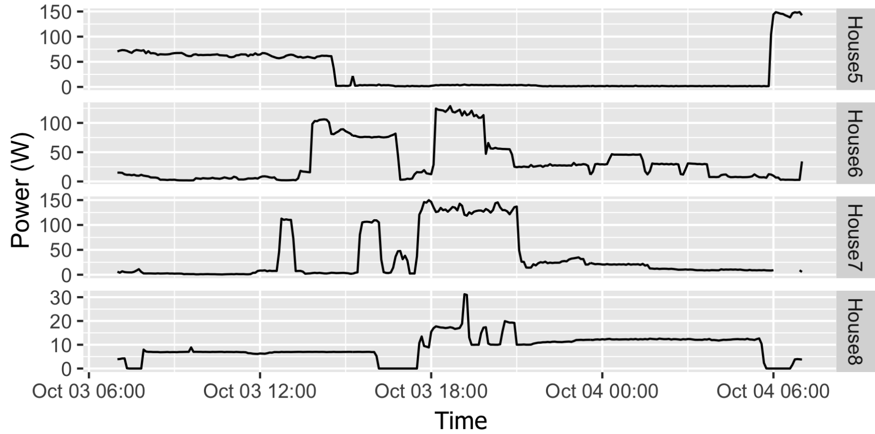


Figure 4.12: Daily energy usage pattern. Power usage (y-axis) at the house level varies significantly for the entire day (x-axis) for each household. Most of the households peak their usage of electricity around 6:00 PM to 9:00 PM (dinner time)

For Village 2, households have an energy quota every day, which is 0.8 kWh. Households are given the responsibility to use their energy quota wisely if they want the 0.8 kWh energy to last for 24 hours. As shown in Figure 4.12, each household reflects their power usage at different times of the day. Figure 4.12 shows high power usage happens between 6:00 AM and 10:00 in the evening.

Figures 4.11 and 4.12 show an actual electricity usage of the households in Village 1 and Village 2, respectively for a given day. A similar usage can be observed on the households in Village 1 from 7:00 PM up to 9:00 PM where their electricity usage peaks. For households in Village 2, most of them peak their electricity usage from 6:00 PM to 9:00 PM. Since Village 1 has electricity available for them from 6:00 PM until 11:00 PM only, all households utilise the available power for the entire duration of the operation of the microgrid, showing a constant electricity usage of the households. However, for Village 2, electricity can be available for 24 hours depending on their usage as they are given a specific energy quota daily. From Figure 4.12, households have several peaks of electricity usage spread in 24 hours compared with households from Village 4.11 that depicts a stable usage from the beginning of the operation of the microgrid.

Both villages have a fixed amount of monthly fees for the corresponding energy allowance. Hence the impact of the monthly bill may have minimal influence on how they use their energy allowance. The electricity usage pattern of Village 1 is perceived to be almost constant for the entire duration of operation of the microgrid however Village 2 presents interesting electricity characteristics as the usage varies for 24 hours depending on their usage of the given energy quota. According to the survey data, 46 % of the households experience a power outage,

Table 4.6: Household composition: Age, household members working and attending school (%).

Household composition	Village 1	Village 2	Village 3
Age			
less than 5 years old	9.81	13.31	15.63
5 to 18 years old	34.97	36.53	38.67
more than 19 years old	55.23	50.15	45.70
Attending school	31.48	35.45	37.11
Working (with regular income)	5.55	7.89	5.86

and 54 % are satisfied with the existing quota and do not use all up the given energy quota daily.

4.6.2 *Description of survey data*

Here, survey data are the responses recorded from the conducted face-to-face interviews with the households in the three villages based on the survey questionnaire. As mentioned in Chapter 2, the survey questionnaire gathers the demographic profiles of the households. In this section, the tabulated responses of the correspondents are presented.

4.6.2.1 *The respondents*

All respondents are identified to be mothers, fathers, or head of the households. This is to ensure that the responses to the questionnaires reflect the household's conditions and status on energy usage. Table 4.6 shows the breakdown of the age of all the participants and their household members, as well as the number of family members working and attending school.

Village 3 has the highest percentage of children attending school with 37.11 %, followed by Village 2 (35.45 %), and Village 1 (31.48 %), as shown in Table 4.6. These percentage values indicate that more than 1/3 of the total population of the villages are children and attending school. Village 1 has the lowest portion of the household members with ages less than 5. These children stay at home with their mother or father attending to them. The number of family members with regular work and sources of income, aside from the household head and spouse, is few with only 5.55 % in Village 1, 7.89 % in Village 2, and 5.86 % in Village 3. Most of the adults are working on a contractual basis with no regular source of income.

Table 4.7: Characteristics of household head and spouse, and average number of occupants per household.

Characteristics	Village 1	Village 2	Village 3
Average age (years)			
Household head	44.69	42.19	41.27
Spouse	44.85	40.34	38.93
Average level of education (completed years)			
Household head	7.92	9.27	8.31
Spouse	7.41	8.93	8.09
Gender of household head (%)			
Female	28.48	16.53	6.67
Male	71.52	83.47	93.33
Average number of occupants per household	6	7	7

4.6.2.2 *Characteristics of household head and spouse and average number of occupants per household*

AS shown in Table 4.7, overall, household heads across all three villages finished at least primary level of education (average education years is 8.50). In Village 2, household heads have average education years of 9.27, the highest of the three villages, indicating 3rd year level in high school, followed by Village 3 with 8.31 and Village 1 with 7.92.

Across all villages, female heads are only 17.22 % while male heads are 82.78 %. Village 1 has a relatively high female head of 28.48 %, followed by Village 2 with 16.53 %, and Village 3 has 6.67 % (the lowest). On the other hand, the average number of household occupants for both Village 1 and Village 2 is 7, 1 point higher than Village 1, which has 6.

4.6.2.3 *Households income and household head occupations*

The majority of the household heads in the selected three villages earn less than the poverty threshold and some even less than the food thresholds (Table 4.8 and Figure 4.13). Both food and poverty thresholds are set by the Philippine Nutrition and Food Research Institute. The food threshold is defined as the minimum monthly income needed to meet the monthly food needs and the nutritional requirement for a Filipino family with five members. The poverty threshold is an expanded food threshold to include non-food needs such as clothing, housing, education, transportation, and health expenses.

As shown in Table 4.7, the average number of occupancy per household for the three villages is higher than 5. From the given thresholds shown in Figure 4.13, there are more than half of the surveyed households in all three villages living with a monthly income under the Food threshold. Table 4.8 shows the breakdown of the monthly income

Table 4.8: Monthly income (range) of the households

Income Range (PhP)	Households (%) Village 1	Village 2	Village 3
Less than the food threshold (6,300.00), approx. £87.5	68.88	59.84	60.47
Within the food and poverty threshold (6,301.00 ~ 9,100.00), approx. £87.51 ~ £125)	10.71	24.59	27.91
Above the thresholds (9,101.00), approx. £125.1 and up	19.90	13.93	16.28

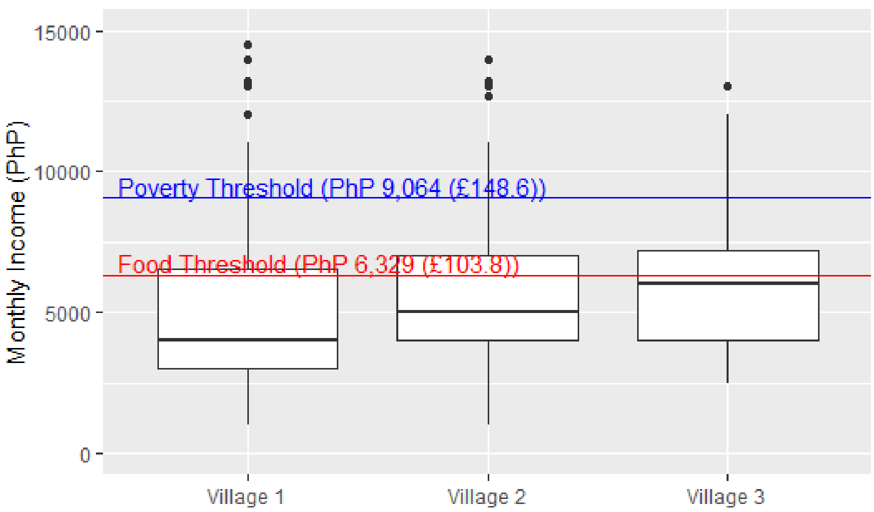


Figure 4.13: Monthly income of the 3 villages compared with the poverty and food thresholds.

Table 4.9: Percentage (%) of Households, by occupation of the HHs head

	Percentage (%)		
Occupation	Village 1	Village 2	Village 3
Manager, supervisor, official, professional	0.66	4.96	
Technician or assoc. professional	6.58	4.96	6.67
Clerk	1.32	2.48	2.22
Service, shop, or market sales worker	17.11	14.88	
Farmer, forester, fisher	45.39	19.01	48.89
Trader	11.84	0.83	
Plant or machine operator or assembler	0.66	2.48	
Laborer or unskilled worker	5.92	41.32	33.33
Housewife	3.29	5.79	2.22
Shellcraft/Special occupation	7.24	3.31	6.67

of the households in each village. There are 68.88 % from Village 1, 59.84 % from Village 2, and 60.47 % from Village 3.

Poverty is common to most of the families in the communities who make a living from agriculture, construction, fishing and any other related activities as shown in Table 4.9. The average income of the three communities, as shown in Figure 4.13, is below the national minimum monthly income, which is PHP 9,064 (£145) and is referred to as the poverty threshold. There are approximately 82 % of the respondents have a monthly income below the poverty threshold. There are 15 % of them earning between PHP 9100 (£150) and PHP 20,000 (£325), and only three % of the households have monthly income more than PHP 20,000 (£325).

The household heads commonly work as farmers, fishers, foresters, labourers, and unskilled workers (Table 4.9). Since most of the household heads completed high school education only (Table 4.7), the occupations they engage in are limited to jobs that do not require a college degree. The income from this type of job is minimum wage, and sometimes even less than the minimum wage mandated by the law.

4.6.2.4 *Households electricity experience*

One of the open-ended questions in the survey questionnaire is "If you will have 24-hour access to energy, what would change in your energy consumption?" in the pretext that the energy available is unlimited. This means that for Village 1, electricity will be available 24 hours daily and not 5 hours and for Village 2, there will be no quota. Their electricity usage will be similar to the households from Village 3 that are connected to the traditional grid.

For Village 1, 96% of the respondents when given to have 24 hours access to electricity want to use it during the day as the temperature in the island can be too warm. With electricity, they can use some electric fan to cool down. Other reasons include to be able to use a refrigerator for the food storage, to watch television any time of the day for entertainment purposes, and want to use electricity for business purposes. The other 4% of the respondents are quite happy with the 5 hours of electricity access.

For Village 2, 83 % of the respondents want to have 24 hours access with no quota so that they can use more electricity for food storage, entertainment, business, and for their children's education. They believe that 24 hours of access can improve the study habits of their children that go to school. For the other 17 %, the existing energy scheme is sufficient for their electricity needs; however if the electricity will be available 24 hours similar to the traditional grid, they may change their electricity usage. Currently, there are 46% of the households in Village 2 that experience electricity outage with the given quota and wanted to have more energy when possible. Other households are quite satisfied as they do not use all up their daily quota, these comprise the 54% of households connected to the microgrid but express willingness to change their electricity usage when the access has no limitation.

Village 3 enjoys electricity access 24 hours as they are connected to the traditional grid, and the only factor that limits them to use electricity is their capability to pay. Their income dictates on how much electricity they use.

4.7 ENERGY USAGE OF THE HOUSEHOLDS

In this section, the average energy usage of each household in Village 2 is investigated as a case study for this research. The data from Village 1 was dropped as the electricity usage of the households is almost constant for the entire 6 hours operation of the microgrid. What makes the data from Village 2 interesting is the fact that households use different electricity in 24 hours depending on their available energy quota daily. The households are given the responsibility to utilise the given quota that would serve them best for 24 hours. It is hypothesised that some households are using energy twice more than the other households. Moreover, these households are expected to experience an energy shortage. From the survey data that 46 % of the household experience electricity outage daily as their energy quota is not sufficient for their needs and there are 54 % of the households that used all up their energy quota daily as they used less electricity than what is given. Hence the motivation of this work can be simplified from this reality of Village 2 that the excess energy quota of the other households can be used by other households that need more energy.

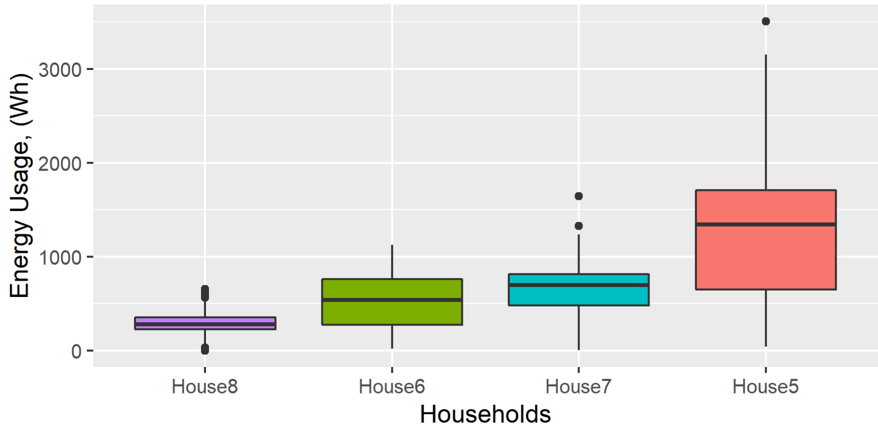


Figure 4.14: Average energy usage of the households in Village 2

To determine the actual energy usage of the households, the average energy usage of the households are determined from the available energy data of PMOG systems. Figure 4.14 shows the average energy usage of households. It can be observed that house 5 has the highest average energy usage and house 8 has the lowest. House 5 also presents the characteristics that it uses beyond the quota given. At first, it was thought that the PMOG monitoring system has some faulty reading the electricity usage of the households. However, it was found out that the household is allowed to have more than the quota being the president of their association in the village. The electricity usage of House 5 is also reflective of the demand of households with a similar profile. On the other hand, House 8 electricity usage is too little when compared to House 5. House 8 is one of the households that do not use all up their given quota daily. According to the survey data, House 8 uses electricity for lightings and ceiling fan only. The light bulbs used for lightings are rated 10W, and the ceiling fan is 15W. House 6 and House 7 can be considered an average user that most of the time, use their energy quota efficiently. Sometimes they experience a power outage, but most of the time they do not use all up their energy quota.

4.8 HOUSEHOLD PROFILES

This section identifies the features of the household profile that would be used as the consumer profiles for the development of the load forecast model in Chapter 5. The forecast model is to predict the next day energy usage of the households. The data needs to represent the 24 hours usage fo the households. Since Village 1 operates for 5 hours only, this does not meet the required 24 hours usage; hence the data was dropped. The features are selected from the survey data that are considered to be significant factors of influencing households use of

Table 4.10: Household profiles

Profile	Occupants	Monthly income	Average No. of appliances	Average Freq. of use (hr/day)	Family members Working	Family members School	Family members Home
A	1 ~ 3	4987	4	23	1	0	1
B	4 ~ 6	7056	4	23	1	2	2
C	7 ~ 8	7030	4	26	2	3	2
D	9 up	6529	3	17	3	5	3

energy. From Section 5.2.3, demographic information survey data, and from the literature review, the following factors (shown in Table 4.10) are selected to be the main features of the household affecting their energy usage. There are four household profiles from grouping the number of occupants of the household. The first group has one to three occupants, the second group has four to six occupants, the third group has seven to nine occupants, and the last group has ten or more occupants. These groups represent the size of the family members occupying a house. According to the study of Hu et al. [Hu+17], the family size and the number of appliances are major influencers of energy consumption for Chinese urban households based on the results of their online survey for 4964 households. Other features as discussed in Chapter 2 such as the monthly income, number of appliances and its frequency of usage, number of family members working, schooling and staying at home were selected from the survey data. Table 4.10 shows the full details of the household profiles considered as inputs aside from the historical energy data, temperature and the weekdays of the forecast model developed in Chapter 5. Households are then selected to represent each profile and to cover the variability of the households in Village 2. House 5 is to represent profile A, House 6 is for profile D, House 7 is for profile C, and House 8 is for profile B.

These data are then used for the training of the MLP-based neural network presented in Chapter 5 to enable the model to predict the energy consumption of each household.

4.9 CHAPTER SUMMARY

In this chapter, the process of gathering the data and initial analysis of the data is presented. All the necessary data needed for the development of a load forecast model is successfully collected using the developed survey questionnaire and the PMOG systems installed in the selected households. The processing of historical energy data is presented. The processing of the data is done to eliminate the extreme values that may affect the real energy consumption of the households. The extreme values were eliminated by applying a threshold on both house level and appliance level monitoring based on the power rating of the available appliances of the households.

The PMOG data from Village 1 and Village 2 is scrutinised and studied well to deduced the electricity usage of each village that is connected to the microgrid. Both villages are powered with different microgrids that are both operating offline. Village 1 is powered by a diesel generator that operates 5 hours daily during night time while Village 2 is powered by a solar power plant that provides energy quota daily to the households. This energy quota allows the households to use the energy for 24 hours depending on their usage. Some households use all up the given energy daily, and experience power outage while other households are satisfied with the existing energy management scheme and do not use all up the given energy quota. There are 46% of the households in Village 2 that experience power outage and 54% do not use all up the given quota. The excess or unused energy quota was given to those households are considered energy wastage that could be used by other households that experience the power outage. Given this scenario, the need to optimally allocate the available energy is considered. This is explained in details in Chapter 6.

The data is also processed to create the necessary input matrix needed for the neural network and the other techniques considered in this research such as RBFN, GPR, and ARIMA.

With the real-world data gathered from the conducted survey and the installed PMOG system to the households, this research is achieving realistic results on the proposed optimal daily energy allocation for households connected to microgrids with limited generation capacity as discussed in Chapter 6. The proposed optimal energy allocation is derived by calculating the optimal value in the formulated optimisation problem considering the constraints posed by the power systems and the number of households connected to the microgrid. The details of this optimisation problem are presented in Chapter 6. The needs of having an optimal energy allocation are also presented in Section 4.5 where some households consume more energy than the others. Also, in this chapter, the consumer profiles are identified as discussed in Section 4.8.

The next chapter presents the process of development of the load forecast model.

5

MULTILAYER PERCEPTRON-BASED FORECAST MODEL

Chapter 4 presents the process of gathering energy and survey data. These data are used for the development of energy forecast model and consequently for the development of optimal energy allocation scheme of daily energy allowance of each household in generation-constrained microgrids, as shown in Chapter 6. Generation-constrained microgrids are microgrids with limited generation capacity. This type of microgrids uses energy management restrictions such as energy consumption quota to provide the basic electricity needs of the households while maintaining a balanced operation. Microgrids that can supply the electricity needs of the households without restrictions are considered to have unconstrained generation capacity.

This chapter presents the development of the energy forecast model based on artificial neural networks (ANN), specifically the multilayer perceptron (MLP). When using the neural network, choosing the proper neural network sizes can be complicated as these affect the performance of the network. Hidden layers and number of neurons influence the networks' forecasting performance in terms of root-mean-square error (RMSE) along with the number of delay window considered in the input stage. The process of selecting values for these three parameters is discussed first. The process includes on how the number of hidden layers HL, number of neurons N, and the number of delay window D affect the performance of the MLP-based forecast model in predicting the next day energy usage of the households. This procedure is done to all input considered in the modelling of MLP-based forecast model. MLP is preferred for being robust in handling real-world data compared to the other techniques mentioned and does not require a priori knowledge as most statistical-based approaches. The data used in developing the forecast model is from village 2, where the data reflects the 24-hours energy usage of the households.

This chapter aims to find the answers for the research question,

> **RQ1:** ***Can the household's daily energy consumption be forecast with reasonable accuracy?***

To answer the above research question, experiments were conducted using four forecasting techniques namely MLP, Radial Basis Function Neural Network (RBFN), Gaussian Progress Regression (GPR), and

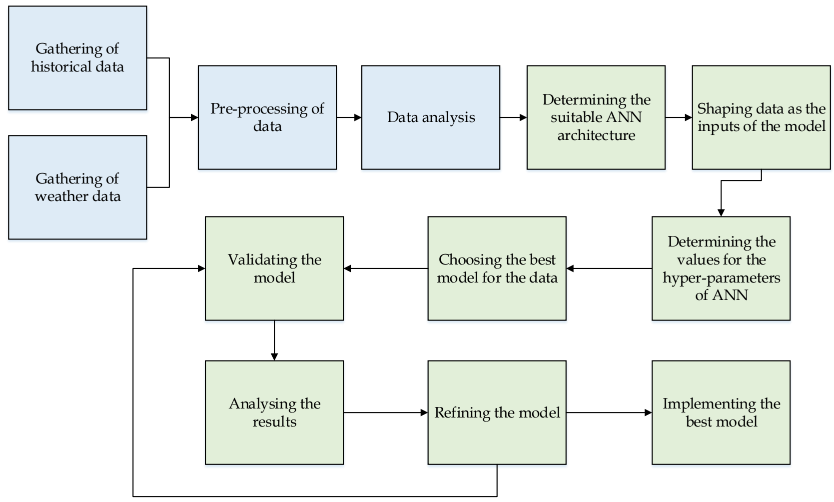


Figure 5.1: Load forecasting model development flow.

Autoregressive Integrated Moving Average (ARIMA). For MLP-based forecast model, simulations were conducted to determine the combination of hidden layer HL, neurons N, and delay window D that generates the least values of RMSE. The RMSE value should meet the threshold set for the forecast model that is 15 % of the actual energy usage. The threshold is set based on the acceptable RMSE as laid out in the work of Hsiao [Hsi15] and Moriano et al. [Mor+16], 20%. All forecast models were developed using the same data as with the MLP-based model for comparison purposes. The performance of the proposed MLP-based forecast model is also compared to existing works of Marnerides and Din [DM17] and Ryu et al. [RNK16].

All forecast models are trained and validated using the data gathered from the survey and the PMOG monitoring systems, as presented in Chapter 4. Figure 5.1, shows the flow of the development of the load forecasting model developed based on the MLP neural network. Gathering the data is described in chapter 4, as well as the pre-processing of data to eliminate unreasonable readings from the PMOG systems. The succeeding sections described the process to determine the proper size of the neural network for parameters such as hidden layers and number of neurons and the appropriate number of historical data delay window D. The results were graphed and tabulated to compare the RMSE results. At the end of the experiment, the combination with the least RMSE values is chosen for the MLP-based forecast model.

5.1 FINDING THE BEST COMBINATION OF NEURAL NETWORK PARAMETERS

It has been established in Section 2.6.2 that the design parameters of the neural network affect the performance of the network in forecasting. Particularly, design parameters such as hidden layers HL, number of neurons N, and delay D, as well as the training data, affect the forecast model performance and generality [Cha+16b]. In this regard, the best combination of the three parameters must be determined to improve the forecast accuracy based on the available data for training. For the neural networks, the selection of the network size is not a straightforward process. The traditional approach usually starts with the simplest architecture and gradually explores complex structures. This approach is followed in the development of the MLP-based forecast model.

The neural network MATLAB toolbox is used in the development of the model. The toolbox's *train* function is used to train the network using the Levenberg-Marquardt algorithm. To identify the values of hidden layers HL and the number of neurons N that would generate the lowest RMSE possible; a heuristic approach is employed. The three variables were considered in the simulations of the model using MATLAB toolbox. A reasonable range for hidden layers HL, number of neurons N and delay D is considered to avoid over-fitting that may lead to erroneous load forecasting.

The process of selecting the values of hidden layers HL, the number of neurons N, and delay D to generate the best performing forecast model is presented in the next section.

5.1.1 *Steps in determining the best combination of hidden layers* HL, *number of neurons* N, *and delay* D*?*

Following the guide on the design procedure of the neural network for forecasting from the work of Palmer et al. [PJS06], below are considered important when designing and developing the network for the MLP-based forecast model.

1.) **Determining the number of outputs:** Any MLP neural network model can have one or more outputs that could correspond to the desired outcome from the model. It could represent the hourly, daily, weekly, monthly, or annual energy consumption. In this work, a single-output model with the output being the next day energy consumption (kWh) of the households is used.

2.) **Identifying the number of inputs:** Determining the inputs before the development of the model is important. The inputs are selected depending on the available data. In this study, the inputs for forecasting the daily energy usage of each household include the historical energy data, weather variables such as temperature, and calendar such as days of the week.

3.) **Identifying the number of hidden layers (HL):** There are no existing common rules in determining the suitable number of hidden layers of the MLP. In this work, a heuristic approach is used to identify the appropriate number of hidden layers with the best performance in terms of root mean square error (RMSE). From the selected range of the HL, more than 100 combinations were used during the simulations.

4.) **Identifying the number of neurons per layer (N):** Same with the hidden layers, there are no common methods in determining the number of neurons per layer that would guarantee a good performance of the network in forecasting. A heuristic approach is also employed in identifying the number of neurons for the MLP with the ultimate goal of having the best performance in predicting the energy consumption of the households.

5.) **Identifying the number of delays, (D):** The number of delays refers to the window of the inputs to be considered in reshaping the historical energy data to form the input matrix. Determining the right number to be used in the network together with the hidden layers HL and the neurons N, requires more than 100 simulations from the selected range of 1–30 days of equivalent energy usage.

The simulation is done using a heuristic approach, and then the selection is made from the tabulated results where the model with the smallest RMSE is chosen. In this research, the desired level of accuracy corresponds to an RMSE of less than 15% of the 0.8 kWh (existing allocation), which is equivalent to an energy of 0.12 kWh or 120 Wh. This amount is considered to be the allowable error for forecasting the energy usage of the households. RMSE is a measure of the difference between the predicted and the actual value over the number of observed data as described by equation 5.1. This error represents the average difference between the predicted values and the actual values. The 15% error is the maximum error allowable based on the previous usage of the households as gathered from the PMOG systems. Thus, the 15% error or less is desirable for forecasting the next day usage of the households.

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{E}_i - E_i)^2}{n}} \tag{5.1}$$

where $\hat{E}_1, \hat{E}_2, \hat{E}_3, ...\hat{E}_n$ is the predicted values, $E_1, E_2, E_3, ...E_n$ is the actual values, and n is the number of observations.

The number of neurons was simulated in the range of five to thirty with 5-unit steps. This range was chosen to observe the performance of the network through its RMSE. The range is considered to be reasonable to avoid the complexity of the network and overfitting due to a large number of neurons in the network. On the other hand, the delay was set in the range of 1 to 21 with 2-unit step. The neural network given with knowledge of a household's current energy usage, the future usage (state) may depend on the previous consumption (states) only to a small degree, i.e. the behaviour is Markovian up to a certain point. Therefore, few days historical data should suffice to have an acceptable accuracy in forecasting. For the number of hidden layers, the network was trained with hidden layers ranging from one up to five hidden layers. This range was chosen to have a possible model that is shallow (with 1 to 2 hidden layers) and not so deep (with 4 to 5 hidden layers) neural network.

To validate the forecast model a k-fold validation was performed with k equal to 10 in all the combinations of inputs used in determining the best combinations of the three parameters that would allow the neural network to provide the lowest RMSE. This is to make sure that each observation from the original data has the chance to appear in training and testing datasets [Koh95]. The validation method works, as shown in Figure 5.2 where I is the number of iterations.

5.1.2 *Input shaping (delay D) and the effect of the network size on the performance of the model in forecasting*

This section aims to investigate the effects of the number of energy historical data points considered as input window or delay (D) to the performance of the neural network in load forecasting.

The performance of the network can be improved or worsen depending on the number of delay window D. If the value of delay D is too small, there may be not sufficient information to make an accurate prediction, and if the value of D is too large, there may be over-fitting.

To avoid over-fitting, simulations were conducted. The number of delay window D is varied to observe the effect of delay D on

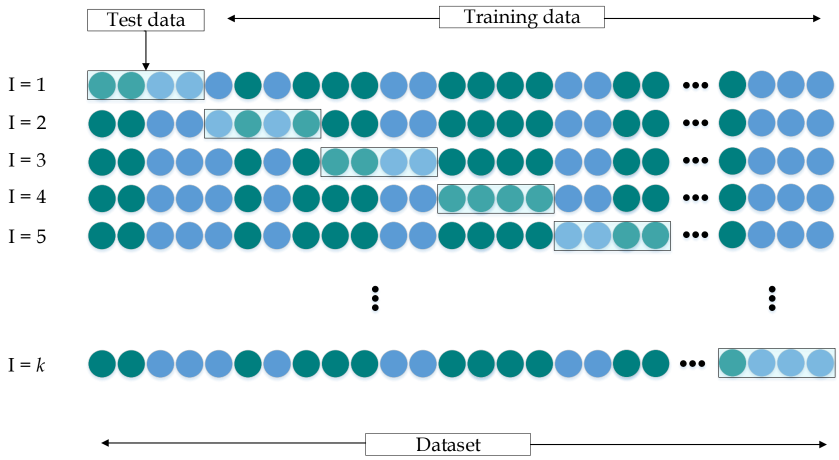


Figure 5.2: K-Fold Cross Validation

the performance of the network and to determine the best value of delay D, which generates the lowest RMSE. The concept of delay D is shown in Figure 5.3. For this research, the experiment is done by considering the past points of historical data to predict the next day energy consumption. This also serves as the input matrix of the MLP-based forecast model.

For example, if $N = 10$ and $D = 5$, so

Energy data: $P_1, P_2, P_3, P_4, P_5, P_6, P_7, P_8, P_9, P_{10}$

Input: Output:

$P_1, P_2, P_3, P_4, P_5 \rightarrow P_6$

$P_2, P_3, P_4, P_5, P_6 \rightarrow P_7$

$P_3, P_4, P_5, P_6, P_7 \rightarrow P_8$

$P_4, P_5, P_6, P_7, P_8 \rightarrow P_9$

$P_5, P_6, P_7, P_8, P_9 \rightarrow P_{10}$

Suppose the energy consumption for 5th of May 2020 is to be predicted with D equal to 5, then the historical data from 30th of April 2020 to 4th of May 2020 will be taken into consideration.

RMSE is used as the performance metric of the MLP-based forecast model [CD14]. RMSE is the measure of difference between the actual energy consumption (E_a) and the forecasted values (E_i). Hence, smaller value of RMSE is preferred. The lower the RMSE, the better the performance of the model to forecast. There are several sets of input tried during the simulation to observe the effects of the input to the performance of the neural network. Since the off-grid system is using batteries, the generation side is considered constant and hence

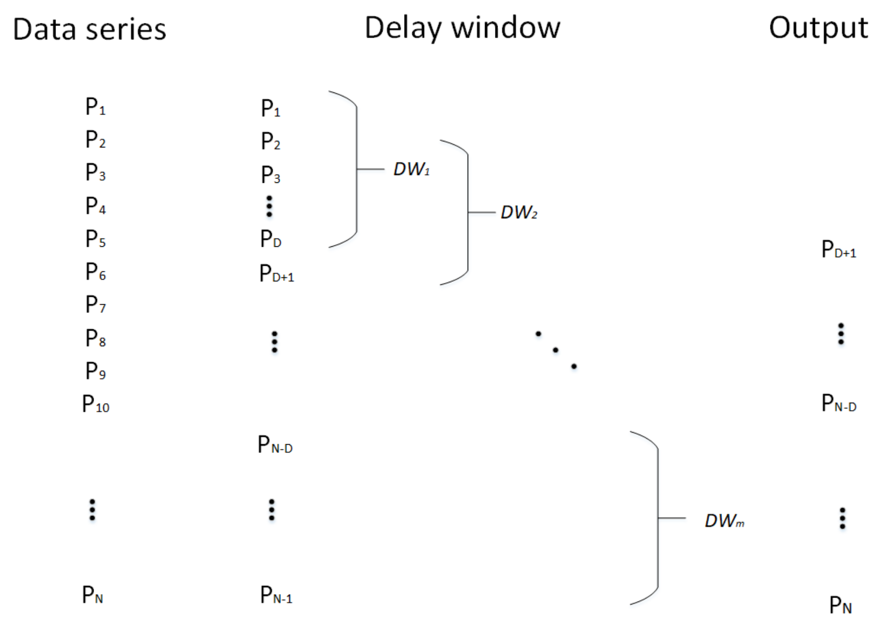


Figure 5.3: Input delay window concept where DW_1 is delay window 1, DW_2 is delay window 2 and DW_m is the total number of delay windows for the given input series.

the variations caused by the solar panels and other factors that affect the generation of the electricity is neglected. Below is the list of inputs (and its combinations) used in developing the forecast model:

1.) Historical energy data (PMOG data) such as power consumption of the household

2.) Household's temperature (indoor)

3.) Calendar days such as weekdays

4.) Household profiles from the survey data (demographics, and monthly energy tariff)

5.1.3 *Standard load forecasting using historical energy data as input*

This section aims to investigate how the delay D affect the performance of the neural network in forecasting. Simulations were conducted using the daily average energy consumption of the households as inputs. It assumes that the number of D significantly affects the performance of the forecasting model. Figure 5.4 shows the results of the simulation with the network's number of neurons are 15, and the hidden layer is one. It can be observed that the performance of the network varies as the delay D increases. At some point, it may seem that the RMSE values decrease as the delay D increases; however, RMSE standard variations are also changing randomly. The lowest average RMSE for

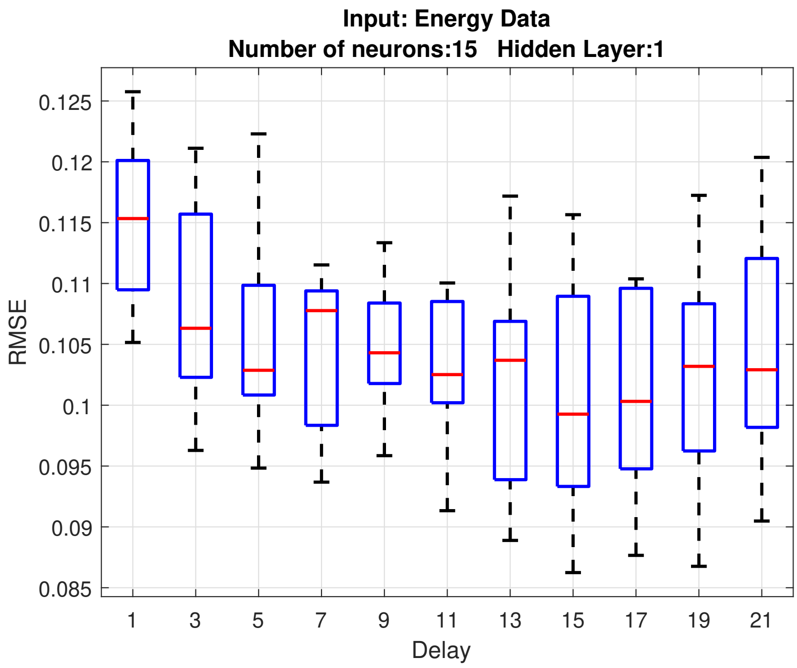


Figure 5.4: RMSE (Wh) results where x-axis shows the delay D and y-axis is the RMSE (Wh) for each delay D showing variations of a k-fold validation.

this network is 0.102 kWh or 102 Wh with a standard deviation of 9 for D = 21. Table 5.1, shows the performance of the network for each neuron considered in this part of the experiment. Across all the values neurons together with values for Figure 5.4, the lowest RMSE is 0.099 kWh or 99 Wh with a standard deviation of 6 for a network with one hidden layer, 30 neurons and historical energy data of 11.

To observe further the effects of the hidden layers and neurons along with the number of historical energy data considered as inputs, the number of hidden layers is increased to 3 and then 5. Tables 5.2 and 5.3 show the RMSE results as the number of hidden layers is increased with historical energy data as the inputs. For a neural network with three hidden layers, the lowest RMSE is 87 Wh with a standard deviation of 22 for a network with 30 neurons N and the delay D is 21. On the other hand, for a network with five hidden layers, the lowest RMSE is 85 Wh with a standard deviation of 15 for a network that 30 neurons and 21 delays. For both networks, the network's performance is at its best when the number of neurons is 30, and D is 21. Both values are extreme values considered in the simulations. Same trends are observed for the values of RMSE that is decreasing as the values of both neurons, and D are increasing with big variations as reflected in the standard deviations of each RMSE corresponding to each neuron N and delay D.

Since the goal is to find the best combination of neurons per layer N, hidden layer HL, and the delay D that generates the lowest RMSE

Table 5.1: Average RMSE (Wh) and the standard deviation as D increases for each neurons of neural network with 1 hidden layer

	Number of Neurons, *N*											
	5		10		15		20		25		30	
Delay, *D*	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD
1	116	6	116	6	116	7	116	6	115	5	115	7
3	108	9	109	7	108	10	107	9	108	7	107	8
5	108	10	107	7	106	7	106	8	105	8	103	10
7	106	8	105	9	106	8	102	9	103	7	104	9
9	105	7	105	6	105	5	106	5	102	8	102	6
11	107	7	103	6	104	6	102	7	104	7	99	6
13	106	10	103	7	105	8	104	8	100	9	103	9
15	104	10	107	9	106	11	100	6	101	9	103	8
17	103	11	106	8	106	10	101	11	106	6	99	12
19	105	11	105	11	103	8	**99**	**9**	104	10	105	11
21	106	10	104	12	102	9	101	12	99	12	103	13

Table 5.2: Average RMSE (Wh) and its standard deviation as the delay D increases for each neurons of neural network with 3 hidden layer

	Number of Neurons, *N*											
	5		10		15		20		25		30	
Delay, *D*	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD
1	115	8	116	8	115	5	115	8	116	7	115	6
3	108	8	107	11	106	9	106	12	104	8	104	12
5	107	9	105	10	102	6	101	7	102	10	101	11
7	105	10	106	7	104	8	105	9	102	10	100	8
9	106	5	103	6	103	8	97	13	98	10	95	13
11	106	6	102	6	101	8	97	10	94	11	92	8
13	103	11	103	11	100	11	102	9	91	13	87	18
15	104	11	106	14	101	12	100	8	**84**	**24**	97	14
17	105	11	105	9	100	14	96	13	96	11	86	18
19	107	12	104	11	100	12	100	9	91	14	95	15
21	107	10	105	12	104	10	94	13	102	12	87	22

Table 5.3: Average RMSE (Wh) and its standard deviation as the delay D increases for each neurons of neural network with 5 hidden layer

	Number of Neurons, *N*											
	5		10		15		20		25		30	
Delay, *D*	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD
1	116	6	116	7	115	6	116	10	115	4	115	5
3	108	10	108	8	104	11	106	9	106	11	104	8
5	107	6	104	9	104	9	103	11	99	13	101	12
7	105	7	106	8	104	9	100	11	103	7	103	11
9	106	6	101	8	99	7	99	8	100	7	104	9
11	106	8	101	9	98	9	98	5	100	10	96	9
13	105	8	101	9	98	10	97	8	102	12	94	13
15	105	10	101	11	92	15	98	14	97	12	95	12
17	102	12	102	9	102	12	92	14	98	12	96	15
19	105	9	99	13	92	13	98	8	100	14	94	10
21	101	12	105	10	94	13	100	12	96	14	**85**	**15**

possible, this process is repeated for all input (temperature, weekdays, and households profiles) and then the acceptable RMSE is chosen.

Note: From this point onwards, the results presented are from MLP-based forecast model with one hidden layer unless otherwise specified. A neural network with one hidden layer is widely accepted in forecasting as discussed in Section 2.6.2.

5.2 IMPROVING THE PERFORMANCE OF MLP-BASED FORECAST MODEL

As mentioned in Chapter 2, factors affecting load forecasting include weather information such as temperature, calendar days such as days of the week, and household demographics such as income, number of household occupants, number of working people and number of children still in school. The next section presents the performance of the neural network, as these inputs are added.

5.2.1 *Adding temperature as input*

With the goal of improving the performance of the forecast model, the temperature inside the houses is added as input. Table 5.4 shows the RMSE results with energy and temperature data as inputs for a neural network with one hidden layer. The lowest average RMSE is 86 Wh with a standard deviation of 8 for a neural network with N = 25 and D = 19. The smallest standard deviation is 4, with average RMSE of 94 Wh for a neural network with N = 10 and D = 21. This is the overall performance of the model for all households in village 2,

Table 5.4: Average RMSE (Wh) and its standard deviation as D increases for each neurons of neural network with 1 hidden layer for energy and temperature data as inputs

	Number of Neurons, *N*											
	5		10		15		20		25		30	
Delay, *D*	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD
1	102	7	103	6	102	7	100	6	101	5	102	7
3	98	7	99	9	98	9	98	7	97	6	100	9
5	96	8	95	8	96	6	97	7	98	8	93	10
7	97	11	96	7	96	8	95	7	95	7	94	8
9	96	6	98	6	94	7	95	8	94	12	96	7
11	95	9	95	8	93	8	91	9	92	6	91	8
13	94	10	94	10	92	11	93	9	91	14	91	14
15	92	10	96	11	92	10	95	8	90	9	91	11
17	96	10	92	10	91	11	95	11	93	8	91	11
19	96	10	95	9	93	9	95	10	**86**	**8**	91	10
21	95	5	94	4	94	5	93	5	91	8	92	7

considering the temperature inside all houses as input. Results show that the performance of the forecast model continues to improve as the number of input increased.

5.2.2 *Adding weekdays as input*

To improve further the performance of the forecast model, the number of weekdays is added as the input of the neural network. Table 5.5 shows the performance of the network for each neuron and delay. The lowest average RMSE is with 88 Wh with a standard deviation of 15 for a neural network with N = 30 and D = 15. The smallest standard deviation is 3, with an average RMSE of 94 Wh for a neural network with N = 5 and D = 21.

5.2.3 *Adding demographic information as input*

This section aims to evaluate the effect of adding the demographic information of each household or the consumer profiles as inputs to the neural network's performance in load forecasting.

An assumption was made that MLP-based load forecast model can perform better when demographic information of the households are considered as inputs.

The demographic information included in the model are:

- HHs total monthly income,
- number of occupants,

Table 5.5: Average RMSE (Wh) as D increases for each neurons of neural network with 1 hidden layer for energy, temperature and weekdays as inputs

	Number of Neurons, *N*											
	5		10		15		20		25		30	
Delay, *D*	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD
1	102	6	105	4	102	8	104	5	102	6	102	5
3	99	8	99	8	97	7	96	5	98	6	93	8
5	96	6	96	10	94	7	96	8	96	11	93	9
7	96	6	97	8	95	8	96	8	93	10	93	9
9	96	6	96	6	95	6	93	8	92	8	91	10
11	96	7	96	6	93	8	92	11	93	11	**88**	**13**
13	96	10	95	10	94	11	93	9	91	14	91	12
15	95	7	95	7	94	10	92	11	92	11	88	15
17	95	10	93	10	93	8	94	8	92	8	91	8
19	95	8	93	9	90	6	92	8	91	9	92	9
21	94	5	94	6	93	7	90	5	91	5	89	10

- number of appliances,
- frequency of using the appliances in a day (in terms of total hours),
- number of children with age less than five years old,
- number of children who are in school, and
- number of HHs member who is working.

The household's total monthly income is selected to be one of the input as income represents the economic status of the household. The number of occupants affects on how the household spend their energy. It is assumed that the larger the family, the more electricity is used. The total number of hours used of the appliance each day gives an idea to the model that this is how long they spend the energy given to them. The children with age less than five are expected to be at home at all time and having the kids at home, means the households need to have some entertainment for them and may use electricity. The number of working members tells the model how many people are inside the house during the day and how many people are away. All this demographic information is considered to be affecting directly or indirectly to energy consumption by using electricity through home appliances as the socio-economic factor in the load forecast model.

By integrating this information, the model has become adaptive to each household.

Table 5.6 shows the average RMSE and the standard deviation for the neural network with HL = 1 for each number of neurons N and delay D. The lowest average RMSE is 85 Wh with a standard deviation

Table 5.6: Average RMSE (Wh) as the delay D increases for each neuron per layer N of neural network with 1 hidden layer HL for energy, temperature and weekdays and the demographic information as inputs

	Number of Neurons, N											
	5		10		15		20		25		30	
Delay, D	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD
1	102	5	102	7	100	7	102	8	101	8	100	7
3	97	6	96	7	95	5	95	6	95	6	95	6
5	95	8	95	8	95	6	93	8	93	9	93	11
7	94	7	94	6	93	7	93	8	92	10	90	10
9	95	7	95	6	91	9	92	10	91	7	91	11
11	94	6	94	7	92	6	94	8	87	10	90	12
13	93	9	93	12	92	10	89	11	92	14	88	12
15	95	7	92	9	91	9	90	10	88	12	92	10
17	94	12	92	9	88	10	91	11	92	9	86	8
19	95	11	93	8	90	8	91	9	91	7	90	15
21	96	5	92	7	93	7	88	7	**85**	**12**	87	14

of 12 for a neural network with N = 25 and D = 21. The smallest standard deviation is 5, with average RMSE of 95 Wh for a neural network with N = 15 and D = 3.

The performance of the model is assessed not only in terms of RMSE but also with the time needed to train the network. Training time for a neural network with one hidden layer HL for the range of neurons per layer N from 5 to 30 and delay D from 1 to 21 is shown in Figure 5.5. Training time increases as the number of neurons per layer N and delays D increases.

5.2.4 *How does the number of hidden layers* HL *affects the performance of the network in load forecasting?*

In this section, the effect of the number of hidden layers to the performance of the neural network in load forecasting is evaluated. To see if the RMSE results vary significantly with the number of hidden layers HL and with all the inputs considered, hidden layer HL was increased from 1 to 3 and then 5. Table 5.7 shows the network's performance with three hidden layers in terms of average RMSE and standard deviation for each number of neurons N, and delay D. The lowest average RMSE is 83 Wh with a standard deviation of 8 for a neural network with N = 25 and D = 21. The smallest standard deviation is 5 for a network with N = 5 for both D = 3 and D = 21 with corresponding average RMSE of 96 Wh and 94 Wh, respectively.

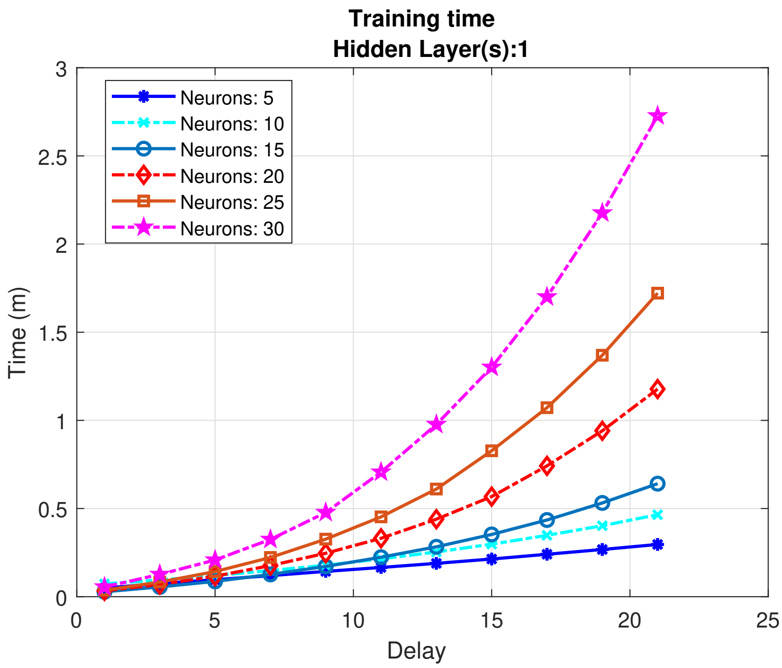


Figure 5.5: Time needed to train the model for each delay, D with the corresponding neurons per layer N for neural network with HL = 1 . X-axis is the range of delay D and Y-axis is the time in minutes m.

Table 5.7: Average RMSE (Wh) as D increases for each number of neurons with 3 hidden layer for energy, temperature, weekdays and the demographic information as inputs

	Number of Neurons, N											
	5		10		15		20		25		30	
Delay, D	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD
1	103	8	101	6	101	8	99	8	101	6	99	7
3	96	5	96	7	94	6	90	9	91	9	92	9
5	93	11	94	10	95	7	93	11	85	13	89	9
7	96	7	91	10	93	10	88	11	89	10	87	15
9	96	6	96	7	93	10	85	18	83	20	88	13
11	93	9	93	12	91	8	93	12	85	17	83	17
13	94	7	92	11	89	16	89	13	87	22	85	16
15	96	11	93	10	88	13	84	13	83	16	83	20
17	94	9	92	9	86	11	85	13	86	7	89	10
19	95	9	92	11	94	13	88	16	86	15	84	17
21	94	5	91	8	88	9	93	8	**83**	**8**	83	20

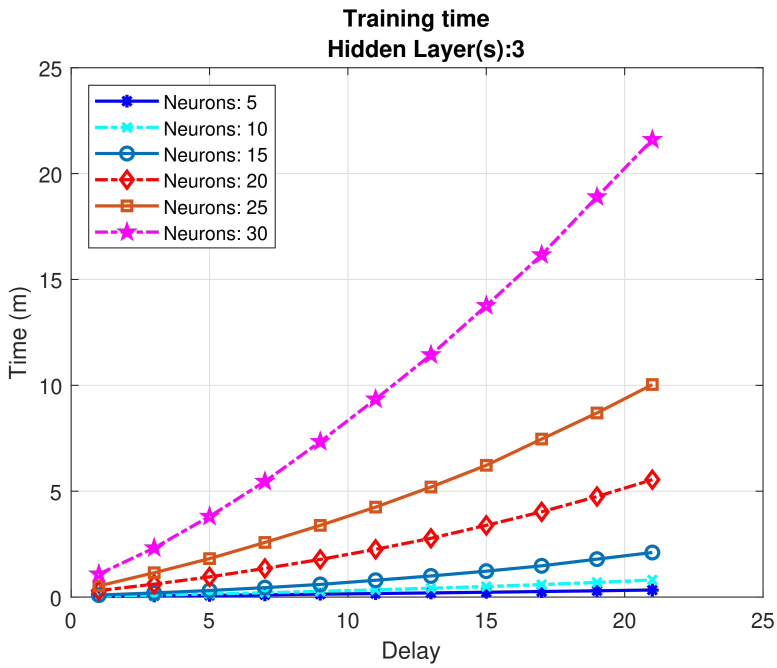


Figure 5.6: Time needed to train the model for each delays, D with the corresponding neurons, N . X-axis is the range of D and Y-axis is the time in minutes, m.

Figure 5.6 the time needed to train the network for each value of neuron for the range of delay D for a network with three hidden layers HL.

For a network with five hidden layers, the tabulated RMSE results are shown in Table 5.8. The lowest RMSE is 80 Wh with a standard deviation of 12 for a neural network with 20 neurons and 21 delays.

Figure 5.7 and Table 5.9 show the time needed to train the network with five hidden layers for each N and range of D. When HL was raised from 3 to 5, training time has increased accordingly.

To understand the effect of hidden layers HL to the performance of the network, the following simulations were conducted. For these simulations, we used HL value from one to five for a neural network with 20 neurons.

As the number of hidden layers of the neural network for the MLP-based forecast model was increased, training time increases proportionally with the number of hidden layers as well as with the number of neurons and the delays.

It was observed from the simulation results that the smallest average RMSE does not have the least standard deviation that makes the selection of the combination of the hidden layers HL, neurons per layer N and delay D even more difficult. The goal is to have the smallest RMSE as possible with the least standard deviation to have a minimum error in prediction using the MLP-based forecast model. From the gathered results of the experiments, there was no instance that the lowest av-

Table 5.8: Average RMSE (Wh) and standard deviation of neural network with 5 hidden layer with energy, temperature, weekdays and the demographic information as inputs for each neuron (N) and delay (D)

	Number of Neurons, N											
	5		10		15		20		25		30	
Delay, D	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD
1	103	8	101	7	101	7	100	7	99	9	97	7
3	97	9	95	9	96	7	94	6	92	6	94	8
5	91	10	95	9	90	9	93	10	89	14	89	10
7	94	9	93	9	89	11	94	7	87	13	86	13
9	97	7	95	9	93	9	92	7	90	11	88	15
11	92	7	96	9	89	16	90	13	94	12	94	10
13	95	7	91	9	86	16	85	14	88	13	92	12
15	93	8	90	13	94	14	85	16	82	20	86	11
17	95	9	91	10	87	11	89	9	91	11	92	14
19	95	9	93	12	89	10	88	9	84	11	93	9
21	94	6	97	4	94	9	**80**	**12**	81	21	95	7

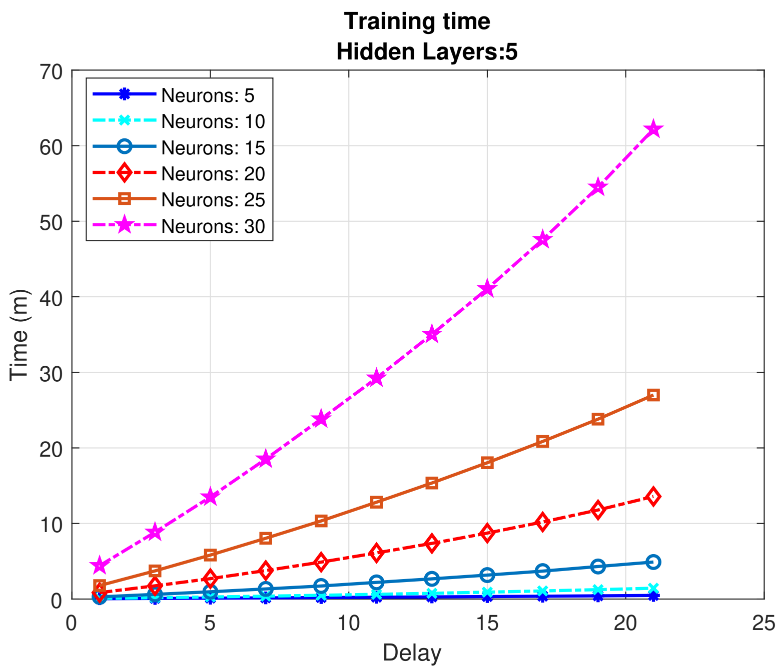


Figure 5.7: Time needed to train the model for each delays, D with the corresponding neurons, N with HL = 5. X-axis is the range of D and Y-axis is the time in minutes, m.

Table 5.9: Training time as the delay D increases for each neurons per layer N of neural network with 5 hidden layer for energy, temperature, weekdays and the demographic information as inputs

	Training time in minutes, T_m					
	Number of neurons, *N*					
Delay, *D*	5	10	15	20	25	30
1	0.04	0.09	0.29	0.85	1.78	4.42
3	0.08	0.18	0.62	1.75	3.73	8.85
5	0.12	0.27	0.96	2.70	5.82	13.50
7	0.16	0.38	1.34	3.77	8.04	18.52
9	0.20	0.50	1.73	4.89	10.34	23.83
11	0.24	0.62	2.20	6.11	12.82	29.24
13	0.28	0.76	2.67	7.37	15.36	35.03
15	0.33	0.91	3.17	8.73	18.04	41.06
17	0.37	1.07	3.70	10.20	20.86	47.56
19	0.42	1.24	4.31	11.79	23.81	54.50
21	0.48	1.43	4.90	13.58	27.00	62.18

Table 5.10: Performance of the NN as D increases for each hidden layer for neural network with N = 20 and with energy, temperature, weekdays and the demographic information as inputs

	Number of hidden layer(s), *HL*									
	1		2		3		4		5	
Delay, *D*	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD	RMSE	SD
1	100	9	100	7	102	8	100	8	100	8
3	93	6	95	8	92	11	93	6	94	7
5	94	7	90	9	92	11	91	10	94	8
7	91	9	94	10	89	12	88	8	87	10
9	92	9	91	11	91	12	92	9	**83**	**16**
11	91	7	85	11	96	17	84	12	85	12
13	93	12	92	11	91	8	87	17	92	10
15	88	11	91	12	89	10	78	23	93	9
17	93	8	87	11	87	16	84	8	90	10
19	91	7	88	7	81	11	87	13	85	13
21	89	7	88	15	90	11	88	9	95	4

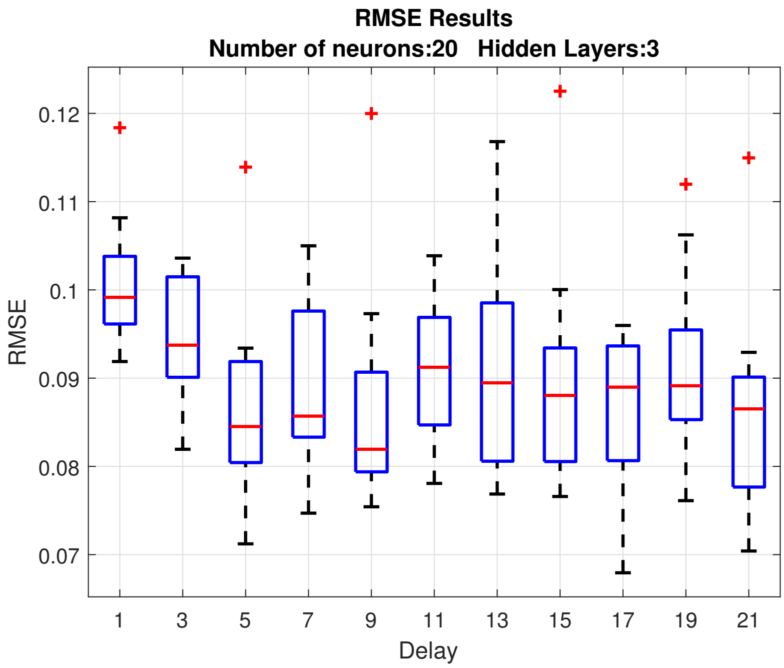


Figure 5.8: RMSE (Wh) values for neural network with 3 hidden layers HL and 20 neurons per layer N for each delay D with energy, temperature, weekdays and the demographic information as inputs.

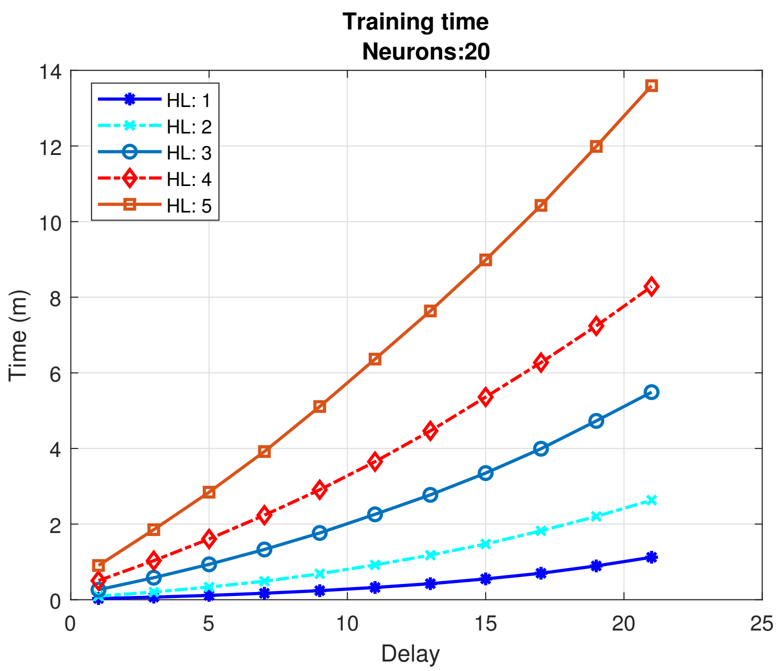


Figure 5.9: Training time for neural network with 20 neurons per layer N and varying hidden layer HL for each delay D with energy, temperature, weekdays and the demographic information as inputs.

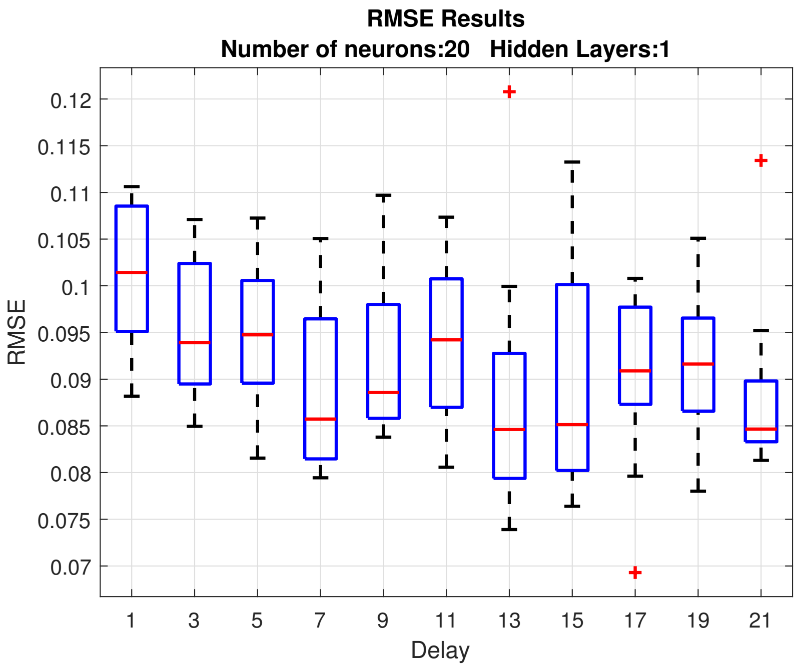


Figure 5.10: RMSE (Wh) values for neural network with 3 hidden layers HL and 20 neurons per layer N for each delay D with energy, temperature, weekdays and the demographic information as inputs.

erage RMSE has the least standard deviation. Results show that the lowest average RMSE sometimes has the largest standard deviation. This made the network undesirable as the forecast model needed to be precise as it can be in forecasting the next-day consumption of the households, hence lowest RMSE with small standard deviation is preferred. Note that the data used for training the forecast model is from September 2016 to December 2018 with 70% for training, 15% for testing and 15% for validation purposes. Finding the best combination of the three parameters which generates the smallest average RMSE with minimum standard deviation needs to be examined thoroughly to ensure the accuracy of the prediction.

5.3 DISCUSSION OF RESULTS

Recall that delay D represents the delay window as presented in Section **??**. From the input shaping and determining the best number of delay D to provide low average RMSE, results show that the delay D affects the performance of the model directly. However, this relationship between the delay D and the RMSE is nonlinear as shown in Figure 5.4 and Figure 5.8. And as for the number of neurons and hidden layers, the effect of these two hyper-parameters to the performance of the neural network in load forecasting is also nonlinear and can be observed in Figure 5.4 and Figure 5.8 as well as from Table 5.1 to Table 5.10.

From the lowest RMSE value in Table 5.1 which is 99 Wh with a standard deviation of 6 (for a neural network with 30 neurons N per layer and delay D of 11), with historical energy data as input, lowest RMSE value goes to 86 Wh with a standard deviation of 8 for a network with 25 neurons N per layer and delay D of 19 (Table 5.4) when households temperature was added as inputs. When calendar information such as weekdays was added as inputs, the lowest RMSE values is 88 Wh with a standard deviation of 13 for a network with 30 neurons per layer and delay D of 11 (Table 5.5). And when the demographic information of the household are added as inputs, the lowest RMSE value is 85 Wh with a standard deviation of 12 from a network with 25 neurons per layer and delay D of 21 (Table 5.6). All these networks have one hidden layer only. From these results, an RMSE of 85 Wh was achieved when the demographic information was added.

To continue to observe the effects of the number of hidden layers HL values is increased from 1 to 3 with the four inputs considered. Results are shown in Section 5.2.4. The performance is improved as the possible lowest RMSE is 83 Wh with a standard deviation of 8 from a network with 25 neurons per layer and delay D of 21. For a neural network with five hidden layers, the lowest RMSE value is 85 Wh with a standard deviation of 15 with 30 neurons per layer and delay D of 21 with energy data as inputs. However, adding the temperature, weekdays and demographic information of the households, the lowest RMSE is down to 80 Wh with a standard deviation of 12 from a neural network with ten neurons per layer and delay D of 21. It can be observed that the average RMSE is decreasing when the number of delay D is less than or equal to 9. This is true for all inputs as seen in Figure 5.4 and Figure 5.8 however RMSE values seem to be unstable when delay D is higher than 10. Several RMSE outliers occur for the range of delay D from 11 to 21. Furthermore, in this range, the standard deviation is bigger than with the lower values of delay D.

The lowest RMSE with the lowest standard deviation is desired as this model can forecast better with small variations in the performance of the network. However, considering the results, the lowest RMSE does not have the lowest standard deviation, which is the ideal preference, and the lowest standard deviation does not have the lowest RMSE. To aid in deciding the proper sizes of the network, the time parameter is considered. The training time is compared for each hidden layer with different neurons per layer N for the range of delay window D. Figures 5.5, 5.6, and 5.7, shows the training time needed to train networks with 1, 3, and 5 hidden layers respectively for each value of neurons per layer and the range of delay D inputs.

It can be observed that the training time takes longer as the delay D increases as well as the values of neurons N per layer and hidden layers HL increases.

Therefore, to maintain a good performance in forecasting, a neural network with 20 neurons per layer N, three hidden layers HL and seven delays D is chosen to be the best network for a load forecast model to generate the lowest RMSE of 81 with a standard deviation of 9 and training time of 24 seconds. Simulation results show that the RMSE values are smaller with demographic information of the households added as input than without it. For the same number of hidden layer HL, neurons N per layer and window delay D, without demographic profile as input, the lowest RMSE result is 128 Wh with a standard deviation of $\pm$ 14.1 and the % error is 20.11 %. When the demographic profile is added, the RMSE value decreased to 81 Wh with a standard deviation of $\pm$ 9 and % error of 13.58 %. The % error improved by 32.47 %. The RMSE of 81 Wh is an acceptable value for this research that is below 15% of the allowable error. As stated earlier, the goal is to develop a forecast model that would generate an RMSE less than 120 Wh or 15 % of the actual energy usage.

Figure 5.11 shows the regression plot of the model that validates the network's performance in forecasting, which exhibits the output of the model for the given data sets for training, validation and test. For the proposed MLP-based model, the regression fit is fairly acceptable with R equal to 0.92, 0.91, and 0.90 for training, validation and test, respectively, with R equal to 0.92 for overall response.

Figure 5.12 shows the actual energy usage and the predicted values using the proposed model from the test data. The data used in this experiment is from Village 2, dated from September 2016 up to December 2018. The performance of the model in terms of RMSE is 93 Wh with a standard deviation of 9. The mean absolute per cent error (MAPE) is 6.2 %. Table 5.11 shows the MAPE and absolute per cent error between the actual energy usage and forecasted energy usage.

The main reason why household profiles are taken into considerations in developing the load forecast model is not only to improve the performance of the network but to make the model adaptive that would enable the model to do village-wide forecast using a single model rather than having one model for each household. This model is expected to work with similar household profiles of Village 2 in forecasting their next-day energy consumption.

Table 5.12 and Figure 5.13 show the performance of the model to forecast for each household load. The highest accuracy is 93.22% for

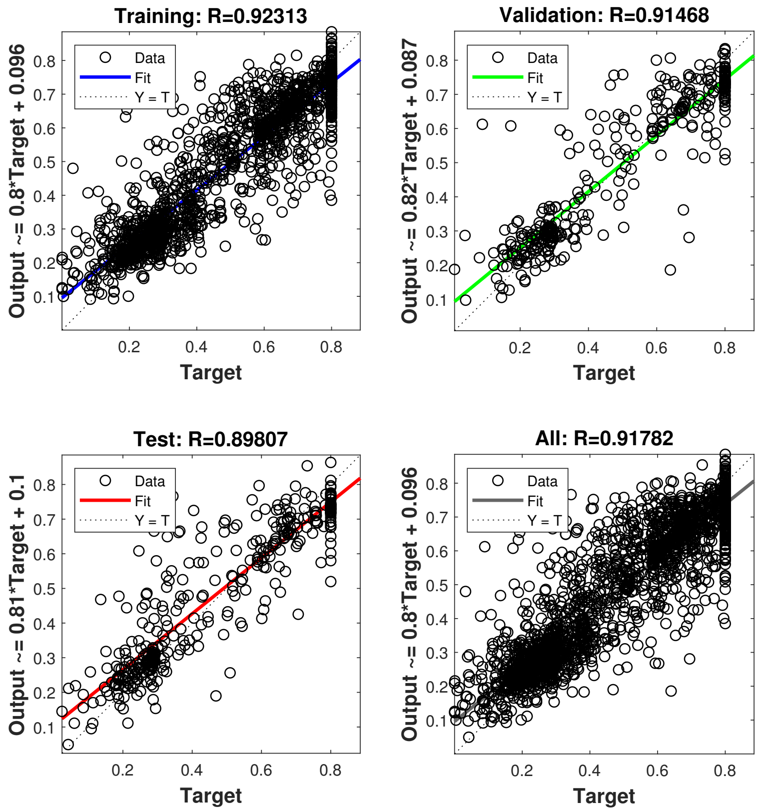


Figure 5.11: Regression plot of the neural network for load forecast model.

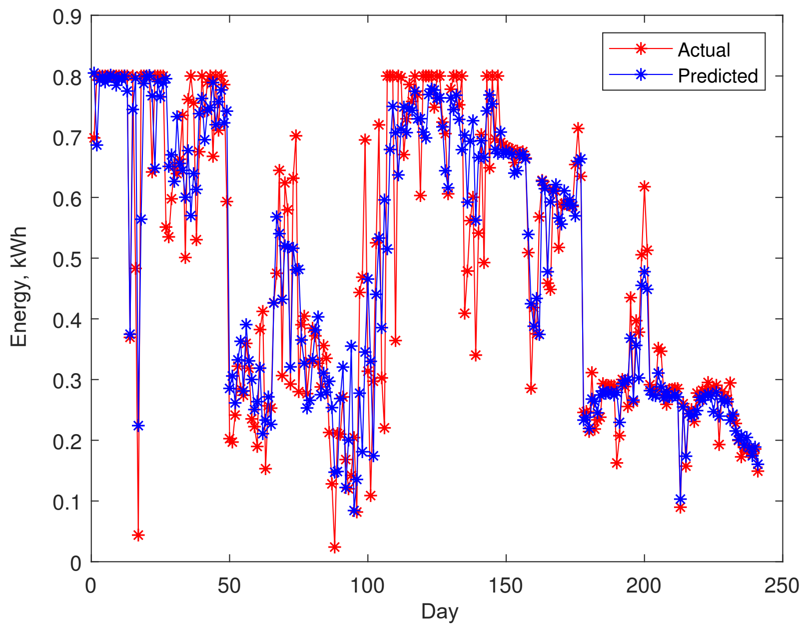


Figure 5.12: MLP-based forecast model performance. The actual energy usage is almost the same with the predicted values with the neural network's MAPE of 6.2 % and RMSE 93 Wh and standard deviation of 90.

Table 5.11: MAPE and absolute percentage error between the actual and forecasted energy usage of the households.

No.	Actual	Predicted	Absolute percent error %	MAPE
1	0.3695	0.3747	0.5255	6.2
2	0.8000	0.7449	5.5130	
3	0.5977	0.6702	7.2436	
4	0.6515	0.6264	2.5083	
5	0.6392	0.7330	9.3832	
6	0.6629	0.6560	0.6902	
7	0.7351	0.6446	9.0556	
8	0.5010	0.6003	9.9298	
9	0.7613	0.6771	8.4213	
10	0.5304	0.6131	8.2791	
11	0.6752	0.7380	6.2812	
12	0.8000	0.7630	3.6984	
13	0.7423	0.6950	4.7251	
14	0.7899	0.7436	4.6375	
15	0.8000	0.7480	5.1960	
16	0.8000	0.7198	8.0227	
17	0.7107	0.7575	4.6820	
18	0.8000	0.7771	2.2945	
19	0.7858	0.7228	6.3018	
20	0.2027	0.2854	8.2730	

Table 5.12: Average forecasting accuracy of the MLP-based load forecast model for households in village 2

House	N	Average accuracy
H5	50	93.2%
H6	50	88.6%
H7	50	90.6%
H8	50	92.5%
Overall	200	91.3%

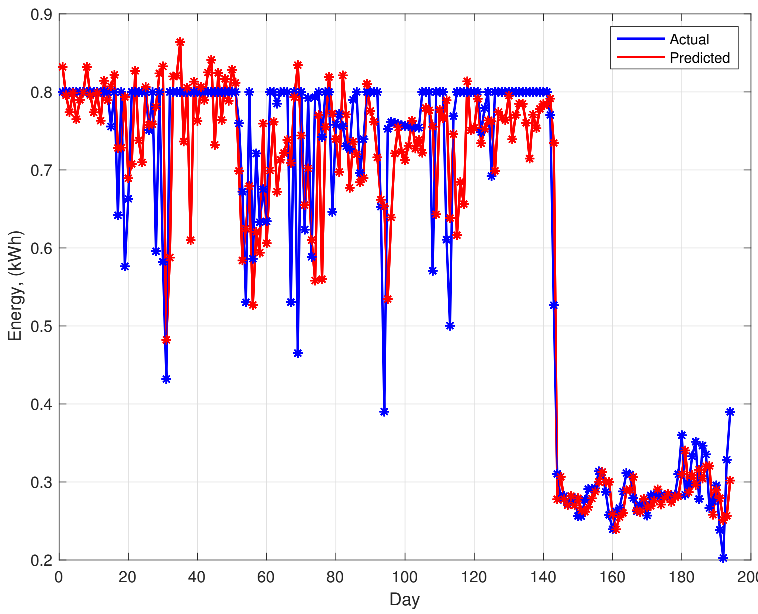


Figure 5.13: Prediction results using MLP-based forecast model

forecasting the energy usage of House 5 H5, and the lowest is 88.6% for House 6 H6. The overall accuracy is 91.3% for forecasting the energy usage of all households.

5.4 EVALUATION AND COMPARISON OF RESULTS

The performance of the proposed MLP-based load forecast model is compared to the existing models using the same data from village 2. Table 5.13 shows the comparison of the neural network architecture and the performance of the model in terms of RMSE.

The lowest RMSE is 77 Wh from the forecast model of Ryu et al. [RNK16] that uses DNN with four hidden layers and 50 neurons. However, this model has a standard deviation of 30, the highest standard deviation amongst the models. This model can forecast the next day energy consumption of the households more accurately than the others. However, the variations are more significant compare to other

Table 5.13: Comparing the performance of the proposed MLP-based load forecast model to the existing models.

Reference	Input Variables	NN	Hidden layer(s)	Neurons	RMSE	Std. Deviation	Training Time (s)
Din and Marnerides [DM17] and Din	Calendar data, weather conditions, historical energy data	RNN	1	20	105	7	62
Ryu et al. [RNK16]	Calendar data, weather conditions, historical energy data weather conditions	DNN	4	50	77	30	1411
This work	Calendar data, weather conditions, historical energy data, household's profile	MLP	3	20	81	9	24

models with lower standard deviation. Moreover, this model takes 1411 s or 23.5 minutes to train the network to learn. A very long time compared to other MLP-based models presented. The work of Din and Marnerides [DM17] is similar to this work. The differences are on the neural network architecture, the former uses RNN with one hidden layer, and the latter uses MLP with three hidden layers, and the input variables considered. This work includes a household's profile aside from the three input variables mentioned in the work of Din and Marnerides. The proposed model offers RMSE of 81 Wh with a standard deviation of 9 compared to the model from the work of Din and Marnerides that generates an RMSE of 105 Wh with a standard deviation of 7. For the training time, the proposed MLP-based forecast model needs 24 s to train the neural network compared to the work of Din and Marnerides that needs 62 s. The training time takes longer as the number of input, and the NN hidden layers increases.

The performance of the network varies with respect to the number of the hidden layers HL, neurons per layer N, and the delay D. Since these parameters influence the performance of the network to forecast the energy usage significantly, the network is trained and evaluated with different data to avoid overfitting and to ensure that the model is working not only with the trained data but also with the new data.

It can be observed that this process can be beneficial in handling big data without performing a specific pre-processing to exclude outliers and still able to get good and acceptable results in forecasting. Since the approach does not require a special process on the data before using it as inputs of the network, makes this method easy to implement.

The MLP-based forecast model presented in this chapter estimated the next day energy consumption of the household within the accepted tolerance, which is 12 % of the current fixed energy allowance that is equivalent to 120 Wh. Since the model is using both historical energy data and household profiles, the model generally estimates the energy consumption of each household. The model is to predict the next-day energy consumption of the households as the inputs were indexed for each profile. The model is then trained to learn the difference between households by the given index for each profile. Hence, when the data is similar to one of the profiles, the model is able to recognise the pattern and predict the next day energy consumption accordingly. Indexing the data through the profiles of the households enables the proposed model to predict the next-day energy consumption of each household without the need of creating another model for each household. For this study, the total number of households profiles is 4, as presented in Chapter 4 Section 4.8. The performance of the model in predicting the next-day usage of the households can be improved further when the number of profiles is increased. Practically, the proposed forecast model with household profile as one of the inputs can predict each household's energy consumption without having special features. The proposed model also shows better performance in terms of RMSE when compared with the other two existing works, as presented in Table 5.13 that use neural networks.

5.5 EXPERIMENTAL RESULTS USING OTHER FORECASTING TECHNIQUES

To assess the overall performance of the MLP-based forecast model, the results were compared with three other existing forecasting techniques such as radial basis function neural network (RBFN), Gaussian progress regression (GPR) and autoregressive integrating moving average (ARIMA).

5.5.1 *Gaussian Process Regression*

For comparison purposes, a Gaussian process regression (GPR) model is also developed to forecast a next-day energy usage of the households in an off-grid community. GPR models are non-parametric probabilistic models.

Matlab GPR tool is used to develop the model for forecasting the next-day energy consumption of the households. The algorithm used in this tool includes estimating the important parameters from the given data such as the covariance function $k(x_i, j_i \div \theta)$, noise covariance, σ^2, vector coefficient of fixed basis function, β. The function 'fitrgp' makes use of the values of the aforementioned parameters to determine the kernel parameters. The vector value of the kernel

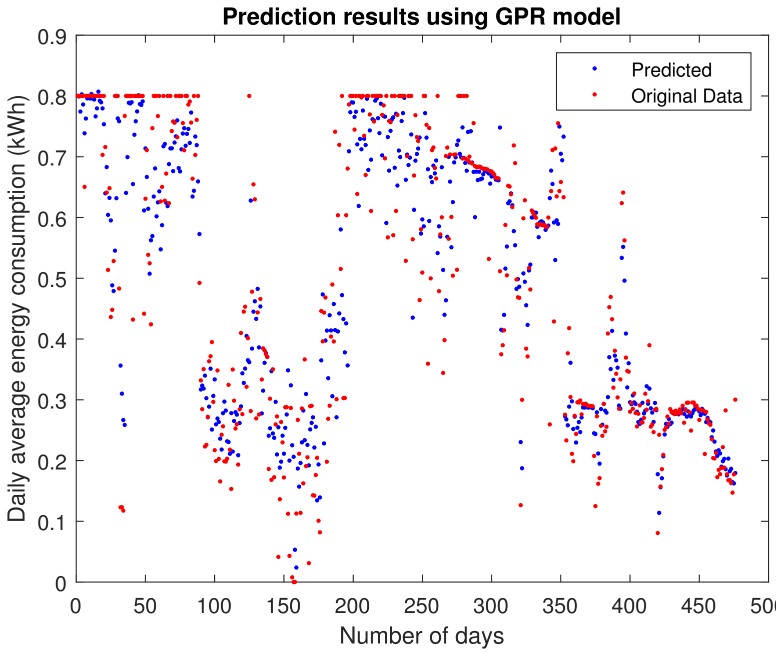


Figure 5.14: Prediction performance of GPR model

parameters argument consists of all the initial values of the data's standard deviation σ_f and the characteristic length scale σ_l.

The performance of the model in terms of RMSE is 97 Wh with a standard deviation of 4.

5.5.2 *Radial basis function neural (RBFN) networks*

Another model is developed for comparison purposes; in this section, the RBFN model is presented. RBFN is one of the simplest forms of neural networks. It consists of 3 layers only: the input layer, a hidden layer, and the output layer. The network has one hidden layer that connects all the neurons from the input layer and the output based on the specific weights specified by the network. Building the RBFN network follows a specific procedure like the feedforward neural networks. The four essential parameters in designing or building the RBFN network considered in this chapter are the initial centroid, the number of neurons, β, and delay.

Training the RBFN network is a bit tricky since in each simulation, the initial values for centroids, neurons, and the beta β need to be initialised. Determining the right combinations of these three hyper-parameters are critical as they dictate the performance of the network in forecasting. Table 5.14 shows the performance of RBFN in terms of RMSE. The lowest RMSE recorded in this simulation is 0.169 kWh with a beta β of 0.001, neurons per layer N of 10, centroid C of 110, and delay D of 3.

Table 5.14: RBFN RMSE Results
($N = 10$, $\beta = 0.001$)

Initial Centroids, C	Delay, d	RMSE (kWH) (Lowest)	Delay, d	RMSE (kWh) (Highest)
20	1	0.224	7	0.275
30	1	0.235	13	0.271
40	1	0.212	7	0.271
50	1	0.181	9	0.270
60	1	0.181	15	0.261
70	2	0.171	8	0.253
80	1	0.172	14	0.249
90	3	0.171	13	0.233
100	2	0.171	12	0.231
110	**3**	**0.169**	14	0.219
120	3	0.172	14	0.217
130	3	0.171	12	0.214
150	3	0.171	13	0.207
200	4	0.171	14	0.196

The performance of the RBFN network is presented in Table 5.14. It can be observed that as the values of beta β are varied and keeping the values for centroids and neurons, the RMSE results either increase or decrease. The beta β controls the range of the variation of the radial function and thus affects the results in a symmetrical manner. The performance of the network depends on the values of the beta β. When the number of neurons is varied while keeping the values of beta β, and centroids C, constant, the performance of the network also varies. Depending on the number of the delay window D, the RMSE is either increased or decreased or both. When the number of centroids C is varied while keeping the values for neurons per layer N, beta β, and the delay D constant, the performance of the network is either increase and decreased. This result is the same when the number of neurons per layer and the beta β are varied. Since the performance of the network does not convey a specific pattern when the parameters are varied, selecting the right combination takes time until all the combinations were considered and simulated. For the RBFN model, the lowest RMSE is selected and compared with the performance of the proposed MLP-based forecast model (Table 5.15).

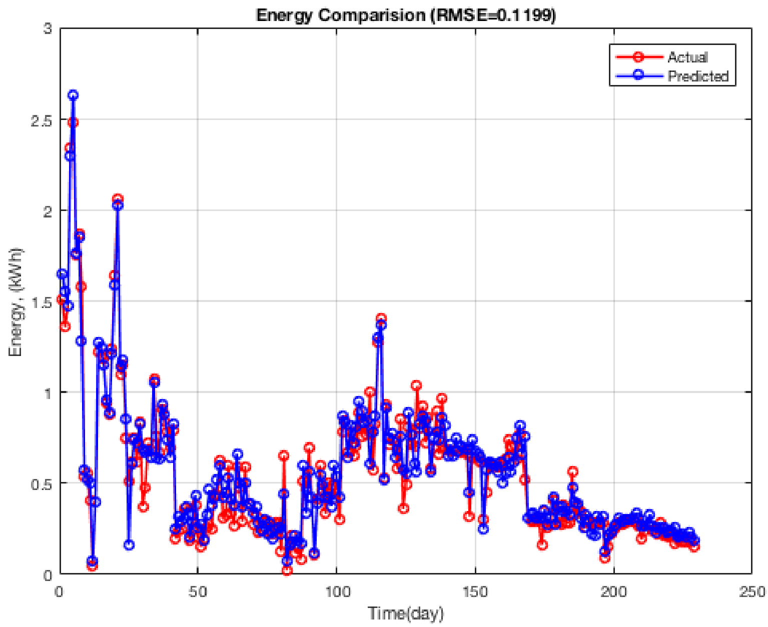


Figure 5.15: Daily predicted values of energy consumption (y-axis)

Table 5.15: Comparison of performance of the forecast model

Techniques	Network size, delays, and model	RMSE (Wh)	SD
MLP	N=20, HL=3, D =7	81	9
RBFN	C=10, D=3, N=10, β=0.001	169	20
GPR	D=7	103	15
ARIMA	p=1, d=0, q=0	120	20

5.5.3 *Autoregressive integrating moving average (ARIMA)*

Another forecasting technique that is popular in load forecasting is ARIMA. The output is determined by averaging the entire data given to the model. Figure 5.15 shows the prediction performance of the ARIMA-based load forecasting with RMSE of 119.9 Wh and a standard deviation of 20.

5.6 Comparison of results

The performance of the proposed model is comparable with the existing model using the available data. From the results shown in Table 5.15, MLP-based model is outperforming the three other techniques in terms of RMSE.

When using MLP-based model forecasting, the model is expected to have an error around 72 Wh to 90 Wh from the actual usage as represented by the RMSE results of 81 Wh with nine a standard deviation. The performance of the other three techniques are comparable however to have an optimal energy allocation, the performance of the forecast model is important thus the lowest RMSE model is preferred which in this case, the MLP-based forecast model.

5.7 CHAPTER SUMMARY

In this chapter, the development of the MLP-based forecast model is presented. The procedure on selecting the value for the three parameters of the network namely the hidden layer HL, the neurons N) and the delay D – the number of the historical data points taken as inputs of the neural network is discussed. The right combination of these three parameters affects the performance of the model directly to forecast the next day energy usage of the households. Thus, in this chapter, a step-by-step process of finding the right combination of the hidden layer HL, number of neurons per layer N and delay D of the neural networks is presented. The range considered in the selection is also explained in details. Careful selection of the values for the three parameters aid the model to have a better prediction as these parameters directly affect the performance of the forecasting model. The model was trained and validated using the data gathered from using PMOG systems, as presented in Chapter 4.

The performance of the MLP-based forecast model was assessed in terms of RMSE and MAPE. Results show that as the input of the network is changed, the RMSE results also change accordingly. The lowest possible RMSE for MLP-based forecast model with historical data as input is 99 Wh, when temperature and weekdays were added as inputs, the lowest values of RMSE are 86 Wh and 88 Wh, respectively. This value goes down to 85 Wh when demographic information was added as input. This shows that the performance of MLP-based forecast model is improved when the demographic information of the households was included as inputs. The final MLP-based forecast model used in this research has 20 neurons, three hidden layers, and seven delays that has 81 Wh RMSE with a standard deviation of 9. This means that the highest possible error would be 89 Wh and the lowest possible error is 72 Wh. This model gives an overall accuracy of 91.3 % with 93.2 % accuracy for House 5 as the highest.

It was hypothesised that the energy consumption of the households could be forecast with reasonable accuracy. From the given results that fall within the threshold set as the allowable error, the hypothesis was answered yes. From the experiment results, the next-day energy consumption of the households can be forecasted within the threshold using MLP-based forecast model employing households profiles as input aside from the historical data, temperature, and weekdays. The RMSE of the proposed model was improved from 128 Wh without household profile as input to 81 Wh with a household profile. The % error is improved by 32.5 %.

The performance of the proposed model is compared with three other existing forecasting techniques such as RBFN, GPR and ARIMA. Compared to the other three models, MLP-based forecast model outperforms RBFN, GPR and ARIMA in terms of RMSE as shown in Table 5.15. The proposed MLP-based forecast model was also compared to two existing works that use the neural network in forecasting. Table 5.13 shows that the proposed MLP-based forecast model outperforms the two other forecast models with the difference in the input sets. The performance of the proposed MLP-based forecast model is better in terms of RMSE and training time.

The forecast model's performance has improved as the consumer profiles were added as inputs together with the historical data. The model's RMSE is less 15%, which successfully achieved the goal. Therefore, the next day energy consumption of the household is forecasted with reasonable accuracy using MLP-based forecast model.

6 OPTIMAL DAILY ENERGY ALLOCATION BASED ON MLP-BASED FORECAST MODEL

This chapter presents the mathematical framework of determining the optimal energy allocation of each household in a community based on their forecasted energy demand. The purpose of determining the optimal energy allocation is to ensure that the utilisation of the available energy is maximised while minimising the energy wastage.

An optimisation is used when a certain variable needs to be minimised or maximised based on known constraints. These constraints are the guiding parameters of the optimisation process. Using Karush-Kuhn-Tucker (KKT) conditions, the function can be minimised when the conditions are met. KKT is one of the optimisation techniques that allow a function to be evaluated with constraints in the forms of equalities and inequalities as shown in the following equations as the general form of optimisation problem:

$$\min_{E \in \mathbb{R}^n} \quad f(E) \tag{6.1}$$

subject to

$$h_i(E) \leqslant 0, i = 1, 2, ..., m \tag{6.2}$$

$$l_j(E) = 0, j = 1, 2, ..., r \tag{6.3}$$

where
$f(E)$ is the objective function to be minimised,
$h_i(E)$ and $l_j(E)$ are the constraints.
The KKT conditions are expressed in the following equations:

$$0 \in \partial f(E) + \sum_{i=1}^{m} \mu_i \partial h_i(E) + \sum_{j=1}^{r} \upsilon_j \partial l_j(E) \tag{6.4}$$

$$\mu_i h_i(E) = 0 \ \forall \, i \tag{6.5}$$

$$h_i(E) \leqslant 0, \quad l_j(E) = 0 \ \forall \, i, \, j \tag{6.6}$$

$$\mu_i \geqslant 0 \ \forall \, i \tag{6.7}$$

where equation 6.4 is the called stationary, equation 6.5 is the complementary slackness, equation 6.6 is the primal feasibility, and equation 6.7 is the dual feasibility. These are the KKT conditions that are vital in solving the optimisation problem. In order to be able to use the KKT approach in solving the optimisation problems, the above conditions must be met. Complementary slackness is the 2nd condition that deals with both primal and dual feasibilities. Complementary slackness states that if the dual variable is greater than zero, then the primal constraint is zero. It also states that if the primal constraint is greater than zero, then the dual variable is zero.

In this research, the aggregated supply from the solar-powered off-grid power systems is considered as constant since the system is using batteries to ensure uninterrupted power source to the households and for simplicity of the calculations. The summation of the proposed optimal energy allocation must be equal to the generated energy by the solar power systems. This is one of the constraints of the optimisation as expressed in equation 6.9. Another constraint considered in the formulation of the optimisation problem is that the proposed energy allocation should be higher or equal to the calculated energy threshold of the households as presented in equation 6.10. The energy threshold ensures that the optimal energy allocation is sufficient for the electricity needs of the households in a day. The constraints for this optimisation problems meet the KKT conditions. Thus KKT approach is used in solving the optimisation problem.

This chapter intends to provide answers to the Research Questions (RQs) 2 and 3:

> ***RQ2: Can knowledge of consumer profiles aid in optimal and adaptive energy allocation?***

> ***RQ3: Can the energy allocation be optimised to improve the energy efficiency under the limited generation capacity?***

Note that for RQ 2, as presented in Chapter 5, knowledge of consumer profiles are used in forecasting the household's energy usage, and the predicted energy usage is used in determining the optimal daily energy allocation of each household. Note also that there is only one load forecast model used in predicting the households next-day energy consumption. The model is adaptive to each household since it uses the historical energy data and the demographic profiles. The optimisation problem is formulated from the issues raised due to the limited generation capacity and the power outage experienced by households as presented in Chapter 4.

6.1 PROBLEM DESCRIPTION

In order to address the above research questions, an optimisation problem is defined. As discussed in chapter 1, two main issues arise within the current existing energy allocation, whereby each household has equal daily energy quota. These issues are re-stated below:

1.) Some households use up the allocated daily quota and experience power outage but may require more energy than what is currently provided to them.

2.) Some households do not use all the allocated energy daily and pay the same fixed monthly tariffs as the households that use all their allocated energy.

The excess energy quotas of the households in scenario 2 can be allocated to the households in scenario 1 and minimise the power outage duration if not eliminated, without increasing the generation capacity of the microgrid.

To address the above issues, a new approach to allocating the daily energy quotas of the household is proposed. This approach involves forecasting the ideal energy usage of the households daily from the historical data first before allocating their optimal energy quotas. The method utilises the forecasted household energy demand from Chapter 4. The approach also considers the limited generation capacity of the microgrid and the basic electricity needs of the households. The proposed approach of allocating the daily energy quota of each household will enable new payment scheme based on their actual usage.

Given the limited generation capacity of the power system, the goal is to minimise the difference between the forecasted energy and the allocated energy. This is to make sure that the allocated energy is as close as possible to the ideal energy demand of the households.

Thus, the optimisation problem is defined to minimise the cost function J as given in equation 6.8 subject to two constraints which are the generation capacity and the minimum threshold energy level for each household.

Note that the ideal demand is the forecasted energy consumption based on the household's historical usage and the households individual profile.

The nonlinear optimisation problem is expressed in the differentiable standard form in equation 6.8,

$$\min J = \sum_{i=1}^{n} (E_i^a - E_i)^2 \tag{6.8}$$

subject to

$$\sum_{i=1}^{n} E_i^a = E_G \tag{6.9}$$

$$E_i^a \geqslant E_{min}, \ \forall\, i \in \{1, 2, ..., n\} \tag{6.10}$$

where

E_i^a is the calculated optimal energy allocation for each household, which is the optimisation variable,

E_i is the ideal energy usage as predicted by the MLP-based forecast model,

E_G is the generated supply by the off-grid power system,

n is the total number of households, and

E_{min} is the daily energy threshold for each household.

Equation (6.8) is the objective function, while equations (6.9) and (6.10) are the equality and inequality constraints (Note that other power losses are neglected). The presence of the inequality constraint allows the optimisation problem to be solved using Karush-Kuhn-Tucker (KKT) conditions.

6.1.1 *Solving the optimisation problem using KKT approach*

In this section, the mathematical analysis of the optimal energy allocation is presented. The methodology for obtaining the optimal energy allocation for each household is derived by solving the optimisation problem presented in the previous section considering the given constraints. The optimal solution is derived by solving the equations analytically using the first-order optimality conditions. Using KKT methods, the equality and inequality equations are expressed in the standard forms $g(x) = 0$ and $h(x) \leqslant 0$, respectively. So, equations 6.9 and 6.10 can be written as

$$\sum_{i=1}^{n} E_i^a - E_G = 0 \tag{6.11}$$

$$E_{min} - E_i^a \leqslant 0, \ \forall\, i \in \{1, 2, ..., n\} \tag{6.12}$$

Given the minimisation problem in equation (6.8), the Langrangian function, L is defined by combining the three equations, (6.8), (6.11), and (6.12) in the form of

$$L = f(x) + \sum_i \lambda_i g_i(x) + \sum_j \mu_j h_j(x) \tag{6.13}$$

which results in:

$$L = \sum_{i=1}^{n} (E_i^a - E_1)^2 + \lambda(\sum_{i=1}^{n} E_i^a - E_G) + \sum_{i=1}^{n} \mu_i (E_{min} - E_i^a) \quad (6.14)$$

where

$$\mu_i \geqslant 0, \; \forall \; i \; \in \; \{1, 2, ..., n\} \quad (6.15)$$

The optimality conditions are obtained by taking the partial derivative of the Lagrangian (equation 6.14) with respect to E_i^a as follows:

$$\frac{\partial L}{\partial E_i^a} = 0$$
$$2(E_i^a - E_i) + \lambda - \mu_i = 0 \quad (6.16)$$

and the partial derivative of the Langrangian with respect to λ,

$$\frac{\partial L}{\partial \lambda} = 0$$
$$\sum_{i=1}^{n} E_i^a - E_G = 0 \quad (6.17)$$

The complementary slackness is given as follows:

$$\mu_i (E_{min} - E_i^a) = 0, \; \forall \; i \; \in \; \{1, 2, ..., n\} \quad (6.18)$$

which implies that either

$$E_{min} < E_i^a \text{ and } \mu_i = 0 \quad (6.19)$$

or

$$E_{min} = E_i^a \text{ and } \mu_i > 0 \quad (6.20)$$

In order to solve the systems of equations given in equation 6.16 and 6.17, let

$$s := \arg \min_i \; E_i$$

That is, s is the index used to identify the households with the smallest amount of predicted ideal demand and (E_{min}) is the minimum energy to be allocated to the households without compromising their basic

electricity needs.
From equation (6.14), for $i = s$, the following is obtained:

$$\begin{aligned} 2(E_s^a - E_s) + \lambda - \mu_s &= 0 \\ \lambda &= \mu_s + 2(E_s - E_s^a) \end{aligned} \tag{6.21}$$

The expression for the optimal energy allocation for each household is obtained as follows:
$\forall j = 1, 2, ..., n; j \neq s$,

$$2(E_j^a - E_j) + \lambda - \mu_j = 0 \tag{6.22}$$

Substituting equation 6.21 into 6.22 gives:

$$2(E_j^a - E_j) + \mu_s + 2(E_s - E_s^a) - \mu_j = 0$$

so that,

$$E_j^a = \frac{\mu_j - \mu_s}{2} - (E_s - E_s^a) + E_j \tag{6.23}$$

On the other hand, from equation 6.17, the aggregate optimal energy allocation, $\sum_{i=1}^{n} E_i^a$ can now be expressed in terms of s and j as follows:

$$\sum_{i=1}^{n} E_i^a = E_s^a + \sum_{j=1, j\neq s}^{n} E_j^a = E_G \tag{6.24}$$

Then E_s^a by substituting equation 6.23 into 6.24, the following is obtained:

$$E_s^a + \sum_{j=1}^{n}\left(\frac{\mu_j - \mu_s}{2} - (E_s - E_s^a) + E_j\right) = E_G \tag{6.25}$$

$$E_s^a + \sum_{j=1, j\neq s}^{n} \frac{\mu_j - \mu_s}{2} - \sum_{j=1, j\neq s}^{n} (E_s - E_s^a) + \sum_{j=1, j\neq s}^{n} E_j = E_G \tag{6.26}$$

$$E_s^a + \sum_{j=1, j\neq s}^{n} \frac{\mu_j - \mu_s}{2} - (n-1)(E_s - E_s^a) + \sum_{j=1, j\neq s}^{n} E_j = E_G \tag{6.27}$$

So,

$$E_s^a = \frac{E_G - \sum_{j=1, j\neq s}^{n} E_j - \sum_{j=1, j\neq s}^{n} \frac{\mu_j - \mu_s}{2} + (n-1)E_s}{n} \tag{6.28}$$

or expressed as

$$E_s^a = \frac{1}{n}\left(E_G - \sum_{j=1,j\neq s}^{n} E_j - \sum_{j=1,j\neq s}^{n} \frac{\mu_j - \mu_s}{2} + (n-1)E_s\right) \tag{6.29}$$

From equation 6.18, the complementary slackness,

$$\mu_i(E_{min} - E_i^a) = 0, \ \forall i \tag{6.30}$$

for $i = s$,

$$\mu_s(E_{min} - E_s^a) = 0 \tag{6.31}$$

In order that the minimum energy, E_{min} is allocated to the household with the smallest ideal energy demand, let

$$E_{min} = E_i^a \tag{6.32}$$

This implies from equation 6.19 and 6.20, the complimentary slackness, that

$$\mu_s \neq 0 \tag{6.33}$$

This also implies that the minimum energy allocation to any household does not fall below E_s^a, i.e., what is allocated to the household with the smallest ideal energy demand E_s amongst all households. Moreover, since the remaining households must be allocated with energy higher than the household with the smallest ideal demand, it follows that

$$E_j^a > E_s^a, \ \forall j \ \in \{1, 2, ..., n\}, j \neq s \tag{6.34}$$

resulting in

$$E_j^a > E_{min}, \ \forall j \ \in \{1, 2, ..., n\}, j \neq s \tag{6.35}$$

since $E_s^a = E_{min}$. Therefore, $\mu_j = 0, \ \forall j \ \in \{1, 2, ..., n\}, j \neq s$ as given in equation 6.19

Thus, to find the optimal energy allocations for all other households $\forall j \ \in \{1, 2, ..., n\}, j \neq s$, let $\mu_j = 0$, and from equation 6.29

$$E_s^a = \frac{1}{n}\left(E_G - \sum_{j=1,j\neq s}^{n} E_j - \sum_{j=1,j\neq s}^{n} \frac{\mu_j - \mu_s}{2} + (n-1)E_s\right)$$

becomes

$$E_s^a = \frac{1}{n}\left(E_G - \sum_{j=1, j\neq s}^{n} E_j + \frac{(n-1)\mu_s}{2} + (n-1)E_s\right) \tag{6.36}$$

Since $E_s^a = E_{min}$, equation 6.36 can be rewritten as:

$$E_{min} = \frac{1}{n}\left(E_G - \sum_{j=1, j\neq s}^{n} E_j + \frac{(n-1)\mu_s}{2} + (n-1)E_s\right)$$

so that:

$$\mu_s = \frac{2}{n-1}\left(nE_{min} - E_G + \sum_{j=1, j\neq s}^{n} E_j - (n-1)E_s\right) \tag{6.37}$$

From equation 6.23,

$$E_j^a = \frac{\mu_j - \mu_s}{2} - (E_s - E_s^a) + E_j$$

thus for $\mu_j = 0$, $\forall j \in \{1, 2, \ldots, n\}, j \neq s$, the following is obtained: we have,

$$E_j^a = \frac{-\mu_s}{2} + (E_s^a - E_s) + E_j \tag{6.38}$$

6.1.2 *Steps in solving the optimal energy allocation*

From the derived equations above, to obtain the optimal energy allocations, we need to:

1. Choose a minimum energy allocation E_{min}
2. Let $E_s^a = E_{min}$
3. Compute μ_s from equation (6.37)
4. Determine optimal allocation for each household using equation (6.38)

6.1.3 *Verification of the optimal solution*

Recall from equation 6.33 that $\mu_s \neq 0$. However, to satisfy the complementary slackness condition given in equations 6.18 and 6.20, μ_s must be shown to be greater than zero, i.e., ($\mu_s > 0$) according to equation 6.15. Note that the complementary slackness captures 2 things in the solving the optimal value of the optimisation process. One, it states that when E_{min} is less than E_i^a, μ must be equal to zero. Two, when E_{min} is equal to E_i^a, μ must be greater than zero. So, from equation (6.37), it follows that:

$$\begin{aligned}\frac{2}{n-1}(nE_{min} - E_G + \sum_{j-1,j\neq s}^{n} E_j - (n-1)E_s) &> 0 \\ nE_{min} - E_G + \sum_{j=1,j\neq s}^{n} E_j - (n-1)E_s &> 0\end{aligned} \tag{6.39}$$

Solving for E_{min} yields:

$$\begin{aligned}nE_{min} &> E_G + (n-1)E_s - \sum_{j=1,j\neq s}^{n} E_j \\ E_{min} &> \frac{1}{n}\left(E_G + (n-1)E_s - \sum_{j=1,j\neq s}^{n} E_j\right)\end{aligned} \tag{6.40}$$

Moreover, from equation (6.12), $E_{min} \leqslant E_i^a$, $\forall i \in \{1, 2, \ldots, n\}$. For $i = s$, $E_s^a = E_{min}$,

$$E_{min} < E_i^a,\ \forall i \in \{1, ..., n\}, i \neq s \tag{6.41}$$

Therefore, by substituting equation 6.38 into 6.41, the following is obtained:

$$\begin{aligned}E_j + (E_s^a - E_s) - \frac{\mu_s}{2} &> E_{min} \\ E_j - E_s - \frac{\mu_s}{2} + E_s^a &> E_{min}\end{aligned} \tag{6.42}$$

but $E_s^a = E_{min}$, therefore,

$$\begin{aligned}E_j - E_s - \frac{\mu_s}{2} + E_{min} &> E_{min} \\ E_j - E_s - \frac{\mu_s}{2} &> 0\end{aligned} \tag{6.43}$$

Thus,

$$\mu_s < 2(E_j - E_s), \forall_j \in \{1, 2, \ldots, n\}, j \neq s \tag{6.44}$$

Substituting equation (6.37) into equation (6.44), to obtain an upper bound for E_{min}, we have

$$\left(nE_{min} - E_G + \sum_{j=1,j\neq s}^{n} E_j - (n-1)E_s\right)\frac{2}{n-1} < 2(E_i - E_s),$$
$$\forall i \in \{1,2,\ldots,n\}$$
$$nE_{min} - E_G + \sum_{j=1,j\neq s}^{n} E_j - (n-1)E_s < (n-1)(E_i - E_s)$$
$$nE_{min} - E_G + \sum_{j=1,j\neq s}^{n} E_j < (n-1)E_i \tag{6.45}$$

thus, for any j

$$E_{min} < \frac{(n-1)E_i + E_G - \sum_{j=1,j\neq s}^{n} E_j}{n}, \forall i \in \{1,2,\ldots,n\}, i \neq s \tag{6.46}$$

Let

$$l = \arg \min_{i\in\{1,2,\ldots,n\},i\neq s} E_i,$$

(Note: l is defined as the index of the household with the second smallest ideal energy demand E_i, after household s.)

then, it suffices to write the set of $(n-1)$ equation in 6.46 as:

$$E_{min} < \frac{1}{n}\left((n-1)E_l + E_G - \sum_{j=1,j\neq s}^{n} E_j\right)$$

Also, recall from equation 6.40 that

$$E_{min} > \frac{1}{n}\left(E_G + (n-1)E_s - \sum_{i=1,i\neq s}^{n} E_i\right)$$

Therefore, the minimum energy allocation to the household should be within the range as expressed by the inequality in 6.47 below:

$$E_G + (n-1)E_s - \sum_{j=1,j\neq s}^{n} E_j < nE_{min} < (n-1)E_l + E_G - \sum_{j=1,j\neq s}^{n} E_j \tag{6.47}$$

6.1.4 *Validating the optimisation results using the forecasted results*

In the previous section, the mathematical framework of the optimisation of energy allocation for each household is presented. Now, the equations derived from the objective function of the optimisation will be used to determine the optimal energy allocation of each household in the generation-constrained microgrids. Firstly, an example of how the equation works is presented.

Consider the following energy consumption values predicted by the MLP-based forecast model for the four selected households connected to the microgrid. These values represent the ideal utilisation of the four houses.

$$E_1 = 0.7845 \text{ kWh}$$

$$E_2 = 0.5075 \text{ kWh}$$

$$E_3 = 0.6394 \text{ kWh}$$

$$E_4 = 0.2914 \text{ kWh}$$

For these 4 houses, the total energy allocation is 3.2 kWh and the smallest forecasted energy usage is $E_4 = 0.2914$ kWh, i.e., $s = 4$, with the second lowest forecasted energy usage being $E_2 = 0.5075$ kWh i.e., $l = 2$, and the summation of the forecasted energy usage excluding E_4 is

$$\sum_{j=1, j\neq s}^{n} E_j = 1.9314 \text{ kWh}.$$

From the steps presented in section 6.1.1, in which the first step is to choose the minimum energy allocation E_{min}. However from equation 6.47, the value of E_s, which is the smallest amount of the predicted ideal demand, must be known before the range for the E_{min} is determined. So, from equation 6.47, the range of E_{min} is determined as follows:

$$\begin{gathered}
E_G + (n-1)E_s - \sum_{j=1, j\neq s}^{n} E_j < nE_{min} < (n-1)E_l + E_G - \sum_{j=1, j\neq s}^{n} E_j \\
\left(3.2 + 3(0.2914) - 1.9314\right)\frac{1}{4} < E_{min} < \frac{1}{4}\left(3(0.5075) + 3.2 - 1.9314\right) \\
0.5402 < E_{min} < 0.7023 \text{ kWh}
\end{gathered} \tag{6.48}$$

The value for E_{min} is chosen within the calculated range as shown above. This means that within this calculated range using equation 6.47, the E_{min} can be chosen arbitrarily and it will lead to the optimal solution. For example, E_{min} is arbitrarily chosen as 0.55 kWh, which is closed to the lower limit as calculated above (equation 6.48). By virtue of the steps described in Section 6.1.2, E_{min} is set equal to E_s^a which means,

$$E_4^a = 0.55 \text{ kWh}.$$

Then, the term μ_s is calculated using equation 6.37:

$$\begin{aligned}
\mu_s &= \frac{2}{n-1}\left(nE_{min} - E_G + \sum_{j=1, j\neq s}^{n} E_j - (n-1)E_s\right) \\
\mu_4 &= \frac{2}{4-1}\left(4(0.55) - 3.2 + 1.9314 - 3(0.2914)\right) \\
\mu_4 &= 0.0381
\end{aligned} \tag{6.49}$$

which satisfy the condition stated in equation 6.44 that μ_s must be less than twice the difference between E_j and E_s as also shown below:

$$\mu_s < 2(E_j - E_s), \forall_j \in \{1, 2, \ldots, n\}, j \neq s$$

For E_1,

$$\begin{aligned}
\mu_s &< 2(E_1 - E_s) \\
\mu_s &< 2(0.7845 - 0.2914) \\
0.0381 &< 0.9862, \text{check}
\end{aligned}$$

For E_2,

$$\begin{aligned}
\mu_s &< 2(E_2 - E_s) \\
\mu_s &< 2(0.5075 - 0.2914) \\
0.0381 &< 0.4322, \text{check}
\end{aligned}$$

For E_3,

$$\begin{aligned}
\mu_s &< 2(E_3 - E_s) \\
\mu_s &< 2(0.6394 - 0.2914) \\
0.0381 &< 0.6960, \text{check}
\end{aligned}$$

Then the optimal energy allocation for the remaining households is calculated using equation 6.38

$$\begin{aligned}
E_j^a &= \frac{-\mu_s}{2} + (E_s^a - E_s) + E_j \\
E_1^a &= \frac{-0.0381}{2} + (0.55 - 0.2914) + 0.7845 \\
E_1^a &= 1.0240 \text{ kWh}
\end{aligned} \tag{6.50}$$

$$\begin{aligned} E_2^a &= \frac{-0.0381}{2} + (0.55 - 0.2914) + 0.5075 \\ E_2^a &= 0.7470 \text{ kWh} \end{aligned} \tag{6.51}$$

$$\begin{aligned} E_3^a &= \frac{-0.0381}{2} + (0.55 - 0.2914) + 0.6394 \\ E_3^a &= 0.8790 \text{ kWh} \end{aligned} \tag{6.52}$$

To check if the results satisfy the constraints of the optimisation problem stated in section 6.1 given by the equations 6.9 and 6.10, the summation of optimal energy allocations is calculated and each allocation is compared to the minimum energy threshold for the households. The summation ($\sum_{i=1}^{n} E_i^a = E_G$) of all the optimal energy allocation is 3.2 kWh which satisfies the first constraint. The optimal energy allocation for each household E_i^a is higher than the minimum energy threshold of E_{min}, which satisfies the second constraint. For this first example of the optimal energy allocation, the objective function J evaluates 0.2390 kWh using the optimal energy allocation compared to 0.3703 kWh for the equal energy allocation which corresponds to a reduction of 54.9% in terms of wastage of energy.

6.1.5 *Energy threshold and its effect on the optimal energy allocation*

Suppose now, the value of E_{min} is chosen arbitrarily as 0.69, which closer to the upper limit. From equation 6.37, μ_s is

$$\begin{aligned} \mu_s &= \frac{2}{n-1}\left(nE_{min} - E_G + \sum_{j=1, j\neq s}^{n} E_j - (n-1)E_s\right) \\ \mu_4 &= \frac{2}{4-1}\Big(4(0.69) - 3.2 + 1.9314 - 3(0.2914)\Big) \\ \mu_4 &= 0.4115 \end{aligned} \tag{6.53}$$

So, the optimal energy allocation for the remaining households is calculated using equation 6.38

$$\begin{aligned} E_j^a &= \frac{-\mu_s}{2} + (E_s^a - E_s) + E_j \\ E_1^a &= \frac{-0.4115}{2} + (0.69 - 0.2914) + 0.7845 \\ E_1^a &= 0.9773 \text{ kWh} \end{aligned} \tag{6.54}$$

$$\begin{aligned} E_2^a &= \frac{-0.4115}{2} + (0.69 - 0.2914) + 0.5075 \\ E_2^a &= 0.7003 \text{ kWh} \end{aligned} \tag{6.55}$$

$$\begin{aligned} E_3^a &= \frac{-0.4115}{2} + (0.69 - 0.2914) + 0.6394 \\ E_3^a &= 0.8322 \text{ kWh} \end{aligned} \tag{6.56}$$

For this example, the summation of the optimal energy allocation is 3.1998 kWh which is approximately 3.2 kWh which satisfies the first constraint like the example 1. Each allocation for each household is greater than the minimum threshold (E_{min}) that is chosen from the calculated range given by the equation 6.47. The objective function J is equal to 0.2704 and when compared with equal allocation, a 36.9% reduction of energy waste is achieved with the proposed optimal energy allocation.

For the next example, E_{min} is chosen from the middle of the range. This time, E_{min} is 0.62 kWh. The examples shown above reflects how the minimum threshold for the energy consumption of households affects the total energy wastage. When the chosen value for energy threshold E_{min} is closer to the lower limit of equation 6.47, the reduction of the energy waste in terms of unused energy or deficit is higher compared when E_{min} is closer to the upper limit. For this reason, the value for the energy threshold E_{min} closer to the lower limit is preferred when choosing the energy threshold in order to maximise the energy usage of the available energy.

Intuitively, one may use ratio and proportion to allocate the available energy. The households can be given energy proportional to their ideal utilisation as predicted by MLP-based load forecast model. For example, given the predicted values in Section 6.1.4 and re-stated here, then according to ratio and proportion, the energy allocation for each household can be calculated as follows:

$$E_i^a = \frac{E_i}{E_T} \times E_G \tag{6.57}$$

where,
E_T is the summation of the ideal energy usage of the households.
E_G is the generated energy by the off-grid microgrid.

Ideal values:

$$E_1 = 0.7845 \text{ kWh}$$

$$E_2 = 0.5075 \text{ kWh}$$

$$E_3 = 0.6394 \text{ kWh}$$

$$E_4 = 0.2914 \text{ kWh}$$

Then, the energy allocation for each household can be calculated using equation 6.57 as follows:

$$E_T = E_1 + E_2 + E_3 + E_4 = 2.2228 \text{ kWh} \tag{6.58}$$

$$E_G = 3.2\text{kWh} \tag{6.59}$$

$$\begin{aligned} E_1^a &= \frac{E_1}{E_T} \times E_G \\ &= \frac{0.7845}{2.2228} \times 3.2 \\ E_1^a &= 1.1294 \text{ kWh} \end{aligned} \tag{6.60}$$

$$\begin{aligned} E_2^a &= \frac{E_2}{E_T} \times E_G \\ &= \frac{0.5075}{2.2228} \times 3.2 \\ E_2^a &= 0.7306 \text{ kWh} \end{aligned} \tag{6.61}$$

$$\begin{aligned} E_3^a &= \frac{E_3}{E_T} \times E_G \\ &= \frac{0.6394}{2.2228} \times 3.2 \\ E_3^a &= 0.9205 \text{ kWh} \end{aligned} \tag{6.62}$$

$$\begin{aligned} E_4^a &= \frac{E_4}{E_T} \times E_G \\ &= \frac{0.2914}{2.2228} \times 3.2 \\ E_4^a &= 0.4195 \text{ kWh} \end{aligned} \tag{6.63}$$

For this example, J is 0.26 using ratio and proportion. Using the proportionality method can be straight forward. However, this method does not consider the constraints that are important when dealing with an optimisation problem. Thus, this method is not used in solving the optimisation problem defined in this chapter (Section 6.1).

6.2 DISCUSSION OF RESULTS

In this section, the answers to the research questions are presented. Using the formulated equations from the previous sections, the optimal energy allocation for each household is calculated. The performance of the proposed optimal energy allocation is evaluated using performance evaluation indices such as root-mean-squared error (RMSE), mean absolute percentage error (MAPE), and mean squared error (MSE). Also, to determine whether the differences in the proposed optimal energy allocation between households are statistically significant, one-way analysis of variance (ANOVA) was performed.

Table 6.1: Descriptive summary of the proposed optimal daily energy allocation (kWh) for each household in Village 2

Household	N	Mean (kWh)	Standard Deviation	Standard Error	Min	Max
H5	288	0.951	0.130	0.008	0.326	1.153
H6	288	0.770	0.165	0.010	0.454	1.104
H7	288	0.936	0.073	0.004	0.506	1.123
H8	288	0.536	0.091	0.005	0.390	0.820
Total	1152	0.798	0.115	0.007	0.419	1.050

6.2.1 *Optimal and adaptive energy allocation: consumer profiles*

RQ2: Can knowledge of consumer profiles aid in optimal and adaptive energy allocation?

In order to show that the consumer profile aids the optimal energy allocation, it needs to be established that the different households are allocated with different daily energy over several days (>180 days). Figure 6.1 shows the daily energy allocation of each household for 288 days. The mean values are 0.9513 kWh, 0.7698 kWh, 0.9362 kWh, and 0.5360 kWh for H5, H6, H7 and H8, respectively. Table 6.1 show the descriptive summary of the proposed optimal energy allocation. H5 has the highest mean, followed by H7 and H6 with H8 having the lowest mean. This confirms the summary of data presented in Section 4.5, wherein Village 2, H5 has the highest peak from the daily energy usage, and H8 has the lowest. According to the ANOVA test results, the significance value (p–value) is 2.98×10^{-268} which is below 0.05 and therefore, there is a statistically significant difference in the means of the optimal energy allocations for each household. This rejects the null hypothesis that the means for each household are the same. The difference in means, as shown in Figure 6.1 is because the household information was used in forecast model to obtain the ideal energy utilisation of the households which are then used for the allocation.

To know specifically which households optimal energy allocations are different from which households, a t-test was performed. Table 6.2 shows the results of the t-test for each pair. Results show that the difference in means is statistically significant for all household except for H5 and H7 where the p–value is 0.1134.

The p–value also suggests that the proposed energy allocation used well the information given and that using the households profiles as inputs aid in deriving an optimal and adaptive energy allocation.

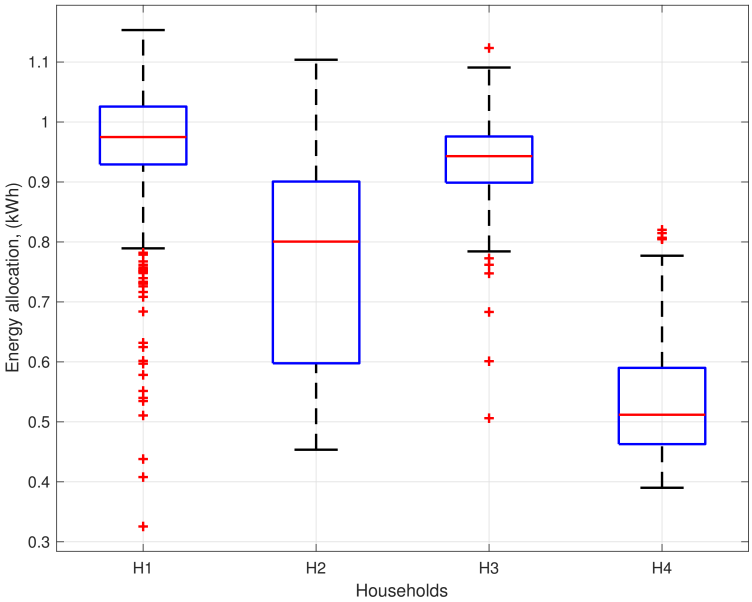


Figure 6.1: Daily energy allocation for each household using the proposed optimal energy allocation scheme for 288 days with mean values of 0.9513 kWh, 0.7698 kWh, 0.9362 kWh, and 0.5360 kWh for H5, H6, H7 and H8, respectively

Table 6.2: Multiple comparisons of the mean of the proposed optimal energy allocations for each household

Group (A)	Group (B)	Mean Difference (A-B), (kWh)	Standard Error	$p-value$
H5	H6	0.181	0.016	1.470×10^{-24}**
	H7	0.015	0.010	0.113
	H8	0.415	0.009	9.170×10^{-132}**
H6	H7	−0.166	0.012	3.050×10^{-35}**
	H8	0.234	0.014	4.240×10^{-46}**
H8	H7	0.400	0.007	3.130×10^{-161}**

** The mean difference is significant at the 0.01 level.

6.2.2 *Energy efficiency under the limited generation capacity*

RQ3: Can the energy allocation be optimised to improve the energy efficiency under the limited generation capacity?

This section provides the answers to the RQ3. In order to show that the energy allocation can be optimised, it needs to be established that the proposed optimal allocation achieves a statistically significant error (in terms of of the objective function) than the equal allocation or with the proportional allocation method. This error corresponds to the energy wastage. Analysis of Variance (ANOVA) is used to determine the difference between the three methods. ANOVA compares the means of the groups and determines whether the means are statistically different from each other, as discussed in Section 3.3.1. ANOVA test the null hypothesis, that is $H_0 = \phi_1 = \phi_2 = \phi_3 = \phi_n$ where ϕ is the group means, and n is the number of groups to be compared. If the ANOVA test results show statistically significant, the alternate hypothesis H_A is accepted that the group means are statistically different from each other.

The objective function, $J = \sum_{i=1}^{n}(E_i^a - E_i)^2$ (as described in Section 6.1), is determined by calculating the aggregated difference of the squared error between the calculated optimal allocations and the ideal allocations which are obtained from the predicted values from Chapter 5. From the calculated values of the optimal energy allocations using the proposed mathematical framework presented in Sections 6.1 and 6.1.1, the energy allocation is calculated optimally for each household. Since the forecast model used the consumer profiles as inputs along with the historical energy usage data, the forecast model becomes adaptive. The consumer profiles enable the forecast model to process the data corresponding to each household. The given consumer profile serves as an identifier when the result for the individual households is needed. With this approach, predicting the next day energy consumption of each household is possible with a single forecast model.

The results show (e.g. Table 6.3 for a given day) that with the proposed optimal energy allocation, the energy wastage/deficit can be reduced from 0.24 kWh to 0.11 kWh which is a 54% decrease from the current equal energy allocation for each household. These results show that the objective function of the optimisation problem is minimised. Using the proportionality approach, the aggregated difference is 0.26 kWh which is higher than the total difference between the ideal and the equal allocations, which is equal to 0.24 kWh. This means that when the proportionality method is used in allocating the energy of the households, higher energy wastage can occur.

Table 6.3: Comparison of ideal energy usage and the energy allocations (equal, proportion, and optimal) of the households

House No.	Ideal (I)	Equal (Eq)	Proportion (Pr_i)	Optimum (E_i^a)	Error1 $(I - Eq)^2$	Error2 $(I - Pr_i^a)^2$	Error3 $(I - E_i^a)^2$
H5	0.78	0.80	1.13	1.02	0.00	0.12	0.05
H6	0.51	0.80	0.73	0.75	0.01	0.05	0.00
H7	0.64	0.80	0.92	0.88	0.00	0.08	0.01
H8	0.29	0.80	0.42	0.55	0.23	0.02	0.05
Error1 $\left(\sum_{i=1}^{n}(I - Eq)^2\right)$					0.24		
Error2 $\left(\sum_{i=1}^{n}(I - Pr_i)^2\right)$						0.26	
Error3 $\left(\sum_{i=1}^{n}(I - E_i^a)^2\right)$							0.11

Figure 6.2, shows the ANOVA results for the three methods of allocations. The different performance of the three allocation methods is described by the difference in their means which is statistically significant with p–value of 2.24×10^{-38}. For 288 days, the aggregated squared error difference between ideal energy usage and the equal allocation is 112.10 kWh^2 or $\pm$ 10.59 kWh, with proportionality the total difference is 73.02 kWh^2 or $\pm$ 8.55 kWh and with the proposed optimal allocation, it is 62.35 kWh^2 or $\pm$ 7.90 kWh (shown in Table 6.4). Thus, using the proposed optimal allocations, the difference between the ideal energy usage is minimised further compared with the other allocation using the method of proportions.

Figure 6.3, shows the difference between the ideal usage of the households and the equal allocation as well as the proposed optimal allocation. The squared error of the ideal and the proposed allocation is preferred to be smaller than the current set up with the equal allocation. From the results shown in Figure 6.3 with 288 days of data for all households, the aggregated squared error between the ideal usage and the proposed optimal energy allocation is 62.35 kWh^2 or $\pm$ 7.90 kWh compared with the existing equal energy allocation which is 112.10 kWh^2 or $\pm$ 10.59 kWh. This difference is equivalent to 44.4% reduction of energy wastage/deficit and 14.6% reduction when compared with the results using the proportion method.

To determine whether there is a statistically significant difference between the two allocations (equal and the proposed optimal allocations), the ANOVA statistical test was performed. The difference in means of the two groups are statistically different with a mean squared error (MSE) of 1.074 and p–value of 6.61×10^{-31} and F–value of 137.3. The p–value suggests that the means of the two groups (equal allocations and the proposed optimal allocations) are different and rejects the null hypothesis that assumes that the means of the groups

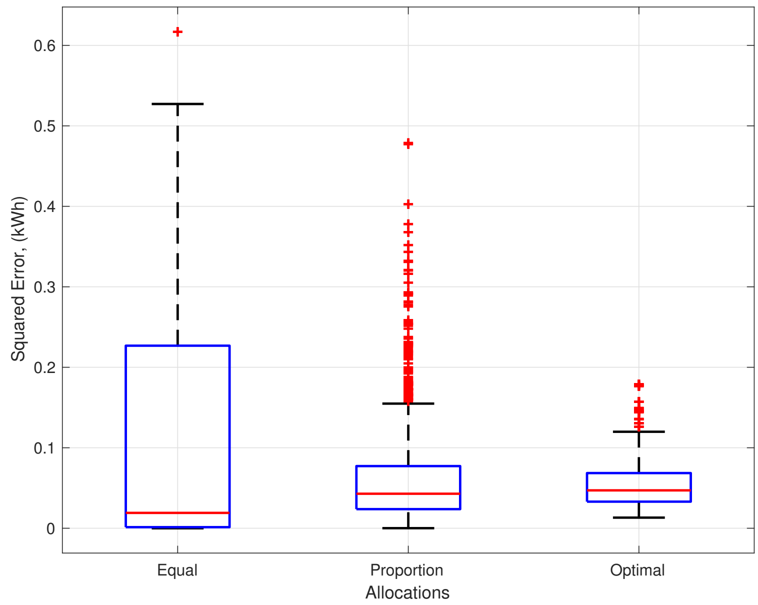


Figure 6.2: ANOVA results for the 3 allocations (Equal, proportion, and optimal), with 288 days data. The difference between the means of the 3 groups are statistically significant with a p–value of 2.24×10^{-38} and F–value is 88.9.

Table 6.4: Results for the objective function J for 288 days

Allocations	Results J
Equal	112.10
Proportion	73.02
Optimal	62.35

are the same. This implies that with equal daily energy allocation, energy wastage/deficit is higher compare with the proposed optimal daily energy allocation.

Another test is also conducted to observe the performance of the proposed optimal energy allocation scheme in terms of mean absolute percentage error (MAPE) for each household. The calculated MAPE for each household are $6.2, 8.0, 5.8$ and 10.4 for H1, H2, H3 and H4, respectively.

In summary, for 288 days, the results of the objective function J is shown in Table 6.4. The proposed optimal energy allocation minimised the energy wastage by 44.4% when compared with equal energy allocation.

The proposed energy allocation assumes that any changes in energy usage of the households are reflected in their past usage. If the households deliberately change their energy usage, this is perceived in the historical energy usage data and accounted in forecasting their

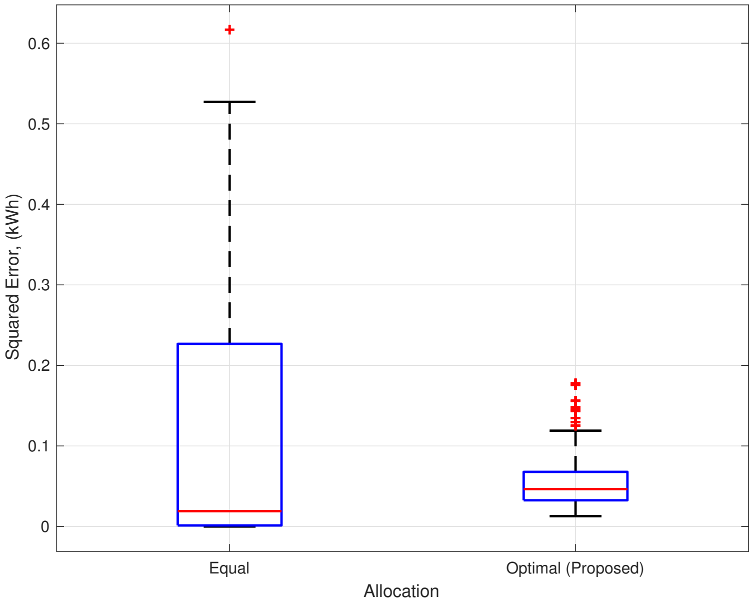


Figure 6.3: Anova test results between the two allocations with $N = 288$. The means of the two groups have statistically significant differences with p–value of 6.61×10^{-31}.

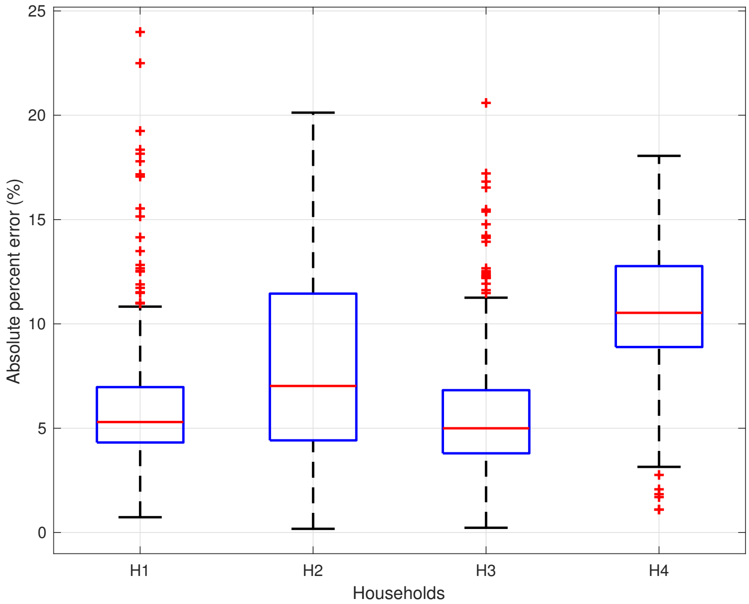


Figure 6.4: Absolute percent error (APE) for each household using the proposed optimal energy allocation. The MAPE for each household are $6.2, 8.0, 5.8$ and 10.4 for H1, H2, H3 and H4, respectively.

ideal usage. Thus, the proposed energy allocation remains optimal according to their previous energy usage.

From the results of this research, the proposed optimal energy allocation can be used for other households connected in microgrids. The proposed energy allocation scheme would generate similar results when used for households that posed similar energy usage and household profiles.

6.3 CHAPTER SUMMARY

Given the two issues highlighted in Chapter 1 with the current set up where daily energy allocation is equal for all households, there is a need to re-allocate the available energy to ensure that the provision of the energy to each household is based on their ideal energy needs. Thus, the re-allocation is done to minimise the unused energy allocated to the households that are not used and maximise the utilisation of the available energy.

Optimal energy allocation is proposed by considering the limited generation capacity of the power systems and the basic electricity needs of each household. The basic electricity needs of each household are taken from the households forecasted energy usage based on their historical usage and the household demographic profile as presented in Chapter 5. The consumer profiles used in the development of the forecast model aid in deriving an optimal and adaptive energy allocation.

The optimal allocation is calculated using the KKT conditions such that the aggregate optimal energy allocation summed up to the available energy generated by the power system and each optimal energy allocation to the households is higher or equal to the minimum energy required by the households. This ensures that the utilisation of the available energy is maximised and the unused energy of some household in the current set up is distributed accordingly to other households that need more than their allocated energy without sacrificing the energy needs of any household.

The optimisation problem is defined in which the cost function is to minimise the squared difference between the optimal allocation and the predicted ideal energy utilisation of the households. The cost function is then subject to the constraints involving the available energy of the power system and the basic energy needs of the households.

The mathematical framework for calculating the optimal energy allocation is unique and new in this field. All the derived equations are confirmed and validated by checking the results using the predicted values from Chapter 5 and assessing if the results have met the stated constraints. The method can be applied to households connected to generation-constrained microgrids.

The optimisation problem is successfully solved, and the allocation can be done adaptively and optimally. The demographics may vary, but the model can dynamically recognise this change and interpret accordingly based on the data given to the model. Thus, the method is considered robust and adaptive.

As presented in this chapter, the means of the optimal energy allocations for each household are significantly different from each group. This signifies that the consumer profiles help the proposed allocation scheme to allocate the energy optimally and adaptively. The energy usage under a microgrid with limited generation capacity was improved by reducing the energy wastage/deficit. Using the proposed optimal energy allocation, the energy wastage/deficit is reduced to 62.3 kWh from 112.1 kWh when using an equal daily energy allocation for each household. That is equivalent to 44.4% reduction of energy wastage/deficit achieved in 288 days. With the proportion method, the energy wastage/deficit is reduced to 73.02 kWh. So when the results with the proposed optimal energy allocation are compared with the results using the proportion method, a 14.6% reduction in energy wastage/deficit is achieved.

The proposed optimal energy allocation is expected to generate similar results when used for other households with similar characteristics, such as their energy usage and household profile. This is regardless of the connectivity of the households to the power system. Whether households are connected to the traditional grid or microgrid (online or offline), the proposed energy allocation is expected to provide optimal energy allocation when all the conditions stated in this chapter are met.

7 CONCLUSION

This research proposed a solution to the In this thesis, the need for optimising the energy allocation of the households connected in off-grid microgrids with limited generation capacity is investigated. The problem defined in Chapter 1 as re-stated here with an equal amount of energy allocated daily and considering the limited generation capacity of the off-grid power system, two main issues are highlighted:

> 1.) Some households use up the allocated daily quota and experience power outage but may require more energy than what is currently provided to them.
>
> 2.) Some households do not use all the allocated energy daily and pay the same fixed monthly tariffs as the households that use all their allocated energy.

To address the above issues, an optimal daily energy allocation for each household in off-grid villages such as the Red Cross village in Daanbantayan, Cebu is proposed. Below are the main considerations of the proposed optimal energy allocation for households connected in off-grid microgrids with limited generation capacity, re-stated from Chapter 1:

1.) Case 1: If the energy allocation is more than the basic needs for a given household, they pay for something they do not use. Therefore, they want an allocation commensurate with their usage.

2.) Case 2: If the allocation is less than the desired utilisation for a given household, they would be dissatisfied with the amount of energy they have, as they would experience shortage every day. Therefore, they want to have an energy allocation that is within their usage.

3.) The allocations in cases 1 and 2 are not guaranteed to be same.

4.) Energy allocation is constrained within the limited generation capacity of the off-grid power system.

Chapter 2 presents the research background on microgrids, energy management system (EMS) and artificial neural networks, and the review on existing literatures related to this study. The literature review covers topics on energy management scheme of microgrids, such as load shedding, time-based operation or scheduling and daily energy allowance or allocation, EMS optimisation, load forecasting, factors affecting load consumption, and the importance of the research data as the baseline data for the development of load forecast model as well as the proposed optimal energy allocation.

Chapter 4 presents collection and processing of data needed for this research. This includes the development and deployment of the Philippines Micro-Off-Grid monitoring system used to gather the energy data and the field survey used to collect demographic profiles of the households. All these data are used in the development of the load forecast model. The PMOG data from Village 1 was dropped as the data available is only for 6 hours a day and the operation of the off-grid power system in this village can not be available for 24 hours due to its technical limitations. In developing the forecast model, the data needs to be representing whole day energy usage that is 24 hours and not part of it. Hence, only data from Village 2 were utilised in the development and training of the forecast model.

From the data gathered, it was found out that some households do not used all the given energy daily quota and some households experienced power outage. Survey data shows that 46 % of the total households from Village 2 experienced power outage daily and 54 % of the total households do not use all up their given energy quota daily. There are 59 households out of 128 total households experienced power outage daily. They want to have more energy quota if possible as they expressed their willingness to pay according to their daily usage. In order to maximise the available energy, the excess or unused energy quota of the remaining 69 households can is re-distributed to the 59 households that needs more energy. Hence the needs of the optimisation of daily energy allocation to each household.

Since the aim of the research is to provide an optimal energy allocation based on the ideal usage of the households, there are 2 things that need to be done. First is to predict the next day energy consumption of the households and second is to calculate the optimal energy allocation using KKT approach.

The first step is done by the Multilayer Perceptron (MLP) -based forecast model. During the development of the model, it was found out that the number of hidden layers and neurons as well as the delay window of inputs affects greatly the performance of the neural network in terms of RMSE. Several cases were considered in selecting the combination of the hidden layers HL, neurons N and delay window D that generate the least value of RMSE. For MLP-based forecast model, RMSE values continue to change as the input varies. The variation is random especially with the average RMSE during the K-fold validation, however, the least RMSE values were achieved when household profiles were added as inputs as presented in section 5.2. Different load forecast models such as RBFN, GPR and ARIMA have been investigated to determine the best performing models in predicting households energy consumption in the context of off-grid villages connected to off-grid power systems with limited generation capacity (as detailed in Chapter 5). Incorporating household profiles as inputs made it possible for the MLP-based forecast model to met the threshold of 15 % or less of the actual energy usage. The household profiles that also serve as indexed of the different profile in input matrix of neural network made it possible to use single model to forecast the next-day energy consumption of each household.

The second step is done by formulating the optimisation problem. A mathematical approach for optimal energy allocation is presented in Chapter 6 that is based on MLP-based forecast model that uses both historical energy data and households profiles to achieve a reasonable accuracy in forecasting. The cost function J is to minimise the difference between the forecasted values E_i using MLP-based forecast model and the calculated optimal energy allocation E_i^a with 2 constraints derived from the limited capacity of the off-grid power system and the minimum threshold of the households (refer to equation 6.8). Given the limited generation capacity of the off-grid power system, the first constraint is that aggregated optimal energy allocation must be equal to the available energy. In this case, the data is from Village 2, and the off-grid power system is using batteries, the total available energy is treated as equal to the summation of the existing allocation (equation 6.9). The second constraint is that the optimal energy allocation E_i^a must be equal or higher than the daily energy threshold of each household E_{min} (equation 6.10). These 2 equations, 6.9 and 6.10 are the equality and inequality constraints of the objective function J (equation6.8). The inequality constraint allows the optimisation problem to be solved using KKT conditions as detailed in Chapter 6.

The work presented in this thesis has therefore focused on the development of the MLP-based load forecast model and the adaptive and optimal energy allocation for households connected in generation-constrained microgrids.

7.1 ANSWERS TO RESEARCH QUESTIONS

This thesis sets out to answer the following research questions:

> ***RQ1: Can the household's daily energy consumption be forecast with reasonable accuracy?***

Answer: Yes.

The accuracy of the proposed adaptive MLP-based load forecast model is important in predicting the different households daily energy consumption given the limited generation capacity of the off-grid power system. Section 5.13 shows the performance of the MLP-based load forecast model compared to other load forecasting techniques. The model's performance is measured by RMSE and the time needed to train the model. The best performance of the model is with a network with 3 hidden layers and 20 neurons and 7 input delays for historical energy data. This was identified via a grid search over the neural network parameters by optimising the predictive accuracy and training time. The experimental process is presented in Section 5.2.4.

The performance of the model is further improved by integrating the household profiles as inputs. The proposed MLP-based forecast model can forecast the next-day energy consumption of each household without the need of different model for each profile. This is possible as the model is developed and trained using different household profile as inputs. The model is able to recognise the different profiles accordingly. Although the performance of the proposed MLP-based forecast model maybe further improved by incorporating more than 4 households profiles and more than 2 years of historical data. Incorporating historical energy data at appliance level as input may also improve the performance of the model in forecasting. In this study, it was planned to have more PMOG system to be deployed and gather more energy data however, due to financial constraints, this plan was never materialised.

RQ2: Can knowledge of consumer profiles aid in optimal and adaptive energy allocation?

Answer: Yes.

Integrating the consumer profiles as inputs for the forecast model, enables the forecast model to predict the energy consumption of the households uniquely. As discussed in Chapter 6, the optimal energy allocation is based on the forecasted values by the MLP-based forecast model presented in Chapter 5. The optimal energy allocation is adaptive because the household profiles are incorporated in the load forecast model as inputs. Households profiles are included to the typical input variables such as historical energy data, temperature and calendar days, in developing a load forecast model.

Households profiles were created based on survey data. There are four consumer profiles identified based on the households' number of occupants, monthly income, number of appliance, frequency of use (in terms of hours for all appliances), number of children in school and with age less than 5 (who are expected to stay home during the day), and number of working family members. The identified consumer profiles are detailed in Section 4.8. Consumer profiles as inputs improves the accuracy of the forecast model. From 20.11 % error down to 13.58 % error without and with consumer profile as input, respectively. Results presented in Section 6.2.1 show that each household has unique energy allocations, based on the optimal algorithm after incorporating the households profiles in the forecast model. According to the ANOVA results, the difference between the means of the energy allocations for each household is statistically significant with p–value of 2.98×10^{-268}.

Given the results of the experiments and analysis of results, it can be concluded that the consumer profiles indeed aid in determining the optimal and adaptive energy allocation of the households. This approach is expected to work when applied to households with similar profile of households in Village 2 as presented in this study.

RQ3: Can the energy allocation be optimised to improve the energy efficiency under the limited generation capacity?

Answer: Yes.

MLP-based forecast model is proposed that uses both historical data and household demographic information to predict the household's day-ahead energy consumption. Using the forecasted values, the optimal energy allocation is then calculated using Karush-Kuhn-Tucker conditions from solving the optimisation problem (stated in Section 6.1) subject to two equality and inequality constraints related to the limited generation capacity of the microgrids and a certain guaranteed energy quota for each household. By providing an optimal energy allocation to each household, the energy wastage in terms of unused energy as well as energy deficit to some households is minimised.

The optimisation problem is defined with a main goal of reducing the difference between the allocated energy and the actual energy consumption in order to maximise the energy consumption in a generation-constrained microgrids. Using the proposed optimal energy allocation, the energy efficiency of off-grid microgrids with limited generation capacity is improved. In this study, the off-grid microgrid with limited generation capacity is said to be efficient when the energy wastage is minimum. The energy wastage is the unused daily energy allocation of the households. According to the simulated results, the energy wastage/deficit is reduced by 44.4% with the proposed optimal and adaptive energy allocation compared to the existing scheme that provides an equal energy allocation in 288 days, and 14.6% compared with a proportional allocation.

As detailed in Chapters 5 and 6, the proposed methodology of allocating energy to the households in generation-constrained microgrids that is adaptive and optimal is successfully investigated and validated in this thesis. The proposed methodology is a combination of load forecasting using MLP and optimisation using KKT approach. The set threshold of RMSE is achieved by employing MLP-based forecast model and incorporating the household profiles as input together with the historical data. The % error is improved by 32.5 % when household profile is included as input. Although this performance can be further improved with more household profiles and historical energy data. When the performance of the forecast model to predict the next-day energy consumption is improved, this also have a positive effect in calculating the optimal energy allocation of the households. The objective function of the optimisation problem defined in this study is to minimised the error difference between the forecasted value of the next-day energy consumption of the households and the calculated optimal energy allocation. When the forecasted values can be made more accurate by improving the performance of the MLP-based forecast model, the optimal energy allocation will also be more accurate as expressed in equation 6.38. Thus, minimising the objective function J. This proposed optimisation using KKT approach is applicable to any optimisation problem that satisfies the KKT conditions. The proposed methodology of determining the optimum energy allocation is applicable to other households in off-grid communities with similar household profile and off-grid power systems.

7.2 CONTRIBUTIONS TO KNOWLEDGE

From the answers to the research questions, the following are the contributions of this work:

- A generalised MLP-based load forecasting model that uses historical data and considers household demographic information to predict the household's day-ahead energy demand.

- A methodology for optimal energy allocation that is adaptive to individual households – optimal because it minimises the energy waste/deficit, and adaptive because it uses the households historical data and demographic information.

The allocation of energy quotas is considered as an optimisation problem [Tan+15; Tia+14], in which the objective is to minimise the collective energy waste as well as minimised energy deficit, in terms of unused allocated energy, while ensuring the generation capacity is not exceeded. The historical usage are modelled and combined with other extracted features for demand prediction to derive an optimal energy allocation based on the forecasted ideal demand.

7.3 SIGNIFICANCE OF THE STUDY

Apart from the direct benefits to the selected villages where the research will be deployed, the work described in this thesis will be beneficial to other researchers interested in micro-grids and energy management systems for off-grid systems, as well as to the energy providers in the Philippines. The integration of the social aspect (household individual profile) into the load forecasting model along with the energy historical usage of each household increases the model's capacity for accuracy and thus generates real-world results.

The community is empowered by giving them an opportunity to use their limited energy supply more efficiently with less energy waste, and incorporate their individual requirements by considering households profile in developing the load forecasting model.

This work can be a good reference in planning and design considerations for energy management systems for off-grid implementations in remote areas.

7.4 FUTURE WORK

In this thesis, a methodology for optimal energy allocation that is adaptive to individual household is proposed. The following are the possible avenue to expand on the work in this thesis:

1. The work can be further improved by including all the inherent losses on generation and distribution lines of the microgrid into the calculation of the energy allocation.

2. The work can be applied in smart grids that want to predict the next day load based on the historical data and the consumer profiles as laid out in this thesis and with possible inclusion of appliance level historical data.

3. Real-time updating of data for dynamic forecasting and energy allocation. Forecasting can be more efficient when the data is updated in real-time and the energy allocation is dynamically changing corresponding to the historical energy data.

4. The work can be used as the basis for energy management financial scheme that would ensure the sustainability of the off-

grid microgrid operation while maintaining the ideal energy usage of the households.

5. This work can be further improved by using Deep Neural Network architecture and/or any other hybrid models for load forecasting.

6. The performance of MLP-based forecast model can be further improved by using more than 4 household profiles and deploy PMOG systems to gather data for each profile.

7. Optimisation approach may be improved further by utilising other optimisation techniques such as sequential quadratic programming (SQP) and genetic algorithm (GA) that essentially minimise the objective function J.

This work is limited by the available data and the implementation of the proposed energy allocation scheme is possible with sufficient financial support and collaboration with the maker of energy management systems (EMS) of off-grid microgrids.

A DEPLOYMENT DOCUMENTS

For data gathering, PMOG systems are installed to the selected households and a field survey were done. Attached here are the documents on the installation of PMOG system and the survey questionnaire.

A.1 PMOG SYSTEM RASPBERRY PI SET UP GUIDE

PMOG Raspberry PI EMS setup

This details the process of installing the PMOG software onto a Raspbian Install

Contents:

- Preparing the SD Card
- Initial configuration and package installation
- RTC setup
- Setup SSH
- Install PMOG code
- Setup AutoSSH

Preparing the SD Card

1. Download the latest copy of the Raspbian Lite from https://www.raspberrypi.org/downloads/raspbian/
2. Copy onto the SD Card (either use dd, or PiBaker)
3. Plug the SD card into the Pi (with keyboard/monitor attached), Apply Power
4. We should now be able to login to the PI (using standard pi/raspberry)

Initial Configuration and package installation

1. Update the source list and upgrade any packages
   sudo apt-get update && sudo apt-get upgrade
2. Configure the raspberry pi
   sudo raspi-config
3. Select the following choices
   Expand filesystem
   Change user password
   Advance options
   A3 set gpu to 0
   A4 SSH set to yes
   reboot
4. Install all the required packages
   sudo apt-get install git mercurial subversion emacs python-smbus autossh oracle
   sudo apt-get install python-setuptools python-dev python-docutils
   sudo easy_install pyserial
   sudo easy_install requests

5. Configure Hostnames
   sudo emacs /etc/hostname
   (Check that it is PMOG *No.?*)
   sudo emacs/etc/hosts
   (Is 127.0.1.1 PMOG *No.?*)

RTC setup

For the software and hardware installation of RTC to pi, refer to PiFace Real Time Clock user guide available at:
http://www.piface.org.uk/assets/piface_clock/PiFaceClockguide.pdf

Setup SSH

1. Generate SSH key

    shh-keygen –t rsa

2. Copy key and ask someone with sudo access to add to pi user on cogentee (James/Ross)

    cat .ssh/id_rsa.pub

3. Test the ssh connection by

   ssh cogentee.coventry.ac.uk

   Reply if necessary to prompt

Install PMOG Code

1. Get PMOG code from subversion

    mkdir -/svn

    cd ~/svn

    svn co svn+ssh://cogentee.coventry.ac.uk/svn/PMOG

2. Move folder to opt

    sudo mv PMOG /opt/PMOG

3. Make data directories

    sudo mkdir /var/log/ch

4. Install python code

   cd opt/PMOG
   sudo python setup.py develop
5. Install start-up scripts

    cd /opt/PMOG/etc

    sudo cp ch-CurrentCost /etc/init.d/

    sudo upgrade-rc.d ch-currentcost defaults sudo update-rc.d ch-currentcost enable

Setup AutoSSH

1. Copy auto-ssh to initi.d

    cd /opt/PMOG/etc

    sudo cp auto-ssh /etc/init.d/

    sudo chmod 755 /etc/init.d/auto-ssh

2. Run the following in a shell, replacing the XXX with an unused number

    Echo REMOTE_PORT=16xxx | sudo tee /etc/default/auto-ssh

3. Set to start at boot

    sudo update-rc.d auto-ssh defaults

    sudo update-rc.d auto-ssh enable

    sudo reboot

4. Check if you can connect through cogentee

A.2 PMOG SYSTEMS INSTALLATION MANUAL

PMOG-CurrentCost Deployment Guide

A. Equipment

1 Server Used to collect and store data from the Wireless Sensor Network (WSN), and push data via 3g to the Cogent Computing Server. Composed of raspberry pi and the 3G/4G dongle with aerial. (Labelled as **PMOG1** ~ **PMOG*N***)

1 Current Cost Node Senses the electricity consumption of the household includes Current Cost set and Current Cost Individual Appliance Monitor (IAM)

1 Router Used to access the server during installation

2 Ethernet Cables Used during installation

B. Installation

1. Map the house to take note where the raspberry pi with the dongle to be installed.
2. Locate the electric main panel/meter and note the desired point of installation for the raspberry pi and Current Cost display monitor.
3. Set up the Current Cost devices and the IAM following the instructions in the manual attached (make sure you get a reading on the display).

   Note: Log the name of the appliances, (if possible with serial no.) plugged in with each individual appliance monitors for each household to the system monitoring log sheet.

4. Connect the Current Cost display monitor to the raspberry pi by plugging in the interface cable between the two.
5. Plug in the Router.
6. Using the Ethernet cables, connect both the pi and your laptop to the router
7. Plug in the dongle to the raspberry pi. (Note the flashing light: Green – connected to 4G network, blue – 3G network, RED light means not connected or no signal)
8. Plug in raspberry pi, check all lights come on.
9. To check if system is logging data, navigate to http://<servername>.local/PMOG/ or open a terminal window and run the following:
   ssh cogentee
   ssh pi@*servername*.coventry.ac.uk (reply if necessary to prompt, when successfully logged in, do the following)
   cd /tmp/
   ls (files containing data should appear)
   cat <filename> (to show the contents of the file, choose any file from the directory shown)
10. Make sure the node and devices are listed under sender and device column at the web page.

A.3 SURVEY QUESTIONNAIRE

Survey Questionnaire

Are you interested in participating in a “user-driven” energy project?

☐ Yes

☐ No

I *Demographic Profiling*

Date: ____________

Control No. ____________

1) Location: ________________________________
2) Name: ________________________________
3) Role in the family:
   _______ Father
   _______ Mother
   _______ Head of the family
   _______ Others: ____________
4) Age: ________________________
5) Gender: ________________________
6) Educational Attainment:
   _____ Elementary
   _____ High School
   _____ College Level
   _____ Vocational/technology
   _____ College graduate
   _____ Others ________________
   ____
7) House Occupancy:
   ___ Single
   ___ Couple
      ___ working
      ___ retired
   ___ Family with children
      ___ < 5 yrs. old
      ___ 5 -18 yrs. old
      ___ > 18 yrs. old
   ___ Extended Family (with grandparents)
   ___ Others:
   ____
8) Occupation: (Please tick one. If not on the list, please specify)
   _____ Farmer
   _____ Fisherman
   _____ Entreprenuer
   _____ Teacher
   _____ Brgy. Official/Worker
   _____ Others: (specify)
   ____
   ____
   ____
9) Total number of people living in the house: ________________
10) Number of children studying(or in school): ________________
11) No. of family members who are working: ________________
12) Monthly Salary/Income (₱)

Range		*Range*
_______ less than 2000		_______ 10001 - 15000
_______ 2000 - 5000		_______ 15001 above
_______ 5001 - 8000		_______ Others, please specify:
_______ 8001 - 10000		________________

13) Other source of income: ________________
14) Total Monthly/Daily income: ________________

II *Energy Consumption Profiling*

1) Who is in the house?

Name	Age	During the day	During the night
example:			
Josephine dela Cruz	**30**	**No**	**6 PM-7 AM**
Juan dela Cruz	**32**	**8 AM - 5 PM**	**No**
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			

2) Do you have appliances? (Please tick below and indicate how often do you use it)

	Everyday (Ave. hours of use)	once a week (Ave. hours of use)	Twice a week (Ave. hours of use)	Others, please specify
____ Light bulbs and/or flourescent				
____ TV				
____ Refrigerator				
____ Electric/ceiling fan				
____ Electric kettle				
____ Rice Cooker				
____ Electric Stove				
____ Others (List the other appliances you used at least once a week)				
1				
2				
3				
4				
5				

3) Monthly electric bill (₱) ____________________

4) Do you use smart phones? ☐ Yes ☐ No

5) Do you have access to 24-hour energy? ☐ Yes (Proceed to Section III ☐ Yes (Proceed to question 6

6) If you will have 24-hour access to energy, what would change in your energy consumption? ____________________

____

____

III ***User-empowerment profiling***

1.) Please rank the following according to your priorities, with 10 as the highest and 1 as the lowest.
(Please place the numbered smileys on the space provided)

__________ Water

__________ employment/job

__________ Sanitation

__________ Community Livelihood program

__________ Road

__________ Health Facilities (i.e. clinic/hospital)

__________ electricity

__________ education/school

__________ Housing

__________ flood/typhoon protection

2.) How aware are you of the environmental impact of energy use?
(Please encircle below : 5 - highest, 1 - lowest)

5 4 3 2 1

3.) How motivated are you to save energy?
(Please encircle below : 5 - highest, 1 - lowest)

5 4 3 2 1

4.) How engaged are you in your local community?
(Please encircle below: 5 - Always, 4 - Often 3- Sometimes, 2 -Occationally , 1 - Never)

4a. I participate in every activity in the local community

5 4 3 2 1

4b. I take part on the decision making for my local community welfare, development and etc.

5 4 3 2 1

5.) How influential are you at changing how your community uses energy?
(Please encircle below : 5 - highest, 1 - lowest)

5 4 3 2 1

A.4 DEPLOYMENT TECHNICAL REPORT

This document is available upon request.

B

FIELD WORK: PMOG SYSTEMS INSTALLATION

There were 10 PMOG systems installed in the selected households and microgrid at the two villages; Village 1 and Village 2. These two villages are both powered by an off-grid power system with limited generation capacity. Each village has 5 PMOG systems, 1 for monitoring the generation side and 4 for the households representing the majority of the households' profile. Households were selected after the survey was done where the demographic information was already gathered. The number of households with the same profile was considered in the selection process. Parameters such as number of appliances, number of occupancies and total household's monthly income were considered in the selection process. The number of households with the same number of those three parameters was tallied. Then one household was selected from the four most numbers of households with the same profile to represent them. Figure B.1 shows the actual PMOG system installed in the households.

The CT jaw sensor of the PMOG was clamped to the main electric panel of the household, and the wireless transmitter was fixed on the wall (as shown in Figure B.1). The sensor is now ready to gather data as the aggregate energy consumption of the household. To gather the data at the appliance level, the individual appliance monitor was deployed. Each appliance was attached with an IAM to determine the amount of energy used. IAM was plugged into the wall socket, and the selected load (appliance) was plugged into the IAM.

CT jaw sensor and each IAM were paired with the Envi display monitor. The wireless communication between the sensors and the Envi display monitor was confirmed by checking the display monitor whether it was showing energy usage of the households from CT jaw sensor and appliances from IAMs before fixing all the wires on the wall. Internet connection was then checked and confirmed during the installation process by checking the webpage in real-time to make sure that the system was working properly before fixing the devices in the household. The webpage, which is running from the remote server, is expected to update the displayed data every 20 minutes after every hour. When the webpage is not updated, PMOG system may need to be checked to confirm its status. The PMOG system is designed to store data in its local server. The CT jaw sensors and the appliance monitors sensed the data every 6 seconds and transmitted it to the

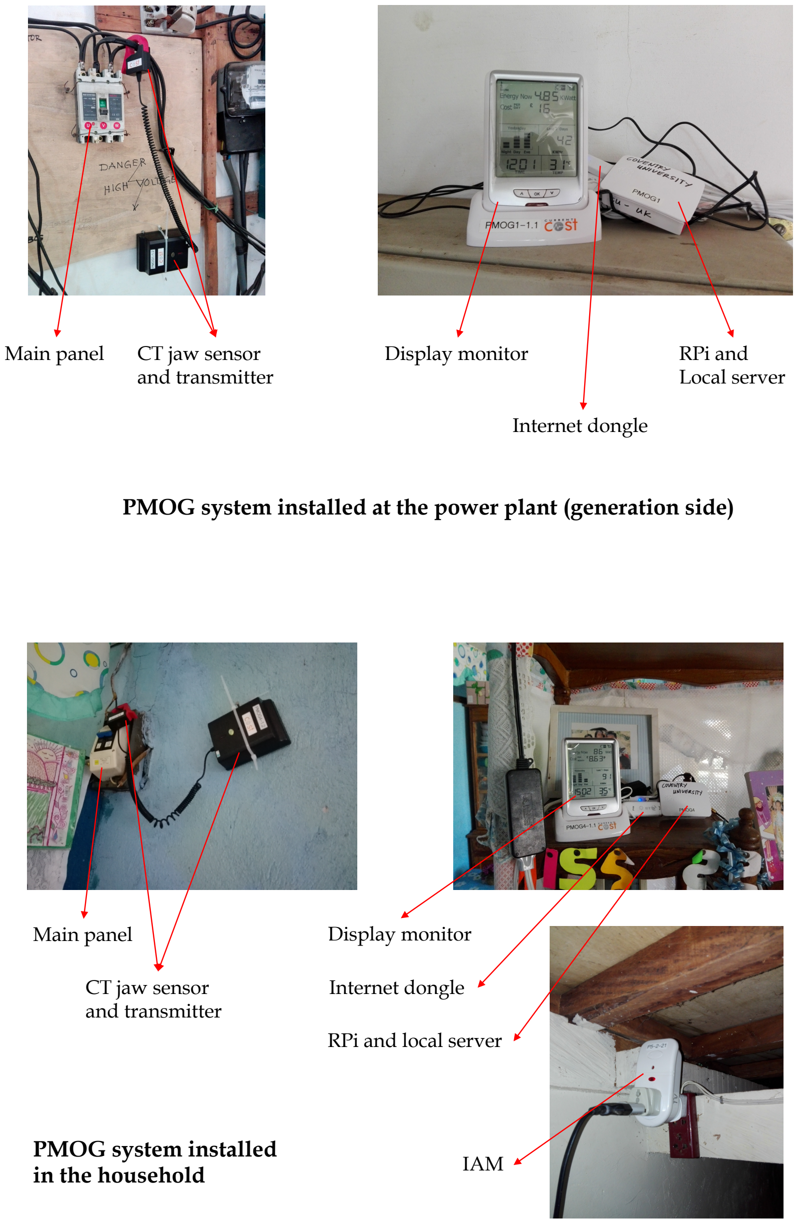
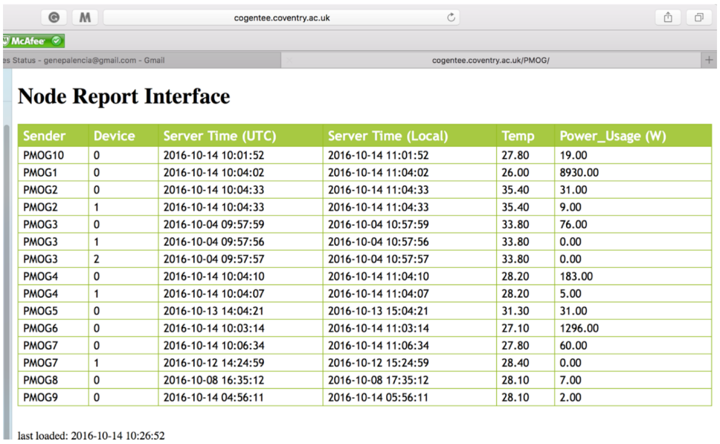


Figure B.1: PMOG systems deployed in the villages collecting energy data on both the off-grid power systems (generation side) and the households with individual appliance monitors (IAMs).

CC monitor and logged in to the Rpi storage. The PMOG system, through its internet dongle, transmits the sensed data from its local server (household) to the remote server (Cogent laboratory) every 20 minutes past hour.

Data logging at the webpage created for the PMOG system was checked every day to monitor the performance of all sensors. The PMOG systems were expected to send data every hour if they were working properly. The last transmission can be checked at the webpage. When the last the transmission was successful, the webpage automatically updates and displays the most current data received. If not, and the last transmission is already one day past, the person-in-charge in the Philippines was contacted to check with the household what causes the missing transmissions and resolve the issues remotely when necessary. Common causes of missing transmission include network problems such as no internet connection, and PMOG systems were not working and turned off.

Figure B.2 is the actual webpage of the PMOG monitoring system. The webpages display sender, device number, server time for both local and remotes servers, and the readings from IAMs, CT jaw sensor and built-in temperature sensor. Appliances monitored by the IAMS were assigned to a specific channel display in the Envi display monitor in which the devices number is displayed on the webpage. Envi display monitor can display individual energy consumption of the appliances through IAMs with channel number from 1 to 9 with channel 0 reserved for CT jaw sensor. The transmitted data is retrieved from the remote server designated to the PMOG system by accessing the server from any computer connected to the internet. The data is in the form of .csv file that can be viewed by a Microsoft excel. The data includes the date and time, electricity usage (power (W)), temperature (degree C), device number, and the server number of the nodes.


cogentee.coventry.ac.uk

McAfee

s Status - genepalencia@gmail.com - Gmail

cogentee.coventry.ac.uk/PMOG/

Node Report Interface

Sender	Device	Server Time (UTC)	Server Time (Local)	Temp	Power_Usage (W)
PMOG10	0	2016-10-14 10:01:52	2016-10-14 11:01:52	27.80	19.00
PMOG1	0	2016-10-14 10:04:02	2016-10-14 11:04:02	26.00	8930.00
PMOG2	0	2016-10-14 10:04:33	2016-10-14 11:04:33	35.40	31.00
PMOG2	1	2016-10-14 10:04:33	2016-10-14 11:04:33	35.40	9.00
PMOG3	0	2016-10-04 09:57:59	2016-10-04 10:57:59	33.80	76.00
PMOG3	1	2016-10-04 09:57:56	2016-10-04 10:57:56	33.80	0.00
PMOG3	2	2016-10-04 09:57:57	2016-10-04 10:57:57	33.80	0.00
PMOG4	0	2016-10-14 10:04:10	2016-10-14 11:04:10	28.20	183.00
PMOG4	1	2016-10-14 10:04:07	2016-10-14 11:04:07	28.20	5.00
PMOG5	0	2016-10-13 14:04:21	2016-10-13 15:04:21	31.30	31.00
PMOG6	0	2016-10-14 10:03:14	2016-10-14 11:03:14	27.10	1296.00
PMOG7	0	2016-10-14 10:06:34	2016-10-14 11:06:34	27.80	60.00
PMOG7	1	2016-10-12 14:24:59	2016-10-12 15:24:59	28.40	0.00
PMOG8	0	2016-10-08 16:35:12	2016-10-08 17:35:12	28.10	7.00
PMOG9	0	2016-10-14 04:56:11	2016-10-14 05:56:11	28.10	2.00

last loaded: 2016-10-14 10:26:52

Figure B.2: PMOG system node report interface. The webpage displays the newest transmitted data to the remote server. The data include the date and time, device number, and PMOG number aside from the main data which are the temperature and power usage of the household

C

RESEARCH DATA

For this research, data refers to the PMOG data and survey data as described in Chapter 4. These data are stored and can be accessed at Cogentee repository [Pal19]. Both raw data and pre-processed data are available at this webpage: http://cogentee.coventry.ac.uk/ gene/researchdata/)

D

ETHICS APPROVAL

This research has undergone the ethical approval process of Coventry University. Attached here are the certificates, and application documents such as the participants information sheet and consent form.

Certificate of Ethical Approval

Applicant:

Gene Fe Palencia

Project Title:

Wireless Sensor Networks To Enable User-Driven Control Of Micro-Power Generation Devices: Baseline Survey

This is to certify that the above named applicant has completed the Coventry University Ethical Approval process and their project has been confirmed and approved as Medium Risk

Date of approval:

25 April 2016

Project Reference Number:

P42996

Certificate of Ethical Approval

Applicant:

Gene Fe Palencia

Project Title:

Wireless Sensor Networks To Enable User-Driven Control Of Micro-Power Generation Devices

This is to certify that the above named applicant has completed the Coventry University Ethical Approval process and their project has been confirmed and approved as Medium Risk

Date of approval:

25 July 2017

Project Reference Number:

P60318

Certificate of Ethical Approval

Applicant:

Gene Fe Palencia

Project Title:

WirelessSensor NetworksToEnableUser-DrivenControl Of Micro- Power Generation Devices

This is to certify that the above named applicant has completed the Coventry University Ethical Approval process and their project has been confirmed and approved as Medium Risk

Date of approval:

22 August 2018

Project Reference Number:

P72455

PARTICIPANT INFORMATION SHEET

Title of the Project: Wireless sensor networks to enable user-driven control of micro-power generation devices – Baseline Survey

This research project aims to investigate the local community's power generation and utilisation of energy generated by the PV plant and to collect primary data that serves as a baseline for each load's power consumption. We are trying to establish a good understanding of the needs and aspirations of the end-user that may affect the energy supply and demand within the local community. The proposed project will undertake a range of monitoring and evaluation activities such as pre-post surveys, interviews with audio or video recordings and pictures.

Your participation in the pre-post surveys and interviews will be a great help in the study. You will not be identified in any of the analyses, reports or publications we produce and we will safeguard your confidentiality.

Participation is entirely voluntary and your help is very much appreciated. If at any time you want to withdraw from the study without prejudice you have only to let us know. In that event, please contact Gene (details below).

This study has been cleared by the ethics committees of Coventry University. You are free to discuss your participation in this study with the project staff (contactable on phone numbers or email below). If you would like to speak to an officer of the University not involved in the study, you may contact the Ethics Officer on +44 2477658278.

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CONSENT FORM

Title of the Project: Wireless sensor networks to enable user-driven control of micro-power generation devices – Baseline Survey

- I have read and understand the attached participant information sheet and by signing below, I consent to participate in this study. I have retained a copy of this sheet for future reference if required.
- I understand that this research project will entail surveys, interviews which will involve images, audio or video recordings for the process of understanding the current conditions of my local community with respect to its energy generation and utilisation.
- I understand that any information taken in note form, pictures, orally or by video will be treated with the utmost confidentiality.
- I understand that participation in the research is voluntary, and I can withdraw at any time without giving a reason.
- I understand that I may choose not to answer particular questions, without being obliged to withdraw completely from the research.
- I understand if I wish to withdraw from the research, I can do so at any time without prejudice.
- I understand that the research has been approved by the Coventry University's Ethical Review Committee.
- I have voluntarily agreed to participate in this research project.

Participant's Name (Please Print) ……………………………………………………….

Participant's Signature …………………………………………………………………..

Date:…………………………

Witnessed by (Please Print) ……………………………………………………….

Witness's Signature ……………………………………………………………….

Researcher's Signature………………………………………………………………

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