Management of Distributed Energy Resources in Energy Systems

Thesis Submitted for the Degree of

Doctor of Philosophy in Electrical Engineering

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Summary of Thesis

This thesis investigated the use cases of Electric Vehicles (EV) and stationary battery storage in a multi-level energy system with high penetration of renewable DER. The different energy system levels considered include large and local level, distribution network and customer premises.

The reduction of excess electricity due to high shares of renewable energy technologies by using EV with Vehicle to Grid capability in a future GB energy system was investigated. It was found that with EV in vehicle to grid mode integrated into the energy system, the utilisation of fluctuating wind power was increased. This was realised by minimising the curtailment of excess electricity and CO_2 emissions. Also in a local energy system with a high share of intermittent renewable energy, EV with Vehicle to Grid capability can reduce electricity import of about 34%.

A microgrid was modelled for evaluating the impact of electrical vehicle charging on voltage profiles and energy losses in a local distribution network with a high share of distributed energy resources. The results show that with a smart charging scheme, the voltage profiles remain within distribution network operator's defined limit. A reduction of energy losses in the microgrid was also noted.

An optimisation tool using an optimisation technique was developed for optimising charging and discharging of a stationary battery storage. This was simulated to evaluate the revenue streams for an existing photovoltaic generation system. The key benefit of the photovoltaic generation system to the owner is the ability to maximise feed in tariff revenue streams by maximising self-consumption using a wholesale electricity tariff. The impact of storage unit cost on the adoption of battery storage for the photovoltaic generation system was also simulated using a time of use tariff. It was found that battery storage for the simulated system will only be economically viable when battery unit cost drops to £138/kWh.

The impact of an optimised distributed energy system simulated in the Lawrence Berkeley's Distributed Energy Resources Customer Adoption Model (DER-CAM) on distribution network constraints was investigated using a soft-linking power flow simulation procedure. It was found that voltage excursions occur mostly during peak day-types. It was found out that not all optimised distributed energy systems are feasible from the distribution network's point of view.

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List of Publications

The following papers were published based on work done for this thesis, or work done within the framework of the doctorate degree:

Journal Papers

1. A.S Hassan, L.M. Cipcigan and N. Jenkins, "Management of Battery Storage Operation with Time of Use tariff for an existing Photovoltaic System" [*under review*].
2. A.S Hassan, L.M. Cipcigan and N. Jenkins, "Impact of optimised Distributed Energy Systems on Microgrid Constraints" [*under review*].

Conference Papers

3. A. S. Hassan, A. Firrincieli, C. Marmaras, L. M. Cipcigan, and M. A. Pastorelli, "Integration of Electric Vehicles in a Microgrid with Distributed Generation." *49th Universities Power Engineering Conference, Cluj-Napoca,* Romania, 2014.
4. A. S. Hassan, C. Marmaras, E.S. Xydas, L. M. Cipcigan, and N. Jenkins, "Integration of wind power using V2G as a flexible storage." *IET Power in Unity: A Whole System Approach,* London, UK, 2013.
5. A. S. Hassan, C. Marmaras, E.S. Xydas, L. M. Cipcigan, and N. Jenkins, "Integration of renewable energy with flexible storage systems: A case study of GB and Greece." *48th Universities Power Engineering Conference, Dublin*, Republic of Ireland, 2013.
6. E.T. Fasina, A. S. Hassan, and L. M. Cipcigan, "Impact of Localised Energy Resources on electric power distribution systems." *50th Universities Power Engineering Conference*, Stoke on Trent, UK, 2015.
7. E.S. Xydas, C. Marmaras, L. M. Cipcigan, A. S. Hassan and N. Jenkins, "Electric Vehicle Load Forecasting using Data Mining Methods." *IET Hybrid and Electric Vehicles Conference*, London, UK, 2013.

8. E.S. Xydas, C. Marmaras, L. M. Cipcigan, A. S. Hassan and N. Jenkins, "Forecasting Electric Vehicle charging demand using Support Vector Machines." *48th Universities Power Engineering Conference, Dublin,* Republic of Ireland, 2013.

IEEE STANDARD STUDENT PAPER COMPETITION

9. A. S. Hassan, "The Impact of Engineering Standards on the Power and Energy Industry" *IEEE Standards Education Committee, United Kingdom and the Republic of Ireland (UK&RI) Student Congress*, *Student Paper Contest*, Bath, UK, 2013.

OTHER PUBLICATION

10. Sambu Kanteh Sakiliba, Abubakar Sani Hassan, Jianzhong Wu, Edward Saja Sanneh, and Sul Ademi, "Assessment of Standalone Residential Solar Photovoltaic Application in Sub-Saharan Africa: A Case Study of Gambia," *Journal of Renewable Energy, vol*. 2015.

List of Abbreviations

AC	Alternating Current
AI	Artificial Intelligence
AIMMS	Advanced Interactive Multidimensional Modelling System
BEV	Battery Electric Vehicles
CS	Case Study
CCC	Committee for Climate Change
CEEP	Critical Excess Electricity Production
CHP	Combined Heat and Power
CIGRE	Conseil International des Grands Réseaux
DECC	Department of Energy and Climate Change
DER	Distributed Energy Resources
DG	Distributed Generation
DNO	Distribution Network Operator
DSM	Demand side management
EV	Electric Vehicles
FC	Fuel Cells
FCEV	Fuel Cell Electric Vehicles
FiT	Feed in Tariff
HEV	Hybrid Electric Vehicles
HOMER	Hybrid Optimisation Model for Electric Renewables
HV	High Voltage
ICE	Internal Combustion Engine
IEA	International Energy Agency
ISGT	Innovative Smart Grid Technologies
LBNL	Lawrence Berkeley National Laboratory
LCNF	Low Carbon Network Fund
LP	Linear Programming
LV	Low Voltage
MAS	Multi-Agent System
MILP	Mixed Integer Linear Programming

MV	Medium Voltage
NLP	Non-Linear Programming
O&M	Operation and Maintenance
OF	Objective Function
OLTC	On-Load Tap Changing
OPF	Optimal Power Flow
PGR	Post Graduate Research
PHEV	Plug-in Hybrid Electric Vehicles
PTDF	Petroleum Technology Development Fund
PV	Photovoltaic
p.u	per unit
RES	Renewable Energy Sources
ROI	Return on Investment
SOC	State of charge
T&D	Transmission and Distribution
ToU	Time of Use
TSO	Transmission System Operator
UKGDN	UK Generic Distribution Network
UKGDS	United Kingdom Generic Distribution System
UK&RI	United Kingdom and the Republic of Ireland
VPP	Virtual Power Plant
V2G	Vehicle to Grid
WEC	Wind Energy Conversion
WECS	Wind Energy Conversion System

Chapter 1

Introduction

This introductory chapter presents the background, motivation, objectives and contributions of this thesis. The structure of the thesis is also outlined.

1.1 Evolution of Distributed Energy Resources (DER)

Renewable based DER such as solar, wind hydro, and biomass are considered to have a negligible environmental impact in terms of CO_2 emissions. Such DER have emerged as alternative energy sources for reducing the dependence on fossil fuel based energy sources since the 1973 oil crises [1]. The high production costs of such DER along with the lack of government incentives ensured a stagnated deployment of renewable DER in energy systems [2].

The issue of climate change globally renewed the interest in the deployment of DER. Also, the technical and economic benefits along with changing energy policies and new technologies have significantly added to the renewed interest in DER deployment globally. For example, as of 1999, there was less than 0.7 GW of installed solar photovoltaic (PV) globally, which rise to 40 GW installed with a cumulative of 180 GW of PV capacity [3].

From the perspective of Distribution Network Operators (DNO), intermittent DER deployed in low voltage (LV) distribution networks can be of benefit technically and economically. However, the high penetration of such DER together with uncertain demand growth has led to challenges in the distribution network ranging from distribution transformer overloading, power losses, voltage rise and voltage drops [4], [5]. Therefore, the concept of the smart grid has evolved to become an important part of the future grid modernisation to facilitate the integration of DER into distribution networks. As an integral part of the future smart power and energy system, a multi-level energy system analysis is presented in this thesis. The key idea of behind the multi-level energy system is to explore the use cases of EV and stationary battery storage in (i) large and local energy systems (ii) distribution networks and (iii) customer premises strategically by considering various technical, economic and environmental factors. The multi-level energy system analysis introduced in this thesis is illustrated in

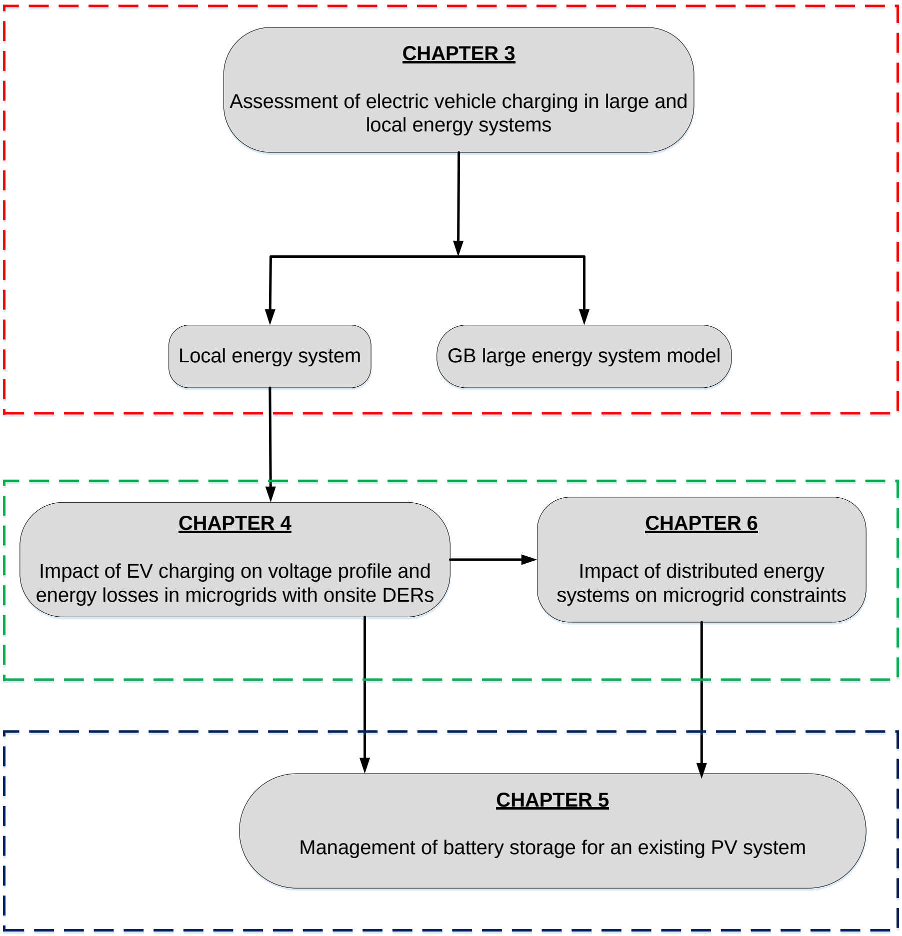


Figure 1.1: Multi-level energy system schematic introduced in this thesis

1.2 DER DEFINITIONS

The term DER is used interchangeably with Distributed Generation (DG) according to [6]. DER refers to the connection of distributed generated electricity and controllable loads to distribution networks. In [7], the term DG was defined as generating power locally at the voltage level of the distribution network using RES and other non-conventional energy sources like Combined Heat and Power (CHP), wind power, solar photovoltaic (PV), Fuel Cells (FC), microturbines, Stirling engines and their integration into the LV distribution network. In [8], DGs are defined as small scale generators located to the loads that are being served. The broadness of DG and DER definition in terms of purpose, power provision, location and the market is highlighted in [9]–[11]. This definition of DER covers the provision of active power, installing and operating power production units directly in the LV network and electricity markets. Therefore, the definition of DER varies from country to country and from one type of distribution network to another. The broad definition of DER which includes Renewable Energy Sources (RES, like wind, PV and biomass), controllable loads and energy storage systems in the energy system will be used in this thesis. In chapter 4 of this thesis, the term DG is used to present the power flow studies analysis of distributed generators on a modelled microgrid.

1.3 DER TECHNOLOGIES IN ENERGY SYSTEMS

The energy systems in Europe has witnessed significant changes in the last 20 years as a result of privatisation of the sector, changing climatic conditions and the increased adoption of DER in energy systems [12], [13]. The role of fossil fuel based thermal power plants in the future energy systems is changing due to climate change policies and increased shares of RES [14].

Significant efforts have been put into investigating new pathways for efficient integration of DER into the future electricity supply system. However, there is a need to focus on smart energy systems that integrate the electricity, heating and transport sectors in order to effectively maximise the use of fluctuating RES [15]. The conventional energy system has been traditionally in the form of "source" (Extraction) to "service" (End-use conversion) as shown in Figure 1.2.

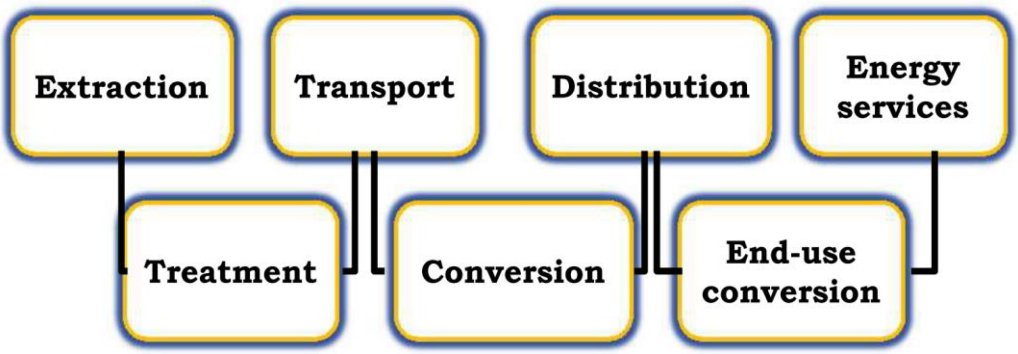


Figure 1.2: Future energy systems [16]

The improvements in the energy system of the future may involve the integration of following technologies into the traditional energy system [16]:

- DER technologies
- Onsite DER generation in buildings
- Energy efficient lighting
- Smart Direct Current (DC) microgrids
- Offshore wind power
- EV
- Virtual Power Plants (VPP)

These new technologies will bring along with them a set of new challenges. Hence there is a need to manage the system in a way to maximise the utilisation of fluctuating RES and minimise CO_2 emissions [17].

1.3.1 EV

EV is a general terminology used to refer to automobiles powered by electric motors. EV are categorised as follows [18]:

- Fuel Cell Electric Vehicles (FCEV).
- Battery Electric Vehicles (BEV).
- Hybrid Electric Vehicles (HEV).
- Plug-in Hybrid Electric Vehicles (PHEV).

The FCEV is powered with FCs, BEV are battery powered, and V2G is a special capability of BEV that can charge and discharge “to” and “from” the electricity network. HEV are powered by both battery and Internal Combustion Engine (ICE). The HEV can be further subdivided based on whether they can charge from the grid or not. HEV with the capability to connect to the electricity network are termed as PHEV.

In this thesis, only BEV and BEV with V2G capability were considered. The term EV in this thesis are used to refer to BEV and in the case where the power from the EV can flow to the grid, EV are referred to as V2G.

1.3.2 Battery Storage

Battery storage stores electrical energy (charging) chemically and can be used (discharged) when required.

The two commonly used types of battery storage for onsite solar PV applications are (i) lithium-ion and (ii) lead-acid batteries. The key features of both technologies are summarised in Table 1.1.

Table 1.1: Battery types and their features [19]

Lithium-ion battery storage	**Lead-acid batteries**
Expensive	Cheaper
Common in residential grid connected Solar PV Systems	Common for standalone applications where more storage is needed
Light	Heavier and larger
Requires integrated controller for managing charging and discharging	Needs charging and discharging routine to maintain battery health
Efficient in handling discharging	Less efficient
Long expected life	Shorter expected life

In this thesis, stationary battery storage can charge from the electrical grid or operate by charging only from DER. The lithium-ion battery specifications used in chapter 5 are taken from [20], [21]. The battery specification used in chapter 6 is taken from [22].

1.3.3 Electricity Tariffs

The electricity tariffs considered in this thesis includes the UK retail electricity tariff, Time of Use (ToU) tariffs and wholesale electricity tariffs [23]. ToU tariffs are defined in this thesis as varying electricity tariffs based on time of the day and season of the year. The ToU used in this thesis include the following:

- Economy 7 (dual tariff) [24], [25].
- California ToU tariffs obtained from Distributed Energy Resource Customer Adoption Model (DER-CAM) database [22].

In the absence of similar electric utility ToU tariffs like that of California in the UK, the wholesale electricity tariffs [23] was utilised in chapter 5 as a real time electricity tariff.

1.3.4 Distribution Networks

Conventionally, the electricity supply network has been designed to accommodate power flows in a unidirectional manner. However, with the increased penetration of

DER at the customer premises, it is becoming imperative to consider effective management strategies both from the DNO and the customer point of views.

The DNO own and manage the assets of the electricity distribution network and are in charge of ensuring quality of service and that voltage profiles are maintained within defined limits [4], [26].

1.3.5 Management of DER

The distribution system has been conventionally designed to receive power from the transmission system and distribute the power to local customers [6], [7], [27]. This means that power flows from higher to lower voltage levels. However, with increasing adoption of DER in customer premises, reverse bi-directional power flow is now obtainable in distribution networks. The impacts that may arise as a result of the bi-directional power flows have been researched into (see [6], [27]–[30]). Some of the challenges that may arise because of the bi-directional power flow in distribution networks are summarised as follows:

- Thermal ratings of network cables.
- Voltage profile issues (voltage rise).
- The sudden connection of large loads.
- Overloading of distribution transformers.

With the proliferation of EV, the complexity of the strain on the LV network will also increase. Therefore, there is a potential for deploying effective energy management systems that will manage the connection of DER to the distributions networks to maintain network operation within statutory limits.

1.4 THESIS OBJECTIVES

This thesis investigated the use cases of EV and stationary battery storage in a multi-level energy system with high penetration of renewable DER. The objective of this research is to:

- **Develop a methodology to evaluate the potential of EV storage** in minimising excess electricity curtailment referred to as Critical Excess Electricity Production (CEEP) and CO_2 emissions in large energy systems with high shares of RES. Assess the benefit of aggregated EV and DER in local energy systems.

- **Developed a heuristic optimisation power flow method in MATPOWER** to assess the impact of managing EV charging in an LV microgrid with high penetration of DER.
- **Formulate and develop an optimisation tool** for managing the charging and discharging of stationary battery storage for an existing PV System benefiting from the Feed UK FiT.
- **Designed a soft-linking procedure** to test the impact of optimised distributed energy systems on a modelled distribution network in the form of a microgrid.

1.5 THESIS STRUCTURE

The remainder of this thesis is organised as follows:

Chapter 2: This Chapter is a review of the relevant literature related to this thesis. It presents the background and state of the art for studies presented in Chapter 3, 4, 5, and 6. An overview is presented with regards to (i) distributed energy technologies (ii) EV charging in energy systems (iii) Integration of DER in distribution networks and (iv) optimisation of distributed energy systems and (v) the impact of optimal distributed energy systems on distribution network constraints.

Chapter 3: In this Chapter, EV and V2G integration were investigated in energy systems with high shares of RES. The impact of EV charging and V2G in energy systems with high shares of RES were evaluated in terms of (i) CEEP and (ii) CO_2 emissions. The term CEEP refers to the energy that must be curtailed because of excess production from RES which cannot be maintained within the energy system's generation – demand balance or through interconnection with other adjacent energy systems.
Excess renewable energy curtailed means not utilising economically the renewable energy capacity in the system. This decreases the Return on Investment (ROI) of the system. The term "CO_2 emissions" is used to refer to the gases released into the atmosphere as a result of combustion of fuels utilised in electricity generation, heating or energy demand to meet transportation needs [31]. The unit of CO_2 emissions used in this thesis is the Million Tonne (Mt).

Case Studies were defined and evaluated in terms of CEEP and CO_2 emissions. The case studies were as categorised as (i) large energy systems with a high share of wind power and (ii) localised energy system with aggregated small scale DER. The CEEP and CO_2 emissions were also calculated with different EV charging rates in the case of the large energy systems.

Chapter 4: In this Chapter, a method of managing EV charging in a modelled microgrid with DER is described. Case Studies were drawn to evaluate the voltage profiles and energy losses for controlled and uncontrolled EV charging regime. The voltage profiles and energy losses were evaluated for (i) summer scenario (representing minimum network loading) and (ii) winter scenario representing (maximum network loading).

Chapter 5: In this Chapter, an optimisation technique for the optimal charging and discharging of battery storage for an existing Photovoltaic (PV) system using ToU tariff is described. The operation of the technique simulates FiT revenue streams for an existing PV generation system looking to maximise FiT revenue with battery storage and wholesale electricity tariff. Case Studies were defined and simulations performed. The optimised schedules of the battery storage charging and discharging for the existing PV system at (i) negative wholesale tariff periods, (ii) low wholesale tariff periods and (iii) high wholesale tariff periods were described. An evaluation and sensitivity analysis were performed on the unit cost of storage and its impact on the optimal decision to adopt or not to adopt battery storage for the existing system.

Chapter 6: In this chapter, the impact of optimised distributed energy systems in distribution networks has been tested using a soft-linking procedure. This Chapter presents the optimised distributed energy systems and results evaluated at the Lawrence Berkeley National Laboratory (LBNL) with DER-CAM. An optimal investment analysis for the adoption of DER for a mid-rise apartment was simulated. Different scenarios of DER with battery storage were simulated. The optimal dispatch schedules for weekdays, peak days and weekend days were evaluated. A soft-linking procedure was developed to evaluate the impact of the optimised schedules on the voltage profile and energy loss of the microgrid connecting the mid-rise apartment.

Chapter 7: A summary of the main conclusions of this thesis are provided. Suggestions for future work are given.

Chapter 2

Background and State of the Art

2.1 Introduction

This chapter describes and sets out the background for the different segments of multi-level energy systems (large energy systems, localised energy systems, distribution network and customer premises) with high penetration of DER. It also outlines the state of the art use cases of EV storage and stationary battery storage in energy systems from the perspectives of the distribution network, optimisation of techniques utilised in distributed energy systems and the impact of optimised distributed energy systems on microgrid constraints.

2.2 DER Integration in Energy Systems

The DER technologies that will be studied in this thesis include the following:

- Wind turbines.
- PV.
- FC and CHP.
- EV.
- Battery Storage.

There is no specific categorisation regarding the technologies that are termed as DG according to [7], but generally, could be categorised and classified as follows:

- Renewable.
- Modular (large DER systems that can be built from small subsystems).
- CHP.

And, according to the size of the DG:

- Micro: 1 W – to < 5 kW
- Small: 5 kW to < 5 MW
- Medium: 5 MW to < 50 MW
- Large: 50 MW < 300 MW

2.2.1 Wind Power

The wind energy conversion system or turbine produces power by utilising the kinetic energy of an incident wind on the turbine rotor. The power that could be extracted from the wind by the turbine is proportional to the cube of wind speed according to Equation 1 [6]:

$$P_w = \frac{1}{2}\rho A V^3 C_p \tag{1}$$

Where P_w is the theoretical wind power (W) that could be extracted from the wind, ρ is the density of air (kg/m^3), A is the swept area (m^2) by the wind turbine rotor, V is the wind speed (m/s) and C_p is referred to as the power coefficient or the rotor efficiency.

In **chapter 3** of this thesis, large scale wind power (onshore and offshore) were considered for the national energy case studies (case study 1 and 2), while small scale wind power was considered in the local energy systems case study (case study 3).

Wind turbines can be classified as large onshore-offshore wind turbines and small scale domestic wind turbines. It is projected that 7% of DER technologies in the UK installed capacity in 2050 will consist of domestic wind turbines, approximately a total of about 1.4 GW [31], [32].

2.2.2 Solar PV

Domestic solar PV despite having high installation costs have high adoption rates. This is largely driven by the FiT schemes in Europe and other parts of the world [33]–[35]. Large scale installations in the form of solar farms are also common due to favourable energy policies [36].

The UK has low solar irradiance compared to the countries in the southern part of Europe, however, even with this drawback, it is projected that about 2% of DER generation capacity in the UK by 2050 will be from PV generation systems [31].

PV can bring about benefits in the energy system in terms of peak load and CO_2 emissions reduction. However with these benefits comes also challenges like a mismatch between generation and load, reverse power flow and voltage rise [17].

The cost has been a major bottleneck in the adoption of solar PV. However, in recent years the cost of PV modules/W and PV systems is witnessing significant reduction according to the International Energy Agency (IEA) PV system trends [3], [37] in

Figure 2.1. This implies an increase in installed capacity in MW as shown in Figure 2.2.

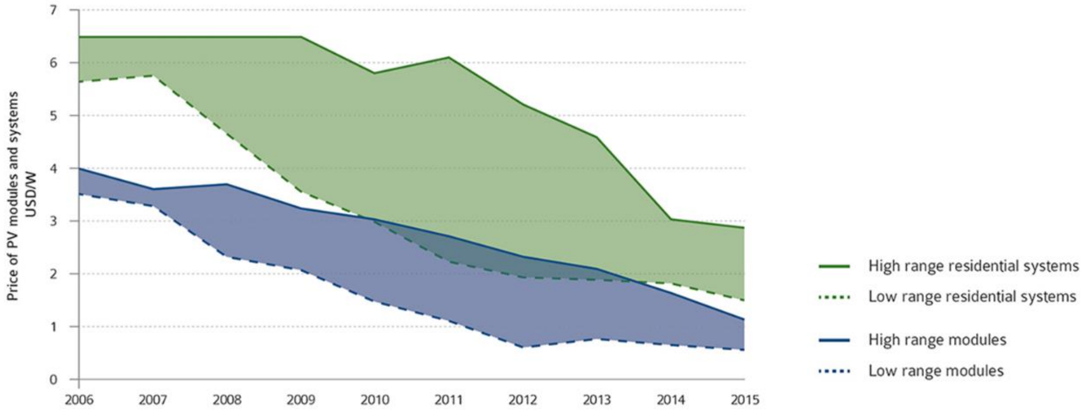


Figure 2.1: Small Scale PV modules System Prices Evolution in selected IEA countries [37].

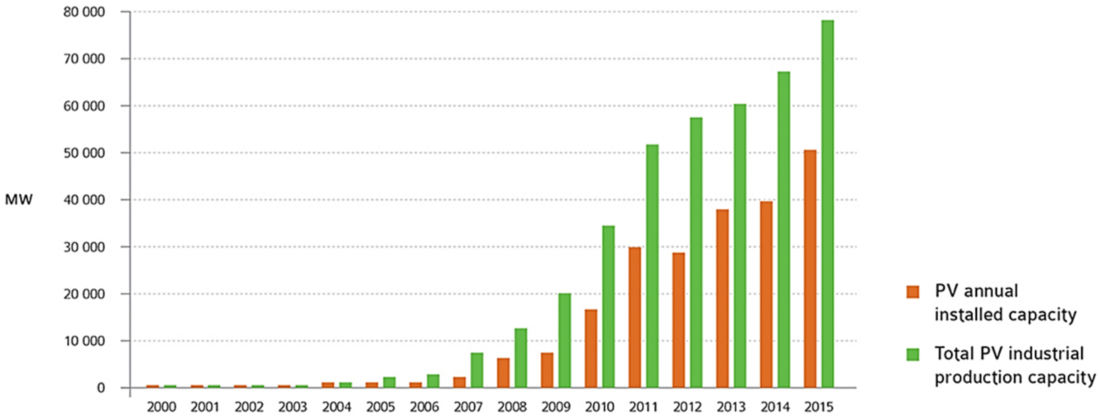


Figure 2.2: IEA PV installation capacity and module production capacity projections [3], [37].

It could be seen from Figure 2.1 that the module cost reduction for small PV systems for low range residential systems falls from about $ 3.5/W in 2006 to $ 0.6/W in 2015. This means an increase in the installation of residential PV which is mainly driven by FiT. However, declining FiT in recent years is slowing the investments in solar farms according to [38]. Hence there is a need for effective energy management strategies with energy storage to maximise self-consumption and improve the economic case of such systems.

2.2.3 FC and CHP Applications

FCs produce a current through electrochemical reactions. In a hybrid fuel cell system connected to an electrolyser, hydrogen produced in the electrolyser system is used with oxygen in the fuel cell unit to produce electricity and water. This could be used in FCEV for extended range EV [39]. FCs though expensive are more efficient than thermal engines [40]. FCs have not been extensively used as DER in VPP applications because of the high initial capital costs, although they have been integrated with CHP plants in a microgrid [41].

2.2.4 Battery Storage

A battery is a device that enables the conversion of chemical energy into electrical energy. This is achieved by oxidation – reduction reaction with packed active materials within a cell chamber [42]. Batteries can provide short-term storage with high charging and discharging capability.

According to [43]–[45], battery adoption in energy systems with high shares of fluctuating DER can mitigate against high-frequency interruption caused by a specific electricity demand or grid connected distributed energy systems.

An important issue in this context is to justify why the need for battery storage in electricity networks. Peak electricity demands in power systems are increasing and high shares of DER creates a mismatch between generation and demand. This means a poor utilisation of generation, Transmission and Distribution (T&D) infrastructure according to [45]. Battery storage can be utilised to maximise the usage of existing network capacity and defer network investments. Figure 2.3 summarises potential battery storage services that could be deployed in the future electricity system.

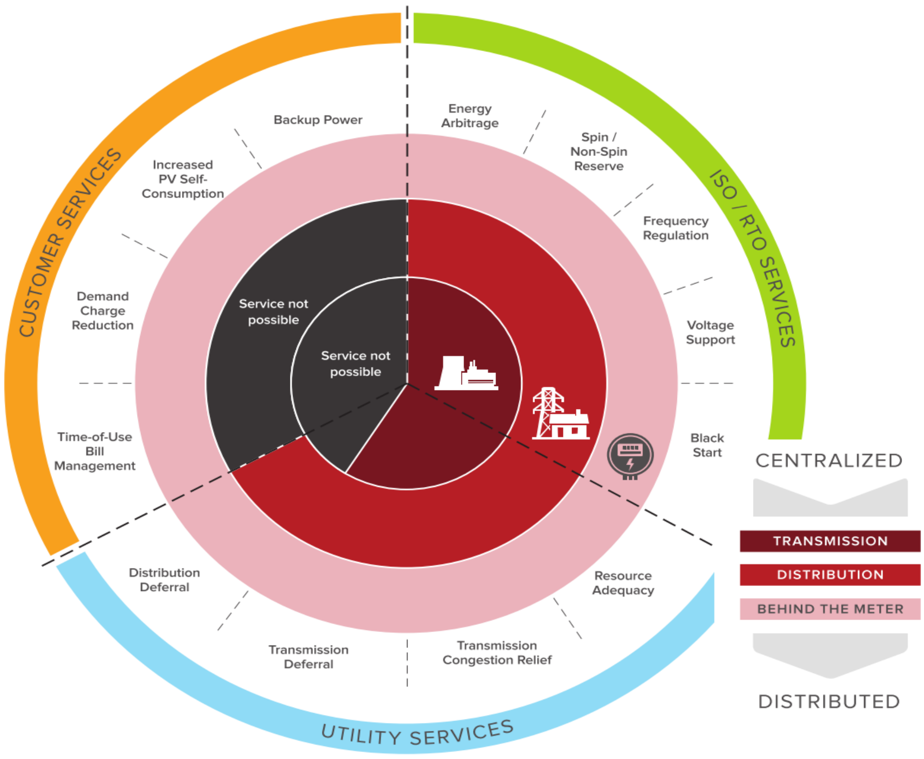


Figure 2.3: Potential battery storage services [46], [47].

The Rocky Mountain Institute report: "*The Economics of Battery Energy Storage: How multi-use, customer-sited batteries deliver the most services and value to customers and the grid*" [47] and also the articles [46], [48], [49] gave an overview of such services. These services include:

- ToU tariff, wholesale electricity Bill Management and increased PV self-consumption. This service type is explored in detail with the optimisation algorithm developed in **chapter 5**.
- Demand charges reduction, for commercial customers to avoid costly peak charges using battery storage paired with PV power can reduce these charges. The application of this service was simulated in the optimal distributed energy systems simulated in **chapter 6**.
- Frequency Response Services.
- Backup power in the event of a failure in the electricity supply system, battery storage paired with an onsite DER can provide backup power at different scales.
- Distribution network upgrade deferral.

Such battery services could be sited at different levels of the electricity supply system: (i) behind the meter seen as customer services providing the highest number of services, (ii) at the distribution level and (iii) at the transmission level [35], [47], [50]–[52]. In [53], the potential benefits of electricity storage for the UK's electricity supply network were highlighted.

However, even with such potentials for electricity storage, the deployment of such storage services is less than 3 GW as of 2015 in Great Britain according to [35], [53]. This provides an opportunity to consider the technical, regulatory and policy barriers limiting the use electricity storage in the UK.

ToU optimisation can be leveraged to provide grid support services which can serve as a platform for new business models [25], [47]. According to [25], [47], battery storage can be contracted to provide grid support services in favour of costly grid upgrades. In **chapter 5 of this thesis**, the impact of battery storage in managing power flows for an existing PV generation system to maximise FiT revenue streams with wholesale electricity and ToU tariffs are presented.

The application of battery storage to maximise FiT revenue streams is becoming attractive because of the significant difference between retail electricity tariff and the FiT export tariff [35].

Typically, distribution infrastructure upgrades are driven by peak electricity demand events that occur on only a few, predictable periods during a year. Transmission upgrades, on the other hand, are driven by the need for transmission congestion management and interconnectors. In the UK, National Grid uses transmission interconnectors to increase the security of energy supplies, help competition in the European electricity market, and integrate RES into the grid [54].

From the distribution network perspective, utilising incremental amounts of DNO owned battery energy storage to deal with limited time duration events can defer large investments and free up capital to be deployed elsewhere in the electricity supply system [5], [55]. This can also avoid over-sizing of the distribution network in a scenario of uncertain electricity demand growth.

From the battery storage review above, it could be deduced future research work for energy storage services in the electricity supply system of the future. It was found the need to develop a modelling framework capable of computing the net value of stacked battery storage services and other DER as alternatives to the conventional generation of electricity and traditional network upgrades. These insights could be driven by questions like how investments into energy efficiency measures and adoption of DER at different levels of the electricity supply system can be leveraged to defer costly investments in T&D network upgrades? The outcomes from such modelling platform should be able to provide policy and regulatory insights that will enable broad adoption of battery storage services and other DER.

2.3 EV CHARGING IN ENERGY SYSTEMS

The need for a future envisioned large scale sustainable energy systems will largely depend on the reduction of CO_2 emissions. However, the main bottlenecks against this vision include (i) the high dependence on fossil fuels in the transport sector and (ii) maintaining a balance in a future energy system with high shares of fluctuating RES [56]–[58].

A future transport industry with increased shares of EV and V2G capabilities can be valuable in ensuring a high utilisation of high shares of RES and the reduction of CO_2 emissions. In [59], [60], the scope and scenarios of EV in the future UK transport sector are presented. The following section reviews EV in energy systems.

2.3.1 EV in Large Energy Systems

According to [61], inland transport in the UK was responsible for 131.4 million tonnes (Mt) of CO_2 emissions in 2007 corresponding to 24% of the total nationally. This shows the need for EV integration in future energy systems capable of paving a pathway for the reduction of carbon emissions in the transport sector. Table 2.1 shows the energy consumption in the transport sector for the UK in 2008. It could be seen that road transport has the highest consumption of petroleum.

Table 2.1: Consumption of energy in the transport sector (000s Tonnes oil equivalent), 2008 [61]

Mode	Petroleum	Biomass	Primary Electricity	2008 Total	% Change 1998 – 2008
Road	41331	821		42152	+2.8
Rail	747		725	1472	+9.9
Aviation	13426			13426	+31.1
Domestic Shipping	1764			1764	+8.9
Total	57268	821	725	58814	+9.4

EV could play a vital role in displacing petroleum consumption in the transport sector and reduction of CO_2 emissions.

However, it is interesting to note that substitution of ICE based vehicles in the transport sector without decarbonising the power sector means shifting CO_2 emissions from the transport sector to the electricity supply system [18], [56], [58], [62].

Therefore, there is a need to effectively manage future integrated energy systems with high shares of RES and EV uptake.

In **chapter 3** of this thesis, large scale energy systems were modelled. The model integrated the electricity, transport and heat sectors including high shares of fluctuating wind power (which is used to represent an energy system with high shares of RES). Different EV charging ratings were simulated to evaluate the level of excess electricity (CEEP) and CO_2 emissions in the system. The EV with V2G capability charging energy demand with different EV charging rates was formulated and developed in EXCEL (see Appendix A and B) and simulated in the EnergyPLAN model.

EnergyPLAN has not been previously used to study the impact of EV in the UK energy system with a high share of RES. In [63], an electricity demand model with EV for the GB and Spain is presented and the impact of EV charging on the distribution networks was evaluated with different charging strategies: dumb charging, delayed charging and smart charging. In **chapter 3** of this thesis, however, the impact of integrating large EV fleets on the energy system with a high share of RES in terms of the excess of electricity production and CO_2 emissions was studied.

In [15], [64], a review of modelling and simulation tools for evaluating RES integration into energy systems was presented. The evaluation was based on the following criteria:

- Type of the model.
- The number of downloads.
- Cost.
- Versions update.
- The scope of the model.
- Time step.

Based on the ability to evaluate EV, EV with V2G capability, high RES shares, review and quality of journal papers [1], [15], [65]–[67] written with results from the model, the EnergyPLAN model was chosen to simulate the studied cases in **chapter 3**.

2.3.2 V2G in Energy Systems

V2G is an EV capability that can deliver power from the EV to the grid. Subject to the availability of the hardware required for the bi-directional power flows, and appropriate control mechanisms, the vehicle's battery could be made available while connected to the grid as an energy buffer for balancing services [68].

Clearly, it would be necessary to restrict the authority of the grid's control over the vehicle battery to ensure a sufficient charge level when the car is next required for use on the road. In [69], a linear programming based peak shaving methodology was proposed to schedule power consumption in a home area with V2G enabled EV.

In [67], a comprehensive review of V2G simulation tools in power and energy systems was presented. This review shows the importance of managing the EV charging and discharging regimes in energy systems with high shares of DER. According to [70], V2G energy storage allows a greater utilisation of available renewable electricity compared to stationary battery storage.

In Chapter 3, a study case was drawn to simulate the impact of V2G with different EV charging rates on the reduction of excess electricity (CEEP) and CO_2 emissions in energy systems with high shares of DER.

2.3.3 EV in Localised Energy Systems

EV in localised energy system with aggregated small scale DER can be leveraged to manage energy flows in a group of buildings in communities. According to [71], significant peak reduction could be obtained with an integrated DER system including demand side management (DSM). Figure 2.4 shows the aggregation of buildings to provide DSM and achieve peak reductions for a localised energy system.

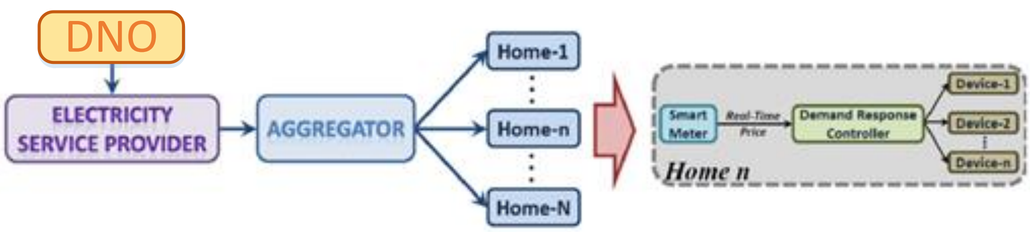


Figure 2.4: Aggregated local energy system [71]

In **chapter 3** of this thesis, a local energy system with high shares of DER was simulated and electricity import reduction for EV and V2G was evaluated.

2.4 INTEGRATION OF DER INTO DISTRIBUTION NETWORKS

Distribution networks have been traditionally designed to receive power from the transmission system and distribute the power to local customers [6], [7], [27]. This means that power flows (active and reactive) from higher to lower voltage levels. However, due to the increased penetration of DER in customer premises, the flow in the network becomes bi-directional. Significant network impacts could arise as a result of the bi-directional power flow as presented in [6], [27]–[30]. The most relevant network impacts of DER connection are thermal constraints (for transformers and cables), voltage rise (for generation connection) and the voltage drop (for EV connection), network losses and problems associated with the tap setting mechanism for the on-load tap changers in transformers.

With the envisioned high uptake of EV in energy systems, the strain on the LV network with RES connection increases. This gives an opportunity to develop energy management systems that will aggregate the connection of DER in distribution networks to meet constraints.

In Chapter 6, the impact of several optimised scenarios of distributed energy systems was evaluated based on voltage profile issues and energy losses on a modelled distribution network.

2.4.1 EV in Distribution Networks

The impacts of EV on LV distribution networks were investigated in [18], [30], [72]. In [68], large scale charging control of aggregated EV/PHEV, V2G frequency regulation, and participation in electricity markets were developed. With DER integration into the LV distribution networks, the complexity of the future energy systems requires complex artificial intelligence methods, optimisation, and agent-based computing [73]. The aim of the work in [73] is to aggregate EV and DER in a VPP and formulate an algorithm that will respect the technical constraints of the network while increasing the visibility of DER. In [18], the effect on the cables thermal loading and the overloading of the distribution transformer as a result of EV integration was extensively studied at the microgrid level using Monte-Carlo method. In [28], [29] the impact of DER integration into the distribution network was presented. In [30], [32], [72], the effects of EV on peak demand on the national level demand was investigated as well as the impact on distribution networks, particularly on steady state voltage, transformer loading and the power line losses. In [74], the technical parameters required for EV with V2G capability to participate in frequency regulation was presented.

In Chapter 4 of this thesis, a method is developed to simulate the EV charging in a microgrid with different levels of DER integration using controlled and uncontrolled EV charging regimes. The voltage profiles and energy losses for summer and winter scenarios were then evaluated.

2.4.2 Management of DER

In [75] and [6], an Optimal Power Flow (OPF) technique, was used to characterise and develop a single operating profile for a Technical VPP with an aggregated load represented by the active and reactive power components. The characterisation of the Technical VPP was presented as follows:

- DER generation profiles.
- Generation limits.
- The minimum stable output from DER generation.
- Maximum generation and load capacity of the Technical VPP.
- Ramp rate.
- Frequency response characteristic.
- Voltage regulating capability.
- Fault levels.
- Fault ride-through characteristics.
- Efficiency.
- Operating cost characteristics.

In [76], [77] an agent-based tool referred to as PowerACE was used to quantify the potential contribution of grid connected vehicles in balancing generation from RES. The simulation method described in [76] is a national case study of Germany and the state of California. To provide generalised models for the analysis of DER and EV, the concept of EV control in an aggregated portfolio of DER is required. In the conventional power system, the Transmission System Operator (TSO) has been responsible for the system security. Increased penetration of DER and EV in residential premises will require active network management in the distribution network. This represents a radical departure from the conventional central control in the power system to a distributed control paradigm, which is applicable to thousands, possibly millions of DER and EV [78], [79]. Using distributed control in the power system means that DER can be decomposed into microgrids or autonomously controlled systems with a central system control. The concept of managing a portfolio of DER sometimes referred to as VPP, can be used to aggregate controllable groups of DER which can be utilised in system and energy management services. In **chapter 4**, the impact of controlled EV charging with aggregated RES on the customer side was evaluated in a benchmark microgrid model.

ToU tariffs have been used to manage DER in energy systems (see [52], [79], [80]). Two main ToU tariffs are currently in use in the UK (i) the economy 7 and (ii) Economy 10. These tariffs charge lower tariffs during a specific number of hours.
The economy 7 tariff is a ToU tariff offering seven off-peak hours (11:00 PM to 6:00 AM) of low electricity rates [81]. About 9% of the UK residential electricity customers are subscribed to this tariff [82]. The remaining hours of the day are charged at high tariff rate.

Economy 10 Tariffs (popularly known as "Heat wise") offers 10 hours of off-peak electricity, which the energy supplier charge at a discounted rate. Like in the case of economy 7, the economy 10 tariff best suits residential electricity customers with storage heaters.

ToU tariffs are not fully implemented in the UK except for economy 7 and 10 but have well been deployed in other parts of the world like California USA. In the case of dynamic ToU tariffs, the assumption is that there is a wide-spread adoption of smart meters. According to the Low Carbon Networks Fund (LCNF) project [79], a strong agreement for the deployment of multi-rate tariffs was observed, 91% of the survey respondents agreed that dynamic ToU tariff should be applied on a wider scale. This agreement is only specific to the survey respondents and cannot be a generalised to a UK-wide scale.

A summary of the related literature to the integration of DER (with and without the consideration of EV/V2G) into the distribution grid and at the customer premises is given in Tables 2.2 and 2.3. Table 2.2 summarises the literature with the consideration of EV while Table 2.3 illustrates the related literature when EV are considered in the DER generation system.

Table 2.2: A summary of related DER studies with consideration of EV

Method	Scope of Study	Research Gap	References
Time Coordinated OPF (TCOPF)	Using TCOPF formulation to control PHEV storage units to minimise energy losses in the distribution network.	Thermal storage for CHP technologies was not considered. Also, stationary battery storage and PV were not considered.	[83]–[85]
EV Integration into a VPP	Case study EV Integration into a VPP was demonstrated.	The value of EV integration into the VPP in terms of electricity reduction was not demonstrated.	[32], [86]
Energy Management System modelled in MATLAB	Investigated the effects of charging point availability on the economics of a VPP.	The impact of optimised VPP on distribution network was not evaluated.	[87]–[89]
Multi-Agent System for Managing VPPs	An architectural solution for the management of aggregated DER in a microgrid is introduced.	Network constraints not considered in the agent system.	[32], [90], [91]
V2G in VPP	A case study on the utilisation of V2G as a distributed energy storage system in a VPP.	Local system cannot buy or sell electricity (autonomous).	[92], [93]

Table 2.3: A summary of related DER studies without the consideration of EV

Method	Scope of Study	Research Gap	References
Optimisation of a VPP	Finding information required to build a local VPP for active control in a distribution grid.	No investment analysis on the adoption of DER.	[94], [95]
Operation Optimisation in a Microgrid	Operational Optimisation applied to maximise profit for a local energy area.	PV and Wind power were not considered in the local energy area.	[96]
Dispatch Optimisation Using Linear Programming	Aggregation of DER in a VPP to minimise conventional power plants costs due to poor RES forecast.	Market prices and energy storage were not included in the system studied.	[97]
Electricity Cluster Oriented Network	Dynamic Models of renewable energy generators developed in MATLAB to study the feasibility of coordinating loosely coupled independent local energy systems.	Investment costs/analysis not considered.	[98]
Economic Evaluation of DGs in a Local Energy System	DG and storage load management in different markets.	The impact of the optimised system was not evaluated on the distribution network level.	[99]
Integration of DER into an Aggregated Energy System	The technical and Commercial viability of the VPP was described.	The value of aggregated DER could provide in the management of distribution grids could be further explored.	[75], [78]

In the surveyed literature above, the value of EV and stationary battery storage are not reflected in a multi-level energy system study (large energy system, local energy system, distribution grid and at the customer premises).

The work reported in this thesis sets out to explore, simulate and test the extent to which EV and stationary battery storage can be utilised to maximise the utilisation of

stochastic RES electricity generation. In **chapter 5**, an energy management optimisation problem was formulated to manage charging and discharging of battery storage for an existing PV generation system using wholesale ToU tariffs. The optimisation problem was formulated based on the customer side of the meter. In **chapter 6**, an optimal investment analysis for the adoption of DER in a group of aggregated buildings aggregated as a mid-rise apartment is simulated as an optimised distributed energy system. The impact of the optimal distributed energy system on a modelled microgrid was evaluated using a soft-linking procedure.
Section 2.5 below reviews the optimisation techniques (being the one the key technique used in this thesis) used in the simulation and analysis of energy systems.

2.5 OPTIMISATION METHODS

In **chapter 5 and 6**, the optimal battery storage charging and discharging are evaluated. A Mixed Integer Linear Programming (MILP) technique is applied for simulation of the case studies of chapter 5 and chapter 6. Optimisation techniques have traditionally been used for optimising schedules of large generators in power systems. The following sections present a review of optimisation methods of which the MILP is used in Chapters 5 and 6.

2.5.1 Formulating a Problem

Optimisation of a function

In any optimisation problem, an objective which must be solved within certain boundaries referred to as constraints. Figure 2.5 shows the sequence for finding a solution to an optimisation problem. To formulate an optimisation algorithm, there is a need to identify the objective of the optimisation problem [100], [101].

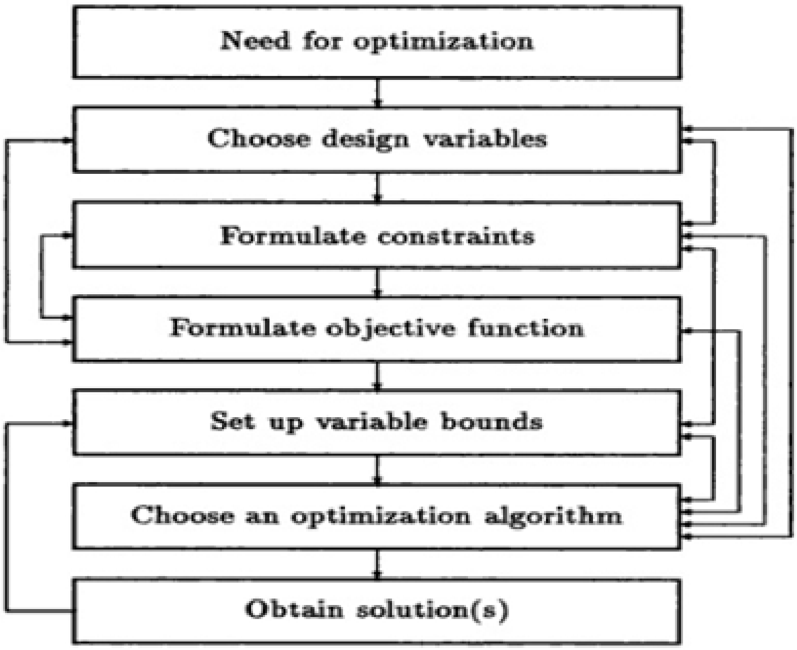


Figure 2.5: Optimal design procedure [102]

Decision variables

The decision variables sometimes referred to as design variables are the unknowns in the optimisation problem and will need to be determined by solving the problem. The speed and efficiency of the optimisation simulation depend on the number of decision variables to a large extent [103].

Constraints

With the design variables identified, the constraints or limitations to such a problem must be chosen. The constraints express the relationship between design variables and other parameters in order to meet the requirement of a physical phenomenon or limitation in resources [104]. Some examples of constraints are battery state of charge in EV and battery storage, voltage boundaries in distribution networks, thermal ratings of distribution network cables. The constraints may take the form of equality (=) or inequality (Less or equal to ≤, or greater than or equal to ≥). According to [102], most constraints in design problems are of the inequality type.

Objective function

The next step after deciding the constraints is the formulation of the target objective referred to as the objective function. There may be multiple objective functions in an optimisation problem which is referred to as multi-objective optimisation. The objective function may be minimised or maximised. With the aid of duality principle, minimisation can be converted to maximisation by multiplying with a factor of (-1) [31], [101], [102],.

Variable bounds

The variable bounds delineate the extent of the optimisation problem by selecting the minimum and maximum bounds on the decision variables.

2.5.2 Optimisation Methods

According to [31], [103], there are two main categories of the optimisation techniques:

(i) Optimisation methods based on numerical and mathematical methods.

(ii) Artificial Intelligence (AI) methods.

The numerical methods are summarised as follows [31]:

- Linear Programming (LP).
- Interior Point.
- Quadratic Programming.
- Non-LP (NLP).
- Integer/Mixed Integer Programming (MIP)/ (MILP).
- Dynamic Programming.

In **chapter 5** of this thesis, an MILP was formulated to manage battery operation for an existing PV generation system.

2.6 Optimised Distributed Energy Systems and Network Constraints

DER planning in energy systems are mainly discussed from the perspective of DNO [105]–[107], electricity customers and large retail aggregators [108], [109].

2.6.1 Customer Optimised DER Systems

Several optimisation models are widely used for finding the optimal configuration and operation of onsite distributed energy technologies. The main objective in most of these models is to find the optimal configuration of distributed energy technologies that will meet a certain demand with the least cost and CO_2 emissions [110]–[112]. Hybrid Optimisation Model for Electric Renewables (HOMER) is an optimisation tool that finds the best microgrid configuration with least Net Present Cost (NPC) [113]–

[116]. DER-CAM is an MILP tool for evaluating adoption options for onsite DER in customer premises [109], [117]–[119].

In [120], a model to determine the optimal DER technologies based on minimising the annual cost of the system was presented. On the other hand in [121], an MILP modelling framework was developed for a microgrid in order to evaluate the optimal system configuration based on the flexibility of DER generating technologies. In [122], an energy management system to maximise profit for a microgrid was developed.

In **chapter 5** of this thesis, an MILP was developed to maximise battery charging and discharging to maximise FiT revenue for an existing PV generation system with ToU. In the reviewed literature above, the network constraints were not considered in the optimisation of the distributed energy system. This implies that some optimal solutions for these systems may not be possible to integrate due to a violation of technical quality constraints like voltage excursions, thermal limits and power losses.

2.6.2 DNO Controlled DER Systems

The DNO perspective of managing distributed energy systems is to use DER in managing distribution network operation and deferring network investments. In [5], an optimisation framework was proposed to manage DNO owned storage devices in order to maximise network assets utilisation.

The vast majority of the DNO perspective is for planning and operation of the distribution network which optimises location and size of network assets and energy storage for minimising cost incurred by the DNO [4], [5], [106], [123]–[125].

2.6.3 Integrated DER Systems with Network Constraints

In the literature reviewed, the constraints of the electricity network are not considered in the formulation of the optimisation problem. From the network perspective, the distributed energy systems are not optimised based on the objectives of DER aggregators or owners. This is partly due to the computational challenge of integrating non-linear Alternating Current (AC) power flow equations in such optimisation models. Linearising these equations to include a Direct Current (DC) power flow instead of AC power flow in the formulation of the model is a method of avoiding the computational time constraint of the AC power flow as presented in [126]. However, such simplifications may not represent a realistic impact of network constraints on the optimal objective function of such models [127], [128]. Most of the existing optimisation models do not take into account the constraints of the local distribution network and assume the network can accommodate all operations and configurations of onsite distributed energy technologies [11], [126].

In **chapter 6**, of this thesis, the impact of an optimised distributed energy system on a modelled microgrid was evaluated with an AC power flow using a soft-linking procedure. Different scenarios of the optimised distributed energy systems were simulated and evaluated based on voltage excursions and energy losses.

2.7 RESEARCH GAPS

The surveyed literature of EV storage with V2G capability in energy systems with high shares of DER has been reported to achieve different objectives. However, the value of EV with V2G capability and different EV charging rates in a large energy system has not been explored. Therefore, in this study, the value of EV storage with V2G capability in large and local energy systems with high shares of DER was investigated (discussed in chapter 3).

The benefits of a multi-period power flow provide have been identified as important to evaluating the benefits of DGs in microgrids. However, techniques for evaluating the benefit of a multi-period heuristic power flow for a microgrid with high penetration of EV and DGs under uncontrolled and dual tariff profiles were not explored. Therefore, in this thesis, the operational benefits (in terms of voltage profiles and energy losses) of EV storage in a microgrid with DG penetration were quantified and reported in chapter 4.

Maximisation of FiT revenue streams at the customer premises for an existing PV generating system benefiting from the UK FiT system can be achieved by using stationary battery storage. However, research conducted on suitable techniques for the evaluating the value of deploying battery storage for an existing PV system (benefiting from the UK FiT) and impact of storage unit costs (£/kWh) with different electricity tariffs were not found. Therefore, in this thesis, an MILP optimisation technique was developed and simulated to evaluate the value of deploying a stationary battery storage for a PV generating system benefiting from the UK FiT (discussed in chapter 5).

Evaluating the impact of optimised distributed energy systems (with battery storage and high DG penetration) can achieve savings for both the DNO and customer. However, in the surveyed literature techniques for evaluating distributed energy systems are only explored from the DNO perspective or the customer perspective. Therefore, in this thesis, a soft-linking procedure was designed to evaluate the impact (in terms of voltage profiles and energy losses) of optimised distributed energy systems on a modelled microgrid (discussed in chapter 6).

2.8 SUMMARY

In this chapter, the literature relevant to this thesis was analysed. A description of the studied DER was given. The use of EV in large energy systems was presented. Also, the use cases of battery storage services in future electricity supply was analysed to give a background to the ToU optimisation developed in **chapter 5,** for managing battery charging and discharging for an existing PV generation system. A review of network constraints and optimised distributed energy systems was presented to provide a background for the soft-linking procedure developed to assess the impact of optimised distributed energy systems in distribution networks.

DER have been identified as key distributed resources in the future energy system mix. The DER that were described includes (i) wind turbines, (ii) PV, (iii) FCs, (iv) EV and (v) battery storage. The benefits of battery storage services with wholesale electricity and ToU tariffs optimisation was presented since it is studied in **chapter 5**.

EV charging in energy systems with high shares of RES was identified as means of decarbonising the electricity and transport sectors. This is done to provide a background for the case studies simulated in **chapter 3**. The EV charging impacts on distribution network were reviewed. Voltage excursions and power losses were identified as one of the potential issues with DER integration into distribution networks. These criteria are applied on a controlled EV charging in a microgrid with DER developed in **chapter 4**.

Techniques for the **optimisation of distributed energy systems** and its application in the management of a battery storage for an existing PV generation system were described. They are used in **chapter 5** to optimise charging and discharging of battery storage for an existing PV system with ToU.

Optimised distributed energy systems and the assessment of network constraints was presented and the perspective of the DNO and customer/aggregator explained. A soft-linking procedure is developed in **chapter 6** for assessing the impact of optimised distributed energy systems in distribution networks.

Chapter 3

EV Charging in Energy Systems

3.1 Introduction

EV are expected to play a key role in the future of transport sector electrification. According to [129], large scale integration of EV into energy systems has the potential of maximising the utilisation of intermittent RES while minimising CO_2 emissions. The energy import dependency in the UK as of 2012 is 36.5% according to [130], the highest in 40 years. To evaluate the potential of EV to maximise the utilisation of fluctuating RES in energy systems, the CEEP and CO_2 emissions incurred because of EV integration should be evaluated.

The objective of this chapter is to calculate the CEEP and CO_2 emissions with varying levels of wind power integration in (i) large and (ii) local energy systems with and without the integration of EV.

Two scenarios of EV were studied: (i) EV only and (ii) EV with the capability of power flowing from the EV battery to the grid referred to as V2G.

A comparison was made with respect to using different EV charging rate by developing an excel tool with hourly energy demand distributions for wind power generation, electricity demand and electric vehicle energy demand (see Appendix A and B) for a complete year. All these were built into the EnergyPLAN model.

As opposed to previous studies [1], [57], [66], [131] this chapter investigates the value of EV with V2G capability in a GB national and local energy system with high penetration of DER. The chapter gives a brief review of the modelled input parameters in EnergyPLAN and presents two case studies to evaluate the value of EV with V2G capability in i) GB large scale system (2012 reference scenario and 2020 alternative scenario and (ii) GB local system.

3.2 ENERGYPLAN MODEL

The EnergyPLAN is a deterministic energy systems analysis tool which optimises the operation of a given energy system based on defined input parameters [57], [132], [133]. The model is used for building national or regional energy systems for the analysis of large scale integration of RES. The main objective is to model a variety of options that can be compared with one another based on defined input conditions. The EnergyPLAN model is a simulation platform rather than optimisation tool for analysing different pathway options for energy systems (electricity heating and transportation). The model is aggregated in its description of the energy systems in contrast to models in which each individual component is described. For example, the district heating systems in EnergyPLAN are aggregated into groups of heating systems.

Figure 3.1 shows the modelling framework of the model, which integrates the electricity, heating and transport sectors.

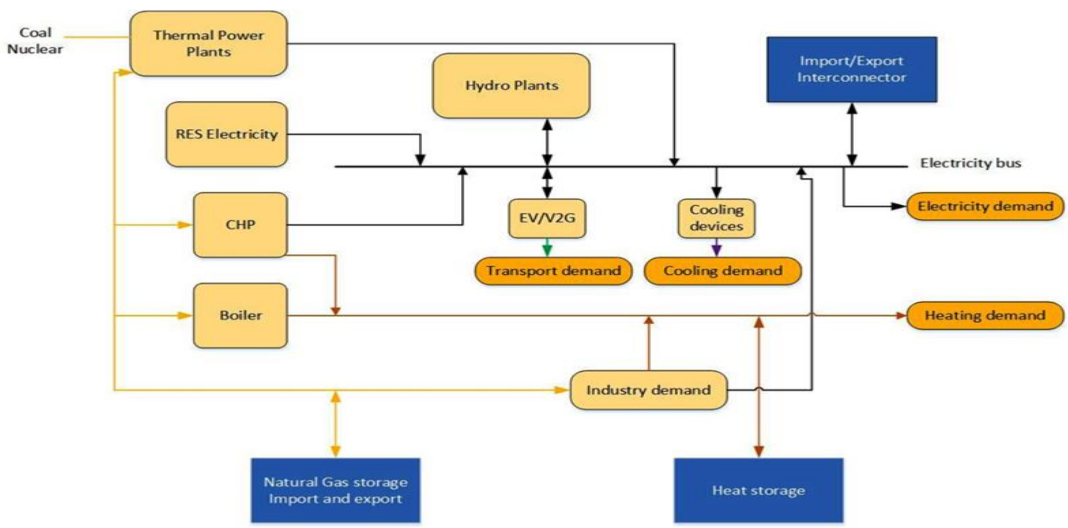


Figure 3.1: Schematic of the EnergyPLAN model

3.2.1 Electricity Demand

The GB system in the future growth scenarios of 2020 has a high penetration of RES [134]. A reference model for the GB energy systems was created in EnergyPLAN considering wind penetration from 0-180TWh. This represents 50% of the electricity demand in GB. Table 3.1 shows the data sources of all the input parameters in Table 3.2 shows the aggregated energy inputs for GB.

Table 3.1: Data sources of the GB EnergyPLAN model parameters

Input Parameter	Data Sources
Electricity demand (TWh)	National Grid UK Future Energy Scenarios 2012 [135] Note: Demand in 2020 excludes electricity demand used for EV in the EnergyPLAN Model.
CHP capacity MWe	DECC Energy Digest, 2012 [130].
District heating demand (TWh)	DECC Energy Digest, 2012 [130].
Total wind power (MW)	ELEXON 2012, National Grid Generation data by fuel type [136] and National Grid Gone Green UK Future Energy Scenarios 2012 [135].
Nuclear (MW)	DECC Electricity Generation by fuel type, 2012 [130], [137].
Condensing power capacity (MW)	DECC Electricity Generation by fuel type, 2012 [130], [137].

Table 3.2: Aggregated GB energy demand for 2012 and 2020

Input	2012	2020
Electricity demand (TWh)	320	322
CHP capacity MWe	6111	11300
District heating demand (TWh)	49	49
Total wind power (MW)	6488	30855
Nuclear (MW)	10633	12000
Condensing power capacity (MW)	68352	62100

To model the reference system in EnergyPLAN, data was collected for 2012 and then compared with future scenarios. The inputs of the model were collected from studies, reports and energy systems projections for the GB, (see, [134]–[138]). These inputs include electricity demand, hourly demand distributions, renewable energy capacities, hourly wind power productions, individual heat demands, industry heat demands and transport demands. UK transport data was collected from [139] which includes hourly traffic distributions and hourly transportation demand.

3.2.2 Heating Demand

Heating demand data is synthesised using normalised hourly distributions in EnergyPLAN with space heating and hot water consumption data obtained from [134]–[138] for the UK.

3.2.3 Transport Energy Demand

The reference model for EV integration into the transport sector in EnergyPLAN is based on the energy consumption of internal combustion cars. The reference models are compared with two alternative scenarios:

- EV without V2G: EV with smart charging but without V2G capability.
- EV with V2G: EV with smart charging and V2G capability.

For modelling the transportation demand for all the studied cases considered, an average battery capacity of 30kWh is assumed for each EV [1]. Based on this assumption and the data collected for the GB, an electric vehicle fleet was defined for GB which is given in Table 3.3.

Table 3.3: GB transport inputs

Inputs	Reference Model	With EV Integrated into the Model
Number of cars (Millions)	28.7	1.7
Petrol and Diesel Consumption (TWh/year) in the reference model with no EV and in the case when 1.7 Million EV are added to the model	456.68	450.94
EV Electricity consumption (TWh/year)	–	5.744
Battery storage capacity (GWh)	–	57.1

EV energy demand

According to [59], there are 33.9 million registered vehicles in the UK, of which 28.72 million are private cars. It was assumed that 6% of the total number of private cars is the 2020 high penetration scenario which implies that by 2020 there will be approximately 1.7 Million EV in the UK. Table 3.5 describes the input parameters used for modelling EV in the transport sector of the model.

Table 3.4: Input parameters for modelling EV in the transport sector

D_{EV}	Transport demand of electric cars in TWh/year
δ_{EV}	The hourly distribution of transportation demand
P_{line}	The power capacity of the grid connection to EV
$V2G_{DrivingShare}$	The share of EV with V2G capability on road and not connected to the grid
$\eta_{Charger}$	The efficiency of the grid to battery connection
η_{Inv}	The efficiency of battery to grid connection
E_S	The capacity of the battery storage in GWh
$V2G_{Connection\_Share}$	The share of parked V2G connected to the grid

Equation 2 calculates the energy demand for each EV which implies that the total electricity demand (D_{EV}) of aggregated EV can be computed:

The EV fuel efficiency and the annual distance in this study are assumed to be 6 km/kWh and 20,000 km/year respectively [140]. To calculate the battery hourly demand as an aggregate of the number of EV, Equation 3 was used together with the hourly traffic distribution data from the UK department of transport.

$$Energy\ /\ \text{year/vehicle} = \frac{\text{Distance/year/vehicle (km/year)}}{\text{Vehicle Efficiency (km/kWh)}} \tag{2}$$

$$e_{EV} = \frac{D_{EV} \times \delta_{EV}}{\sum \delta_{EV}} \times \eta_{Charger} \tag{3}$$

Figure 3.2 represents the hourly distribution of transport demand derived from Equation 3 by using the hourly traffic distribution data (δ_{EV}) from the study of the GB energy system. This is integrated into the model and use for the analysis EV integration into the energy system.

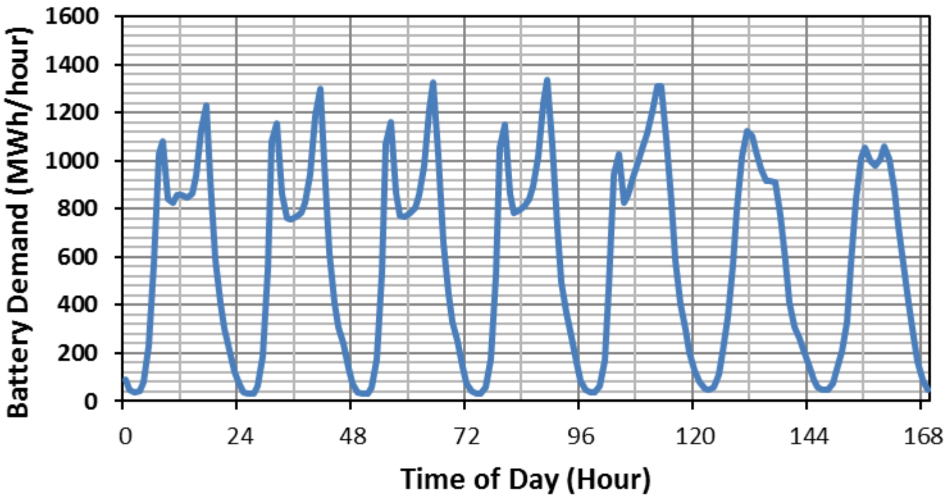


Figure 3.2: Hourly battery demand for a typical week

To analyse the energy system by integrating EV with Vehicle to Grid (V2G) capability, Equation 4 was used to compute the hourly distribution for a year of the aggregated V2G fleet (p_{V2G}):

$$p_{V2G} = P_{line} \times V2G_{Connection\_Share} \times \left[(1 - V2G_{DrivingShare}) + V2G_{DrivingShare} \times (1 - \frac{\delta_{EV}}{Max(\delta_{EV})}) \right] \quad (4)$$

Equation 4 consists of three main factors. The first factor is P_{line} which denotes the power capacity of the entire EV with V2G capability fleet. This is multiplied by $V2G_{Connection\_Share}$, which is the fraction of parked cars that are plugged into the grid. The second factor in parenthesis $(1 - V2G_{DrivingShare})$ represents the minimum fractions of cars that are parked. The sub-factor $(1 - \frac{\delta_{EV}}{Max(\delta_{EV})})$ calculates the fraction of cars on the road at each hour. The third factor is a multiplication of $V2G_{DrivingShare}$ and $(1 - \frac{\delta_{EV}}{Max(\delta_{EV})})$, which calculates the additional fraction of cars parked during non-rush hour periods. The subject of the formula in Equation 4 p_{V2G} calculates the power capacity of all connected EV with V2G capability at any given hour.

A combination of $V2G_{DrivingShare}$, $V2G_{Connection\_Share}$ and charging rates (P_{line}) could be made to obtain the V2G fleet distribution. In the study carried out for the GB energy system, p_{V2G} was computed using 3kW, 7kW, 11kW and 22kW as P_{line}. The different charging capacities were used to evaluate the impact of EV charger capacity on the reduction of curtailed electricity from excess wind energy generation in the GB EnergyPLAN model. The charging capacities (3 – 22 kW) were based on the National Grid/Ricardo report: Bucks for Balancing [68]. For the realistic scenario the parameters $V2G_{Connection\_Share}$ and $V2G_{DrivingShare}$ were assumed to be 0.7 and 0.2 respectively [1]. This means that 20% of the EV are on the road driving, and the remaining EV are connected and charging. Figures 3.3 represents the power capacity of the aggregated EV with V2G capability for every hour of a typical week.

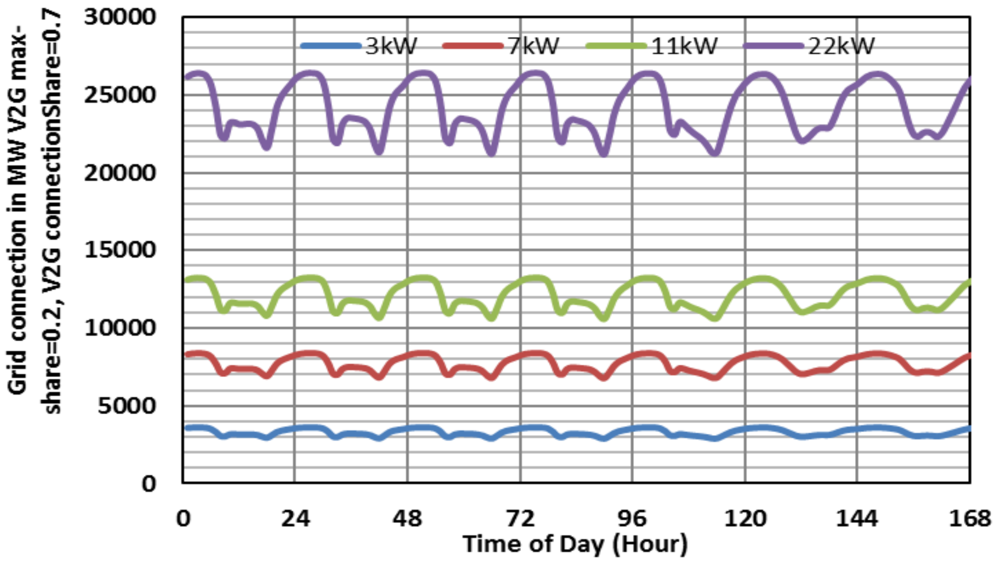


Figure 3.3: V2G distribution for GB

A 2020 projected number of 1.7 million EV for the GB transport system means that for an 11kW per vehicle line capacity, the total instantaneous grid connection is 18.96GW. The aggregated EV with V2G capability capacities for different charging rates is computed as a function of the number of EV. Table 3.6 summarises the aggregated V2G capacities:

Table 3.5: Aggregated EV with V2G Capacities

Charger Rate (kW)	V2G Capacity (GW)
3	5.17
7	12.06
11	18.96
22	37.91

The model refines the computations from errors by iterating the calculations till an equilibrium is reached between the initial and final battery capacity. The initial EV battery state of charge (storage content) is defined as 0.5 of the battery storage capacity [1], [57], [140]. The next section evaluates the studied system with two case studies i) national ii) local level.

3.3 CASE STUDIES

The results of the GB energy system are computed in terms of two graphs: CEEP and CO_2 emissions against a range of wind power penetration representing 0-50% of the electricity demand. The UK localised energy system simulation results are computed in terms of electricity import into the local system against a range of wind power penetration. The snapshots of the EV and V2G distributions integrated to the EnergyPLAN model for all the studied cases is shown in Appendix A and B.

3.3.1 GB Energy System

Three different scenarios were modelled for the electricity sector in 2020 in addition to conventional power plants:

- CHP scenario considering a system with CHP capacity of 11,300 MWe.
- A non-CHP scenario where the CHP capacity is removed from the system to evaluate the impact of CHP on the excess of electricity production.
- GB model with different EV charging rates.

The non-CHP case was added to the simulated scenarios as a reference to compare the impact of CHP based heating in the reduction of CO_2 emissions in the GB EnergyPLAN model.

CHP case

Figure 3.4 shows the result of the GB model described in previous sections. As the wind penetration increases beyond 80 TWh, there is little excess. An increase of 60 TWh yields an excess of 12.27 TWh and rises exponentially to 59.51 TWh at 180 TWh of wind penetration in the reference case. There is little improvement in the reduction of CEEP in the case of GB system with EV without V2G capability. This is because only 1.7 million EV were modelled in comparison to 28.7 million combustion cars used for the reference case.

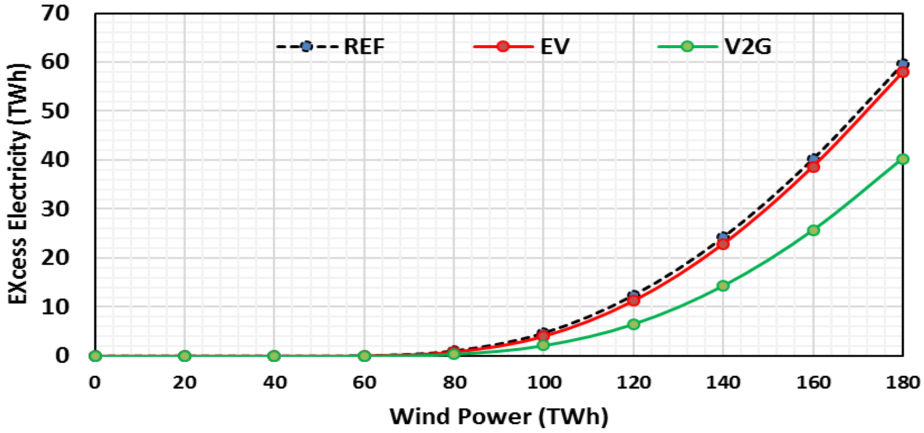


Figure 3.4: CEEP for the CHP case

Figure 3.6 shows the CO_2 emissions for the GB CHP reference case, with alternative EV and EV with V2G capability.

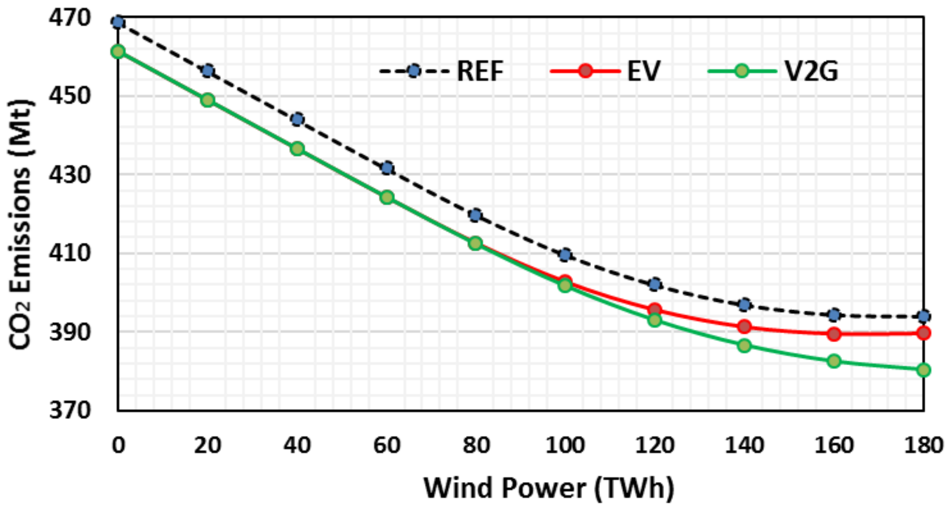


Figure 3.5: CO_2 emissions for the CHP case

In the V2G case, there is a significant reduction in CEEP from 59.51 TWh to 40.21 TWh at 180 TWh of wind power penetration. In Figure 3.6, it could be seen that CO_2 emissions decrease for all the three cases with increasing penetration of wind power into the system. The gap between the reference and the two alternative cases shows a constant reduction in CO_2 emissions of about 7 Mt, until about 140-160 TWh of wind power penetration. At that point, the CO_2 emissions of the EV without V2G case stop decreasing, while for the EV with V2G the drop continuous. This shows that at higher penetration of wind power, EV with V2G capability can store this energy and send it back to the grid when required.

Non-CHP case

In the non-CHP system represented in Figures 3.6 and 3.7, similar results were obtained compared to the alternative CHP system. However, it could be seen from Figure 3.7 less excess electricity is generated in the system because CHP electricity production was removed. It also takes more than 80 TWh of wind power penetration before excess electricity is recorded. This creates an opportunity for more wind power integration in the system using EV with V2G capability than in the CHP case. In this scenario, only 22 TWh of excess electricity was produced compared to 40 TWh excess produced in the CHP case.

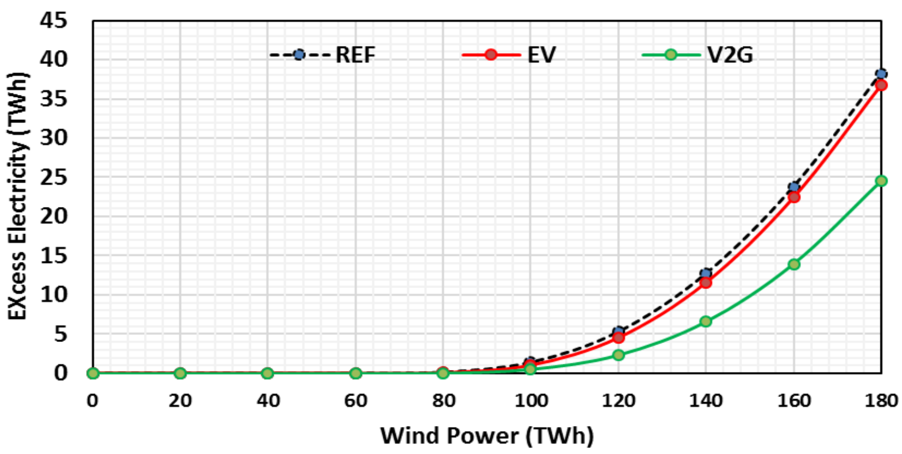


Figure 3.6: CEEP for the non-CHP case

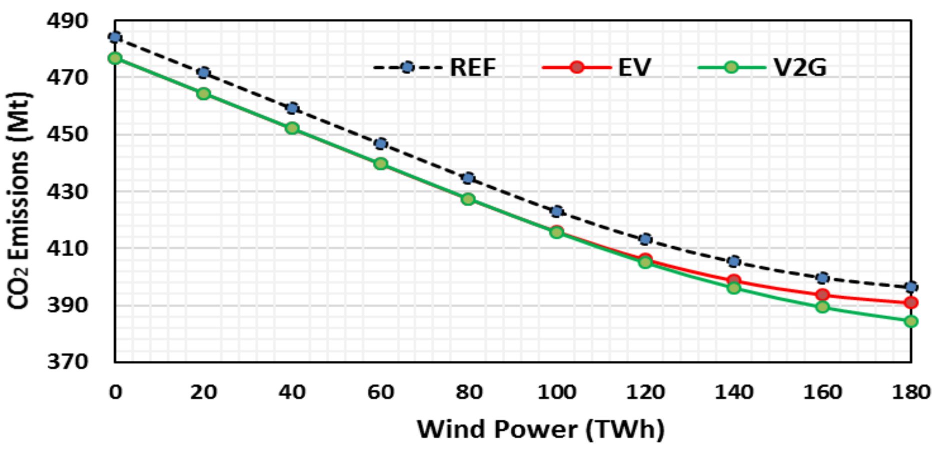


Figure 3.7: CO_2 emissions for the non-CHP case

Figure 3.7 shows that the CO_2 emissions increases in the non-CHP system. This is due to the CHP heating demand transferred to district heating based on boilers. It is also noticed an increase in CO_2 emissions from 470 to about 490Mt compared with the results of the CHP system. This shows the value of CHP in the reduction of CO_2 emissions.

GB Model with different charging rates

The model was simulated for EV charging rates of 3kW, 7kW, 11kW and 22kW. Figures 3.8 and 3.9 shows the CEEP and CO_2 emissions for the respective charging rates. The different charging rates show a significant reduction in CEEP for the EV with V2G (see Figure 3.8). The value of the storage in EV with V2G capability case increases as the charging rate is increased. Also, the CO_2 emissions decrease with increasing wind power penetration for all cases considered. The V2G with higher charging rates decreases CO_2 emissions significantly at higher penetrations of wind power (see Figure 3.9).

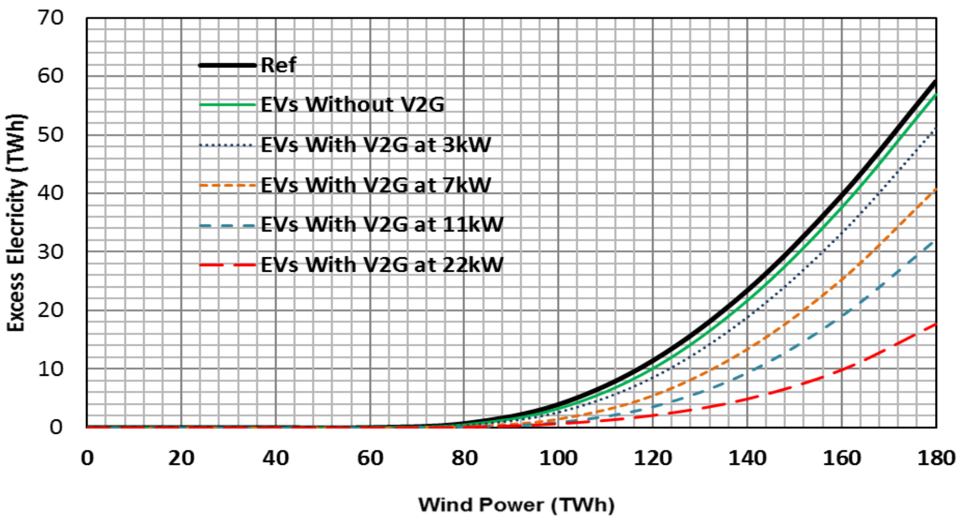


Figure 3.8: Curtailed electricity for the GB case with different EV charging rates

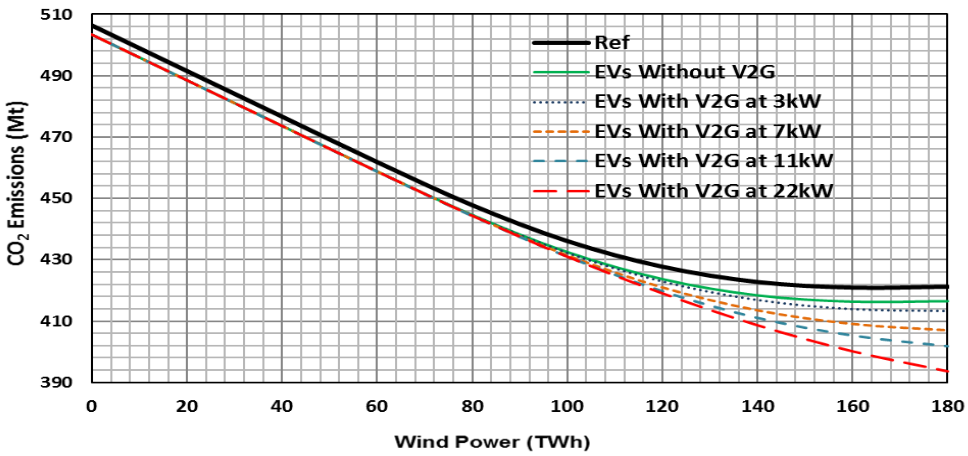


Figure 3.9: CO_2 emissions for the GB case with different EV charging rates

At higher penetration of wind power, EV with V2G capability can store excess energy and give it back to the grid when required. This energy replaces part of the energy generated from conventional power plants and the CO_2 emissions are further reduced. The results also show that there is an insignificant difference between the CEEP when EV are charging without V2G for different charging rates. This explains the reason why different charging rates for the EV without V2G capability are represented in one scenario, namely "EV without V2G capability". Additionally, CEEP decreases significantly (see Figure 3.8) as the charging rate is increased from 3kW to 22 kW which shows that V2G has the potential to significantly reduce CEEP.

3.3.2 GB Local Energy System

In this case study, the concept of the aggregated portfolio of DER was applied to a typical local energy system with high penetration of small sale DER. The system was modelled in EnergyPLAN using data from [86], [141]–[143]. Figure 3.10 shows schematic the local energy system with generators, loads and EV.

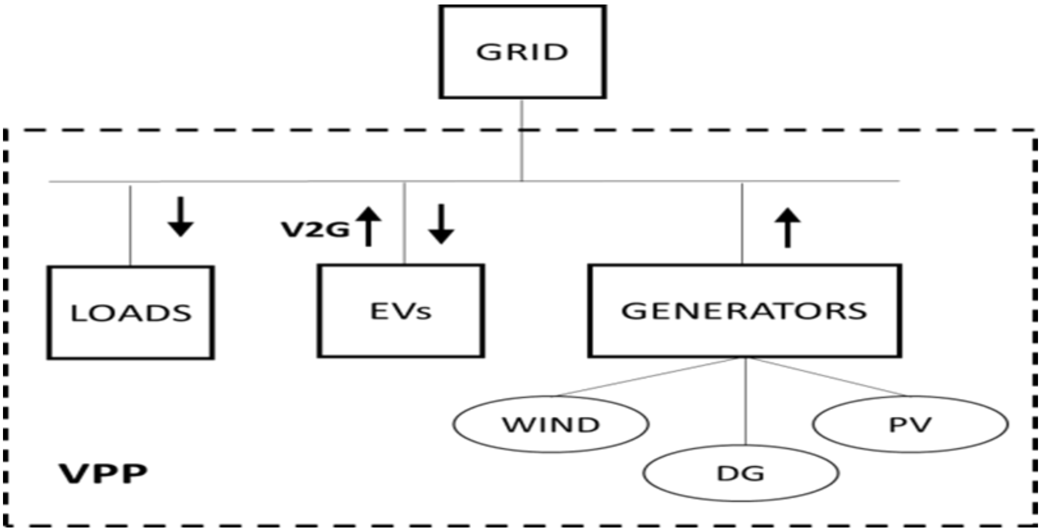


Figure 3.10: Schematic of the modelled local energy system

In this local system, loads represent the electricity demand of 18432 residential customers. This number of customers is based on UK Generic Distribution Network (UKGDN). The UKGDN consists of 48 microgrids each with 384 customers (384 × 48 = 18432) [142]. Figure 3.11 shows the studied local system. The dotted line shows the modelled local area with 18432 residential customers.

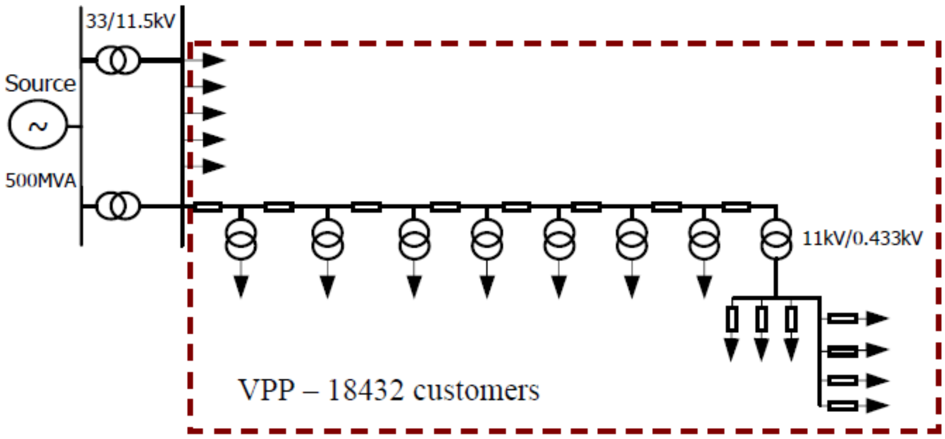


Figure 3.11: Studied Local System with 18432 residential customers

Generators refer to all the aggregated energy production from the wind, PV and CHP. In addition, EV can behave both as loads and flexible storage. When they are charging, there is energy consumption, but in V2G mode they act as flexible storage, storing and giving energy back to the system when it is required.

To model the local energy system in EnergyPLAN electricity load profile data was collected from [143] with the assumption of a daily minimum of 0.16 kW and a maximum of 1.3 kW as described in [141]. The high penetration scenario of microgeneration for the year 2030 was taken from [142] and summarised in Table 3.7. All data in Table 3.7 is based on the high microgeneration penetration of the article: (Carbon optimised Virtual Power Plant with Electric Vehicles, [142]). As it can be seen from the Table 3.7 the total installed power capacity of the local energy system is approximately 20 MW.

Table 3.6: Microgeneration penetration scenario for the studied system [142]

Microgeneration Type		**Unit (kW)**	**Microgeneration Units**	**Total Power (kW)**
Wind Turbines		2.5	1824	4560
Photovoltaic		1.5	960	1440
Fuel Cell (Natural Gas)	**CHP Units**	3	1536	4608
Micro Turbine (Biogas)		3	720	2160
Stirling Engine (Wood Pellets)		1.2	6144	7372.8
Total		11.2	11184	20140.8

Based on the studies carried out by [62], there are 30 million vehicles in the UK with a population of over 60 million. It is assumed that half of the customers in the local energy system have private cars, and according to the high penetration scenario of [141], [142] for 2030, there will be 70% penetration of EV in the local energy system. Based on the domestic nature of the studied local energy system, a 3 kW charging rate was used in modelling the EV within the system.

The model for the local energy system was simulated for a range of wind power penetration from 0 to 100% of the annual electricity demand of the localised energy system (91.9 GWh, evaluated from the load profile). The aim of the simulation is to evaluate the electricity import reduction in the local energy system for EV without V2G and EV with V2G capability as penetration of small scale DER is increased. Three different scenarios were modelled:

- Only internal combustion cars.
- EV without V2G capability (70% penetration).
- EV with V2G capability (70% penetration).

Simulation Results

Figure 3.11 shows that all three cases, the electricity import into the local energy system decrease with increasing penetration of wind power into the VPP. The reference case with no EV shows the system reduces import more than the scenario with EV. This is because EV are added loads to the system, however, the V2G scenario with added storage capability can reduce electricity import more than the scenario with EV having no V2G capability.

The import reduction rate as a percentage for the V2G case is represented in Figure 3.12. With V2G, Figure 3.12 is showing that with no wind penetration, there is about 24 % decrease in electricity import due the added capability of the V2G.

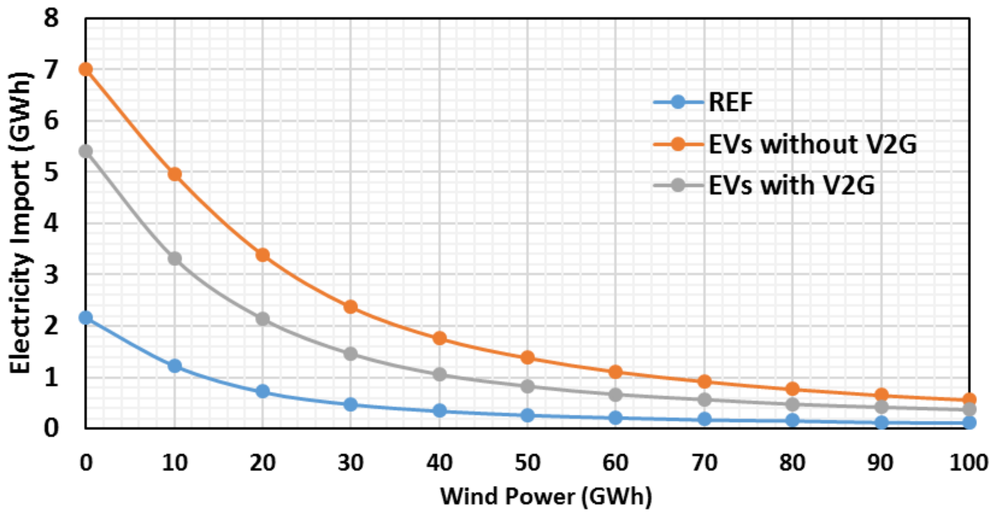


Figure 3.12: Electricity import in the studied local energy system

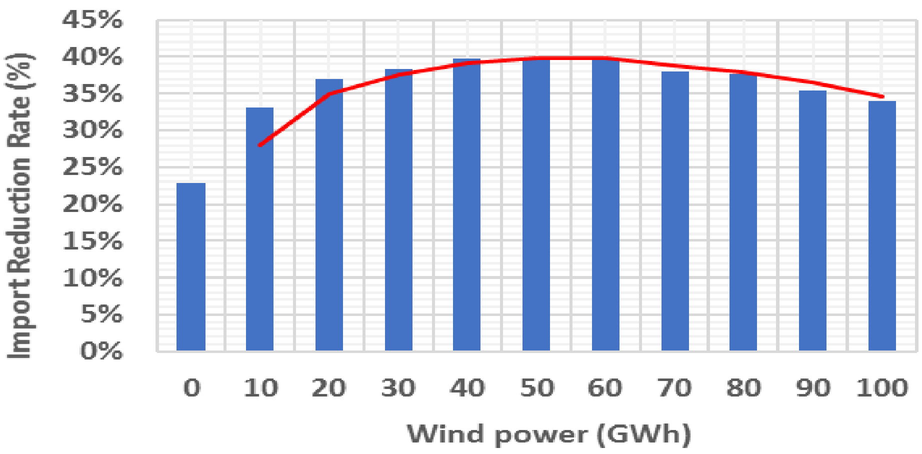


Figure 3.13: Import reduction rate with V2G

It could also be seen that with 10 GWh wind power penetration, the electricity import to the localised energy system is decreased by 34 % when EV have the V2G capability. It is worth mentioning, that the optimal reduction rate is attained with 40 GWh of wind power penetration in the case with V2G (see Figure 3.12).

3.4 DISCUSSION

The results in this section have shown the value of EV storage with V2G capability in large energy systems of reduction of CEEP and CO_2 emissions. Also, up to 34% electricity, import could be reduced when EV with V2G capability in a local energy system with high DER penetration. The non-CHP case was only used a reference point to evaluate the impact of CHP plants and CO_2 emissions in large energy systems. It is seen from the results that the power rating of the EV charger (3 – 22 kW) plays a significant role in the amount of curtailed electricity (CEEP).

This method for the GB has not been previously carried out in the surveyed literature [1], [57], [66], [131].

The input data used in the model have been drawn from plausible sources (see Table 3.1). However, these input parameters can be replaced by equally plausible alternatives which will result in different outcomes.

Also, the EnergyPLAN model is a one node energy balance model and does not model the electricity network. Going forward, there is a need to evaluate the value of EV integration in a local distribution network with DG penetration. Therefore, in chapter

4, the analysis of EV integration in a modelled microgrid with high DG penetration is further explored.

3.5 SUMMARY

In this chapter, the integration of wind power in combination with EV with and without V2G capability as flexible storage was studied in three case studies:

- One for the GB national energy system with CHP and non-CHP scenario.
- GB national model with various charging rates of 3kW, 7kW, 11kW and 22kW.
- A local energy system with high shares of aggregated DER.

In the first study case, the **GB energy system** was modelled using the 2020 projection data for electricity, heating and transport sectors in EnergyPLAN. In this scenario, two different energy systems were considered, one with CHP and the other without CHP which is typical for the GB energy system. For these two systems, three different vehicle fleets were examined: one only with internal combustion cars, and the other two with EV with and without V2G capability. The results showed that EV with V2G capability can reduce CO_2 emissions and excess electricity production. That means that more wind power can be integrated with of V2G as a flexible storage.

In the second case study **(GB with different charging rates)**, the results show that there is an insignificant difference between the CEEP when EV are charging without V2G for different charging rates. This explains the reason why different charging rates for the EV without V2G capability are represented in one scenario, namely "EV without V2G". However, in the V2G scenario, CEEP decreases significantly as the charging rate is increased from 3kW to 22 kW which shows the potential of V2G in the significant reduction of CEEP.

In the last case study case, **a localised energy system** was simulated in EnergyPLAN tool. This system consisted of **18432** customers with microgenerators and EV with V2G and without V2G capability. It was found out that EV with V2G capability can reduce the electricity imports, which makes the system more self-sustaining. This shows that integrating wind power when using V2G as a flexible storage, can reduce the electricity imports in the studied local energy system by about **40%.**

CHAPTER 4

EV CHARGING MANAGEMENT IN A MICROGRID DISTRIBUTION NETWORK

4.1 INTRODUCTION

RES in LV networks are causing important changes in the operation of the electric power system[73], [144]. Generally, the integration of RES largely occurs in medium and LV networks. This leads to the concept of the microgrid, defined as a small scale, LV distribution network mainly configured to supply electricity and heat loads in small communities and local industrial sites[145].Microgrids have the potential to optimise the performance of LV distribution networks. Technically, a microgrid is defined as an autonomous group of controllable plug and play micro-sources and energy storage devices optimally placed and operated for the benefit of the customers [7].

DER are increasingly becoming a key component in the operation of distribution networks. This is partly because of the technology improvement of many DER technologies such as wind energy, photovoltaic, FC, and CHP. The integration of such DER is important for the reduction of CO_2 emissions and the improvement of operation, efficiency and security of distribution networks[146]. Microgrids as active LV networks can potentially provide an increase in the reliability and quality of services offered to the users. For this research, the benchmark microgrid [147] is used. The DER considered in the model include Micro-CHP, Wind Energy Conversion System (WECS), solar PV and FC.

Two research projects, **microgrids and more microgrids** were funded by the European Commission to investigate microgrids. The main objectives of these projects were to increase the penetration level of renewable energy generation and use DER to improve the reliability of power supply through intentional islanding, reduce the overall system losses, and enhance the power quality [148]. This demonstrates the importance of microgrids in the future electric power system. EV uptake in the transportation sector is widely anticipated to be a key policy driver that will facilitate the shifting of transport energy demand from fossil fuels to an electric power system based on RES and low carbon microgenerators [149].

The increasing penetration of EV charging is likely to occur in LV networks EV mobile batteries in VPPs and microgrids can be used to increase the utilisation of intermittent RES [72], [150].

EV charging can be carried out in an uncontrolled manner or in a controlled pattern using two-step tariff profiles like the economy 7, also referred to as a dual tariff model. In the uncontrolled mode, the utility/aggregators make no effort to control or influence the timing and amount of EV charging loads [151]. The dual tariff charging mode is a policy based on a lower electricity price during the night hours. This could create saving opportunities for the EV owners which begin their charging at 23:00 and finish at approximately 6.00 [152].

In this **chapter** a time series load flow study over a 24-hour period was carried out using a benchmark microgrid model described in [153], with different EV charging modes and different DG penetration levels. The network is modelled using typical residential load profiles for summer and winter and typical DG generation profiles obtained from the [31], [143], [154]. The modelling study is carried out to evaluate the impact of EV charging profile (uncontrolled and dual tariff) and the integration of different penetration levels of DG in the microgrid. It was evaluated the voltage profiles and energy losses for **summer and winter** load profiles representing different loading conditions of the network.

The DGs impact on voltage level in the benchmark model is presented. The impact of EV charging on the voltage level considering different levels of penetration and charging modes (uncontrolled and dual tariff) is analysed. Also, the energy losses in the benchmark model for a fixed penetration of DG and for two EV charging modes (uncontrolled and dual tariff) and for summer and winter load profiles were analysed.

4.2 BENCHMARK MICROGRID MODEL

The Conseil International des Grands Réseaux Électriques (CIGRE) benchmark microgrid simulated in this chapter is based on the data from [147], [155]. The reference microgrid (Figure 4.1) with residential loads and representative renewable sources from DER technologies, was modelled using MATPOWER a power system analysis toolbox based on MATLAB.

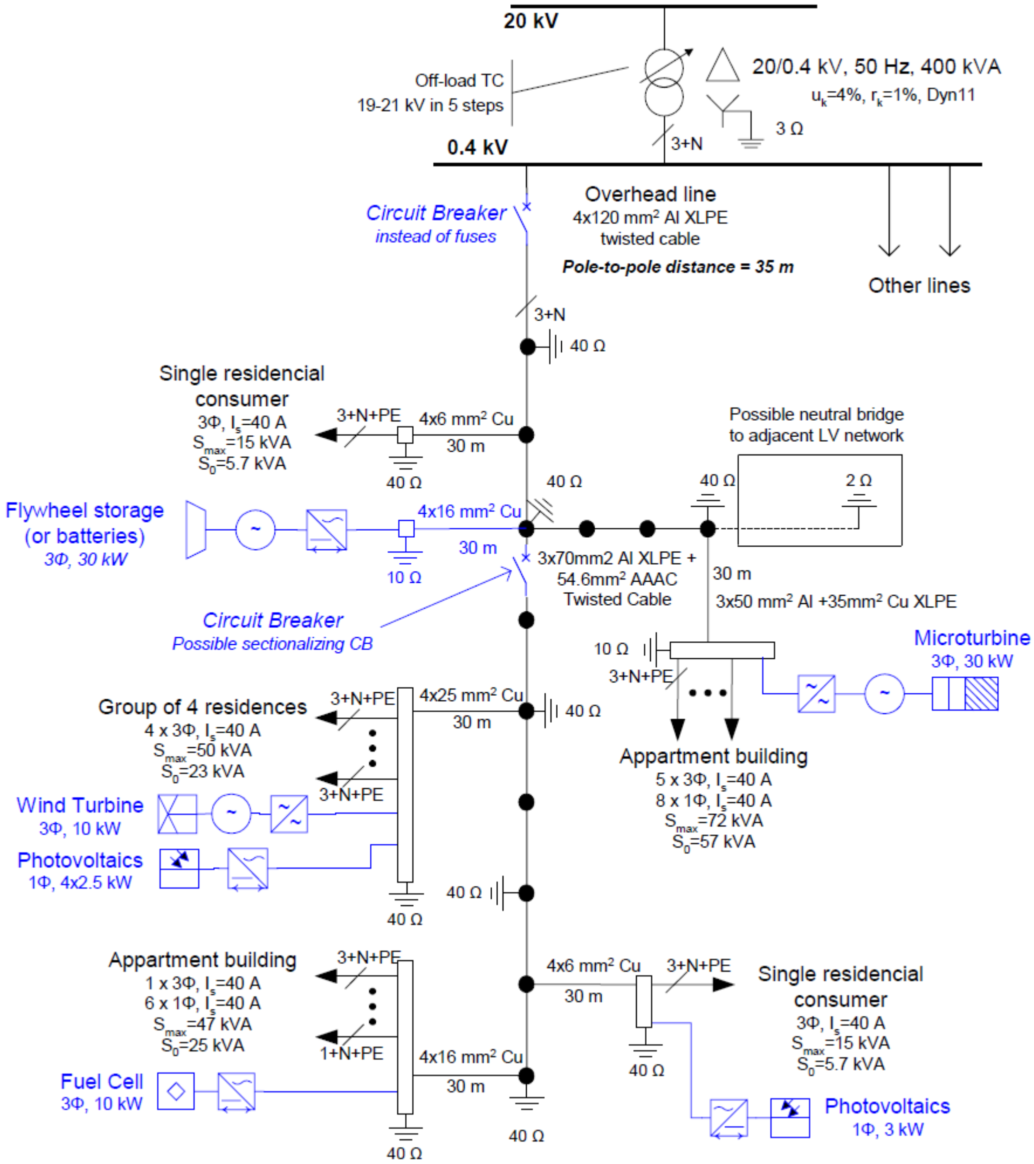


Figure 4.1: CIGRE Benchmark model [147]

4.2.1 Network Data

Figure 4.2 shows the buses modelled buses of the CIGRE benchmark model. The network parameters were taken from the CIGRE microgrid model (see Figure 4.1). An MV/LV transformer connects the microgrid and the Medium Voltage (MV) distribution network.

The grid electricity import into the microgrid is kept to a minimum in times when electricity supplied by onsite DGs is adequate to meet the electricity demand.

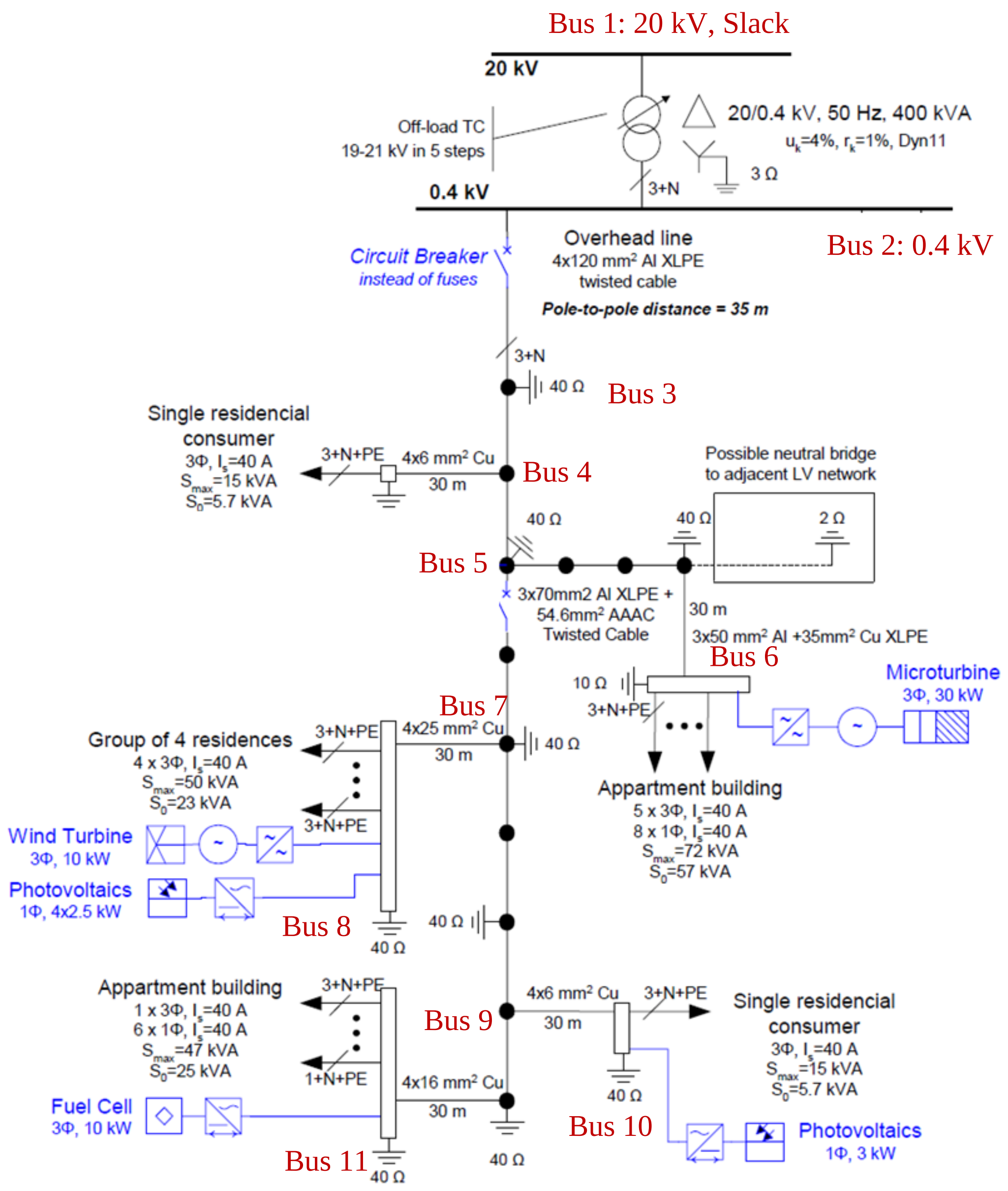


Figure 4.2: Configuration of the benchmark microgrid

The MV/LV transformer parameters and network cable data are given in Table 4.1 and 4.2 respectively. The transformer is a 400 kVA, 20/0.4 kV with the impedance of 0.01+ j 0.04 p.u. The transformer is equipped with off-loading taps at the High Voltage (HV) winding, providing a typical regulation range of ± 5%. Its connection group is Dyn11, corresponding to a delta-connected primary and wye-connected secondary winding.

Table 4.1: Microgrid transformer parameters

Capacity (kVA)	Primary (kV)	Secondary (kV)	R (per unit)	X (per unit)
400	20	0.4	0.01	0.04

Table 4.2: Microgrid data

From bus To bus	Branch	Conductors Type	Rph (Ω/km)	Xph (Ω/km)	Length (km)	Per Unit values
1-2	Transformer	-	-	-	-	0.01+j0.04
2-3	1	Overhead line 4x120 mm^2 Al XLPE	0.284	0.083	0.07	0.0497+j0.0145
3-4	2	Service Connection 4x6 mm^2 Cu	3.690	0.094	0.03	0.276+j0.007
3-5	3	Overhead line 4x120 mm^2 Al XLPE	0.284	0.083	0.035	0.0248+j0.007
5-6	4	Overhead line 3x70 mm^2 Al	0.497	0.086	0.105	0.130+j0.022
5-6	4	Service Connection 3x50 mm^2 Al	0.822	0.077	0.03	0.061+j0.0057
5-7	5	Overhead line 4x120 mm^2 Al XLPE	0.284	0.083	0.07	0.0497+j0.0145
7-8	6	Service Connection	0.871	0.081	0.03	0.0653+j0.0060

		4x25 mm^2 Cu				
7-9	7	Overhead line 4x120 mm^2 Al XLPE	0.284	0.083	0.105	0.0745+j0.0217
9-10	8	Service Connection 4x6 mm^2 Cu	3.690	0.094	0.03	0.276+j0.0075
9-11	9	Overhead line 4x120 mm^2 Al XLPE	0.284	0.083	0.035	0.0248+j0.0072
9-11	9	Service Connection 4x16 mm^2 Cu	1.380	0.082	0.03	0.103+0.0062

The per unit data was calculated with the assumption of the base values for apparent power and voltage as shown in Equations 5, 6 and 7.

$$S_{base} = 400\ kVA \tag{5}$$

$$V_{base} = 0.4\ kVA \tag{6}$$

$$Z_{base} = \frac{V_{base}^2}{S_{base}} \tag{7}$$

Based on the value of Z_{base}, the per unit (p.u) values of the branch parameter resistance R_{pu} and reactance X_{pu} are obtained from Equations 8 and 9.

$$R_{line} = R_{ph} \times length \Rightarrow R_{pu} = \frac{R_{line}}{Z_{base}} \tag{8}$$

$$X_{line} = X_{ph} \times length \Rightarrow X_{pu} = \frac{X_{line}}{Z_{base}} \tag{9}$$

4.2.2 Load Data

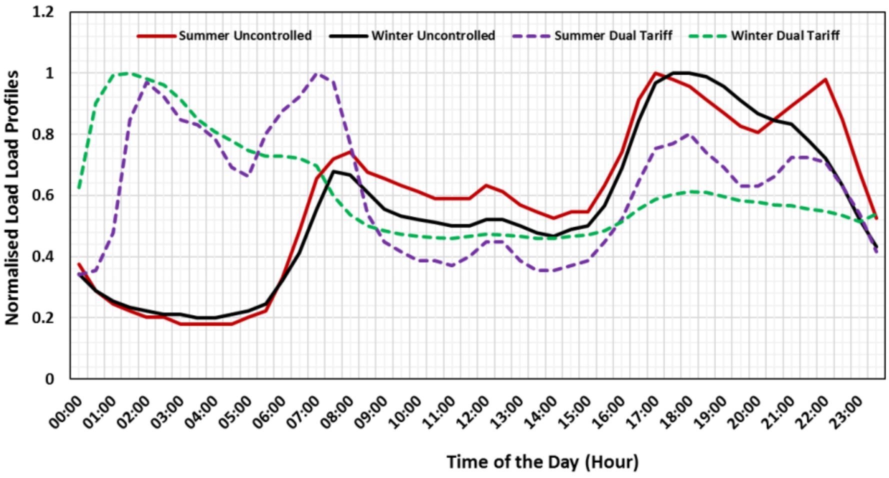
In the modelled microgrid, the loads are mainly different types of residential buildings. Table 4.3 gives a description of the loads and power factor (to calculate the active power) in the modelled buses.

Table 4.3: Load description

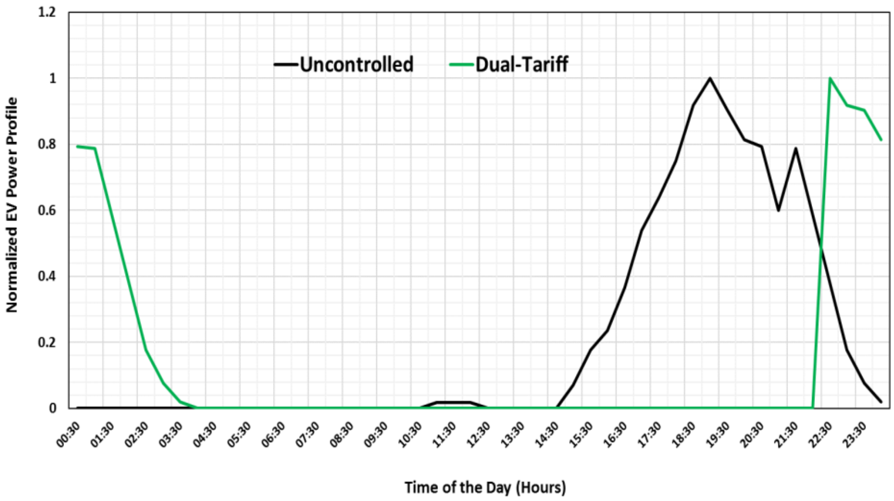
Bus	Description	So (min) (*kVA)*	S (max) (*kVA)*	Power factor
3	Single Residential	5.7	15	0.85
6	Apartment Building	57	72	0.85
8	Group of four residences	23	50	0.85
10	Single Residential	25	47	0.85
11	Apartment Building	5.7	15	0.85

The maximum demand (Smax) of each consumer group, depends on the number of individual consumers within each group and is found using standardised coincidence factor for residential consumers, which become smaller as the number of consumers increases. For this reason, the contribution of minimum demand (So) of each group to the maximum demand of the feeder will be further reduced. The total maximum demand of the aggregated loads is 116 kVA (given by the sum of all So in Table 4.3). The power factor of all consumers is assumed to be 0.85.

A standard domestic unrestricted load profile is taken from [143] and was used in modelling the domestic loads in the microgrid. This is achieved by fitting the minimum and maximum loads presented Table 4.3 into the load profile shapes. The load profiles are representing average residential load for weekdays in two typical UK seasons: Summer and Winter. Figure 4.3A shows the normalised summer and winter load profile for uncontrolled residential and dual tariff Elexon load classes. The additional EV load profile is shown as a normalised profile (uncontrolled and dual tariff) in Figure 4.3B.



(A)



(B)

Figure 4.3: A) Normalised Elexon Summer and Winter weekdays load profile for uncontrolled and dual tariff load classes [143], [156]. B) Normalised uncontrolled and dual tariff EV load profile.

It could be seen that the normalised summer uncontrolled Elexon load profile has a similar shape with the winter uncontrolled profile. EV load profiles (see Figure 4.3B) are added to the load profiles of Figure 4.3A to obtain the total load profile of each of the buses in the CIGRE microgrid benchmark model.

4.2.3 DG Profiles

The microgrid has different DG technologies. Table 4.4 shows the placement of DGs in the microgrid and their capacities.

Table 4.4: Reference DG in the microgrid

Bus	Description	Capacity (kW)
6	Microturbine CHP	30
8	Wind + PV	10+10
10	PV	3
11	Fuel cell	10

The DG profiles used in this chapter were taken from the United Kingdom Generic Distribution System (UKGDS) [154]. Figures 4.4 and 4.5 shows the generation profiles for the DGs studied in this chapter.

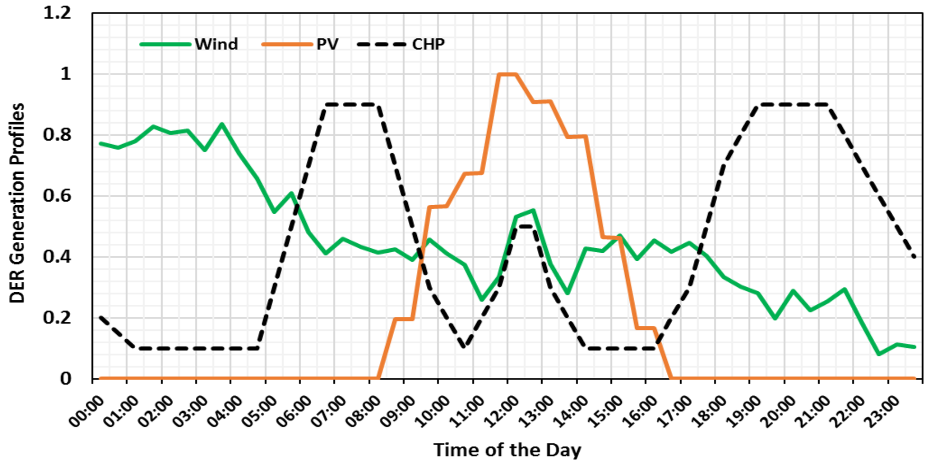


Figure 4.4: Normalised generation profiles for the wind, PV and CHP

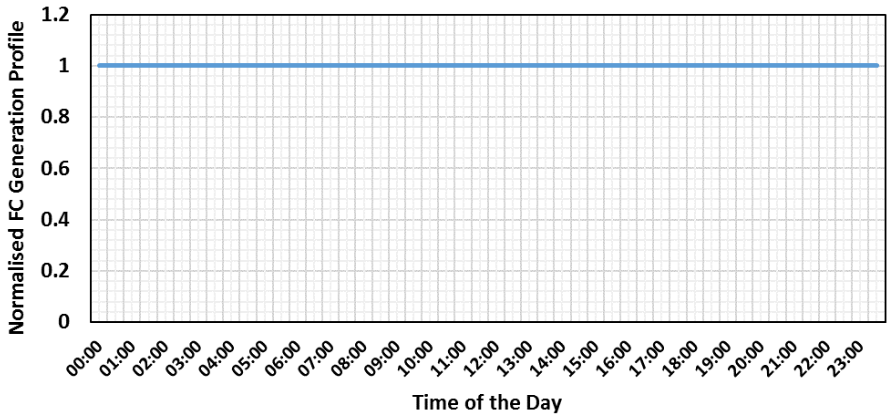


Figure 4.5: Normalised FC generation profile

The DG generation profiles were used as data input for the simulation of the case studies. The PV, wind and CHP the profiles were obtained in a normalised format from the UKGDS and adapted to the DER capacities in the microgrid case study.

To run time series simulations, real power outputs curve for the different types of DGs and typical residential load pattern were obtained from the normalised profiles of Figures 4.4 and 4.5 considering two different loading conditions of the network (winter high and summer low). These profiles (demand and generation) have half-hourly time step, so they represent electricity demand and generation for each half-hour of the day (48 time steps).

4.3 MODELLING PROCEDURE

4.3.1 MATPOWER Description

The microgrid is modelled in MATPOWER, a package of MATLAB script files used for solving power flow and OPF problems [157], [158].

4.3.2 Power Flow Procedure

For the study of the network model, it was used the power flow study commonly referred to as load flow. Power flow is a mathematical procedure based on Newton-Raphson numerical analysis technique. It is used to study steady state analysis during normal operation of the Microgrid. To do this, the operation of the microgrid was assumed to be in a balanced operating condition. Load flow study usually uses simplified notations like a one-line diagram and per unit system. The network model is required to be converted to single line diagram which is a simplified notation for representing a complex three-phase power system. The single line diagram is used in a per unit system format. This expresses the system quantities as fractions of a defined base quantity. When power flow routine is completed the results provide voltage, active and reactive power injection for all the buses of the network. Figure 4.6 shows a flowchart representing the power flow routine used in this study.

The branch data, node data (loads and generation) of the modelled network are passed to MATPOWER. A programming script was then developed in MATLAB environment. This script makes use of a combination of nested loops to simulate the operation with different scenarios of the microgrid modelled in MATPOWER.

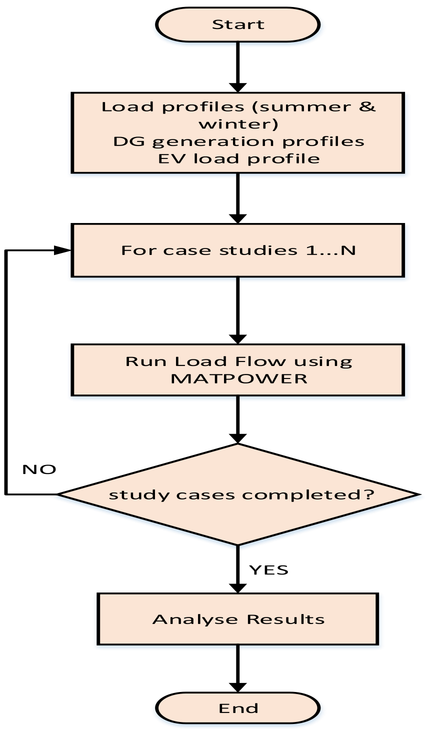


Figure 4.6: Power flow routine for all studied cases

4.4 Case Studies

The case studies described in Table 4.5 were considered and simulated in the MATLAB – MATPOWER model:

Table 4.5: Case study description

Case Study (CS)	Description
CS1	Integration of DGs only (no EV)
CS2	Integration of EV only (no DGs)
CS3	Integration of EV + 50% more DGs than the reference DGs
CS4	Energy losses for different EV and DG penetration

For **CS1**, additional DG penetration level are added as a percentage (0%, 25%,50%,75%, and 100%) considering DGs presented in Table 4.4

In **CS2**, the reference DGs in Table 4.4 stays the same, however, EV uptake levels are considered in the form of a percentage (0%, 25%,50%,75%, and 100%) of the original number of EV uptake shown in Table 4.6.

Table 4.6: Number of EV connected to each bus

Bus Number	Description	
	Number of EV	Charging rate
4	1	3 kW
6	13	3 kW
8	4	3 kW
10	1	3 kW
11	7	3 kW

It could be seen from Table 4.6, that bus 6 is the bus with the highest number of customers and the highest number of connected EV. Therefore, all the load flow results presented in this chapter would be based on bus 6. This is because of the potential large voltage deviations compared to the other buses.

In **CS3**, a 50% increase in penetration level is added to the reference DG level presented in Table 4.4. Then a variation of EV uptake levels based on percentage increments (0%, 25%,50%,75%, and 100%) is simulated in the load flow routine. This is to evaluate the potential of DG contribution in minimising the voltage drop (due to the EV connection). At the same time, it is shown a decrease of the power flow from the grid because EV are charging using the local generation from DG.

CS5 evaluates the microgrid' s energy losses with different (i) EV uptake levels, (ii) EV charging modes and (iii) DG penetration levels into the microgrid.

CS1, CS2, and CS3 are evaluated based on:

- Daily voltage profile.
- Summer and winter network loading.
- Uncontrolled and dual tariff EV charging regimes.

CS4 is evaluated based on:

- Energy losses.
- Summer and winter network loading.
- Uncontrolled and dual tariff EV charging regimes.

4.5 SIMULATION RESULTS

4.5.1 Voltage Profiles

The voltage simulation profiles are presented in this section for all scenarios defined in Table 4.5 and are evaluated based on the 2002 UK Electricity Safety, Quality and Continuity Regulations distribution network steady state voltage statutory limits. These limits are 230V+10% (Upper Limit) and 230V – 6% (Lower Limit) [159], [160].

DG only case (CS1)

To study the impact of DG integration on the voltage excursions at bus 6, different levels of DG penetration were considered. This assumption is based on the continuous development of RES technologies, and the efficiencies improvement of these technologies[161], [162].

Four levels of DG penetration were assumed expressed in percent (25%, 50%, 75%, and 100%) increment, to the reference DG level in the microgrid (see Table 4.4).

Figures 4.7 and 4.8 are presenting the voltage profiles for summer and winter respectively.

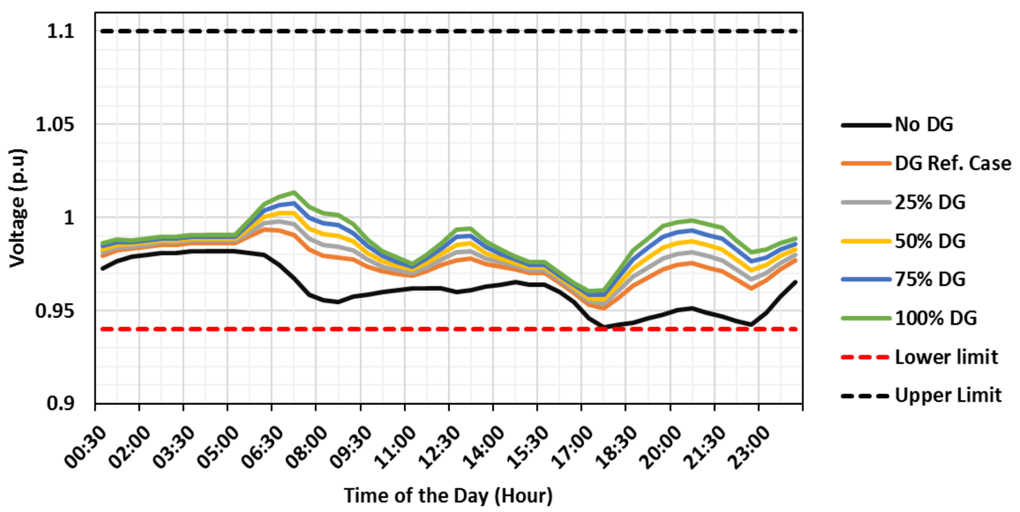


Figure 4.7: Voltage profile in summer

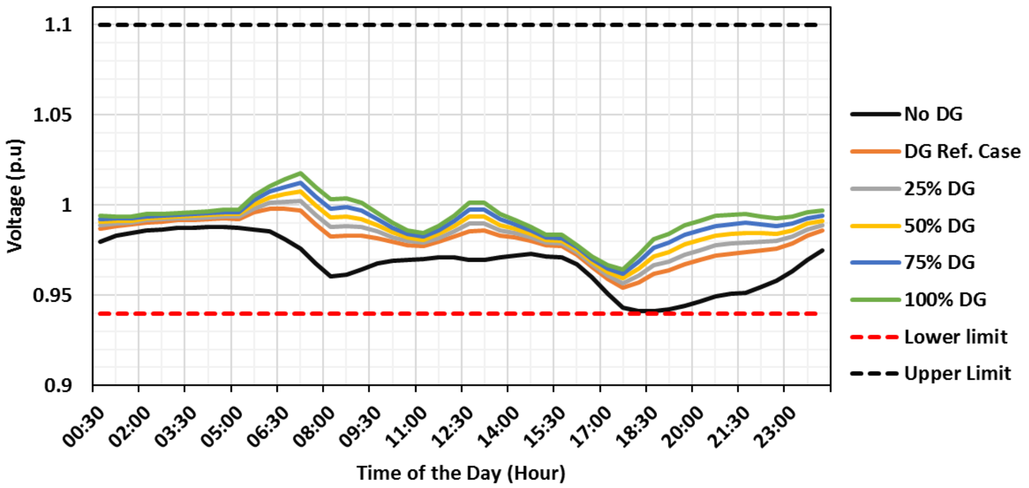


Figure 4.8: Voltage profile in winter

It could be seen that the voltage profile fluctuates within the day. This is caused by the daily variation of the load pattern and the variability of stochastic renewable energy resources. As expected the voltage rises when the DG penetration is increased. The voltage measurements were also found to be within the statutory limits (230 V+10%and -6% in the UK) for both summer and winter scenario. Little difference is observed in the voltage profiles of Figures 4.7 and 4.8 due to the similar shapes of the normalised Elexon load profiles presented in Figure 4.3

EV only case (CS2)

The impact of dispersed EV battery charging in a microgrid is presented in this study case. The assumed charging rate of each EV is 3 kW which is common for most residential applications [1]. The placement of EV in each bus of the microgrid is shown in Table 4.6. EV uptake levels of 25%, 50%, 75% and 50%, taken from [163], were simulated. “Uncontrolled” and “dual tariff” EV charging regimes were considered for managing the EV charging in the microgrid. In the “uncontrolled” charging regime, the EV owners start charging their vehicles when arriving home. However, in the “dual tariff” regime, the EV charging is assumed to be delayed. This charging delay is based on the economy 7 (dual tariff regime) in which between the hours 22:30 and 03:30, a cheaper night electricity tariff is available.

Figures 4.9 and 4.10 presents the voltage profiles for summer and winter respectively.

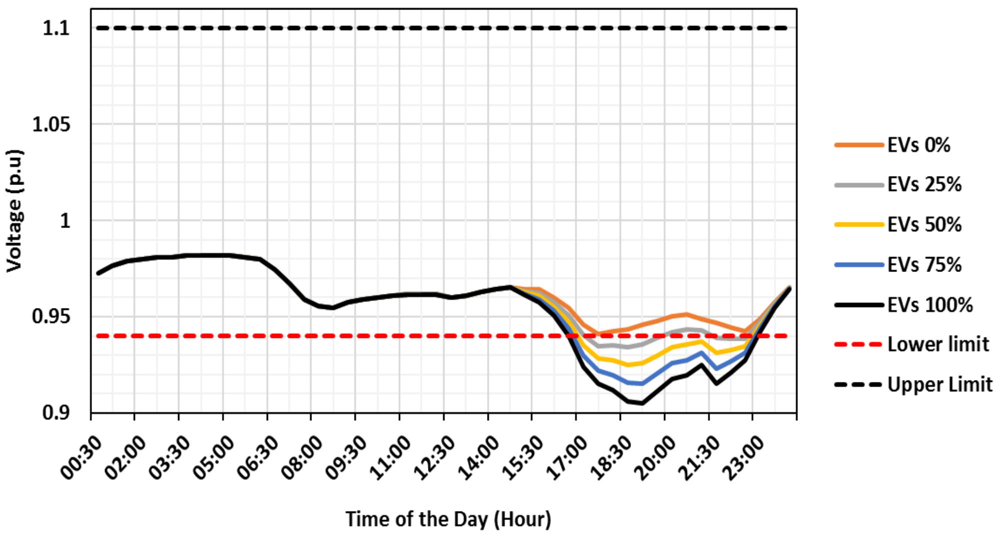


Figure 4.9: Voltage profiles in summer (uncontrolled)

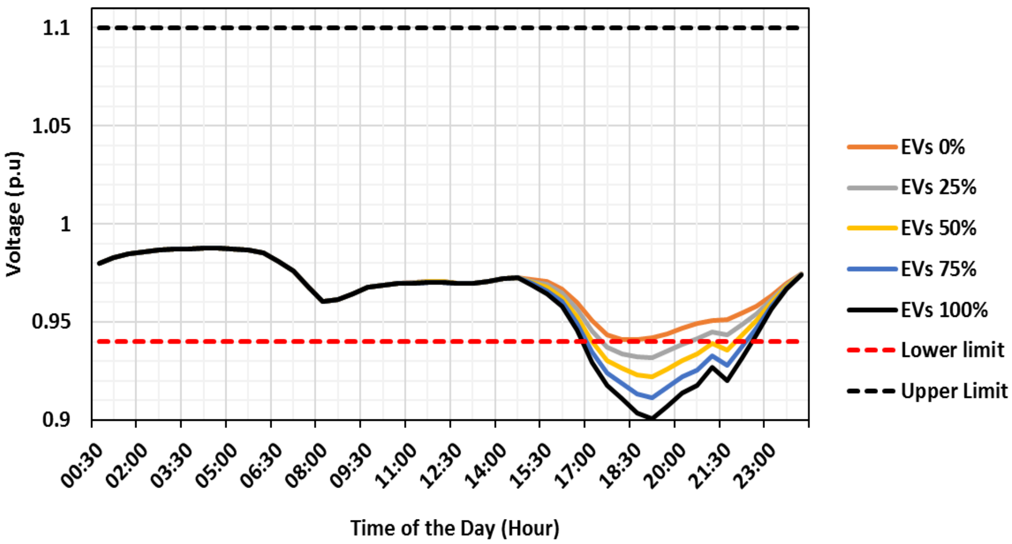


Figure 4.10: Voltage profiles in winter (uncontrolled)

Figure 4.9 shows the voltage in bus 6 for the uncontrolled charging considering different uptake levels of EV. It is noted that between 15.00 – 22.00 hours, the voltage drops from, about 0.94 to 0.91 p.u. Similar voltage excursions occur in the winter case as shown in Figure 4.10, however, the voltage drop is higher due to the higher winter load profile (see Figure 4.3) between the hours 18:30 – 20:00.

Figures 4.11 and 4.12 present the voltage profile for the dual tariff charging considering different EV uptake levels. EV begin charging at 22:00 and finish at hour 03:00.

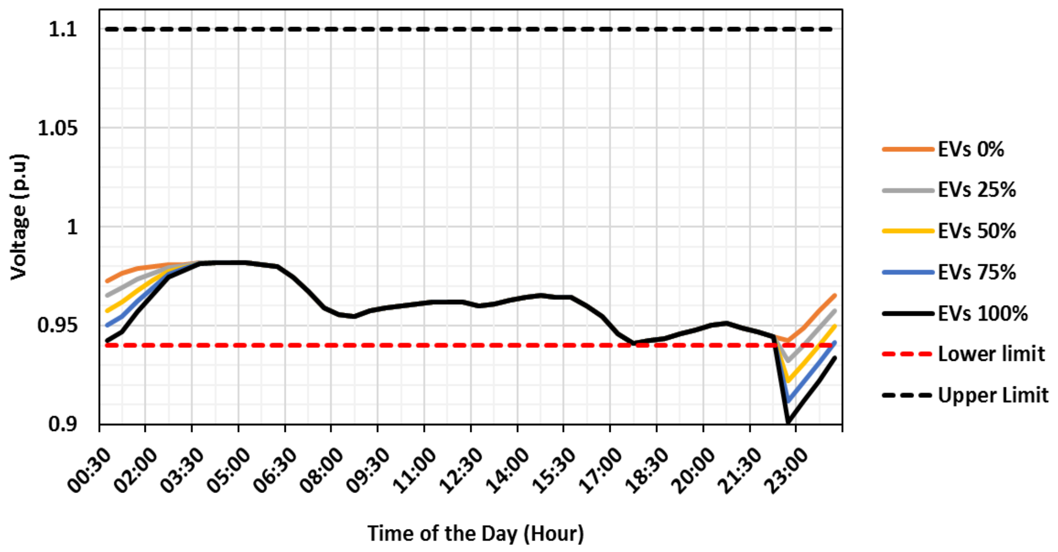


Figure 4.11: Voltage profiles summer (dual tariff)

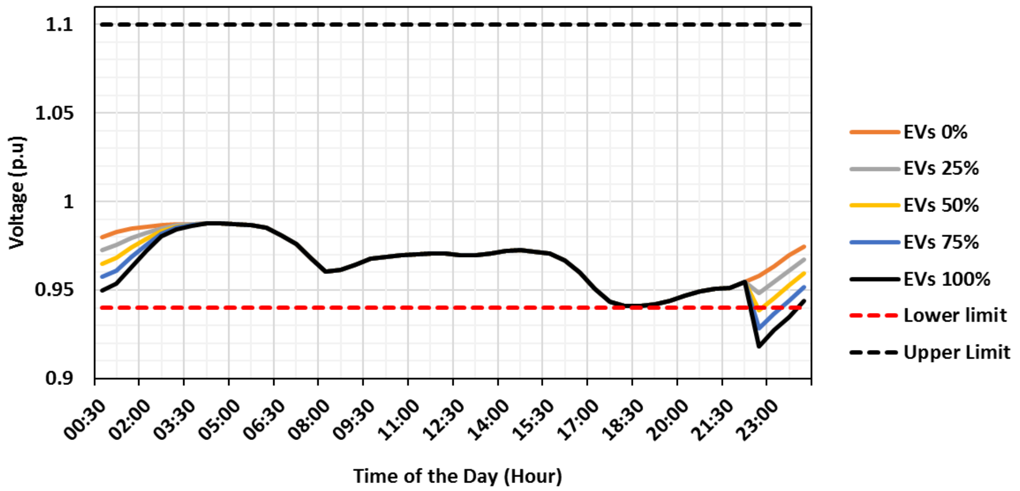


Figure 4.12: Voltage profiles winter (dual tariff)

The voltage drops to about 0.92 p.u. for winter scenario (see Figure 4.12) compared to about 0.9 p.u. for the summer scenario (see Figure 4.11). The voltage drop is more significant in the hours 21.00 to 23.00 compared to the hours 0.00 to 3.00 for both scenarios. In both scenarios, even when EV charging is a controlled manner, there may be some hours that the voltage excursions may occur due to the simultaneous charging of EV within that period.

EV with 50% additional DG to the reference DG level

In this scenario, 150% DG penetration is considered (that is 50% additional DG to the reference DG level in the microgrid) and the EV uptake levels varied from 25% to 100%. Figures 4.13 and 4.14 represents the uncontrolled scenario.

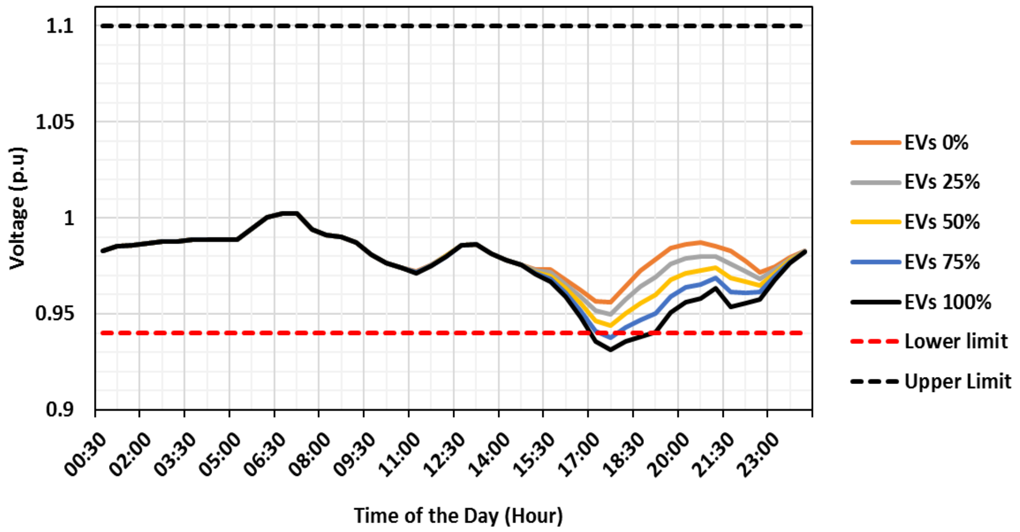


Figure 4.13: Voltage profiles in the summer (uncontrolled)

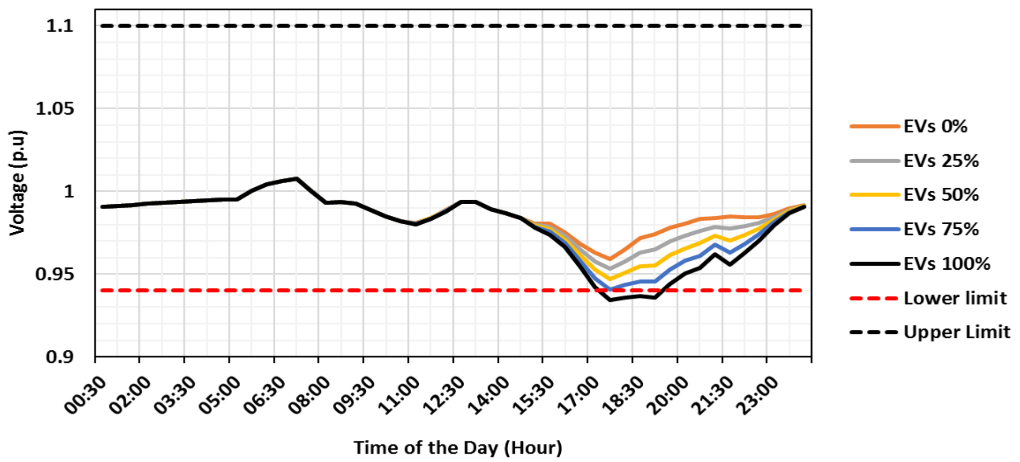


Figure 4.14: Voltage profiles in the winter (uncontrolled)

It can be seen a drop to about 0.93 p.u. between the hours 15.00 – 18.00 for both EV charging scenarios in Figures 4.13 and 4.13. Compared with the reference DG case in Figures 4.9 and 4.13, the voltage excursions are minimised.

With dual tariff EV charging regime, there is a smaller voltage drop between 21.00 to 23.00 hours in the summer case (see Figure 4.15) compared to the winter loading condition as presented in Figure 4.16. As expected, the voltage drops increase at higher EV uptakes.

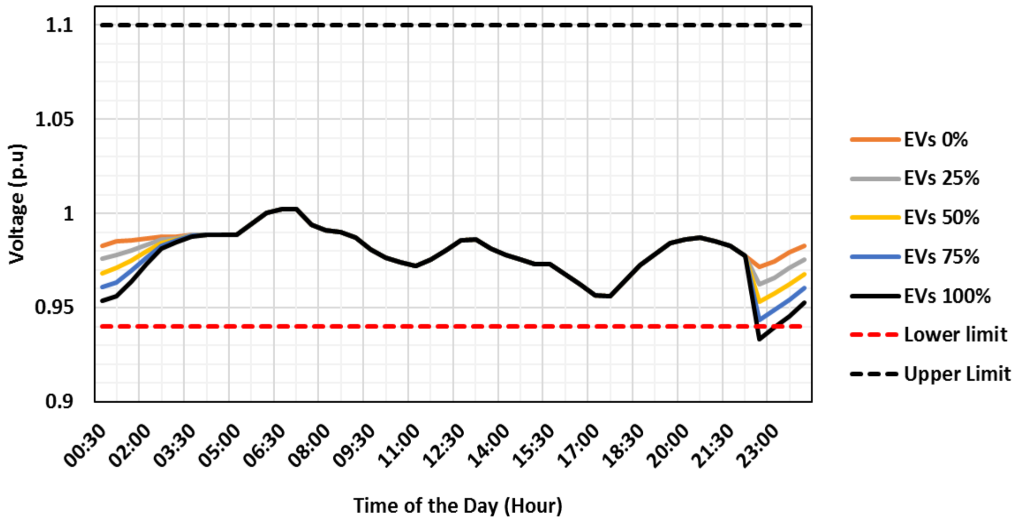


Figure 4.15: Voltage profiles in the summer (dual tariff)

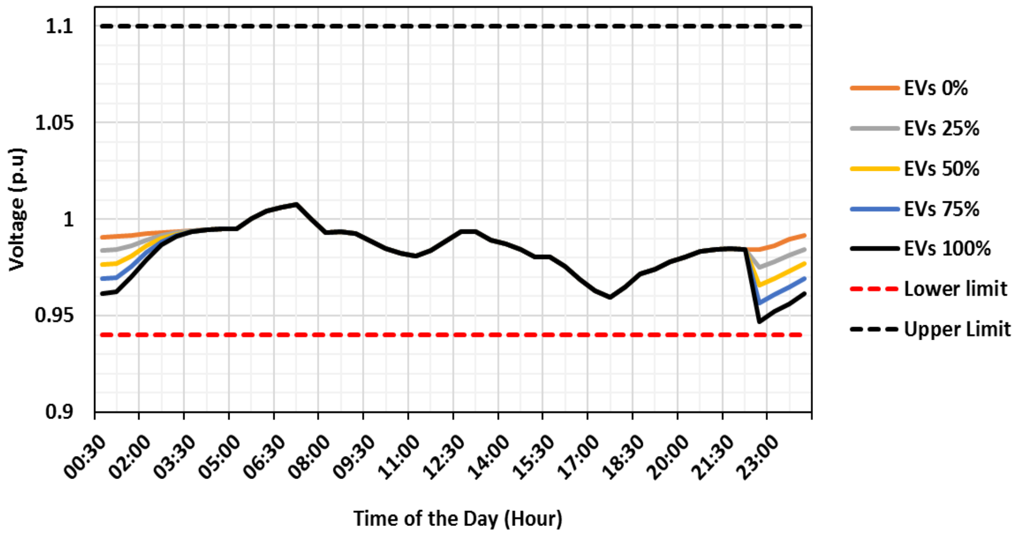


Figure 4.16: Voltage profiles in the winter (dual tariff)

The winter voltage profiles with dual tariff regime completely stay within the UK distribution network statutory voltage limits. This shows that for the extreme case of minimum load and maximum generation the voltage excursions are higher.

4.5.2 Energy Losses

Energy losses for the modelled microgrid were computed for four different scenarios:

- An uncontrolled EV charging regime with summer load profile for different DG penetration levels.

- A dual tariff EV charging regime with summer load profile for different DG penetration levels.
- An uncontrolled EV charging regime with winter load profile for different DG penetration levels.
- A dual tariff EV charging regime with winter load profile for different DG penetration levels.

Summer Loading case

The uncontrolled charging regime without DG connected in the microgrid is recording the highest energy losses (see Figure 4.17) with more than 0.21 MWh. The energy losses in the dual tariff charging regime (Figure 4.18) is 0.04 MWh lower than the uncontrolled charging case.

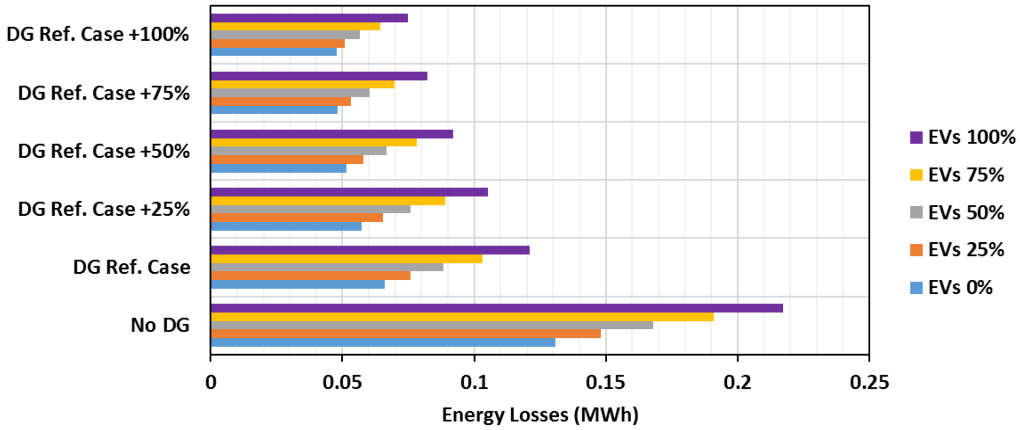


Figure 4.17: Energy losses in summer (uncontrolled)

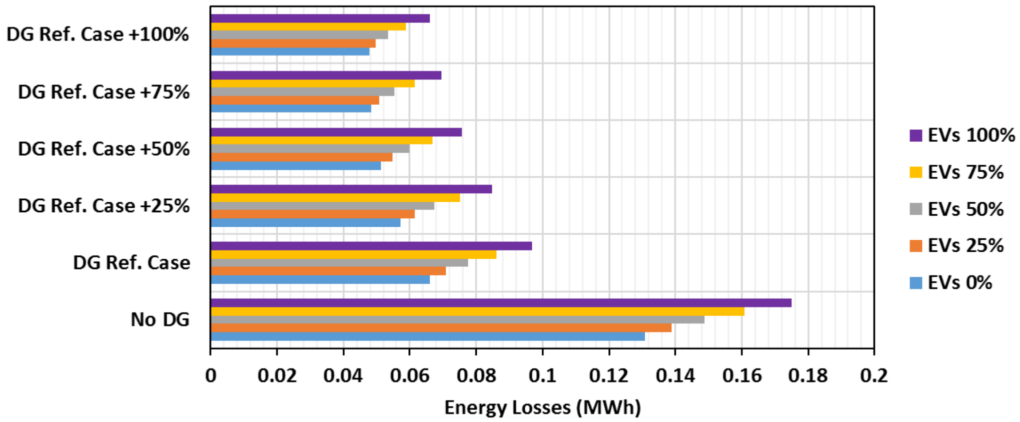


Figure 4.18: Energy losses in summer (dual tariff)

The energy losses are decreasing when DG penetration is increasing. This shows the value of connecting both controlled EV charging and DGs in minimising the energy losses in microgrids.

Winter Load case

Figures 4.19 and 4.20 shows the energy losses for winter scenario. It is noted that the energy losses are smaller, below 0.2 MWh in the uncontrolled charging regime and below 0.15 MWh in the dual tariff charging regime. This indicates the importance of the loading conditions in the network. With summer network loading (see Figure 4.17 and 4.18) and maximum DG penetration, the losses are more significant.

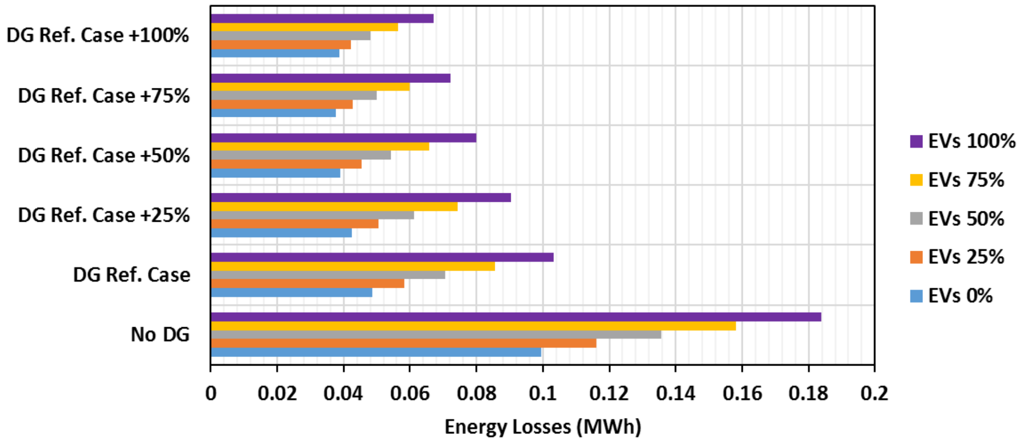


Figure 4.19: Energy losses in winter (uncontrolled)

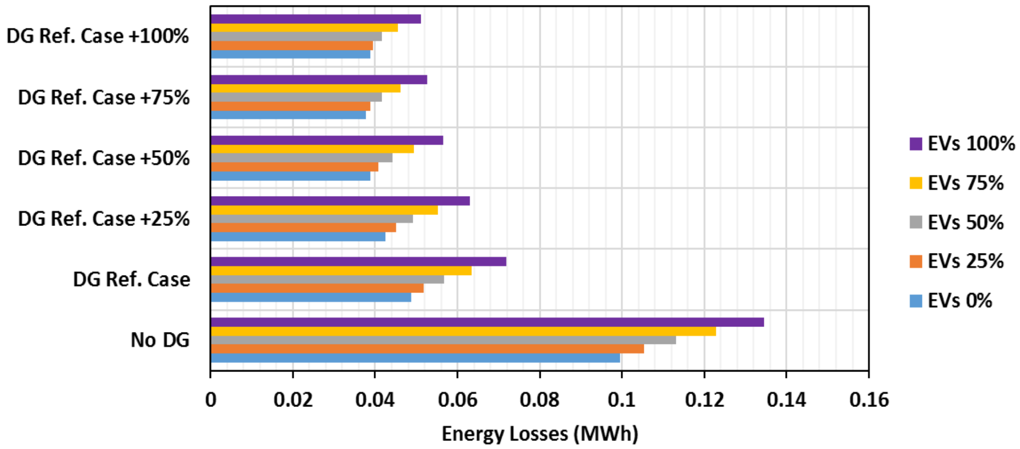


Figure 4.20: Energy losses in winter (dual tariff)

The dual tariff case, presented in Figure 4.20, shows a further reduction in energy losses compared with the uncontrolled case in Figure 4.19. This demonstrates the value of delayed EV charging in managing the energy losses in the microgrid.

4.6 DISCUSSION

This chapter presented a multi-period heuristic power flow technique developed to extend the capability of MATPOWER. This is applied to a microgrid with high penetration of EV and DGs under two different tariff typical Elexon [156] residential load profiles i) uncontrolled and (ii) dual tariff. This was not explored in other previous studies [83], [84], [92].

The voltage profile and energy loss analysis is based on the normalised load profiles of Figure 4.3 and DG generation profiles of Figures 4.4 and 4.5. It is seen that the loading condition is playing a key role in voltage profile variation and energy losses in the microgrid. The load profiles are based on the Elexon profiles and as such could be improved by integrating suitable load modelling and forecasting techniques into the multi-period heuristic power flow technique.

No cost data for DGs, wholesale tariff and stationary battery storage has been considered in this chapter, therefore in chapter 5, an MILP optimisation technique is further explored to evaluate the impact of adopting a battery storage for an existing PV system benefiting from the UK FiT.

4.7 SUMMARY

In this **chapter**, the impact on voltage profiles over a 24-hour period and energy losses for varying levels of EV and DGs penetration in a microgrid were investigated. An LV benchmark model was simulated using a time series load flow.

Voltage Profiles and EV charging regimes: Based on the simulation results, the integration of EV into microgrids in an uncontrolled manner leads to a significant voltage drop that may exceed the UK distribution network statutory voltage limits., particularly in the summer loading and maximum generation scenario.

However, with a dual tariff charging regime and the integration of different levels of DG penetration the voltage drop is less significant. This shows that effective utilisation of DGs in microgrids by charging EV preferentially from renewables could be leveraged in managing power flows in LV distribution networks.

Energy losses and Network loading conditions: The energy losses are less significant in the dual tariff EV charging regime compared with the uncontrolled charging regime. The loading conditions (summer and winter) are playing an important role in improving the voltage profile. With summer load profile, the energy losses are more severe compared with the winter loading conditions.

Chapter 5

Management of Battery Storage Operation for an existing Photovoltaic System

5.1 Introduction

Energy policies across Europe are designed to increase the security of energy supply while minimising the cost of supply [33]. This extends to the installation of distributed energy systems in residential premises. From 2010 it was recorded an increase of PV installation due to the decrease of the module cost and the implementation of incentive-based programmes like the FiT policies [17], [164]. The recent changes in the FiT policies in the UK and the closure of the Renewable Obligation scheme applied to a small scale solar PV with a capacity less than or equal to 5MW will drastically affect the scale of domestic PV installations [38], [165]–[167].

The intermittent nature of solar PV and the mismatch between customer-sited solar PV power output and the residential electricity load profiles makes battery storage a potential option to maximise savings for customers with onsite DG [81], [110], [168]. The cost of battery packs is falling, about 25% reduction for lithium-ion battery between 2009 and 2014 according to [33]. The domestic electricity storage battery could provide support to an existing customer-sited PV enrolled in the FiT scheme.

According to [169], the value of the California's Public Utilities Commission policy on supporting affordable solar PV installations in multi-family housing could be enhanced by battery storage systems. This means that the value proposition for solar PV owners in respect to changes in electricity rates and tariffs could be improved considerably with a well-managed battery energy storage system. In Spain for example, the parliament have signed an agreement to remove the decree against self-consumption [170], [171]. This implies that the net metering and self-consumption are permitted. This shows a clear opportunity for the deployment of battery energy storage in existing solar PV systems benefiting from FiT schemes.

Therefore, it is important to study the management of energy flows in existing solar PV generation systems with battery storage to maximise the revenue streams from FiT. Maximising the use of battery storage for grid connected residential solar PV applications has been studied and the benefits to the DNO has been demonstrated in [5], [55]. By optimising charging and discharging of battery storage coupled to a residential PV the effect of variable PV output is minimised. LP and MILP methods using optimisation software tools have been proposed for maximising the scheduling of DER with battery storage systems [44], [172], [173].

Smart tariffs have the potential to encourage DER adoption, however, in the UK, the only ToU tariff offered are the economy 7 and economy 10. In [174]–[177], an OPF management scheme was proposed for a standalone backup generator. The objective of the work in [176] is to minimise the fuel costs of a backup generator for a residential building using battery energy storage coupled to a grid connected solar PV. In [5], [55], an LV DNO owned battery storage was used to control the power flows in the network. In [5], smart ToU tariffs were used to maximise daily revenue streams for a residential solar PV connected to a battery storage, however, no FiT incentive was considered in the optimisation process. The work in [178], investigated the usage of battery storage in the residential LV distribution network to defer costly network upgrades, a multi-objective optimisation technique to evaluate the trade-offs between voltage regulation, peak power reduction and the annual cost of electricity supply was developed. In [80], an optimisation based approach that maximises daily operational savings for grid connected solar PV customers is presented. An OPF management framework for a grid connected PV with battery storage in order to maximise peak shaving service is presented in [179]. Another study [180] simulated the impact of using a combination of solar PV, battery storage, Stirling Engine CHP on electricity self-sufficiency, intermittent grid demand and customer economic costs. Other studies have considered the optimisation of battery storage operation under different tariff structures (example, [80], [181], [182]). Others have looked into large scale operational planning of RES (solar PV and wind power) in combination with battery energy storage (example, [183]–[186]).

The previous works (example, [108], [174], [176], [177], [179]) focused on using varying ToU tariff structures to optimise the operation of customer owned solar PV in combination battery storage system over a 24 hour period. In [108], the optimal benefit of battery energy storage was only computed for a typical day in summer and winter and then computed for the year using projected estimates.

In the surveyed literature above, no suitable techniques for evaluating the value of deploying battery storage for an existing PV system (benefiting from the UK FiT) and impact of storage unit costs (£/kWh) with different electricity tariffs were found. Therefore, in this chapter, the benefit of deploying battery storage system to an existing customer owned solar PV system benefiting from the UK feed in tariff structure was evaluated. An optimisation technique was developed using wholesale electricity tariff. The aim of the optimisation technique is to optimise the operation of the battery storage system coupled to an existing customer owned PV generation system benefiting from the feed in tariff scheme. For the validation of the optimisation model, a set of real half-hourly PV output data and residential load data over a period of one year was simulated in AIMMS. Case studies for the existing PV system are presented for the (i) retail electricity tariff with no battery storage (ii) wholesale tariff (optimal dispatch schedules for negative, low and high wholesale tariff periods) and (iii) the impact of storage unit costs on the adoption of battery storage for the existing PV system (using economy 7 tariff).

5.2 SYSTEM MODEL

The system studied is presented in Figure 5.1. The solar PV is an existing system benefiting from the FiT scheme. The main components of the system in Figure 5.1 are the existing PV generation system, the proposed battery storage, customer aggregated electricity loads, the LV grid and power electronic converters.

An MILP optimisation algorithm is developed to optimise the battery storage charging and discharging under a wholesale electricity tariff to maximise FiT revenue for the solar PV owner. In the UK, FiT system, the existing PV installation is assumed to be paid 12.57 p/kWh for each kWh generated and 4.64 p/kWh for each kWh exported based on the data from [35]. The large difference between the generation tariff and export tariff makes it attractive for battery storage systems. The battery storage system has the potential to maximise self-consumption for solar PV owners benefiting from the FiT scheme. The use case for a residential battery storage coupled to an existing solar PV generation system in maximising FiT revenue is investigated in this **chapter**. The battery storage system can maximise the usage of peak solar PV output power by storing excess PV power output for use inexpensive peak ToU tariff hours as illustrated in Figure 5.2. Thus, avoiding high electricity costs in such hours.

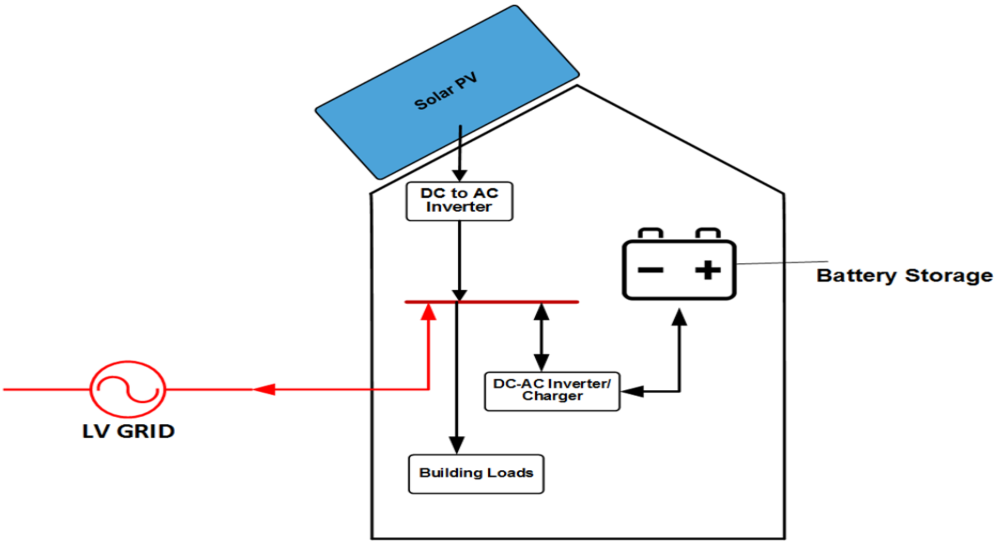


Figure 5.1: Residential battery storage configuration

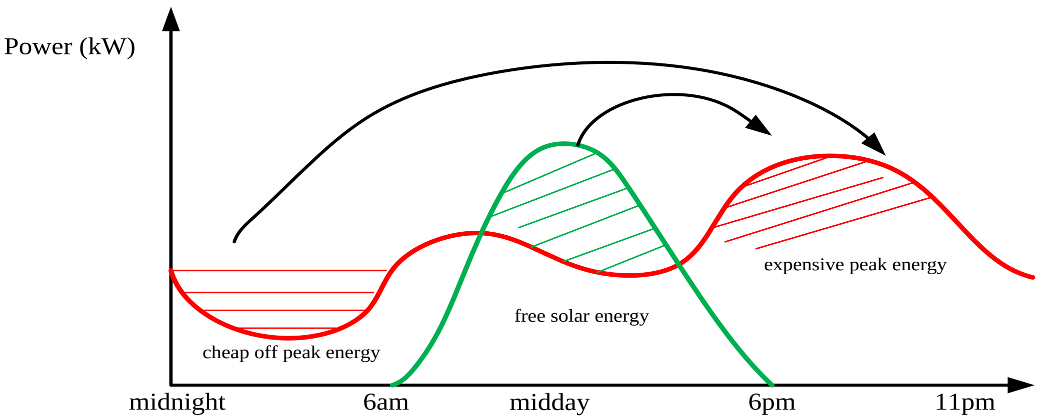


Figure 5.2: Potential of shifting energy usage and power flows with battery storage

5.2.1 Assumptions of the Optimisation Model

The validity of the developed optimisation algorithm for managing charging and discharging of the battery storage system coupled to a PV generation system benefiting from the FiT scheme is based on the following assumptions:

- The residential customer has an existing PV generation system enrolled in the UK FiT scheme. This scheme sets the generation tariff at 12.57p/kWh and the export FiT at 4.64 p/kWh [35].
- A smart meter is installed at the customer premises, as such export is accurately measured. The current system caps exported energy (kWh) as 50% of the generated energy (kWh) by the PV system [187].
- The battery storage specifications were taken from [20], [21].
- The optimisation algorithm for managing the battery storage charging and discharging coupled to the existing PV generation system is simulated using historical electricity demand and real PV power output data of a residential customer obtained from [156], [188].
- Three different grid purchase tariffs are used in this chapter (i) Retail tariff [189] (ii) wholesale electricity price [23] for evaluating the impact of varying tariffs on the objective function of the optimisation algorithm and (iii) Economy 7 tariff [24] for simulating and evaluating the impact of battery storage unit cost (£/kWh) on the adoption of the battery storage for the existing PV generation system in DER-CAM.
- The unit cost in (£/kWh) of $990/kWh (equivalent to £683/kWh) for the battery storage is taken from [190].

5.2.2 Electricity Load Profiles

Half-hourly residential electricity load profiles were taken from ELEXON [156] for a complete year with a minimum load equal to 0.213kW and the maximum load equal to 0.95kW.

5.2.3 PV Generation Data

The PV monitoring data was taken from the Sheffield microgeneration database [188], [191], [192]. The Sheffield microgeneration database records PV generation in the UK by collecting data from donor volunteers. A year's worth of half-hourly PV generation from 50 PV systems was selected at random from the microgeneration database. The generation data was obtained in the form of cumulative half-hourly export meter readings. The total installed capacity of the solar PV generation system used in the simulation of the optimisation model is 3.36 kW covering an area of 23 m^2.

5.2.4 Retail Electricity Tariff

The retail electricity prices in the UK have fairly seen no variation in recent years as shown in Figure 5.3 according to Committee for Climate Change (CCC) projection [189].

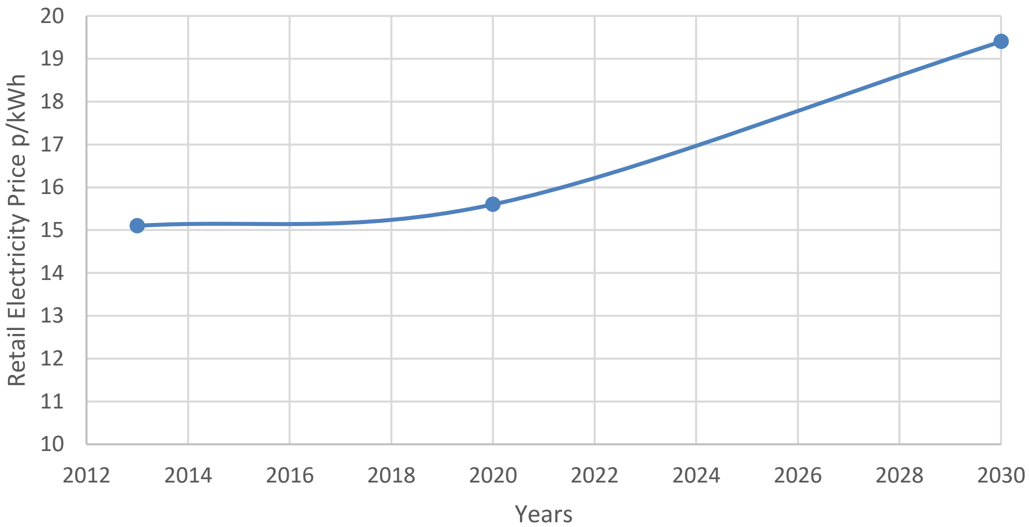


Figure 5.3: Retail electricity price projections from 2013 to 2030 [189]

5.2.5 Wholesale Electricity Tariff

A wholesale tariff data obtained from [23] is used to evaluate the impact of varying tariff rates on the objective function value. Figure 5. shows a plot of the wholesale tariff for the year 2015.

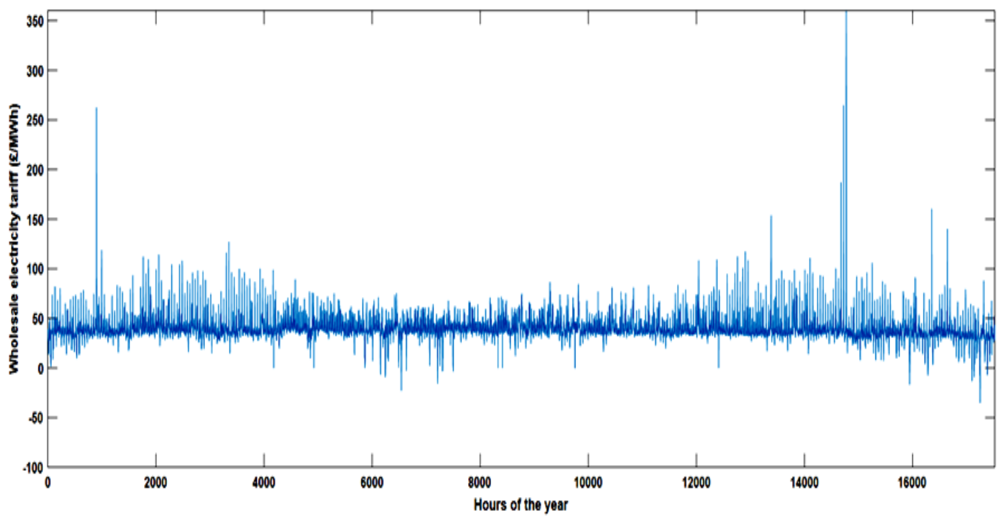


Figure 5.4: Plotted wholesale price

Table 5.1 shows the summary of the wholesale electricity tariff data. It could be seen from Table 5.1 that the minimum value of the wholesale tariff is negative at about minus 3p/kWh, the maximum goes up to about 36p/kWh and the standard deviation is about 1p/kWh.

Table 5.1: Annual wholesale electricity tariff data

Wholesale electricity tariff statistics	
Min (£/MWh)	-34.98
Max(£/MWh)	359.63
Average(£/MWh)	39.9
Standard Deviation (£/MWh)	12.82

5.2.6 FiT in the UK

The FiT was introduced in the UK by the Department of Energy and Climate Change (DECC) on 1 April 2010 as a financial incentive to encourage uptake of DER [187], [193]. Most residential electricity customers with onsite DER qualify for this scheme. The FiT scheme includes a generation tariff and export tariff. The generation tariff is paid for every kWh of PV generated and the export tariff is paid for every kWh of PV generation exported.

5.3 BATTERY OPERATION OPTIMISATION

The battery storage (charging and discharging) operation optimisation for an existing solar PV generation is described in this section.

The optimisation model is formulated as an MILP problem and solved in Advanced Interactive Multidimensional Modelling System (AIMMS) [104]. AIMMS is an integrated development environment that allows developers to create customised solutions. It enables the development of optimisation models through a unique set of design tools for model building, data modelling and graphical user interface creation. Results can easily be validated by creating visual representations of outcomes [194].

The flexibility of AIMMS (i) ensures model separation from data, (ii) makes it easy to repeat different scenarios with new datasets and (iii) easily scale up to larger models. Figure 5.5 shows the optimisation model setup.

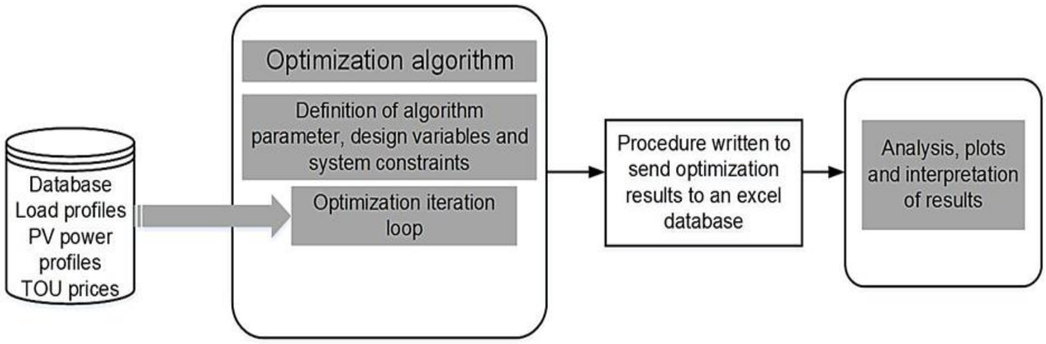


Figure 5.5: Optimisation model setup

5.3.1 Objective Function

The optimisation model is indexed by the sets *(d, t)*, where *d* is the set of days in a year ($1 \leq d \leq 365$) and *h* is the set representing the half-hour periods in each day ($1 \leq h \leq 48$). The objective function (OF) presented in Equation 10 seeks to maximise the FiT revenue streams and minimise the grid electricity import for an existing residential solar PV with and without the installation of battery energy storage. This is evaluated for two import tariff cases i) flat retail tariff and ii) varying wholesale electricity tariff.

$$OF = \sum_{(d,t)} (P\_pv(d,t) \times p\_FIT + P\_pv\_\text{export}(d,t) \times p\_\text{export} \\ - P\_grid(d,t) \times p\_retail) \times \Delta t \tag{10}$$

The OF in Equation 10 is modified to include the wholesale tariff. The new equation with the wholesale electricity tariff is shown in Equation 11.

$$OF = \sum_{(d,t)} ((P\_pv(d,t) \times p\_FIT) + (P\_pv\_\text{export}(d,t) \times p\_\text{export}) \\ -(P\_grid(d,t) \times p\_wholesale) - (P\_charge\_grid(d,t) \times p\_wholesale) \\ +(P\_discharge(d,t) \times p\_wholesale)) \times \Delta t \tag{11}$$

The OF computes the net revenue from onsite generation $P\_pv(d,t)$ and the export of electricity $P\_pv\_\text{export}(d,t)$. The model parameters and decision variables are described in the following sections.

5.3.2 Optimisation Model Parameters

The optimisation model parameters are described in Table 5.2.

Table 5.2: Model parameters

Model Parameters	Description
$P\_pv(d,t)$	Generated PV Power at every time step (kW).
$P\_dmd(d,t)$	Electricity demand at each time step.
p_FIT	Generation FiT (pence/kWh) (12.57p/kWh) [35].
p_export	Export FiT (pence/kWh) (4.64p/kWh) [35].
p_retail	Standard retail electricity tariff (15p/kWh) [35].
$p\_wholesale$	Wholesale tariff (p/kWh).
Δt	Optimisation time step: half-hourly.
$P\_dmd\_unmet(d,t)$	Unmet electricity demand at each time step (kW).
$P\_pv\_excess(d,t)$	Excess electricity from PV at each time step (kW).
$P\_pv\_onsite(d,t)$	PV power output used for self-consumption (kW).
$Pch\_\min$	Minimum battery charging power (kW).
$Pch\_\max$	Maximum battery charging power (kW).
$Pdis\_\min$	Minimum battery charging power (kW).
$Pdis\_\max$	Maximum battery discharge power (kW).
e^c	Battery charging efficiency.
e^d	Battery discharging efficiency.
$Ebatt\_\min$	Battery minimum energy state of charge (kWh).
$Ebatt\_\max$	Battery maximum energy state of charge (kWh).
M	Big M is an arbitrary number that should be big enough to ensure a feasible solution with defined storage constraints.

5.3.3 Decision Variables

The decision variables are the unknowns in the optimisation model. Table 5.3 describes the model's decision variables.

Table 5.3:Model decision variables

Decision Variables	Description
$P\_pv\_\mathrm{export}(d,t)$	PV power sold to the grid at each time step (kW).
$P\_grid(d,t)$	Grid Electricity Imported at each time step (kW).
$P\_charge(d,t)$	The power used to charge the battery from excess PV (kW).
$P\_charge\_grid(d,t)$	The power used to charge the battery from the grid (kW).
$Y(d,t)$	Binary variable at each time steps that constraints charging power in order to prevent charging and discharging simultaneously.
$Z(d,t)$	Binary variable at each time steps that constraints discharging power in order to prevent charging and discharging simultaneously.
P_discharge(d,t)	The power discharged by the battery in order to meet unmet demand (kW).
$E\_s(d,t)$	Battery energy state of charge at each time step (kWh).
$E\_s(d,t-1)$	Battery energy state of charge at the previous time step (kWh).
$X(d,t)$	A binary variable that prevents buying and selling of electricity simultaneously at each time step.

5.3.4 Model Constraints

The decision variables and the OF in the optimisation model are subject to the following constraints:

$$0 \le P\_grid(d,t) \le P\_dmd\_unmet(d,t) \tag{12}$$

$$\begin{cases} \text{if } P\_dmd(d,t) > P\_pv(d,t), \text{ then} \\ \quad P\_dmd\_unmet(d,t) = P\_dmd(d,t) - P\_pv(d,t) \\ else \\ P\_dmd\_unmet(d,t) = 0 \\ endif \end{cases} \tag{13}$$

$$0 \le P\_pv\_\mathrm{export}(d,t) \le P\_pv\_excess(d,t) \tag{14}$$

$$\begin{cases} \text{if } P\_pv(d,t) - P\_dmd(d,t), \text{ then} \\ \quad P\_pv\_excess(d,t) = P\_pv(d,t) - P\_dmd(d,t) \\ else \\ P\_pv\_excess(d,t) = 0 \\ endif \end{cases} \tag{15}$$

The OF is modified to include battery charging and discharging schedule when battery storage is considered in the model (See Equations 10 and 11). With battery storage coupled to the existing PV generation system the following constraints are added to the model:

$$Y(d,t)Pch\_\min \leq P\_charge(d,t) \leq Y(d,t)Pch\_\max \tag{16}$$

$$Z(d,t)Pdis\_\min \leq P\_discharge(d,t) \leq Z(d,t)Pdis\_\max \tag{17}$$

$$Y(d,t) + Z(d,t) \leq 1 \tag{18}$$

$$\sum_{(d,t)} P\_discharge(d,t) \leq \sum_{(d,t)} P\_charge(d,t) \tag{19}$$

$$\begin{aligned} &E\_s(d,t) = E\_s(d,t-1) + \\ &\left(e^c P\_charge(d,t) + e^c P\_charge\_grid(d,t) - \frac{P\_discharge(d,t)}{e^d} \right) \end{aligned} \tag{20}$$

$$P\_pv\_export(d,t) \leq M(1 - X(d,t)) \tag{21}$$

$$Ebatt\_\min \leq E\_s(d,t) \leq Ebatt\_\max \tag{22}$$

$$P\_grid(d,t) \leq MX(d,t) \tag{23}$$

$$\begin{aligned} &P\_grid(d,t) + P\_pv(d,t) - P\_pv\_export(d,t) - P\_charge(d,t) \\ &- P\_charge\_grid(d,t) + P\_discharge(d,t) = P\_dmd(d,t) \end{aligned} \tag{24}$$

$$P\_pv\_export(d,t) \leq P\_pv(d,t) \tag{25}$$

$$P\_grid(d,t) \leq P\_dmd\_unmet(d,t) \tag{26}$$

$$P\_discharge(d,t) + P\_grid(d,t) = P\_dmd\_unmet(d,t) \tag{27}$$

Once the optimisation algorithm is executed, a set of solutions is produced for each day of the year and each half-hour period of each day. The optimisation algorithm formulated in AIMMS is presented in Appendix C.

5.4 Case Studies

Two case studies were simulated to evaluate the (OFs) of the optimisation model in Equations 10 and 11.

Case study 1: PV (standard flat tariff as electricity import tariff). This case study serves as the reference case. The grid import is evaluated based on the electricity demand profile and the solar PV output profile.

Figure 5.6 below shows the system configuration for case study 1.

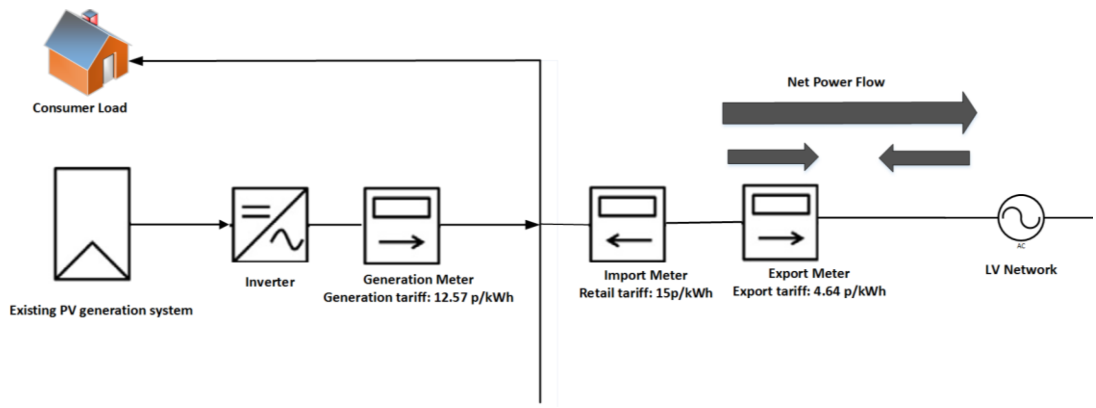


Figure 5.6: PV generation system without battery storage

Case study 2: PV with battery storage (wholesale tariff as electricity import tariff)
Figure 5.7 shows the system configuration for case study 2.

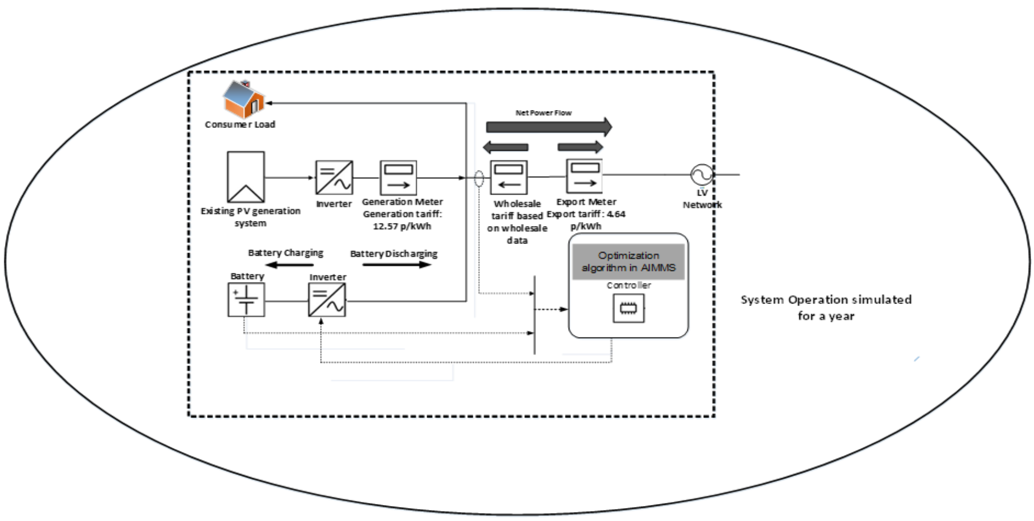


Figure 5.7: PV generation system with battery storage (case study 2)

For case study 2, the OF is modified to include battery charging and discharging as decision variables. In case study 2, the wholesale retail electricity tariff taken from [23] is considered.

A simulation of the optimisation algorithm was performed. For case study 1, an example of optimised scheduled profiles for the system is presented for **winter** (representing high electricity loads and low PV generation) and **summer** (representing high PV power generation and low electricity loads). In case study 2, an example of optimal dispatch profiles for the PV – Battery system for the periods of negative, low and high wholesale electricity tariffs are presented.

5.4.1 Case Study 1

The results of this case study are evaluated for a typical winter and summer day of the year.

Winter

On a winter typical day, early in the morning, the grid import is required to meet the electricity demand. This is due to the low solar irradiance. The grid electricity import steadily decreases as the PV generation builds up during the day

Electricity imported from the grid is evaluated and simulated if onsite electricity demand is greater than the PV power output. The amount of PV generation utilised for export and self-consumption is shown in Figure 5.8.

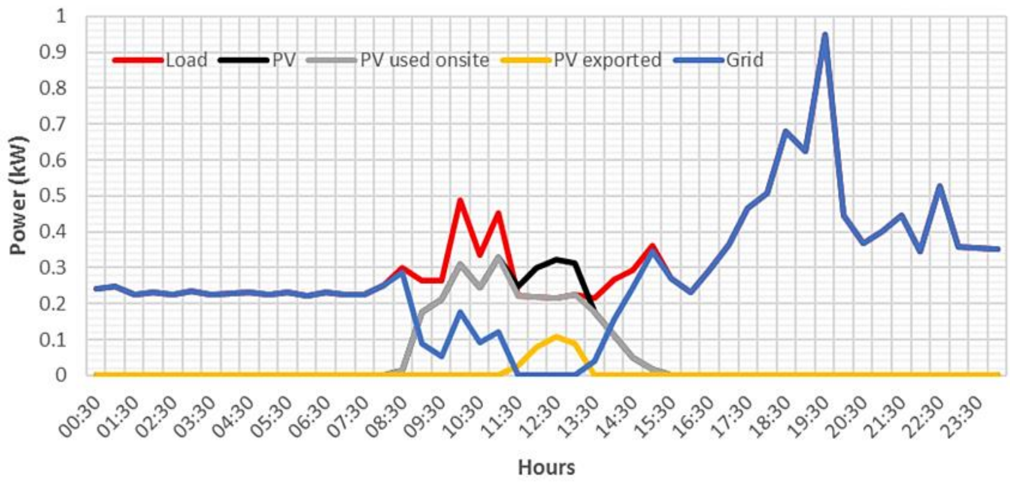


Figure 5.8: Power profiles of the PV system with no battery storage (winter)

The exported power in the winter case is low and most of the PV generation is consumed onsite. When the PV decreases to zero at 15:30 hour, the site is starting to import electricity to meet demand. This implies an increase in the total costs to meet the peak electricity demand by importing electricity from the grid. The grid electricity imported (blue curve in Figure 5.8) is following the electricity demand (red curve in Figure 5.8)

Summer

On a summer, typical day, there is a significant generation from the PV in the mid-day. The electricity demand is at its minimum compared with the rest of the year. Therefore, the electricity imported from the grid is low and the export of PV power increases as shown in Figure 5.9. However, because there is no battery storage at the site, the excess PV electricity generated is sold at the export tariff (4.64p/kWh).

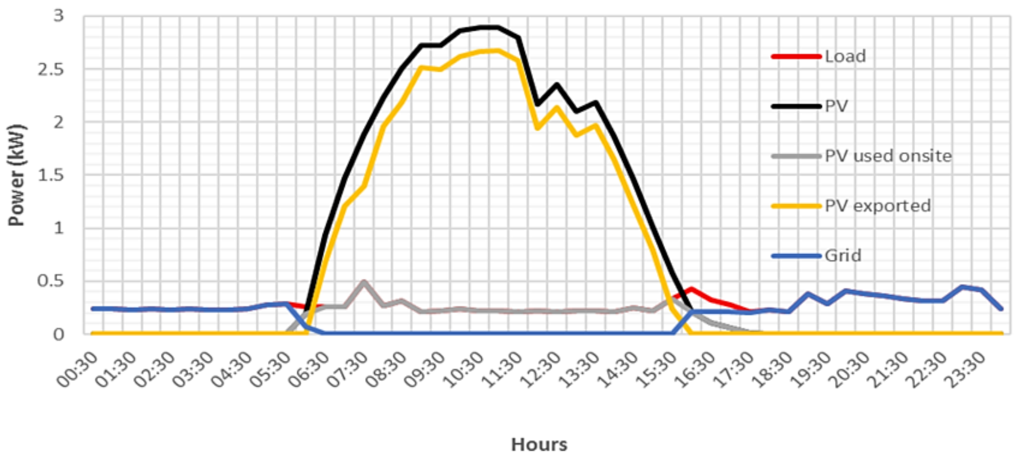


Figure 5.9: Power profiles of the PV system with no battery storage (summer)

5.4.2 Case Study 2

Over the course of a year, electricity demand and PV power generation are changing as seen from the historical PV generation data (due to varying weather conditions and energy consumption behaviour). This case study presents the optimal flow of power for an existing PV generation system combined with a battery storage in order to maximise the FiT revenue streams. Three examples, representing periods of negative, low and high wholesale electricity tariff optimal dispatch schedules, over the course of the year are presented using the optimisation algorithm.

Negative wholesale tariff periods

On a typical day within the year when hours (04:30 – 06:30) have negative wholesale electricity tariff price shown by the dashed line on the secondary axis of Figure 5.10, the battery charges from the grid (red line). This is because the negative wholesale price implies that customers are paid to consume electricity. Therefore, cheap electricity is available for charging the battery storage. With this low wholesale electricity tariff, the optimiser in the controller of the PV generation system chooses to export the excess of electricity from the PV system at 4.64 p/kWh while using the residual generation for self-consumption.

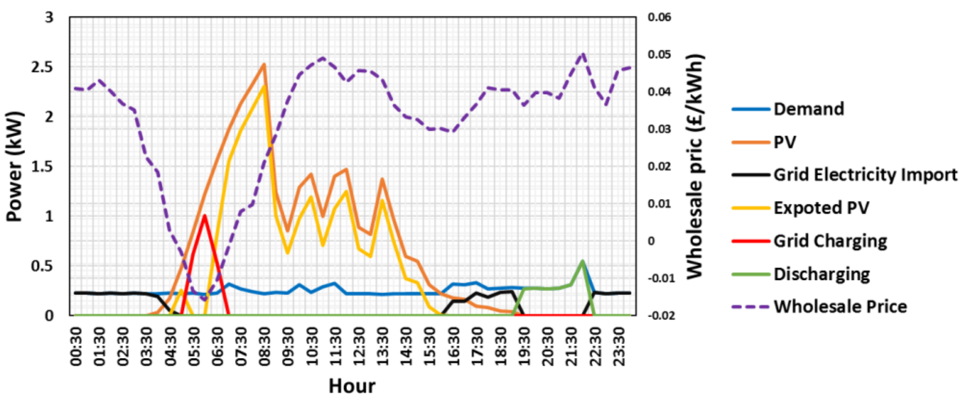


Figure 5.10: Optimal power profiles for the PV system with battery storage and negative wholesale tariff

Starting at 16:00 hour, the solar PV generation drops to zero, and grid electricity import steadily rises (black line), and drops to zero when the wholesale electricity price suddenly increases. The battery that was charged with negative wholesale electricity tariff is discharged between the hours (19:30 – 22:30) in order to minimise grid purchase associated with the sudden rise of wholesale electricity tariff.

This shows that self-consumption is maximised and grid electricity import is minimised within that period.

Low wholesale tariff periods

Figure 5.11 presents the same optimisation process of battery charging and discharging but in this case with low wholesale electricity tariff periods. It could be seen that the grid electricity import (black line) follows and match the electricity demand (blue curve) in the hours where PV generation is zero.

However, when PV generation begins (brown line) to ramp up at hour 08:30, PV generation is used to meet the onsite demand and the generation excess is used for export at 4.64p/kWh. The grid electricity import becomes zero within this period. At hour 11:30 when the wholesale price drops below 5p/kWh, the PV export (yellow line) begins to reduce and charging from the grid begins, and this drops to zero at 12:30 when solar PV generation is highest. At that point, the battery charges from the excess PV generated (shown in the ash coloured dotted line).

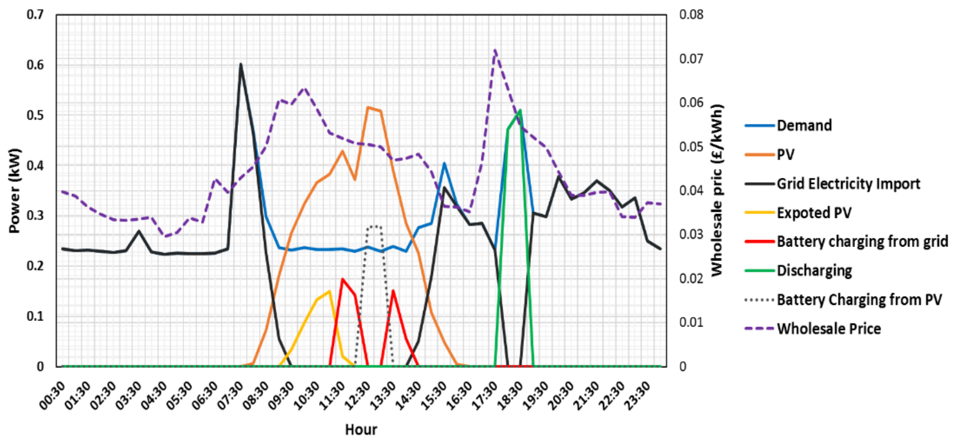


Figure 5.11: Optimal power profiles for the existing PV system with battery storage and low wholesale tariff

As the wholesale electricity tariff continue to drop and the PV generation reduces, the battery charges from the grid again (red line). When the electricity demand of the building ramps up at 15:30, and the wholesale tariff is less than 4p/kWh, grid electricity is used to meet this demand. The battery discharges (green line) between the hours 17:30 and 19:30 when the wholesale electricity tariff is highest, this in turns avoid relatively high grid purchase costs within that period.

<u>High wholesale tariff periods</u>

In this section, an optimal schedule example for the existing PV generation system within a period of extremely high wholesale electricity tariff is presented. Figure 5.12 shows that the grid electricity import matches the building electricity demand from 00:30 – 08:30 when the PV system is not generating electricity.

However, when the PV generation system begins to produce electricity, and wholesale the electricity tariff is just below 5p/kWh, the battery charges from the excess PV generation (shown in the ash coloured dotted lines) equivalent with the battery's charging capacity. This occurs after the self-consumption have been met. The remaining surplus, after the battery is charged, is exported (shown in yellow line). As the wholesale electricity tariff drops further, between hours 13:30 and 15:30 and the PV generation drops, the battery is charging from the grid (shown in red line).

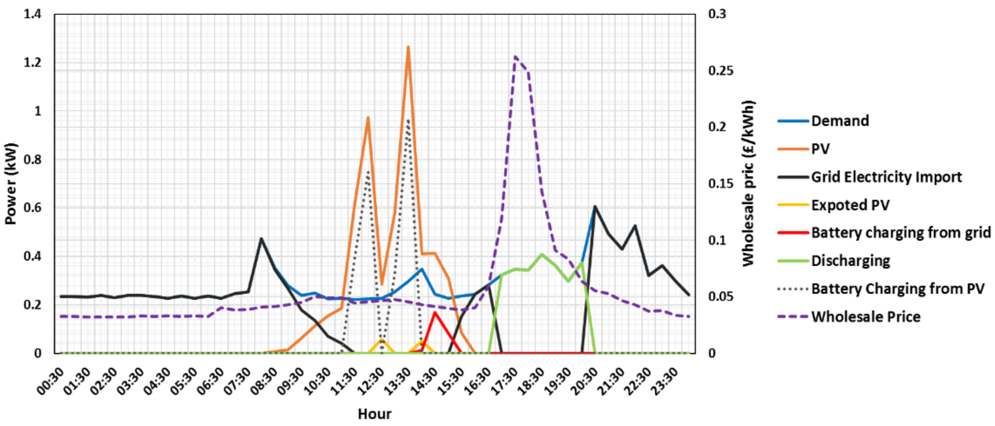


Figure 5.12: Optimal power profiles for the existing PV system with battery storage and high wholesale tariff

It was observed that at hour 16:30, the wholesale electricity tariff begins to ramps up, and reaches a maximum of 26p/kWh at hour 18:00. This maximum value is 11p greater than the retail price of electricity. Within this period, the battery discharges (shown in green line) and avoids the high electricity cost associated with importing electricity from the grid.

5.5 OF RESULTS

In this section, the results of sensitivity analysis carried out for case study 2 in order to evaluate the impact of battery capacity (kWh) on the OF value are presented.
In addition, the summary results of the case study 1 and 2 are presented in terms of the OF in Equations 10 and 11.

5.5.1 Sensitivity Analysis

In order to evaluate the effect of the battery size in (kWh) on the (OF) of case study 2, a sensitivity analysis was carried out using the AIMMS procedure in the developed optimisation algorithm. The procedure is expressed as follows:

for (*i*) *do*
Ebatt := BatteryCapacityPoints(i);
Run MainOptimizationExecution;
OptimalBenefit(i) := TotalBenefit;
endfor;

The sensitivity analysis is carried out by varying the battery capacity (kWh) parameter in the optimisation algorithm and performing a simulation to quantify the impact of that parameter on the OF. This is utilised as a strategy to find the optimal battery capacity that maximises the OF.

The optimal solution procedure is looped over varying battery capacity sizes and the optimisation procedure is run over this loop. Figure 5.13 shows the effect of this procedure for case study 2. In Figure 5.13, the *x*-axis is representing the range of energy capacities in kWh considered and the *y*-axis is representing the OF value. The revenue increases as the battery size increase until 3 kWh of battery size capacity is reached and no further increase in revenue is obtained. This shows that the optimal battery storage size for the load and PV dataset used in this work could be increased to 3kWh for a marginal increase in revenue.

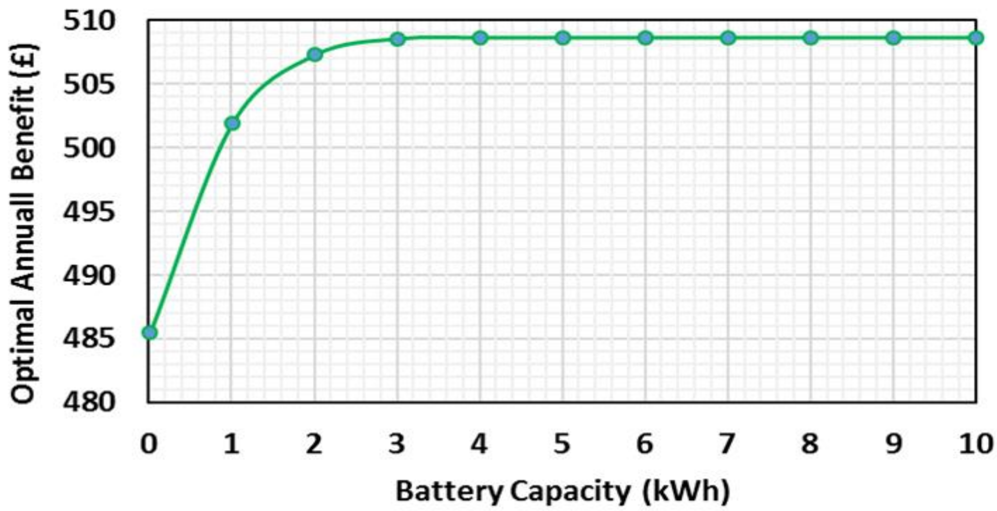


Figure 5.13: Impact of varying battery capacity on the OF for case study 2

Such a procedure can be used to evaluate the battery storage capacity that will maximise revenue streams for an existing residential PV generation systems.

5.5.2 OF for Case Study 1 and 2

Table 5.2 shows the OF value obtained after a year's operation of the existing PV generation system for case study 1 and 2.

Table 5.4: Revenue for PV owner in case study 1 and 2

Study Case	OF (£)
Case Study 1	314.04
Case Study 2	507.28

It was found that for the wholesale electricity tariff, the OF increases from £314 in the base case (Case study 1) to £507. This shows that with varying smart electricity tariffs and falling battery costs, the economic case for battery storage coupled to an existing PV generation system could be enhanced. Section 5.6 analyses the impact of battery unit cost (£/kWh) on the adoption of battery storage for an existing PV generation system.

5.6 IMPACT OF BATTERY UNIT COST ON REVENUES

The revenue streams for the existing PV generation system will largely depend on the battery installation costs. According to [33], lower battery prices will ensure battery energy storage coupled with existing PV generation systems are attractive with good payback periods. The existing PV generation system with an option for battery installation is simulated in DER-CAM. DER-CAM was used to determine the battery unit costs (£/kWh) required to make an economically viable investment into battery storage for the existing PV generation system. The access to the DER-CAM source code was provided during a two months' research visit to the LBNL, California USA (see Appendix D).

5.6.1 Modification in DER-CAM

The detailed mathematical formulation in DER-CAM is reported in [195]–[197]. See also chapter six.

The high-level formulation of the OF is expressed in Equation 28:

$$\begin{aligned}&Minimize\\&AnnualEnergySupplyCost:\\&energy\_purchase\_cost + amortized\_DER\_technology\_capital\_cost\\&+annual\_O\&M\_cost\end{aligned} \tag{28}$$

Equation 28 was slightly modified to include the UK FiT in order to model the PV generation system presented in this Chapter. The modification is presented in Equation 29:

$$\begin{aligned}&Minimize\\&AnnualEnergySupplyCost:\\&energy\_purchase\_cost + amortized\_DER\_technology\_capital\_cost\\&+annual\_O\&M\_cost\\&-p\_FIT \times TotalPV\_generated - p\_export \times TotalPV\_exported\end{aligned} \tag{29}$$

Where $TotalPV\_generated$ is the total kWh generated by the existing PV system that is eligible for the generation tariff (p_FIT), and $TotalPV\_exported$ is the amount of kWh exported to the grid that is eligible for the export tariff (p_export).

5.6.2 ToU Tariff in DER-CAM

To simplify the modelling of ToU tariffs in DER-CAM, the economy 7 tariff data was used. The economy 7 has a two-tier tariff, one for 7 hours' off-peak period and the other hours for the peak period. Figure 5.14 shows the economy 7 tariff.

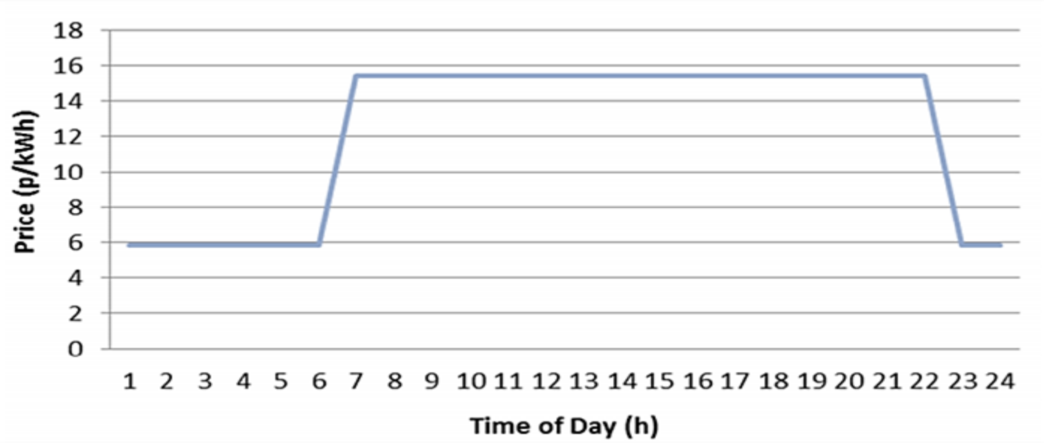


Figure 5.14: Economy 7 tariff [24], [198]

It could be seen from Figure 5.14, the off-peak tariff is about 6p/kWh between the hours (1:00 – 6:00) and (23:00 – 24:00). The peak is charged at about 15.8p/kWh between the hours (7:00 – 22:00).

5.6.3 Simulation Results

The existing PV generation system was simulated in DER-CAM with the datasets for electricity demand and the existing PV generation system reported in section 5.22 to 5.24. However, the electricity tariff data in Figure 5.14 is used as electricity import tariff in DER-CAM. The payback period is constraint to 10 years.

Four scenarios are run in DER-CAM, all with the economy 7 as a ToU tariff:

- Scenario 1 (S1): Reference, no PV generation system.
- Scenario 2 (S2): PV + FiT.
- Scenario 3 (S3): PV + FiT + Battery storage at a unit cost of \$990/kWh (£683/kWh) [190].
- Scenario 4 (S4): PV + FiT + Battery storage with a sensitivity analysis on the costs in scenario 3.

Scenarios 3 and 4 are simulated to evaluate the minimum unit cost of storage that will make economically viable the battery storage for the existing PV generation system. Table 5.5 shows the results when no battery storage is considered for the existing PV generation system. S1 shows that the system total cost of meeting electricity demand with no PV is about £328.

Table 5.5: Results for scenarios 1 and 2 (no battery storage considered)

Scenario	Annual Electricity Costs (£)	Savings (%)	Optimised OF (£)
S1	328.21	0	328.21
S2	161.76	168.8	-228.34

With S2, the FiT is applied and the OF becomes negative meaning that the amount earned from generation and export tariff is greater than the cost of electricity imported from the grid to meet the onsite electricity demand.

Table 5.6 presents the scenarios where battery storage is considered. It is observed that at the battery unit cost of £683/kWh, the battery storage was not adopted by the optimisation algorithm in DER-CAM, meaning that at such unit costs, the battery storage does not make economic sense for the existing PV generation system.

Table 5.6: Results for scenarios 3 and 4

Scenario	Annual Electricity Costs (£)	Savings (%)	Optimised OF (£)	Battery Power(kW)	Battery Capacity (kWh)
S3	161.7636	168.8	-228.34584	0	0
S4	100.9194	172.1	-239.14779	1.27	2

However, the optimisation in DER-CAM only adopts battery storage for the existing PV generation system when the unit cost reaches £138/kWh (scenario 4). A 2 kWh battery is installed showing that battery unit cost must drop the cost to £138/kWh or lesser for battery storage to be economically viable for existing PV generation systems with FiT revenue streams.

5.7 DISCUSSION

Maximisation of FiT revenue stream for existing PV systems using battery storage benefiting from the UK FiT system is becoming attractive due the significant difference between retail tariff (15 p/kWh used in this chapter, [35]) and FiT export tariff (4.64 p/kWh used in this chapter, [35]). However, previously reviewed literature in section 5.1 did not find a suitable technique to evaluate the value of battery storage for the existing PV system benefiting from the UK FiT. This chapter examined the value of battery storage with wholesale electricity tariff and the impact of the unit cost of battery storage on the adoption of the battery storage system.

However, if electricity customers with onsite distributed energy systems are to optimise their systems with battery storage, what will be the impact of their connection to a local distribution network? This question was not addressed in this chapter. Chapter 6 answers this question by designing a soft-linking procedure to analyse the impact of optimised distributed energy systems on a modelled microgrid.

5.8 SUMMARY

In this chapter, an optimisation algorithm was used to optimise FiT revenue streams for an existing PV generation system coupled with battery storage. The optimisation algorithm was simulated for a complete year with real half-hourly PV generation profiles. **Two case studies** were presented (i) PV generation system with flat electricity tariff and (ii) PV generation system with wholesale electricity tariff and battery storage system. **A sensitivity analysis** was carried out to evaluate the impact of varying battery capacity on the OF. **DER-CAM** was used to simulate the existing PV generation system with dual economy 7 tariff and, the **impact of battery unit costs (£/kWh)** on the economic adoption of battery storage was evaluated.

The main findings are stated below:

Optimal scheduled profiles: The optimal profiles for the battery charging and discharging for the **case with no battery storage using flat tariff as import tariff,** and the **case with battery storage using wholesale tariff as import tariff** were drawn. It was found that in the case of the system with no battery storage the PV generation is used for self-consumption and any generation excess is sold at 4.64p/kWh. However, with wholesale electricity tariff, the battery charges from the grid when the electricity tariffs are low or negative and discharge at high electricity tariff periods. Also, it was found that the battery prefers to charge when the PV generation is at its maximum and switches to charge using grid electricity when the PV generation drops and wholesale electricity tariff is low.

Battery Capacity: The sensitivity analysis shows that with the wholesale sale electricity tariff in case study 2, the battery capacity could be increased to **3kWh** for a marginal increase in revenue.

FiT Revenue: The results shows that with battery storage, the FiT revenue for the existing PV owner increases from **£314** with standard retail tariff (case study 1) to about **£507** in the case of wholesale tariffs (case study 2). However, this revenue streams will depend on the reduction of battery unit costs.

The impact of unit cost (£/kWh) on the adoption of battery storage for the existing PV generation system: The simulation DER-CAM shows that battery adoption (with Economy 7 ToU tariff) for the existing PV generation system presented in this Chapter will only be economically viable when battery unit cost drops to **£138/kWh**.

Chapter 6

Impact of Optimised Distributed Energy Systems on Microgrid Constraints

6.1 Introduction

Optimal investment decisions for the adoption of DER in a mid-rise apartment were evaluated at the Grid Integration Group, LBNL, California, USA. The case study was simulated using LBNL's DER-CAM. This was carried out as part of a two months' research visit to the LBNL (see Appendix D).

A procedure was then developed to evaluate the impact of optimal decisions from DER-CAM on distribution network constraints using a time series power flow.

Several optimisation models are widely used for finding the optimal configuration and operation of onsite distributed energy technologies. The main objective in most of these models is to find the optimal configuration of distributed energy technologies that will meet a certain demand with the least cost and CO_2 emissions [110]–[112]. HOMER is an optimisation tool that finds the best microgrid configuration with least Net Present Cost (NPC) [113]–[116]. DER-CAM is an MILP tool for investigating adoption options for onsite DER on customer premises [109], [117]–[119]. In the reviewed literature, the constraints of the electricity network (voltage limits, thermal constraints) are not considered in the formulation of the optimisation problem. This is partly due to the computational challenge of integrating non-linear AC power flow equations in such optimisation models. Linearising these equations to include a Direct Current (DC) power flow in the formulation of the model is a method of avoiding the computational time constraint of the AC power flow as presented in [126]. However, such simplifications may not represent the realistic impact of network constraints on the optimal OF in these models [127], [128]. Most of the existing optimisation models do not take into account the constraints of the local distribution network and assume the network can accommodate all operations and configurations of onsite DER [11], [126].

The purpose of the procedure presented in this chapter is to extend the concept of optimal investment decisions for the adoption of DER to consider local grid constraints. The approach is implemented using a soft-linking procedure to evaluate the impact of different optimised scenarios of investment decisions on a modelled local electrical grid. It inherits the benefit of detailed optimisation models such as DER-CAM while adding a soft-linking approach for evaluating the impact of these solutions on the local distribution network constraints. The outcome is presented in this chapter.

6.2 DER-CAM OPTIMISATION FRAMEWORK

DER-CAM is a decision support tool for evaluating the worthiness of investing in onsite distributed energy technologies in buildings and microgrids. The tool models energy profiles of buildings as microgrids and evaluates the adoption options given a set of DER based on an MILP framework. There is a wide range of distributed energy technologies that can be modelled in DER-CAM. Figure 6.1 shows the modelling structure in DER-CAM. The full mathematical formulation of the optimisation problem in DER-CAM is reported in [195], [197], [199]. DER-CAM is formulated as a mixed integer linear optimisation model that considers energy balances and constraints of demand, DER technologies and ToU tariff data applicable to the building or microgrid.

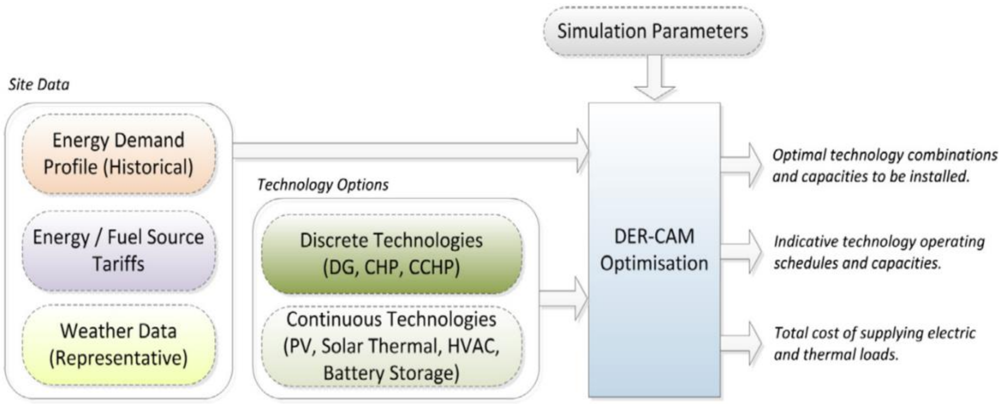


Figure 6.1: DER-CAM optimisation framework [109]

DER-CAM simulates three typical load profiles (weekday, weekend and peak days), and weather data for each month of the year. The model determines the optimal dispatch of the DER onsite and optimal grid electricity import.

6.2.1 Distributed Energy Technologies in DER-CAM

Distributed energy technologies in DER-CAM are modelled as:

- Continuous technologies
- Discrete technologies

The continuous technologies modelled in this case study are modelled with a continuous variable in DER-CAM and they include:

- Electric storage (stationary battery storage).
- Solar PV.
- Air-Source Heat Pump.

Only continuous technologies are modelled for the mid-rise apartment studied in this chapter.

6.2.2 Input Data

The datasets used for the case studies in this chapter is for a mid-rise apartment building. All the datasets are obtained from the DER-CAM database [22]. The mid-rise apartment's electricity loads are highest in summer due to additional loads (see Figure 6.2 – 6.4). The DER-CAM input data are summarised as follows:

- Weather and location data like the solar insolation (for each month of the year) in kW/m^2. Figure 6.2 shows the monthly insolation data for the location of the mid-rise apartment. The highest insolation occurs in September with insolation greater than 0.9 kW/m^2.
- End-use hourly load profiles (for electricity, cooling, gas, hot water, and space heating). These data sets are defined over three day-types: weekdays, weekend days and peak days (the peak days represent outliers in the data set for each month of the year that energy demand is greatest). Figures 6.3 – 6.5 shows the aggregated demand of the mid-rise apartment.
- Electricity tariff and natural gas prices.

- Capital costs, operation and maintenance (O&M) costs and fuel costs for available distributed energy technologies.
- Interest rates on investments and maximum payback period.

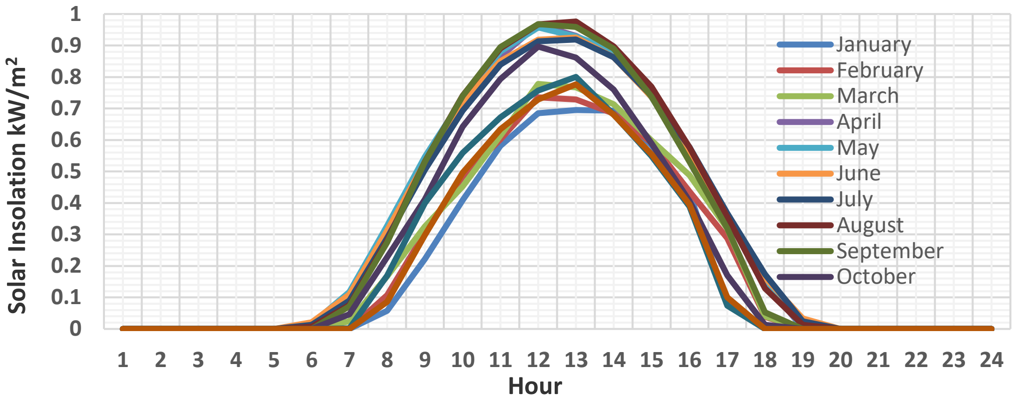


Figure 6.2: Typical solar insolation for the mid-rise apartment's location

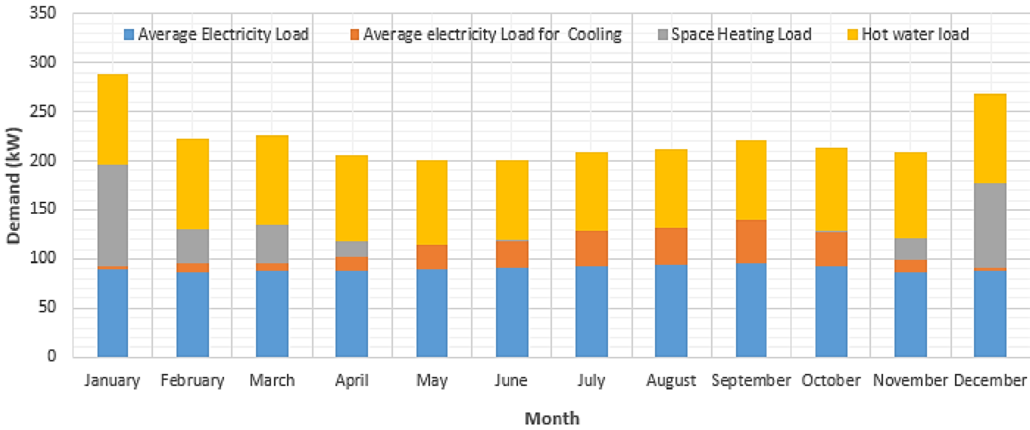


Figure 6.3: Average demand for the mid-rise apartment over the weekdays

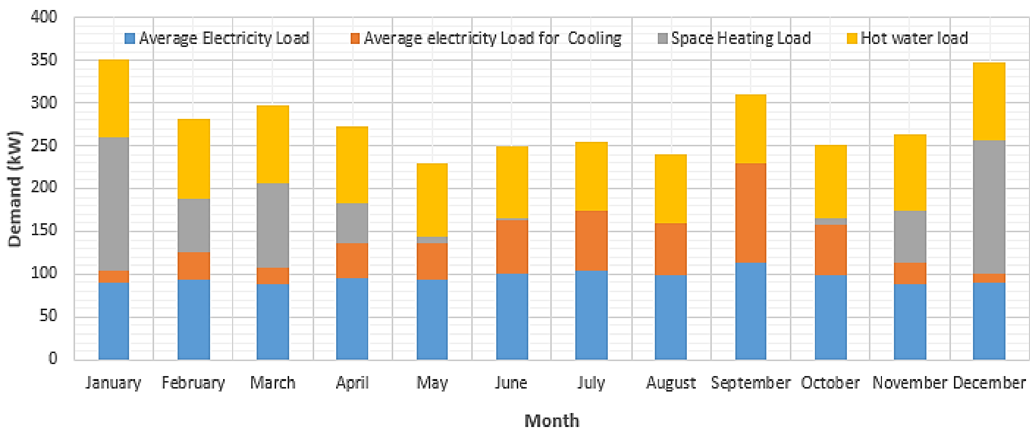


Figure 6.4: Average demand for the mid-rise apartment over the peak days

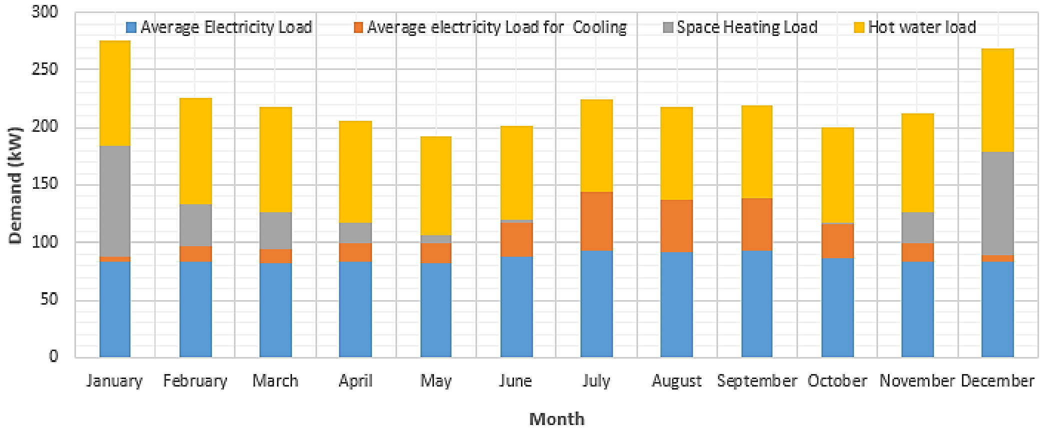


Figure 6.5: Average demand for the mid-rise apartment over the weekend days

The tariff data used in this case study is made of:

- Volumetric energy costs in ($/kWh). The volumetric energy costs depend on the energy usage and are defined as ToU rates using three categories. Peak, mid-peak and off-peak hours. Table 6.1 shows the ToU rates considered in computing the energy costs.
- Power demand charges in ($/kW), which are set on a daily or monthly basis. Power demand charges depend on the maximum demand observed within a specific control period. These control periods include peak, mid-peak and off-peak. Table 6.2 shows the power demand charges for each month of the year. The coincident hour refers to the hour when the electricity grid observes the global system peak and this hour is set by the utility company monthly. Demand charges form a significant part of the energy bill, therefore, there is an opportunity to consider onsite distributed energy generators to mitigate against high demand charges.

Table 6.1: ToU rates [22]

Energy charge ($/kWh)	On Peak	Mid Peak	Off Peak
January	0	0.09451	0.07885
February	0	0.09451	0.07885
March	0	0.09451	0.07885
April	0	0.09451	0.07885
May	0.14026	0.09916	0.07512
June	0.14026	0.09916	0.07512
July	0.14026	0.09916	0.07512
August	0.14026	0.09916	0.07512
September	0.14026	0.09916	0.07512
October	0.14026	0.09916	0.07512
November	0	0.09451	0.07885
December	0	0.09451	0.07885

Table 6.2: Power demand charges [22]

Demand Charge ($/kW)	Coincident	Non coincident	On Peak	Mid Peak	Off Peak
January	0	9.71	0	0.24	0
February	0	9.71	0	0.24	0
March	0	9.71	0	0.24	0
April	0	9.71	0	0.24	0
May	0	16.04	9.71	3.33	0
June	0	16.04	9.71	3.33	0
July	0	16.04	9.71	3.33	0
August	0	16.04	9.71	3.33	0
September	0	16.04	9.71	3.33	0
October	0	16.04	9.71	3.33	0
November	0	9.71	0	0.24	0
December	0	9.71	0	0.24	0

The output data from the model as shown in Figure 6.1 includes the following:

- Investment decisions: Optimal capacities of onsite distributed energy technologies.

- Optimised strategic dispatch of all distributed energy technologies and energy flows.
- Economics of the system including total cost of energy supply.
- CO_2 emissions.

6.3 DER INVESTMENT SCENARIOS

The focus of this chapter is to evaluate the impact of investment decisions made in DER-CAM for the adoption of distributed energy technologies on a modelled local distribution network. Eight different scenarios were modelled in DER-CAM, each representing the adoption of different DER configuration that will minimise the cost of energy supply to the mid-rise apartment. The description of each scenario is shown in Table 6.3. These investment scenarios are compared to a base case where no investment into onsite distributed energy technologies is made, all energy demand is met from the utility grid **(Business as usual, no DER investment allowed).**
Scenario 1, provides a base case for evaluating scenarios 2 to 8. All power generated onsite in scenarios 2 to 5 was constrained to be consumed onsite, while in scenarios 6 to 8, the PV electricity export is allowed in order to evaluate the impact of net power flows on the local distribution network constraints.

Table 6.3: Description of simulated scenarios in DER-CAM

Scenarios	Description
Scenario 1 (S1)	Base case, all energy supplies and demand are met by the utility grid
Scenario 2 (S2)	Investment in solar PV (self-consumption) and Battery is considered
Scenario 3 (S3)	Investment in solar PV (self-consumption) and Battery with load shifting as a demand response strategy is considered
Scenario 4 (S4)	Investment in solar PV (self-consumption), Battery and Air-Source Heat Pump considered
Scenario 5 (S5)	Investment in solar PV (self-consumption), Battery and Air-Source Heat Pump. Load shifting as a demand response strategy is considered
Scenario 6 (S6)	Investment in solar PV (excess export) and Battery considered
Scenario 7 (S7)	Investment in solar PV (excess export), Battery and Air-Source Heat Pump
Scenario 8 (S8)	Investment in solar PV (excess export enabled), Battery and Air-Source Heat Pump. Load shifting as a demand response strategy is considered

Load shifting is a form of energy management strategy in DER-CAM. The total energy remains unchanged when the load shifting strategy is applied, which is represented by the following parameters in the optimisation code:

- Percentage Schedulable Peak: The percentage of the load that can be scheduled daily on peak days.
- Percentage Schedulable Week: The percentage of load that can be scheduled daily on weekdays.
- Percentage Schedulable Weekend: The percentage of the load that can be scheduled on weekend days.
- Maximum load in each hour: Maximum load that can be scheduled in any hour (kW).
- Load increase: Maximum load that can be added in any hour (kW).

It is assumed that no costs are associated with the load shifting parameter, which implies a high tendency to shift demand from periods of high ToU rates to lower rates. As a result, load shifting flattens the load profiles which minimises demand charges and energy purchase costs.

6.4 OPTIMISATION RESULTS AND DISCUSSIONS

For each run of the optimisation procedure in DER-CAM, the minimised total cost of energy supply, total CO_2 emissions and optimal dispatch strategy is obtained.

6.4.1 Optimal Investment Decisions

Table 6.4 presents a summary of the optimal DER configuration for each of the scenario. Scenario 8 achieves the highest savings (40.1%) for the mid-rise apartment. However, even with minimised costs of scenario 8, scenario 5 has a lower amount of CO_2 emissions partly due to the absence of battery storage and self-consumption of PV electricity generated onsite.

Table 6.4: Optimal investment decisions for each scenario

Scenario	PV size (kW)	Battery Storage Size (kWh)	Battery Power (kW)	Air-Source Heat Pump (kW)	PV Exports	Load Shifting	Total Annual Energy Costs (k$)	Total Annual CO_2 Emissions (kg CO_2 emissions)	Total Savings Percent
Base case (S1)	0	0	0	0	No	No	601.1	736600	-
S2	107	72	56.0	0	No	No	461.9	605900	23.9
S3	107	2	1.9	0	No	Yes	431.8	603000	28.9
S4	107	61	52.5	67	No	No	387.5	466800	36.2
S5	107	0	0	61	No	Yes	365.4	464700	39.8
S6	107	222	172.8	0	Yes	No	458.6	670900	24.5
S7	107	128	99.7	63	Yes	No	386.8	500500	36.3
S8	107	6	4.3	61	Yes	Yes	363.3	481200	40.1

6.4.2 Optimised Dispatch Schedules

With each optimal configuration in each scenario, an indicative dispatch strategy for all three day-types and months of the year is obtained. The detailed dispatch schedules for scenario 8 (the scenario with the highest savings for the mid-rise apartment) are illustrated in Figures 6.7 and 6.9. The optimal dispatch schedules for scenarios 1, 2, 3, 4, 5, 6 and 7 are presented in Appendix G. The dispatch schedules for a typical weekday in winter (represented by a typical day in January) and summer (represented by a typical day in July) are shown in Figures 6.7 and 6.9 respectively.

Figure 6.6 shows the winter ToU rates ($/kWh). It could be seen that the electricity consumption of the air-source heat pump is highest during the off-peak period (1:00 – 8:00) of the ToU rate in Figure 6.6. Figure 6.7 shows that at the highest PV production between the hours (9:00 – 16:00), the grid electricity import plunges to zero and the new load profile (thick black) line increases as the PV production varies to maximise self-consumption as much as possible. The battery state of charge (shown as a dashed line of the secondary axis of Figure 6.7) rises to a maximum in order to charge with excess PV generation and discharges at the peak ToU electricity rates of Figure 6.6.

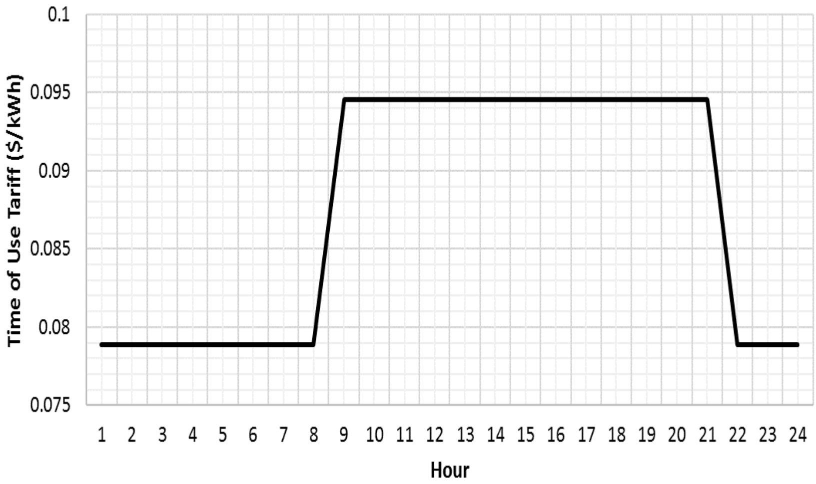


Figure 6.6: Winter ToU tariff

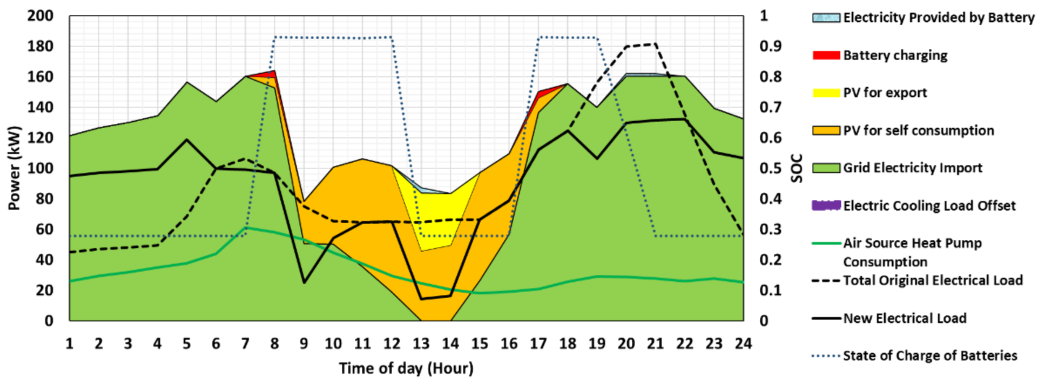


Figure 6.7: Optimal Electricity Dispatch for a typical day in January

It could be observed that there is no electricity load offset for cooling in the winter (represented by a typical weekday in January) for the mid-rise apartment.

However, in the summer the ToU tariff shown in Figure 6.8 with on peak, mid-peak and off-peak is applicable. Figure 6.9 shows the summer optimal dispatch schedules with high solar insolation, which implies high PV generation for self-consumption. Electricity consumption increases during the off-peak hours (1:00 – 8:00) of Figure 6.8. This is to take advantage of the load shifting strategy (see the thick black line in Figure 6.9) and low tariff rates within that period.

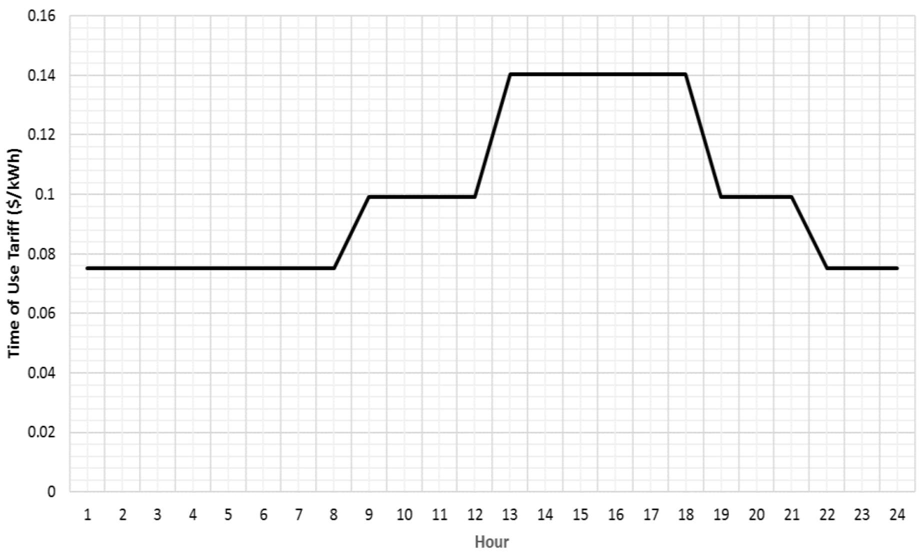


Figure 6.8: Summer ToU tariffs

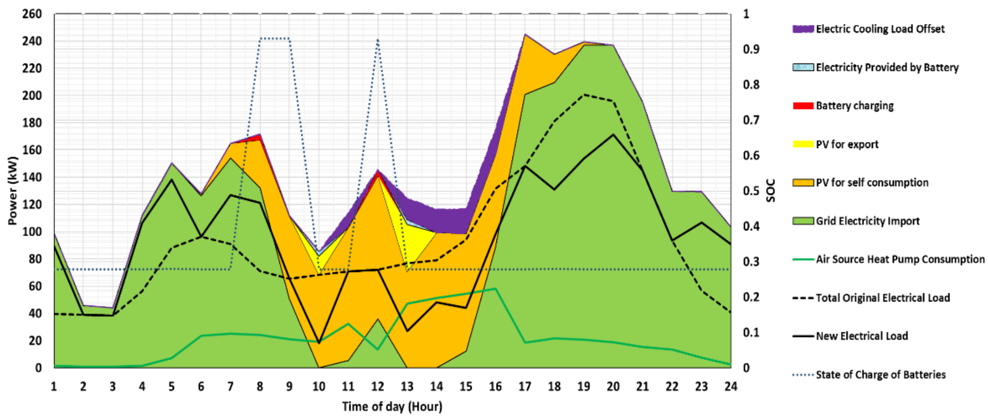


Figure 6.9: Optimal Electricity Dispatch for a typical day in July (summer)

The cooling offset for the summer case increases compared with the winter case with no cooling load offset (see Figure 6.9). This is due to the increase in electricity demand for cooling by the mid-rise apartment during summer. The battery state of charge (SOC) ramps up and down between the hours (8:00 – 13:00) representing charging (red area on the stacked graph in Figure 6.9) and discharging (the light blue area on the stacked graph in Figure 6.9). The discharging falls within the period of the high ToU rates and demand charges of Figure 6.8 and Table 6.2 respectively. This offset the energy supply cost due to high demand charges and time use rates within that period.

6.5 IMPACT OF OPTIMISED DISTRIBUTED ENERGY SYSTEMS ON LOCAL MICROGRID CONSTRAINTS

In this section, the optimal investment decisions of DER-CAM to meet the energy demand requirements of the mid-rise apartment using onsite distributed energy resources and the utility grid are tested on a distribution network model. This was simulated using a time series sequential power flow in NEPLAN.

The procedure **evaluates the impact** of DER-CAM optimal decisions and dispatch schedules on distribution network constraints **(voltage profiles and power losses)**.

The evaluation is carried out for the eight scenarios simulated in DER-CAM. The detailed description of each scenario is shown in Table 6.3. The investment decisions (cost of energy supply) and DER capacities adopted for each scenario are shown in Table 6.4.

6.5.1 Assessment Procedure

To assess the impact of the optimal investment DER configuration and operation from DER-CAM, a MATLAB script (see Appendix E) is written to read the output of DER-CAM in each scenario and net power flows are computed and send to a modelled distribution network in NEPLAN.

The validity of the assessment procedure is based on the following assumptions:

- The mid-rise apartment is connected to bus 9 of the CIGRE benchmark model [147], [148], [200] (see Figure 6.10).
- The CIGRE benchmark model is assumed to be in a climatic condition like that of the mid-rise apartment where electricity demand is maximum in the summer (due to additional cooling loads) and minimum in the winter.
- The voltage quality limits are based on [201]: ±10% of the nominal voltage that is: between 0.9 p. u and 1.1 p. u.

<u>Microgrid Distribution Network Model</u>

The microgrid distribution network is modelled in NEPLAN (a power systems and analysis software) and the data of the network is obtained from [200]. The network is a 20/0.4 kV CIGRE benchmark LV microgrid model. Figure 6.10 shows the modelled network and the node where the mid-rise apartment was connected. The modelled network in NEPLAN is shown in Appendix F. The transformer and impedance data of the network obtained from [200] are shown in Tables 6.5 and 6.6 respectively.

Table 6.5:Transformer data of the Microgrid [200]

Capacity (kVA)	**Primary Side (kV)**	**Secondary Side (kV)**	**R (pu)**	**X (pu)**
400	20	0.4	0.01	0.04

Table 6.6: Network cable impedance data [200]

Conductors	Rph (Ω / km)	Xph (Ω / km)
OL – Twisted cable 4×120 mm^2 Al	0.284	0.083
OL – Twisted cable 3×70 mm^2 Al + 54.6 mm^2 AAAC	0.497	0.086
SC – 4×6 mm^2 Cu	3.690	0.094
SC – 4×16 mm^2 Cu	1.380	0.082
SC – 4×25 mm^2 Cu	0.871	0.081
SC – 4×50 mm^2 Cu Al + 35 mm^2 Cu	0.822	0.077
SC – 4×95 mm^2 Cu Al + 35 mm^2 Cu	0.410	0.071

The block diagram of the implemented procedure is shown in Figure 6.11.

Net Load

The net load in bus 9 is computed using Equation 30 and iterated over all scenarios.

$$P_{NET}(daytype, hour) = \sum_{i}^{n} (P_{DER\_ONSITE}(daytype, hour)) + P_{GRID}(daytype, hour) - P_{DEMAND}(daytype, hour) \tag{30}$$

Where $(daytype, hour)$ represents the optimisation, set indexed by **day type** (weekdays, peak days and weekend days) for one day type in each month of the year. Hour represents the hours in each day type (1:00 – 24:00). A time series load flow with load profiles is then simulated in NEPLAN for each scenario.

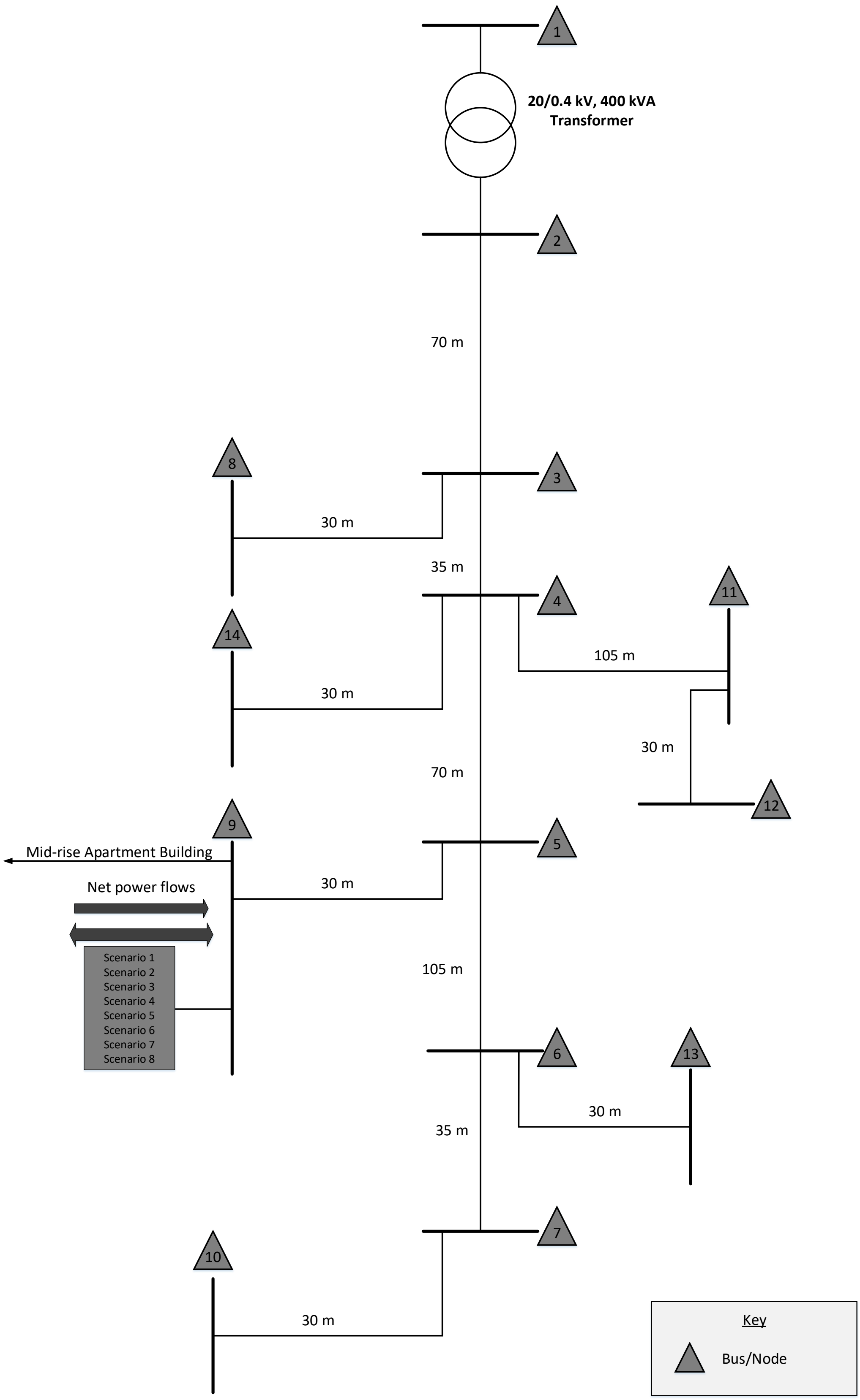


Figure 6.10: Modelled CIGRE network with mid-rise apartment connected to bus 9

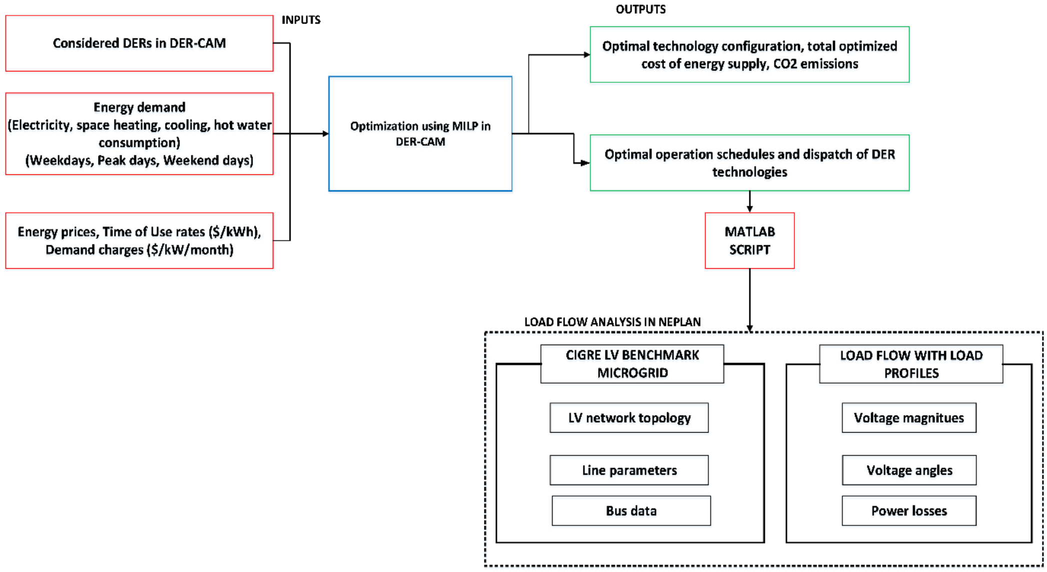


Figure 6.11: Block diagram of the procedure

The results are written to a text file and are analysed by plotting the voltage profiles and overall network energy losses for each day type (weekdays, peak days and weekend days).

6.6 Results

The load flow is run over a period of 24 hours for each typical day in each month of the year (24×12 = 288 hours representing the year).

6.6.1 Voltage Profiles

The load flow results were evaluated in terms of voltage profiles (Weekdays, Peak days and weekend days) for node 9 (the mid-rise apartment is connected to node 9). In the section describing the results for **typical weekdays**, only the voltage profiles for scenarios 6 and 8 are presented. This is because scenario 1 and 6 have the most extreme voltage excursions during weekdays. During the **typical peak days**, the voltage profiles for scenarios 1, 6, and 8 are presented. This is because scenario 1 in the peak days also had voltage excursions beyond the -10% lower limit. The voltage profiles for the **typical weekend** days are presented with only scenarios 6 and 8, given that scenario 6 had a small voltage excursion beyond the -10% lower limit. Scenario 8 (being the scenario with highest savings and lowest cost) is included in all the typical days (week, peak and weekends) to evaluate its performance from the distribution network perspective.

The combined voltage profiles plot for all the scenarios are shown in Appendix H.

Weekdays

The peak days are outliers within the data set and occupancy level is highest within this period compared with the weekdays and weekend days. Figure 6.12 shows the voltage profiles for scenarios 6 and 8 during typical weekdays in the year. It could be seen that the voltage drops for scenario 8 are within the ±10% limit except for scenario 6. The voltage excursion beyond the -10% lower limit in the case of scenario 6 occurs between hour 144 and 228, and these hours correspond to the month of June and July where the highest demand for cooling occurs for the mid-rise apartment.

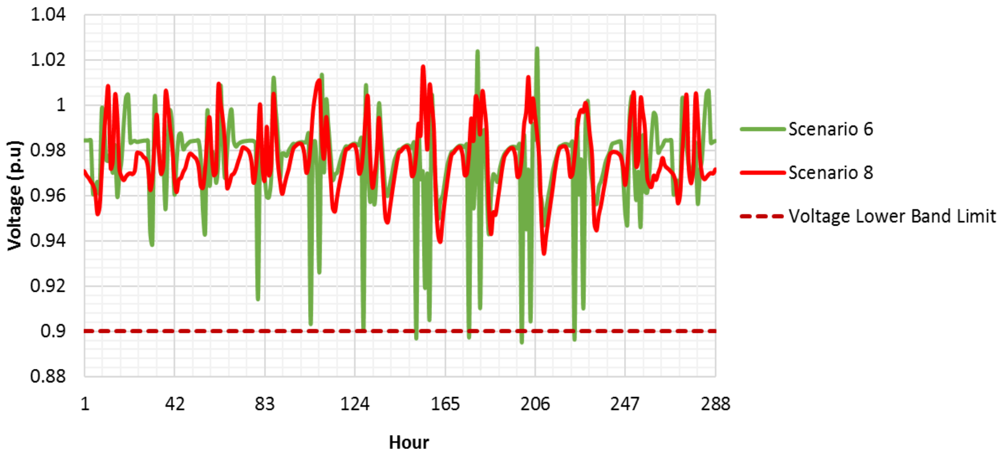


Figure 6.12: Voltage profiles for typical weekdays

The voltage profile in scenario 8 which has the lowest cost and highest savings in terms of energy supply (see Table 6.4) are within the ±10% limit. This is partly due to the optimal investment in an air-source heat pump, battery storage and load shifting strategy which minimises grid electricity import and high demand charges during the summer months.

Peak days

As mentioned earlier the typical peak days are outliers within the energy demand data of the mid-rise apartment. Figure 6.13 represents the voltage profiles for the typical outlier data sets in scenarios 1, 6 and 8.

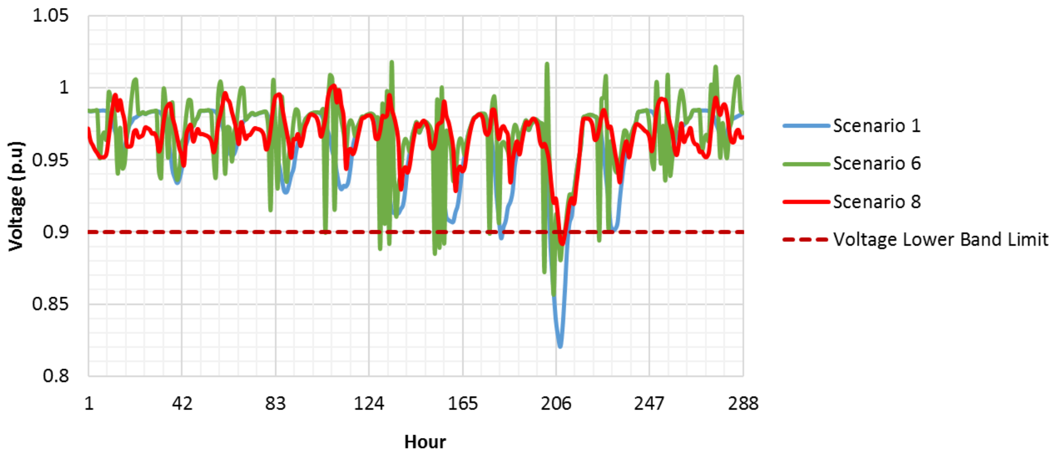


Figure 6.13: Voltage profiles for typical peak days

It is interesting to note that the -10% lower limit is violated from 0.9 p.u down to about 0.83 p.u in the case of scenario 1 **(which represents the base case where no investment in DER is considered**). The voltage drops that violates the -10% lower limit in the case of scenario 1 occurs between the hours 204 and 216. These hours occur in September which is within the summer months in the dataset of the mid-rise apartment. This is due to the high cooling demand in the hours (11:00 – 16:00) (see Figure 6.9). Scenario 6 and 8 slightly violates the -10% lower limit at 206 hours, which represents a typical peak outlier with high electricity demand for cooling during the summer.

Weekend days

The weekend days represents a slightly higher occupancy levels compared to typical weekdays for a residential building. Figure 6.14 shows the voltage profiles at the node connecting the mid-rise apartment.

Figure 6.14: Voltage profiles for typical weekend days

It is observed that only scenario 6 has voltage violation issues in hours 156 and 204, these hours represent 12 noon in July and September respectively. This is partly due to an increase in cooling demand and fluctuation in PV generation output. This scenario has a total optimised savings of 24.5% (see Table 6.4), and is not a good alternative to investing both in terms of the optimisation results and impact on node 9 bus voltage profiles.

6.6.2 Energy Losses

The total energy losses of the microgrid for each scenario were evaluated and represented in Figure 6.15. As expected the business as usual case (scenario 1, with no investment in DER) leads to the highest energy losses (about 2.76MWh) compared with all other scenarios. The lowest energy losses compared to other scenarios is achieved in scenarios 2 and 3 and these are 1.57MWh and 1.58MWh respectively. However, these two scenarios produce savings compared to **scenario 1** costs **(after investment**) of 23.9% and 28.9% respectively as shown in Table 6.5, which is lower than the 40.1% savings achieved in scenario 8.

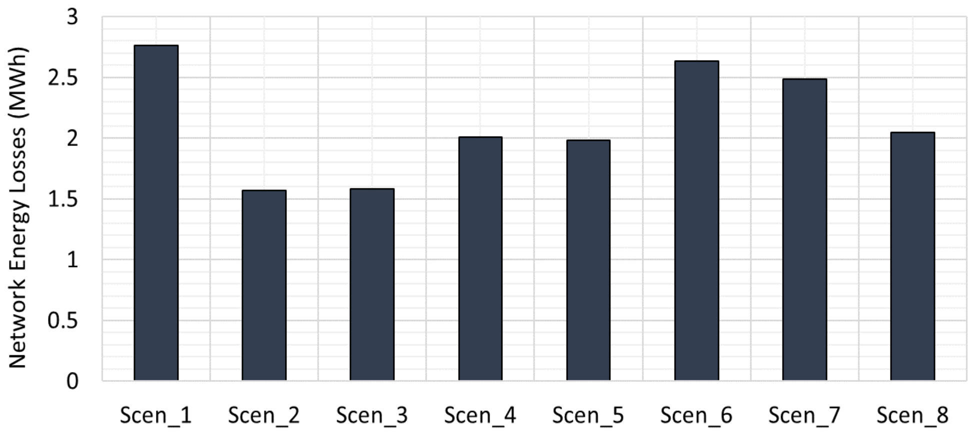


Figure 6.15: Microgrid Energy losses

Although scenario 8 produces high savings from the optimisation point of view, it increases the energy losses of the microgrid by about 0.48 MWh when compared to scenarios 2 and 3.

This shows that there may be many solutions obtained using distributed energy technologies planning optimisation models that are optimal from the point of view of DER owners but not feasible from the local electricity network’s technical constraints point of view.

6.7 DISCUSSION

Evaluating the impact of optimised distributed energy systems (with battery storage and high DG penetration) can achieve savings for both the DNO and customer. However, in the surveyed literature (see section 2.6 of chapter 2), techniques for evaluating distributed energy systems are only explored from the DNO perspective or the customer perspective. Therefore, in this thesis, a soft-linking procedure was designed to evaluate the impact (in terms of voltage profiles and energy losses) of optimised distributed energy systems on a modelled microgrid (discussed in chapter 6).

The results indicate that not all optimised distributed energy systems solutions from the customer perspectives are feasible from the DNO point of view. This work can, however, be extended by developing a multi-objective decision support system for evaluating distributed energy systems from the DNO and customer perspectives. A trade-off analysis can be carried out to evaluate Pareto optimal points for DNO and customer perspective.

6.8 SUMMARY

In this chapter, a procedure for the assessment of the impact of optimal investment decisions from DER planning and optimisation tools on the local electricity network was developed. Eight different scenarios were considered in the optimisation simulation: Table 6.7 recalls the description of each of the considered scenarios.

Table 6.7: Description of all scenarios considered in the optimisation simulation

Scenarios	Description
Scenario 1 (S1)	Base case, all energy supplies and demand are met by the utility grid
Scenario 2 (S2)	Investment in solar PV (self-consumption) and Battery is considered
Scenario 3 (S3)	Investment in solar PV (self-consumption) and Battery with load shifting as a demand response strategy is considered
Scenario 4 (S4)	Investment in solar PV (self-consumption), Battery and Air-Source Heat Pump considered
Scenario 5 (S5)	Investment in solar PV (self-consumption), Battery and Air-Source Heat Pump. Load shifting as a demand response strategy is considered
Scenario 6 (S6)	Investment in solar PV (excess export) and Battery considered
Scenario 7 (S7)	Investment in solar PV (excess export), Battery and Air-Source Heat Pump
Scenario 8 (S8)	Investment in solar PV (excess export enabled), Battery and Air-Source Heat Pump. Load shifting as a demand response strategy is considered

A case study was presented for a mid-rise apartment building using the Lawrence Berkeley's Distributed Energy Resources Customer Adoption Model (DER-CAM). The optimal investment decisions and schedules were interfaced (using a script written in MATLAB) to a time series load flow model.

The results demonstrated that a combination of DER technologies and demand response strategies (load shifting and ToU rates in this case) can produce savings for onsite DER and the same time operate within the limit of the local electricity network constraints as seen in the case of scenario 8. Using the procedure developed in MATLAB to read DER-CAM optimal dispatch schedules to a modelled CIGRE distribution network model, the following main findings are:

- During typical peak days within the year, **scenarios 1 and 6** violates the ±10% voltage lower limit (from 0.9 p.u down to about 0.83 p.u in the case of scenario 1), when compared to the weekdays and weekend days.
- The business as usual case with no investment in DER contributed to the highest overall microgrid energy loss of 2.76 MWh. This shows that properly managed onsite DER can reduce the energy losses on the local distribution grid.
- Not all optimal solutions obtained using distributed energy technologies planning optimisation models are feasible from the local electricity network's perspective in terms of voltage and energy loss constraints.

With optimal decisions in optimisation tools such as DER-CAM, the main finding is summarised are summarised as follows:

- Significant potential savings could be achieved for buildings and microgrids by investing into onsite DER using optimisation with a combination of DER technologies, ToU rates and load shifting (e.g. demand response).

- The procedure presented in this chapter can be of benefit to an aggregator of buildings in a community looking to optimise investment decisions in low carbon technologies within their local distribution network constraints. It inherits the benefit of detailed optimisation models such as DER-CAM while adding a soft-linking approach of evaluating the impact of these solutions on the local distribution network constraints.

Chapter 7

Conclusions and Future Work

7.1 Conclusions

Multi-scale energy systems based on high penetration of DER are to provide opportunities for the deployment of electricity storage in the form of EV and stationary battery storage. This thesis investigated the management of DER with electricity storage (EV and stationary battery storage), at three different scales: i) national and local (ii) distribution network level and (iii) customer premises (see Figure 1.1).

7.1.1 Management of EV Charging in Energy Systems with High Penetration of DER (National and Local Scale)

A one node/bus bar GB energy system model was built in **EnergyPLAN** with a library of hourly electricity demand, heating demand and transportation distributions for a reference year and an alternative future scenario.

This was used to evaluate:

- The extent to which aggregated EV and EV with V2G capability can be utilised to minimise curtailed electricity and reduce CO_2 emissions in future energy systems with high shares of wind power.
- The benefit of an aggregated DER cluster with EV and EV with V2G capability in a local community energy system in the reduction of electricity import.

It was found that in a future GB energy system with high shares of wind power, aggregated EV battery can be used to increase the wind power utilisation, and reduce wind power curtailment in the energy system.

It was also found that, with higher EV charging rate (7-22 kW), the fraction of curtailed electricity reduces. In the V2G mode, curtailed electricity decreases significantly as the charging rate is increased from 3 kW to 22 kW which shows the potential of using V2G in the reduction of curtailed electricity.

At the local energy system level with onsite DG generation, EV with V2G capability have the potential to reduce electricity import. Both EV and V2G reduces the import of electricity with increasing amount of RES, however, with V2G, the reduction rate is higher compared to the EV mode. This is due to the added capability of discharging the EV battery for use onsite. The modelled system can achieve approximately **40%** import reduction with EV having V2G capability while increasing the utilisation of fluctuating RES.

7.1.2 Managing EV Charging in a Microgrid (Distribution Network Scale)

An alternative model for evaluating the impacts of charging EV in a microgrid with high DER penetration was developed. The model was developed in MATPOWER with customer load profiles, DER generation profiles, EV charging profiles (uncontrolled and dual tariff) to evaluate the impact of distribution network loading on voltage profile and energy losses over a 24-hour period. The model evaluates how uncontrolled and dual tariff EV charging modes affects voltage profiles and energy losses in the microgrid.

It was found out that with winter load profiles and uncontrolled EV charging mode, the networks suffer voltage deviation from the network statutory voltage limits. With the addition of 50% of the reference distribution generation, the voltage excursion reduces. With controlled EV, the voltage profiles stay within the network statutory voltage limits

The voltage profiles with summer load profiles and uncontrolled EV charging regime improves the voltage deviations compared to the winter scenario with uncontrolled EV charging. However, when the EV charging is managed and DG uptake levels are increased, all voltages in the summer case stay well within the network statutory voltage limits.

At maximum loading and controlled EV charging, energy losses decrease with increasing DG penetration compared to the uncontrolled EV charging scenario. However, with minimum network loading (represented by summer load profiles) and uncontrolled EV charging, the highest energy losses are incurred. Also at **maximum generation** and **minimum network loading (represented by summer load profiles),** the losses are most significant, which points out on a non-utilisation of network assets

7.1.3 Optimal Battery Operation for an Existing PV Generation System (Customer Premises Scale)

An optimisation algorithm was developed to manage charging and discharging of a battery storage for an existing solar PV generation system at customer premises using wholesale electricity pricing 9 (as a form of a real time pricing). The optimisation algorithm maximises revenue streams for the existing solar PV owner using FiT incentives, half-hourly PV output and load dataset over a period of one year. The algorithm was simulated for a complete year with real half-hourly PV generation profiles.

It was found that in the case of the wholesale electricity tariff, the battery charges from the grid when the electricity tariffs are low or negative and discharges at high electricity tariff periods. Also, it was found that the battery prefers to charge when the PV generation is at its maximum and switches to charge with grid electricity when the PV generation drops and wholesale electricity tariff is low. Within the high wholesale tariff period of about **26p/kWh**, the battery discharges using energy stored during hours of low wholesale tariff and avoids costly grid purchase. This maximises the OF. For the modelled existing PV generation coupled with battery storage, the FiT revenue for the existing PV owner increase from **£314** with standard retail tariff (case study 1) to about **£507** in the case of wholesale electricity tariffs (case study 2). It was concluded that with wholesale electricity tariff/time use tariff, self-consumption is maximised and FiT revenue increases compared with the reference case with no battery storage and flat tariff. The proposed battery capacity for the existing PV system could be increased to **3kWh** for a marginal increase in revenue. The battery storage adoption (with economy 7 as ToU tariff) for the existing PV generation system presented in **chapter 5** will only become economically viable when battery unit cost drops to **£138/kWh or less.**

7.1.4 Impact of Optimised Distributed Energy Systems on Microgrid Constraints (Distribution Network and Customer Premises Scale)

A procedure was developed to evaluate the impact of optimised distributed energy systems simulated in an optimisation tool (DER-CAM) on distribution network constraints using a time series power flow. In peak typical days of the year, more voltage excursions occur compared to typical weekdays and weekend days.

The business as usual case with no investment in DER contributed to the highest overall microgrid energy loss of **2.76 MWh**. This shows that properly managed onsite DER can reduce the energy losses on the local distribution grid. Also, not all optimal solutions obtained using distributed energy technologies planning optimisation models are feasible from the local electricity network's perspective (in terms of voltage and energy loss constraints). Therefore, network constraints can be modelled in DER energy planning tools. By using optimisation tools to evaluate the investment decisions for the adoption of onsite DER, significant savings could be achieved for buildings and microgrids. This is achieved by investing into onsite and considering different DER technologies, ToU rates, load shifting and demand response strategies.

7.1.5 Contributions of the Thesis

Through this PhD study, the contributions can be summarised as:

- A methodology was built into EnergyPLAN for assessing the benefit of EV storage in large & local energy systems with high shares of RES.
- A heuristic optimisation method was developed for evaluating the impact of controlled and uncontrolled EV charging was developed using MATPOWER. The method can be used to evaluate the impact of network loading and EV charging (controlled and uncontrolled) on voltage profile and energy losses over a 24-hour period. (Chapter 4).
- An optimisation methodology was developed for managing battery storage operation for an existing PV system benefiting from the UK FiT system.
- A soft-linking procedure was designed to evaluate the impact of optimised distributed energy systems simulated in DER-CAM on microgrid constraints using a time series power flow in NEPLAN. The procedure can be utilised to evaluate the impact of optimised schedules from DER planning tools on the local distribution network. (Chapter 6).

7.2 FUTURE WORK

Following the analysis of simulated results described in this PhD thesis, a summary of further research directions is outlined as follows:

1. The energy system model presented in **chapter 3** can be extended with an economic optimisation to evaluate the costs of curtailed electricity. A trade-off analysis can then be carried out to determine the best option: between minimising the cost curtailed of electricity and minimising CO_2 emissions.
2. The MATPOWER technique developed in **chapter 4** for evaluating EV charging in a microgrid could be enhanced by using a detailed building model like EnergyPLUS to model the microgrids loads.
3. Stochastic programming techniques can be utilised to account for uncertainty in load demand for the optimisation model presented in **chapter 5**.
4. Include AC power flow network constraints directly into the AIMMS optimisation model and compare with the soft-linking procedure used **in chapter 6.**
5. Compare EV and stationary battery storage for the optimisation model developed in **chapter 5**.
6. Study the communication systems that can be used for the management of battery storage services with smart electricity tariffs.

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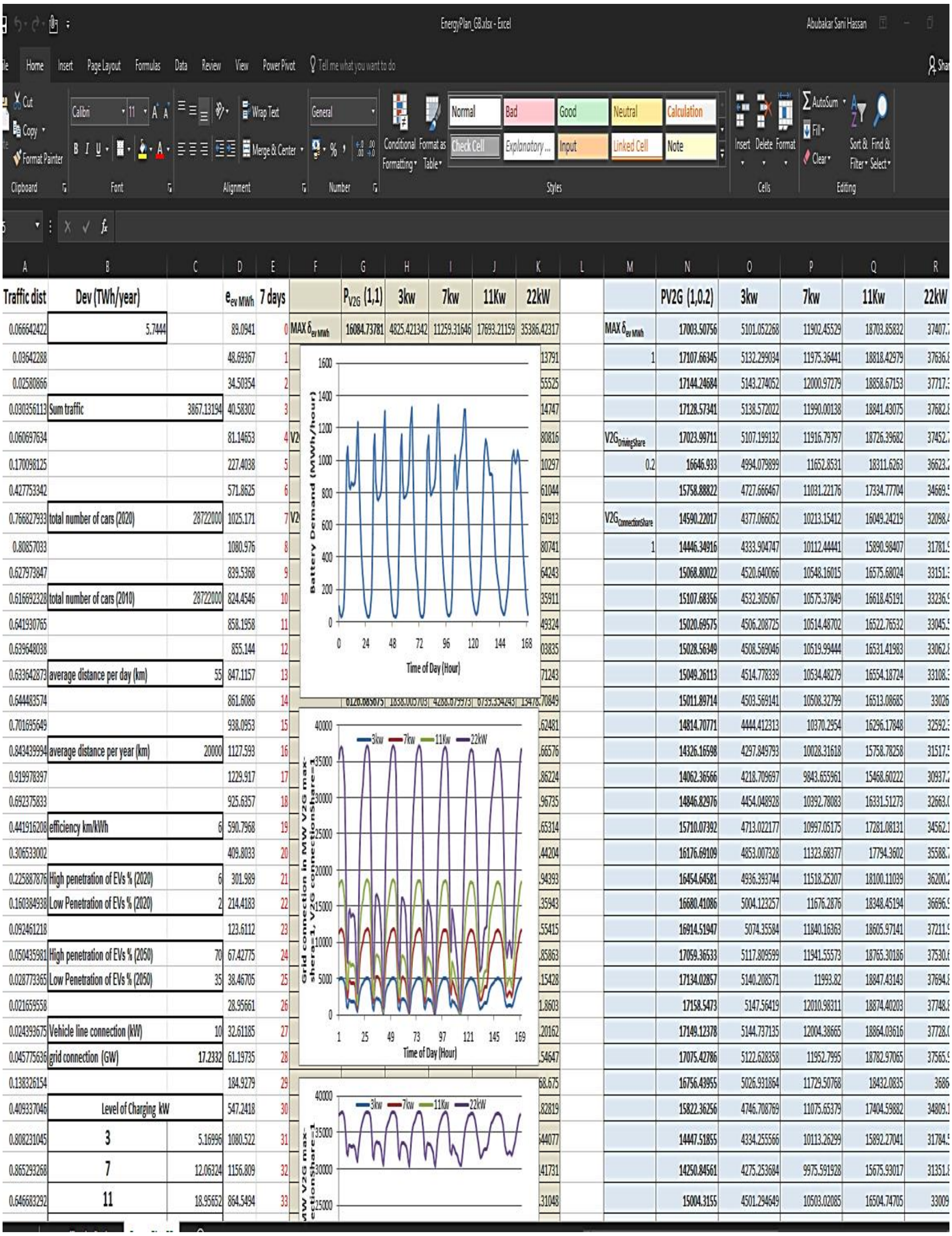
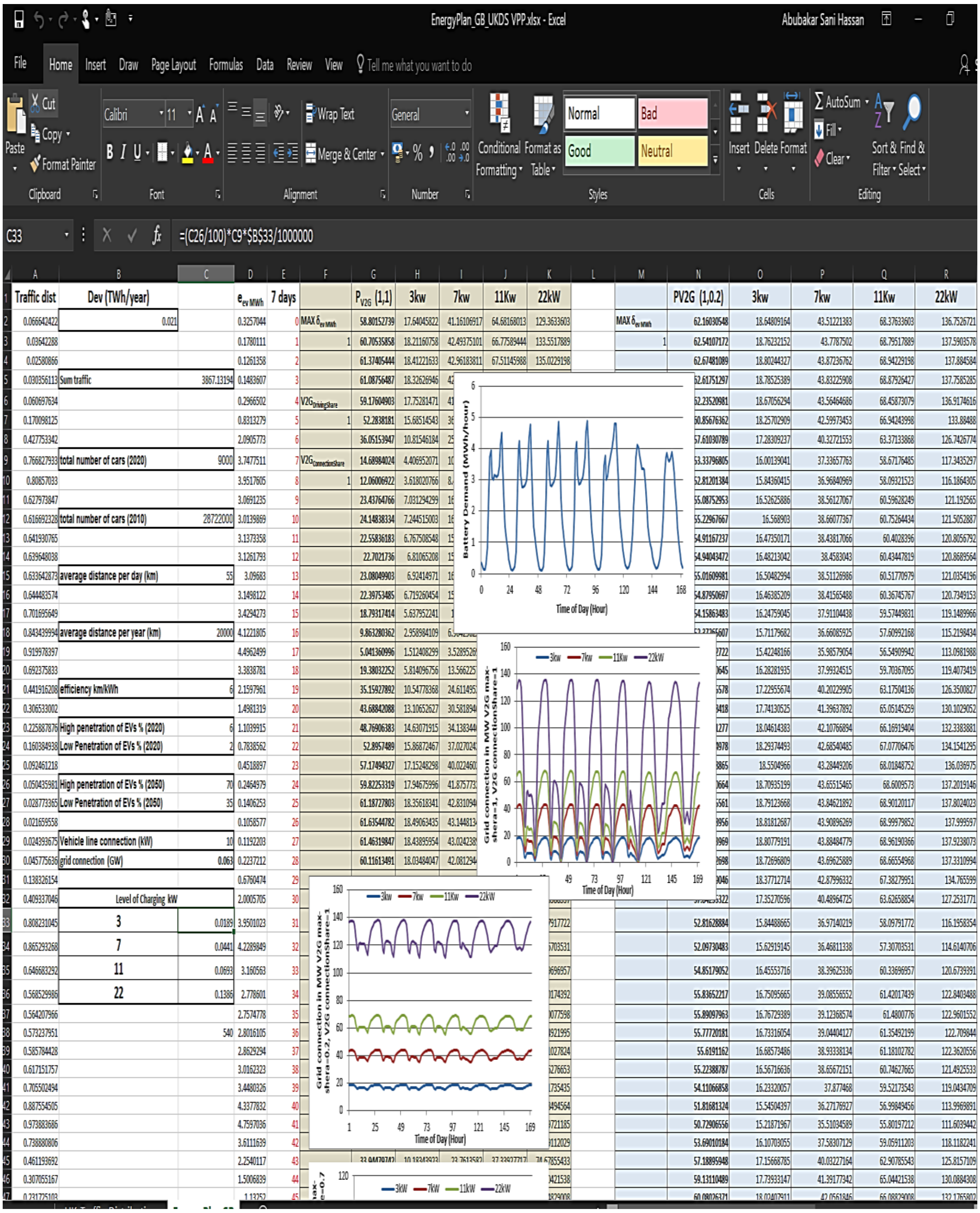
Appendix A

EV with V2G capability distributions snapshot (GB)



Appendix B

EV and V2G distributions snapshot (local energy systems)



Appendix C

Optimisation script developed in Chapter 5

```
Model Main_sabo44 {
 Set time {
 Index: t;
 Definition: ElementRange(1,48);
 }
 Set daytype {
 Index: d;
 Definition: ElementRange(1,365);
 }
 Parameter P_dmd {
 IndexDomain: (d,t);
 }
 Parameter P_pv {
 IndexDomain: (d,t);
 }
 Parameter P_dmd_unmet {
 IndexDomain: (d,t);
 Definition: {
 if P_dmd(d,t)>P_pv(d,t) then
 P_dmd(d,t)-P_pv(d,t)
 else
 0
 endif;
 }
 }
 Parameter P_pv_excess {
 IndexDomain: (d,t);
 Definition: {
 if P_pv(d,t)>P_dmd(d,t) then
 P_pv(d,t)-P_dmd(d,t)
 else
 0
 endif;
 }
 }
 Parameter p_retail {
 Definition: 0.15;
 }
 Parameter p_export {
 Definition: 0.0464;
 }
 Parameter p_FIT {
 Definition: 0.1257;
 }
 Parameter Ebatt;
 Parameter Ebatt_min {
 Definition: 0.0*Ebatt;
 }
 Parameter Ebatt_max {
 Definition: Ebatt*1;
 }
 Parameter Pch_min {
 Definition: 0.255;
 }
 Parameter Pch_max {
 Definition: 1.5;
 }
```

```
Parameter Pdis_min {
Definition: 0.255;
}
Parameter Pdis_max {
Definition: 1.5;
}
Parameter p_tou {
IndexDomain: (d,t);
}
Parameter dt {
Definition: 0.5;
}
Parameter e_c {
Definition: 0.954;
}
Parameter e_d {
Definition: 0.954;
}
Parameter M {
Definition: 30;
}
Variable P_grid {
IndexDomain: (d,t);
Range: nonnegative;
}
Variable P_pv_export {
IndexDomain: (d,t);
Range: nonnegative;
}
Variable P_charge {
IndexDomain: (d,t);
Range: nonnegative;
}
Variable P_charge_grid {
IndexDomain: (d,t);
Range: nonnegative;
}
Variable P_discharge {
IndexDomain: (d,t);
Range: nonnegative;
}
Variable E_s {
IndexDomain: (d,t);
Range: nonnegative;
}
Variable X {
IndexDomain: (d,t);
Range: binary;
}
Variable Y {
IndexDomain: (d,t);
Range: binary;
}
Variable Z {
IndexDomain: (d,t);
Range: binary;
}
Variable TotalBenefit {
Range: free;
Definition: sum((d,t), P_pv(d,t)*p_FIT*dt + P_pv_export(d,t)*p_export*dt -
P_charge_grid(d,t)*p_tou(d,t)*dt + P_discharge(d,t)*p_tou(d,t)*dt +
E_s(d,t)*0.00001 - P_grid(d,t)*p_tou(d, t)*dt);
}
Constraint ES1 {
IndexDomain: (d,t);
Definition: P_charge(d,t)<=Pch_max*Y(d,t);
}
Constraint ES2 {
```

```
 IndexDomain: (d,t);
 Definition: P_charge(d,t)>=Pch_min*Y(d,t);
 }
 Constraint ES3 {
 IndexDomain: (d,t);
 Definition: P_discharge(d,t)<=Pdis_max*Z(d,t);
 }
 Constraint ES4 {
 IndexDomain: (d,t);
 Definition: P_discharge(d,t)>=Pdis_min*Z(d,t);
 }
 Constraint ES5 {
 IndexDomain: (d,t);
 Definition: Y(d,t)+Z(d,t)<=1;
 }
 Constraint ES6 {
 Definition: sum((d,t),
P_discharge(d,t))<=sum((d,t),P_charge(d,t)+P_charge_grid(d,t));
 }
 Constraint SOCC {
 IndexDomain: (d,t);
 Definition: E_s(d,t)=E_s(d,t-
1)+(e_c*dt*P_charge(d,t)+e_c*dt*P_charge_grid(d,t))-
(P_discharge(d,t)*dt/e_d);
 }
 Constraint SOCC2 {
 IndexDomain: (d,t);
 Definition: Ebatt_min<=E_s(d,t)<=Ebatt_max;
 }
 Constraint export {
 IndexDomain: (d,t);
 Definition: P_pv_export(d,t)<=(1-X(d,t))*M;
 }
 Constraint import {
 IndexDomain: (d,t);
 Definition: P_grid(d,t)<=X(d,t)*M;
 }
 Constraint PowerBalance {
 IndexDomain: (d,t);
 Definition: P_grid(d,t)+P_pv(d,t)-P_pv_export(d,t)-P_charge(d,t)-
P_charge_grid(d,t)+P_discharge(d,t)=P_dmd(d,t);
 }
 Constraint d1 {
 IndexDomain: (d,t);
 Definition: P_pv_export(d,t)<=P_pv_excess(d,t);
 }
 Constraint d3 {
 IndexDomain: (d,t);
 Definition: 0<=P_grid(d,t)<=P_dmd_unmet(d,t);
 }
 Constraint d4 {
 IndexDomain: (d,t);
 Definition: P_discharge(d,t)+P_grid(d,t)=P_dmd_unmet(d,t);
 }
 Constraint gh {
 IndexDomain: (d,t);
 Definition: P_charge_grid(d,t)<=Pch_max;
 }
 MathematicalProgram BenefitModel {
 Objective: TotalBenefit;
 Direction: maximise;
 Constraints: AllConstraints;
 Variables: AllVariables;
 Type: Automatic;
 }
 Parameter SOC {
 IndexDomain: (d,t);
 Definition: E_s(d,t)/Ebatt;
```

```
}
Parameter TotalGridP {
Definition: sum((d,t),P_grid(d,t));
}
Parameter TotalGridE {
Definition: sum((d,t),P_grid(d,t)*dt);
}
Parameter TotalExport {
Definition: sum((d,t),P_pv_export(d,t));
}
Parameter BattE {
Definition: sum((d,t),E_s(d,t));
}
Parameter steps {
Definition: 10;
}
Set CurvePoints {
SubsetOf: Integers;
Index: i_cp;
Definition: ElementRange(0,steps);
}
Parameter min1 {
Definition: 0.01;
}
Parameter max2 {
Definition: 10;
}
Parameter OptimalBenefit {
IndexDomain: i_cp;
}
Parameter BatteryCapacityPoints {
IndexDomain: (i_cp);
Definition: min1 + i_cp*(max2-min1)/steps;
}
Procedure RunBenefitModel {
Body: {
for (i_cp) do
Ebatt := BatteryCapacityPoints(i_cp);
MainExecution;
OptimalBenefit(i_cp) := TotalBenefit;
endfor;
}
}
Procedure MainInitialization;
Procedure MainExecution {
Body: {
SpreadSheet::RetrieveParameter("input.xlsx", P_dmd,"A1:AV1:AV365","load");
SpreadSheet::RetrieveParameter("input.xlsx", P_pv,"A1:AV1:AV365","pv");
SpreadSheet::RetrieveParameter("input.xlsx", p_tou,"A1:AV1:AV365","tou");
solve BenefitModel;

SpreadSheet::AssignParameter("output22.xlsx",P_dmd,"A1:AV1:AV365","demand",0
);

SpreadSheet::AssignParameter("output22.xlsx",P_pv,"A1:AV1:AV365","pv_profile
s",0);

SpreadSheet::AssignParameter("output22.xlsx",P_grid,"A1:AV1:AV365","GridPurc
hase",0);

SpreadSheet::AssignParameter("output22.xlsx",P_pv_export,"A1:AV1:AV365","Exp
orted_PV",0);

SpreadSheet::AssignParameter("output22.xlsx",P_charge,"A1:AV1:AV365","Chargi
ng",0);

SpreadSheet::AssignParameter("output22.xlsx",P_discharge,"A1:AV1:AV365","Dis
charging",0);
```

```
SpreadSheet::AssignParameter("output22.xlsx",E_s,"A1:AV1:AV365","BatteryEner
gy",0);
 SpreadSheet::AssignParameter("output22.xlsx",SOC,"A1:AV1:AV365","SOC",0);
 SpreadSheet::AssignParameter("output22.xlsx",X,"A1:AV1:AV365","BinaryX",0);
 SpreadSheet::AssignParameter("output22.xlsx",Y,"A1:AV1:AV365","BinaryY",0);
 SpreadSheet::AssignParameter("output22.xlsx",Z,"A1:AV1:AV365","BinaryZ",0);

SpreadSheet::AssignParameter("output22.xlsx",P_charge_grid,"A1:AV1:AV365","G
rid_Charge",0);
 }
 }
 Procedure MainTermination {
 Body: {
 return DataManagementExit();
 }
 }
}
```

Appendix D

LBNL confirmation of Attendance (Chapter 6)

ERNEST ORLANDO LAWRENCE
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Operated for the United States Department of Energy

To
Richard Jeans
Cardiff School of Engineering
PGR International Experience Fund

Monday, 29 June 2015

CONFIRMATION OF ATTENDENCE

Dear Richard,

This is to confirm that Abubakar Sani Hassan has been with the Grid Integration Group, Lawrence Berkeley National Laboratory as an affiliate research student from 15/04/2015 to 16/06/2015.

Within this period he utilized very successfully the Investment and Planning version of Distributed Energy Resources Customer Adoption Model (DER-CAM) to assess Distributed Energy Resources (DER) adoption in clusters of residential and commercial buildings, using data from the United Kingdom. He then designed his own MATLAB script to read the DER-CAM results into the power flow program NEPLAN in order to assess the impact of DER adoption options on the Low Voltage Distribution Network. He plans to extend the work to evaluate Demand Response (DR) using DER-CAM's DR and Load Shifting (LS) capabilities and network upgrade options when power flow limits are violated as a result of power flows to and from the DER clusters.

It was our pleasure to host him and we are sorry to see him leaving.

Please contact me at +1.510-486-4929 or at mstadler@lbl.gov if you have any questions or if there is any other way that we can be of assistance.

Sincerely,

Stadler Michael

Dr. Michael Stadler
Staff Scientist
Group Leader Grid Integration Group
Microgrid Team Lead
Energy Technologies Area

Appendix E

Sample MATLAB script that Reads and links DER-CAM output to NEPLAN (Chapter 6)

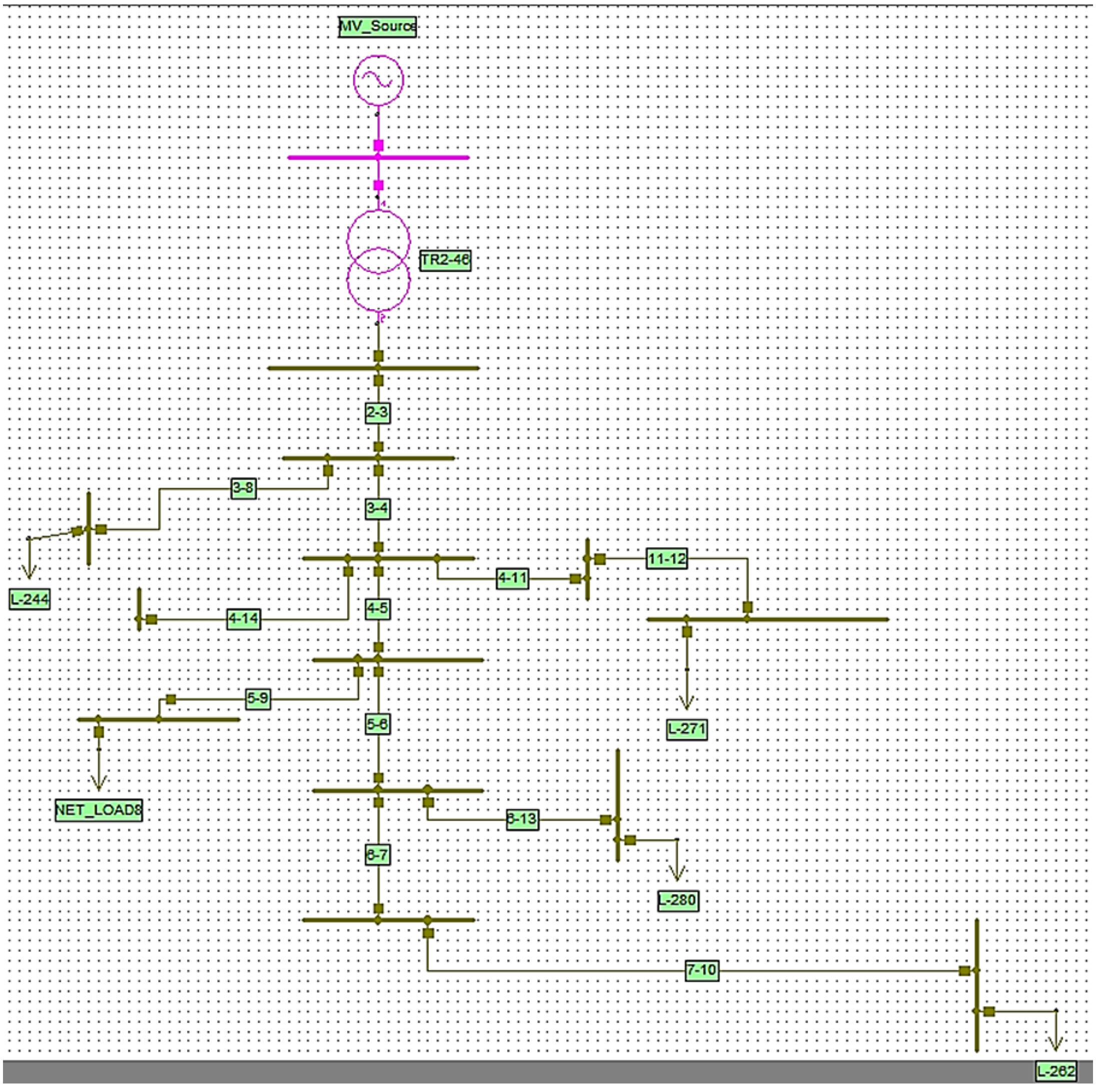
```
A_01=xlsread('N:\Dropbox\MATLAB\DER-
CAM_NEPLAN\reference.xlsm','Detailed Results','B612:Y612:Y623');
B_01=xlsread('N:\Dropbox\MATLAB\DER-
CAM_NEPLAN\reference.xlsm','Detailed Results','B625:Y625:Y636');
C_01=xlsread('N:\Dropbox\MATLAB\DER-
CAM_NEPLAN\reference.xlsm','Detailed Results', 'B638:Y638:Y649');
D_01 = transpose(A_01);
E_01 = transpose(B_01);
F_01 = transpose(C_01);
weekdays1 = D_01(:);
peak1 = E_01(:);
weekend1 = F_01(:);
total_profile1=[weekdays1;peak1;weekend1];

A_02=xlsread('N:\Dropbox\MATLAB\DER-
CAM_NEPLAN\reference.xlsm','Detailed Results','B782:Y782:Y793');
B_02=xlsread ('N:\Dropbox\MATLAB\DER-
CAM_NEPLAN\reference.xlsm','Detailed Results','B795:Y795:Y806');
C_02=xlsread('N:\Dropbox\MATLAB\DER-
CAM_NEPLAN\reference.xlsm','Detailed Results', 'B808:Y808:Y819');
D_02 = transpose(A_02);
E_02 = transpose(B_02);
F_02 = transpose(C_02);
weekdays2 = D_02(:);
peak2 = E_02(:);
weekend2 = F_02(:);
total_profile2=[weekdays2;peak2;weekend2];

xlswrite('N:\Dropbox\MATLAB\DER-CAM_NEPLAN\neplan
input.xlsx',total_profile1,'neplan','A1');
xlswrite('N:\Dropbox\MATLAB\DER-CAM_NEPLAN\neplan
input.xlsx',total_profile2,'neplan','B1');
```

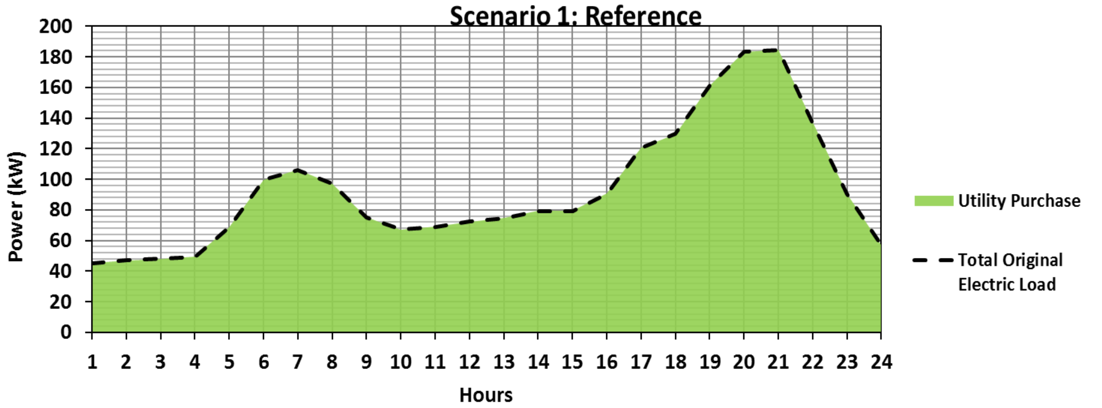
Appendix F

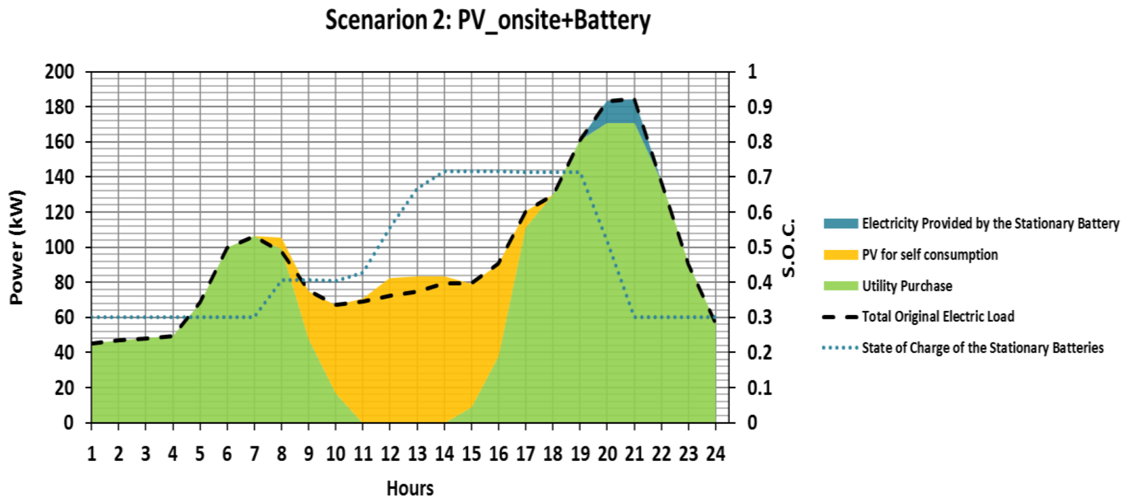
Modelled Microgrid in NEPLAN (Chapter 6)

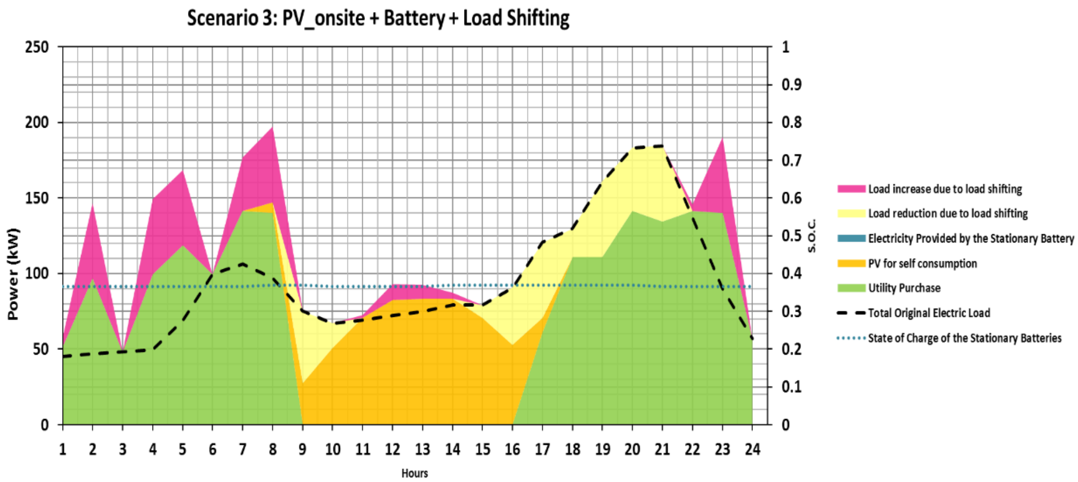


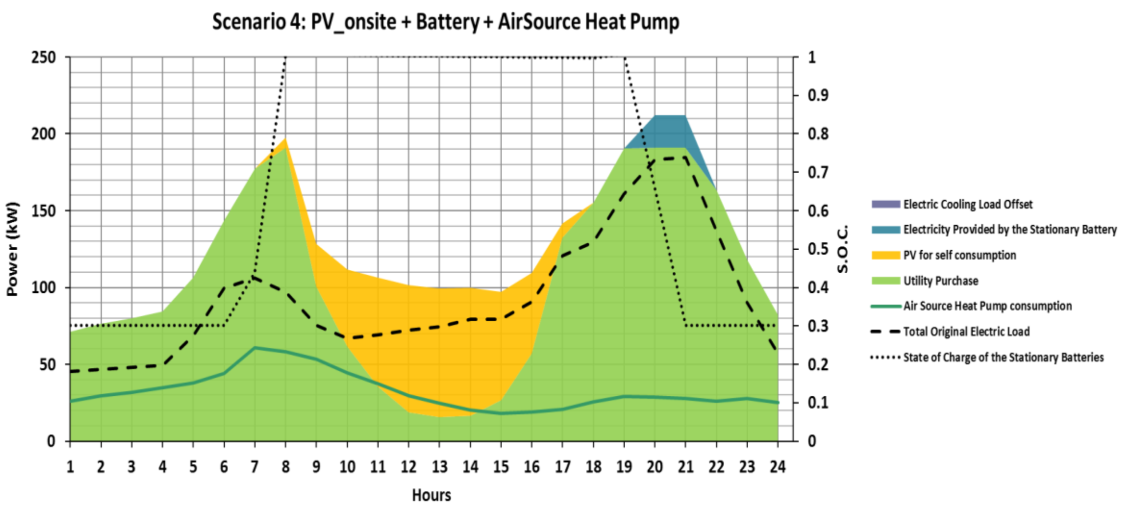
Appendix G

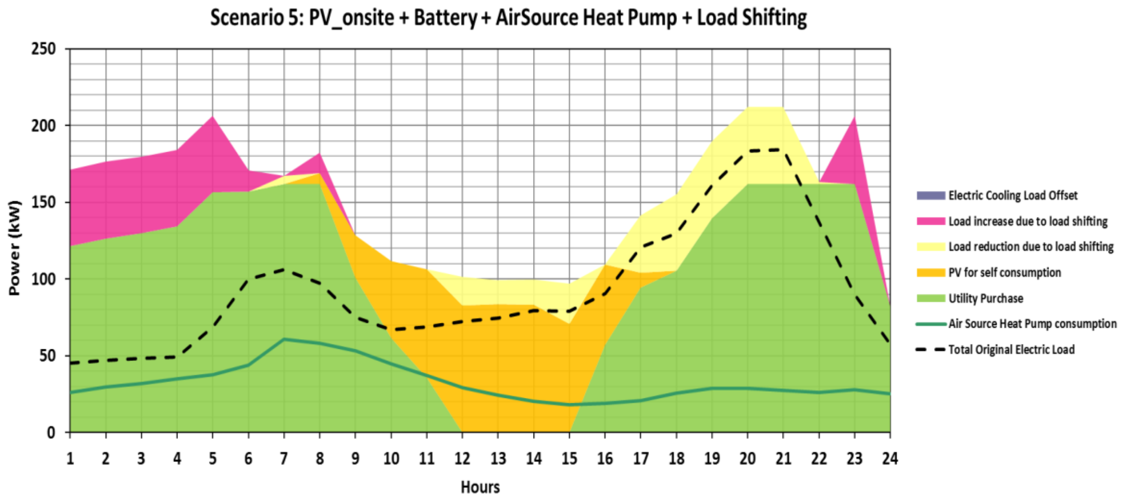
Optimal Dispatch Schedules for Scenarios 1,2,3,4,5,6, and 7 in January (Chapter 6)

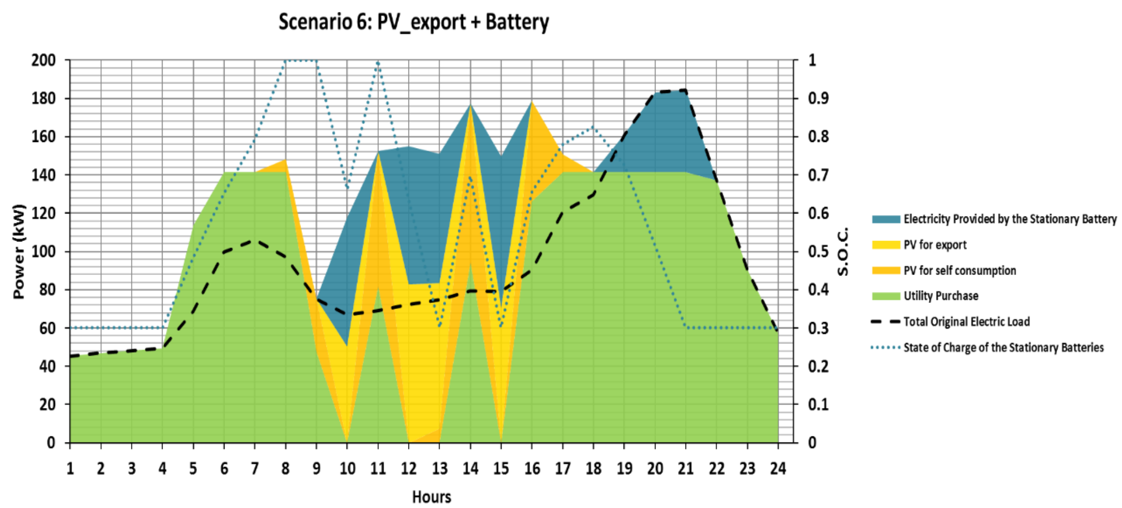


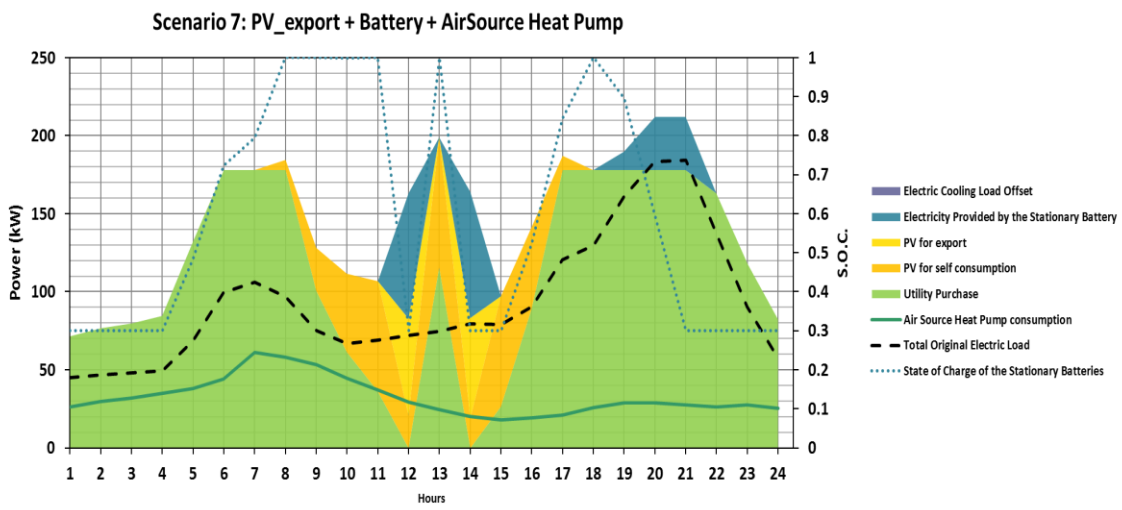





Scenario 4: PV_onsite + Battery + AirSource Heat Pump
Power (kW)
S.O.C.
Hours
Electric Cooling Load Offset
Electricity Provided by the Stationary Battery
PV for self consumption
Utility Purchase
Air Source Heat Pump consumption
Total Original Electric Load
State of Charge of the Stationary Batteries


Scenario 5: PV_onsite + Battery + AirSource Heat Pump + Load Shifting
Power (kW)
Hours
Electric Cooling Load Offset
Load increase due to load shifting
Load reduction due to load shifting
PV for self consumption
Utility Purchase
Air Source Heat Pump consumption
Total Original Electric Load

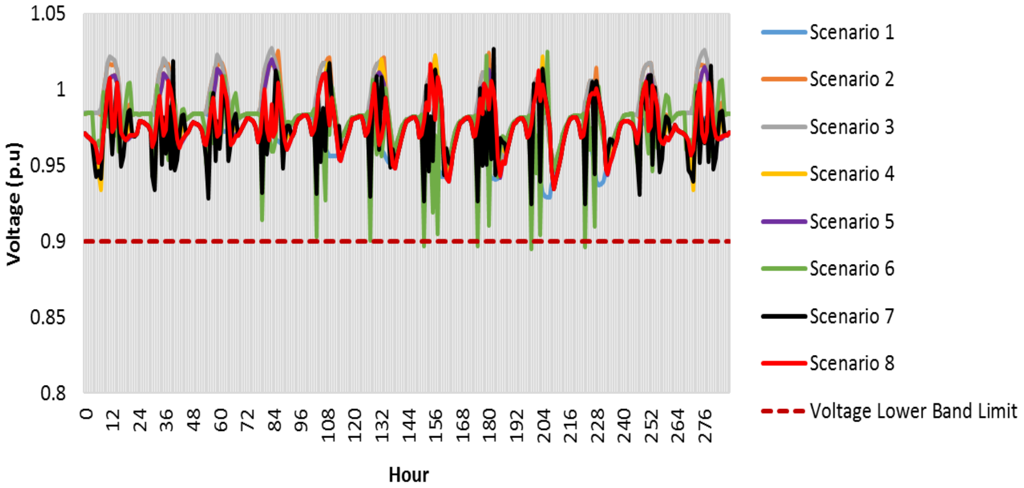

Scenario 6: PV_export + Battery
Power (kW)
S.O.C.
Hours
Electricity Provided by the Stationary Battery
PV for export
PV for self consumption
Utility Purchase
Total Original Electric Load
State of Charge of the Stationary Batteries


Scenario 7: PV_export + Battery + AirSource Heat Pump
Power (kW)
S.O.C.
Hours
Electric Cooling Load Offset
Electricity Provided by the Stationary Battery
PV for export
PV for self consumption
Utility Purchase
Air Source Heat Pump consumption
Total Original Electric Load
State of Charge of the Stationary Batteries

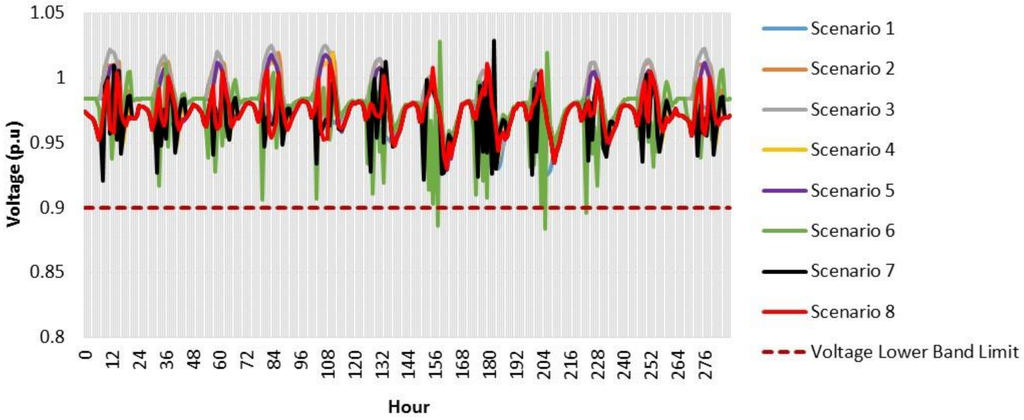
Appendix H

Voltage profile plots for all simulated scenarios (Chapter 6)

WEEKDAYS



PEAK DAYS



WEEKEND DAYS