Impact Analysis of Domestic Building Energy Demand and Electric Vehicles Charging on Low Voltage Distribution Networks

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Abstract

There are lots of worldwide attentions paid to the greenhouse gas (GHG) emissions, which can result in serious climate change issues. Hence, finding ways to save energy and GHG emissions become important. Moreover, the energy demand from the residential sector accounts for around 30% of the total energy demand, which shows that it can be a potential way to contribute to reducing GHG emissions. Furthermore, the electric vehicle (EV) is going to play an important role in reducing GHG emissions, however, with the growth of EVs in the community, the low voltage (LV) distribution network (DN) will be affected directly. Therefore, investigating reducing the energy demand from domestic dwellings and minimising the impacts of EVs charging on dwellings and DNs become significantly important.

Firstly, the energy demand of a domestic dwelling is modelled in the EnergyPlus. Potential energy savings from building material, photovoltaic/thermal (PV/T) panels, LED lights and occupants' behaviours are analysed and improving the energy efficiency is investigated.

Then, coupling by EnergyPlus and Matlab through Building Control Virtual Test Bed (BCVTB) interface, the Dwelling-EV Integration Model (DEIM) is established as the foundation for impact analysis of EVs charging on the energy demand in the dwellings and DNs. An individual domestic dwelling is modelled. Then load-shifting method and the battery storage energy system (BSES) are used to reduce the peak power demand in the dwelling, which are proved to be feasible and be able to smooth the daily power demand profile.

Further, in order to solve the issues caused by EVs charging, such as voltage drop, power loss etc. on DN, the impacts of EVs charging on the LV DN are analysed based on a typical network, and the concept of dwelling's micro-grid, consisting of the PV and a battery storage system, is proposed. The dwelling's micro-grid is used to minimise the impacts of EVs charging, and it is proved to be useful for reducing the voltage drop, the voltage disqualification rate and the power loss.

Finally, an ordered charging strategy (OCS) of EVs using the expected power is proposed to minimise unbalanced load and increasing unqualified voltage caused by EVs charging. Additionally, the OCS using the expected power is combined with the BSES to further reduce the impacts. This method not only reduces the capacity of BSES, makes the voltage of DN qualify, but also smoothes the daily power demand. It solves the voltage drop caused by random EVs charging and overcomes the disadvantage of the large deployment of EVs on the DN.

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List of Nomenclature

ASHP	Air Sourced Heat Pump
BCVTB	Building Control Virtual Test Bed
BEM	Battery Management System
BEV	Battery Electric Vehicle
BSES	Battery Storage Energy System
CHP	Combined Heat and Power
DEIM	Dwelling-EV Integration Model
DHW	Domestic Hot Water
DN	Distribution Network
DOE	Department of Energy
EMS	Energy Management System
EV	Electric Vehicle
FEV	Full Electric Vehicle
GHG	Greenhouse Gas
GSHP	Ground Source Heat Pump
HDD	Heating Degree Day
HEMS	Home Energy Management System
HEV	Hybrid Electric Vehicle
HVAC	Heating, Ventilating and Air Conditioning
LBNL	Lawrence Berkeley National Laboratory

LV	Low Voltage
OCS	Ordered Charging Strategy
PHEV	Plug-in Hybrid Electric Vehicle
PV	Photovoltaic
PV/T	Photovoltaic/thermal
SCT	Start Charging Time
SDF	Synchronous Data Flow
SOC	State Of Charge

Chapter 1

Introduction

The climate change caused by the Greenhouse Gas (GHG) emissions has been paid attention from all over the world and reducing the emissions becomes crucial. The energy demand from the residential sector accounts for 30% of the total energy demand, which indicates that it has potential energy savings to help to reduce the GHG emissions [1]. Furthermore, uptake electric vehicle (EV) also take an important role to reduce the GHG emissions, however, with the growth of EVs, the distribution network (DN) will be impacted directly [2]. Therefore, the research on how to reduce the energy demand of the dwellings and minimise the impacts of EVs charging on the dwellings and DN becomes significant.

1.1 The Trend of GHG Emission

Coal, oil and natural gas, the major fossil fuels, have greatly promoted the development of the modern civilization. However, on the other side, excessive usage in the past few decades has resulted in dramatic global emissions of GHG, which can affect many aspects. The most well-known effect is global warming, which can trigger many critical problems such as the ice melting, sea level raising etc. [3].

Climate change and global warming have been gradually drawn attention by public recent years. In the UK, a legally binding target was set for CO2 emission reductions of at least 26% by 2020 and 80% by 2050, compared to 1990 level [4]. Committee on Climate Change (CCC) has released a series of carbon budgets to accomplish this target by identifying contributions from each sector. As buildings are responsible for carbon emissions, especially for the residential sector, CCC expects carbon reductions by 2020 saving of 10%-20% from 2005 [5][6]. Furthermore, the goals of reducing energy consumption and emissions become achievable when building energy consumption is well understood and properly estimated.

According to the current crucial needs of reducing the GHG emission and decreasing reliance on foreign oil supplies, the development of renewable energy becomes a very important key step in the whole chain, such as photovoltaic (PV), wind generator, heat pumps, and EV. The EV is powered by the electricity that is drawn from the grid, and it becomes even more environmental friendly when the electricity is generated from renewable energy sources.

Overall, the objective of reducing the GHG emissions is able to achieve through using renewable energy, such as PV and wind power generation, and low carbon technologies, such as heat pumps and EVs.

1.2 The Changes of Energy Demand in Dwellings and Potential Energy Savings

Energy consumption of the residential sector takes account for averages around 30% worldwide, particularly 31% for the UK shown in Figure 1.1 [7]. Due to this significant energy consumption level, more and more attention has been paid to understand the characteristics of energy consumption in the residential sector, which will help guide the network operators regarding any reinforcements of system infrastructure. And investigating the potential energy saving of dwellings to reduce the energy demand becomes useful.

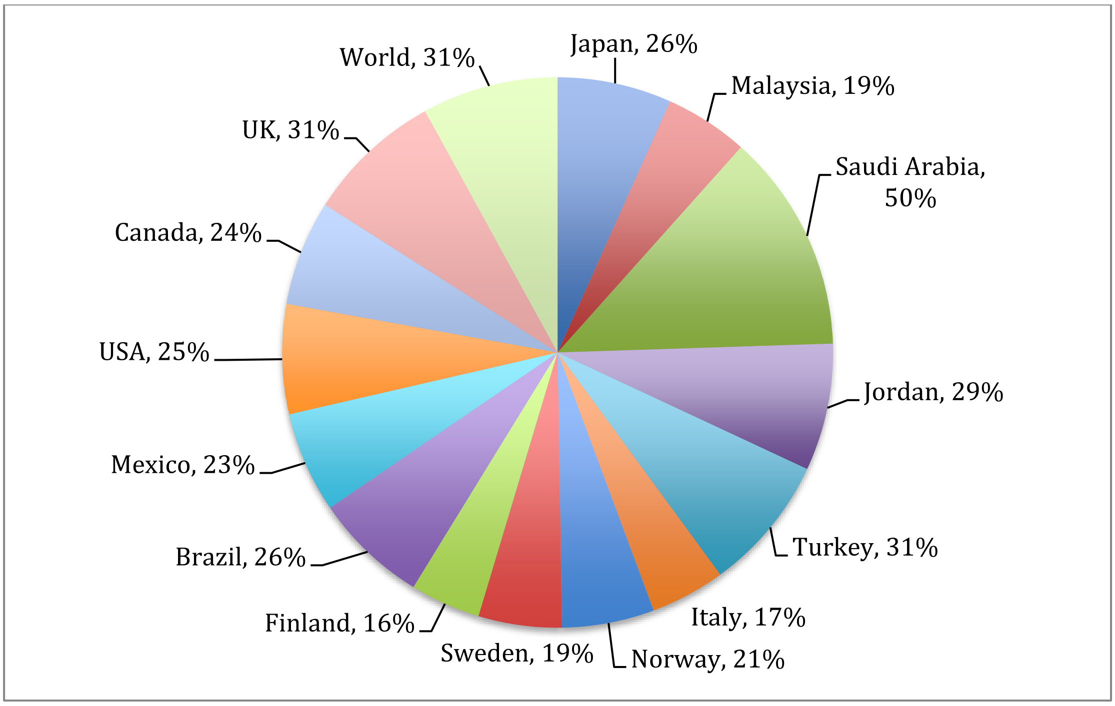


Figure 1.1 Worldwide Residential Energy Consumption [7]

In order to response the climate change and energy supply/demand, interest has been paid in understanding the detailed energy demand characteristics of the residential sector to encourage efficiency, technology implementation etc., such as solar thermal panels, PV panels, small wind generator, and heat pump etc.

The energy demand of residential buildings consists of many sub end-use groups, and the percentage of end-use over all energy consumption is shown in Figure 1.2 [8]. The space heating is the major requirement for the domestic dwellings in the UK during the winter period, while the space cooling is less needed during some hot summer times. This energy demand is used to support the thermal losses incurred across the building elements due to the conduction, convection, and infiltration/ventilation for maintaining a comfortable temperature in the dwellings. Domestic hot water (DHT), the energy is required to heat water to an appropriate temperature for occupants and appliance uses. Appliances and lighting consume energy in order to keep their normal operations.

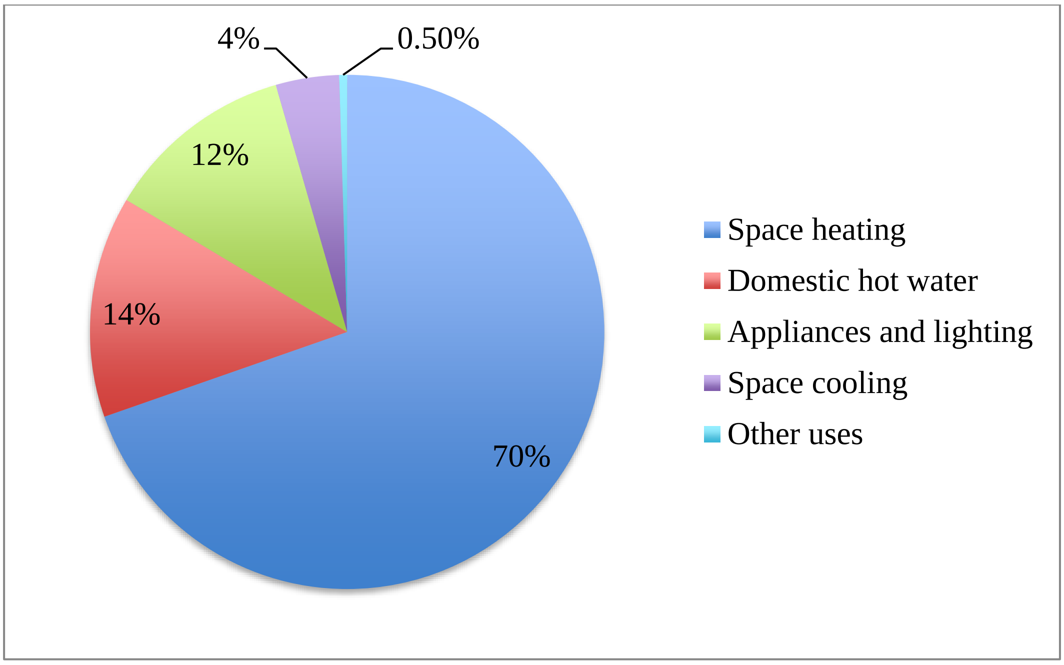


Figure 1.2 Percentage of Each Sub End-use Energy Consumption[8]

The energy demand of the residential sector is changing. Consequently, there is definitely a need for understanding the characteristic of future domestic dwellings and investigating ways to save energy of dwellings.

1.3 The Benefits and Challenges of EVs Uptake

Nowadays, EV is utilised widely in many countries as a new renewable technology. And it is powered by the electricity which is able to achieve zero or low emissions. Promotion of EVs is regarded as one of the solutions for alleviating problems caused by energy crisis, environmental pollution and climate warming based on relevant researches. EVs are low-carbon travel as well as consumption part of intermittent renewable energy.

1.3.1 EVs' Growing

In order to respond to the global warming effect, EVs become an important equipment worldwide. Many countries have announced policies to encourage the development and deployment of EVs. By the end of 2014, there were over 0.66 million EVs driving on the road worldwide, accounting 0.08% of total vehicles [9]. Brief EV stock amongst different countries is illustrated by International Energy Agency (IEA) shown in Figure 1.3

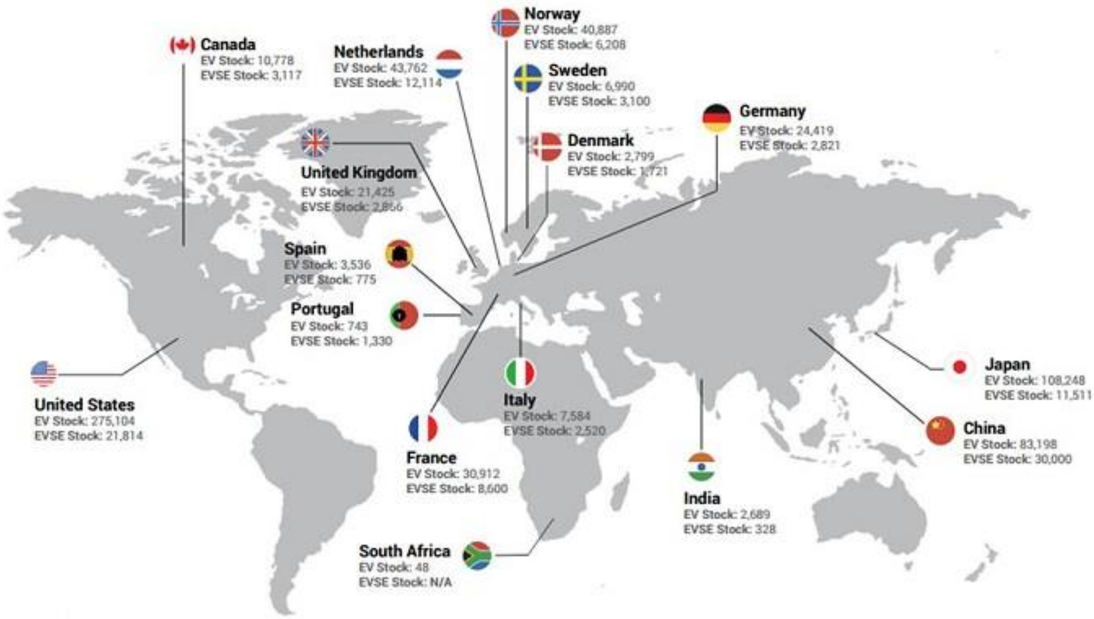


Figure 1.3 EV Stock Levels Around the World [9]

From Figure 1.3, it can be seen that the USA, Japan, and China are the top three countries having the largest EV fleets among the global EV stock, which are 39%, 16% and 12%, respectively. The countries in Europe have relatively less stock of EVs, there are still six countries in the top ten list, which are Netherlands, Norway, France, Germany, the Great Britain, and Italy. And the energy demand of EVs is going to take account of around 10% of the total energy in some European countries [10][11].

1.3.2 EVs Charging Impacts on DNs

With large penetration uptakes of EVs, it is crucial to understand how the EV charging demand is distributed across the network, in order to assess the load affecting the power grid.

The EVs charging behaviour is hard to expect and predict as it is totally up to the driver's willing, and different drivers with different traveling needs will have different charging patterns. The charging pattern can be varied in terms of charging power, charging period, charging start time and charging location.

According to the EV manufacturer, the charging power of an EV is quite huge (3 kW at least) comparing with all other appliances in the dwelling when the charging process occurs at home, which means the EV charging demand will contribute the highest electricity consumption among household appliances. Consequently, a large amount of EVs may impose a significant impact on the DN operation and planning, such as power quality issues. Then in order to analyse, quantify and minimise the impacts caused by the EVs, it is necessary to have a better understanding of EVs charging demand.

With the EVs uptake, EVs charging impacts on the DN will be huge. It will increase the total demand of the current DN and effect on each sector of the network, which will result in creating new peak power demand, voltage drop, frequency stabilisation issues, power losses and shorting equipment lifetime [12][13][14]. Therefore, EVs charging on the DN is threatening the network safety and operation.

1.4The Challenge of DNs Operation Based on New Energy Demand

With the fast developing in the integration of renewable energy and low carbon technologies into domestic dwellings, such as PV panels, heat pumps and EVs etc., in response to the UK emission target, the characteristics of this new energy demand will clearly have different impacts on DN in terms of spatial and temporal aspects.

The implementation of PV panels, small wind generator, and heat pump will dramatically change the characteristics of energy demand in domestic dwellings as these renewable technologies will improve the energy efficiency, especially the energy generators can provide on-site electricity usage within the dwellings instead of drawing the electricity from the grid. Moreover, the improved building fabric, LED lights and optimised occupants' behaviours will contribute to increasing energy efficiency.

Based on the nature of EVs charging events, the energy demand of EVs charging will have spatial and temporal characteristics. And the most of the charging event is going to occur at home level as for most of EVs' final destination will be their home. Consequently, the energy demand of domestic dwellings will be changed, and the new peaks of the electricity demand will occur correspondingly [15].

All these innovations will bring many positive impacts for reducing the GHG emission and achieving the UK target. However, the new integrated energy demand may have a massive impact on the DN operation and planning. On the operation side, it can lead to voltage violation, thermal limit violation, power losses, phase imbalance, and harmonics. On the planning side, it may create much bigger peak power demand than the current level, ending with additional investment on network reinforcement. Hence, it is necessary to minimise the impacts by using the dwelling's micro-grid concept, load-shifting method and ordered control of EVs charging.

1.5Research Contributions

The main contributions of this thesis are categorised as follow:

- **The Analysis of Potential Energy Savings of a Future Domestic Dwelling using EnergyPlus**

The energy demand of a domestic dwelling is modelled using EnergyPlus based on an existing Electric Home from Corby. And the potential energy savings from new building material, photovoltaic/thermal (PV/T) panels, LED lights and occupants' behaviours are investigated to increase the energy efficiency of the dwelling.

- **Reducing the Peak Power Demand of the Dwelling caused by the EV Charging using the DEIM**

Based on the analysis of the EV charging demand and the energy demand in the dwelling, the Dwelling-EV Integration Model (DEIM) is established via Building

Control Virtual TEST BED (BCVTB), which is the foundation of the further analysis. An individual dwelling is modelled to analyse the impacts of the energy demand in the dwelling caused by the EV charging, and load-shifting method and the Battery Storage Energy System (BSES) are used to reduce the peak power demand and smooth the daily power demand in the dwelling.

- **Minimising the Impacts of EVs Charging on LV DN using the Dwelling's Micro-grid**

Large scales of EVs charging will cause lots of issues on the Low Voltage (LV) DN. Based on the occupants' behaviours and stochastic characteristics of the EV mobility, the model of EVs charging demand is established and it is used for investigating the impacts of EVs charging on the LV DN. And the dwelling's micro-grid is proposed to minimise the impacts of EVs charging, such as voltage drop and power losses.

- **The OCS of EVs using the Expected Power with the BSES**

In order to address the issues caused by the uncontrolled EVs charging on the LV DN, an Ordered Control Strategy (OCS) using the expected power is proposed, which is approved to be feasible. Additionally, the OCS using the expected power is combined with the BSES is proposed, which can reduce the capacity of the BSES and smooth the power demand of the network that overcomes the stochastic characteristic of EVs charging.

1.6 The Framework and Outline of the Thesis

- **The Framework of the Thesis**

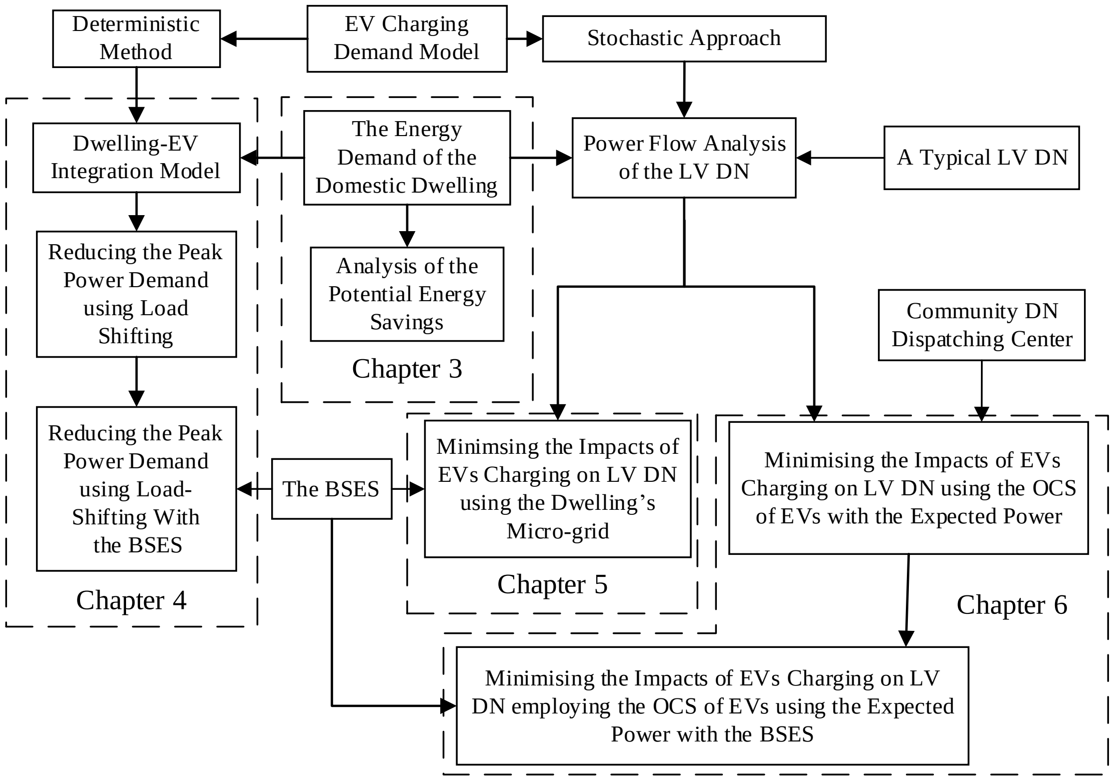


Figure 1.4 The Framework of the Research

The framework of the whole research is shown in Figure 1.4. Firstly, the energy demand of an individual dwelling is modelled in the EnergyPlus and the potential energy savings have been analysed. Then, the DEIM has been established through BCVTB and an individual dwelling is investigated to reduce the peak power demand of the dwelling using the load shifting and the BSES methods. And last but not the least, based on the occupants' behaviours and the stochastic characteristics of EVs mobility, EVs charging demand is modelled. Furthermore, EVs charging impacts of the LV DN are investigated and different methods, the BSES and an OCS of EVs using the expected power are proposed to minimise the impacts.

• Outline of the Thesis

In chapter 2, a comprehensive literature review is given regarding available methods and approaches of energy demand modelling of dwellings, current states of the EV technology and the impacts of EVs charging on the DN.

In chapter 3, the energy demand of the domestic dwelling is modelled in the EnergyPlus based on the Corby Electric home, and also the factors, including new building materials, PV/T panels, LED lights and the occupants' behaviours are investigated to analyse the potential energy savings in the dwelling, in order to improve the energy efficiency of the dwelling.

In chapter 4, the DEIM is established using the BCVTB. And an individual dwelling is modelled to analyse the impacts of the energy demand in the dwelling caused by the EV charging, and load-shifting method and the BSES are used to reduce the peak power demand in the dwelling.

In chapter 5, the power demand of EVs charging is modelled considering the occupants' behaviours and EVs' mobility. And the impacts of large scales of EVs charging on a UK typical LV DN is analysed. Then, the concept of the dwelling's micro-grid is proposed to minimise the impacts of EVs charging on the DN.

In chapter 6, an OCS using the expected power and the BSES is proposed to address the impacts of the uncontrolled EVs charging on the LV DN. And this strategy is not only able to reduce the capacity of the BSES, but also smooth the daily power demand of the network.

In chapter 7, the findings from this study are summarised and the future works, that can be done to improve the current work, are mentioned as well.

Chapter 2

Literature Review

2.1 Introduction

In this chapter, a comprehensive literature review is given regarding energy demand modelling and energy savings in residential buildings, integrating modelling, the current state of EV technology, the modelling of the EV charging demand and studies carried out by many other researches on impacts and minimising methods of EVs charging on DN.

2.2 Modelling of Energy Demand in Residential Buildings

Energy consumption of the residential sector takes account for 16-50% of total energy, and averages around 30% worldwide, particularly 31% for UK [7]. Due to this significant energy consumption level, more and more attention has been paid to understand the characteristics of energy consumption in the residential sector.

Energy consumption of other major sectors such as commercial, industrial is well understood than residential sector due to their centralised ownership, self-interest and high levels of regulation and documentation. Compare with those sectors, the reasons why residential sector is still undefined are that a) it has a wide variety of structure sizes, materials and geometries, b) the occupant behaviour varies widely and could be the dominant factor impacting energy consumption, c) privacy issues and cost effect limit the meter distribution and energy data collection.

In response to energy demand estimation, climate change, GHG emission and the lack of the knowledge, there is a need of better insight into detailed energy consumption characteristics of the residential sector in an effort to promote conservation, efficiency and low carbon technology implementation, such as on-site renewable energy, PV, combined heat and power (CHP) and EV.

2.2.1The Modelling Classification of Building Energy Demand

The high level of classifications of modelling building energy demand in the residential sector can be broadly categorised into, top-down and bottom-up [17], shown in Figure 2.1. Top-down models use the estimation of total residential sector energy demand with other related variables to attribute the energy demand to make up the entire housing sector. Bottom-up models simulate the energy demand of each individual or a small group of houses and then expend these results with reasonable weight factors to represent the national level. In this research, the focus was made on the bottom-up method.

The top-down approach works at an aggregated level, especially pointing at fitting a historical time series of national energy consumption data. And it tends to be used to investigate the relation between the energy sector and economy [18] and identify factors defining changes in energy consumption trends on the long-term. However, it does not distinguish energy demand of residential sector, due to individual end uses.

There are commonly two groups of top-down models: econometric and technological [17]. The former models are based primarily on price and income, and the latter models are made up according to broad information of housing stock.

The advantages of top-down modelling are the less input data information needed compared with the bottom-up approach, which the aggregated data are widely available. And the drawback of this approach is its reliance on historical data. Furthermore, the top-down modelling approach is not capable of identifying key areas for improvements for reduction of energy consumption considering its lack of detail in the energy consumption of individual end-use, and the impact of deployment of new low carbon technologies integrated into residential buildings is not able to be evaluated regarding energy consumption reduction.

The bottom-up approach is based on the energy consumption of individual end-use, houses or a small group of houses and then a representative weight factor of the samples is applied to reveal the energy consumption at the national level. Normally, there are three methods in the bottom-up approach, statistical, engineering and hybrid methods.

Statistical methods, also known as ‘black box’, is based on historical data, the regression analysis is utilised to establish the relation between the end-use and building energy consumption. Then the model can be used to estimate the energy demand of buildings that represent the residential stock. Engineering methods, also known as ‘white box’, is a method that uses power ratings and use of equipment and system to account for the energy consumption in dwellings. The hybrid method, also known as ‘grey box’, it is hybrid with two methods introduced early. It formulates a physical model to represent the structure of the dwelling and then identifies the important parameters.

Corresponding to the characteristics of the bottom-up approach, the input data is required in detail, including building properties such as geometry, material, and construction in fabric, equipment and appliances, weather conditions, occupants' activities, indoor comfort settings and schedules of equipment and appliances.

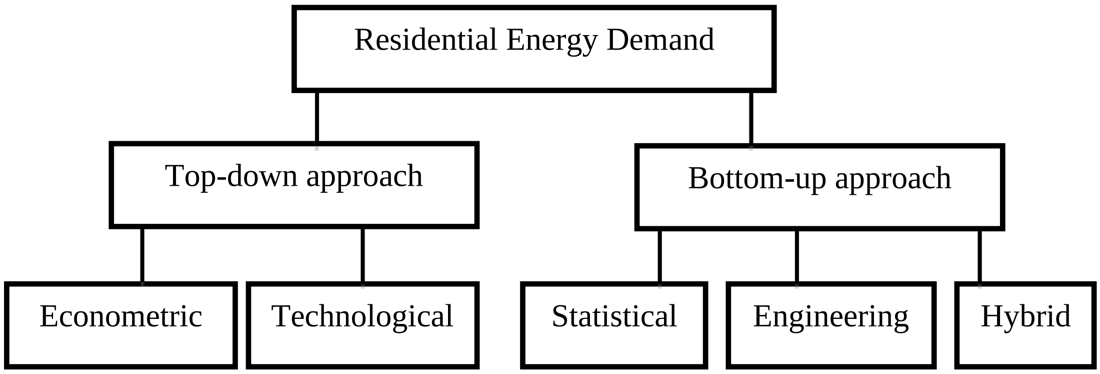


Figure 2.1 The High-Level Classifications of Modelling Energy Demand in the Residential Sector[17]

The most important advantage of the bottom-up approach is that it has the capability of identifying the areas to improve in dwellings to reduce the energy demand since it determines the energy consumption of each end-use. Furthermore, it is able to model integrated new technologies in each individual dwelling. The drawbacks of the bottom-up approach normally are the difficulty in gathering so much detailed information, complexity in calculation process and explicit prediction in occupants' behaviours in dwellings that could vary widely.

2.2.2 Input Data Information

Modelling energy demand of residential buildings is complicated, and it relies on input data to calculate or simulate energy consumption. Depending on the availability of the detailed input data, which can be dramatically varied, modelling techniques will be different. Input data required to develop energy demand models of residential buildings include physical characteristics of the dwellings, occupants' behaviours, appliances usage, weather conditions, and historical energy consumptions. This information can be in national level or individual dwelling values.

The preliminary estimation of the energy consumption of residential buildings is normally published by governments. However, this estimation may be treated as the indicators, as it could be inaccurate since it does not account for unreported energy consumptions.

In order to obtain more detailed information, house surveys are the basic data collection method. These surveys target at a small sample of populations to determine the characteristics of buildings, occupants and appliances penetration levels and attempted to define the house geometry and envelop, occupants' level, installation of appliances, thermal comfort settings. In the UK, Time Use Survey (TUS), 2000 [16] was conducted by NatCen and undertook by thousands of participants, and it contains detailed 24-hour dairies completed at the 10-mins granularity of time spent by population on varies activities. TUS can be employed for the purpose of modelling energy demand in residential buildings.

The estimation of usage of appliances in residential buildings can be achieved by using the energy meters. This method installs energy metering devices on each household appliance, which consumes large energy, to determine both energy consumption and the usage profile as a function of time. However, this detailed level of data information is very rare considering its prohibitive cost.

2.2.3Engineering Method of Energy Demand Modelling in Dwellings

The engineering method is the only method that can be used to fully develop the energy demand in dwellings without any historical energy consumption data. And the models developed in this research is based on the engineering method, therefore in the later section, this method will be explicitly introduced.

In the engineering method, models can be as simple as an estimate of space heating, which is the energy required to maintain the living space at a comfortable temperature by supplying thermal losses incurred across the building envelope, based on the climate through the use of heating degree day (HDD), or it can be as complex as a thermodynamic and heat transfer analysis on all type of energy conservations within the dwellings. Usually, there are three techniques defined in the engineering method, distributions, archetypes and sample [17].

Distributions are the technique that employs distributions of appliances ownership and use the power rating of each equipment or appliance to calculate the energy demand of each end-use. Since the energy demand in residential buildings is calculated separately, the interactions among end-uses cannot be revealed. Through aggregating the equipment and appliances to a national level, the energy demand in the residential sector can be estimated. Saidur et al. [7]developed a residential energy model of Malaysia based on different distribution estimates of ownership, power rating, schedule of appliances. The national annual energy consumption was estimated based on each appliance's variable. Capaso et al. [19] built up an appliance use profile of the Italian residential sector based on distributions obtained from housing surveys. Richardson et al. [20]developed a high-resolution energy demand models of UK by using the Markov-chain method. This model was based on the appliances' information obtained from Time Use Data, 2000.

Archetypes are the technique that firstly categorises the housing stock based on age, size and house type etc., and then for each category, one archetype can be developed to estimate the energy demand. Finally, all modelled archetypes are scaled up to represent the national housing stock by multiplying the numbers of houses, which are in each archetype. Huang and Broderick [21] developed a model of space heating and cooling loads of the American buildings using two archetypes of residential buildings, which were simulated in 16 different regions. Shimoda et al. [22] built up a residential end-use energy consumption model of city Osaka. 20 dwelling types and 23 occupant types were defined to represent the diversity of households in the city. Clarke et al. [23] used the main determinants of energy demand in Scottish buildings to develop the representative thermodynamic class, which was modelled and simulated in the building performance simulation software ESP-r.

The sample is the technique that uses the actual sample house information as the input data to the modelling. This method is capable of capturing the wide diversity of houses with the stock. By using an appropriate weighting factor, the modelling of the sample house can represent the energy demand in residential buildings on the national level. One of the advantages of the sample technique is that it can realistically reflect the high degree of variety of actual dwellings. Larsen and Nesbakken [24] developed a model of Norway's dwellings using 2013 household information. It was found that unspecified end-uses must be estimated in order to account for every end-use in energy demand modelling. Swan et al. [25] were focusing on a national residential energy model of Canada using nearly 17,000 houses. The detailed household information was converted to detailed house models for building energy demand modelling in ESP-r.

In this research, the engineering method of bottom-up approach was utilised since the actual and detailed residential building information is available for modelling the energy demand in dwellings, which is also an advantage of this study.

2.3 Energy Savings in the Dwelling

The factors that affect the energy demand in the dwelling consist of the building insulation, lighting system, and occupants' behaviours etc. In this section, the building material, PV/T panels, LED lights and occupants' behaviours are considered as the potential energy saving ways in the dwelling and will be analysed.

2.3.1 The Building Material

In order to maintain a comfortable living environment in the dwelling, a lot of energy will be consumed. Hence, improving the insulation of the exterior wall of the dwelling to reducing the energy demand of dwelling, especially for winter, becomes an effective way [26]. Furthermore, through reducing the energy demand in the dwelling, the needs of the fossil fuel will also be reduced and the GHG emission will be reduced consequently [27][28].

Using insulation material is a simple way to achieve energy savings and reduce energy demand in buildings, and it is easy to be implemented in domestic, commercial and industrial buildings. The insulation material is normally formed by the heat-resisted or composite material, such as such as fibreglass, mineral wool, and foam etc. and it is capable of reducing the heat flows [29], which contributes to lower the heat exchange between the dwelling[30] and the external environment and maintain the indoor temperature. And also, it can reduce the cost of building and operating the dwelling [31].

Normally, the insulation material can be divided into inorganic and organic. The inorganic insulation material is formed by non-renewable material, such as mineral wool and fibreglass. The organic insulation material is made up by natural vegetation or renewable material, such as kapok, wool and wood fibre [32], and it has been widely used because of its renewable, recycling and non-toxic characteristics[33]. Combining inorganic and organic insulation material is able to achieve well-insulated performance with low cost. Additionally, transparent material is widely used as skylight because of its capability of absorbing solar energy [34].

The code for sustainable homes is a method for certifying and assessing the design and construction of new sustainable dwellings, including nine aspects, which are energy and carbon dioxide emissions, water, material, pollution, and waste etc. And the code is rated from 1 to 6, the bigger the number is, the more sustainable the dwelling is [35]. And in this research, the energy demand and potential savings of the dwellings with code 3 and code 4 [36]are investigated respectively through the insulation material using the attributes of the U value.

2.3.2 PV/T Panels

Solar can provide thermal energy and electricity for the dwelling needs, which solar panels and PV panels are the typical applications. The solar panels are only able to provide thermal energy, which is not in high demand in summer and the energy generated will be wasted. The PV panels are able to generate electricity, which can be mostly used in the dwelling, however, the efficiency of the PV panels is relatively low, 10%-20%. PV/T panels can generate thermal energy and electricity which increase the efficiency of using solar energy and contributing the energy savings in the dwelling. Therefore, implementing PV/T panels is a reasonable and efficient way to help to reduce the energy demand in the dwelling [37].

Even PV/T panels are not accounting much in the market, improving the technology is still a hot topic in research. He et al. [38] designed a PV/T panel using aluminium alloy material and the system efficiency can reach 40%. Pei et al. [39] proposed a PV/T panels that using new thermal pipes and the thermal and electrical efficiency are 41.9% and 9.4%. Li et al. [40] used conductive silica of PV/T panels to improve the thermal and electricity to 37.37% and 14.08%. Nowadays, combining the PV/T panels with heat pumps becomes popular. Xu et al. [41] introduced a system of integrating heat pump and low-concentrating solar PV/T panels, it has the electrical efficiency of 17.5% in summer.

Reducing the energy demand in the dwelling can be accomplished by improving the utilisation of solar energy. In this research, solar panels, PV panels, and PV/T panels will be compared.

2.3.3 LED Lights

Installing LED lights is not only helping to save building energy[42], but also reducing the emissions of carbon dioxide [43]. In the lighting system, LED lights are one of the most advanced technologies [44], and it can reduce the energy demand by 85% with longer lifetime [45]. However, LED lights were not widely used in some European countries [52]. Hence, in 2009, European Commission Regulation set a statue to encourage LED lights in the dwelling instead of incandescent lamps [46]. In this research, incandescent lamps and LED lights are going to be compared regarding the energy savings of the dwelling.

2.3.4 Occupants' Behaviours

Occupant's behaviour is one important factor in impacting the energy demand in the dwellings and it is one of the input characteristics of the bottom-up modelling method

[47]. The occupant's behaviour is complex due to many uncertainties, such as lifestyles and culture differences [48], and recently, it is proved to be one of the most important factors of determining the heating demand [49]. Especially, the desired indoor temperature is different for each occupant, which will impact the energy demand in the dwelling directly [50]. From the questionnaire and analysis carried out in China, Ruan at el [51] concluded that orderly people need higher indoor temperature, which results in higher energy demand in the dwelling. Moreover, occupants living in the dwelling depend on the natural ventilation and infiltration, which also will impact the energy demand in the dwelling [52].

According to the current research, there are some models of the occupants' behaviours available [20][53][54]. For all of these models, the TUS data [16] is used, which is based on the analysis of thousands of people's daily life routines. In this research, TUS is also used to model a typical office worker living in the dwelling, and the occupant's behaviour is modelled through controlling the thermostats and the heat pump in the dwelling.

Although energy savings in the dwelling has drawn a lot of world-wide attention, the current researches are more focusing on the savings from the individual aspect, and comprehensive applications are not proposed. In this research, the factors including new building material, PV/T panel, LED lights and occupants' behaviour, are investigated to prove their capabilities of improving the energy efficiency in the dwelling.

2.4 Integrating Modelling

There is some software developed for designing and modelling buildings, and they are able to estimate the energy demand, model the Heating, Ventilating and Air Conditioning (HVAC) system, lighting system, illumination, and acoustics etc. Each software has its own outstanding features than others, however, all of them has limitations and may not fulfil all the users' needs [55]. In order to satisfy the requirements from the user, it will need lots of engineers to develop and update the software, which needs financial support. Therefore, integrating the currently available software to achieve multiple objectives of the users' needs is a feasible way.

Integrating modelling is formed to satisfy the special needs of users and at least two software will be employed to solve differential algebraic equations and achieve exchange data [55]. For the energy demand modelling of dwellings, Lawrence Berkeley National Laboratory (LBNL) and Eindhoven University of Technology have done lots of researches and committed to developing modelling tools.

Many researchers have done some works trying to establish a connection between different modelling tools. Treka et al. [56] suggested a method to ensure the accuracy of the results from integrating different modelling tools. Wetter et al. [57] discussed the definition and principle of integrating modelling tools and developed the BCVTB as a platform to connect and integrate different software. Riedere et al. [58] developed a method to integrate the MATLAB/Simulink and TRNSYS to model characteristics of buildings. Sagerschnig et al. employed BCVTB as the interface to integrate the EnergyPlus and one office building set up in MATLAB to model and estimate the energy demand. The office structure and HVAC system are modelled in the EnergyPlus and the control signal is generated from MATLAB, which the advantages of both software are utilised. However, the simulation times are dramatically increased [59]. Jones integrated TRNSYS and MATLAB, using the genetic algorithm toolbox in the MATLAB to solve the optimisation issues in sustainable dwellings. However, the operation and optimisation of the HVAC system were not considered [60]. Yahiaoui et al. [61] proposed a method to link MATLAB and ESP-r through TCP/IP, Internet socket to achieve integration. And it is approved that MATLAB is better in control than ESP-r. Beausolei-Morison et al. proposed a simulator that contains the characteristics of TRNSYS and ESP-r and it has been tested [62].

In this research, the BCVTB is used to integrate EnergyPlus and MATLAB to achieve the modelling and analysis of the energy demand of dwellings. Furthermore, the heat pump and the EV will be controlled by MATLAB to reduce the peak power demand in the dwelling.

2.5 The EV Technology

The use of EVs is a widely well-recognised low carbon technology in the world, not only due to its source of power can be obtained from renewable energy, but also its help on reducing the GHG emission from the transport sector. And moreover, it can contribute to reducing the energy crisis of those countries that rely on imported petroleum.

- **Types of EVs**

There are three main types of EVs on the market, which are classified by the degree of electricity used as their energy source.

The first one is called Hybrid Electric Vehicles (HEVs), which is powered by both petrol and electricity. The electric energy is generated by the vehicle itself via braking system to recharging the battery. The electric motor helps to slow the vehicle and uses some of the energy normally converted to heat by the brakes. HEVs stat off using the electric motor, and then the petrol engine steps in as speed rises. These two motors are controlled by an internal computer, which ensures the best economy behaviour for the driving conditions. In the market, HEVs are very common EVs on the road, such as Honda Civic Hybrid and Toyota Camry Hybrid.

The second one is named Plug-in Hybrid Electric Vehicles (PHEVs), this type of EV is powered by both petrol and electricity as well. However, the battery installed in PHEVs can be recharged by both the braking system and an external electrical charger. The petrol engine extends the range of the vehicle by recharging the battery as it gets low. The manufactures of these PHEVs vary greatly depending on the choice of primary energy sources, such as Toyota Prius and Mitsubishi Outlander PHEV.

The last one is Battery Electric Vehicles (BEVs), also known as Full Electric Vehicles (FEVs). This type of EVs is only powered by electricity and does not need a petrol engine, fuel tank or exhaust pipe, which makes it the most environmental friendly as it produce zero CO_2 emissions. It needs to be charged by an external electrical charging outlet to charge the battery, additionally, it can also be charged by the braking system. There are many manufacturers offer this type of EVs, such as BMW i3 and Nissan Leaf.

- **EV uptakes in the UK**

The fast-growing ownership of EVs has been happening over the last few years. More than 192,000 light-duty EVs had been registered in the UK until Dec. 2018 [63]. Until Dec. 2016, the Plug-in fleet in the British was the fourth largest in Europe. And the registered EVs from Jan. 2011 to Dec. 2017 is shown in Figure 2.2 [64], it can be seen that PHEVs is growing fast during these years than BEVs as it is much easier accepted by people, by comparing the cost and also the anxiety of the battery capacity in EVs for driving between PHEVs and BEVs.

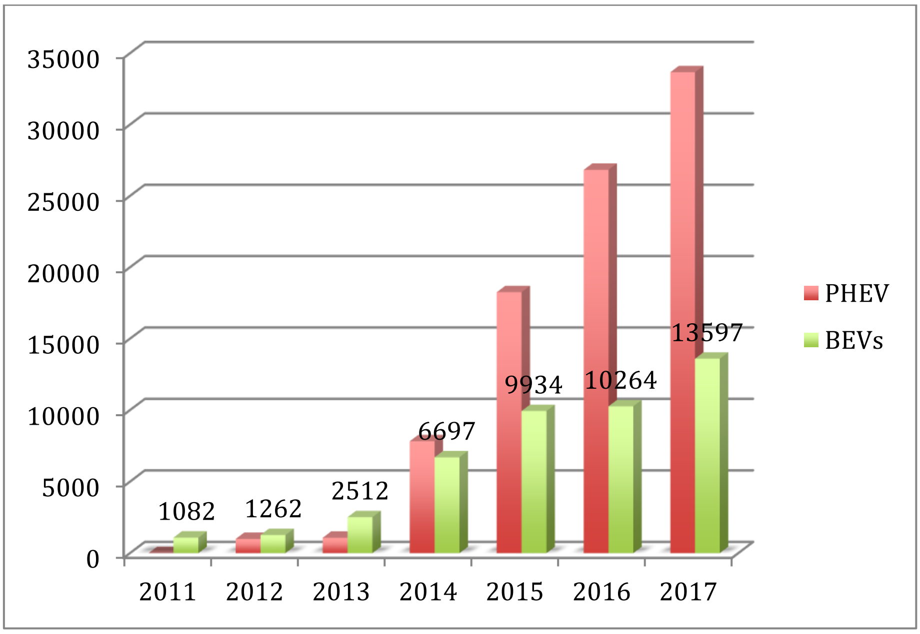


Figure 2.2 Registered EVs until DEC. 2017 [64]

In the manufacturing market, the registered numbers of the top 15 best-selling EVs are shown in Figure 2.3, provided by Next Green Car [63]. It illustrated many popular EVs in the UK from 2014 to 2017, and the all-time best selling EV is Mitsubishi Outlander PHEV around 30,000 registered by the 3rd quarter of 2017. The Nissan Leaf ranks followed by the Mitsubishi Outlander PHEV is the second best-selling EVs in the UK market. Furthermore, there are Mercedes Benz C 350e, BMW i3 and Renault Zoe etc.

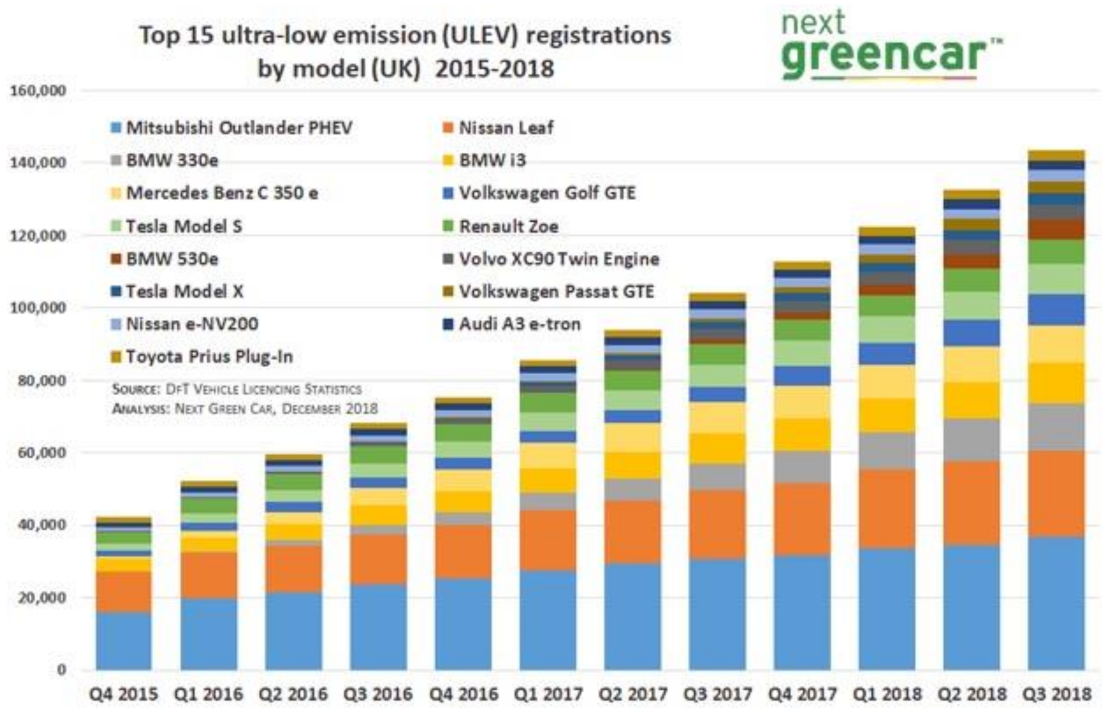


Figure 2.3 Top 15 ULEV Registrations by Model (UK) 2015- 2018[63]

• UK Government support

UK government is carrying out many EV trials and grants to strongly support EV uptake in the UK, for EV trails such as My Electric Avenue, Electric Nation, for EV grants such as Plug-in Car Grant, EV Home Charging Scheme.

My Electric Avenue is a 3 year Ofgem's Low Carbon Networks funded project that has been carrying out trails to discover the impact that charging clusters of EVs might have on local electricity networks at peak times. And it has been hosted by Scottish and Southern Energy Power Distribution and led by EV Technology.

Electric Nation is a Western Power Distribution (WPD) and Network Innovation Allowance funded project [65], and it is on track to achieve its target of recruiting 700 people buying or leasing new EVs to take part in a trial to ensure the UK can charge EVs at peak times as the uptake of EVs. This Electric Nation trial is only taking place in certain locations in the UK, which is the WPD network area in the South West, South Wales, West and East Midlands.

The Plug-in Car Grant offers the opportunity of price reduction for the people who purchase qualified EVs, and it is automatically deducted from the retail price, hence, no additional paperwork needs to be complete. The savings is approximately 35% of the cost of a car, up to a maximum of either £2500 or £4500 depending on the category the model belongs to, also it applies to vans and motorcycle.

Electric Vehicle Home Charger Grant (EVHCG) provides a grant of up to £600 for individual EV owners who have taken keepership of a new or second-hand eligible EV on or after 1st 2018[66], this EVHCG offers the opportunities for EV owners to offset some of the upfront cost of the purchase and installation of a domestic recharging unit.

From what has been introduced above, it can be clearly seen that the UK government is strongly supporting the EV developing and also the associated charging infrastructure. With the rapid EV uptakes, the charging needs of EVs will have huge impacts on the DN, therefore, the impact analysis becomes important

2.6 The Current State of Modelling EVs Charging Demand

Expected large penetration of EVs in the future will lead to an increase in electricity demand. In order to assess the effects on the power system, an estimation of EVs charging demand is necessary. Many researchers paid attention to modelling EVs charging demand, and there are many models in the literature. Therefore, in this section, the state-of-art of EVs charging demand modelling was elaborated.

In the literature, there are mainly two approaches to model EVs charging demand, which can be categorised as deterministic and stochastic approaches.

• Deterministic Approach

In reference [67]-[68], EVs charging demand was modelled using a deterministic approach. The EV charging load was modelled based on some typical and realistic EVs in the vehicle's market.

Waraich et al. [67] presented an agent-based traffic demand model to model the charging demand of EVs over a day. And a simple PEV model with a standard charging rate was assumed, which is 3.5kW.

Hadley et al. [69] forecasted the potential impacts of PHEVs on electricity demand, generation structure and emissions levels in 2020 and 2030 in the U.S. The charging characteristics of PHEVs were presented with constant charging rate at 1.4kW, 2kW and 6kW were selected in this study, and also the charging schedule was assumed as evening charging at 5 pm, 6 pm and night charging at 10 pm, 11 pm.

In [70], Richardson et al. demonstrated how controlling the rate at which EVs charge can lead to better utilization of existing networks. A technique based on linear programming is employed to determine the optimal charging rate for each individual simulated EV to maximize the total power can be delivered to EVs while within network limits. Regarding EVs charging demand modelling, the EV battery was based on a lithium-ion battery technology of 20kWh, with a constant charging rate at 4kW until 95% state of charge (SOC) of battery and then 1.5kW until fully charged.

Valsera et al. [71] analysed the impact of EVs charging on a MV power gird through determining a relation between EV model battery characteristics and its charging process. The typical EV, Mitsubishi i-MiEV, was used in this paper. Additionally, for each individual simulated EV, the initial SOC before the charge was assumed at 20%, and 4 hours to be charged to 100%.

Guo et al. [72] established a model to evaluate the impact of factors on the aggregated EV load. EV battery size, charging power rate, charging habits and time-of-use pricing (TOU) policy are the main factors examined in the paper. And the linear regression method was used to build a linear EV charging model. The constant charging rate was employed in the model, and also the EV energy consumption was reasonably assumed to be 3.042miles/kWh.

Kintner et al. [68] estimated the regional percentages of the energy requirements for the U.S. light-duty vehicles stock that could be supported by the existing infrastructure, which took into account congestion in regional transmission and distribution systems. Regarding the EVs' mobility modelling, all EVs were assigned with a certain distance travelled per day in this study.

- **Stochastic Approach**

The uncertainties of modelling of EVs charging include when and how EV is going to be charged and how long it is going to be charging. All these factors are determined by 2 aspects, which are EVs' driving patterns and EVs' charging characteristics. The former one, EVs' driving patterns, is mostly depending upon the drivers' behaviour, and it has stochastic nature, which is normally difficult to predict and model. The latter one, EVs' charging characteristics, is driven by the SOC of EV battery, which has the relation with the battery type, the capacity of the EV battery and distance travelled.

In[73]-[74], the characteristic of EVs' mobility was modelled using a stochastic approach, the EVs' charging load is based on some reasonable assumption

Lojowska et al. [73] presented a stochastic modelling of EVs charging demand driven by transportation patterns using Monte Carlo procedure, where three key variables, time of vehicles' arrival and departure time at and from charging locations and travelled distances, were selected from a transportation database for modelling the mobility of EVs. And also the impact of EV load on the national power demand of The Netherlands was analysed.

Soares et al. [75] proposed a stochastic model considering mobility variables, and the EVs' characteristics, battery capacity, energy consumption and charging demand, are determined by a Gaussian distribution with given values derived from a project database.

Rassaei et al. [76] modelled the stochastic nature of EVs' charging behaviour and answered the question of EVs' demand response in helping to minimize the peak power demand. And the results showed that it is possible to accommodate EVs for all the users in the system. For EVs' mobility modelling, the author employed Gaussian distribution and non-uniform distribution for determining the arrival time, charging time and departure time of EVs, respectively. And a Nissan-leaf with 24kWh battery capacity was assumed in this study.

Mohsenian et al. [77] pointed out that an uncertain departure time significantly changed the analysis in optimizing the charging schedule of EV, and also the author obtained a closed form solution for the stochastic optimization problem that is formulated to schedule charging of EVs with uncertain departure times.

In [78], Pantos adopted Monte Carlo technique in this paper, and it was used to generate a set of future EVs' charging demand profiles based on information about an expected future EVs' load and an expected amount of uncertainty involved. For detailed EVs' charging modelling, EV was based on a fixed battery capacity at 25kWh.

Shahidinejad et al. [79] addressed the shortcomings of standard driving cycles used in mimicking the real-world driving behaviours by using a large database of one year of measured data collected from many participated cities. And the authors described a methodology for statistical analysis of collected data and used it for modelling the power demand of EVs. It took into account various factors including distance driven, car velocity, trip duration, trip purpose, a deferred charging event.

Wang and Infield [80] made an effort on generating accurate EV driving patterns by using high-resolution data through a Marco Chain Monte Carlo simulation. Then simulated driving patterns were assigned to each EV, in order to analyse the network impacts due to EVs charging. When looking at the individual EV charging demand modelling, the BMW i3 was utilised and charging rates were assumed at standard charging at 2.4kW and fast charging rate at 7.4kW.

In [74], authors Ashtari et al. compared deterministic simulation results with stochastic methods regarding how the EVs' mobility and charging habits modelled. And the result was shown that the stochastic method proposed by authors in this study was more accurately captures the relationship of EVs' departure, arrival and travelling time.

Overall, there are two approaching of modelling EVs charging demand, which are the determinism and the stochastic method. In this research, determinism is used to model an individual EV charging demand and its impact on the dwelling, furthermore, the ways to minimise the impact are proposed. When considering a community level, there are a lot of EVs, the daily travel distance, charging needs and occupants' behaviours are showing stochastic characteristics, hence, the stochastic method of modelling EVs charging demand is employed to reveal these characteristics. And the impact caused by EVs charging and the ways to reduce it are analysed.

2.7 Impacts of EVs Charging on DNs

With the increasing penetration of EVs, the stochastic characteristics of EVs charging will definitely increase the uncertainty in network operation and large sales of EVs uncontrolled charging can result in disastrous impacts on DN. The impacts come from stability, power quality of the network.

- **Impacts of The Network Stability**

From [81], it pointed the impacts of EVs charging to the power demand, that with 10% penetration of EVs, the power demand is increased 17.9% and 20% of EVs, the power demand is increased 35.8%.

In [82], authors J. Taylor et al. concluded that the important factors to analyse EVs charging on the DN are the penetration level and the stochastic behaviours. And two methods are proposed, determinism and stochastic analysis method.

W. Denholm et al.[83] pointed out that the uncontrolled EVs charging may further increase the peak-valley and when EVs charging is shifted to the midnight, the efficiency of the network is increased.

From [84], a method was proposed based on a typical DN to evaluate the impacts of EVs charging on the network. And two case studies were carried out and the investment and energy demand with different EVs penetrations were analysed. And, the relations amongst the penetration level, investment, and power loss were concluded.

In [85], the impacts of EVs charging demand on the capacity of the network equipment were investigated. And from the investigation, it showed that even with low penetration of EVs in the network, it is still possible to overload the current equipment.

From [86], it showed that during the off-peak period of the network, EVs charging demand can be accommodated, however, there is still a possibility that the system is overloaded.

And a real DN in Portuguese was analyses by C. Camus et al. [87], and it indicated that with high penetration of EVs charging, the overload might occur.

- **Impacts of Power Quality**

The impact of EVs charging of the power quality in the network was investigated by G. A. Putrus et al. [88]. It pointed out that the uncontrolled EVs charging could result in unbalanced voltage distribution, even voltage instability.

The impacts of uncontrolled EVs charging of the voltage quality and power loss in the network were analysed based on a real Indian DN data [89]. 10%, 20% and 30% penetration level of EVs were considered, and it showed that the impacts of uncontrolled EVs charging on DN is little during the off-peak period. However, during the peak period, the power loss was increased and the voltage quality was reduced.

In [70] Richardson et al. modelled the EV charging demand and also investigated the effects of this charging on the power system, especially for existing DN. And demonstrated how controlling the rate at which EVs charge can lead to better utilization of existing networks. And authors conducted a conclusion that by controlling the charging rate of individual vehicles, high penetrations can be accommodated on existing residential networks with only a little or no need for the system infrastructure upgrading.

Lee et al. [90] pointed out that when many EVs connected to grid during a short time, the power quality problems can occur such as voltage violation, unbalance, harmonics, and emphasised that it is necessary to analyse the effect of power quality on the distribution system. Authors developed a model of an EV battery charger and carried out simulations in DN, considering typical charging variables such as the number of EV connected each hour and EV penetration level. And a conclusion was made that about 20% EV penetration the voltage exceeds the limit. However, in this study, only the impacts of residential EV charging on voltage violations were analysed.

C. Farmer et al. [91] pointed out that due to the stochastic characteristic of EVs charging demand, which is unique and different. The impacts of EVs charging on the network were analysed and the issues it could be increased power demand, overloaded, harmonics and unbalanced voltage etc.

Overall, with the increasing penetration of the EVs in the DN, the impacts caused by EVs charging are dramatically increased. Currently, most of the researches concentrate on two aspects to quantify the impacts, which are reliability, power quality, and operation economy. The methods of investigating these aspects are normally based on certain assumptions and scenarios, such as all EVs charging are happening during the off-peak period, which is able to satisfy EVs charging needs, but does not consider the users' preferences. Hence, it is necessary to analyse the impacts caused by EVs charging during the actual charging period and the stochastic behaviours of EVs.

2.8 The Charging Strategies of EVs

The LV DN will be firstly impacted by large scales of EVs charging, hence, most of the optimised EVs charging strategies focus on avoiding overload, reducing peak-valley and power loss, and saving investment cost. And an optimised charging strategy of EVs is able to minimise the peak-valley demand [92], which will be further discussed in detail.

From [93], S. Gao et al. concluded the impacts of the EV connected to the DN from the steady-state and dynamic point of view. And it provided a reference of dynamic analysis of impacts caused by EVs charging.

In [94], three EVs charging strategies were proposed by T. K. Kristoffersen et al. based on the constraints of network security, including uncontrolled charging, delayed charging and smart charging. The relation between the charging strategies and the maximum capacity of accommodating the EVs was analysed, and it pointed out that ordered control of EVs charging is an inevitable requirement to increase the EV penetration.

Mullan et al. [95] investigated the potential impacts of EVs on the Western Australian electricity grid, the options for managing those potential impacts and constraints. In this study, the authors evaluated the worst case scenarios by assuming all vehicles are EVs, which account for over 200,000 EVs. The authors pointed out the electricity supply and transmission industry can achieve significant short- and long-term benefits.

Chao et al. [96] developed a statistical time series based approach to quantify the voltage violation due to EVs and small wind turbines. This statistical approach allows for a quick analysis of the probability of daily voltage violations in DN, and thus provides effective solutions in system regulation. And authors have conducted that the approach they introduced is capable of reducing the computational requirement by over 98%. However, the EV charging types and characteristics utilised in this study are simplified.

Babaei et al. [97] analysed the effects of plug-in EVs charging on the local 400V and 10kV electric distribution systems in the city of Gothenburg, Sweden, using steady state power flow analysis, where the yearly peak load is selected for simulation. Authors made a conclusion of that overloading of line and transformers would occur when simultaneous charging of the plug-in EVs during the peak load period and voltage drops in both residential and commercial systems are acceptable.

From [98], it showed that the simulation time and complexity become an advantage when the objective is to minimise the power loss with the constraints of minimum load fluctuation, which is important to the real-time dispatch.

In [99][100], the optimised charging strategy of EVs was based on the minimising the charging cost. The relation between the battery charging rate and the SOC was considered. And it proved that the proposed charging strategy has the advantage of reducing the charging cost and peak-valley power demand.

In [101], the queuing theory and broadcast were involved to guide EVs charging. And it concluded that through reasonably choosing the information from broadcast, the average number of EVs charging during peak period is the lowest.

Denholm P et al. [106] proposed a way to reduce the new peak power demand caused by EVs charging by controlling the charging time. And the TOU electricity price was employed to arrange EVs charging during the off-peak period, which might result in creating a new peak power demand. Hence, dividing the charging time and interlacing charging were used to avoiding creating a new peak.

In [102], the economic incentive was used to control the charging time of EVs, such as TOU electricity price, which could lead users choosing to charge EVs between 23:00 and 07:00. However, it only introduced the ideas.

Overall, the charging strategies of EVs are mainly focusing on minimising the power loss and voltage drop. Besides these, reducing peak power demand, increasing penetration level and reducing charging cost are feasible. Using reasonable charging strategy of EVs charging is able to reduce the impacts of the network reliability and economy operation and it is an essential step to accommodate large penetrations of EVs.

Consequently, in this research, the occupants' behaviours and stochastic characteristics are considered to investigate the impacts of EVs charging on a typical UK LV DN, and the methods to minimise the impacts. Additionally, it can contribute to providing a theoretical principle for the large deployment of EVs.

2.9 Summary

In this chapter, the modelling approach of energy demand in residential dwellings and the potential energy savings are revealed and summarised. Then the modelling of EVs charging, its impacts on the DN and the feasible methods to minimise the impacts are categorised. Based on the current research status, the following research gaps and needs are proposed:

Current methods of modelling the energy demand of dwellings and the potential energy savings are mostly focusing on the attribute of the material or equipment, such as improving the material insulation of the dwelling, increasing the efficiency of using solar energy and investigating the characteristics of the occupants' behaviours etc. However, the sensitive analysis of each aspect has not been undertaken comprehensively. Hence, in this study, the EnergyPlus is employed to establish the detailed model of the Electric home in Corby, analyse the energy demand of the dwelling and the sensitive analysis of the potential energy savings is carried out to investigate the ways of improving the energy efficiency in the dwellings.

It is obvious that when large scales of EVs located in dwellings, the energy demand and peak power demand of the dwelling will increase correspondingly which will results in many effects on networks. Most of the current researches are only focusing on the control of electrical equipment in the dwelling to curtail the impacts of EVs charging, however, the comfort level is not taken into consideration. Therefore, in this research, the BCVTB is employed to connect the detailed dwelling model and the determined EV model. With the consideration of the comfort level, the control strategies are proposed to minimise the EVs charging impacts.

At the moment, the most analysis of the large scales of EVs charging on DN is using the deterministic method, which is failed to represent the stochastic behaviours of EVs and not able to reveal the actual EV charging behaviours, especially, some worst-case scenarios may not be considered. Therefore, in this study, the occupants’ behaviours and EVs’ mobility have been taken into consideration for establishing the model of EVs charging demand and analysing the impacts of the EVs charging on the DN. Through building the Dwelling’s Micro-gird, the BSES is employed to reduce the impacts caused by EVs charging.

Ordered charging is recognised as an effective method to minimise the impacts of EVs charging on LV DN. Most of current state of the research is capable of smoothing the power curve when EVs are charging, which is not targeting at the whole day time period. In this study, based on the ordered charging, the OCS of EVs charging using expected power with the BSES is proposed to minimise the impacts of the EVs charging on LV DN, which is proved that it is able to smooth the power demand curve during whole day.

Chapter 3

The Analysis of Potential Energy Savings of a Future Domestic Dwelling using EnergyPlus

3.1 Introduction of Energy Demand of Domestic Dwellings

The planning of a DN is normally based on the prediction of the energy demand of the considered area, hence the prediction of the energy demand of the certain area becomes crucial. According to the previous analysis， the residential sector contributes a huge percentage in the energy demand over all sectors. Therefore, it is essential to understand and evaluate the format of the energy demand of domestic dwellings.

With the innovation in the new building material and low carbon technologies (EVs and PV/T etc.), the energy demand in future buildings is changing. Hence, the understanding of the energy demand of future domestic dwelling is important, which is analysed in this chapter. The Electric home of the Corby homes is employed in this chapter and EnergyPlus is used to investigate the electricity demand in the dwelling. Moreover, the new building material, PV/T, LED lighting and occupants' behaviours, are analysed to evaluate the impacts of different factors on the energy demand of the domestic dwellings. Regarding the impacts of EVs charging, it will be investigated in the following chapters.

The energy demand in the dwelling, analysed in this chapter, mainly focus on the electricity part. Because of the investigation in the later chapters of the impacts of an EV charging in a residential building and large scales of EVs charging on the DN, the electrical power is the major concern.

3.2 EnergyPlus

3.2.1 Introduction

EnergyPlus, a thermal simulation engine, has been developed by the United States Department of Energy (DOE) and LBNL. It works for architects, engineers, and many researches. EnergyPlus can simulate building energy performance, aim at investigating the relation among building parameters, environmental variables, and the HVAC system. It helps to point out the places where the energy efficiency can be improved of building system[1].

3.2.2 The Concept and Function of The EnergyPlus

EnergyPlus is a time-to-time simulation engine for modelling energy demand in dwellings, and it adopts forward modelling method. The forward modelling method's output variables (energy demand) are predicted after input variables and system structure and characteristics are determined. There are mainly three modules, the load module, the system module, and the device module, simulating together to model the energy demand in a building[103].

The load module is used to simulate the interaction among building envelope, outdoor environment and indoor loads; The system module is used to simulate air loop equipment, fan, coil, and related control devices of the air conditioning system; The device module is used to simulation cooling and heating source device, such as boilers, pumps, cooling towers, energy storage equipment and power generation equipment etc. In EnergyPlus, these modules are simulated simultaneously and the flow chart of the simulation is shown below in Figure 3.1[104].

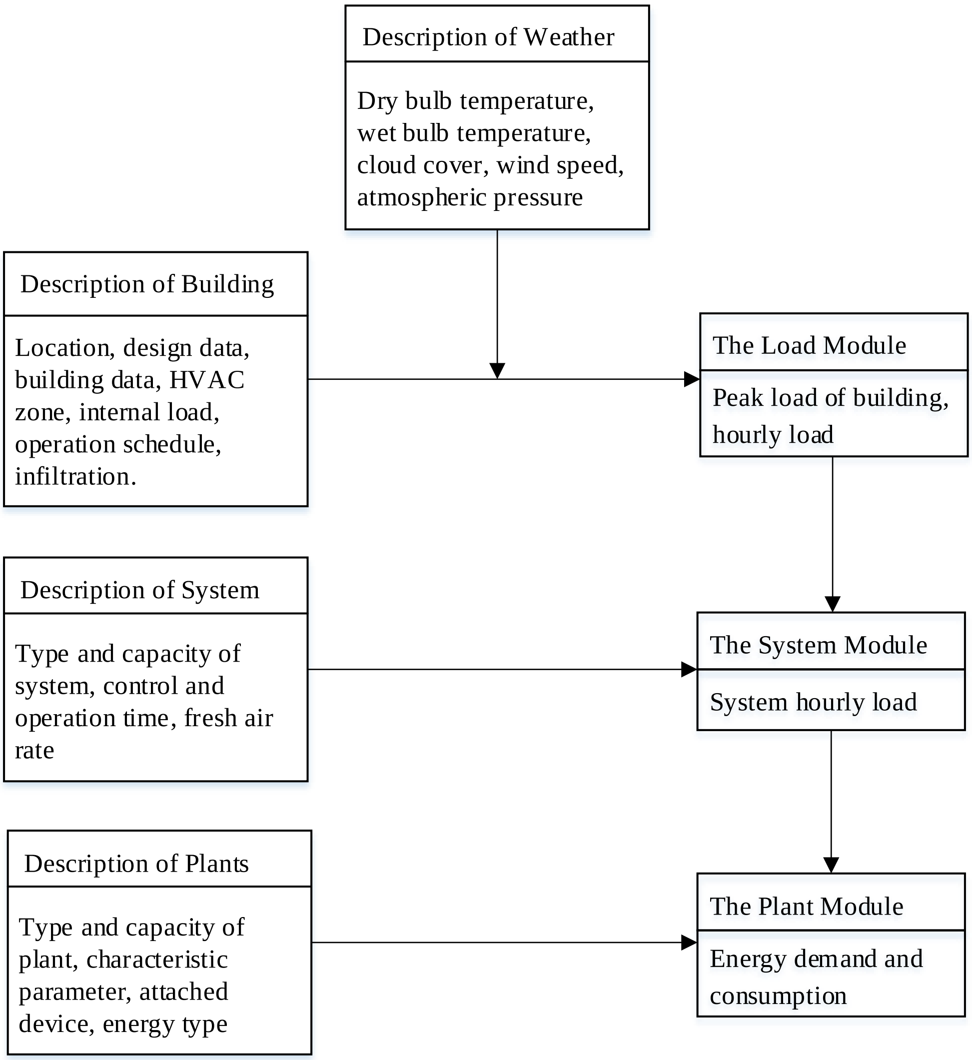


Figure 3.1 The Flow Chart of the Simulation Procedure in EnergyPlus[104]

• The Load Module

The load module is the simulation based on the outdoor environment, the building envelope and the indoor load. In EnergyPlus, the simulation time step can be customised up to 1min, normally 10mins or 15mins is selected.

The heat balance method is used in EnergyPlus to calculate the load according to the first law of thermodynamics. The equation of the heat balance is established based on the outside heat balance process, wall conduction process and inside heat balance process[105], and the schematic diagram of the heat balance method is shown in Figure 3.2[105].

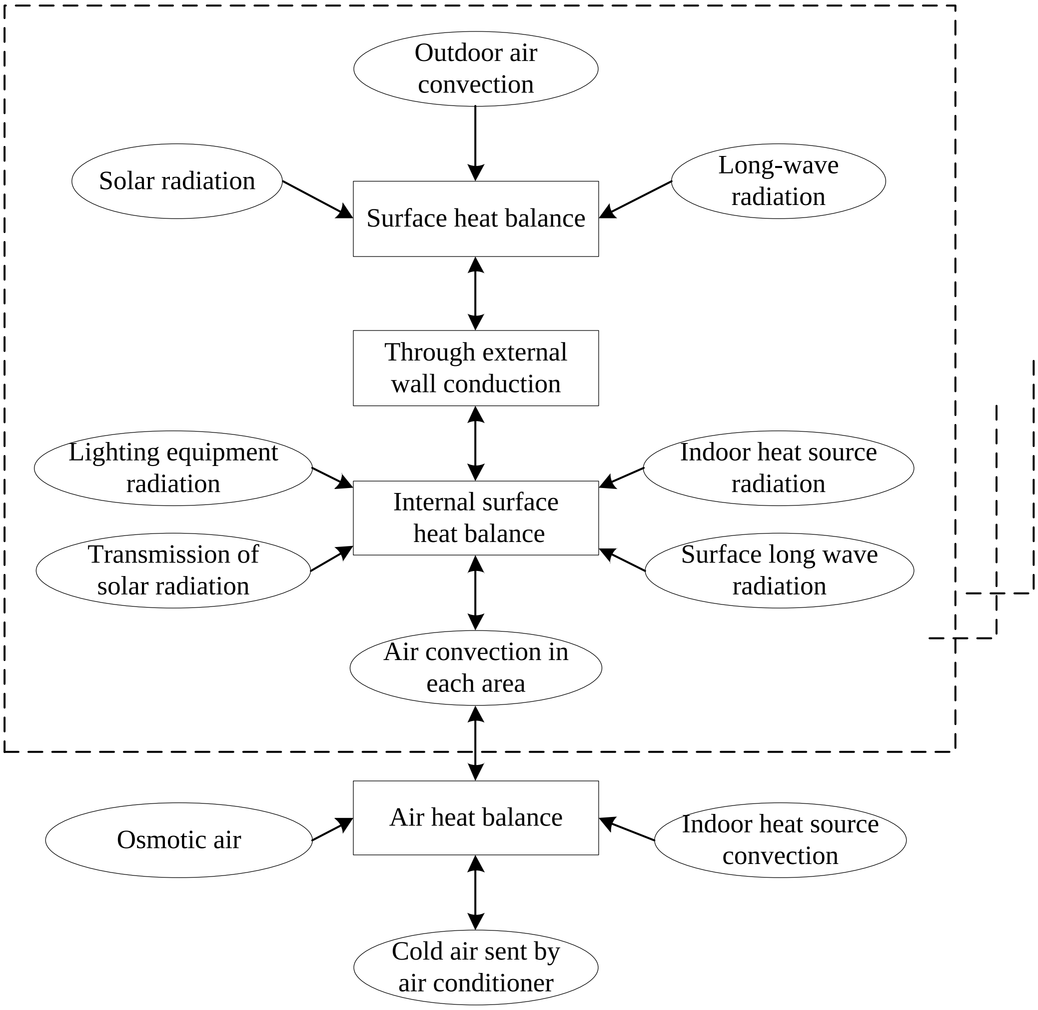


Figure 3.2 Schematic Diagram of the Heat Balance Method in EnergyPlus[105]

• The System Module

The system module, controlling the air conditioning components of the cooling and heating equipment, includes transmission and distribution equipment[103]. It is controlled by many different schedules, through changing those schedules and temperature set points. The air sourced heat pump (ASHP) is employed as the heat source.

- **The Device Module**

The device module in EnergyPlus includes cooling and heating equipment, such as boilers, heat pumps, lighting equipment, and appliances etc.[103] And it is modelled by regression fitting method in EnergyPlus, which the performance data from the manufactory is used to obtain the equation for describing the operation characteristics and energy consumption of the equipment. For the lighting equipment and appliances, the rated power and heat-related parameters have to be the available inputs for the simulation.

3.3 The Energy Demand in Future Domestic Dwellings

3.3.1 Introduction

The domestic dwellings constructed in Corby consist of three types, named Control, Electric, and Gas homes. The Control home represents the semi-detached dwelling of the UK current standard, which is used as the baseline in this work. The Electric and Gas homes are purposely built to be Zero Energy Bill homes, apparently, both of them are equipped with low carbon technologies and tried to increase the efficiency of the energy system and reduce the annual energy bills. Moreover, the concept of Zero

Energy Bill homes also aims to reduce GHG emissions and helps to achieve the target set by the UK government[106].

These three types of dwellings are located in Corby, which is a city in Nottinghamshire UK. They are constructed by Electric Corby, who aims to make contributions of building a sustainable community. And in this research, the dwelling named, Electric Home is used as the modelling base.

3.3.2 The Construction and Material

The construction of Electric home is shown in Figure 3.3. The information is provided by the McBains Cooper Consulting Ltd. It can be seen that the ground floor comprises of a hall, a kitchen, a WC, a dining room and a living room while 3 bedrooms, an en-suite, a bathroom, a store room, and an electrical room constitute the first floor of the dwelling.

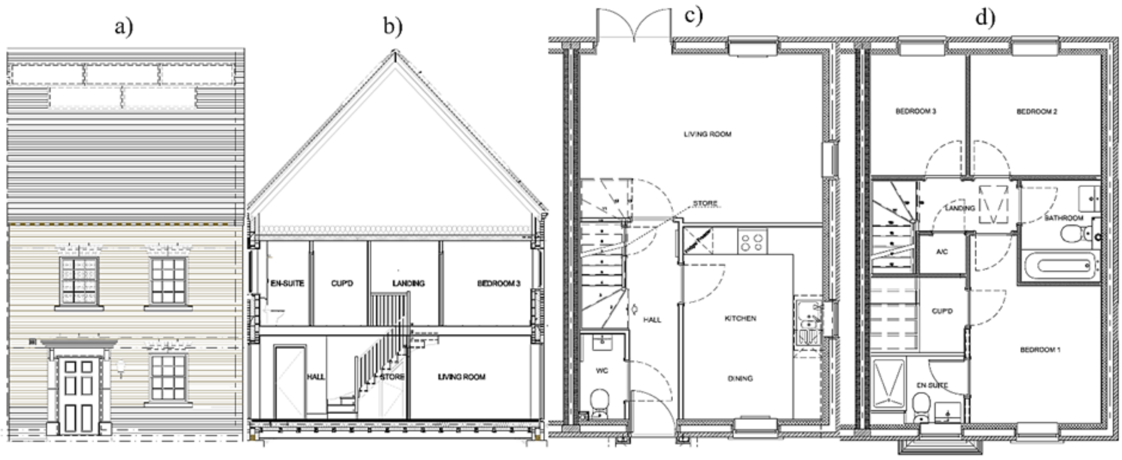


Figure 3.3 The Construction of Electric Home

The material characteristics of each building element of an Electric home is shown in Appendix, Table A-1. All the thermal characteristics of building material are obtained from architecture plan provided by the constructor.

One more thing in here needs to be mentioned is that before modelling the building contracture in EnergyPlus, the location and orientation of the building have to be set in advance via longitude and latitude, as location and the orientation will affect the calculation of solar irradiations and also solar heat gains in buildings. The Electric home selected for the modelling is facing Northeast with 0.638° east longitude and 52.505° north latitude.

The information of the construction and material of the Electric home is the input of the modelling and is established in DesignBuilder firstly, and then will be exported to EnergyPlus for the main simulation process.

DesignBuilder, a commercial software, normally is employed as a user-friendly interface for EnergyPlus. After drawing the building structure and setting up all the materials of each building element in DesignBuilder software, the Electric home is ready to be export to EnergyPlus for further modelling and simulation. The Electric home drawing in DesignBuilder is shown in Figure 3.4.

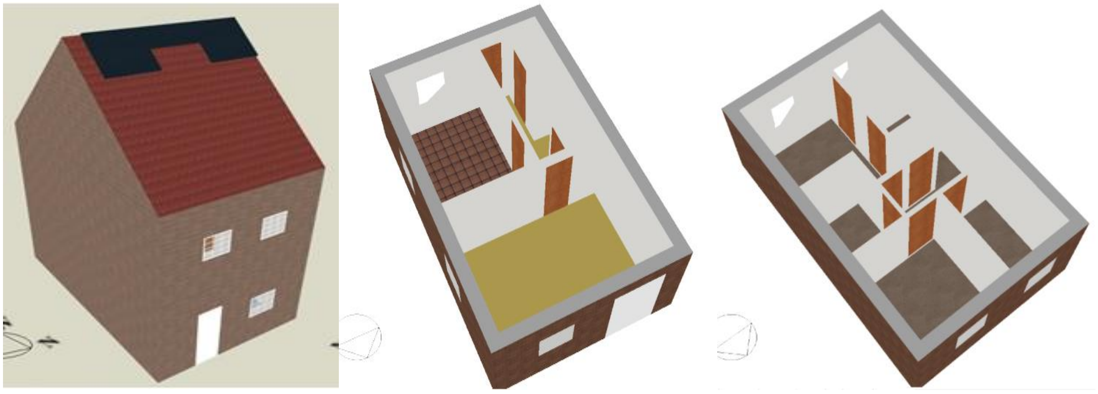


Figure 3.4 Electric Home Modelled in DesignBuilder

3.3.3 HVAC System

The Electric home consists of a loft-mounted ASHP, connecting with PV/T panels as the main energy source. The energy system of Electric home is shown in Figure 3.5. In the HVAC system of the Electric home, the storage tank is supplied by the ASHP and PV/T panels and it will support the space heating via underfloor heating and fan assisted radiators, to maintain the dwelling within the comfortable range.

The heat pump is a well-known low carbon technology in the renewable energy market. Typically, there are two types of heat pumps widely deployed in the UK, ground source heat pump (GSHP) and ASHP. The GSHP absorbs heat from the ground, while ASHP absorbs it from the air. Compared with the GSHP, the advantages of ASHP are, firstly, the installation cost is lower, and secondly, the space of the installation is relatively smaller.

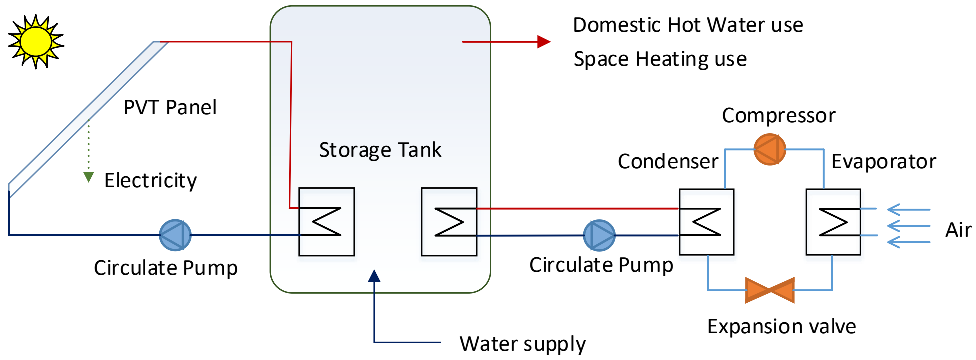


Figure 3.5 The Energy System of Electric Home

Heat pumps normally have two operation modes, cooling, and heating. Typically, in the UK, most of the heat pumps are installed for the space heating in winter. An evaporator, a condenser, an expansion valve, and a compressor are the basic components for a heat pump, and two working cycles are evaporation and condensation, which are introduced below. And in this research, the ASHP is used in the modelling, same as in the Electric Home.

After the refrigerant gas compressed in a compressor, then it will be passed to the condenser. In the condensation process, the high pressure and hot gas are liquefied by going through a heat exchanger and usually transferred the heat to either the water of the storage tank or surrounding indoor air. Subsequently, the relatively high-temperature liquefied refrigerant passes through the expansion valve where it expands to the cold liquefied refrigerant. Then it comes to the last process, the cold liquefied refrigerant reaches the evaporator, and it becomes a low pressure and low-temperature gas by absorbing the heat from ambient air.

The electric power of ASHP can be obtained from equation (3-1), where Q is the output of the ASHP in thermal energy and COP is the coefficient of performance[107].

$$P_e = \frac{Q}{COP} \tag{3-1}$$

The thermal energy generated by the ASHP can be calculated from equation (3-2), where Q_H is the rated thermal capacity and z_1 is the coefficient of the thermal capacity[107].

$$Q = z_1 Q_H \tag{3-2}$$

In this chapter, the rated thermal capacity of the ASHP is 8kW with 3.2 COP, and the inlet air temperature of the ASHP is 22°C. The operating temperature in the storage tank is between 64°C and 69°C. The operating relation between the ASHP and storage tank is shown in Figure 3.6. Additionally, the indoor temperature is set to 23°C.

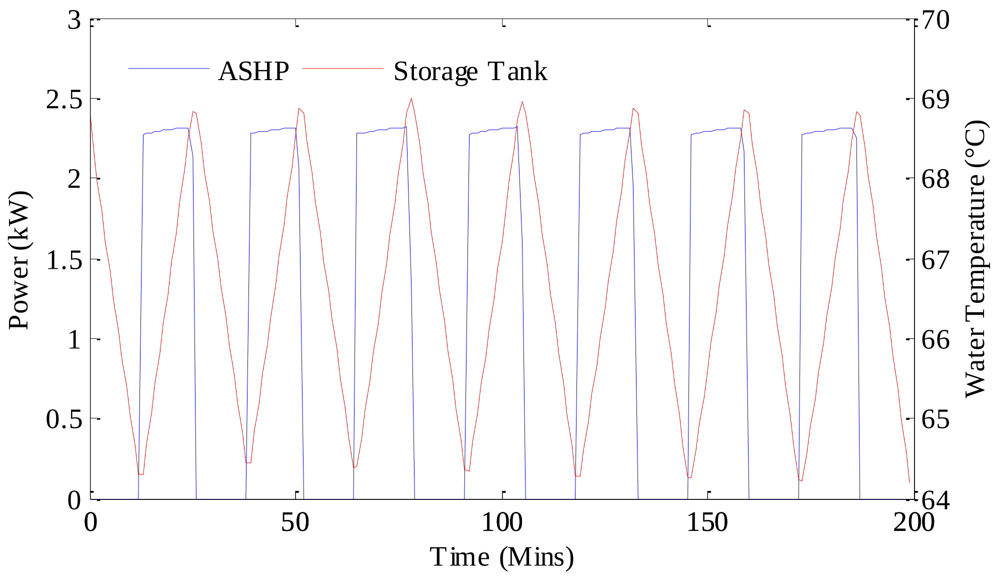


Figure 3.6 The Operating Relation Between the ASHP and Storage Tank

PV/T panels are adopted in Electric homes. Regarding normal PV panel, it only generates electricity from solar radiation, whereas the thermal energy being wasted and the efficiency of the PV panel is reduced by around half percent for every degree of temperature rise above 25 degrees on average [108]. While the PV/T panel, a hybrid technology, overcomes the drawbacks mentioned above, and it also saves lots of space of the roof. In each Electric home, an aggregated 20 PV/T panels have been installed on the roof with a different orientation to contribute the energy demands in the dwelling.

The process of the electricity generation in PV/T panels is followed the same principle as the normal PV panels. When solar radiation is incident upon the PV part of the PV/T panel, the electrons in the panel get active and enter the conduction band resulting in the generation of DC electricity. Then an inverter is necessarily employed here to convert generated electricity from DC to AC. The protection of isolators is compulsory by the law when any local generation integrated into a building, which is basically a mechanical disconnector employed. G59 relay was installed in Corby homes as a protection device. This device monitors the power quality of the mains supply considering its voltage and frequency when it detects the power quality is compromised, and then the PV/T generation will be disconnected from the system.

The thermal energy generated from PV/T panels follows a simple procedure similar to a solar thermal panel. Water, as the circulated fluid, runs through pips absorbing the heat produced by the PV generation process. The thermal energy stored in this high-temperature water will be transferred in the storage tank and used later for Domestic Hot Water (DHW) usage and space heating.

Theoretically, the approach of modelling the PV/T panels in EnergyPlus regarding electrical power P and thermal energy $Q_{thermal}$ are defined in [108]:

$$P = A_{surf} G_T f_{active} \eta_{total} \tag{3-3}$$

Where A_{surf} is the total surface area, G_T is the total incident solar radiation, f_{active} represents the fraction of active solar cells and η_{total} indicates the total efficiency.

$$Q_{thermal} = A_{surf} G_T f_{active} \eta_{thermal} \tag{3-4}$$

Where f_{active} is active fraction of the PV/T collector, and $\eta_{thermal}$ indicates the thermal efficiency.

The total area of PV/T panels adopted in the Electric home is 26.474m^2, the coefficient effective area is 0.9, and the electrical efficiency and thermal efficiency are 14.08% and 37.37%[40]. The solar radiation and outdoor temperature are used the Birmingham weather profile[109].

3.3.4 Occupants' Behaviours

Occupants' behaviours actually take a dominant role in energy consumption of residential buildings. For instance, the occupants' daily use of appliances, lighting, heating and the DHW will all affect the energy demand in the dwelling. And many researchers stress at the importance of occupants' behaviours in residential buildings with regards to the estimation of energy demand, such as [110][111].

The pattern of occupants' behaviours is recognised as a major uncertainty factor in estimate energy demand in residential buildings, and it is very hard to predict, in[112], the Lee et al. made a comprehensive overview of the state-of-art of occupants-related data collection, monitoring, and modelling approaches. Yilmaz et al. presented a new approach to bottom-up stochastic occupant behaviour modelling in residential buildings, and it stated that occupant behaviour varies dramatically between households.

In this chapter, an office worker is assumed to live in the Electric home. And the occupant's activity, the usage of the appliances, the DHW, the HVAC and the lighting from the occupant are the factors considered and controlled by schedules in the EnergyPlus. The office worker's activity in each room in weekdays and weekends is categorised in Table 3-2, the hours showing in each room represents the occupant is active during that period.

The DHW usage along the time of the office worker is shown in Table 3-3, the actual usage is equal to the product of peak flow rate and flow rate. The HVAC system is set to available any time with the control availability from the occupant.

Table 3-1 Occupant's Activity in Different Rooms.

Name	Weekdays	Weekends
Kitchen	06:00~07:00, 18:00~20:00	08:00~09:00,18:00~20:00
Living room	07:00~08:00, 20:30~22:00	09:00~10:00, 17:00~18:00, 20:30~22:00
Bathroom	20:00~20:30	20:00~20:30
Bedroom3 (Waking)	22:00~23:00	22:00~00:00
Bedroom3(Asleep)	23:00~06:00	00:00~06:00

Table 3-2 Usage of the Hot Water

Name	Peak Flow Rate (L/s)	Schedule	
		Weekdays	Weekends
Ground Floor:	0.002	06:00~06:10 is 1,	08:00~08:10 is 1,

Kitchen Water Outlet		07:50~08:00 is 0.2, 18:00~18:10 is 1, 19:50~20:00 is 0.2;	09:50~10:00 is 0.2, 18:00~18:10 is 1, 19:50~20:00 is 0.2
Ground Floor: WC Water Outlet	0.002	06:10~06:20 is 0.2, 19:50~20:00 is 0.5, 22:50~23:00 is 0.3	08:10~08:20 is 0.2, 19:50~20:00 is 0.5, 23:50~24:00 is 0.3
First Floor: Bathroom Water Outlet	0.02	06:10~06:30 is 0.2, 20:00~20:30 is 1	08:10~08:30 is 0.2, 20:00~20:30 is 1

3.3.5 Lighting System

The lighting system is normally recognised as a major component of energy consumption in commercial buildings, but it also accounts for an important consumer in residential buildings. The lighting system is not only treated as a significant electricity consumer but also it acts as an internal heat gain. It dissipates appreciable heat to the space during the operating period, which can be used as an internal heat gain, thus reduces the heat required for the space heating. Needless to mention, an accurate estimate of the lighting system is of importance.

Table 3-3 Usage of the Lighting System

Location	Power(W)	Schedule	
		Weekdays	Weekends
Ground Floor: Stairs1	15	06:00~08:00, 18:00~23:00	08:00~10:00, 17:00~24:00
Ground Floor: Hall	25	07:30~08:00, 18:00~18:30	09:30~10:00, 17:00~17:30
Ground Floor: Kitchen	50	06:00~07:00, 18:00~20:00	08:00~09:00, 18:00~20:00
Ground Floor: Storage Room	15	06:00~08:00, 18:00~23:00	08:00~10:00, 17:00~24:00
Ground Floor: Dining	40	07:00~08:00, 20:00~21:00	09:00~10:00, 20:00~21:00

Ground Floor: WC	15	06:00~08:00, 18:00~23:00	08:00~10:00, 17:00~24:00
Ground Floor: Living Room	40	06:00~08:00, 18:00~23:00	08:00~10:00, 17:00~24:00
First Floor:Stairs2	15	06:00~08:00, 18:00~23:00	08:00~10:00, 17:00~24:00
First Floor: A_C	15	06:00~08:00, 18:00~23:00	08:00~10:00, 17:00~24:00
First Floor:Bedroom1	40	0	0
First Floor: Bathroom	15	20:00~21:00	20:00~21:00
First Floor: EnSuite	15	20:00~21:00	20:00~21:00
First Floor: Bedroom3	40	22:00~23:00	22:00~24:00
First Floor: Bedroom2	40	0	0

The electricity consumed by a lighting system depends on how many lights installed in the building, the power rate and the total operating time. The primary source of heat from lighting comes from emitting elements and it consists of radiation and convection, which is normally determined by the fraction of consumed energy. The power rate, fractions and schedule of the lighting in each room are summarised in Table 3-4, and the Visible fraction and the Convection fraction of the lights are 0.16, 0.84 respectively [45].

3.3.6 Appliances

Electrical appliances installed in the residential buildings also account for a considerable bulk percentage of total electricity consumption. The attention needs to be paid here is that, in many circumstances, the peak power demand in residential buildings usually occurs coincidently with many electrical appliances used at the same time. The energy consumed by electrical appliances is highly dependent upon the occupants' behaviours, for example, while the use of eclectic kettles, an electric hob or microwave can also be occupied for making dinner.

Moreover, some of the appliances also have similar characteristics as the lighting, and it can provide the heat to the space around it. For example, when TVs and computer monitors are on the operating mode, the heat is going to be emitted to the surrounding air. In EnergyPlus, this heat emitting is represented through convection fraction, and the variables of modelling appliances in the Electric home are listed in Table 3-5.

Table 3-4 Usage of Appliances

Equipment	Location	Power(W)	Convection Fraction	Schedule	
				Weekdays	Weekends
Fridge/Freezer	Ground Floor: Kitchen	50 (mean value)	0.2	00:00-24:00	00:00-24:00
Kettle	Ground Floor: Kitchen	2000	0	06:00~06:30, 18:00~18:30	08:00~08:30, 18:00~18:30
Microwave	Ground Floor: Kitchen	1250	0	06:30~07:00	08:30~09:00
TV1	Ground Floor: Living Room	124	0.1	07:00~08:00	09:00~10:00; 17:00~18:00
Oven	Ground Floor: Kitchen	2125	0	19:00~19:30	19:00~19:30
Washing Machine	Ground Floor: Kitchen	406	0.2	20:00~20:30	20:00~20:30
Hob	Ground Floor: Kitchen	2400	0	18:30~19:00	18:30~19:00
Laptop	Ground Floor: Living Room	141	0.1	20:30~22:00	20:30~22:00
TV2	First Floor: Bedroom3	124	0.1	22:00~23:00	22:00~24:00

3.3.7 The Modelling of the Energy Demand in the Electric Home

The annual energy demand of the Electric home is summarised in Table 3-6 and Figure 3.7. And in the modelling, 1st January and 3rd January are selected as the typical weekend and weekday for winter, 1st July and 3rd July are chosen for typical weekend and weekday in summer.

The net total energy demand in the dwelling is the energy demand obtained from the power grid, which the electricity generation from the PV/T is considered. The corresponding daily power demand and the room temperature for each typical day are illustrated in Figure 3.8. And the energy demand and the peak power demand of Electric Home on each typical day are summarised in Table 3-7.

Table 3-5 Annual Energy Demand of Electric Home

Source	Total	PV/T Electricity Generation	Net Total	ASHP	Appliances	Fans and Pumps	Lighting
Electricity (kWh)	8439.14	2948.61	5490.53	4769.26	2490.04	738.77	441.07

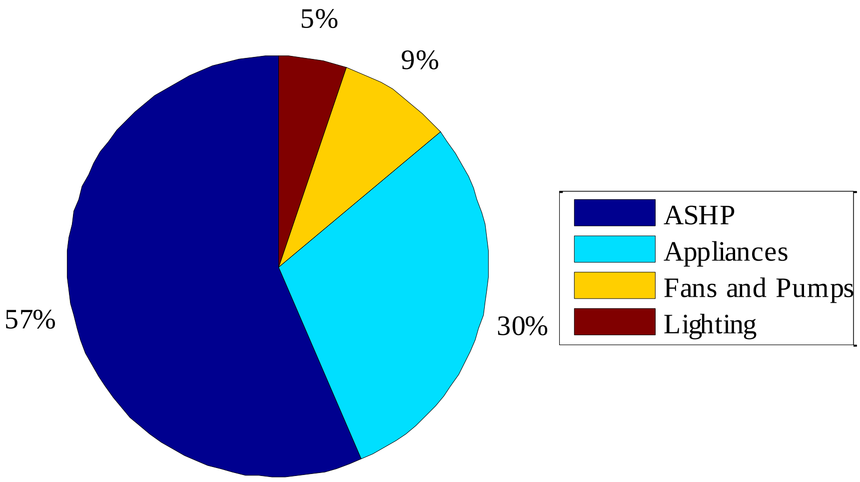
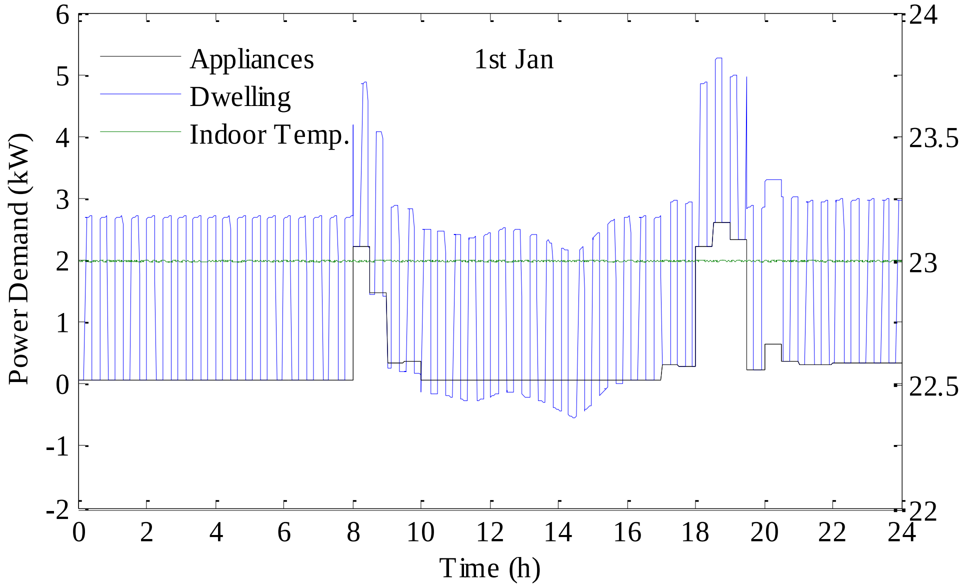


Figure 3.7 The Energy Demand of Electric Home in Different Segment

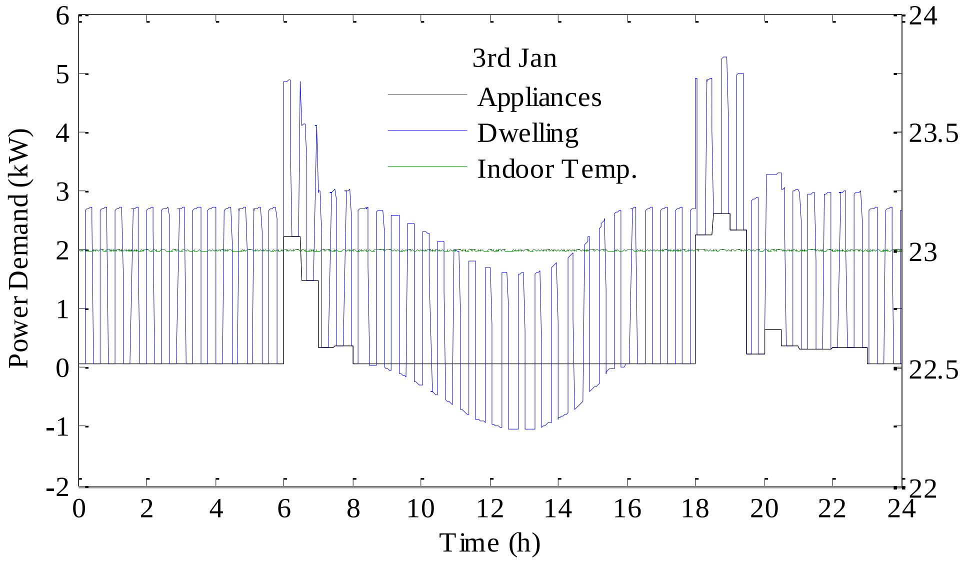
From Table 3-6 and Figure 3.7, it can be seen that the ASHP is the dominant segment of the net total energy demand in the Electric home, which accounts for 57%. The appliances are 30% over the net total energy demand and only 5% of the energy demand is from lighting. Consequently, reducing the space heating demand can be considered as a potential way of saving energy in a dwelling.

Table 3-6 The Energy Demand and the Peak Power Demand of Electric Home on Typical Days

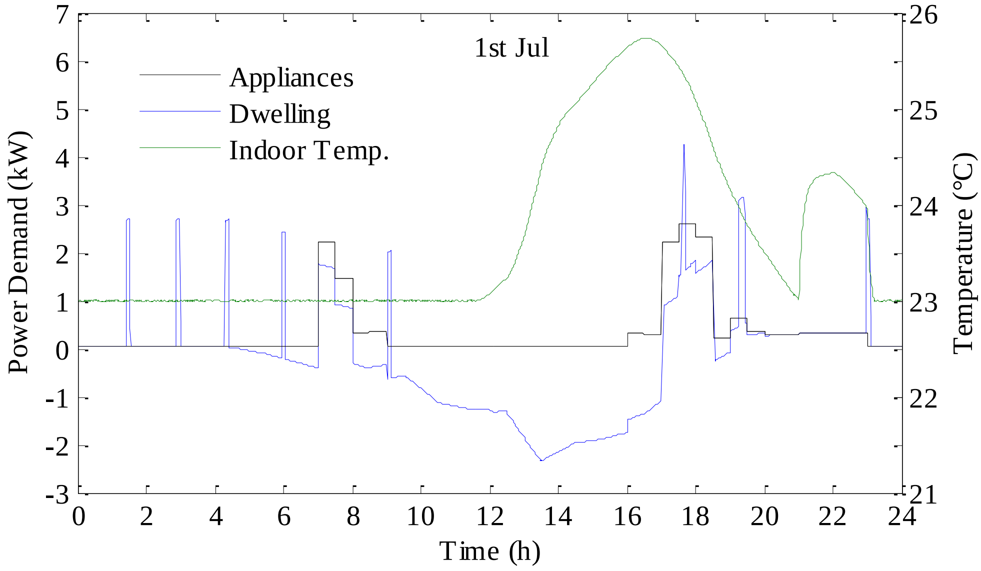
Time	1st Jan	3rd Jan	1st Jul	3rd Jul
Net Total Energy (kWh)	40.12	38	11.27	11.14
Peak Demand (kW)	5.277	5.275	4.274	4.813



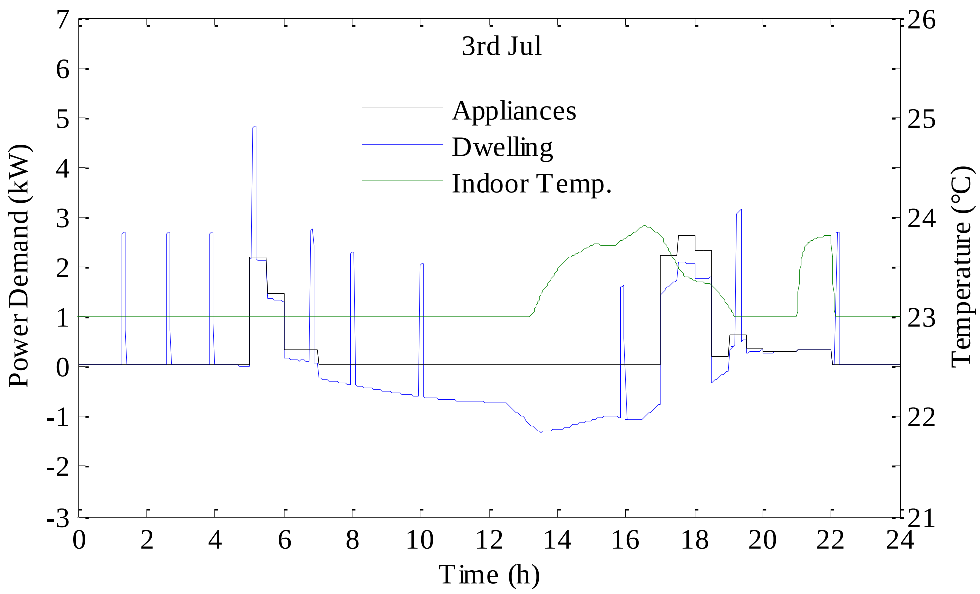
(a) Typical Weekend in Winter



(b) Typical Weekday in Winter



(c) Typical Weekend in Summer



(d) Typical Weekday in Summer

Figure 3.8 Daily Power Demand and the Room Temperature for Each Typical Day

From Figure 3.8 and Table 3-7, it can be obtained that the total power demand in the weekday and the weekend is quite similar, only the peak during the day occurred at a different time determined by the occupant's behaviours. However, the total power demand in winter is much higher than in summer. Because of the space heating demand in winter is higher than in summer and the DHW needs will be the main demand in summer.

3.4 The Impact Analysis of the Energy Demand in the Dwelling Considering Different Factors

In this section, new building materials, PV/T, LED Lighting and occupants' behaviours are chose as the factors for analysing the impacts of the energy demand in the dwelling. And daily, monthly and annual energy demands are illustrated for the analysis, respectively.

3.4.1 Building Materials

Regarding building materials, the U value is defined to determine the insulation level and the lower the U value is, the higher the insulation is. In this section, different U values are employed to represent the different building materials.

Normally, the external walls and windows of a dwelling are layered up by many different materials, and the U value in each layer is different which can be expressed in the following equations.

$$R_w(i) = d / \lambda \tag{3-5}$$

$$R_w = \sum_{i=1}^{n} R_w(i) \tag{3-6}$$

$$U = 1/R_w \tag{3-7}$$

Where R_w is the thermal resistance, d is the width and λ is the thermal conductivity. And n is the total layer numbers.

Hence, the U value of the external walls and windows of the Electric home can be calculated from Table 3-1, which are 0.23W/m^{2}K and 1.39W/m^{2}K, respectively.

The Code for Sustainable Homes is a nationwide assessment method for rating and certifying the performance of new homes. It works by awarding new homes a star rating from 1 to 6. Some issues within the design categories are mandatory, others are tradable. The assessment score is calculated based on the total percentage points achieved for meeting mandatory and tradable requirements. The U value for the building elements in UK Code Level 3 and Level 4 is listed in Table 3-8[36].

Table 3-7 U Values of the UK Code Level 3 and 4 for the Building Elements.

Element	UK Code Level 3 W/m^{2}K	UK Code Level 4 W/m^{2}K
External wall	0.25	0.23
Floor	0.22	0.22
Roof	0.18	0.18
Windows	1.6	1.4
Doors	2.0	2.0

According to the material characteristics categorised in Table 3-1, the Electric home is qualified for the UK code level 4. And, for current built in the UK, most of the domestic dwellings are qualified for the UK code level 3. Therefore, the impacts of new building materials on energy demand will be investigated for the dwelling with the UK code level 3 and code level 4. Moreover, the focus is made on the materials of the wall and the window, which are shown in Table 3-9.

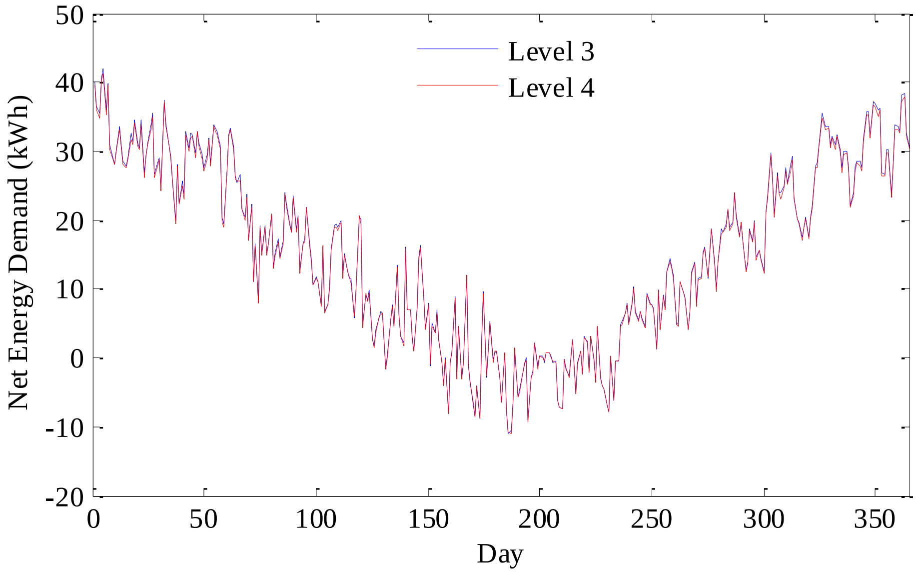
Table 3-8 U Values of the UK Code Level 3 and 4 in Materials

Element	Material	UK code level 4		UK code level 3	
		Thickness (mm)	U Value (W/m^2K)	Thickness (mm)	U Value (W/m^2K)
Wall	Facing brick	102.5	0.23	102.5	0.25
	EPS-Expanded Polystyrene	150		140	
	Concrete block	100		100	
	Plasterboard	12.5		12.5	
Window	Glazing	4	1.39	4	1.64
	Air gap	19		16	
	Glazing	4		4	

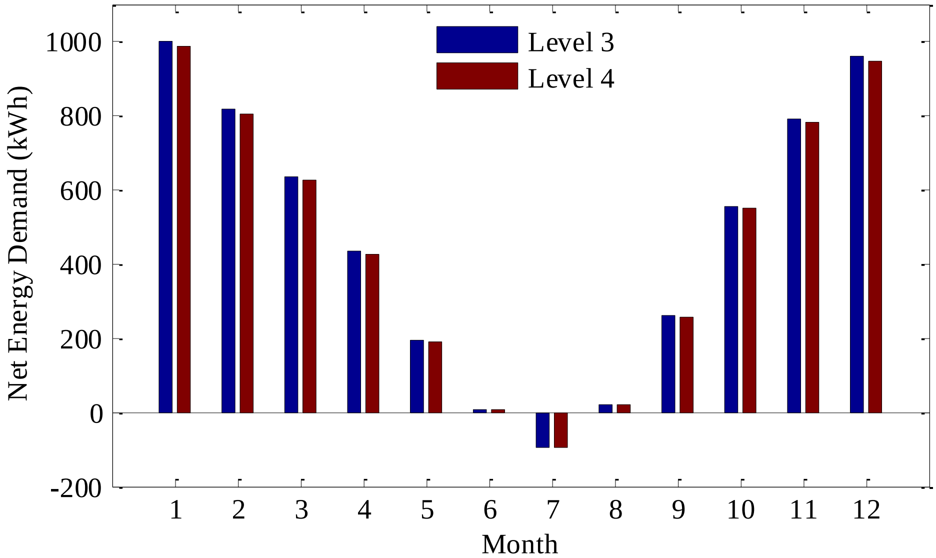
From the simulation results, the energy demand in the dwelling with the UK code level 3 and code level 4 is shown in Table 3-10. It can be seen that, with the higher UK code level of the dwelling, the annual energy demand is reduced by 90.42kWh. Especially, the energy demand from the ASHP is saved by 78.75kWh.

Table 3-9 The Net Total Energy Demand in the Dwelling with Different UK Code Level

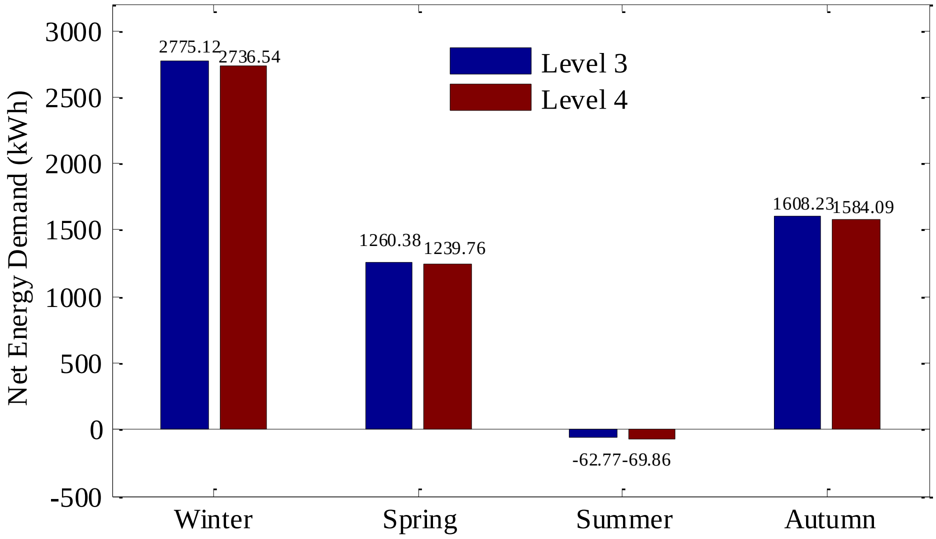
Source	Annual		Winter		Summer	
	Net Total Energy Demand [kWh]	ASHP Energy Demand [kwh]	Net Total Energy Demand [kWh]	ASHP Energy Demand [kWh]	Net Total Energy Demand [kWh]	ASHP Energy Demand [kWh]
UK code level 3	5580.95	4848.01	2775.12	2013.92	-62.77	357.57
UK code level 4	5490.53	4769.26	2736.54	1980.31	-69.86	351.40
Savings	90.42	78.75	38.58	33.61	7.09	6.17



(a) Daily Net Total Energy Demand in the Dwelling



(b) Monthly Net Total Energy Demand in the Dwelling



(c) Annual Net Total Energy Demand in the Dwelling

Figure 3.9 The Energy Demand in the Dwelling Separately Different Building Materials

In Figure 3.9, it shows the daily, monthly and annual net total energy demand in the dwelling with different UK code level. It can be seen that the net total energy demand is reduced in each month when the dwelling having the higher UK code level. Especially, in winter, the net total energy demand is reduced by 38.58kWh, and 21.02kWh in autumn, 17.95kWh in spring and last but not least, 7.09kWh in summer.

Therefore, it can be conducted that the new building materials with the lower U value are able to save energy in the dwelling, especially for winter.

3.4.2 Solar Energy

Table 3-10 Characteristic of the Solar Thermal panel, PV panel and PV/T panel.

Technology	Electrical Efficiency	Thermal Efficiency	General Efficiency
Solar Thermal Panel	0	55%	55%
PV Panel	12%	0	31.5%
PV/T Panel	14.08%	37.37%	70.72%

Solar energy is clean energy and also known as a renewable energy source, which normally used as solar thermal panels, PV panels, and PV/T panels. Hence, in this section, these three technologies are utilised as the factors to analyse the impacts of the energy demand in the dwelling. The detailed characteristics of the solar thermal panel, PV panels, and PV/T panels are categorised in Table 3-11[8]. The area of these three panels is chosen from the Corby home. The reason for the relatively small area of the solar panel is that it is used to only supply DHW and part of the space heating, however, the PV and PV/T panels are able to generate electricity for dwellings' needs or even supporting the power grid, that normally, the larger area is, the more electricity is generated.

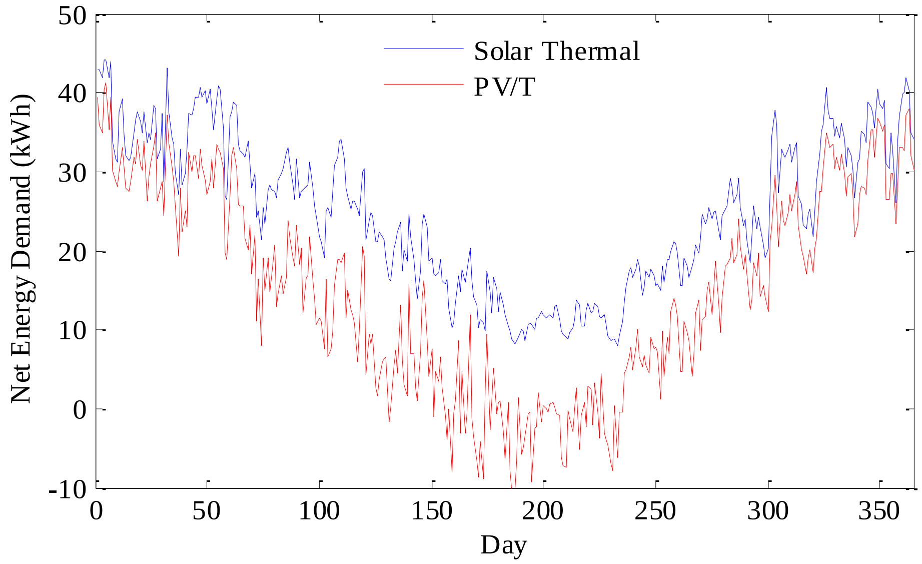
• Solar Thermal Panel and PV/T Panel

The energy demand in the dwelling separately with the solar thermal panel and PV/T panels is summarised in Table 3-12. It can be seen that the thermal energy generated from the dwelling with PV/T panels are higher than the one installed solar thermal panel, which is 1619.48kWh. Hence, the operation need of the ASHP is less, and the total energy demand in the dwelling is reduced by 600.93kWh. Moreover, because of the electricity generation from PV/T panels, the net total energy demand in the dwelling is reduced by 3549.54kWh.

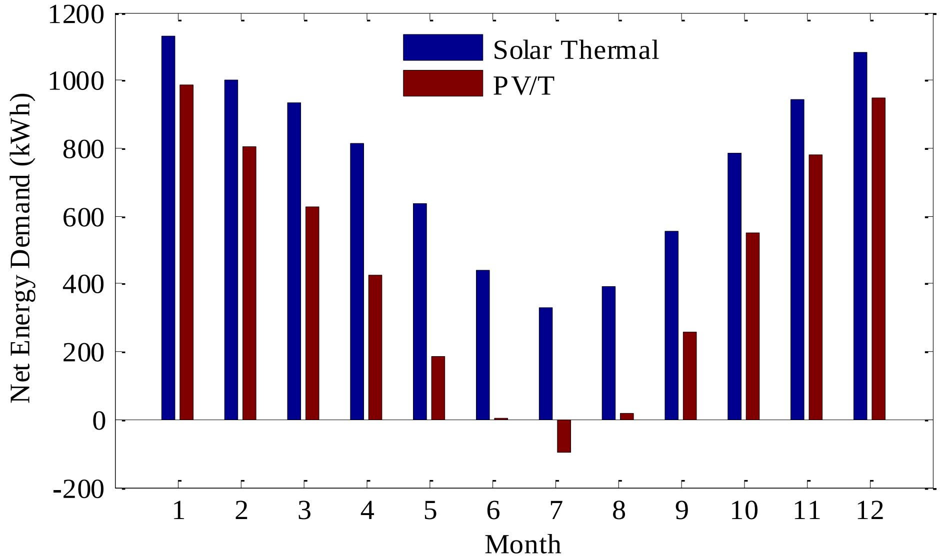
Table 3-11 The Energy Demand in the dwelling with Solar Thermal Panel and PV/T Panels

Source	Annual					Winter		Summer	
	Total Energy Demand [kWh]	Net Total Energy Demand [kWh]	ASHP Energy Deman [kwh]	Electricity Generation [kWh]	Thermal Generation [kWh]	Net Total Energy Demand [kWh]	ASHP Energy Demand [kWh]	Net Total Energy Demand [kWh]	ASHP Energy Demand [kWh]
PV/T	8439.14	5490.53	4769.26	2948.61	2105.34	2736.54	1980.31	-69.86	351.40
Solar Thermal	9040.07	9040.7	5313.43	0	485.86	3216.27	2169.13	1158.58	364.35
Difference	600.93	3549.54	544.17	2948.61	1619.48	479.73	188.82	1228.44	12.95

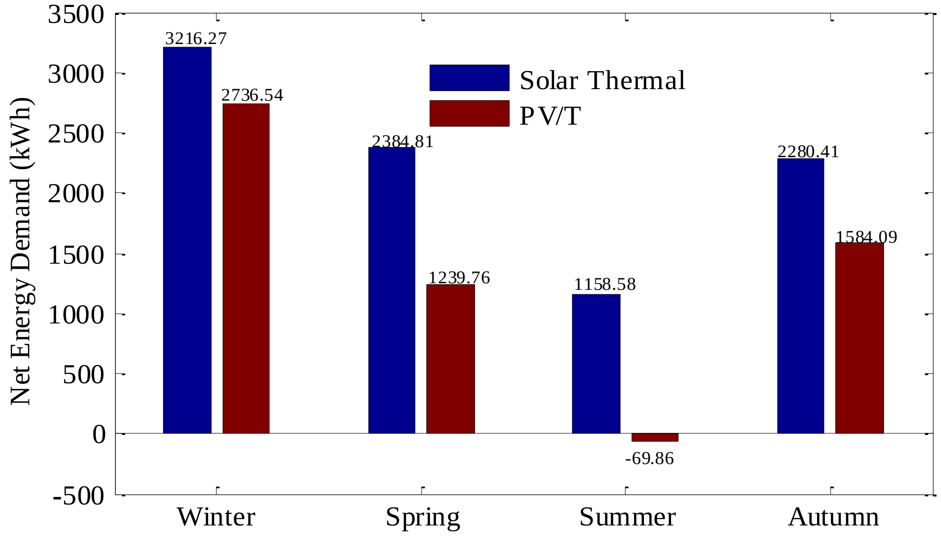
In Figure 3.10, the daily, monthly and seasonal net total energy demands in the dwelling separately with the solar thermal panel and PV/T panels are illustrated. And from Figure 3.10, it can be conducted that the capability of the PV/T saving the



(a) Daily Net Total Energy Demand in the Dwelling



(b) Monthly Net Total Energy Demand in the Dwelling



(c) Seasonal Net Total Energy Demand in the Dwelling

Figure 3.10 The Energy Demand in the Dwelling Separately with Solar Thermal Panel and PV/T Panels energy is depending on the time period. The net total energy demand in summer is reduced by 1288.44kWh, whereas 479.73kWh in winter.

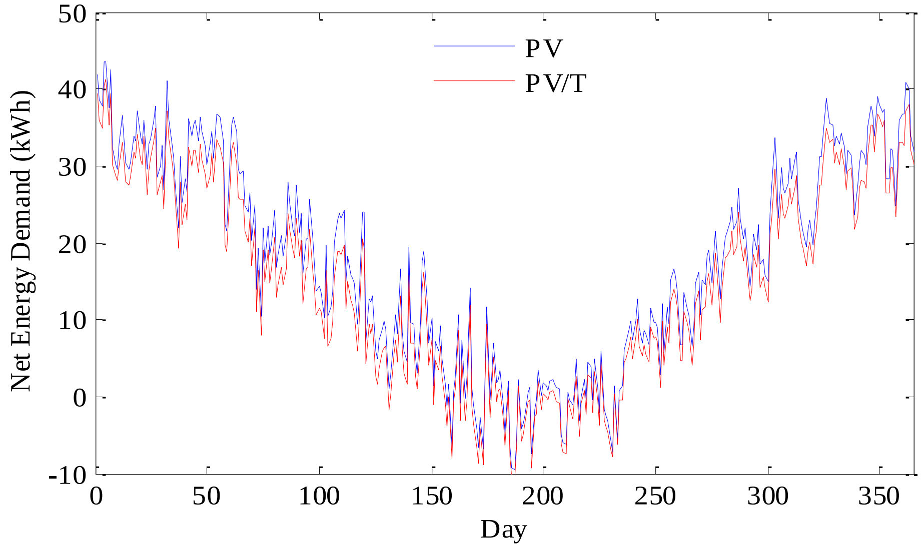
• PV panels and PV/T panels

The energy demand in the dwelling separately with PV panels and PV/T panels is summarised in Table 3-13. And the daily, monthly and seasonal net total energy demands in the dwelling separately with PV panels and PV/T panels are illustrated in Figure 3.11.

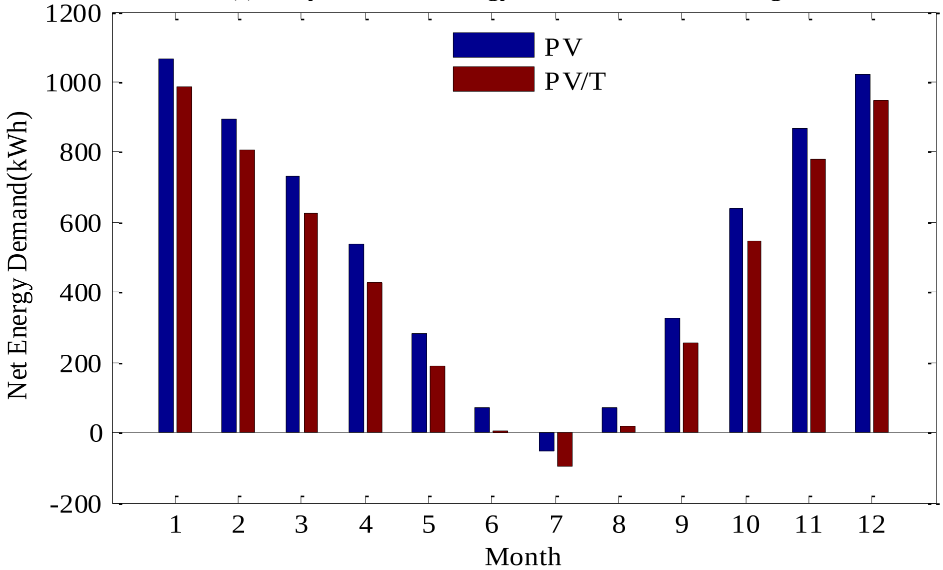
Table 3-12 The Energy Demand in the Dwelling with PV Panels and PV/T Panels

Source	Annual					Winter		Summer	
	Total Energy Demand [kWh]	Net Total Energy Demand [kWh]	ASHP Energy Demand [kwh]	Electricity Generation [kWh]	Thermal Generation [kWh]	Net Total Energy Demand [kWh]	ASHP Energy Demand [kWh]	Net Total Energy Demand [kWh]	ASHP Energy Demand [kWh]
PV/T	8439.14	5490.53	4769.26	2948.61	2105.34	2736.54	1980.31	-69.86	351.40
PV	9246.00	6453.76	5469.56	2792.24	0	2982.69	2182.03	88.77	432.29
Difference	806.86	963.23	700.30	156.37	2105.34	246.15	201.72	158.63	80.89

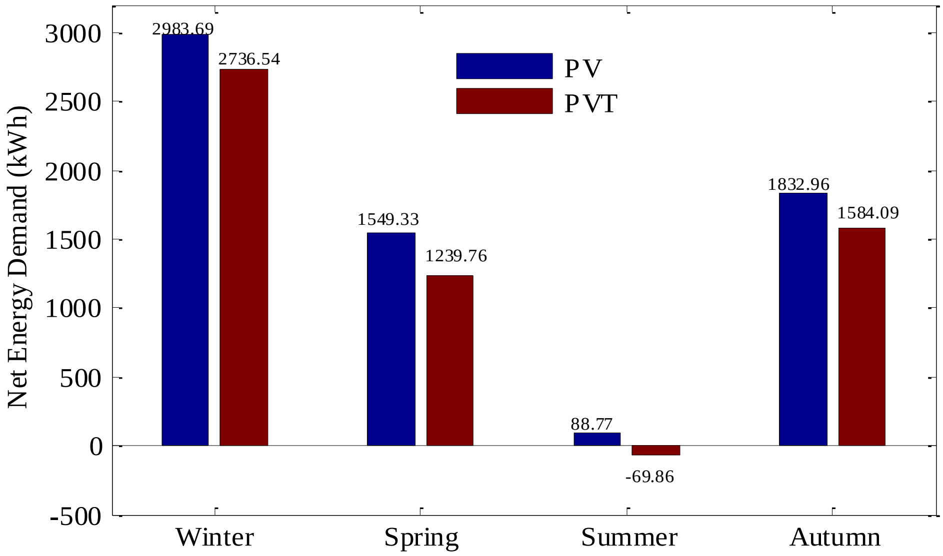
From Table 3-13 and Figure 3.11, it can be conducted that the electricity generation from PV/T panels is 156.37kWh higher than PV panels, because of the efficiency improved by the circulating fluid reducing the temperature of the panels. Hence, PV/T panels are able to generate thermal energy, which saves the total energy demand and net total energy by 806.86kWh and 963.23kWh. Moreover, from Figure 3.11(b), the net total energy demand in the dwellings installed PV/T panels is lower than the dwelling with PV panels in each month.



(a) Daily Net Total Energy Demand in the Dwelling



(b) Monthly Net Total Energy Demand in the Dwelling



(c) Seasonal Net Total Energy Demand in the Dwelling

Figure 3.11 The Energy Demand in the Dwelling Separately with PV Panels and PV/T Panels

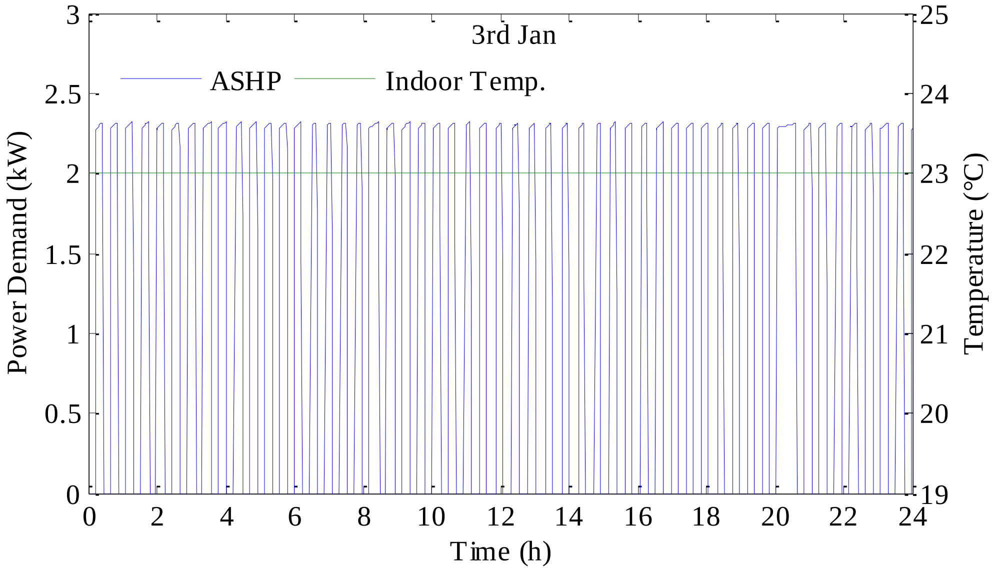
From the analysis above, the solar thermal panel is only able to support a part of the thermal demand in the dwelling and the area of the roof is not occupied in an efficient way. The PV panels can only generate electricity to contribute energy savings in the dwelling, which the capability of this energy saving is limited as its efficiency drops when the temperature of the panel getting higher, while the PV/T panels are able to generate electrical and thermal energy simultaneously with higher general efficiency. Moreover, the solar energy is better used for the energy saving in the dwelling when the PV/T panels are installed.

3.4.3 The Occupants' Behaviours

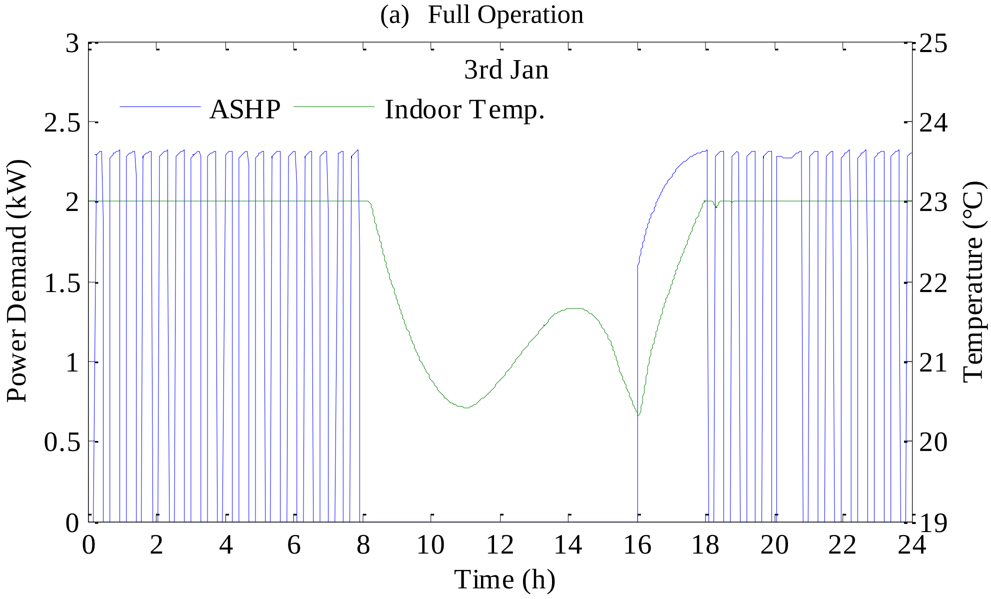
The energy demand in a dwelling can be impacted by the occupants' behaviours, which including the occupants' movements, the usage of the appliances, the DHW, the lighting, and HVAC system. Because of the difficulty of describing and modelling the occupants' movements[48] and it is not the main focus in this work, hence, it is not considered in this chapter. The usage of the appliances, the DHW, the lighting is modelled and discussed in chapter 3.3. Therefore, the operation of the ASHP and the thermostat controlled by the occupants are analysed in the following section to investigate the impacts of the occupants' behaviours on the energy demand in the Dwelling.

- **The Operation of the ASHP**

Normally, the ASHP is set to be fully operational in order to satisfy the needs of the space heating and the DHW at any time. However, the dwelling is not occupied by the office worker during most of the daytime. Hence, the ASHP can be shut down until 2 hours before the office worker returns. In this section, those two operation schemes of the ASHP, the full operation, and shut-down control will be used to investigate the impacts on the energy demand in the Dwelling. And typical weekdays in winter (3rd Jan.) and summer (3rd Jul.) are selected for the modelling.



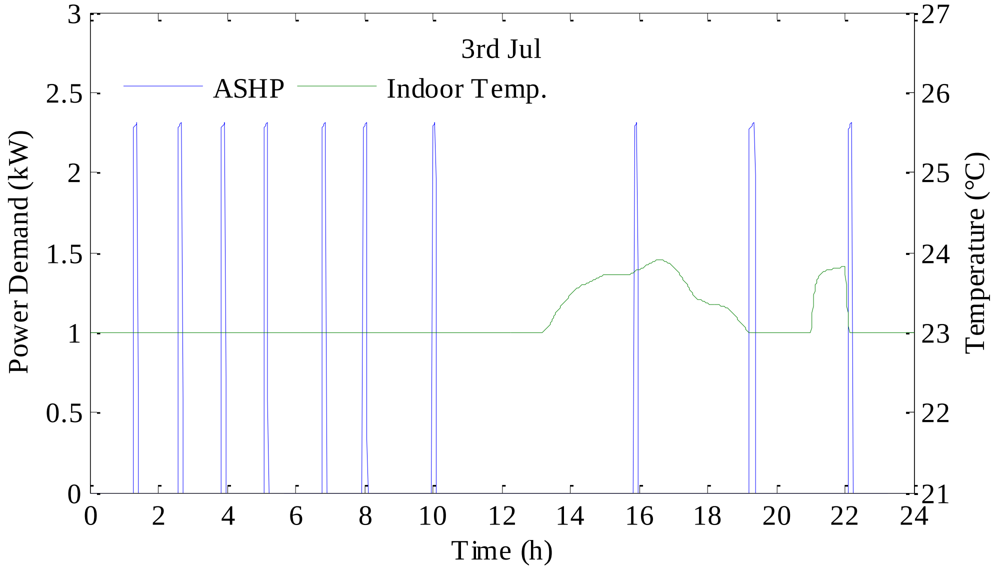
(a) Full Operation



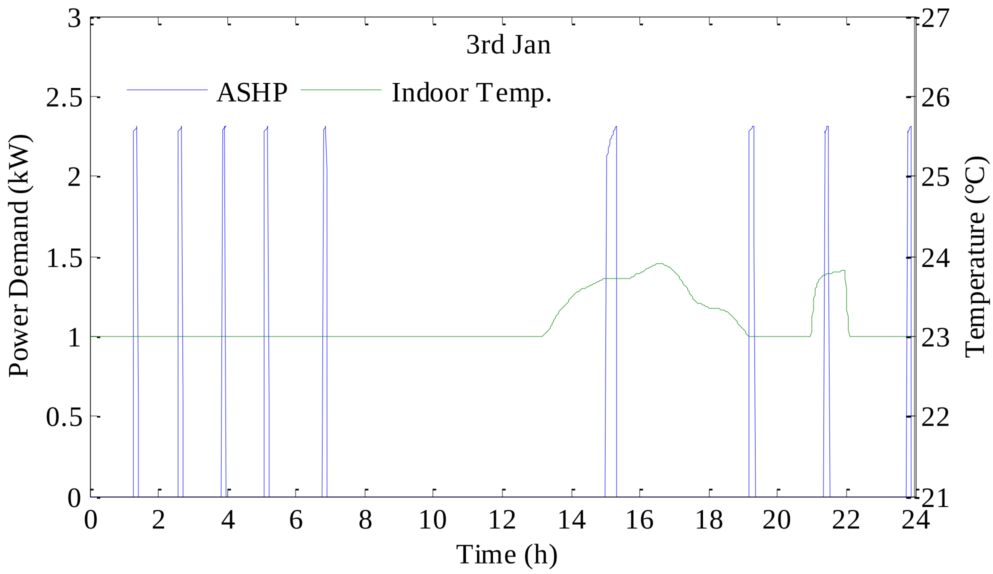
(b) Shut-Down Control

Figure 3.12 The Power Demand of the ASHP and the Indoor Temperature in the Dwelling on 3rd Jan

Between 08:00 and 16:00, the ASHP is set to be shut down based on the office worker's activity in the weekday. The power demand of the ASHP and the indoor temperature under two different operation schemes are shown in Figure 3.12 and Figure 3.13.



(a) Full Operation



(b) Shut-down Control

Figure 3.13 The Power Demand of the ASHP and the Indoor Temperature in the Dwelling on 3rd Jul

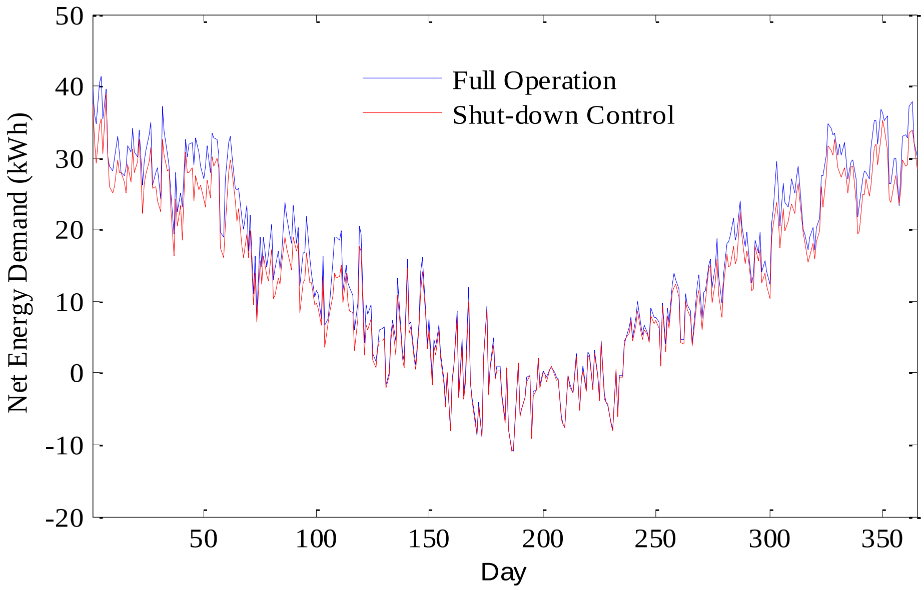
From Figure 3.12 and Figure 3.13, it can be seen that the indoor temperature of the dwelling in winter and summer are maintained within the comfortable living range. Therefore, shut-down control of the ASHP is feasible.

The energy demands in the dwelling with two different ASHP operation schemes are shown in Table 3-14, and the daily, monthly and seasonal net total energy demands in the dwelling are illustrated in Figure 3.14.

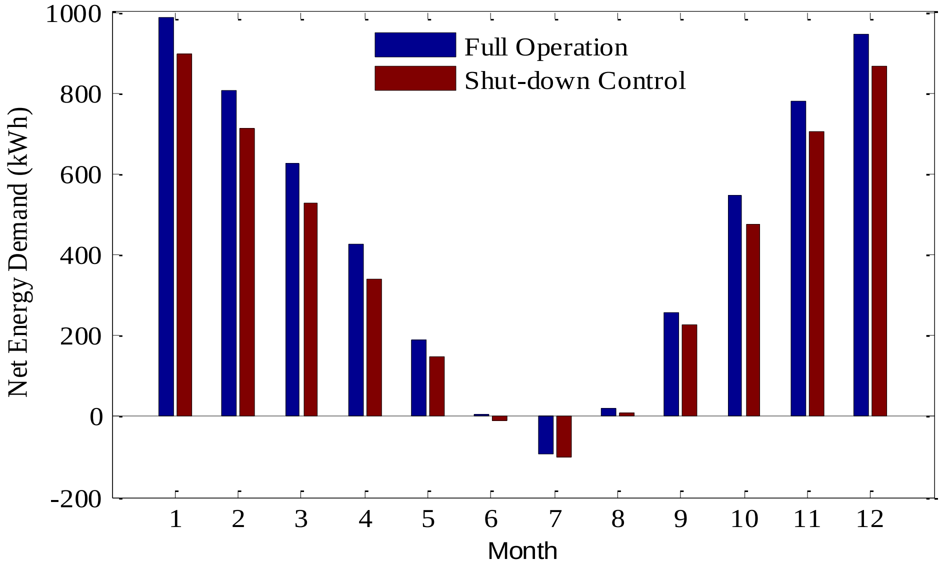
Table 3-13 The Energy Demand in the Dwelling with Different ASHP Operation Schemes

Source	Annual			Winter		Summer	
	Total Energy Demand [kWh]	Net Total Energy Demand [kWh]	ASHP [kwh]	Net Total Energy Demand [kWh]	ASHP [kWh]	Net Total Energy Demand [kWh]	ASHP [kWh]
Full Operation	8439.14	5490.53	4769.26	2736.54	1980.31	-69.86	351.40
Shunt-down Control	7751.38	4802.89	4155.10	2474.61	1743.94	-101.87	323.09
Savings	687.76	687.64	614.16	261.93	236.37	32.01	28.31

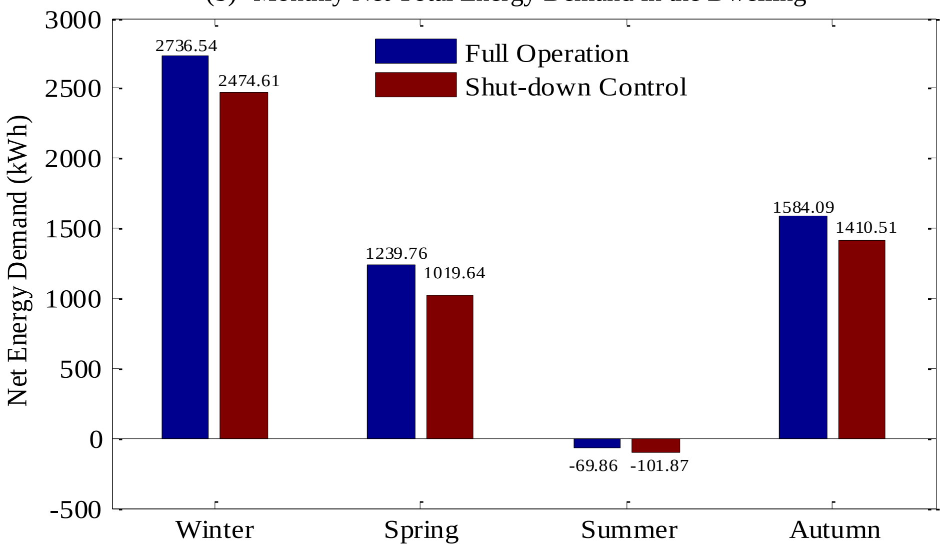
From Table 3-14 and Figure 3-14, when using the shut-down control of the ASHP operation, the total energy demand in the dwelling is reduced by 687.76kWh. Especially, the energy demand of the ASHP is reduced by 614.16kWh. Moreover, in summer, the energy demand in the dwelling is relatively low, so that the energy demands of the ASHP under two different operation schemes are not much different. While in winter, the energy demand of the ASHP is dramatically reduced by 236.37kWh by using shut-down control.



(a) Daily Net Total Energy Demand in the Dwelling



(b) Monthly Net Total Energy Demand in the Dwelling



(c) Seasonal Net Total Energy Demand in the Dwelling

Figure 3.14 The Energy Demand in the Dwelling with Two ASHP Operation Schemes

- **The Thermostat of the Dwelling**

According to the ASHRAE 55, the comfortable temperature of the domestic dwelling is between 19.4°C and 27.7°C [113]. Therefore, the thermostat is set from 19°C to 27°C to investigate the impacts on the energy demand in the dwelling.

Table 3-14 The Energy Demand in the Dwelling with Different Thermostat Setting

Thermostat (°C)	19	20	21	22	23	24	25	26	27
Total Energy (kWh)	7490.6	7708.6	7943.5	8188.4	8439.1	8698.0	8963.7	9235.2	9525.5

From Table 3-15, it can be seen that the total energy demand in the dwelling is increased with the increasing thermostat settings. Furthermore, the total energy demand can be reduced by around 226kWh when the thermostat decreasing one degree. Therefore, changing the thermostat setting within the comfortable range can be a feasible way to achieve the energy saving in the dwelling.

3.4.4 LED Lighting

From Table 3-6, it can be seen that the lighting also consumes a lot of energy in the dwelling. Therefore, using LED lighting instead of the normal lighting can be a potential way to achieve energy saving in the dwelling. In this section, the LED lights with 0.8 visible fraction and 0.2 convection fraction are used to compare the normal lights modelled in chapter 3.3.5. Assumed having the same illumination, the rated power of the normal lights and LED lights are listed in Table 3-16. And the energy demands in the dwelling with two different lighting are categorised in Table 3-17.

Table 3-15 The Rated Power of the Normal Lights and LED Lights

Local	Stairs1	Hall	Kitchen	Storage Room	Dining	WC	Living Room
Normal Lights (W)	15	25	50	15	40	15	40
LED Lights (W)	3	5	10	3	8	3	8
	Stairs2	A_C	Bedroom1	Bathroom	EnSuite	Bedroom3	Bedroom2
Normal Lights (W)	15	15	40	15	15	40	40
LED Lights (W)	3	3	8	3	3	8	8

Table 3-16 The Energy Demands in the Dwelling with Two Different Lighting.

Source	Total Energy [kWh]	Lighting System [kWh]	Heat Pump [kWh]	Pumps and Fans [kWh]
Normal Lights	8439.14	441.07	4769.26	738.77
LED Lights	8216.04	88.21	4882.29	755.5
Savings	223.1	352.86	-113.03	-16.73

According to Table 3-17, the energy demand from the lighting can be reduced by 352.86kWh when the dwelling installed LED lighting instead of the normal lighting. However, the LED lights belong to cold lights, that the heat emitted from the lights is low. This characteristic of the LED lights will result in the increasing needs of the ASHP to support the spacing heating in the dwelling. And it can be seen from Table 3-

16, the energy demand of the ASHP is increased by 113.03kWh and the energy demand of the fan and circulating pump is also increased by 16.73kWh. Overall, the total energy demand in the dwelling is still reduced by 223.1kWh. Therefore, from the analysis above, the LED lighting is a feasible way to achieve energy savings in the dwelling.

3.5 Summary

In this chapter, the energy demand of the domestic dwelling is analysed through modelling a representing dwelling, Corby Electric home, in EnergyPlus, and also the factors, including new building materials, PV/T panels, the occupants' behaviours, and the LED lighting, are investigated to analyse the potential energy savings in the dwelling. The conclusions can be conducted as follow:

(1) The space heating is the dominant segment in the energy demand of a dwelling. Using the new building material with lower U value can be an important way to reduce the energy demand in the dwelling. And with lower U value, the energy demand is reduced most in winter, then autumn, spring, lastly in summer due to less energy needed.

(2) The solar thermal panel installed in the dwelling is only sufficient for part of heat demand, and its efficiency is relatively low. The PV panels are installed to generate the electricity, however, when the temperature rising on the panel, the efficiency drops. The PV/T panels are able to generate both electricity and heat energy, which results in higher efficiency. Therefore, PV/T installed in the dwelling is recognised as a better way to use solar energy to reduce the energy demand.

(3) When the comfort level is satisfied, the ASHP with the shut-down control is proved to be a solution to achieve the energy savings in the dwelling. And through controlling the thermostat setting, the energy demand in the dwelling also can be reduced.

(4) Through installing the LED lighting in the dwelling, the energy demand is reduced dramatically. Because of the characteristics of the cold light, the space heating demand is increased, however, overall the energy demand in the dwelling is clearly reduced. Hence, using LED lights is a feasible way to reduce the energy demand.

Chapter 4

Reducing the Peak Power Demand of the Dwelling caused by the EV Charging using the DEIM

4.1 Introduction

With the large penetration of the EVs, understanding and predicting the charging demand of EVs become important for DN operation and reinforcement. While planning and operating the DN, it is a challenge for the operators to reserve reasonable capacity for any future loads. And also it is crucial for the current network to reduce the peak power demand of the dwelling caused by the EV charging.

The EV charging profile can be evaluated by using either a deterministic method or a stochastic approach. The deterministic method is suitable for evaluating the EV charging needs under any certain scenarios, while the stochastic approach is capable of revealing the random nature of EV drivers' behaviours under any uncertain scenarios[114].

In this chapter, the deterministic method is used with the consideration of the EV battery type, the EV battery capacity, SOC etc. for deriving the EV charging profile. Moreover, based on the analysis of the energy demand of the domestic dwellings using EnergyPlus in chapter 3, the BCVTB is employed in this chapter for achieving real-time control from MATLAB. Therefore, the DEIM is established.

An individual household is chosen in this chapter, the energy demand of the household with the EV charging can be analysed through DEIM. Furthermore, the peak demand created by the EV charging is possible to be reduced by using shiftable loads and BSES, which will be investigated in the following sections.

4.2 The Analysis of EVs Charging Demand

4.2.1 EV Classification and Distribution

EVs can be classified in different ways. According to the type of technologies, the main three types of EVs are HEVs, PHEVs, and BEVs. And based on the type of vehicles, the BEVs can be classified into four types [115][116], shown in Table 4-1, according to the EVs market investigation in Europe. Additionally, based on the use of vehicles, more than 60% of the vehicles are owned primarily for commuting between home and working place (Home Based Work, HBW) in the UK[116]. Therefore, the BEV, type M1, under HBW, is chosen to be the EV modelled in this chapter.

Table 4-1 EV Classification Based on the Type of Vehicles[115]

Vehicle Type	Characteristics
L7e	Four wheels with the maximum unladen mass of 550kg for goods carrying vehicles
M1	Passenger vehicle with up to 8 seats
N1	Goods carrying vehicle, with the maximum laden mass of 3500kg
N2	Goods carrying vehicle, with laden mass 3500kg-12000kg

The vehicles availability of households in 2016 from Road Use Statistics Great Britain 2016 is shown in Figure 4.1[117], it can be seen that approximately 77% of households have at least one vehicle, and the average number of vehicle per household is 1.2 [16], hence, in this research, one household with one EV is assumed.

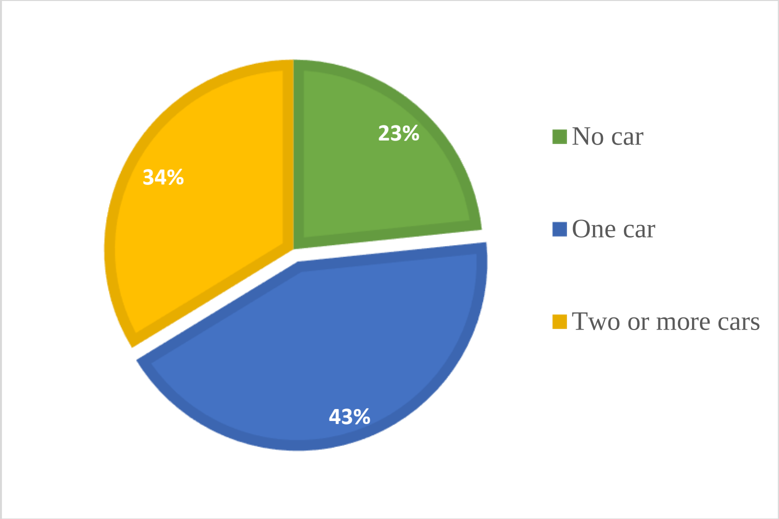


Figure 4.1 The Vehicle Availability of Households in 2016 [116]

In order to formulate the profile of the EV charging demand, it is necessary to have a better understanding of the charging rate of an EV, which depends on the EV type and also where and how the EV is going to charge. Till now the standard of EV charging is not yet available worldwide [118].

In order to formulate the EV charging demand, it is necessary to have a better understanding of the charging process of an EV, which depends on the type of the EV and also where and how the EV is going to be charged. Up to now, the worldwide standard of the EV charging is not yet available [118]. In this chapter, the EV is charged at a constant power rate, 6.5kW.

4.2.2 The Battery Capacity and The Travel Range of EVs

In most of the urban areas, the lifestyles and traveling behaviours of people may have certain patterns. And different patterns will require and determine some attributes of EVs, such as the battery capacity and the travel range.

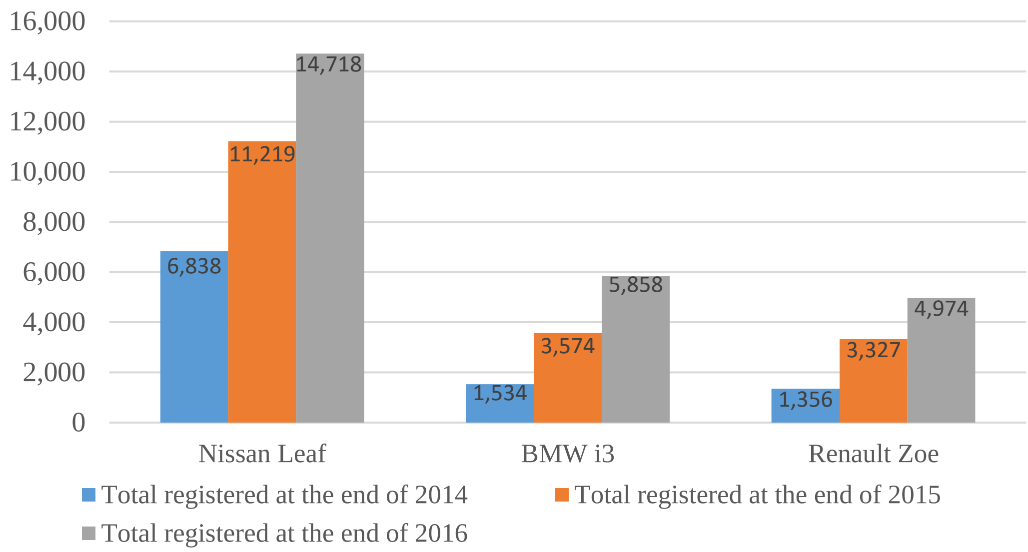


Figure 4.2 Top 3 EV Models Registered in the UK Between 2014 and 2016

In the database of EU EMERGE project [116], the smallest battery capacity is 10kWh and largest is 72kWh. Obviously, the maximum travel range of EVs is closely related to the battery capacity. And according to the latest road use statistics Great Britain 2016, most driving trips that people made are short trips, which 66% are less 5 miles and 95% daily driving trips are less than 25miles [117]. In the UK, the top-selling EVs are Nissan Leaf, BMW i3 and Renault Zoe etc., and the total registered EVs of those manufacturers between 2014 and 2016 are shown in Figure 4.2, and their battery capacity and travel range are listed in Table 4-2.

From Table 4-2, it clearly shows that the battery capacities of the most popular EVs are between 22kWh and 30kWh, and the travel ranges are between 84miles and 114miles. Based on this information, a fully charged EV is sufficient for the most daily traveling purpose. Consequently, most of the charging events are going to happen in the households. Therefore, in this chapter, the EV charging demand is investigated on the household level.

Table 4-2 EVs Travel Range and Battery Capacity

EV Model	**Nissan Leaf**		**BMW I3**	**Renault Zeo**
	Leaf24	Leaf30		
Travel range(miles/km)	84/135	107/171	114/183	94/151

Overall, the deterministic method is employed to analysis the EV charging demand in a household with only one EV assumed. The Nissan Leaf, 24kWh, 6.5kW charging rate, is chosen to be the EV model. And the charging scenario is that the maximum travel range of the EV is reached, which means the SOC before the charge is 10%, and the EV will be charged to 90% SOC.

4.3 The DEIM

According to the EV charging characteristics and charging events mostly happen at the household. The impacts of the power demand of the EV charging in a dwelling will be obviously massive. Especially, when an EV is charging around the peak power demand of a dwelling, thus the new peak of the household will be created. However, the capability of EnergyPlus modelling the EV charging in the dwelling and achieving any control strategies is very limited. Therefore, the BCVTB is introduced to establish the connection between EnergyPlus and MATLAB, achieving real-time control through DEIM.

4.3.1 Coupling the EnergyPlus and MATLAB via the BCVTB

• The Characteristics of EnergyPlus and MATLAB

EnergyPlus is a professional software for simulating the building energy performance. It uses a lot of detailed information of building construction and weather condition to investigate the energy demand in dwelling segments, such as heating, cooling, lighting, and ventilation, and it holds great value for engineering application. However, the control of any appliances or equipment is achieved by using predefined time schedules, and the real-time control of any appliances and equipment cannot be accomplished directly in the EnergyPlus.

MATLAB is a software, which is capable of integrating many different computing languages, program algorithm, and create interface etc. and it aims for many applications, such as engineering computing, control design, and signal processing etc. Therefore, the integration of EnergyPlus and MATLAB will benefit from the advantages of both software and it will give an opportunity for controlling any appliances and equipment in any dwellings in real time.

• Introduction of the BCVTB

In the literature, there are some researches accomplished the direct coupling different building energy analysis programs [119][120][56][121]. However, the direct coupling is facing some issues, such as the complex interfaces and slow simulation speed. The architecture of the BCVTB is different from the above approach, it uses a modular middleware to couple any number of simulation programs. This approach provides a central point for starting the simulation of all programs, establishing the communication channels, synchronizing the simulation time and stopping the programs, and it takes advantages of all software and will make models more feasible, simulating much fast. Therefore, BCVTB is selected for this chapter.

The software architecture is a modular design based on Ptolemy II, a software environment for design and analysis of heterogeneous systems. It provides a graphical modelling environment, synchronizes the exchanged data and visualises the system evolution during run-time[57]. Figure 4.3 shows the architecture of the BCVTB.

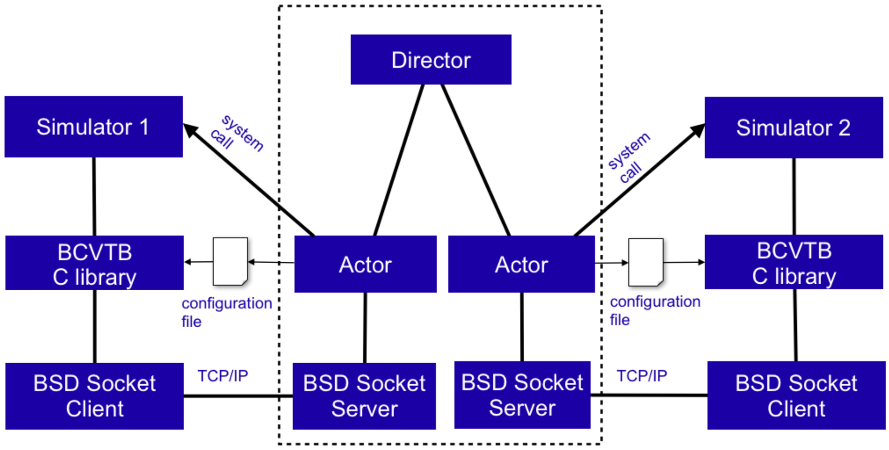


Figure 4.3 Architecture of the BCVTB[57]

In Figure 4.3, the middle with the dotted line, it marks the middleware that is used to implement the BCVTB. The middleware has a director that triggers off each actor at the synchronization time step. The director also organises the data exchange between the actors. Each actor controls one simulation program. Prior to the simulation, the actor writes a configuration file that specifies how the simulator can connect to the actor. Finally, it sends a process signal to start the simulation. It also starts a server that uses the Berkeley Software Distribution socket (BSD socket). The simulation program reads the configuration file and connects to the actor through a BSD socket. This socket is used to exchange data between the simulator and the actor.

In BCVTB, data is exchanged between the different simulation programs using a fixed synchronization time step. And the sequence of exchanging data between simulators and Ptolemy II is illustrated in Figure 4.4.

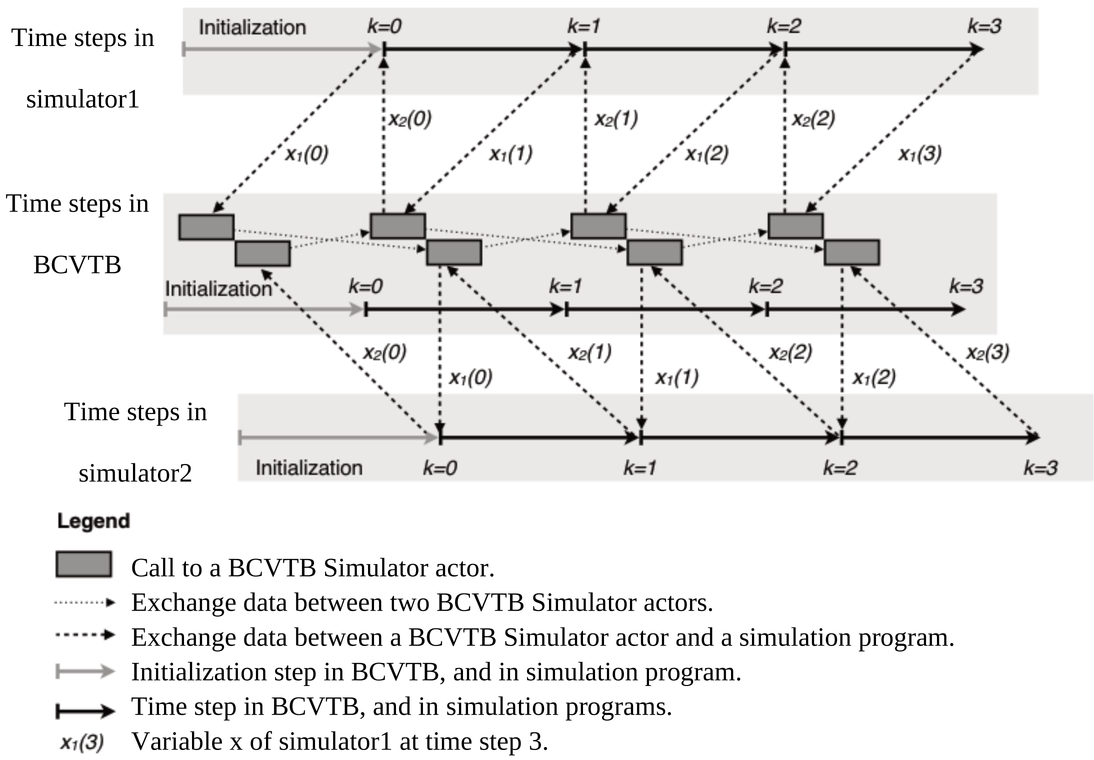


Figure 4.4 The Schematic Diagram of Data Exchange between Simulators and BCVTB [57]

In Figure 4.4, two simulators are going to exchange data via BCVTB, but more simulators are feasible if needed. The dashed arrows indicate the data exchange between the simulators and Ptolemy II and the dotted arrows show the data exchange inside Ptolemy II.

Firstly, the simulators have to initialise their data, and then these initial values will be written to BCVTB, as illustrated by the arrow $x_1(0)$ for simulator1. And then BCVTB will send these initial values to the other BCVTB actors, as indicated by the dotted arrows. Then, the process starts, Ptolemy II sends the data including initial conditions of simulators to the BSD sockets and the simulators receive them. This is indicated by the arrow labeled $x_2(0)$. When simulator1 receives the data and calculates the results, which will be sent to BCVTB, then it will receive the new data from BCVTB. This procedure will be repeated until the Ptolemy II reaches its last time step.

4.3.2 Interfaces Set up and the Establishment of DEIM

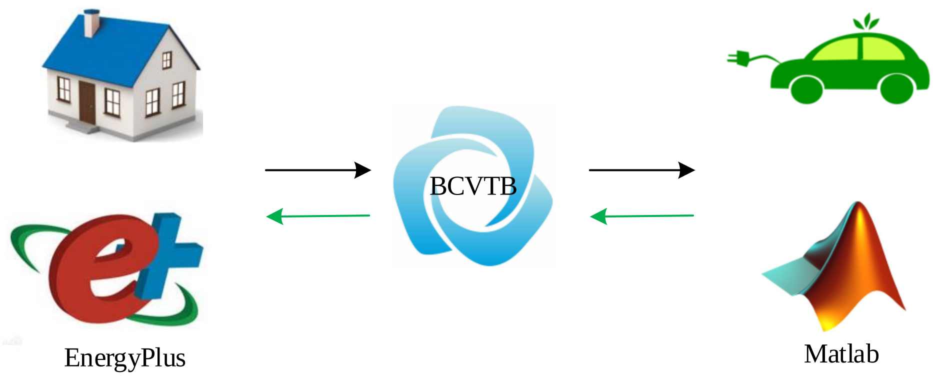


Figure 4.5 The Frame of DEIM

The frame of DEIM is shown in Figure 4.5, where the model of the energy demand in the dwelling is built in EnergyPlus and the EV is modelled in MATLAB. The black arrows indicate the data transmission of the temperature and power demand in the dwelling and the green arrows represent the data transmission of the control signals. The current temperature and power demand in the dwelling are sent to MATLAB through BCVTB, and the control signal of the EV charging and heating system of the dwelling will be determined in the MATLAB and sent back to EnergyPlus, based on the EV charging requirement with the data received from BCVTB. It can be seen that through using BCVTB, the data exchange between two simulators can be achieved, and corresponding interfaces set up will be introduced in detail.

- **Interfaces set up**

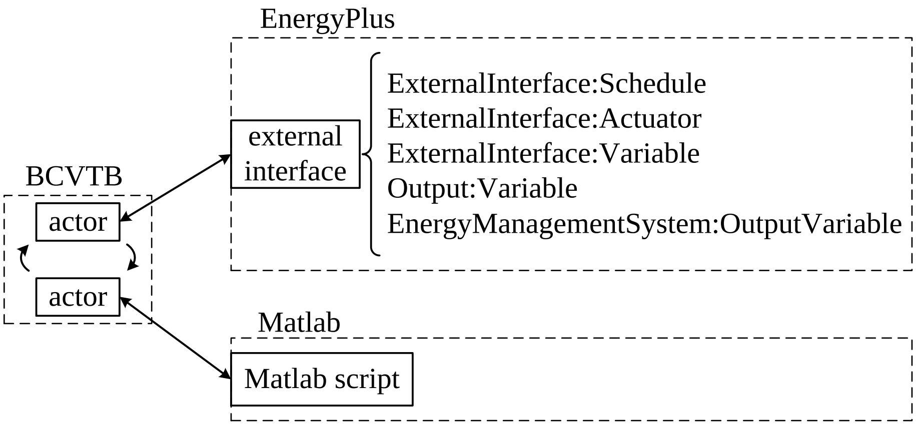


Figure 4.6 Interfaces Set up of EnergyPlus and Matlab

From Figure 4.6, it shows the necessary interfaces set up in both EnergyPlus and Matlab for using BCVTB. And it can be seen that an external interface module has to be placed in the EnergyPlus, which has the control availability of Schedule, Actuator, and Variable. The schedule can be used to overwrite schedules, which is widely used in EnergyPlus for controlling appliances, equipment etc. The other two objects are used in place of Energy Management System (EMS) actuators and EMS variables. The ExternalInterface will receive the data sending from BCVTB and send the required information back to BCVTB. And the set up of ExternalInterface in EnergyPlus is shown in Figure 4.7.

```
!-   ===========  ALL OBJECTS IN CLASS: EXTERNALINTERFACE ===========

ExternalInterface,
    PtolemyServer;           !- Name of External Interface

!-   ===========  ALL OBJECTS IN CLASS: EXTERNALINTERFACE:SCHEDULE ===========

ExternalInterface:Schedule,
    HeatingSystemStatus,     !- Name
    Any number,              !- Schedule Type Limits Name
    1;                       !- Initial Value
```

Figure 4.7 ExternalInterface Set Up in EnergyPlus

In Figure 4.7, the HeatingSystemStatus is a variable created for controlling the heating system of the dwelling, which is determined in MATLAB. And the initial value is set to 1, which means the heating system in the warm-up period is always on and it is only valid in the warm-up period. When the heating system in the dwelling is operating, the variable HeatingSystemStatus is determined by the control strategy in the MATLAB. And when HeatingSystemStatus is equal to 1 represents the heating system is on and 0 is off.

In MATLAB, it provides the interface for connecting the BCVTB and a MATLAB script is used to set up the interface, which is shown in Figure 4.8.

From Figure 4.8, it can be seen that all variables have to be initialised first and the path has to be added to the library. And then the soockfd function is invoked to establish a BSD socket connection between MATLAB and EnergyPlus, and based on this connection, the exchangeDoublesWithSocket function is used to achieve the data exchange between MATLAB and EnergyPlus at each time step. In Figure 4.8, retVal ，flaRea，simTimRea and u represent the values obtained from BCVTB and will be used in the MATLAB. And MATLAB has to submit sockfd，flaWri，length(u)，simTimWri and w to the BCVTB.

```
% Initialize variables
% ... (not shown)
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Add path to BCVTB matlab libraries
addpath( strcat(getenv('BCVTB_HOME'), '/lib/matlab'));
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Establish the socket connection
sockfd = establishClientSocket('socket.cfg');
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Exchange data (call this at each time step)
% ... (loop over each time step)
[retVal, flaRea, simTimRea, dblValRea ] = ...
  exchangeDoublesWithSocket(sockfd, flaWri, length(u), simTimWri,w);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Close socket at the end of the simulation
closeIPC(sockfd);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Exit MATLAB
exit
```

Figure 4.8 The MATLAB Script for Interface Set Up

• Establishment of DEIM

With the interfaces set up successfully in the early section, the EnergyPlus and MATLAB are able to be connected via BCVTB, therefore The DEIM is ready to use and the configuration is shown in Figure 4.9.

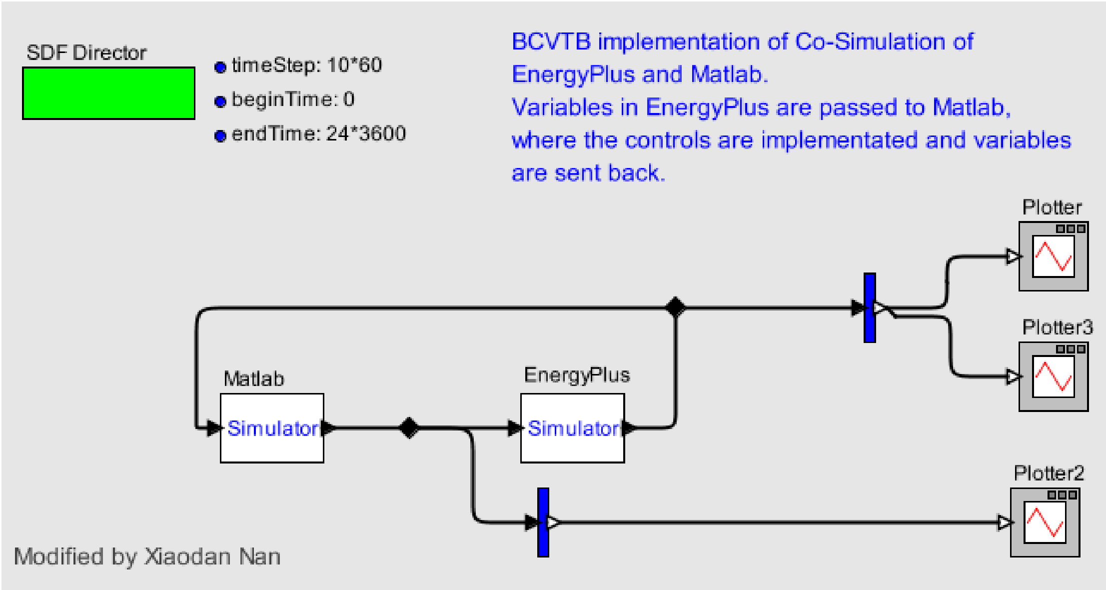


Figure 4.9 The Configuration of the DEIM

On the top left of Figure 4.9, in green colour, is the Synchronous Data Flow (SDF) director, which is used for controlling the communication between simulators. The section next to the SDF director is the place to set the time step, begin and finish time of the simulation, and it has to be noticed that all those information has to be set exactly the same in both EnergyPlus and MATLAB simulators, otherwise, it will not work. EnergyPlus sends the dwelling’s temperature and power demand at each time step to MATLAB, and then MATLAB will determine the heating system status and EV charging needs in the dwelling for the next time step based on the control strategy, and send the control signal of the heating system back to EnergyPlus through BCVTB.

4.3.3 The Impact of the EV Charging on the Dwelling

Based on the DEIM, the energy demand in the dwelling considering the EV charging can be modelled. The dwelling and appliances usage are the same as in chapter 3.3 and

Nissan Leaf 24 is selected, with Li-thium battery, 24kWh capacity, 6.5kW of charging rate and 84 miles of the maximum travel range[122]. And, the SOC before charging is assumed to be 10% and SOC after charging is 90% with 67.2 miles. Furthermore, 3rd Jan and Birmingham weather file is selected for the modelling.

According to the energy demand model established in chapter 3, the power demand in the dwelling, when there is no EV charging while ASHP using shut-down control, is shown in Figure 4.10.

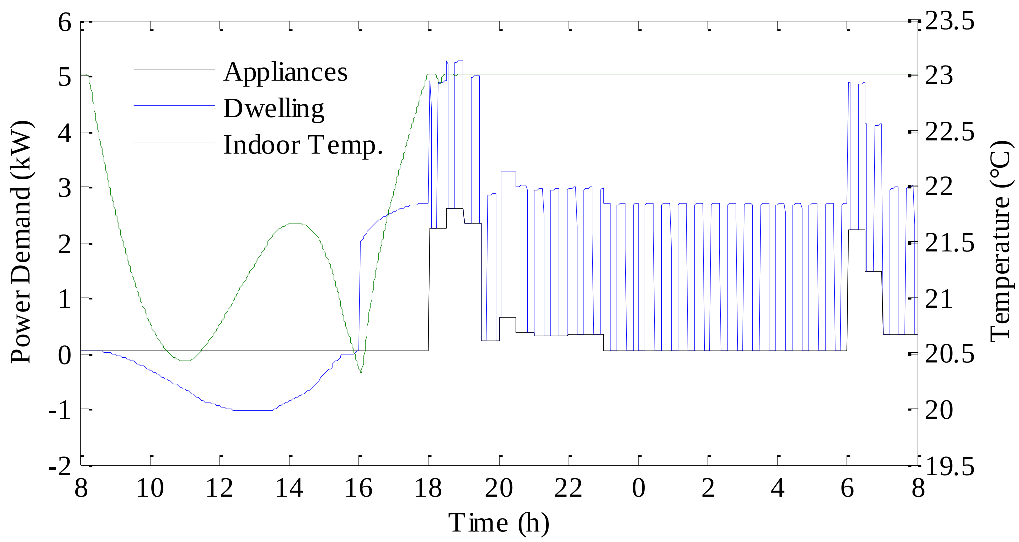


Figure 4.10 The Power Demand in the Dwelling without the EV Charging

In Figure 4.10, the blue line (Dwelling) is the total power demand of the dwelling, the black line (Appliances) indicates the power demand of the appliances and the green line (Indoor Temp.) represents the dwelling temperature. From Figure 4.10, it can be seen that because of the occupant’s behaviour, normally, the morning peak power demand occurs between 6:00-8:00, and it is 4.878kW at 6:04 in this modelling. And between 8:00-16:00, the occupant is out for work and the ASHP is shut down, only few appliances are in operation, like fridge. Additionally, the PV/T panels are generating electricity during this period and result in negative values in power demand. In the evening, the occupant arrives home and the evening peak power demand occurs around 18:00-19:30, and it is 5.279kW at 18:31 in this modelling. During other periods of the day, the ASHP is operated based on the dwelling needs of maintaining the comfort temperature.

According to [117], the most likely time of EV arriving home is 18:00, therefore, the start charging time (SCT) of the EV is assumed to be 18:00. The total power demand in the dwelling considering an EV is illustrated in Figure 4.11, indicated by the red line, Dwelling (+EV).

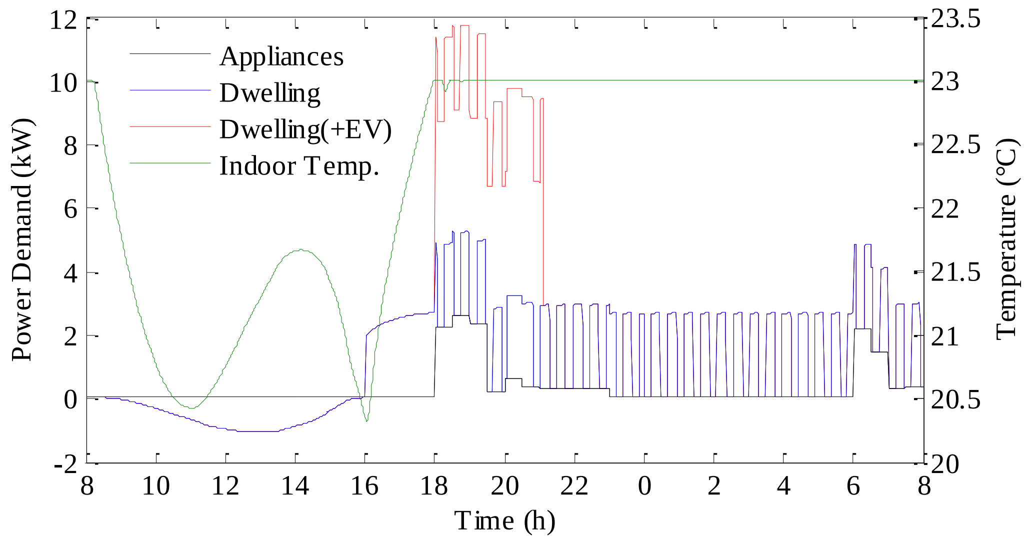


Figure 4.11 The Power Demand in the Dwelling with the EV Charging

Figure 4.11 illustrates the power demand in the dwelling when EV is considered and it clearly shows that the evening peak power demand occurs at 18:31, 11.779kW, due to the coincidence of the charging need of the EV and the original peak power of the dwelling, the peak power demand of the dwelling is increased significantly by 123%. And this will have an enormous impact on the DN. Furthermore, the power quality, power loss etc. of the DN will be impacted directly when a lot of dwellings are having peak power demands around the same time.

4.4 Reducing the Peak Power Demand of the Dwelling Caused by the EV Charging

From chapter 4.3, it can be seen that due to the EV charging needs, the peak power demand of the dwelling will be increased dramatically and it will directly affect the power quality, power losses etc. on the DN. In order to minimise the impact, load-shifting and battery storage system are considered in this chapter.

4.4.1 Reducing the Peak Power Demand of the Dwelling using Load-shifting Method

Load shifting method will be employed when the comfortable level of occupants is ensured to reduce the peak power demand of the dwelling and minimise the impacts of the EV charging on the dwelling and the LV DN.

When considering load shifting, the characteristics of the power demand in the dwelling have to be understood clearly. From Table 3-4 and Table 3-5, it can be seen that the power demand of lightings, computers, fridges etc. is highly depending on the occupants' behaviours, which cannot be shifted. The heat pump of the heating system has a periodic characteristic, and it aims to maintain the dwelling within the comfort level, which is recognised as a controllable load. Furthermore, the EV charging needs to be finished before the next departure and it can be shifted along the time but the total energy demand of the charging is fixed. Therefore, the heat pump of the heating system is controlled to reduce the peak power demand of the dwelling and also the EV charging is shifted to move the peak power demand. And three scenarios, ‘Shit Charging’, ‘Shift + Gap Charging’ and ‘Shift + Adjust Charging’, are proposed in Table 4-3 in this chapter to reduce the peak power demand of the dwelling caused by the EV charging. The characteristics of the EV are used the same as in Chapter 4.3.3.

Table 4-3 Three Scenarios of the Load Shifting Method

Scenarios	Description
‘Shift Charging’	EV charging starts from 23:00
‘Shift + Gap Charging’	EV charging starts from 23:00 and it charges when heat pump of the heating system is off
‘Shift + Adjust Charging’	EV charging starts from 23:00 and it charges when heat pump of the heating system is off while the dwelling temperature is set to a lower value

- **‘Shift Charging’ Scenario**

In ‘Shift Charging’ scenario, the EV charging demand will be shifted in order to avoid adding up the evening peak power demand. When considering the power demand in the dwelling, the EV charging starts from 23:00. In Figure 4.12, it shows the power demand in the dwelling with ‘Shift Charging’. And it can be seen that the peak power demand is reduced from 11.779kW to 9.215kW and reduced by 21.8%.

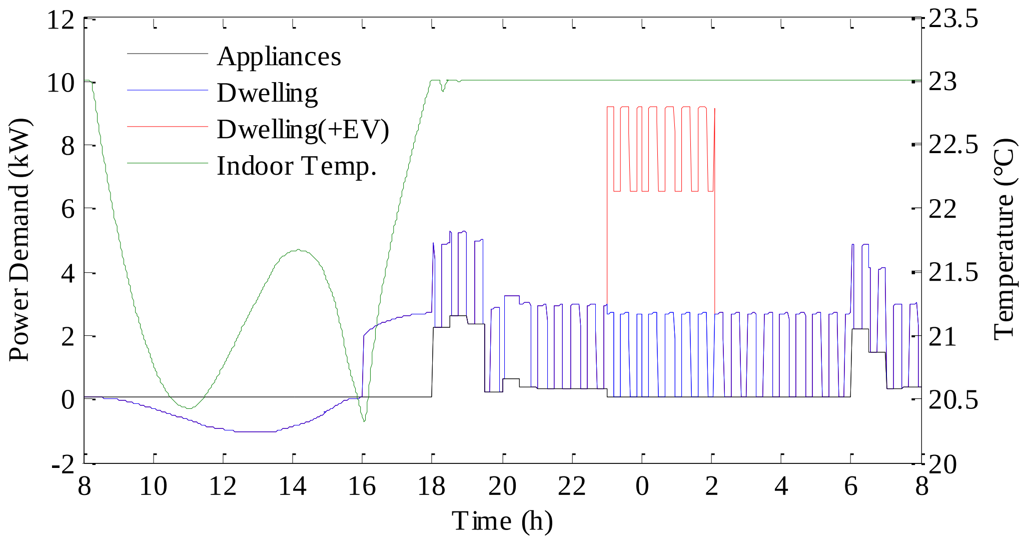


Figure 4.12 Power Demand in the Dwelling with 'Shift Charging'

• 'Shift + Gap Charging' Scenario

In this scenario, EV will be charged when the heat pump of the heating system is off to avoid adding up of the power demand of the EV and heat pump simultaneously. And EnergyPlus will send the status of the heat pump, dwelling temperature and current power demand to MATLAB through BCVTB, and then MATLAB will determine the charging strategy of the EV.

Figure 4.13 is showing the power demand in the dwelling with 'Shift + Gap Charging' scenario. It can be seen that the peak power demand is reduced from 11.779kW to 8.716kW at 06:11, which reduced by 26.0%. And comparing with 'Shift Charging', the peak power demand is reduced even more.

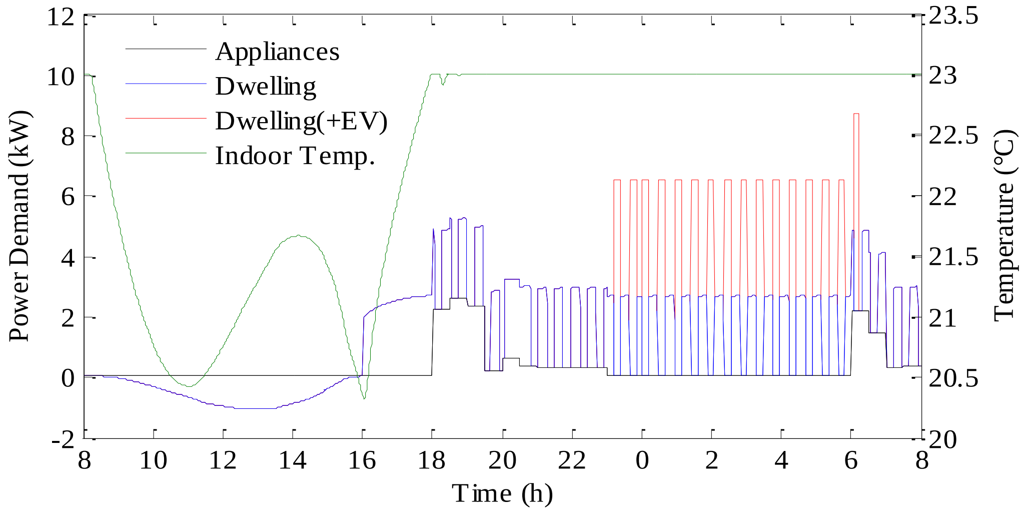


Figure 4.13 Power Demand in the Dwelling with 'Shift + Gap Charging'

From Figure 4.13, it can be seen that due to the shifted EV charging, there is a new peak created in the morning, which indicates that the selected charging period is not reasonable. Therefore, the EV charging starts from 21:00 is chosen, and the power demand in the dwelling is shown in Figure 4.14. The peak power demand is further reduced to 6.830kW at 22:25, which is reduced by 42% compared with no scenarios at all.

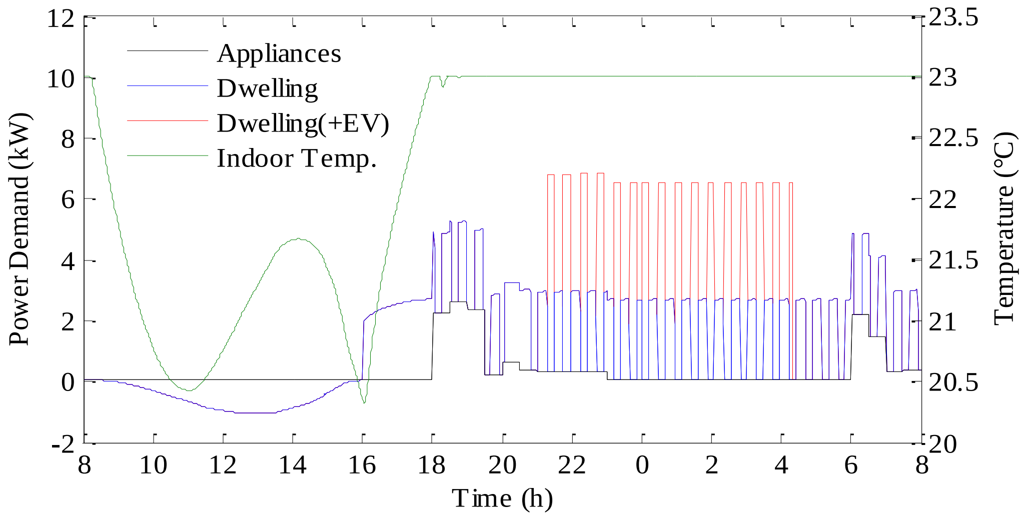


Figure 4.14 Power Demand in the Dwelling with 'Shift + Gap Charging' (21:00)

From Figure 4.14, the valid charging time of the EV is 3hrs between charging period 23:00 and 06:00, which means that the SOC of EV can be maximumly charged to 77%. Therefore, when the EV charging need is over 77%, the SCT has to be set to 21:00 and if not, 23:00 will be used.

Figure 4.15 shows the power demand in the dwelling when EV charging need is 70% and starts charging at 23:00. It can be seen that the peak power demand is reduced from 11.779kW to 6.552kW, which is reduced by 44.4%.

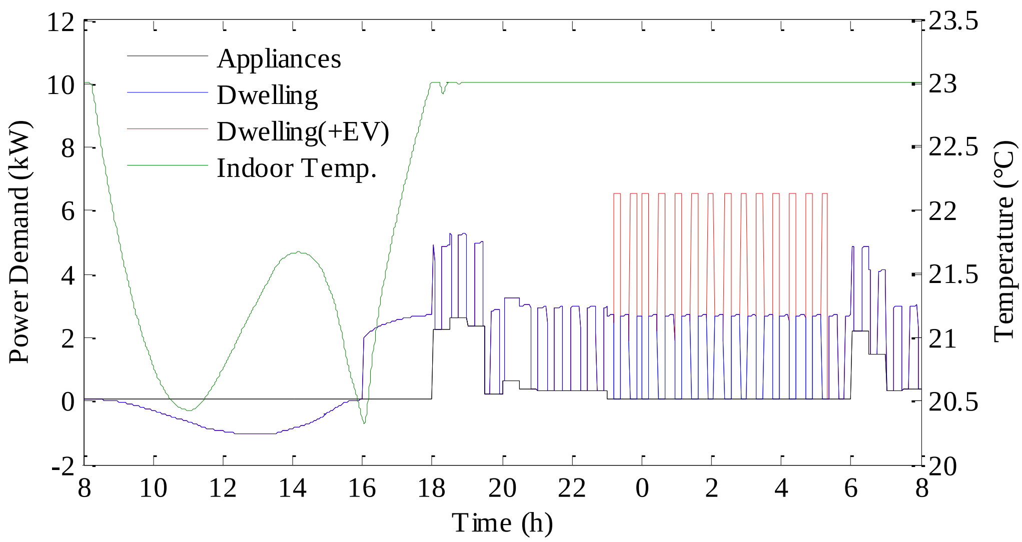


Figure 4.15 Power Demand in the Dwelling with ‘Shift + Gap Charging’ (70%)

Overall, with ‘Shift + Gap Charging’, when the EV charging need is smaller than 77%, the SCT is set to 23:00, and if the EV charging need is over 77%, it will be 21:00 to reduce the peak power demand.

- **‘Shift + Adjust Charging’ Scenario**

The 'Shift + Adjust Charging' Scenario sets the dwelling temperature to relatively low values, but the comfort level of the dwelling is still satisfied, and the EV will also be charged while the heat pump is off.

From 23:00, when the dwelling temperature is over 22 degrees, the heat pump is off and then EV is going to charge if the dwelling temperature is below 21 degrees, the heat pump is on and then EV stops charging. This process will repeat until EV is fully charged.

In order to achieve this scenario, the BCVTB will be used. EnergyPlus sends the status of the heat pump, dwelling temperature and current power demand to MATLAB through BCVTB, and then MATLAB will determine the status of the heat pump and EV charging process of the next time step based on the information from BCVTB. The control signal of the heat pump will be sent back to EnergyPlus and the control of the EV is competed in MATLAB.

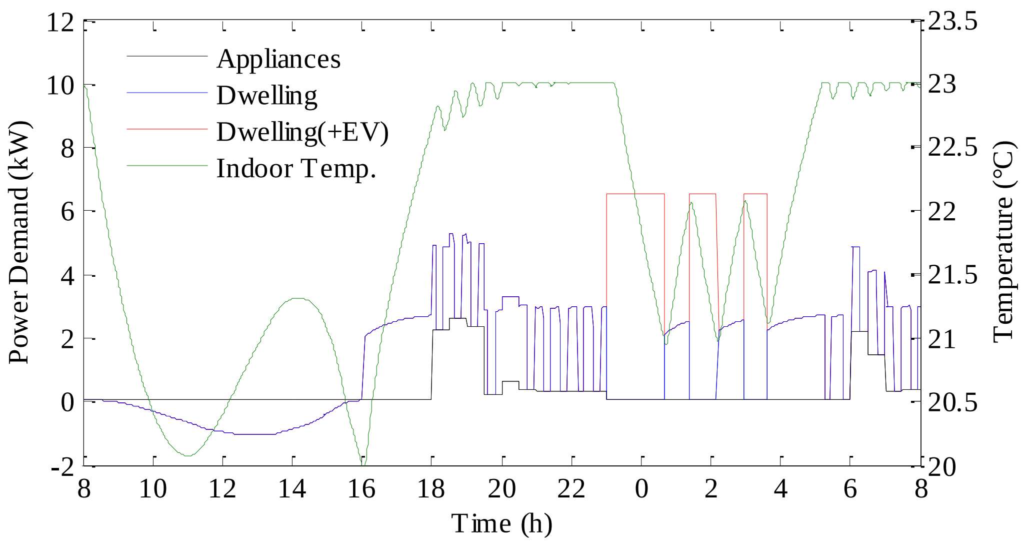


Figure 4.16 Power Demand in the Dwelling with 'Shift + Adjust Charging'

Figure 4.16 is the power demand in the dwelling with the ‘Shift + Adjust Charging’. It can be seen that the peak power demand is reduced to 6.552kW, which is 44.4% compared with no scenario employed.

Table 4-4 shows the dwelling temperature and peak power demand under different scenarios. It can be seen that the dwelling temperature is not affected in the ‘Shift Charging’ and the ‘Shift + Gap Charging’ scenarios, and in the ‘Shift + Adjust Charging’, the dwelling temperature is between 21 and 22 degrees, which is within the comfort level.

Table 4-4 The Dwelling Temperature and Peak Power Demand under Different Scenarios

<table>
<tr><th colspan="2">Scenarios</th><th>Peak Power Demand
kW</th><th>Reduced Percentage
%</th><th>Dwelling Temperature
℃</th></tr>
<tr><td colspan="2">None</td><td>11.779</td><td>0</td><td>23</td></tr>
<tr><td colspan="2">‘Shift Charging’</td><td>9.215</td><td>21.8</td><td>23</td></tr>
<tr><td rowspan="3">‘Shift + Gap Charging’</td><td>23:00 & >77%</td><td>8.716</td><td>26.0</td><td>23</td></tr>
<tr><td>21:00 & >77%</td><td>6.830</td><td>42.0</td><td>23</td></tr>
<tr><td>23:00 & <77%</td><td>6.552</td><td>44.4</td><td>23</td></tr>
<tr><td colspan="2">‘Shift + Adjust Charging’</td><td>6.552</td><td>44.4</td><td>21~22</td></tr>
</table>

From Table 4-4, it clearly shows that the peak power demand of the dwelling is dramatically reduced through employing these three scenarios, especially two latter scenarios, the peak power demand is close to the charging power of the EV. And all these scenarios successfully reduce the peak power demand of the dwelling caused by the EV charging and are able to minimise the impacts on the LV DN.

4.4.2 Reducing the Peak Power Demand using Load-shifting Method with the BSES

In Chapter 4.4.1, through using load shifting, the peak power demand of the dwelling is dramatically reduced. The power demand, while the occupants are not in the dwelling, is relatively low and even the power is sent back to the grid when the PV/T panels are generating. However, the power demand is quite high while the occupants are in the dwelling. Therefore, there is a clear peak-valley curve of the power demand in the dwelling, which will affect the operation of the LV DN.

Hence, a BSES is installed in the dwelling together with the load shifting applied. When the power demand is relatively low in the dwelling, the BSES will be charged and is going to discharge when the EV is charging or the power demand is high. It is able to achieve peak load shifting and smooth the power demand curve of the dwelling.

According to [117], 95% of the daily trip is shorter than 25 miles. And when the daily trip is 25 miles, the energy demand is 7.51 kWh for Nissan LEAF 24 based on the assumption of 80% rated capacity of the battery. Therefore, 10kWh BSES is selected with 8kWh effective capacity. From Chapter 3, the annual electricity generation is 2948.60kWh and daily average generation is 8.078kWh, which the BSES can be satisfied.

The charging period of the BSES, $T_{b\text{-}charging}$ is between 08:00 and 16:00, because of the power generating of the PV/T panels and relatively low power demand in the dwelling.

And the BSES is charged at a constant power rate, P_{inb}, which can be expressed in equation (4-1),

$$P_{inb} = \frac{\left(0.9 - SOC_{b\text{-}left}\right)}{\eta_{inb} T_{b-charging}} C_b \tag{4-1}$$

where $SOC_{b\text{-}left}$ indicates the energy left in the BSES from the previous day, η_{inb} is the charging efficiency, 0.95 is used, and C_b is the capacity of the BSES.

When the charging demand of the EV is smaller than the energy stored in the BSES (EV < BSES), the BSES will be discharged at 6.5kW and the EV charging will not affect the peak power demand in the dwelling. Furthermore, if there is much energy left in the BSES, then it will be used to reduce the peak power demand in the dwelling. When the charging demand of the EV is larger than the energy stored in the BSES (EV > BSES), the BSES will be discharged at a constant rate until 10% of the rated capacity reached. This process is done in the MATLAB of the DEIM.

- **EV < BSES**

When the charging demand of the EV is smaller than the energy stored in the BSES, the BSES is going to discharge at a constant rate, 6.5kW, and the EV charging is not going to increase the peak power in the dwelling. When EV charging is finished and there is energy left in the BSES, SOC_{left}, and then it can be used to reduce the original peak power demand in the dwelling.

The discharging power rate of the BSES when EV charging is finished, P_{outb}, can be expressed in equation (4-2), where t_{peak} is the total time of the original peak power demand of the dwelling lasts and η_{outb} is the discharging efficiency, 0.95 is selected, and the BSES is discharging at a constant rate.

$$P_{outb} = \frac{\eta_{outb}\left(SOC_{left} - 0.1\right)}{t_{peak}} C_b \tag{4-2}$$

P_{min} is the minimum power rate of the dwelling during t_{peak}, when $P_{outb} <= P_{min}$, the BSES is going to discharge as P_{outb}, when $P_{outb} > P_{min}$, the BSES is discharged as P_{min}. When the EV charging occurs at the same time of the original peak power demand in the dwelling, the discharging power rate of the BSES is the total of the P_{outb} and the EV charging power rate. And From Figure 4.10, the t_{peak} is 2.5hr and P_{min} is 1.465kW.

When the daily trip is assumed as 5miles, the power demand in the dwelling is shown in Figure 4.17. The black line (BSES) is the charging power rate of the BSES, the blue line (Dwelling (+EV)) represents the power demand in the dwelling without the BSES and the red line (Dwelling (+EV)with BSES) indicates the power demand in the dwelling considering the BSES. From Figure 4.17, it can be seen that the BSES is charging between 08:00 and 16:00 constantly, and discharging during 18:00 and 19:30 when power demands in the dwelling increases, which reduce the peak power from 5.279kW to 3.814kW, equally 27.8%. When the EV starts charging from 23:00, the BSES is discharging to compensate the power demand caused by the EV. And when the power demand in the dwelling starts increases in the morning, the BSES discharges again and it helps to reduce the peak power from 4.878kW to 3.413kW, which is 30%. From the overall view, the daily power demand in the dwelling becomes smoother.

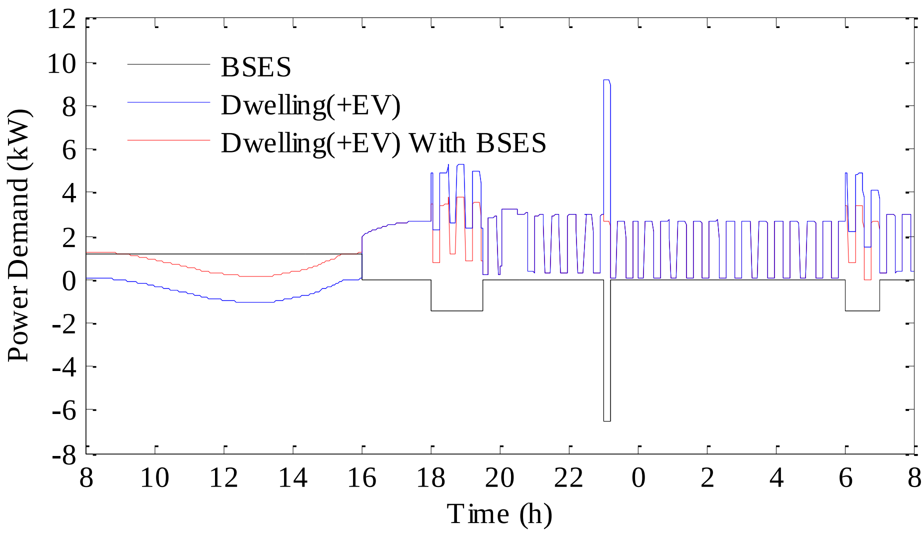


Figure 4.17 Power Demand in the Dwelling with the BSES

- **EV > BSES**

When the charging demand of the EV is greater than the energy stored in the BSES, the BSES is going to discharge at a constant power rate until reaching the 10% of the rated capacity.

When detects an EV starts charging, the charging time can be calculated based on the SOC of the EV, SOC_{bef}, which is shown in equation (4-3)

$$T_{charging} = \frac{0.9 - SOC_{bef}}{\eta_{inev} P_{EV}} C_{EV} \tag{4-3}$$

where P_{EV} is the charging power rate of the EV, 6.5kW is used, and η_{inev} represents the efficiency of the EV charging, 0.95 is used.

And the discharging power rate P_{outb} of the BSES is determined by equation (4-4).

$$P_{outb} = \frac{(0.9\text{-}0.1)C_b}{T_{charging}} \tag{4-4}$$

C_b is the capacity of the BSES, assume that the SOC of BSES ranges from 90% to 10%.

Assuming the dwelling is under 'Shift Charging' scenario, the power demand in the dwelling is shown in Figure 4.18. It can be seen that the BSES is charging between 08:00 and 16:00 and discharging from 23:00 at 2.451kW when the EV starts charging. And the peak power demand is reduced from 9.215kW to 6.764kW, which is 26.6%. Moreover, the daily power demand in the dwelling is smoothed.

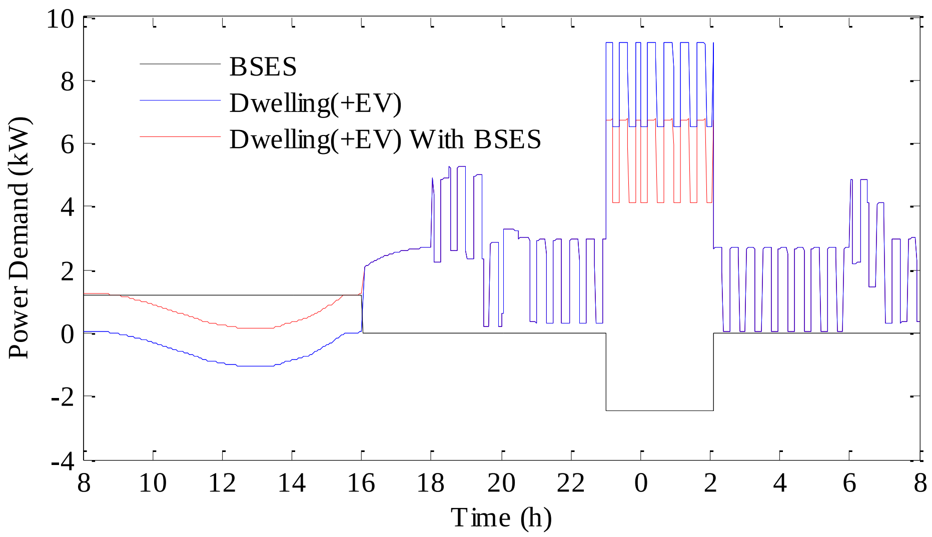


Figure 4.18 Power Demand in the Dwelling under 'Shift Charging' with the BSES

Above all, when the dwelling installed the BSES, the peak power demand is further reduced and it smooths the peak-valley curve of the power demand, which minimises the impacts on the LV DN.

4.5 Summary

In this chapter, based on the analysis of the charging need of the EV, the DEIM is established using the BCVTB to achieve integrating the energy demand model in the dwelling and the EV charging model. It is the essential foundation for the further analysis of the impacts of the EV charging of the dwelling and the LV DN.

Based on the DEIM, an individual dwelling is modelled in order to analyse the power demand in the dwelling when considering the EV charging. And through using load shifting method and the BSES, the peak power demand of the dwelling caused by the EV charging is reduced.

(1) Based on the load shifting method, three scenarios, 'Shift Charging', 'Shift + Gap Charging' and 'Shift + Adjust Charging', are proposed to reduce the peak power demand in the dwelling. And from the results, the dwelling temperature is maintained under 'Shift Charging' and 'Shift + Gap Charging' scenario, while under 'Shift + Adjust Charging' scenario, the dwelling temperature is within the range of 21-22 degrees. Most importantly, the peak power demand of the dwelling is reduced dramatically, especially in the latter two scenarios, which can reduce the impacts on the LV DN.

(2) Based on the load shifting method, the BSES is considered in the dwelling to further reduce the peak power demand caused by the EV and also the other peak. From the results, it does help to reduce the peak power demand and also smooth the daily power demand profile, which is good for the network operation.

In this chapter, the peak power demand of an individual dwelling considering an EV charging is dramatically reduced. However, when looking at a large scale of EVs charging, the impacts on the LV DN and possible ways to minimise the impacts will be discussed in the following chapters.

Chapter 5

Minimising the Impacts of EVs Charging on LV DN using the Dwelling's Micro-grid

5.1 Introduction

Impact of large scales of EVs charging on distribution systems has been evaluated by many researchers, however, the majority of the early studies have used a deterministic approach to establish the travel patterns, collected data directly or expected values and averages of EVs characteristics [123]. This approach fails to reveal the stochastic nature of travel behaviours of EV and the deterministic or averaged variables of EV characteristic may not always reflect the actual behaviours of EVs charging, even some extreme situation might be missed. In this section, EVs charging demand profiles with different granularity are presented, and the impact of EVs charging on LV DN is investigated in different EV penetration.

In chapter 4, the deterministic method is used to reduce the peak demand of a dwelling when an EV is charged. However, the deterministic method does not reveal the random nature of EV drivers' behaviours [114] and due to the increasing diversity of EVs in the urban area, the daily travel distance, battery capacity and driving patterns of EVs will have stochastic characteristics, consequently, these characteristics might result in a new peak power demand.

Therefore, in this chapter, a community level of households is analysed rather than an individual dwelling in chapter 4, and various factors are involved, such as EV battery types, EV battery capacity, SOC, daily travel range, maximum travel range etc. Monte Carlo simulation, as a stochastic modelling approach, is one of the most popular choices in many literatures [80], also is employed in this chapter. Based on these methods, the impacts of EVs charging on LV DN are investigated, and a feasible method to reduce the impacts from EVs charging is developed. In this method, each individual dwelling is treated as a micro-grid and a storage battery is installed in the dwelling to store PV generation. When EVs are starting to charge, the storage battery will discharge to compensate the peak power demand created by EVs and reduce the voltage drop and power loss of the DN.

5.2 The Mathematical Modelling of EVs Charging Demand

A reliable model, which is capable of translating the travel patterns of EVs into the respective power demands, is the key of establishing the profiles of EVs charging demands. According to the drivers' preferences and travel patterns, the battery types and capacity, travel range of EVs, SCT, daily travel distance and etc. can be modelled based on certain distributions. In many literatures, the charging power of an EV was assumed to be a constant value [124][80][123][125], which is not able to reflect the stochastic characteristics of EVs charging. Hence, in this section, the mathematical model of the charging demand profiles of EVs will be formulated using the stochastic method.

5.2.1 Battery Types, Capacity and Travel Range of EVs

Through looking at the current EV market in the UK, there are two dominant EV battery technologies Lead-acid and Lithium-ion. Lead-acid battery is the most widely used batteries in the EV world, because the cost is relatively low, and it can be found and bought easily from the local market, also it is generally considered to be the safe battery.

However, Lead-acid battery is heavier compared with Lithium-ion battery, which affects the overall efficiency. Lithium-ion battery can offer top performance and optimum vehicle capacity. Moreover, regarding battery lifespan, it lasts longer than Lead-acid battery. And in this research, it was assumed that 40% of EVs are using Lead-acid battery, and 60% are Lithium-ion.

The power demand, P_d, and SOC, SOC_d, of Lithium-ion [126] and Lead-acid [127] are shown in Figure 5.1 and 5.2 with the 10mins time step.

Regarding the characteristics of the SOC and power demand profiles, it can be seen that the EV using Lithium-ion battery is able to be fully charged in 5hrs, however, the charging time costs longer to 7hrs for the EV installed Lead-acid battery. Moreover, it can be found that, for the Lithium-ion battery, the charging power is mostly stable in 4.5hrs at the peak value of 6.5kW and then drops dramatically in the last half an hour. And in Lead-acid battery, the charging power is increased rapidly in first half an hour then slowly reaches the peak of 6.4kW, and then it is gradually down in 5hrs. Additionally, the SOC of Lead-acid battery reaches the 80% in approximately 3hrs, and it takes around 3.6hrs for Lithium-ion battery.

EV battery capacity C_{EV} of type M1 is determined by the capacity data from the EV database of EU MERGE project [116], with the battery capacity between 10kWh and 72kWh. And the most proper probability density function of type M1 is found to be Gamma distribution shown in equation (5-1) with the parameter α = 4.5 and β = 6.3,

$$f(C_{EV}|\alpha,\beta)=\frac{\beta^{\alpha}}{\Gamma(\alpha)}C_{EV}{}^{\alpha-1}-\beta C_{EV} \tag{5-1}$$

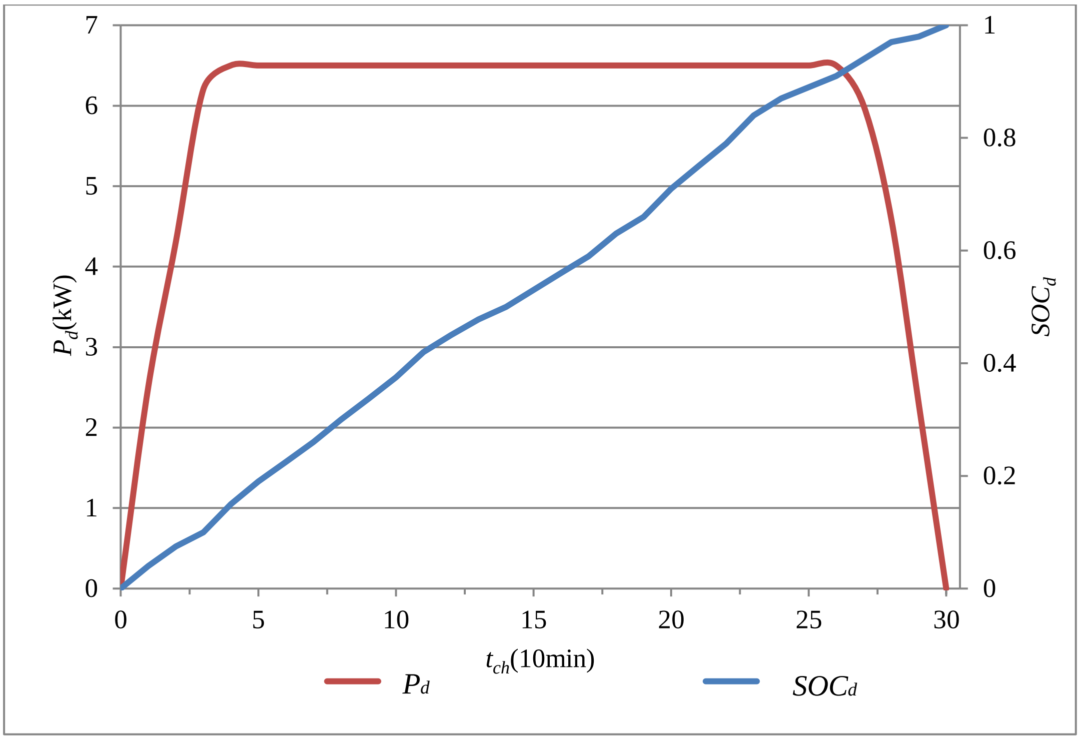


Figure 5.1 The SOC and Power Demand Profile of the Lithium-ion Battery [126]

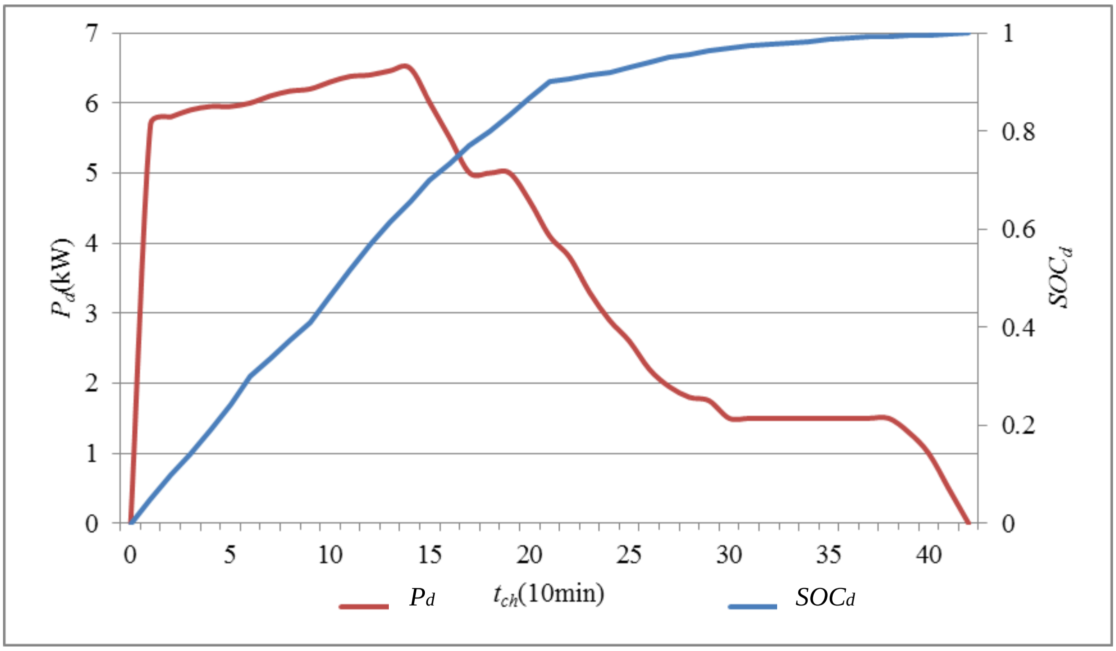


Figure 5.2 The SOC and Power Demand Profile of the Lead-acid Battery [127]

EV maximum travel range, D_{max} is determined by the battery capacity. In the EV database, the C_{EV} and D_{max} data of EVs are provided, the mathematical relationship between C_{EV} and D_{max} parameters can be found by employing polynomial fitting shown in Figure 5.3.

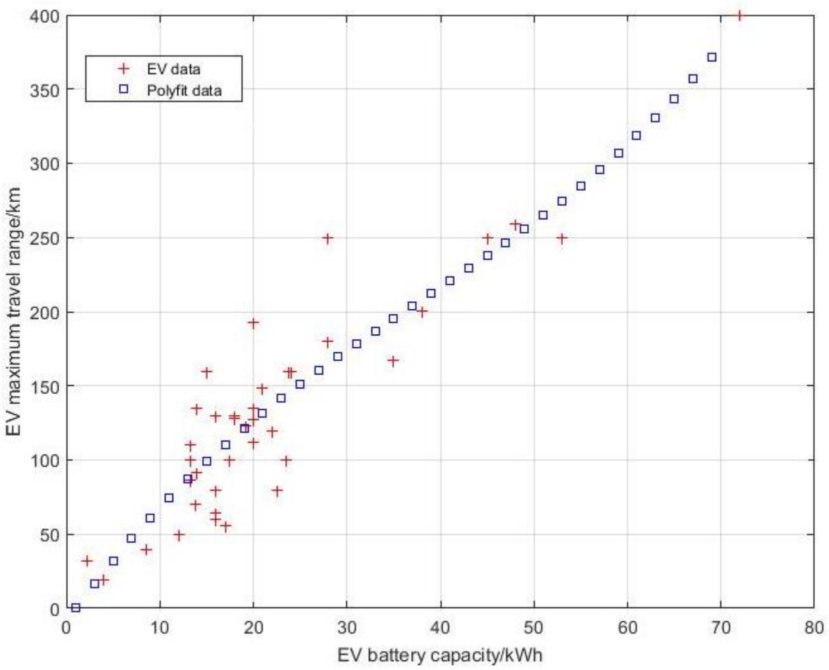


Figure 5.3 The Mathematical Relationship between EV Battery Capacity and Maximum Travel Range

The red plus sign indicates each individual EV battery capacity and its corresponding maximum travel range from the database, and the blue square sign shows the polynomial fitting results that obtained from equation (5-2).

$$D_{max} = 0.0011C_{EV}^{\ 3} - 0.1223C_{EV}^{\ 2} + 8.7723C_{EV} - 8.604 \tag{5-2}$$

5.2.2 The SCT of EVs

The EV SCT most likely depends on the drivers' travel behaviours, which are assumed to comply with their lifestyles. And it is assumed in this chapter that an EV starts charging once it arrives home. As discussed in the early section, the drivers' travel patterns have stochastic nature which is hard to capture by using deterministic approach, therefore, the SCT of each individual EV in the modelling is determined based on the probability of vehicles arriving home from the Time Use Survey (TUS), 2000 United Kingdom [16]. Particularly, there are some other surveys, like National Travel Survey (NTS), Transport Statistics bulletin-national travel survey, providing the participants day-to-day activities, however, the TUS data, it offers the detailed data on privately owned vehicle use recorded over a 24-hour period (04:00 am to 03:50 am), including time of vehicle departure and arrival home, average daily driving time and length etc. Moreover, the data recorded in TUS has a higher resolution, 10mins granularity, compared with other similar types of surveys [128]. Therefore, TUS data is employed in this chapter for calculating the SCT.

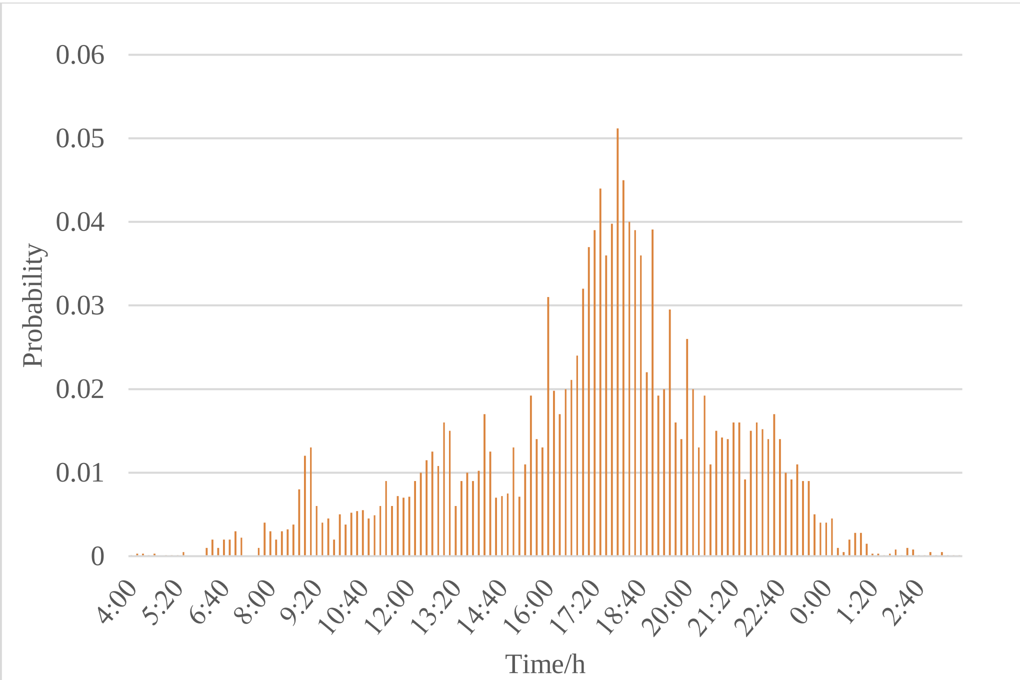


Figure 5.4 The Probability of Vehicles Arriving Home [16]

The probability of vehicles arriving home from TUS shown in Figure 5.4, it can be seen that around half of the vehicles recorded in the survey were arriving home between 16:00 and 20:00. In order to establish the probability modelling of the SCT of each individual EV, the Gaussian distribution, shown in equation (5-3), is employed with the parameters, mean and standard deviation, μ=108(18:00), σ=10.8.

$$g(SCT|\mu,\sigma^2)=\frac{1}{\sqrt{2\pi\sigma^2}}e^{\frac{(STC-\mu)^2}{2\sigma^2}} \quad (5\text{-}3)$$

5.2.3 The SOC of EVs before Charging

Developing the SOC of EVs before charging is one of the key steps in the whole modelling of EV charging load profiles. It dominates the power demand profile in the charging process of each individual EV. In literatures, the SOC before charging was normally assumed at a certain level when EV arrived at home, in [124], it was assumed that battery returned with half its capacity. This assumption is reasonable based on the fact that most of the daily trips are short, but it could not reveal the stochastic nature of EVs travelling mobility.

Therefore, in this research with the objective of capturing the stochastic nature of EVs travelling mobility, the SOC of EVs before charging is calculated based on daily travel range, D_{tre}, of each individual EV. According to the general information available on private vehicle travel [129], the probability distribution of daily travel range can be obtained, and the probability density function of the daily travel range of EVs can be expressed in equation (5-4).

$$h(D_{tre}|\mu,\sigma^2)=\frac{1}{D_{tre}\sqrt{2\pi\sigma^2}}e^{-\frac{1}{2}(\frac{\ln D_{tre}-\mu}{\sigma})^2} \quad D_{tre}>0 \quad (5\text{-}4)$$

Where the μ is the mean and σ is the standard deviation of the probability function. Based on the data extracted from [130], for type M1, the mean of the distribution is 22.3miles and the standard deviation is 12.2miles.

When the daily travel range is determined, the SOC of EVs before charging then can be derived from the equation (5-5), by assuming the SOC of the individual EV drops linearly with the range traveled [81],

$$SOC_{bef} = \lambda(SOC_{in} - D_{tre}/D_{max}) \tag{5-5}$$

where λ represents the coefficient of the energy efficiency of EVs, it is utilised for considering the energy loss caused by the acceleration and deceleration of EVs derived on the road when facing real traffic, and it could be varied randomly in the range of [0.9,1.0]. SOC_{in} is the SOC of an individual EV before travel and it is assumed to be uniformly between 0.8 and 0.9.

5.2.4 The Charging Demand Modelling of EVs

From Figure 5.1 and Figure 5.2, the power demand and SOC of an individual EV at charging time t_{ch} can be expressed in the following equation (5-6) and (5-7),

$$P_d = f\left(t_{ch}\right) \tag{5-6}$$

$$SOC_d = f\left(t_{ch}\right) \tag{5-7}$$

Where t_{ch} is the charging time in Figure 5.1 or Figure 5.2, P_d is the power demand at time t_{ch} of an individual EV, SOC_d is the SOC of the EV at time t_{ch}.

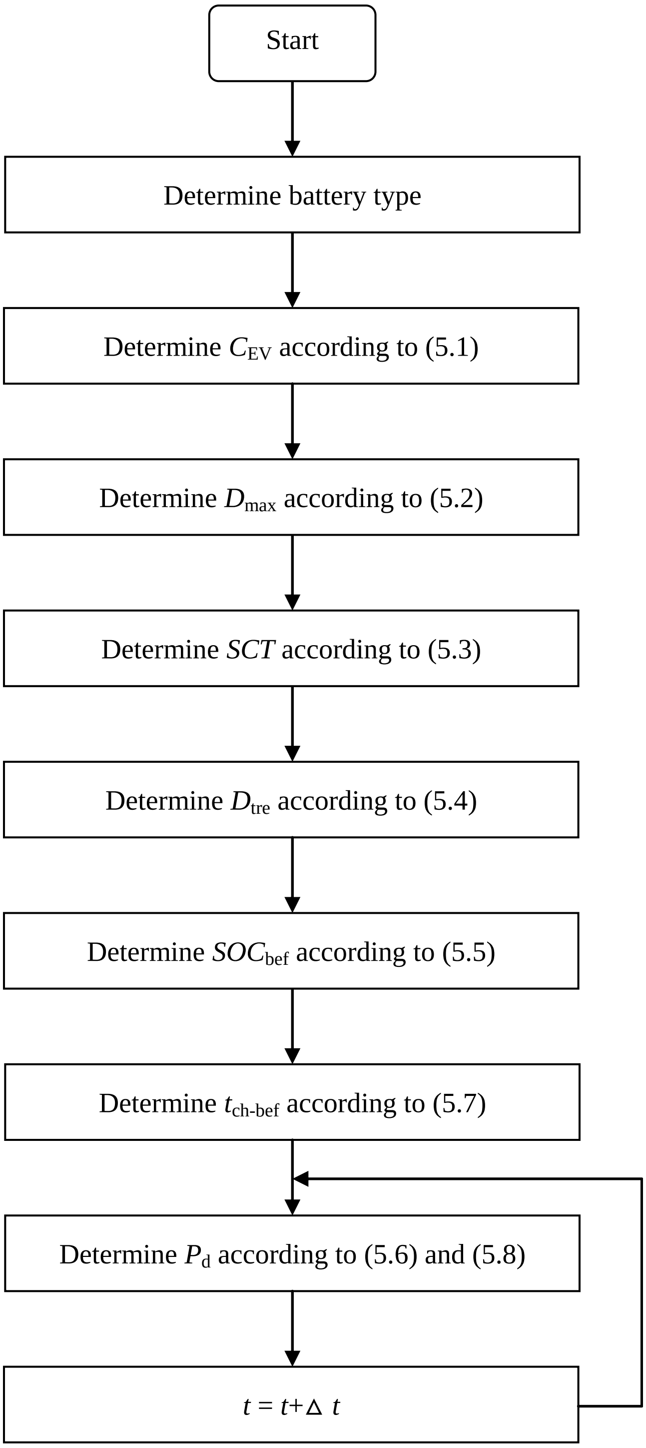


Figure 5.5 The Overall Structure of the Model.

When the SOC before charging of the EV, SOC_{bef}, is determined, the $t_{ch\text{-}bef}$ can be found on either Figure 5.1 or Figure 5.2. And t_{ch} can be calculated from equation (5-8). Consequently, the power demand and SOC of an individual EV at any time t can be calculated from equation (5-6).

$$t_{ch} = t_{ch\text{-}bef} + t - SCT \tag{5-8}$$

The overall structure of charging demand modelling of EVs is illustrated in the flowchart shown below in Figure 5.5.

5.3 The Impacts of EVs Charging on LV DN and the Minimisation

5.3.1 Introduction of the LV DN

A typical LV DN [131] is selected for analysing the impacts of large scales, community level, of EVs' charging. The configuration of the network is shown in Figure 5.6 and the detailed information of the network is categorised in Appendix B, Table B-1. The left side of the 500kVA transformer is the sufficient network supply, and at Bus 2, there are 4 feeders, three of them are assumed to be constant loads with each of 62.4kW and one of them is modelled as a community feeder supplying 96 households with 24 households distributed on each bus, each phase has 8 households.

The Electric home is selected as the modelled dwelling in this chapter. The main electrical consumers are electrical equipment and the EV, and the power generation is from PV/T panels. The power factor is assumed to be 0.9 and the reactive power from PV/T panels and EV's charging are neglected.

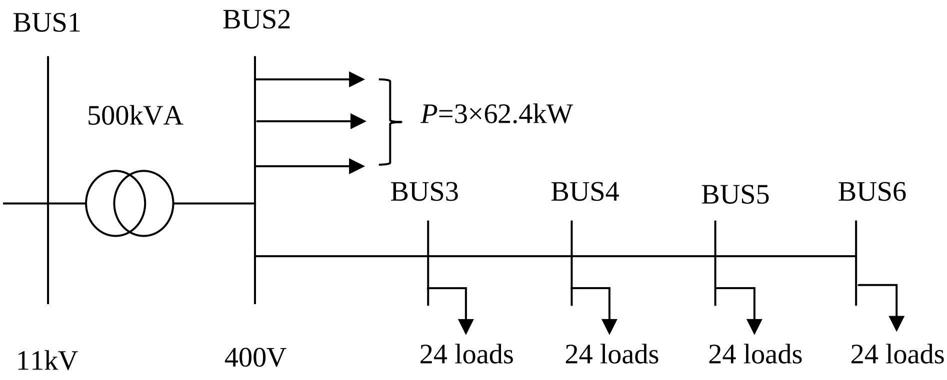


Figure 5.6 The Configuration of LV DN

Apparently, the worse impact of EVs charging on LV DN has much more chance happening in January as power generation from PV panels is low and the usage of electrical equipment is high. The power demand for electrical equipment is generated from [20] and the average generated power of PV panels in January is shown in Figure 5.7. Due to all households are located closely, the power generation for each individual dwelling is assumed to be the same.

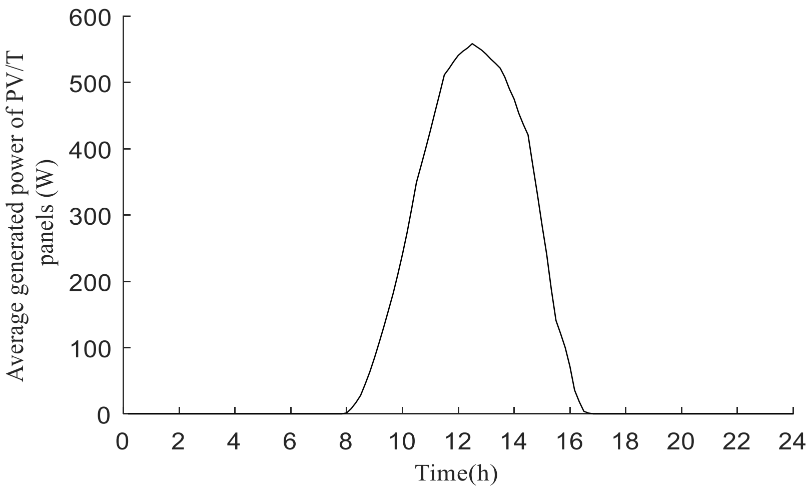


Figure 5.7 Averaged PV Generation in January

5.3.2 The Impacts of EVs Charging on LV DN

The time period for the impact analysis is selected from 00:10 to 24:00 and the time step is 10mins.

• The analysis of the LV DN without EVs charging

The power demand profile of the electrical equipment for each 96 households is generated based on the usage probability with Monte Carlo simulation method [20], and then the power flow analysis of the DN can be carried out using Newton-Raphson method. With the increasing simulation times, the minimum voltage of the community feeder is shown in Figure 5.8 in red dots, and the black line represents the average minimum voltage. When the number of simulation times is small, the values of the average minimum voltage are varied. And with the increasing number of simulation times, the average minimum voltage is going to be converted. Moreover, when the number of simulation times reaches 10,000, the average minimum voltage of the community feeder is converged at 97.57%, with standard deviation 0.25%, which means the average voltage drop is 2.43%.

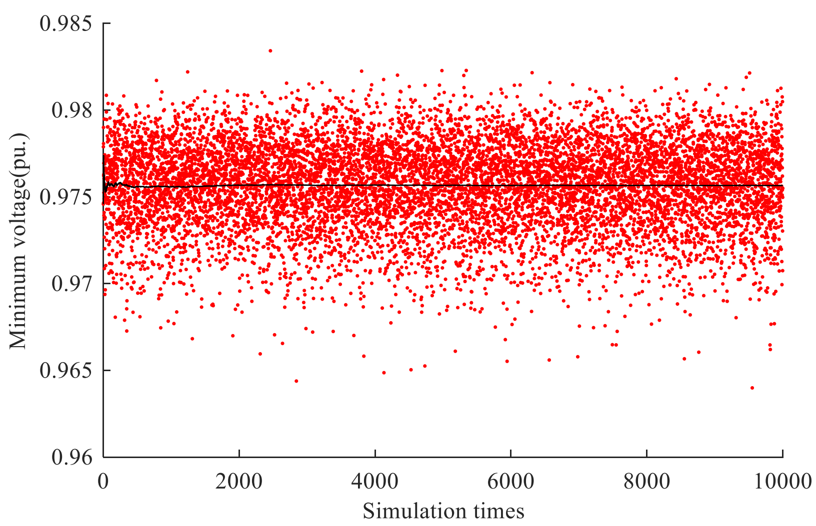


Figure 5.8 The Minimum Voltage along Simulation Times without EVs Charging

The probability of voltage drop on each bus in the network is listed in Table 5-2. It can be seen that the voltage drop on BUS6 mainly occurs between 2% and 3%, and the voltage drop on each bus is within the UK voltage regulation, -6% to +10%.

Table 5-1 The Probability of Voltage Drop on Each Bus without EVs Charging

Unit:%

Drop / Bus	[0 1%]	(1% 2%)	(2% 3%)	(3% 4%)	(4% ∞)
BUS2	100	0	0	0	0
BUS3	73.76	26.24	0	0	0
BUS4	0	99.95	0.05	0	0
BUS5	0	33.26	66.72	0.02	0
BUS6	0	2.23	95.73	2.04	0

The average bus voltage of the community feeder is illustrated in Figure 5.9. It can be conducted that the maximum average voltage drop, 1.93%, occurs on BUS6 at 17:40. Moreover, in Figure 5.8, it illustrated the minimum bus voltage distribution and its average value varied with simulation times, while, Figure 5.9 indicates the average bus voltage of the community feeder along the time. Hence, the former value should be lower than the latter one.

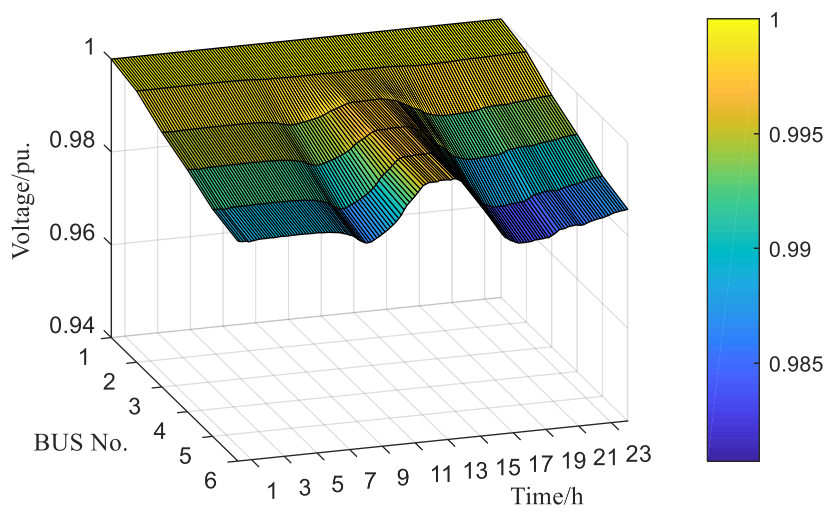


Figure 5.9 The Average Bus Voltage Distribution of the Community Feeder without EVs Charging

The voltage distribution on BUS6 is shown in Figure 5.10, the black solid line indicates the average voltage. Due to the peak power generation of the PV panels around 12:40, the voltage drop at this time is the smallest. And, the BUS6 voltage of 28th, 364th, and 8531th simulation are also shown in Figure 5.10, they all follow the similar trend with the curve of the average voltage, but the individual stochastic characteristic is also revealed.

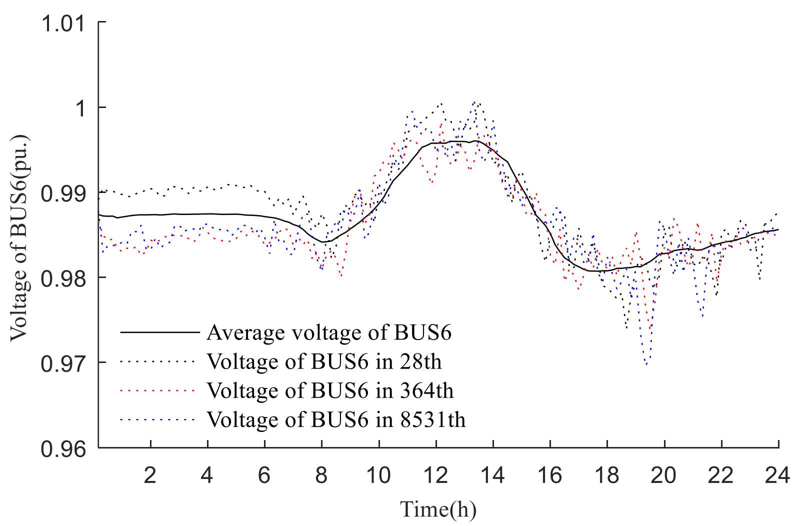


Figure 5.10 The Voltage on BUS6 of the Community Feeder without EVs Charging

• The Impacts Analysis of EVs Charging on the LV DN

Only one EV is assumed in each household when EVs charging in the community is considered. And the stochastic behaviour of EVs charging is modelled based on the method introduced in chapter 5.2. Then the power flow analysis of the DN can be carried out using the Newton-Raphson method. The minimum voltage of the community feeder when EVs are charging is illustrated in Figure 5.11 in red dots, and the black line represents the average minimum voltage. And it can be seen that with the increasing simulation times, the average minimum voltage is converged at 93.49% with standard deviation of 0.67%, which means the average voltage drop is 6.51%.

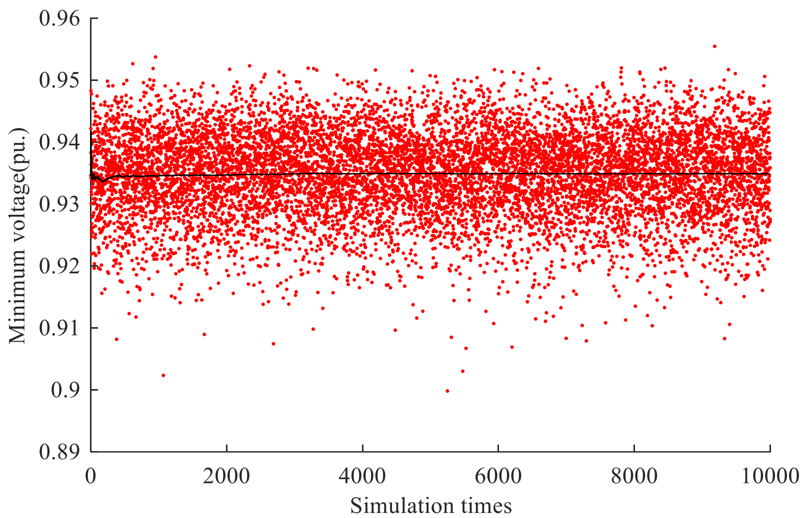


Figure 5.11 The Minimum Voltage along Simulation Times with EVs Charging

Furthermore, the standard deviation of the average minimum voltage of the community feeder when considering EVs charging is much bigger than the one, which is 0.25%, when the network is without EVs. Therefore, it can be derived that the stochastic behaviour of EVs charging considered in the community results in the worse voltage distribution in the network.

Table 5-2 The Probability of Voltage Drop on Each Bus with EVs Charging

Unit:%

Drop / Bus	(0 1%)	(1% 2%)	(2% 3%)	(3% 4%)	(4% 5%)	(5% 6%)	(6% 7%)	(7% 8%)	(8% 9%)	(9% ∞)
BUS2	100	0	0	0	0	0	0	0	0	0
BUS3	0	15.62	84.33	0.05	0	0	0	0	0	0
BUS4	0	0	1.69	83.95	14.29	0.07	0	0	0	0
BUS5	0	0	0	0.03	16.60	64.50	17.95	0.88	0.04	0
BUS6	0	0	0	0	0.41	22.51	54.65	20.19	2.10	0.14

The probability of voltage drop on each bus of the community feeder with EVs charging is catergorised in Table 5-3. It can be seen that on BUS5, 18.87% of voltage drop is over 6% and 77.08% for BUS6. Consequently, this is a serious issue on the DN, which necessary actions have to be made.

The comparison of the probability of voltage drop on BUS6 of the community feeder between the network without EVs charging and considering EVs charging is shown in Figure 5.12. The black one represents the voltage drop distribution of the network without EVs charging and the red one indicates the one considering EVs charging. From the figure, it clearly shows that the voltage drop on BUS6 of the community feeder when EVs charging involved is much worse than the one without EVs charging.

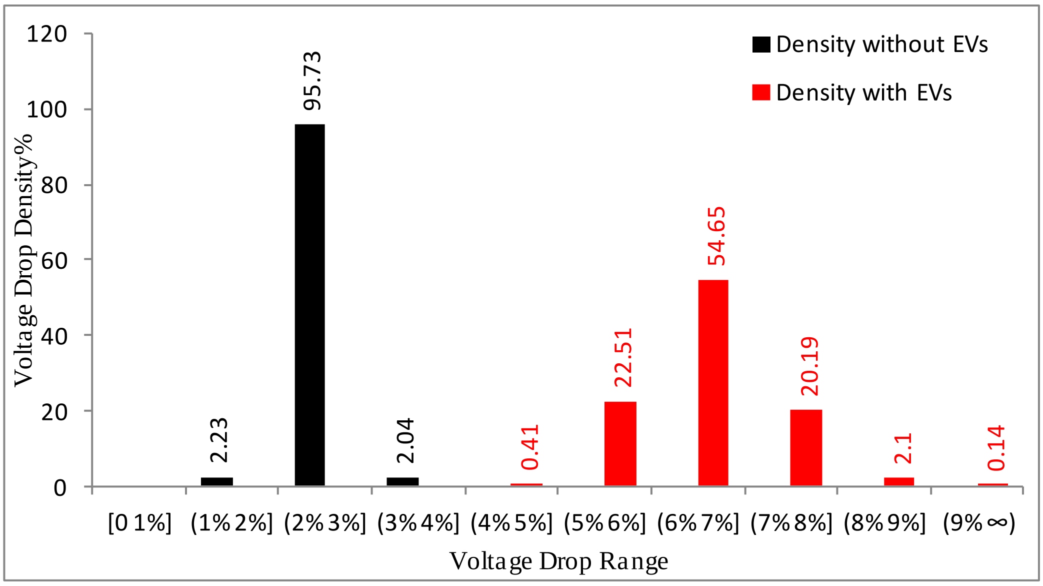


Figure 5.12 The Probability of Voltage Drop on BUS6 of the Community Feeder with/without EVs Charging

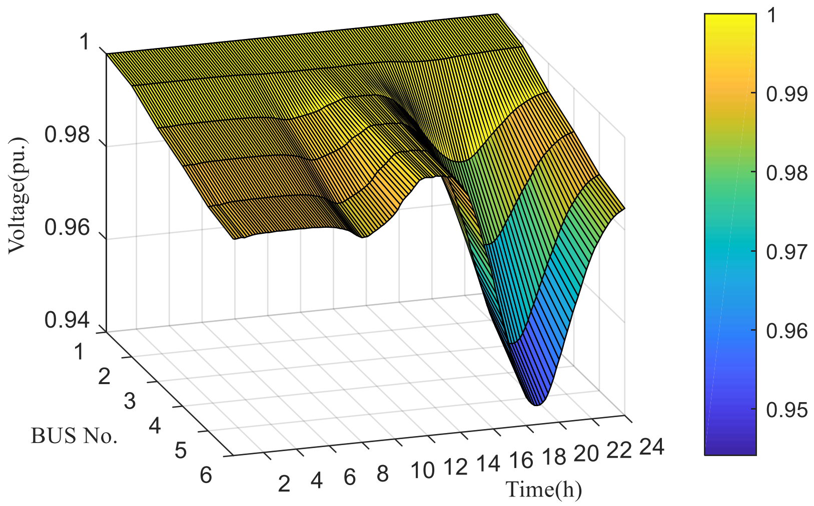


Figure 5.13 The Average Bus Voltage Distribution of the Community Feeder with EVs Charging

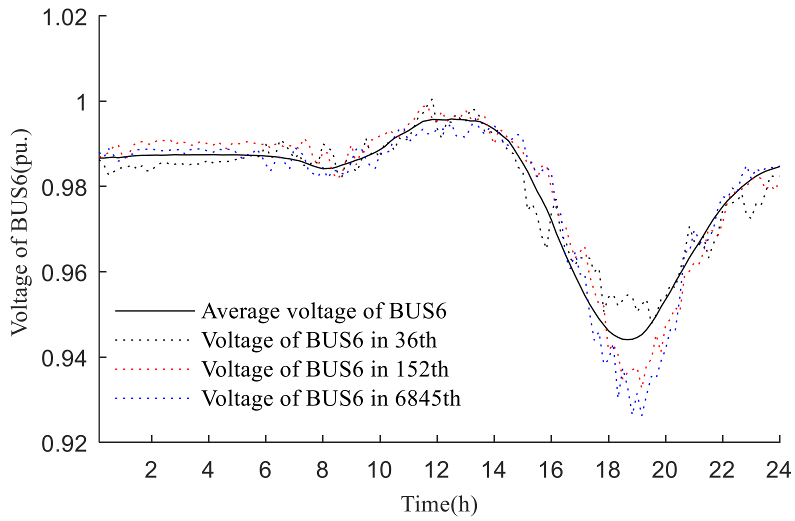


Figure 5.14 The Voltage on BUS6 of the Community Feeder with EVs Charging

The average bus voltage of the community feeder is illustrated in Figure 5.13. It can be seen that the maximum average voltage drop, 5.59%, occurs on BUS6 at 18:40. The black solid line in Figure 5.14 shows the average voltage of BUS6, and the 36^{th}, 152^{th} and 6845^{th} simulation results of the BUS6 voltage are also illustrated. It can be conducted that the bus voltage of the random samples follows a similar trend as the average value, however, the individual characteristics can be found because of the stochastic behaviour of EVs charging. In Figure 5.13, due to the peak power generated from the PV panels around 12:40, the average voltage drop is the smallest on all buses, whereas, the maximum average voltage drop happens around 18:40 because of EVs charging.

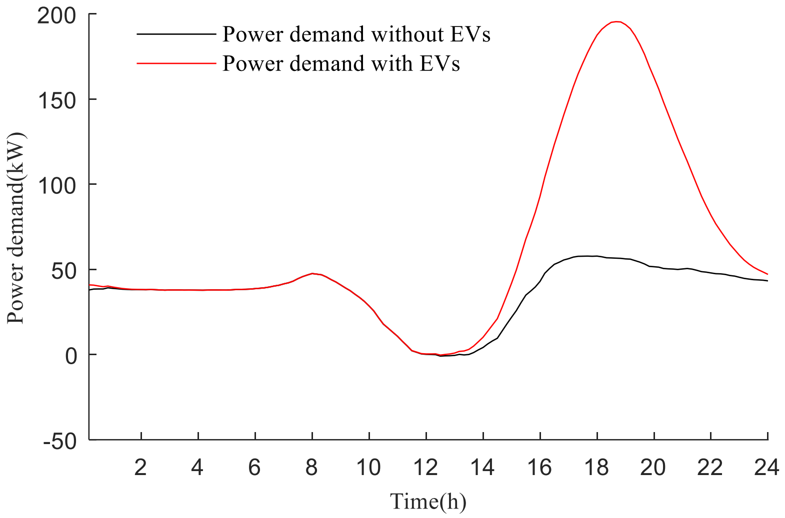


Figure 5.15 The Total Power Demand of the Community Feeder with/without EVs Charging

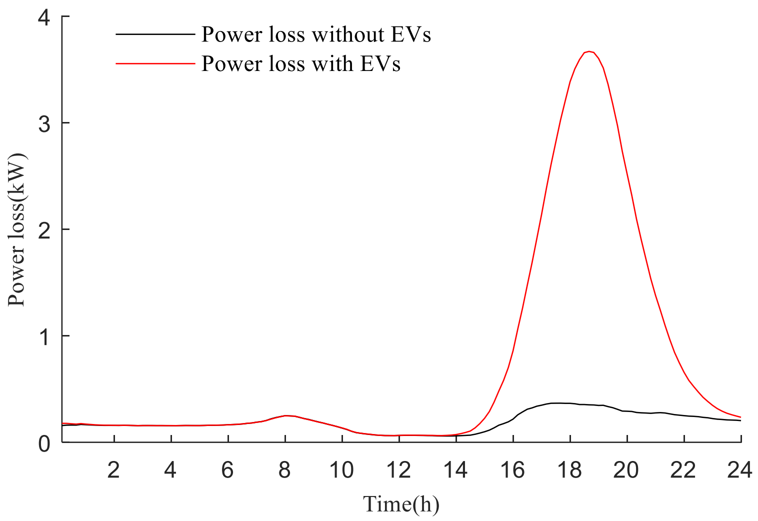


Figure 5.16 The Total Power Demand of the Community Feeder with/without EVs Charging

The total power demand of the community feeder is illustrated in Figure 5.15 and the total power loss is shown in Figure 5.16. In both figures, the black line shows the scenario that without EVs charging and the red line indicates the scenario considering EVs charging. From Figure 5.15 and 5.16, it can be conducted that the total power demand and the power loss are increased dramatically when EVs are charging, and the peak power demand occurs around 18:40.

From the analysis above, when EVs are connected in the community, the probability of the voltage being out of the UK regulation is quite high, 18.87% on BUS5, and much worse on BUS6, which is 77.08%. Therefore, it is necessary to take actions addressing the impacts of EVs charging on the DN.

5.3.3 The Configuration of the Dwelling's Micro-grid

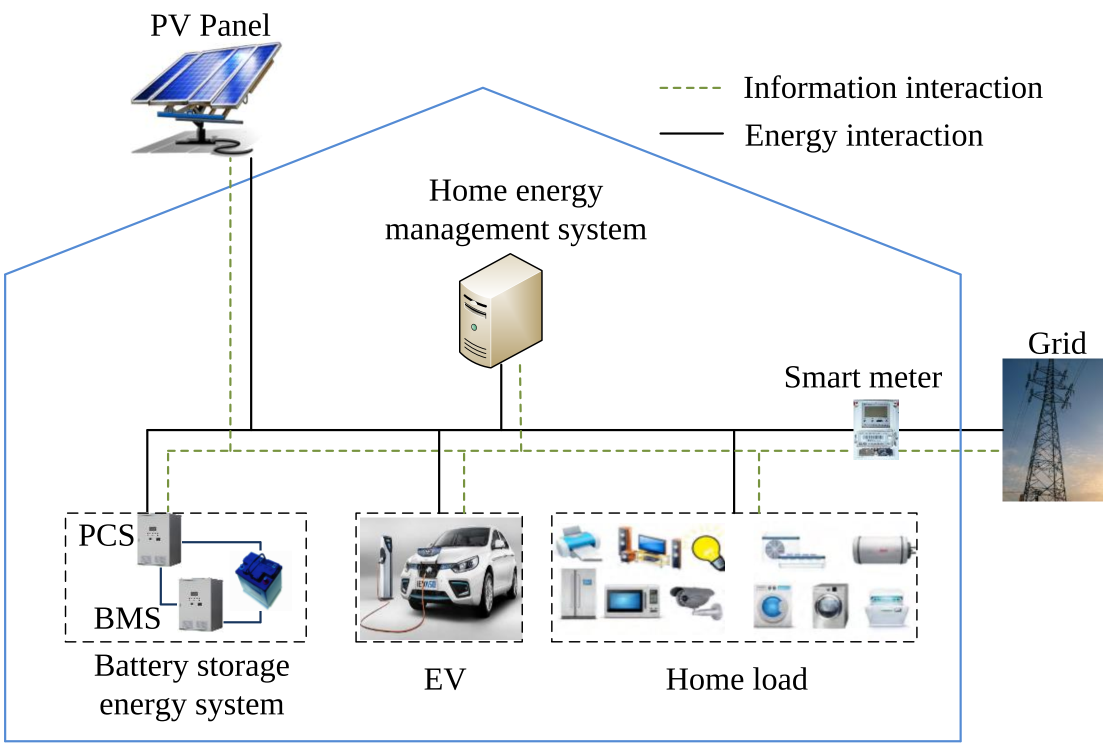


Figure 5.17 The Configuration of the Dwelling's Micro-grid.

In order to address the impacts caused by EVs charging on the LV DN, a system, consisting PV generation and BSES, is established to form the dwelling's micro gird which is shown in Figure 5.17. The Home Energy Management System (HEMS) is created to gather the information of power demand in the dwelling. Based on the household loads, which is created by the electrical equipment, PV generation and power demand of EVs charging, the Battery Management System (BMS) of charging and discharging storage battery is controlled to minimise the impacts caused by EVs charging on the DN.

The charging and discharging ranges of storage battery are assumed to be between 10% and 90% of the rated capacity [132] and the power rate of charging and discharging of storage battery are adjustable. The BSES will be charged when the power demand of a dwelling is lower than the expected value, P_{inlim} and also the BSES does not reach 90% of the rated capacity. And it is able to smooth the power demand in the dwelling. The charging power rate of the BSES can be expressed in the following equation (5-9)

$$P_{inb}(t) = \begin{cases} P_{inlim} - P_h(t) + P_{PV}(t) & P_{inlim} > P_h(t) - P_{PV}(t) \,\&\, SOC_b < 0.9 \\ 0 & others \end{cases} \tag{5-9}$$

where P_{inlim} is the expected power demand in the dwelling.

P_h is the dwelling loads from appliances.

P_{PV} is the PV generation.

SOC_b represents the status of the energy stored in the BSES.

When HEMS detects an EV starts charging, the charging time can be calculated based on the SOC of the EV, which is shown in equation (5-10)

$$T_{charging} = \frac{0.9 - SOC_{bef}}{\eta_{inev} P_{EV}} C_{EV} \tag{5-10}$$

where P_{EV} is the average charging power demand of the EV and η_{inev} represents the efficiency of the EV charging.

During the EV's charging period, if the energy stored in the BSES is sufficient for the EV's charging process, the discharging power rate of the BSES is equal to the charging power of the EV's. Otherwise, the BSES will discharge at a constant power rate until it reaches the 10% of the rated capacity. Therefore the discharging power rate of the BSES can be derived in equation (5-11), which ignoring the efficiency of EVs charging.

$$P_{outb} = \begin{cases} \dfrac{\eta_{outb}\left(SOC_b - 0.1\right)}{T_{charging}} C_b & \eta_{outb}\left(SOC_b - 0.1\right)C_b < \left(0.9 - SOC_d\right)\cdot C_{EV} \\ P_{EV} & \eta_{outb}\left(SOC_b - 0.1\right)C_b \geq \left(0.9 - SOC_d\right)\cdot C_{EV} \end{cases} \quad (5\text{-}11)$$

where η_{outb} is the discharging efficiency of the BSES.

SOC_b is calculated by ampere-hour integration approach, the equation is shown as (5.12), which ignoring self-discharge rate and charge and discharge efficiency[133].

$$SOC_b = SOC_{b0} + \frac{1}{C_b}\int_0^t P_{\text{inb}}\, d\tau \quad (5.12)$$

where SOC_{b0} represents the initial SOC of the BSES.

$P_b > 0$, represents charging status, $P_b < 0$, represents discharging status.

Based on the mathematical modelling of the EV charging demand introduced in chapter 5.2, the density and distribution of an EV charging probability are shown in Figure 5.18 and 5.19.

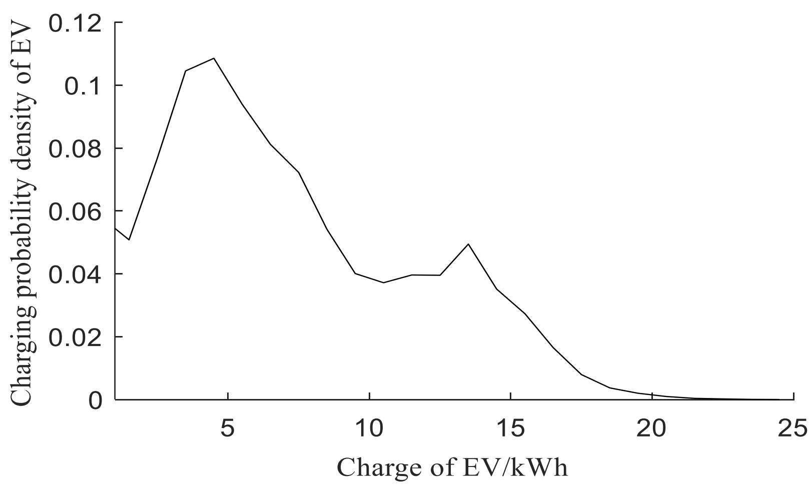


Figure 5.18 The Density of an EV Charging Probability

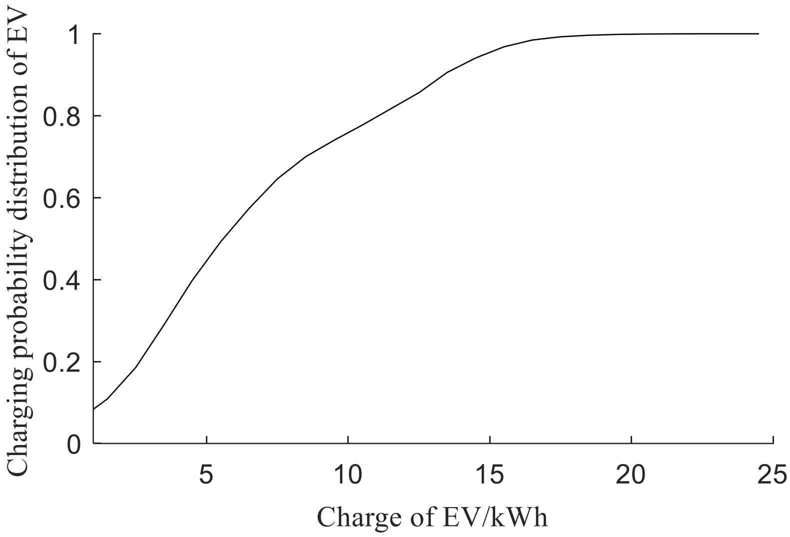


Figure 5.19 The Distribution of an EV Charging Probability

From Figure 5.19, it can be seen that the charging demand of 50% EVs is less than 5.59kWh, 6.86kWh for 60% EVs, 8.50kWh for 70% EVs and 11.07kWh for 80% EVs.

Because of the normal charging and discharging range of a BSES is between 10% and 90% of the rated capacity, the efficiency of the BSES in discharging mode is assumed to be 95% to satisfy 50%, 60%, 70% and 80% EVs charging needs in 24hrs, thus 8kWh, 10kWh, 12kWh and 15kWh for the selected capacity of the BSES.

BSES installed in each dwelling not only helps to reduce the peak demand and minimise the impact on DN caused by EVs charging, but also reduce the electricity cost for the household when the time of use pricing system is employed in the network.

5.3.4 Minimising the Impacts of EVs Charging on LV DN using the Dwelling's Micro-grid

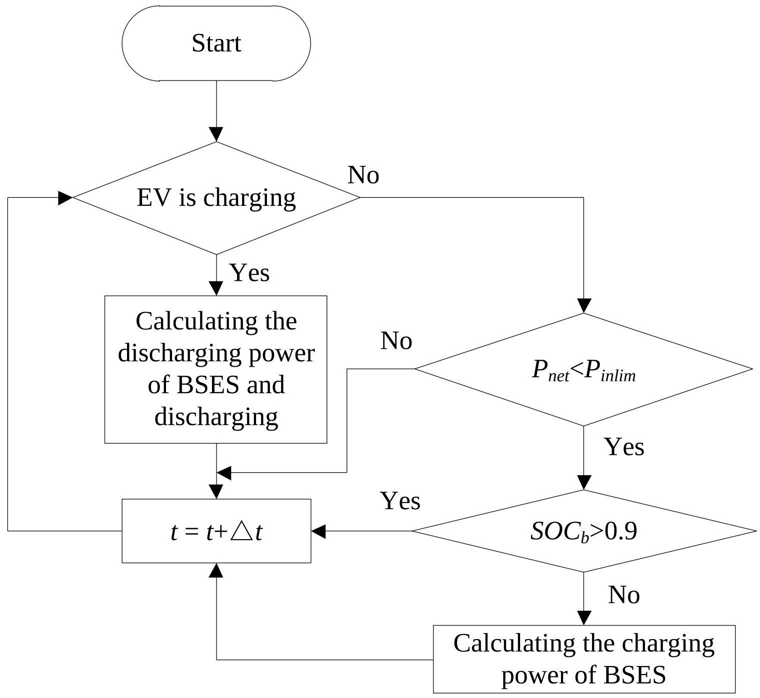


Figure 5.20 The Flow Chart of the BSES Operation.

In order to minimise the impacts of EVs charging on the network, assuming the BSES is not charged when the EV is charging, the power demand in the dwelling should be maintained around at $P_{inlim.}$ And the flow chart of the charging and discharging process of the BSES is shown in Figure 5.20. When the EV is starting charging, then the BSES will be discharged to minimise the possible peak power demand on the network created by EVs charging. During other time periods, the charging power rate of the BSES is determined by the power demand in the dwelling, which helps to keep the power demand in the dwelling close to the expected value.

It is crucial to determine the expected power, P_{inlim}. Higher P_{inlim} selected will result in the too short charging period of the BSES and the charging process of the BSES might be finished early, which could result in the peak power demand in the dwelling. On the other hand, if lower P_{inlim} is selected, the energy stored in the BSES for later usage might not be sufficient. Therefore, the optimal expected power, P_{inlim}, should satisfy the following criteria:

(1) Make the best use of the PV generation.

(2) There is energy left in some BSES when EVs charging is finished.

(3) The BSES can be charging as full as possible while the total power demand in the dwelling could be smoothed.

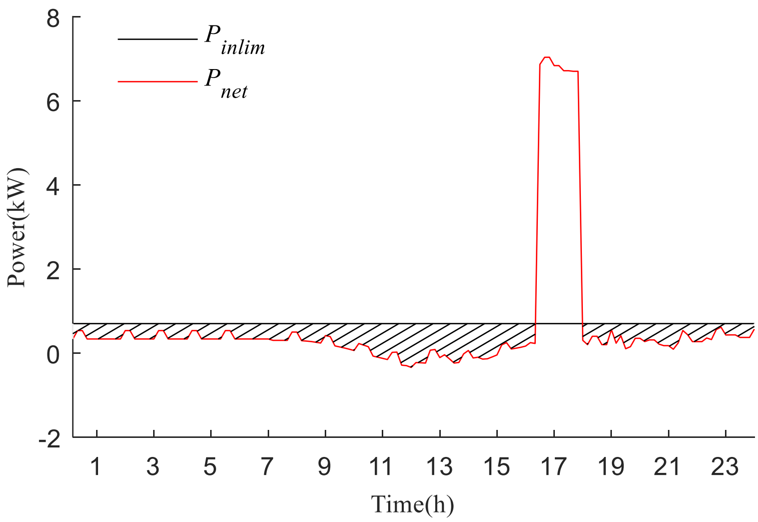


Figure 5.21 The Schematic Diagram of the Charging Process of the BSES.

Figure 5.21 is the schematic diagram of the charging process of the BSES. The red line represents the power demand in the dwelling. When $P_{net}<P_{inlim}$, the BSES is charging and the energy can be stored in the BSES is represented as the shaded area in Figure 5.21 and it is equal to $(0.9\text{-}SOC_{b0})C_b/\eta_{inb}$, where SOC_{b0} is the initial SOC of the BSES, η_{inb} the charging efficiency of the BSES.

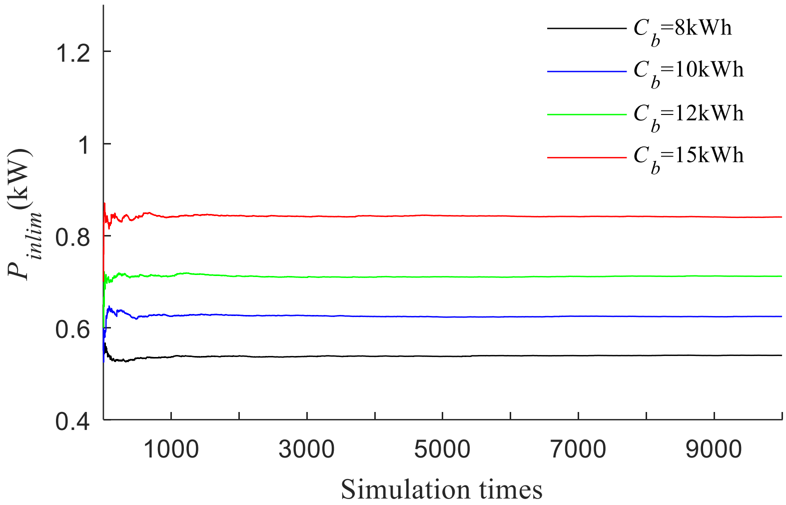
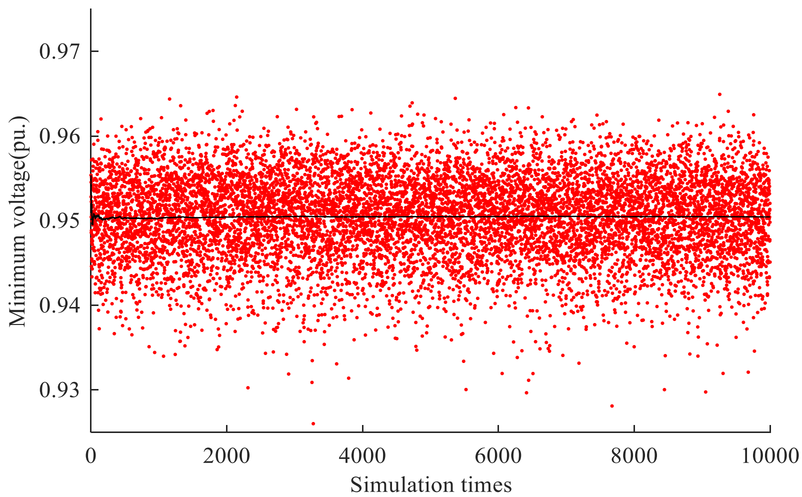
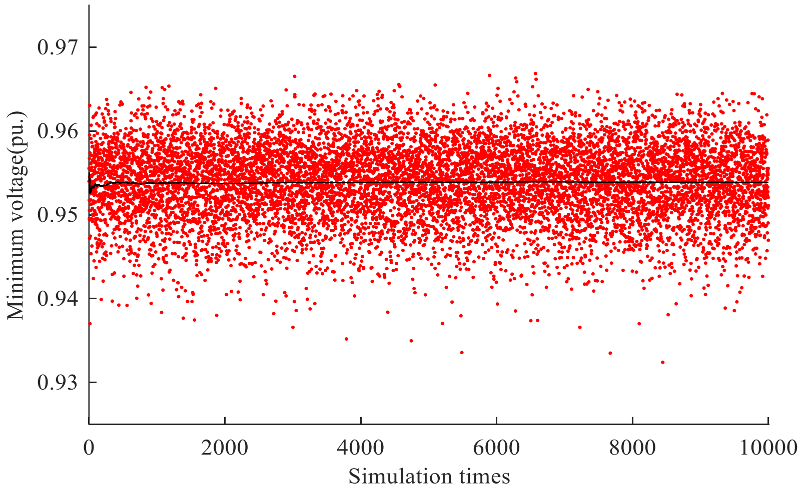


Figure 5.22 The Expected Power Demand in Dwellings, P_{inlim}

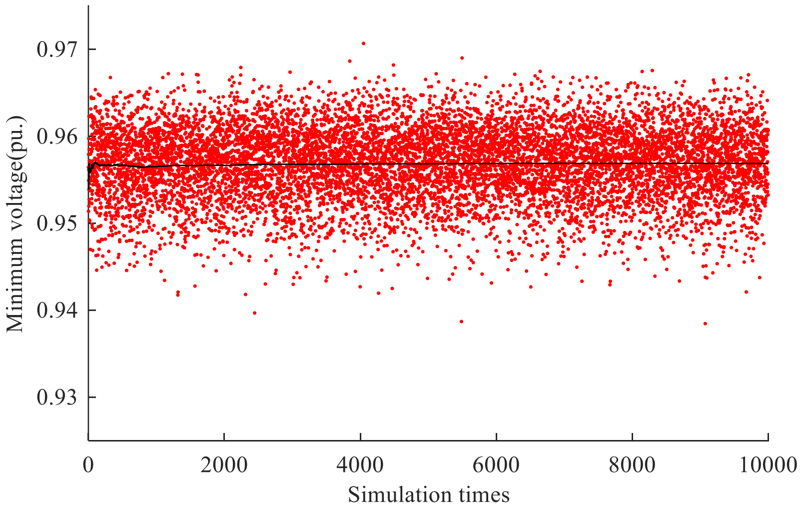
The Mento Carlo method is used to model and generate the power demand in dwellings and EVs charging for 96 households. Initial SOC of the BSES is driven from the last iteration, where the first initial SOC of the BSES is assumed equally distributed between 0.1 and 0.9. The expected power, P_{inlim}, will converge eventually. When the capacity of the BSES is selected as 8kWh, 10kWh, 12kWh and 15kWh, the corresponding P_{inlim} are shown in Figure 5.22. It can be seen that with the increasing number of simulation times, the P_{inlim}, is converged to 538.5W, 623.7W, 710W and 839.2W, hence 600W, 700W, 800W and 900W of P_{inlim} are selected for the BSES.



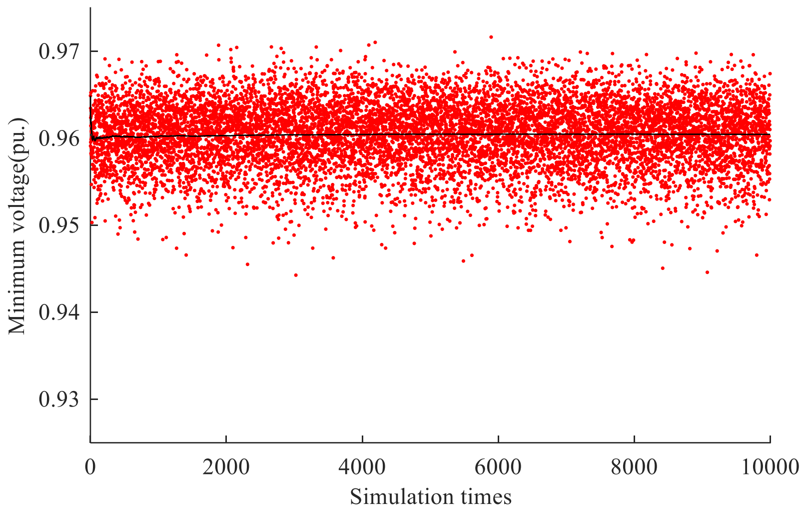
(0) 8kWh of the BSES



(0) 10kWh of the BSES



(0) I12kWh of the BSES



(0) 15kWh of the BSES

Figure 5.23 The Minimum Voltage of the Community Feeder with Different Capacity of the BSES

Based on different capacities of the BSES with its P_{inlim}, using the same method in chapter 5.3.2 to investigate the impacts of EVs charging on the DN, the minimum voltage of the community feeder is shown in Figure 5.23 in red dots and the black line represents the average minimum voltage. It can be seen that with the increasing amount of simulation times, the average minimum voltage converges at a certain value, which are 95.04%、95.39%、95.69%、96.05% with the standard deviation of 0.49%、0.45%、0.41%、0.37% for 8kWh, 10kWh, 12kWh and 15kWh BSES respectively. And the corresponding average voltage drop is 4.96%、4.61%、4.31%、3.95%. Furthermore, with the increasing capacity of the BSES, the voltage drop and the standard deviation are both reduced, which indicates the larger the capacity of the BSES is, the better the minimisation of the impacts caused by EVs charging on the DN.

Table 5-3 The Probability of Voltage Drop on Each Bus with Different BSES Capacities.

(a) 8kWh of the BSES Unit:%

Drop / Bus	[0 1%]	(1% 2%)	(2% 3%)	(3% 4%)	(4% 5%)	(5% 6%)	(6% 7%)	(7% ∞)
BUS2	100	0	0	0	0	0	0	0
BUS3	0	96.18	3.82	0	0	0	0	0
BUS4	0	0	77.72	22.27	0.01	0	0	0
BUS5	0	0	0	29.73	66.69	3.56	0.02	0
BUS6	0	0	0	1.41	54.99	41.08	2.48	0.04

(b) 10kWh of the BSES Unit:%

Drop / Bus	[0 1%]	(1% 2%)	(2% 3%)	(3% 4%)	(4% 5%)	(5% 6%)	(6% 7%)	(7% ∞)
BUS2	100	0	0	0	0	0	0	0
BUS3	0	99.51	0.49	0	0	0	0	0
BUS4	0	0.03	93.94	6.03	0	0	0	0
BUS5	0	0	0.08	58.53	40.86	0.53	0	0
BUS6	0	0	0	7.45	73.78	18.36	0.41	0

I 12kWh of the BSES Unit:%

Drop / Bus	[0 1%]	(1% 2%)	(2% 3%)	(3% 4%)	(4% 5%)	(5% 6%)	(6% ∞)
BUS2	100	0	0	0	0	0	0
BUS3	0	99.90	0.1	0	0	0	0
BUS4	0	0.47	98.49	1.04	0	0	0
BUS5	0	0	1.20	81.33	17.45	0.02	0
BUS6	0	0	0.01	22.67	71.51	5.78	0.03

(d) 15kWh of the BSES Unit:%

Drop / Bus	[0 1%]	(1% 2%)	(2% 3%)	(3% 4%)	(4% 5%)	(5% 6%)
BUS2	100	0	0	0	0	0
BUS3	100	0	0	0	0	0
BUS4	0	5.20	94.75	0.05	0	0
BUS5	0	0	9.05	88.19	2.76	0
BUS6	0	0	0.10	57.52	41.73	0.65

The voltage drop on each bus in the network is listed in Table 5-4 with different capacities of the BSES, and especially, the probability of voltage drop on BUS6 is categorised in Figure 5.24. It can be driven that the voltage drop is reducing with the increasing capacity of the BSES. Moreover, the voltage drop over 6% on BUS6 is 2.52%, 0.41%, 0.03%, and 0% respectively, which means when the 15kWh BSES is used, the voltage on each bus is satisfied the UK regulation.

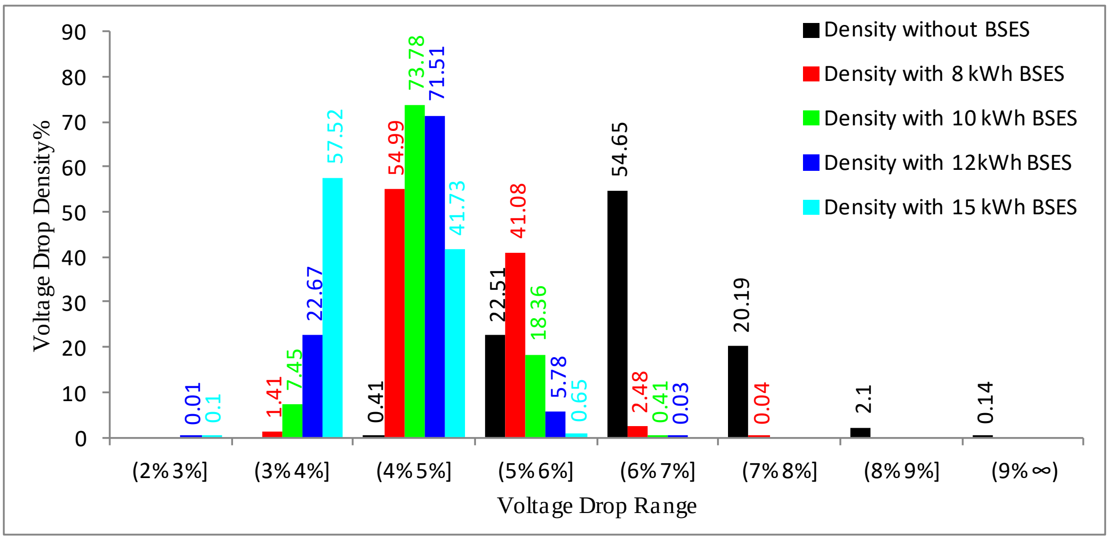
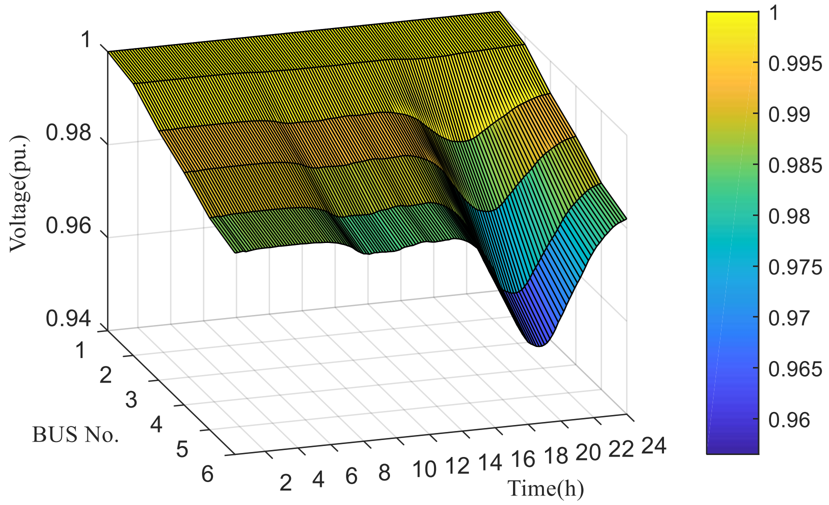
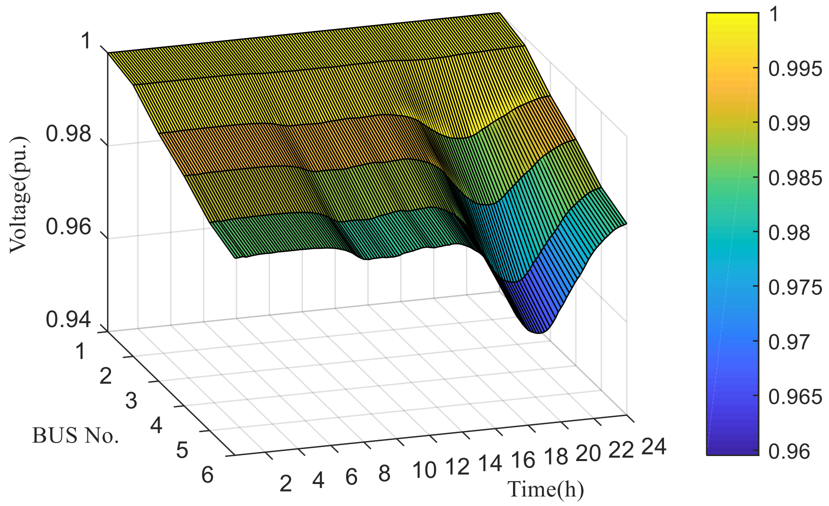


Figure 5.24 The Probability of Voltage Drop on BUS6 of the Community Feeder with Different BSES Capacities

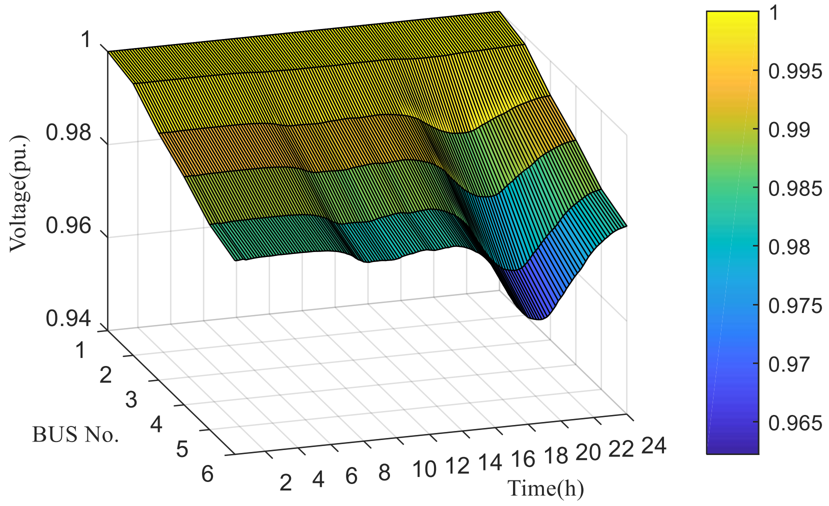
The average bus voltage of the community feeder with different BSES capacities is shown in Figure 5.25, and it can be seen that the maximum average voltage drop occurs on BUS6. The average minimum voltage of 8kWh, 10kWh, 12kWh and 15kWh of the BSES is 95.65%, 95.95%, 96.22%, and 96.56% respectively, which means the corresponding maximum average voltage drop is 4.35%, 4.05%, 3.78%, and 3.44%.



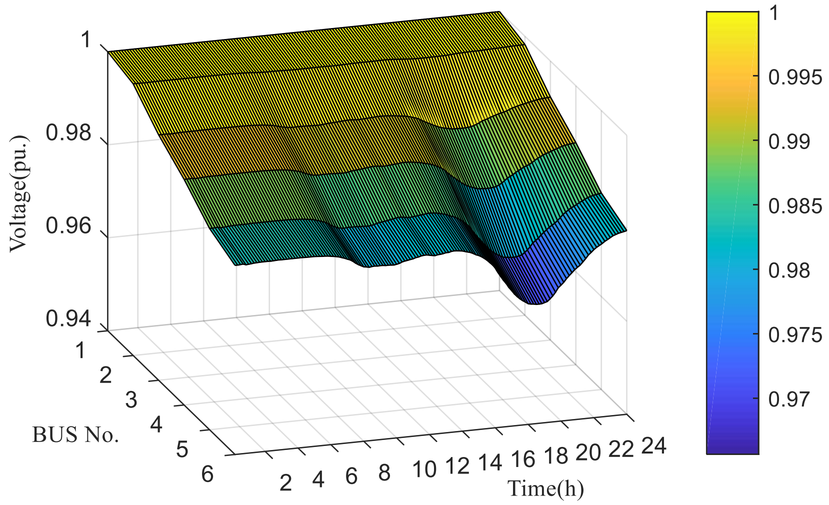
(0) 8kWh of the BSES



(0) 10kWh of the BSES



(0) I12kWh of the BSES



(0) 15kWh of the BSES

Figure 5.25 The Average Bus Voltage of the Community Feeder with Different BSES Capacities

Furthermore, in Figure 5.26, it illustrates the average voltage on BUS6 of the community feeder with different BSES capacities. From the figure, it can be conducted that when the higher capacity of the BSES used in the dwelling, the average voltage on BUS6 becomes much smoother. During the period when EVs are not charging, the voltage drop on BUS6 will be increased when the BSES capacity is larger. Because of the larger capacity of the BSES is, the higher charging power of the BSES is, and on the other side, the voltage drop becomes smaller while most of the EVs are charging.

The total power demand and the total power loss of the community feeder with different BSES capacities are shown in Figure 5.27 and Figure 5.28. It can be seen that when the BSES is employed in the dwelling, the peak power demand and the total power loss of the community feeder are both reduced. And also during the off-peak period, the power demand is increased. Hence, the curve of the total power demand becomes smooth, furthermore, the larger the BSES capacity is, the smoother the total power demand of the community feeder is.

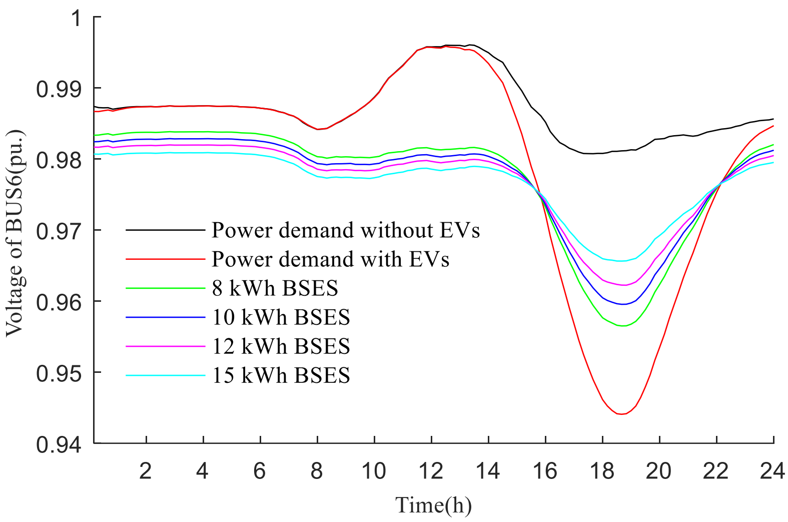


Figure 5.26 The Average Voltage on BUS6 of the Community Feeder with Different BSES Capacities.

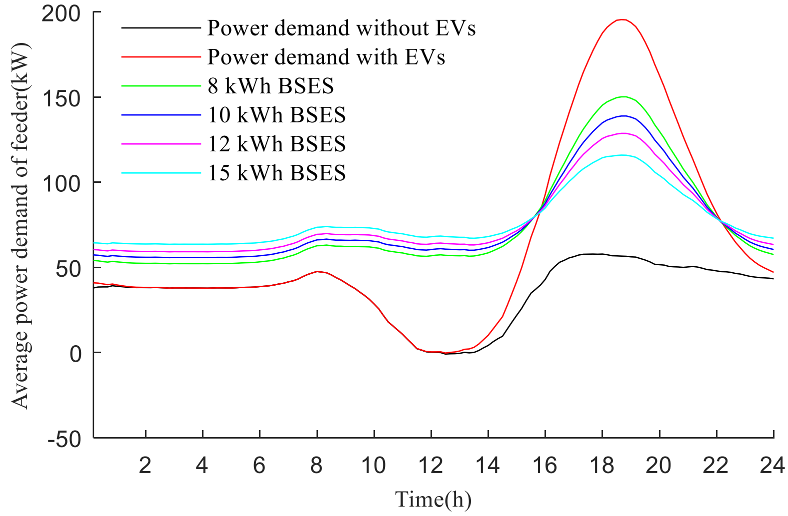


Figure 5.27 The Total Power Demand of the Community Feeder with Different BSES Capacities

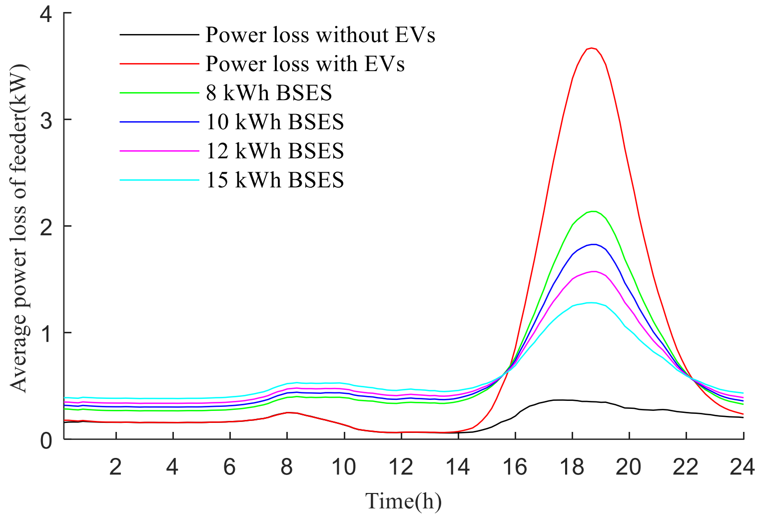


Figure 5.28 The Total Power Loss of the Community Feeder with Different BSES Capacities

The charging and discharging process of the BSES is shown in Figure 5.29 and Figure 5.30. Comparing with the PV generation in Figure 5.7, the charging process of the BSES has similar characteristics, which indicates that the PV generation has been made the most of use by the BSES. In Figure 5.30, when EVs charging reach the peak period, the BSES is also discharged at the peak power. This indicates that the discharging process of the BSES is able to reduce the peak power demand created by EVs charging.

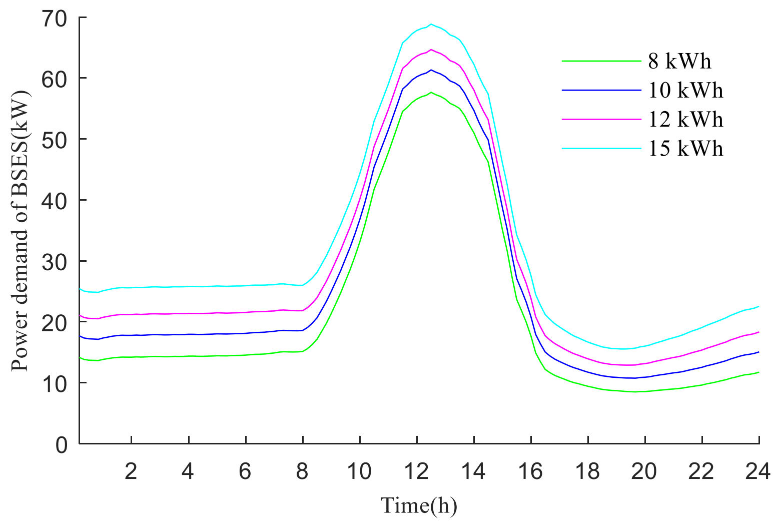


Figure 5.29 The Charging Power Demand of the BSES

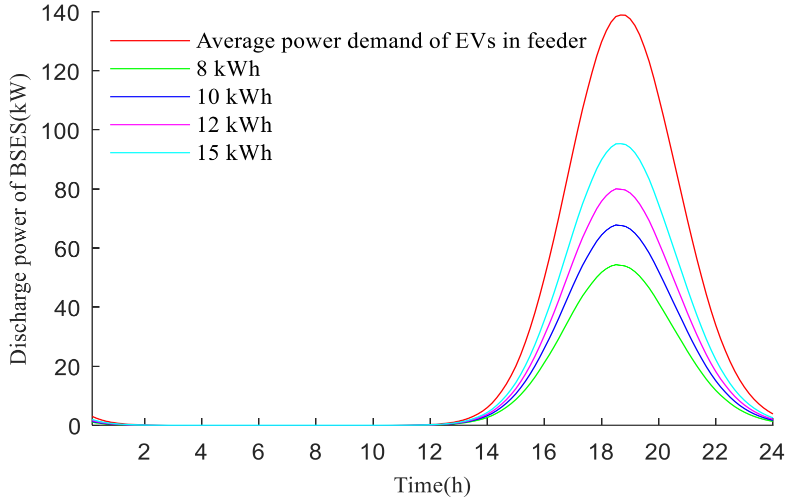


Figure 5.30 The Discharging Power Rate of the BSES

Table 5-4 The Important Network Parameters

Key indexes	EVs Charging with BSES				EVs Charging without BSES	No EVs Charging
BSES Capacity C_b/kWh	8	10	12	15	——	——
The Average Voltage Drop of the Community Feeder V/%	4.96	4.61	4.31	3.95	6.51	2.43
The Peak Power Demand of the Community Feeder P_{max}/kW	150.1	138.9	128.7	115.9	195.5	57.82
The Total Energy Losses of the Community Feeder E_{loss}/kWh	15.23	14.79	14.48	14.24	17.36	4.60
Probability of the BUS6 Voltage out of the UK Regulation %	2.52	0.41	0.03	0	77.08	0

The important results from the above anlaysis are listed in Table 5-5 and shown in Figure 5.31. V is the average voltage drop of the community feeder, E_{loss} is the total energy loss on the community feeder and the P_{max} is the peak power demand of the community feeder. It can be seen that V, E_{loss}, P_{max} and the probability of the BUS6 voltage out of the UK voltage regulation are all reducing while the increasing capacity of the BSES. Moreover, the relation between the average voltage drop, the peak power demand, and the BSES capacity are almost linear. And the total energy loss is slowly reducing with the increasing capacity of the BSES.

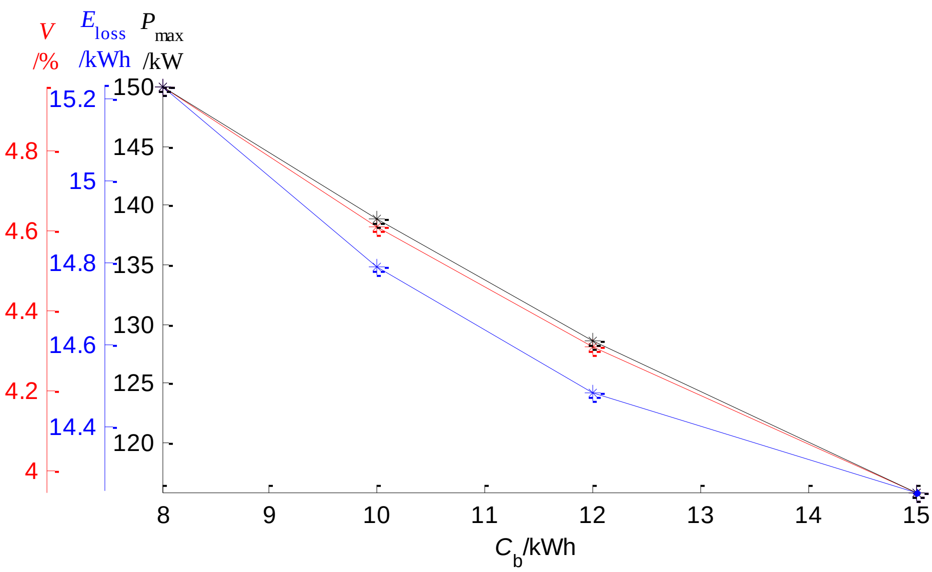


Figure 5.31 The Important Network Parameters under Different Capacities of the BSES

From the analysis in this section, it can be conducted that the peak power demand, the probability of the BUS6 voltage out of the UK voltage regulation, average voltage drop and power loss of the community feeder are all reduced when the dwelling's micro gird with the BSES is employed in the community. Moreover, the impacts caused by EVs charging on the DN can be further minimised with a larger capacity of the BSES. However, when the capacity of the BSES is selected too large, the investment and maintenance cost will be increased.

From the statistics point of view, when the valid capacity of the BSES is equal to the energy required from the EVs, this BSES capacity should be the optimal choice. The total energy demand of EVs charging can be calculated as the integration of the red line from Figure 5.30, the total energy demand of EVs charging without the BSES, which is 669.99kWh. Considering the capacity of the BSES is between 10% and 90% of the rated capacity and the efficiency of the charging and discharging process, the average capacity of the BSES in each household is 9.59kWh, that closes to 10kWh, which is sufficient for the needs of 60% EVs charging, therefore, the 10kWh of the BSES is selected.

5.3.5 Minimising the Impacts of EVs Charging on LV DN using Limited Charging Time of the BSES

From Figure 5.27, it can be observed that the peak power demand occurs around 18:40, and in Figure 5.30, around this time, most of the BSES are in discharging mode that is able to help reduce the peak power demand caused by EVs charging. However, from Figure 5.29, it also can be seen that there are some of the BSES are in charging mode around the same time that could result in a new peak power demand on the community feeder and might curtail the advantage of the BSES.

Therefore, the charging period of both BSES and EVs can be distributed in the different time period to avoid the possible new peak power demand. And from the Figure 5.30, the needs of EVs charging highly occur between 16:00 to 22:00. Hence, the BSES is limited during this time period for charging, and the flow chart of the BSES operation is shown in Figure 5.32.

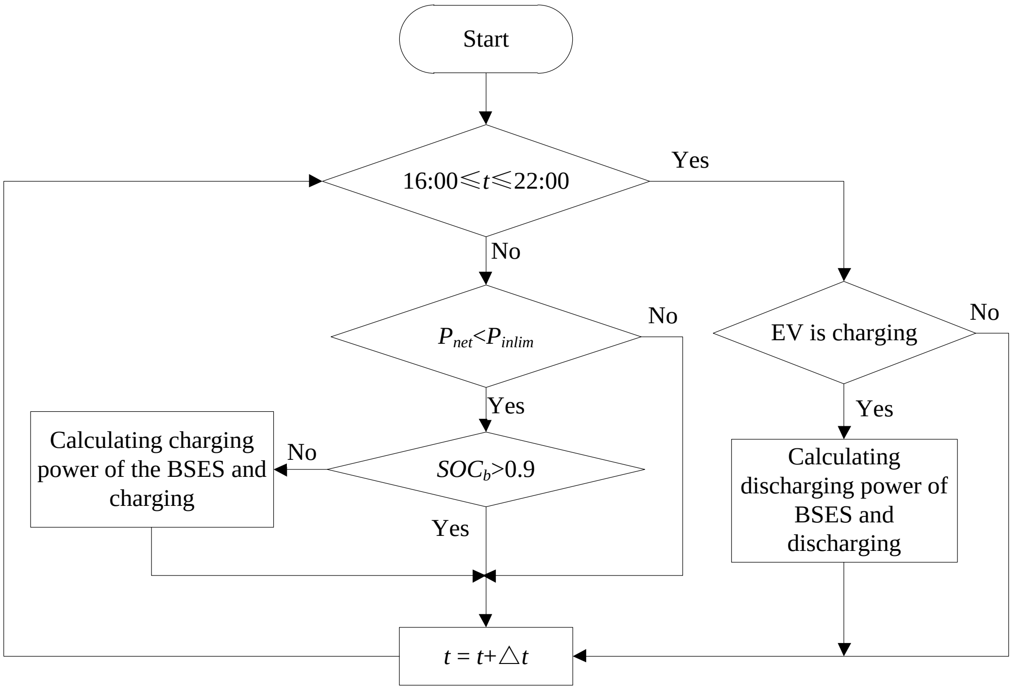


Figure 5.32 The Flow Chart of the BSES Operation with Limited Charging Time

The 10kWh BSES is selected in this section for the further analysis. When the charging time of the BSES is limited, the charging process is illustrated in Figure 5.33, and the shaded area represents the total energy will be stored in the BSES. Through using the same method introduced in chapter 5.3.4, the expected power is calculated as 712.1W, which 720W is used in this section.

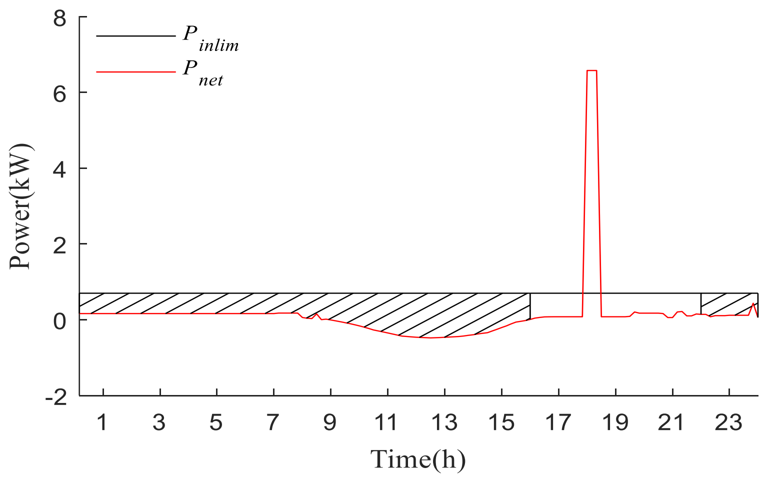


Figure 5.33 The Schematic Diagram of the Charging Process of the BSES with Limited Charging Time

While the capacity of the BSES is 10kWh, the charging time is limited between 16:00 and 22:00, the discharging strategy is the same as in chapter 5.3.3. Hence, the minimum voltage of the community feeder is shown in Figure 5.34 in red dots and the black line indicates the average minimum voltage along with the increasing simulation times. It can be seen that the average minimum voltage converges at a certain value, 95.60% when the simulation times reach around 10,000. And the corresponding average voltage drop is 4.40% with the standard deviation of 0.47%.

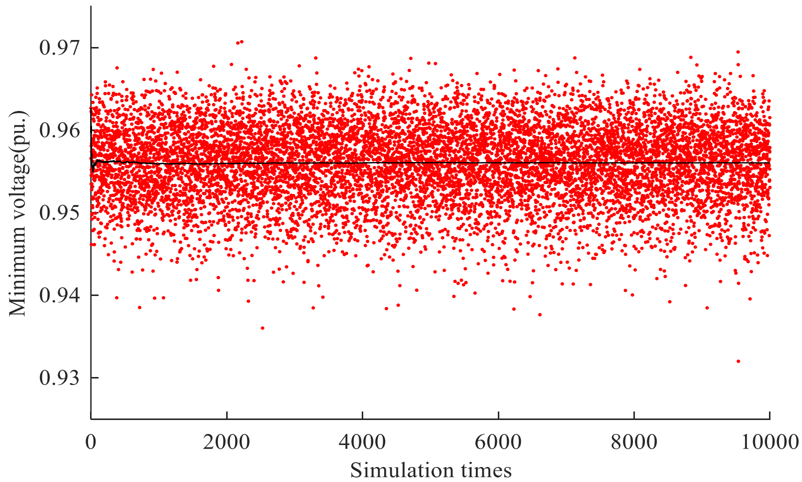


Figure 5.34 The Minimum Voltage of the Community Feeder with Limited Charging Time of the BSES

Table 5-5 The Probability of Voltage Drop on Each Bus with Optimised Charging Time of the BSES

Unit:%

Voltage / Bus	[0 1%]	(1% 2%)	(2% 3%)	(3% 4%)	(4% 5%)	(5% 6%)	(6% ∞)
BUS2	100	0	0	0	0	0	0
BUS3	0	99.75	0.25	0	0	0	0
BUS4	0	0.62	96.66	2.72	0	0	0
BUS5	0	0	1.26	73.61	24.93	0.2	0
BUS6	0	0	0.02	20.39	69.35	10.06	0.18

The probability of voltage drop on each bus of the community feeder is listed in Table 5-6, and especially, the voltage drop on BUS6 of two scenarios, with and without limited charging time of the BSES, is illustrated in Figure 5.35. It can be driven that when the charging time of the BSES is limited, the voltage drop is reduced, where the probability of the voltage drop over 6% is reduced from 0.41% to 0.18%.

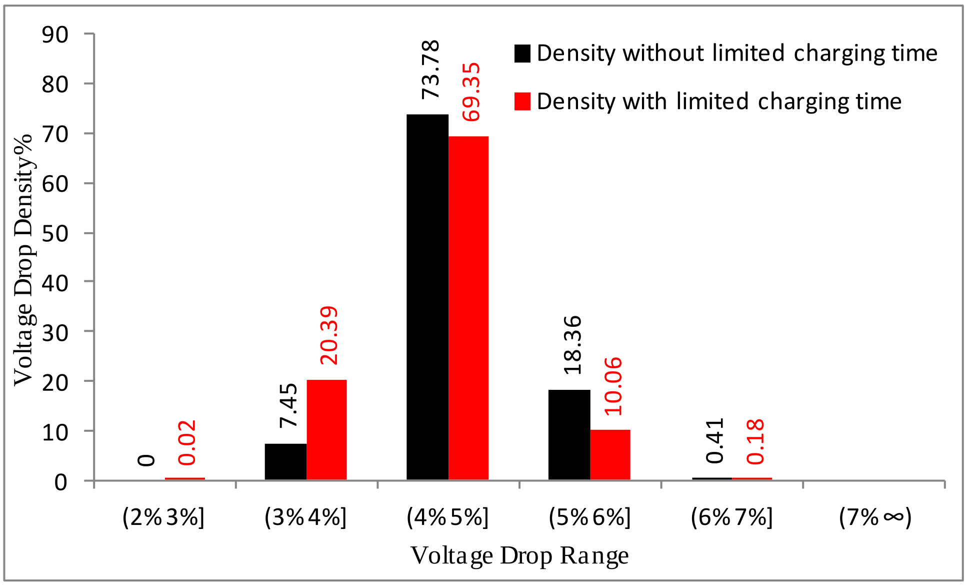


Figure 5.35 The Probability of Voltage Drop on BUS6 of the Community Feeder with Limited Charging Time

The average bus voltage of the community feeder with limited charging time of the BSES is shown in Figure 5.36, and it can be seen that the maximum average voltage drop also occurs on BUS6, which the minimum voltage is 96.19%, which means the corresponding maximum average voltage drop is 3.81%.

The average voltage of the BUS6 with limited charging time is shown in Figure 5.37. It can be seen that the voltage drop is reduced during EVs charging period, while the voltage drop is increased during the BSES charging period. When looking at the whole day period, the average voltage becomes smooth, which indicates the method of using limited charging time of the BSES works.

In Figure 5.36 and 5.37, there are spikes of the voltage at both time 16:00 and 22:00. The reason for these spikes is that at time 16:00, there might be some BSES have not finished the charging yet. Whereas, the charging process of the BSES has to be stopped according to the strategy, which will result in the spike of the voltage. The same issue happens in Figure 5.38 at 16:00. On the other hand, before time 22:00, there are some total power demands in the dwellings are lower than the P_{inlim}, which means the BSES should start charging but it could not when the strategy of the limited charging time is applied. Hence, when the limited is over, the charging process is started together, which results in the voltage dropping dramatically at time 22:00. The same situation happens in Figure 5.38 at 22:00.

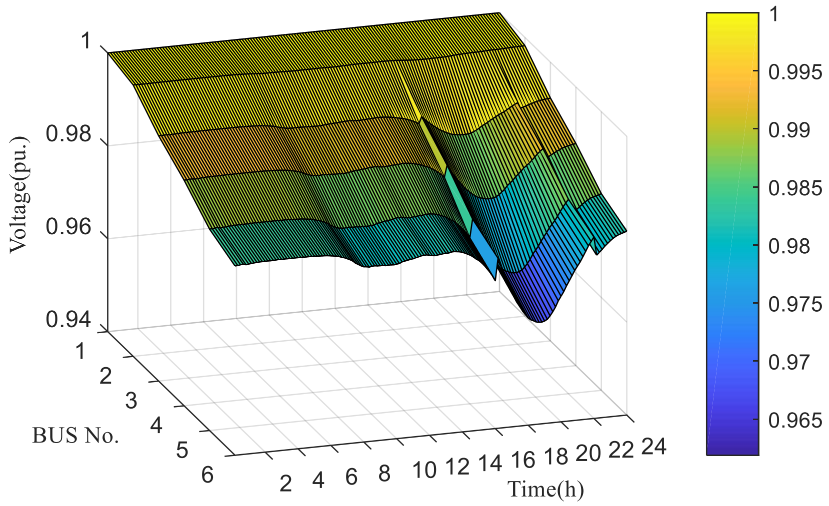


Figure 5.36 The Average Bus Voltage of the Community Feeder with Limited Charging Time of the BSES

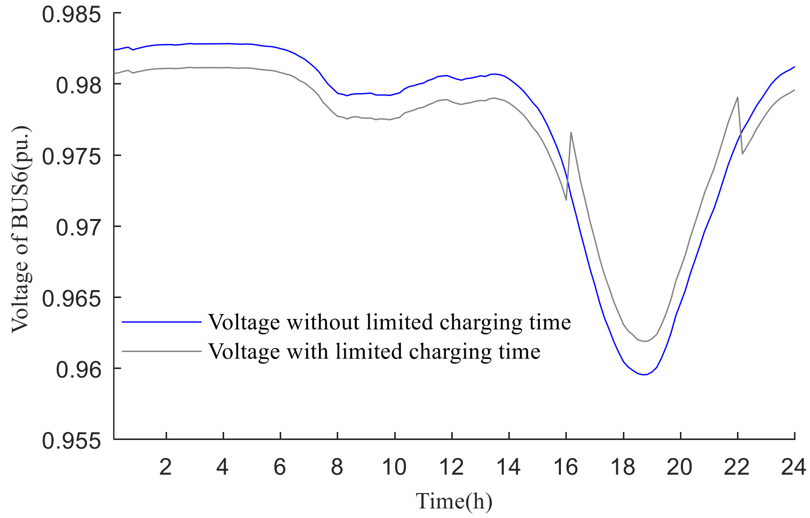


Figure 5.37 The Average Voltage of the BUS6 with Limited Charging Time

The total power demand and the total power loss of the community feeder are shown in Figure 5.38 and Figure 5.39, it can be driven that with limited charging time of the BSES, the peak power demand and the total power loss are both reduced while the power demand of the off-peak period is increased, whereas the total power demand of the community feeder becomes smooth.

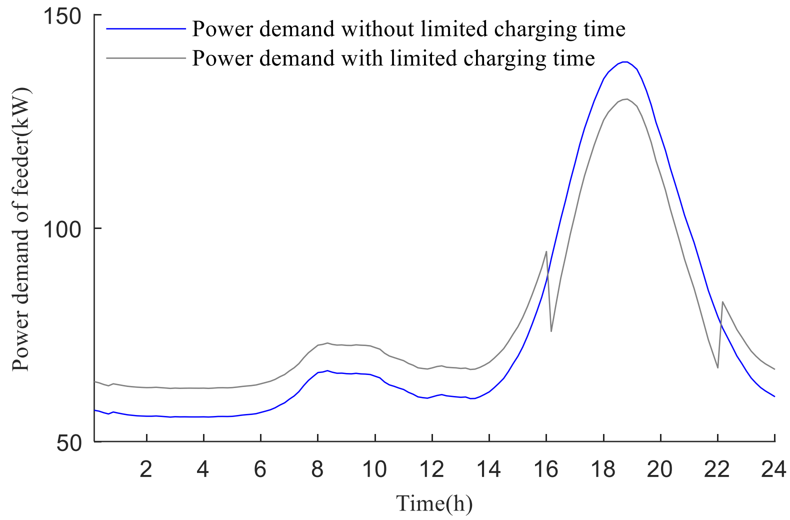


Figure 5.38 The Total Power Demand of the Community Feeder with Limited Charging Time of the BSES

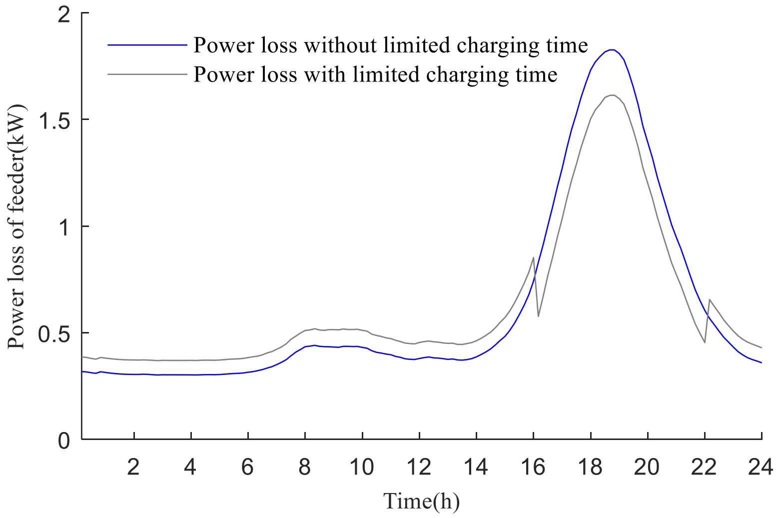


Figure 5.39 The Total Power Loss of the Community Feeder with Limited Charging Time of the BSES

The charging process of the BSES with limited charging time is shown in Figure 5.40. It can be seen that when the charging time of the BSES is limited, the BSES is not charged, which minimised the power demand during peak time. However, the power demand is increased in other time period.

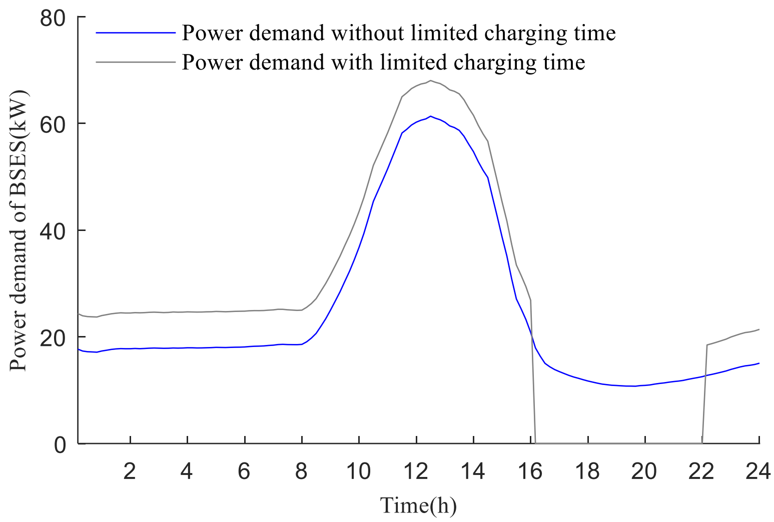


Figure 5.40 The Charging Power Demand of the BSES with Limited Charging Time of the BSES

The important network parameters using Limited Charging Time of the BSES and Dwelling's Micro-grid are listed in Table 5-7. Under the Dwelling's Micro-grid scenario, some BSES are already in charging mode during peak time, which will clearly increase the peak power demand of the network. While the Limited Charging Time of the BSES is employed, the charging process of the BSES is limited, when most of EVs are charging during the peak time, in order to enhance the effect of BSES for reducing the peak power demand. Therefore, the method of the Limited Charging Time of the BSES can be used for further reducing the impact of EVs charging on the LV DN.

Table 5-6 The Important Network Parameters using Limited Charging Time of the BSES

Key indexes	Limited Charging Time of the BSES	Dwelling's Micro-grid
The Average Voltage Drop of the Community Feeder V/%	4.40	4.61
The Peak Power Demand of the Community Feeder P_{max}/kW	130.2	138.9
The Total Energy Loss of the Community Feeder E_{loss}/kWh	14.91	14.79
The probability of the BUS6 Voltage out of the UK Regulation %	0.18	0.41

5.4 Summary

In chapter 5, considered the occupants' behaviours and EVs' mobility, the power demand of EVs charging is modelled. And the impacts of large scales of EVs charging on a UK typical LV DN is analysed, and it can be conducted that:

(1) When only one EV is considered in each household, the total power demand and the total power loss of the community feeder in the network are increased dramatically. And the peak demand happens around 18:40. The possibility of the bus voltage being out of the UK regulation on BUS5 and BUS6 are 18.87% and

77.08%. Therefore, when large scales of EVs located in the community, the voltage drop dramatically in the network, which can result in poor power quality, hence, the necessary actions have to be taken in order to minimise the impacts.

(2) When the Dwelling's Micro-grid with the BSES is used in each household, it is able to reduce the maximum voltage drop, peak power demand, the probability of the bus voltage being out of the UK regulation and the power loss. And with the increasing capacity of the BSES, the impacts of EVs charging on the network can be further minimised.

(3) Under the same capacity of the BSES, through using the limited charging time of the BSES, the impacts caused by EVs charging of the community feeder on the network can be further reduced, however, the total energy loss is not affected much.

Chapter 6

The OCS of EVs using the Expected Power with the BSES

The behaviour of EVs charging mainly states stochastic nature, and also shows certain statistical pattern, according to the analysis in Chapter 5. It creates massive impacts on the LV DN, and two major impacts are the voltage drop and the power loss. Though integrating BSES with the dwelling, the voltage drop and the power loss will be reduced, however, in order to have a better result of minimising the impacts, large battery capacity is necessary, hence the cost is increased dramatically. In this chapter, BSES considering an OCS of EVs will be introduced to mitigate the adverse effects of EVs charging.

6.1 The Control Structure of EVs Ordered Charging

The behaviour of EVs charging has stochastic nature and each EV will be connected to the smart charging box once it arrives at home and the information includes of battery capacity, time of return home, expected time of departure, SOC and expected SOC of departure etc. will be collected by HEMS. The EVs charging strategy will be formulated according to the collected information of EVs and power demand in the dwelling. As a matter of fact, in reality, the EV may be connected randomly or may not departure as expected in the case of an emergency, therefore, the original charging strategy needs to be rescheduled. In this work, an EV which is randomly connected to the smart charging box or departures early from the smart charging box will be treated as a ‘trigger event’. Once any form of ‘trigger event’ occurs, the charging strategy of EVs needs to be rescheduled.

The frame of handling any ‘trigger event’ is shown in Figure 6.1 and the green line shows the power flow and the purple line shows the information flow. Event *I* means an EV is randomly connected to the smart charging box and event *j* means an EV is going to departure early than expected. Once the 'trigger event' is occurred, all the information of current EVs will be updated and the charging strategy will be rescheduled. Then it will be sent back to each smart charging box. This charging strategy will be active until the next 'trigger event' occurred.

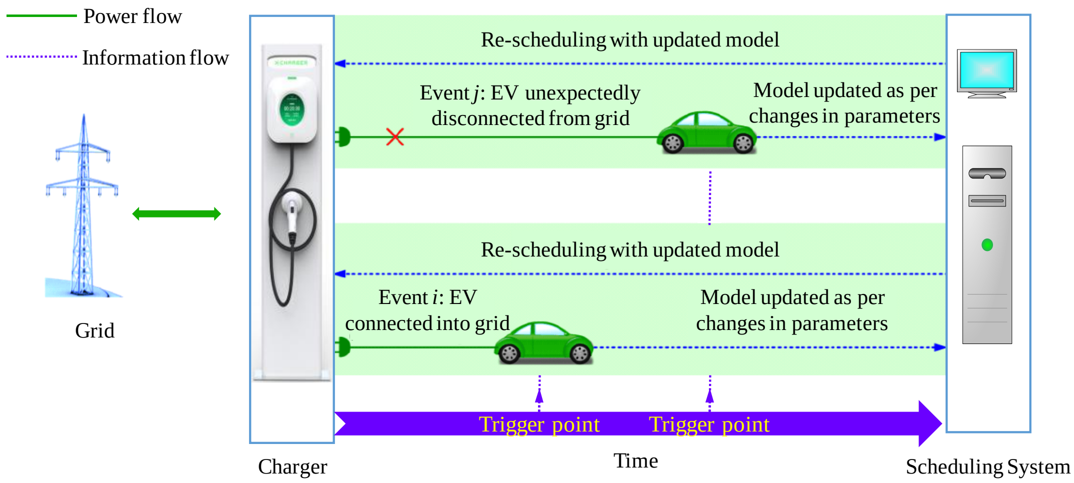


Figure 6.1 The Frame of Handling 'Trigger Event'

6.2 The OCS of EVs using the Expected Power

6.2.1 Period Selection and Discretization

Normally, 24hrs is selected as the investigating period. According to the characteristic of EVs charging, most charging events start from the evening and most drivers leave home in the morning. While considering the continuous characteristic of EVs charging, therefore, in this chapter, the period of 07:00 to 07:00 (next day) is selected.

The investigating period is discretized into several time periods and the time length of each time period is recorded as ΔT , the number of time periods n_T can be calculated by equation (6-1):

$$n_T = \frac{24}{\Delta T} \tag{6-1}$$

The length of each time period is 10 minutes based on Chapter 5.

6.2.2 The Definition of the OCS of EVs using the Expected Power

When considering a large scale of households in a typical community, the total power demand has a certain statistical pattern, which can be modelled. Therefore, the total power demand in the community can be maintained to an expected value when using a charging strategy to control EVs' charging.

In this chapter, an Ordered Charging Strategy (OCS) of EVs using the expected power is proposed. Firstly, the control period and the expected power have to be determined. Then, the charging priority is calculated based on the needs of the driver. Finally, EVs will be charged according to the charging priority to maintain the total power demand around the expected value obtained in the first step until all EVs have been charged.

- **The Expected Power Demand**

The expected power demand is defined as the average of the total power demand of the community during the control period, which can be expressed as (6-2):

$$P_{limit} = \frac{\int_{t_s}^{t_e} \left[P_h(t) + P_{EV}(t) - P_{PV}(t) \right] dt}{t_e - t_s} \tag{6-2}$$

where $P_h(t)$ is the total power demand of all other appliances except the EV and PVs at time t, $P_{PV}(t)$ is the total electric power generated from PV panels at time t, t_s and t_e are the start and finish time.

$$P_{EV}(t) = \sum_{i=1}^{m} P_{EV,i}(t) \tag{6-3}$$

$$P_h(t) = \sum_{i=1}^{n} P_{h,i}(t) \tag{6-4}$$

$$P_{PV}(t) = \sum_{i=1}^{n} P_{PV,i}(t) \tag{6-5}$$

where, $P_{EV,i}(t)$ is the power demand of EV_i at time t, m is the total number of the charging EVs, $P_{h,i}(t)$ represents the total power demand of all other appliances except the EV and PVs of household I at time t, $P_{PV,i}(t)$ is the electric power generated of household I at time t, and n is the total household number.

• Data Pre-processing

The charging time T_c of the EV_i can be expressed in (6-6):

$$T_{c,i} = \frac{\left(SOC_{de,i} - SOC_{bef,i} \right) \times C_{EV,i}}{P_{EV,i} \times \eta_i} \tag{6-6}$$

where, $SOC_{de,I}$ is the expected SOC of departure, $SOC_{bef,I}$ is the SOC before charging and $C_{EV,I}$ is the battery capacity, $P_{EV,I}$ is the average charging power of EV, η_i is the charging efficiency of the EV_i.

The time period of the EV_i stayed at household i:

$$T_{stay,i} = t_{leave,i} - t_{back,i} \tag{6-7}$$

where, $t_{back,I}$ is the arrival time and $t_{leave,I}$ is the departure time of EV_i.

The time left before EV_i expected departure at time t:

$$T_i(t) = t_{leave,i} - t \tag{6-8}$$

• Priority Definition

The EVs charging priority is defined based on satisfying the expected SOC of each EV when departure, and follows the principle of first-come-first-served. The charging priority of EV_i at time t can be formulated in equation (6-9):

$$a_i(t) = \frac{T_{stay,i} - T_i(t)}{T_{stay,i} - T_{c,i}} \tag{6-9}$$

The charging priority a_i is between 0 and 1. When $T_i(t) \leqslant T_{c,i}$, i.e $a_i = 1$, in order to ensure the SOC of each individual EV reaches $SOC_{de,i}$, it is necessary to start charging immediately. When $a_i < 1$, which indicates that the EV can wait for charging.

• The Ordering Strategy

The power margin, P_a, is defined in equation (6-10), in order to achieve the ordered control of EVs charging.

$$P_a(t) = P_{limit} - P_h(t) + P_{PV}(t) - P_{EV}(t) \tag{6-10}$$

When the power margin, P_a, is bigger than the permitted range, all uncharged EVs will be charged based on the priority until P_a falling in the permitted range or all EVs are charging. When P_a is smaller than the permitted range, all charging EVs will be made an order based on the priority, and the EV charging will be stopped with lower priority until the P_a falling in the permitted range or all charging EVs have been stopped.

6.2.3 The Control Logic of the OCS of EVs using the Expected Power

Assuming the total numbers of EVs participating the charging in the community is n, the amount of EVs that the charging process has already been finished is F_n, the amount of charging EVs is C_n and the number of EVs that are waiting to be charged is E_n. The OCS can be described as follows, and the flow chart is shown in Figure 6.2.

(1) A new EV in the community needs to be charged at time t can be detected by the HEMS, and it will be included in the E_n. If it does not need to be charged, go to step (2).

(2) If an EV has finished charging or is going to departure at time t is detected, for an EV that has finished charging, it will be added to the F_n and removed from the C_n. For the EV is going to departure, it should be removed from C_n if the EV was charging, and it should be removed from E_n if the EV was waiting to charge, and it should be removed from F_n if the EV has been finished charging.

(3) The charging priority, a_i, of the EVs in E_n and C_n should be calculated and the EVs with $a_i = 1$ are moved to C_n.

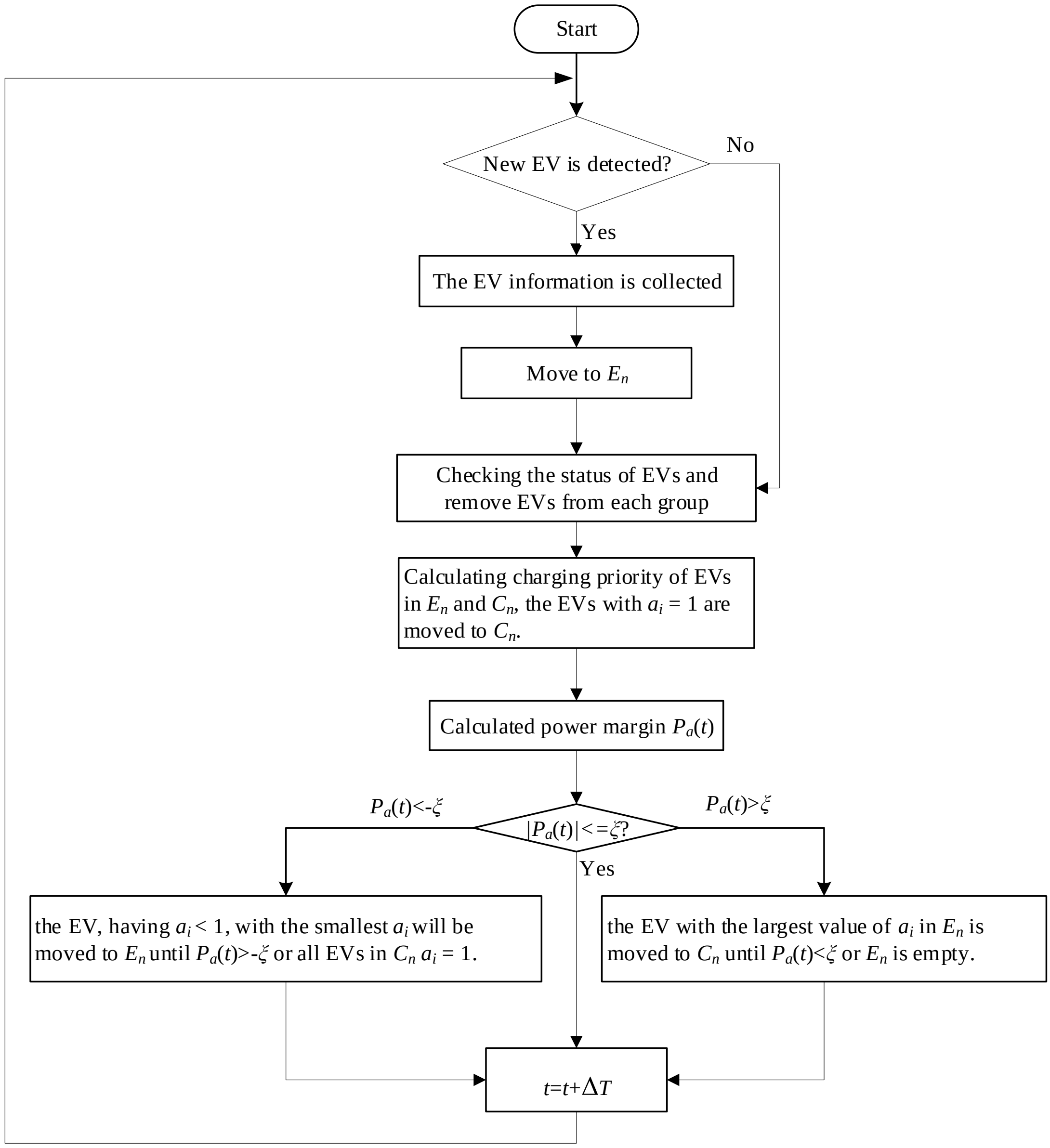


Figure 6.2 The Flow Chart of the OCS using the Expected Power

(4) The power margin P_a can be obtained from equation (6-10).

(5) If $|P_a(t)|<=\xi$, go to next time step t. If $P_a(t)<-\xi$, the EV, having a_i < 1, with the smallest a_i will be moved to E_n until $P_a(t)>-\xi$ or all a_i of EVs in C_n is equal to 1. If $P_a(t)$)>ξ, the EV with the largest value of a_i in E_n is continuously moved to C_n until $P_a(t)<\xi$ or E_n is empty.

The flow of the OCS is shown in Figure 6.2.

Table 6-1 The characteristics of all three EVs.

	EV1	EV2	EV3
Arriving time/t_{back}	17:00	18:00	19:30
Departing time/ t_{leave}	06:00	20:00	05:00
Stayed time/T_{stay}	13hrs	2hrs	9.5hrs
SOC before charging/ SOC_{bef}	10%	40%	10%
Charging time/ T_c	4hr20mins	3hrs	4hrs20mins

Figure 6.3 shows three examples of the EVs' charging process with the OCS using the expected power, which indicates the ordered charging operation and its advantages. Three Lithium-ion battery EVs, EV1, EV2 and EV3 are located in three households, and the characteristics of all three EVs are listed in Table 6-1. The SOC and charging power demand profiles are obtained from Figure 5.1.

When EVs charging are nonordered, which means that EVs are charging straight away when arriving home, the power demand is shown in Figure 6.3. It can be seen that all three EVs are charging at the same time between 19:30 and 20:00, and it results in higher power demand, which the peak power is 24.95kW.

demand is shown in Figure 6.3. When EV1 is arriving home at 17:00, the power margin $P_a(t) < \xi$ and the charging priority a_1<1, EV1 will not be charged immediately. However, the charging priority of EV1 is gradually increasing along the time. When EV2 arrives home at 18:00, the time period of EV2 stays at household 2, $T_{stay,2}$, is 2hrs, which is shorter than the charging time, $T_{c,2}$, 3hrs. Hence, the charging priority of EV2, a_2=1, which means that EV2 starts charging immediately.

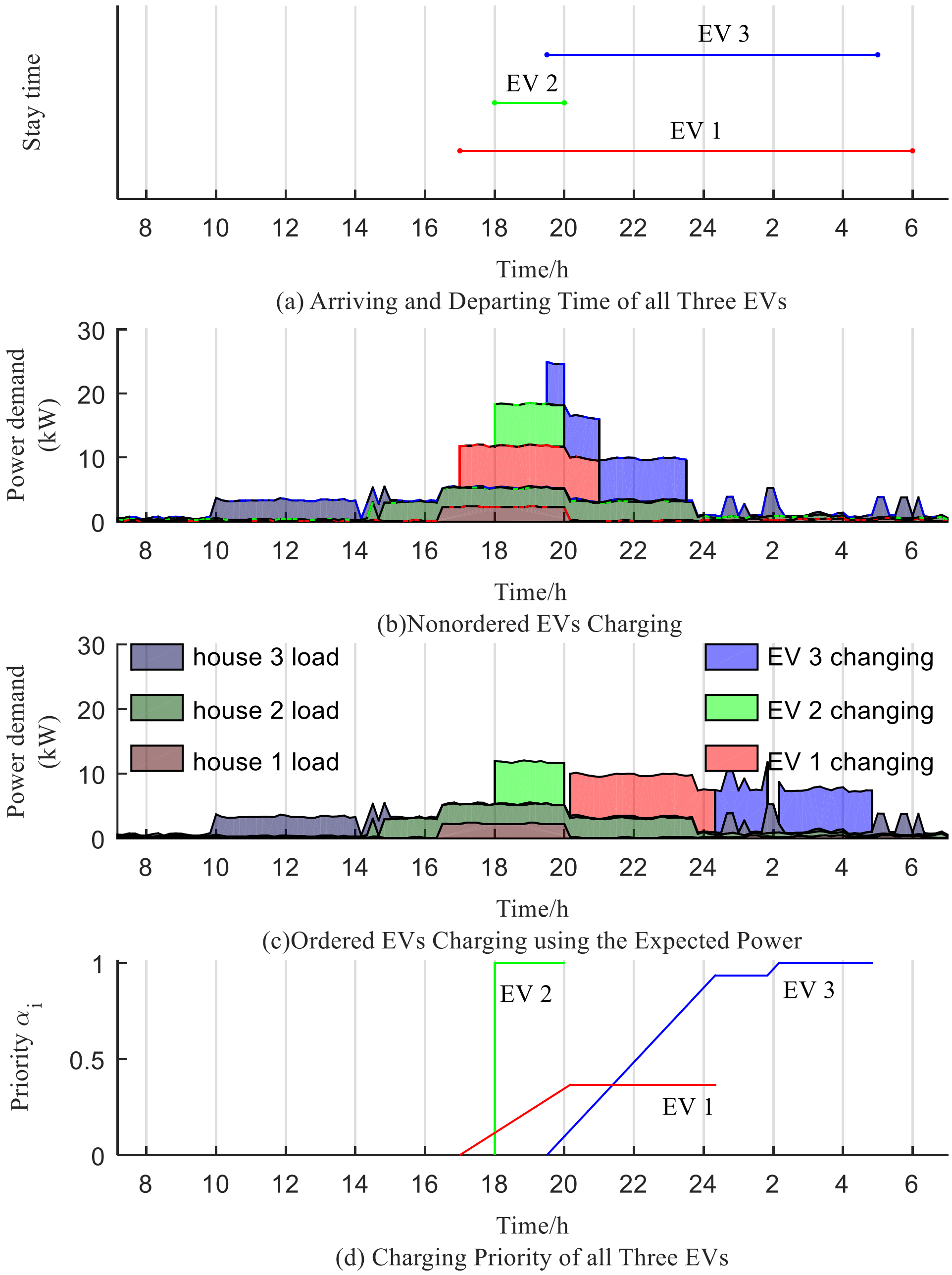


Figure 6.3 The EVs' charging process with the OCS using the expected power

The house load becomes lower at 20:10, the power margin $P_a(t) > \xi$ and the charging priority of EV1 is higher than EV3, hence, EV1 is going to be charged and EV3 is waiting to be charged. The house load becomes higher at 01:50, $P_a(t)$<- ξ then EV3 stops charging, and it starts charging again at 02:10 when the house load is low.

When EVs charging are ordered using the expected power, through the charging priority, the power demand is reduced from 24.95kW to 11.97kW. It clearly shows the advantage of the charging priority of the OCS of EVs charging using the expected power.

6.2.4 The Impacts of EVs with the OCS using Expected Power on the LV DN

The LV DN used in this section has been introduced in Figure 5.6. One EV is assumed in each household, which means total 96 EVs in the community.

For the working day, it is assumed that all EVs need to leave at 7:00 a.m. From the results in Figure 5.15 in the red line, the total power demand of the community feeder can be obtained. A number of EVs start arriving home from 16:00, the total energy demand of the time between 16:00 and 07:00 can be calculated, which is 1296.5 kWh, and the average expected power can be obtained as 86.4 kW. In order to avoid too many EVs charging before 07:00, the expected power will be selected as 1.1 times which is 95.1kW.

The minimum voltage of the community feeder when EVs are charging with the ordered control using the expected power is shown in Figure 6.4 in red dots, and the black line represents the average minimum voltage. It can be seen that when the simulation time reaches around 10,000, the average minimum voltage converges to 96.35%, and the average voltage drop is 3.65% with standard deviation of 0.33%.

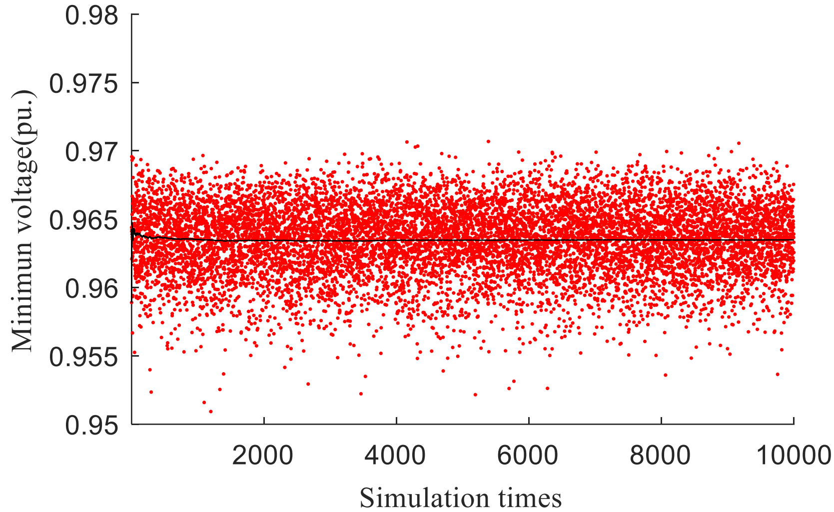


Figure 6.4 The Minimum Voltage of the Community Feeder with the OCS using the Expected Power

Table 6-2 The Probability of Voltage Drop on Each Bus with the OCS using the Expected Power

Unit:%

Drop / Bus	[0 1%]	(1% 2%)	(2% 3%)	(3% 4%)	(4% 5%)	(5% ∞)
BUS2	100	0	0	0	0	0
BUS3	0	100	0	0	0	0
BUS4	0	35.48	64.52	0	0	0
BUS5	0	0	36.86	63.07	0.07	0
BUS6	0	0	0.06	90.25	9.69	0

The probability of voltage drop on each bus of the community feeder is listed in Table 6-2. It can be seen that the voltage drop occurs on BUS6 mainly between 3%-4%, only 9.69% is between 4%-5% and none is over 6%. Therefore, it is clear that the voltage regulation of this network is successfully satisfied. The average bus voltage of the community feeder is illustrated in Figure 6.5, and the minimum voltage happens on Bus6, and its voltage distribution is shown in Figure 6.6.

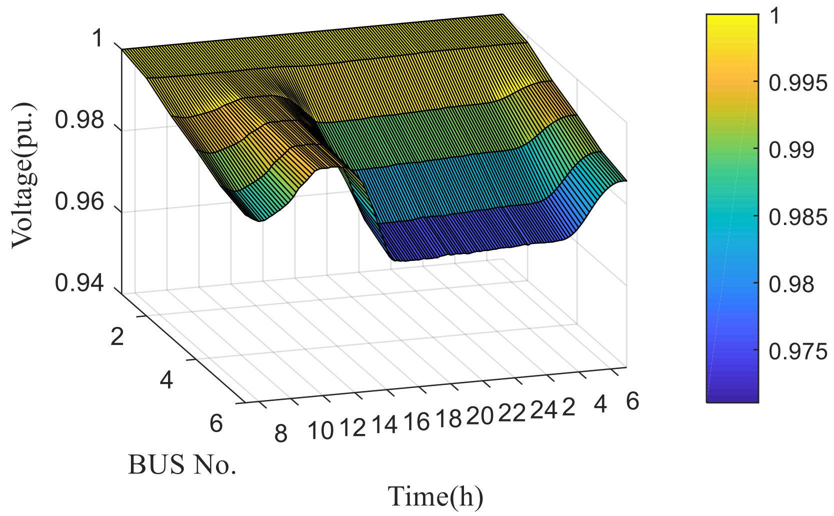


Figure 6.5 The Average Bus Voltage Distribution of the Community Feeder with the OCS using the Expected Power

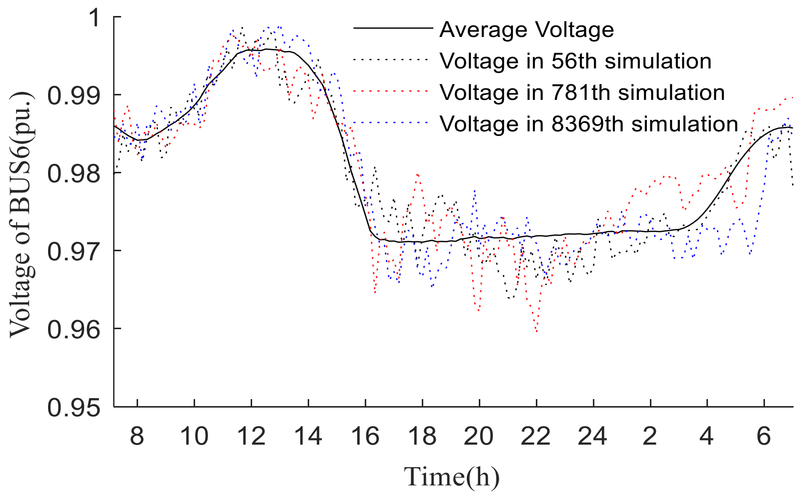


Figure 6.6 The Voltage on BUS6 of the Community Feeder with the OCS using the Expected Power

In Figure 6.6, while PV panels are generating electricity during the daytime, the voltage drop is small, however, it becomes bigger when EVs are charging during evening time and close to a certain value. This is caused by the OCS of EVs proposed in 6.2.3, that the total charging power of EVs closes to the expected power. And the maximum average voltage drop is 2.91%. The BUS6 voltage of 56th, 781th, and 8369th simulation are also shown in Figure 6.6, they all follow the similar trend with the average curve, but they all have the individual stochastic characteristic.

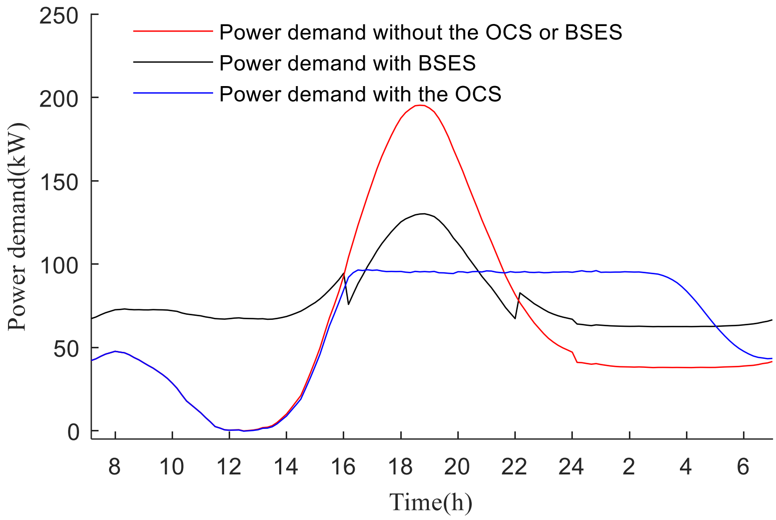


Figure 6.7 The Total Power Demand of the Community Feeder under Different Scenarios

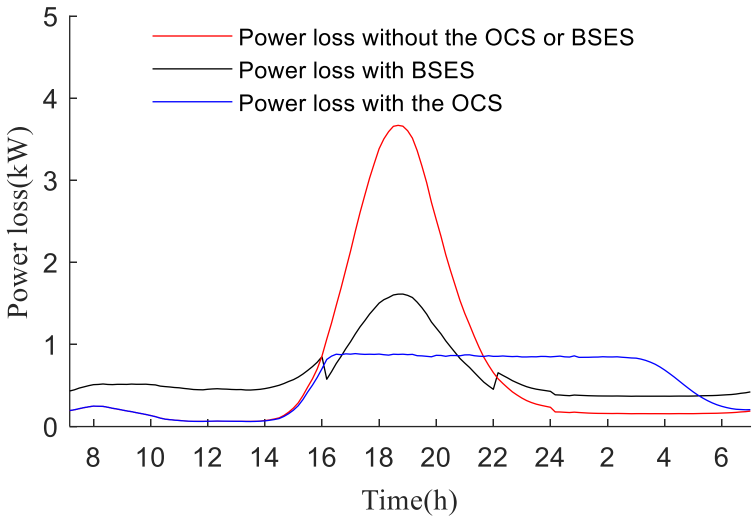


Figure 6.8 The Total Power Loss of the Community Feeder under Different Scenarios

The total power demand of the community feeder, when the OCS is employed, is illustrated by the blue line in Figure 6.7 and the total power loss is shown by the blue line in Figure 6.8. In both figures, the red line shows the scenario that without any OCS or the BSES and the black line indicate the scenario using the BSES, which indicates the BSES, having 10kWh capacity and limited charging time, without any OCS.

From Figure 6.7 and 6.8, the curve of total power demand and power loss of the community feeder under the OCS using expected power scenario is much smoother during typical peak power period, moreover, the peak power demand and power loss are lower than other scenarios. However, while PV panels are generating electricity during the daytime, there is a valley of the total power demand in the community. On the other side, the curve of total power demand of the community feeder under using the BSES scenario is smoother when considering a whole daytime period.

From the above analysis, it can be conducted that when the OCS of EVs using expected power is employed in the scenario, EVs charging impacts, the voltage drop, peak power demand, and the power loss, on the DN are dramatically reduced. However, when this scenario is used, the total power demand during daytime has a relative valley.

6.3 The OCS of EVs using the Expected Power with the BSES

From Figure 6.7, it can be seen that the total power demand curve on the community feeder using the OCS of EVs has an obvious valley during PV panels generating electricity. Whereas, the total power demand curve is relatively smooth during the whole day when using the 10kWh BSES with limited charging time. This situation is caused by the temporal characteristic of EVs charging and PV panels generating. Most of EVs charging occur after 16:00 while PV panels generating mainly happens between 9:00 and 16:00, which results in lower demand during this period in the community.

When the BSES is employed, it helps to shift the demand to smooth the power demand curve. Therefore, in this section, these two methods will be combined in order to reduce the impacts caused by EVs charging.

6.3.1 The Configuration of the OCS of EVs using the Expected Power with the BSES

The core stone of the OCS used in the early section is that the total power demand can be reduced and maintained around the desired value, though using calculated expected power to schedule EVs charging. While the BSES used in the early scenario is also able to minimise the impacts of EVs charging though shifting the power demand of the households.

Therefore, in this section, these two methods will be considered together to reduce the impacts of EVs charging on the DN. Firstly, the BSES will be employed to shift the power demand of the households to reduce the peak power created by EVs charging. When the capacity of BSES is not sufficient for EVs charging needs, then, the OCS will be used to schedule EVs charging in the community.

When EVs arrived at home, if the BSES is sufficient for EVs charging needs, then the BSES will be discharged following the charging power rate of EVs. Under this scenario, the demand is not required from the grid, the charging information will not be uploaded and the EVs are not considered for the further charging strategy. If EVs charging needs cannot be fully satisfied by the BSES, then the shortage will be solved through the grid. While EVs are charging, the BSES will be discharged with the constant power rate until 10% rated capacity. The method of calculation of the discharging power rate is used as the same in equation (5-11) of the chapter 5 and the power margin can be calculated in equation (6-11),

$$P_a(t) = P_{limit} - P_h(t) + P_{PV}(t) - P_{EV}(t) + P_{outb}(t) \tag{6-11}$$

where $P_{outb}(t)$ is the discharging power rate of the BSES.

The charging and discharging strategy are used as the same in Chapter 5.3.5. While the power demand of the household is relatively low and PV panels are generating electricity, the BSES will be charged. When EVs need to be charged, the BSES will start to discharge.

6.3.2 Minimising the Impacts of EVs Charging on LV DN employing the OCS using the Expected Power with the BSES

The characteristics of the LV DN and the households' loads are used the same as in section 6.2.4. In Figure 6.6, from the total power demand of the community feeder without any charging strategy or the BSES, the average total power demand for one day is 64.337kW, thus 70.8kW is selected for the expected power of the community feeder considering 10% power margin.

During peak power demand period, 535.7kWh is the total energy that when the power demand is over the expected power. Based on the consideration of the range of the BSES capacity, 10%-90% of the rated capacity, the capacity of each individual household will be 6.97kWh. Hence, 7kWh is selected for the BSES in each household.

Moreover, in Figure 6.7, from the total power demand curve of the community feeder with the OCS, the major power demand happens between 16:00 and 07:00 (next day). Therefore, the charging period of the BSES is considered between 07:00 and 16:00 when the total power demand is relatively low. While the BSES is charging, the expected power of each household is 0.74kW and its charging power rate is the difference between the expected power and household power demand.

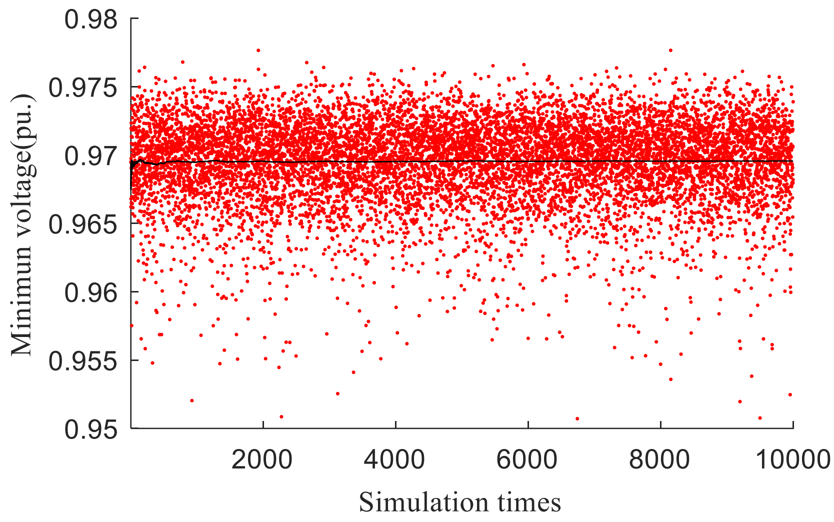


Figure 6.9 The Minimum Voltage of the Community Feeder employing the OCS using Expected Power with the BSES

The minimum voltage of the community feeder, considering the OCS using expected power with the BSES is shown in Figure 6.9 as red dots, and the average minimum voltage is indicated in the black line. It can be seen that the average minimum voltage converges to 96.95% when the simulation times reach around 10,000， and the average voltage drop is 3.05% with standard deviation of 0.31%.

The standard divination is reduced from 0.33% to 0.31% compared with the previous OCS, the voltage drop is reduced consequently and it also shows that the voltage distribution will be more close to the average value.

The probability of voltage drop on each Bus while EVs Charging is listed in Table 6-3.

Table 6-3 The Probability of Voltage Drop on Each Bus while EVs are Charging

Unit:%

Drop / Bus	[0 1%]	(1% 2%)	(2% 3%)	(3% 4%)	(4% 5%)	(5% 6%)
BUS2	100	0	0	0	0	0
BUS3	7.73	92.27	0	0	0	0
BUS4	0	92.68	7.31	0.01	0	0
BUS5	0	0.05	93.74	6.13	0.08	0
BUS6	0	0	49.12	49.66	1.21	0

The probability of voltage drop is shown in Figure 6.10, the red bar chart is the probability of voltage drop without any charging strategies or the BSES, the black bar chart is with the BSES, the blue bar chart is with the OCS only and the pink bar chart represents the probability of voltage drop of the OCS with the BSES. From Figure 6.10, it can be seen that the maximum voltage drop, employing the OCS with the BSES, mainly distributes between 2% to 4%, and only 1.21% distributes between 4%-5% and none is over 6%. Furthermore, this is fully within the voltage regulation. Comparing with the scenario that only the OCS employed, the maximum voltage drop mainly distributed between 3% and 4%, which conducted in section 6.2.4.

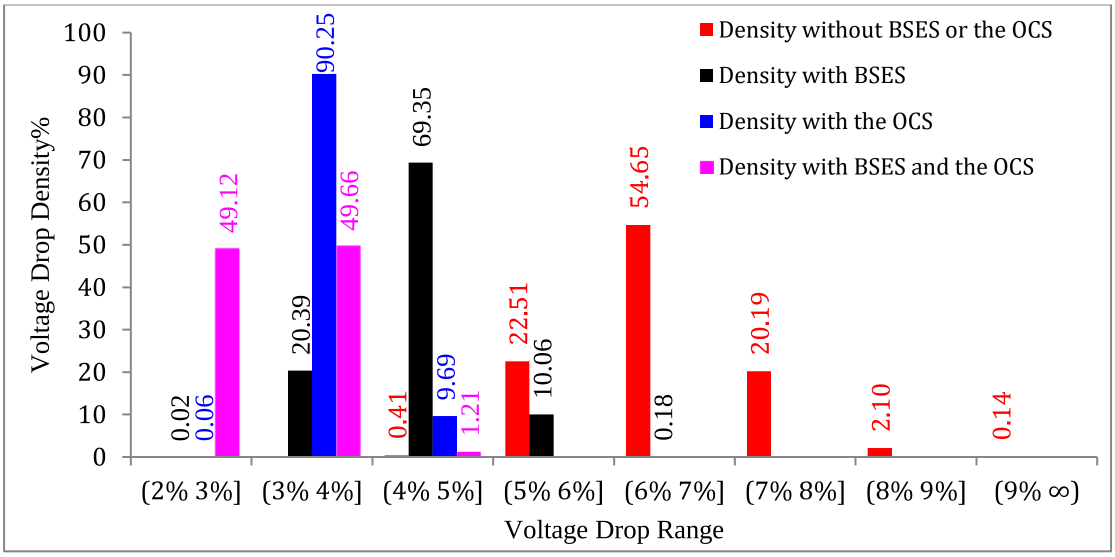


Figure 6.10 The Probability of Voltage Drop on BUS6 of Different Scenarios

The average bus voltage distribution of the community feeder is shown in Figure 6.11, it can be conducted that the minimum voltage happens on BUS6 and the average bus voltage becomes smooth. The average voltage of the BUS6 is shown in Figure 6.12.

Comparing with the scenario under the OCS only, the average voltage becomes much smoothed, and the maximum average voltage drop of the average voltage is 2.25%, which is reduced dramatically from 2.91%. Moreover, in Figure 6.12, it also illustrates the 85th, 964th and 7538th simulation results of the voltage distribution.

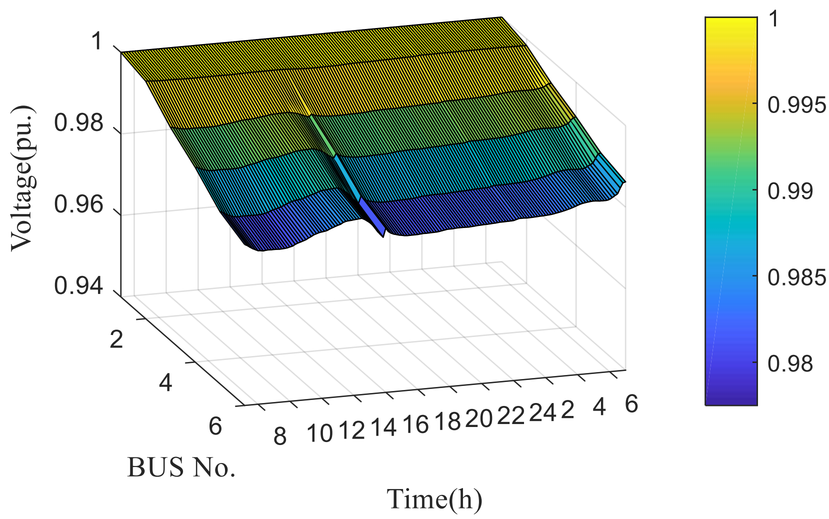


Figure 6.11 The Average Bus Voltage Distribution of the Community Feeder employing the OCS using Expected Power with the BSES

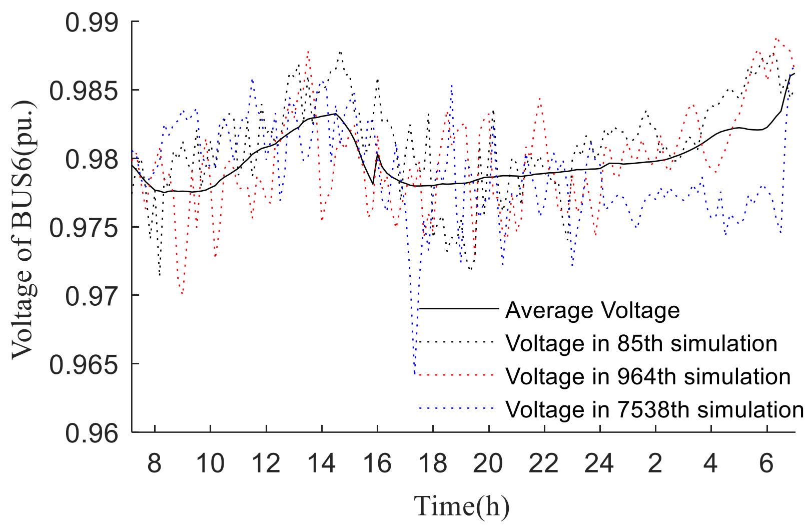


Figure 6.12 The Voltage on BUS6 of the Community Feeder employing the OCS using Expected Power with the BSES

Figure 6.13 shows the total power demand of the community, Figure 6.14 indicates the total power loss of the community and Figure 6.15 is average voltage on BUS 6. The red line represents the scenario without any charging strategies or the BSES, the black line indicates the scenario using the BSES, the blue line is the scenario with the OCS only and the pink represents the scenarios with the OCS and the BSES.

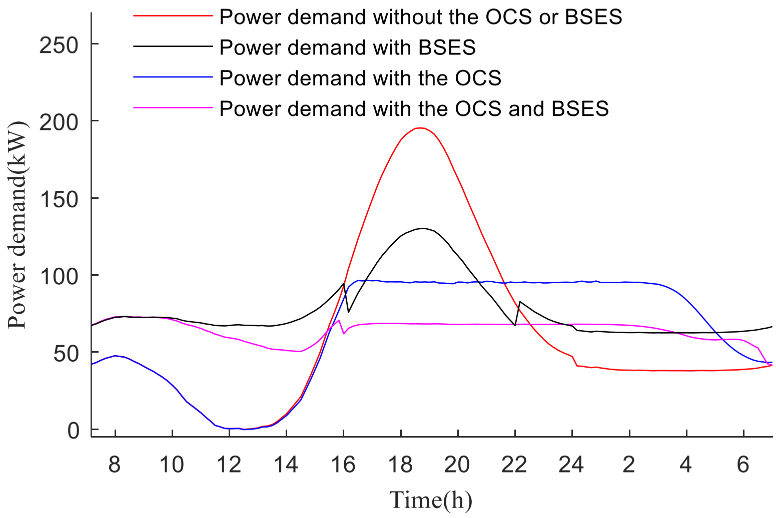


Figure 6.13 The Total Power Demand of the Community Feeder under Different Scenarios

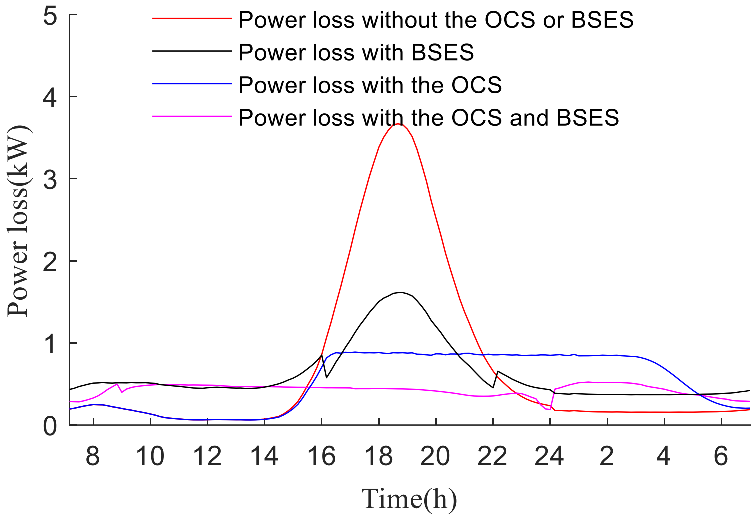


Figure 6.14 The Total Power Loss of the Community Feeder under Different Scenarios

From Figure 6.13 and Figure 6.14, it can be seen that the scenario with OCS of EVs using the expected power with the BSES is utilizing the BSES to fulfil the load valley during daytime when PV is in operation and is utilizing the OCS to reduce the peak. And these features smooth the curve of power demand, power loss of the community feeder. From Figure 6.15, it can be conducted that the scenario using OCS of EVs using the expected power with the BSES is increasing the average voltage drop on BUS6 during PV generating electricity due to the BSES and reducing the average voltage drop through OCS. By combining these contributions, the voltage drop is smoothed during whole day, which also means that the load is distributed evenly throughout the day. Therefore, the OCS of EVs using the expected power with the BSES is able to address the stochastic behaviour of EVs and UK voltage regulation can be satisfied at the same time.

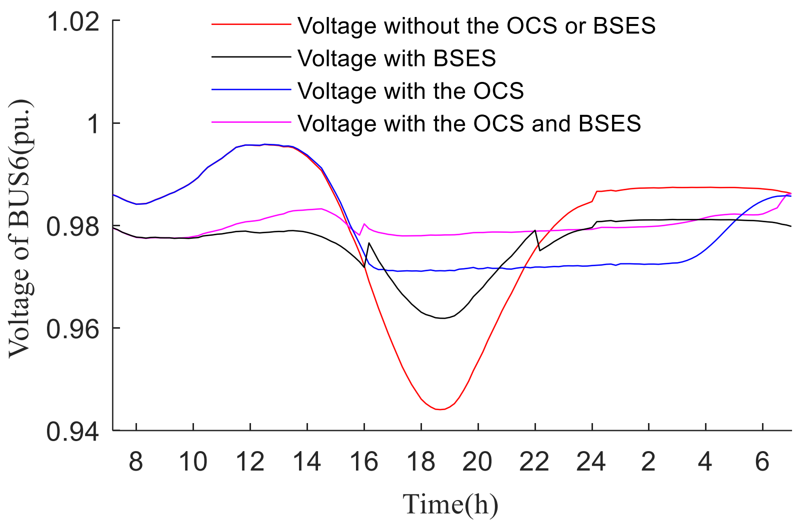


Figure 6.15 The Average Voltage of BUS6 under Different Scenarios

Table 6-4 Some Important Network Variables under Different Scenarios

Key indexes	Without BSES or the OCS	With BSES	With the OCS	With BSES and the OCS
The Peak Power Demand of the Community Feeder P_{max}/kW	195.5	130.2	96.58	70.61
The Average Voltage Drop of the Community Feeder V/%	6.51	4.40	3.65	3.05
Total Energy Loss of the Community Feeder E_{loss}/kWh	17.36	14.91	12.78	10.20
The Standard Deviation of the Minimum Voltage /%	0.67	0.47	0.33	0.31

Some important network variables under different scenarios are summarised in Table 6-4. From the summary in Table 6-4, though the implementation of the OCS using the expected power or the BSES, the average voltage drop and the standard deviation of the minimum voltage of the community feeder are both reduced dramatically, which means the voltage distributes closer to the average value. Moreover, the total energy loss of the community feeder is also minimised. While combining the two methods, the peak power demand, voltage drop, the total energy loss and the standard deviation of the minimum voltage all are the lowest among other methods. Therefore, the method of combining the BSES and the OCS using the expected power effectively minimise the impacts of EVs charging on LV DN. And the original objective has been achieved.

6.4 Summary

In this chapter, the OCS of EVs using expected power is introduced to address the issues caused by the uncontrolled EVs charging on the LV DN, then it is combined with the BSES, and the combined method is able to further smooth the power demand profile throughout the whole day. Through the analysis, it is proved that the OCS of the EVs using expected power with the BSES is capable of minimising the impacts caused by the large scales of EVs charging and addressing the stochastic characteristics of EVs. The conclusion can be conducted as follow:

(1) Comparing with the BSES deployment in the dwellings, the OCS of EVs using expected power is able to further reduce the voltage drop, peak power demand and power loss of the DN. And each bus voltage of the community feeder is within the UK voltage regulation. However, there is a relative valley during the daytime.

(2) The method that combined the OCS with the BSES is capable of maintaining the total power demand being around the expected value, and the total power demand and power loss of the community feeder become much smoother. Moreover, the peak power demand, voltage drop, standard deviation of the minimum voltage and power loss are all the smallest, which reducing the impacts caused by EVs charging is achieved. Furthermore, the selected capacity of the BSES is reduced. Overall, this method is able to overcome the disadvantage of EVs development, which is the stochastic characteristic of EVs mobility, in the community.

Chapter 7

Conclusion and Future Work

This chapter outlines the major contributions and findings from the research. It also presents the possible further work from this research.

7.1 Conclusion

The climate change caused by the GHG emissions has been paid attention from all over the world and finding feasible ways to reduce the GHG emissions becomes crucial. The energy demand from the residential sector accounts for 30% of the total energy demand, which indicates that it has potential energy savings to help to reduce the GHG emissions. Furthermore, the large deployment of EVs in the community will also have an important role to reduce the GHG emissions, however, with the growth of EVs, the LV DN will be impacted directly. Therefore, the research on how to reduce the energy demand in the dwellings and at the meantime, minimise the impacts of EVs charging on the dwellings and LV DN becomes significant.

7.1.1 The Analysis of Potential Energy Savings of a Future Domestic Dwelling using EnergyPlus

Using EnergyPlus and existing Electric Home from Corby, the energy demand in a domestic dwelling is modelled. Potential energy savings from new building material, PV/T panels, LED lights and occupants' behaviours are analysed. And improving the energy efficiency of the dwelling is investigated. The conclusion can be obtained:

(1) The space heating is the dominant sector of the energy demand of a domestic dwelling. Using the new building material with a lower U value is an important

way to reduce the energy demand in the dwelling. And with the lower U value, the energy demand is reduced most in winter, then autumn, spring, lastly in summer due to less energy needed.

(2) The solar thermal panel is only providing heat energy to the dwelling and it cannot use the solar energy in an efficient way. The PV panel is only able to generate electricity, and when the temperature of the panels rising, the efficiency drops. The PV/T panel generates electricity and heat to supply the dwelling, which the efficiency is improved. Comparing the ways of using solar energy, the PV/T is the most efficient way, which contributes both electrical and thermal energy to reduce the energy demand in the dwelling.

(3) When the comfort level is satisfied in the dwelling, the ASHP with the shut-down control is proved to be a solution to achieve the energy savings. And through controlling the thermostat setting, the energy demand in the dwelling also can be reduced.

(4) Through installing the LED lights, the energy demand in the dwelling is reduced dramatically. Because of the attribute of the cold light, the space heating demand is increased, however, the overall energy demand in the dwelling is reduced. Therefore, installing the LED lights is recognised as a potential way to save energy in the dwelling.

7.1.2 Reducing the Peak Power Demand of the Dwelling caused by the EV Charging using the DEIM

According to the analysis of the charging demand of the EV and the energy demand in the dwelling, the DEIM is established through BCVTB. An individual dwelling is modelled to analyse the impacts of the energy demand in the dwelling caused by the EV charging, and load shifting method and the BSES are used to reduce the peak power demand in the dwelling.

(1) Based on the load shifting method, three scenarios, ‘Shift Charging’, ‘Shift + Gap Charging’ and ‘Shift + Adjust Charging’, are proposed to reduce the peak power demand in the dwelling. And from the results, the dwelling temperature is maintained within the comfortable level under each scenario. Most importantly, the peak power demand of the dwelling is reduced dramatically, especially the latter two scenarios, it reduced closely to the EV charging power, which helps to maintain the power quality of the LV DN and minimise the power loss.

(2) Based on the load shifting method, the BSES is installed in the dwelling to further reduce the peak power demand. And it not only helps to reduce the peak power demand caused by the EV charging, but also smooths the daily power demand profile.

7.1.3 Minimising the Impacts of EVs Charging on LV DN using the Dwelling's Micro-grid

With the rapid development of the EVs in communities, EVs charging will cause lots of issues on the LV DN. Based on the occupants' behaviours and stochastic characteristics of the EV mobility, the model of EVs charging demand is established and it is used for investigating the impacts of EVs charging on the LV DN. And the dwelling's micro-grid is proposed to minimise the impacts of EVs charging of the LV DN.

(1) When one EV is assumed in each dwelling, the total power demand and the total power loss of the community feeder in the network are increased dramatically. And the peak demand happens when most of EVs start charging. The possibility of the bus voltage being out of the UK regulation is even over 70% on some BUS. Therefore, when large scales of EVs are in the community, the voltage drops dramatically and power quality will be affected. The necessary actions have to be taken in order to minimise the impacts.

(2) When the Dwelling's Micro-grid with the BSES is installed in each dwelling, it is able to reduce the maximum voltage drop, peak power demand, the probability of the bus voltage being out of the UK regulation and the power loss. And with the increasing capacity of the BSES, the impacts of EVs charging on the network can be further minimised, moreover, the capacity of the BSES is recommended.

(3) Under the same capacity of the BSES, by using the limited charging time of the BSES, the impacts caused by EVs charging of the community feeder on the network can be further reduced, however, the total energy loss is not affected much.

7.1.4 The OCS of EVs using the Expected Power with the BSES

In this study, an OCS of EVs using the expected power is proposed to address the issues caused by the uncontrolled EVs charging on the LV DN, such as creating a peak-valley curve of the power demand and increasing the probability of the voltage being out of the normal range. Additionally, the proposed OCS is combined with the BSES which is proved to be even more effective of minimising the impacts caused by the large scales of EVs charging.

(1) Comparing with only the BSES installed in dwellings, the OCS of EVs using expected power is able to further reduce the voltage drop, peak power demand and power loss of the DN. And each bus voltage of the community feeder is within the UK voltage regulation. However, there is a relative valley during the daytime.

(2) The method that combined the OCS with the BSES is capable of maintaining the total power demand being around the expected value, and the total power demand and power loss of the community feeder become much smoother. Moreover, the peak power demand, voltage drop, standard deviation of the minimum voltage and power loss are all the smallest, which reducing the impacts caused by EVs charging is achieved. Furthermore, the selected capacity of the BSES is reduced. Overall, this method not only reduces the capacity of the BSES, which reduce the costs but

also smooths the daily power demand, overcomes the disadvantage of large EVs deployment on the DN.

7.2 Future Works

There are some future works that can be extended from this research:

7.2.1 The Effects of Three-Phase Unbalance and Harmonics

For the steady state of power flow analysis, the three-phase unbalancing and harmonic effect are not considered within this research scale, however, they are important aspects of the power system security. Although the impacts of EVs charging on DN operation are investigated in this research, the impacts on network planning are also an important aspect for network operators, which can be analysed in future works.

7.2.2 Economics Analysis

In this research, the impact analysis of EVs charging concentrates on the network operation side, the economic side of each method is not compared. And also, the economic can be considered as a factor when making any strategies. For example, the OCS of EVs using expected power and the BSES proposed in chapter 6, the BSES is installed in each dwelling, however, if the centralised BSES used, the costs could be reduced, which can be done in the future work.

7.2.3 Electricity Market Reconfiguration

The EVs customers and their managements will become the new roles in the electricity market, therefore, how to construct the operation framework of electricity market that inspires all parties to participate, how to deal with the additional load caused by the large penetration of EVs and how to defining the differential electricity price of the new energy structure etc. all of them can be the future work.

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Appendix

Appendix A. Data for Corby Electric Home

Table A-1 The Material of Building Elements of Corby Electric Home

Element	Material	Thickness (mm)	Density (kg/m^3)	Specific Heat (J/kg-K)	Conductivity (W/m-K)
Wall	Facing brick	102.5	650	2000	0.96
	EPS-Expanded Polystyrene	150	15	1400	0.04
	Concrete block	100	1400	1000	0.51
	Plasterboard	12.5	400	837	0.08
Floor	Urea Formaldehyde Foam	199.9	10	1400	0.04
	Cast Concrete	100	2000	1000	1.13
	EPS	80	15	1300	0.04
	Limestone	8	2600	1000	2.3
Roof	Plywood	10	700	1420	0.15
	MW glass wool	131.9	12	840	0.04
	Cast Concrete	1000	1200	1000	0.38
	Air gap	2000	1.29	1003	0.0267
	Plasterboard	130	2800	896	0.25
Window	Glazing	4	2.5	750	1
	Air gap	19	1.29	1003	0.0267
	Glazing	4	2.5	750	1

Appendix B. Data for LV DN

Table B-1 LV DN Model Parameters

Component	Description	Comments
Transformer	• The ratio of transformer 11/0.433kV • 500Kva • 5% impedance • Dy11 windings • X/R ratio of 15 • Taps set at -2.5% on HV side	
400V Detailed Feeder	• Four outgoing 400V 3 phase feeders • Feeder comprises two segments of cable, 150m of 95mm2 CNE cable • 96 customers distributed evenly along the feeder • Customers distributed evenly across three phases • Service joints distributed evenly along feeder cable segments • Up to four consumers per service joint	• Three feeders modelled as lumped loads • 95mm2 CNE cable parameters: 0.32+j0.075Ω/km (phase) 0.32+j0.016Ω/km (neutral)
Individual Customers	• ADMD of 1.3kVA, 0.9pf • Minimum demand of 0.16kVA, 0.9pf	