The Use of Direct Current Distribution Systems in Delivering Scalable Charging Infrastructure for Battery Electric Vehicles

PhD Thesis

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May 22, 2020

Abstract

The use of low voltage direct current (LVDC) distribution is becoming recognised as a technology enabler that can be used to efficiently network native DC generators with DC loads, offer improved power sharing capabilities, reduce power system material resource requirements and enhance the performance of variable speed machinery. Practical deployment opportunities for LVDC range from small-scale microgrids in the context of energy for development to sophisticated, modern building-level power distribution systems for commercial office spaces, manufacturing applications and industrial processes. However, the incumbent AC distribution system benefits from existing technical product and safety standards, which makes the early adoption of LVDC systems challenging from a risk and cost perspective.

Concurrently, the demand for native DC loads such as Battery Electric Transportation Systems is growing. This is especially significant in the area of private electric vehicles (EVs), taxis and buses, but the prospect of electric trucks, ferries and short-range aircraft are also tangible opportunities. The success of this electric transport revolution depends on several factors, one of which is the availability of battery charging infrastructure that can cost effectively integrate with the existing electrical network, deliver adequate energy transfer rates and adapt to the rapid technical development of this industry.

This thesis explores the application of two, novel LVDC distribution systems for the development of scalable EV charging networks; where charging infrastructure has the ability to scale with increasing EV adoption and has a lower risk of becoming a stranded asset in the future. The modelling is supported by real, rapid DC charger utilisation data from the national charging network in Scotland, comprising over 192 chargers and 400,000 charging events.

During the work of this thesis, it was found that a combined heat and power (CHP) system can economically support short duration charging scenarios by providing additional power capacity in a congested electrical grid. In this case the highest system efficiency and Net Present Value (NPV) is achieved with a fuel cell directly connected to the DC charging network, compared to other gas reciprocating CHP options. Furthermore, the proposition of a reconfigurable LVDC charging network, interfaced to the public AC distribution network, reduces the capital outlay, offers a higher NPV and improved scalability compared to other charging solutions. For charging system designers and operators, it was found that rapid DC chargers can be classified by specific locations, each possessing a distinct Gaussian arrival pattern and Gamma distribution for charging energy delivered.

Contents

List of Figures

List of Tables

Acknowledgements

This research would not have been possible without the support from the Future Power Networks and Smart Grids CDT team and industrial sponsors, Rolls Royce. Thank you for the innovative curriculum and insight into the opportunities and challenges that are associated with the transition towards more sustainable, reliable and economical energy systems.

Over the past three years I was fortunate to have been supervised by Professor Stuart Galloway, who always found time for me and humoured my regular, tangential ideas - thank you for keeping me on track. I was also fortunate to work with talented researchers and power system engineers like Dr Lesiba Mokogonyana, Dr Abdullah Emhemmed, Dr Jethro Browell and Ciaran Gilbert - thank you for introducing me to the world of LVDC, MILP and forecasting. The value of this work has been enhanced by the provision of charging data from the Charge Place Scotland network - many thanks to Transport Scotland for permitting access to this data and to Charge Your Car for supporting the requests for specific data extracts.

To my wife, thank you for your patience, I can now get back to the DIY list.

Abbreviations

AC .... Alternating Current
ANN ..... Artificial Neural Networks
ARIMA... Auto-Regressive Integrated Moving Average
ARX ..... Auto-Regressive Exogenous
BESS..... Battery Energy Storage System
BET...... Battery Electric Transport
BMS...... Battery Management System
CCS ..... Combined charging system
CHP...... Combined Heat & Power
CMZ ..... Constraint Management Zone
CPO...... Charge Point Operator
CPS ...... Charge Place Scotland
DC .... Direct Current
DHN ..... District Heating Network
DNO ..... Distribution Network Operator
EMS...... Energy Management System
EV .... Electric Vehicle
EVSE .... Electric Vehicle Supply Equipment
FMEA.... Failure Modes & Effects Analysis
GMM..... Gaussian Mixture Model
HPC...... High Power Charge
HVDC.... High Voltage Direct Current
IEC ...... International Electrotechnical Committee
ICE ...... Internal Combustion Engine

IGBT .... Insulated Gate Bipolar Transister

LED......... Light Emitting Diode

LIB .... Lithium Ion Battery

LP .... Linear Programming

LVAC .... Low Voltage Alternating Current

LVDC....... Low Voltage Direct Current

MILP .... Mixed Integer Linear Programming

MMC .... Multi-modular Converters

MOSFET ... Metal Oxide Field Effect Transister

MT-LVDC... Multi-terminal Low Voltage Direct Current

OCPP....... Open Charge Point Protocol

PCC .... Point of Common Coupling

PE.......... Protective Earth

PEV .... Plug-in Electric Vehicle

PLC......... Power Line Communication

PV.......... Photovoltaic

SOC......... State of Charge

SOH .... State of Health

SSCB .... Solid State Circuit Breaker

RMS........ Root Mean Square

RPN .... Risk Priority Number

TOU .... Time of Use

TSO......... Transmission System Operator

VSD......... Variable Speed Drive

VTOL....... Vertical Take Off & Landing

WPT........ Wireless Power Transfer

Chapter 1

Introduction

1.1 The (re)emergence of LVDC Distribution

The use of direct current (DC) power distribution is not new. In fact, it was the first standard electrical distribution system at the end of the 19th century [1]. However, at the time, the inability to transform DC voltages limited the use of DC to local power stations close to electrical loads. The introduction of alternating current (AC) in the 1880s and the invention of transformers facilitated the transmission of power over long distances; AC systems have since become fundamental to the operation of modern, highly interconnected power systems. The growth of public AC power networks quickly relegated the use of DC to specific applications such as trams, elevator motors and battery-operated systems. But, as shown in (Figure 1.1), the development of industrial electronics such as the mercury arc valve in 1902 and the transistor in 1947 has allowed DC systems to evolve over the past century and we now see DC power used in high voltage transmission lines, consumer electronics and industrial variable speed drives [2].

More recently, the increased understanding and concern about the effects of centralised fossil fueled power stations on the environment has initiated a clean power revolution that is starting to challenge the one-hundred-year old power system paradigm. Modern, renewable power generators are geographically distributed and either produce DC power natively or utilise DC to regulate the power generation from variable speed generators, such as wind turbines [3]. Furthermore, the technical advancement

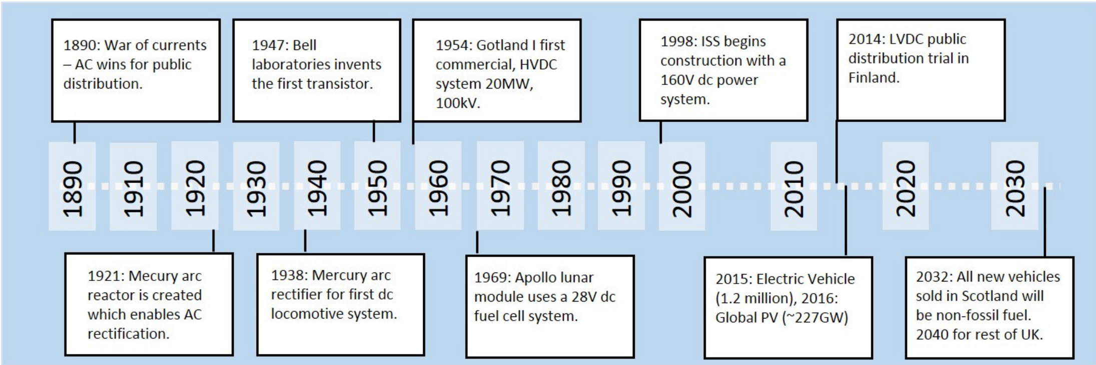


Figure 1.1: Development of LVDC distribution systems.

in lithium ion batteries since the turn of the millennium has seen the cost reduction and energy density reach a level where electric vehicles are becoming a real proposition for mainstream consumers [4]. Collectively, the increasing volume of DC generators, modern electronic loads and energy storage systems raises the question as to whether DC distribution would be a more efficient and economical public power distribution medium.

While the use of High Voltage DC (HVDC) power transmission has been commercially and technically validated for efficient bulk power transfer over distances of 80 km [5] (as the alternative High Voltage AC losses justify the additional capital expense for HVDC converter stations at this transmission distance threshold), the application of DC to lower voltage power networks has yet to reach technical maturity and is absent of a clear business case [6]. Some research work, and early trial projects, are investigating the application of Medium Voltage DC (MVDC) distribution networks, to alleviate power constraints by increasing the distribution voltage on the network and by more accurately controlling power flow [7]. At the LVDC level, researchers and engineers recognise the potential for energy efficiency improvements [8], enhanced cable power transfer [9] and greater power quality control [10], however, the development of suitable protection solutions [11], network stability challenges [12] and the absence of electrical standards [13] has limited the commercial uptake of LVDC distribution to date.

This thesis concentrates on DC distribution systems that possess voltage levels between 120-1500 Vdc and are defined as low-voltage according to IEC 60038 [14].

This classification represents an area of novel power networks which interface native DC generators such as solar PV, fuel cells, battery storage and wind turbines with native DC loads like LED lights, EVs, computers and even variable speed drives (VSD). This chapter broadly introduces the applications for LVDC distribution and establishes the case for EV charging networks as a practical application for LVDC distribution systems. This chapter provides the justification for further investigation into DC EV charging behaviour and the development of two novel LVDC charging solutions that offer improved energy efficiency and lower infrastructure costs.

1.1.1 LVDC Applications & Development Trajectory

Through pilot projects and trial sites [15], [16], it is becoming clearer that DC distribution can offer some technical benefits compared to the existing AC power systems, however, it is unclear whether these technical improvements yield strong commercial benefits for system owners. The commercial drivers for the adoption of DC distribution can be divided into two areas: capital and operational cost benefits. The capital cost benefits for DC distribution compared to AC relate to a reduction in copper cabling required for equivalent power flows and distances, the need for fewer power converter units and, in weak grid environments, a DC microgrid can mitigate the need for appliance-based voltage protection units. Furthermore, in the transportation sectors such as marine power systems, weight and size reductions of the electrical system can have secondary capital cost benefits in the form of optimised structural designs and reduced material requirements to support and house the electrical system [17].

From an operational cost perspective, energy efficiency and reliability are arguably two of the primary commercial drivers for electrical power engineers. Consequently, power dense electrical systems will recognise the highest operational cost benefits with any marginal percentage efficiency gains that could be delivered through the adoption of DC distribution. Power dense applications will also have an economy of scale advantage whereby the power converter kW to price metric will be lower compared to smaller power converters for less dense applications (as is the case in other power system applications [18]). Secondary operational cost benefits should also be considered such as reduced cooling requirements in a DC powered datacentre [19], reduced fuel consumption in transportation applications due to a lighter electrical system [17] and the potential for more reliable power networks and components [16].

As with any new technology or system there is a level of risk associated with its (widespread) adoption, as this would impact on existing operational practices and pricing [20]. This risk perception is particularly acute in the power engineering sector as any disruption to the electrical service can have severe economic and safety repercussions. Therefore, the implementation of commercial DC distribution solutions has been slow in most sectors (out-with the telecommunication and traction applications which have historically used DC power). This is due to a lack of familiarity with the technology, availability of suitable protection solutions and concerns over the reliability of components. To address this risk perception and realise the potential long term benefits that LVDC can offer, the work of this thesis will target applications where the introduction of DC distribution will have minimal impact on a wider power network or engineering system. This risk perception or factor could be considered crucial to the early development of LVDC systems. It could be argued that by implementing DC distribution systems in low risk applications the technical products, control systems and standards can be defined and verified to then enable more widespread adoption in what might be considered more critical infrastructure. To pursue this technical development approach it is therefore necessary to identify and score potential LVDC applications based on a perceived level of risk, this could be accomplished using the established Technology Readiness Level indicators (TRL) [20] but it fails to capture the consequences of a technology failure, however, in Failure Modes and Effects Analysis (FMEA) the engineer must consider the impact of a component or system failure.

In FMEA a component or system is examined to determine possible failure points and what effect that would produce should a failure occur [21]. This analysis yields a Risk Priority Number (RPN) for the component or system which is the product of failure detection, the probability of the failure occurring and the severity should the failure occur. With respect to DC distribution and its potential applications, it can be assumed that similar products and protection solutions are utilised within each of the distribution system applications and therefore the RPN is primarily determined by the severity or consequences should a failure occur on the electrical system. Figure 1.2 and Table 1.1 present a number of DC distribution applications and attaches a severity rating from 1 to 10 which is based on a qualitative assessment of the consequences should a failure occur on the electrical system, "1" being low severity and "10" high. In addition to the severity metric, a power density assessment is applied where "10" indicates an application with a high power density and "1" a low power density. Combining these two metrics can offer an estimated near-term development trajectory for commercially viable low voltage DC distribution applications.

The severity of a failure in each of the DC applications is dependent upon the types of loads that are serviced within the power network, for example, a supermarket that uses a DC distribution system to link a roof-top solar PV system to its LED lighting will have a lower severity risk than a supermarket whose DC power system integrates the refrigeration units to the network. The consequences of a component failure and loss of power will be much higher in this case than in a stand-alone lighting application due to the potential loss of produce.

The analysis presented in Figure 1.2[1] and Table 1.1 is a subjective assessment but it is interesting to note that the first commercial DC projects are focusing on warehouses and commercial office spaces as well as the deployment of DC nanogrids in emerging countries [22], [23], [19]. The use of DC in shipboard power systems has large potential benefits but much risk is associated with its adoption and therefore little acceptance has occurred within the industry thus far [22]. EV charging is closest to the top left quadrant as it is a self-contained network, has a high power density with limited adverse consequences if failure occurs. Therefore a natural progression for LVDC research is to focus on these low risk, isolated applications first in order to prove the effective operation and reliability of power converters, protection systems and network control. With more practical deployments of DC distribution, the technology will become "de-risked" and ultimately unlock the more ubiquitous power applications in the top-right

[1] Applications that fall in the top left quadrant have a low risk and high power density which indicates a near-term, commercially viable development opportunity for LVDC distribution.

Table 1.1: Descriptions for LVDC distribution application positioning, based on power density and risk severity.

Application	Risk Severity	Power Density	Justification
Residential	5	1	Moderate severity considering a component failure would cut supply to a household and may take time to repair. Low power density.
Hotels	9	6	High risk factor as any failure in the dc network would affect customer experience and revenue. Power density could be quite high.
Supermarkets	8	8	High risk as failure could affect cold stores, high power density due to refrigeration, space heating and lighting
Warehouses	6	7	Dependent on warehouse, the risk severity could change. If only LED lighting and PV this would have a low risk, if climate control and refrigeration is included then risk increases. Power density can also vary.
Commercial Offices	7	6	Depending on the office, a loss of power could have significant impact on productivity but this is likely to be repaired quickly. Relatively high power usage from lighting, computers potentially HVAC and EV charging.
Data Centres	9	8	High operational risk in adopting new distribution system as a component failure would seriously impact the business. However, dc datacentres tend to have fewer components than ac systems but they do have a single point of failure PCC. High power density.
Point to Point	10	9	Conversion of LVAC or MVAC has a high risk potential as the failure of the AC/DC power converter could impact multiple households and businesses downstream. A high power density would be expected considering a large number of customers connected to the network.
Marine Vessels	10	9.3	Shipboard power systems must be highly reliable considering health and safety of crew, commercial value of goods and mission readiness. New technology must be thoroughly tested and understood. High power density and efficiency improvements are possible.
Street Lighting	3	3	Low risk, isolated networks that would cause limited harm to public or loss of revenue if failure occurred. Low power density (2-5kW per lighting run).
Lighting & EV Charging	3	4	Same risk as stand-alone dc lighting but higher power density due to integration of DC charging points on the network.
EV Charging Networks	2	5	Low risk to public but some loss of revenue could be expected if failure occurs, however, this would be the core business for the network owner and a speedy repair would be expected. A high power density would be expected depending on the number of charging units - each rated between 50 to 350kW.
Nanogrids	1	3	In most cases nano-grids are deployed in areas without existing access to electricity, therefore some relaxation in reliability may be afforded for cost reductions considering no prior power existed, however, these grids are generally of low power density (5-10kW).

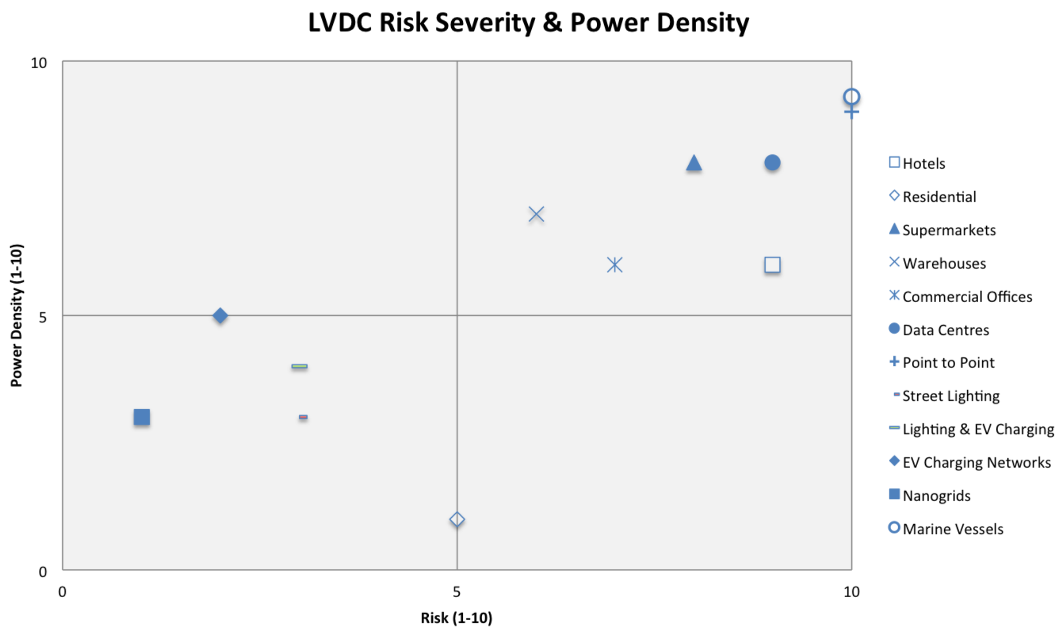


Figure 1.2: LVDC distribution application positioning, based on power density and risk severity.

quadrant of the chart.

To date little research has taken a holistic view of LVDC as a ‘tool’ for integrating EV charging infrastructure to the existing AC electrical grid. Much of the research thus far has explored the technical challenges associated with protecting and managing LVDC networks where EV charging may may be considered as one type of DC load [24] [25] [10], however, [26] and [27] have presented novel LVDC networks that facilitate EV charging infrastructure and are referred to in more detail later in this thesis. Within the EV charging sector, DC charging is evolving as a rapid charging medium, however, these charging installations exist as standalone power electronic systems and have yet to integrate other low carbon technologies, they also require dedicated grid connections and a large capital outlay [28]. This thesis therefore explores how LVDC distribution can assist the deployment of EV charging systems by utilising existing electrical infrastructure, while combining local generation and optimising the utilisation of chargers in a phased approach to deployment. What might these networks look like? Where would they be deployed? How would they be operated and do they offer a viable alternative solution to the existing charging infrastructure planning philosophies? These questions are central to the work of this thesis, but first it is necessary to examine the evolving EV market, the existing available charging options and the standards to which these novel LVDC charging networks must conform.

1.2 The Need for Flexible EV Charging Networks

It is now widely accepted that personal vehicles, buses, commercial trucks, ships and potentially aircraft will become increasingly reliant upon battery electric power systems. The United Kingdom and France have banned the sale of fossil fuel vehicles from 2040 onwards [29] and, motivated by strict EURO7 emissions standards, major automotive manufacturers have announced new hybrid and full electric models to be brought into production from 2019-2022 [30]. The success of this electric transport revolution depends on several factors, one of which is the availability of battery charging infrastructure that can cost effectively integrate with the existing electrical network, deliver adequate energy transfer rates and adapt to the rapid technical development of this industry.

In modern power systems the word ‘flexibility’ is often used to describe certain types of power generation and energy demand that can vary their requirements over time and according to changing criteria. In essence, flexibility describes something that has the ability to be easily modified and this should arguably apply to the deployment of EV charging infrastructure. In this thesis, the term ‘flexibility’ refers to a charging solution that is scalable, minimises the cost of infrastructure deployment, can offer more than one service to the power industry and has a low risk of becoming stranded in the future. This thesis will identify the opportunities and quantify the value that LVDC distribution can bring to the implementation of flexible charging infrastructure.

1.2.1 EV Charging Infrastructure Planning Theory

When a vehicle with an internal combustion engine (ICE) arrives at a filling station consider the rate at which energy is transferred from the petrol pump to the vehicle.

In many cases, an ICE vehicle with a 60 litre tank can refuel from empty in less than 1 minute. The specific energy capacity of petrol is 9.7kWh/litre [31], therefore energy is transferred at an equivalent rate of 35MW. However, much of the energy transferred and stored in an ICE vehicle's tank is lost as heat, noise and vibration, only 17-21% of the stored energy is converted to motive power [32]. Whereas EVs can convert 59-62% of their stored energy to motive power [32]. To equal the refueling time of ICE vehicles, an EV with a 100kWh battery still requires a 6MW charger. Although it is not impossible to achieve a grid connection capacity of this scale, there are still unresolved challenges on the EV side such as the EV battery structure and its ability to accept high current and voltage levels [33]. In addition, there are physical and ergonomic limitations in terms of cable sizing and the ability of the user to lift the charging cable and maneuver its plug into position - the higher the current rating, the larger the cross-sectional area of the cable and therefore the heavier the cable becomes. At the time of writing, the closest similar EV charging technology to liquid refueling is a 350kW High Power Charger (HPC). These systems utilise 900-1000Vdc and in most instances they employ liquid cooled cables to allow for smaller cable cross-sectional areas and an overall reduction in the cable weight [34]. Recently significant announcements have been made in the UK and Europe regarding the deployment of HPC systems: Ionity, a collaboration of automotive manufacturers have committed to deploying 400 charging stations on key routes through Europe by 2020 and Pivot Power in the UK has indicated an appetite to deploy 2GW of battery storage systems and integrated charging solutions around the UK [35], [36]. Both projects represent significant investment and are likely intended to capture an early market share of the anticipated EV future. But where should this charging infrastructure be deployed and will HPC service stations become the preferred charging medium?

At the other end of the power spectrum, EV users can plug their vehicles into a 3kW - 7kW outlet at home. The prospect of this ubiquitous user charging scenario has spawned a plethora of research papers that address the impact of EV charging on the Low Voltage AC (LVAC) grid [37], [38], [39]. Based on the conclusions of a UK wide consultation conducted by Scottish and Southern Energy Networks[2], it is now generally perceived that once EV penetration reaches 40-70% of residential premises, coordinated charging at the domestic level will be required to avoid unnecessary infrastructure upgrade costs which are estimated in the region of £2.2 billion through to 2050 [40]. But is it realistic to assume that everyone should have the ability to charge their car overnight, at home? Considering the wide range of multiple occupancy buildings in UK cities this does not seem practical.

Besides user convenience, the primary technical motivator for at home charging is that EVs are stationary for long periods of time and can take advantage of 'off-peak' electricity prices. However, as intermittent renewable generation increases, the traditional demand profile will become generation led i.e. when the wind is blowing, the sun is shining or the tide is turning electricity prices will drop, indicating the optimal economic moment to use electricity [41]. These events can happen at anytime throughout the day but intuitively, in sunny geographic regions, the lowest electricity prices will regularly occur during the day with peak solar PV output, in this situation it would suggest at work charging could be superior to at home charging. Furthermore, in regions like the UK, where domestic electrical supplies are limited to 100A single phase connections, congestion will occur on the low voltage network during low electricity pricing events - so who determines which customers can take advantage of the low electricity prices on the wider power system considering the LV network constraint will limit the local power demand? Finally, if the DNO decides to remove this constraint on the LV network by upgrading the local secondary distribution transformer and/or replacing cables, this expense will be socialised across all electricity customers regardless if they own an EV. It therefore seems that a series of issues remain to be addressed if at home charging is going to continue to play a primary role in the EV charging infrastructure plan [42].

Currently, the general planning theory in the UK and the US is that users should have the ability to charge their vehicles at home, at work and at fast charging stations while traveling long distances [43], [44]. This is a broad planning strategy that, accord-

[2]https://www.eatechnology.com/engineering-projects/smart-ev/

ing to [43] requires further refinement with a more cohesive, cost effective approach to infrastructure. In future infrastructure planning it is important to consider technology evolution and its impact on user behaviour: As battery technology improves and prices reduce, EVs will posses higher capacities and longer ranges therefore reducing the frequency of charging events - will this reduce the requirement to charge at home? How will charging patterns change as society transitions from manually driven EVs to autonomous EVs and towards mobility as a service? Where will vehicle to grid services be offered if EV users prefer to rapidly charge and are therefore connected to the grid for shorter periods of time? The charging infrastructure deployed today must therefore have the ability to adapt to a rapidly evolving technology environment and in a manner that minimises the economic burden on society.

1.2.2 Building for an Uncertain Future

In the UK there are 14 distribution network zones and 7 distribution network operators (DNO) [45]. Over the next decade the DNOs are expected to evolve from a traditional "fit and forget" or static asset management role to a more dynamic system operator role, akin to the existing Transmission System Operator (TSO) responsibilities [46]. This transition is required to more effectively manage distributed energy resources and the expected demand increase from electric transportation and heating. From an EV charging infrastructure development perspective, it is necessary to ensure that infrastructure being deployed now is in line with the broader Distribution System Operator (DSO) objectives and can adapt to future opportunities or challenges during this DSO transition.

Figire 1.3 highlights the key technical and commercial changes that are necessary to transition from the current DNO model to the new DSO philosophy [46]. This diagramme is annotated to include possible EV charging infrastructure development trajectories that both support the transition but also exploit the opportunities offered under the new operating regime. The primary opportunities offered under the DSO model include the creation of flexible products, local 'smart' tariffs, constraint management zones and improved demand forecasting. The siting and design of future charging systems should therefore consider these operational characteristics of the DSO model to enhance the business case by creating ancillary revenue options.

It is not only the distribution network environment that is changing but many urban councils are implementing low emission zones and encouraging the use of public transport by introducing park and ride facilities[3] and low emission zones[4]. The extent of these zones within existing accessible urban areas may compromise existing charging infrastructure in city centres but then also increase utilisation of charging infrastructure located on the periphery of cities. Alternatively, there may also be opportunities for integrated urban energy systems that can integrate the gas grid with fuel cells or reciprocating engines to alleviate electrical grid congestion in urban environments and

[3]https://www.transport.gov.scot/publication/strategic-transport-projects-review-report-4-summary-report/j10194c-13/

[4]https://www.lowemissionzones.scot/

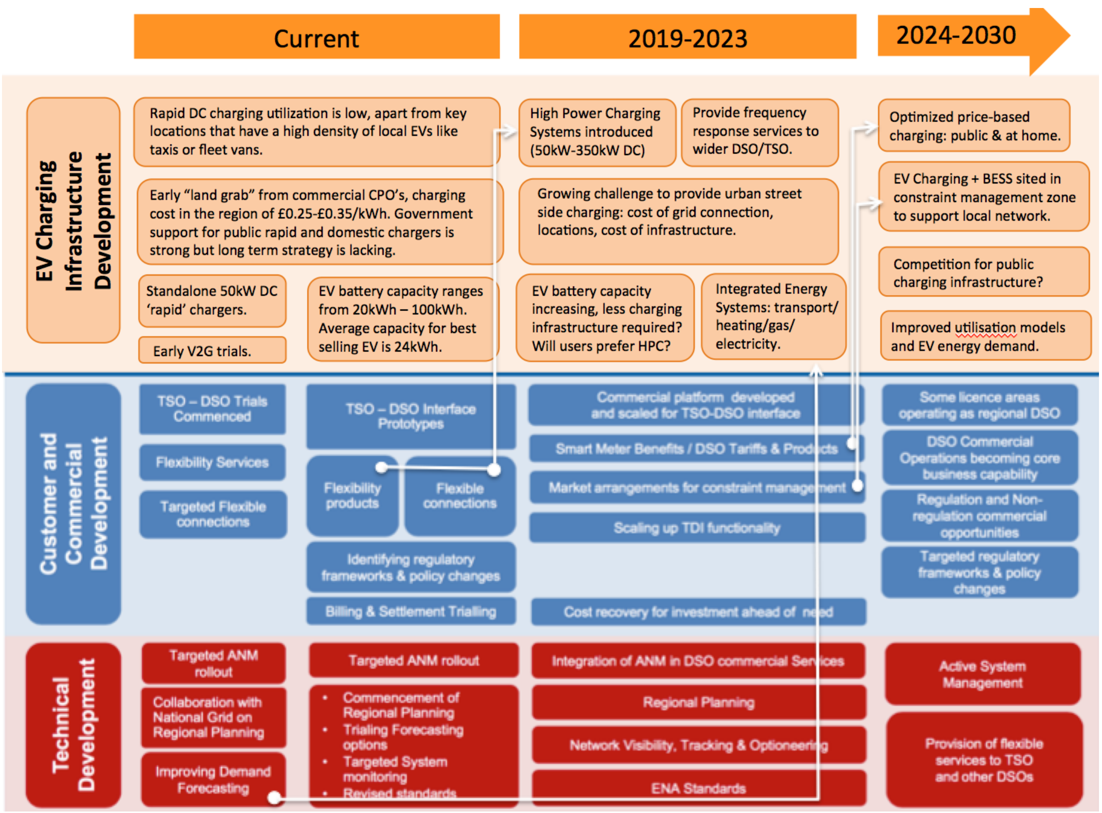


Figure 1.3: An adapted version of the Energy Network Association's DSO transition model.

make available charging capacity for electric taxis and buses. The building density within these urban environments is also sufficient for heat networks and therefore the waste heat from generation can either be supplied to a dedicated building or a wider heating network. It is these integrated energy systems that may offer the best value for energy consumers and an optimal approach to decarbonisation [47].

Furthermore, the charging technology itself is evolving; communication protocols and operational standards are emerging and there is still a lack of consensus on standard plug configurations. Most public rapid DC chargers deployed in the UK have at least three plug and cable combinations (see Chapter 2), but this arguably adds cost to the infrastructure and user confusion. It will soon be necessary for regulatory bodies to intervene and facilitate a coalescence towards an international, standard charging plug, such as the work that is on-going with the charging standards group CharIn[5].

However, perhaps the biggest uncertainty is the rate at which EVs are expected to be adopted and the subsequent user charging behaviour. This introduces the "chicken and egg" scenario, whereby the presence of charging infrastructure is required to offer confidence for prospective EV buyers but the utilisation of these charging assets maybe low for a number of years. It is therefore difficult to justify commercial investment and instead, government programmes are necessary to bridge this investment gap. Although, improved technical solutions and phased charging deployment can reduce the investment risk and enable the Charge Point Operators (CPO) to adapt their assets to changing circumstances. The work presented in this thesis is a timely contribution towards managing charging infrastructure uncertainty as it suggests that LVDC charging networks are both scalable and 'upwardly' compatible with charging technology trends.

1.2.3 Wider Energy System Benefits & Commercial Opportunities

The transition to electric transportation offers multiple broader benefits for society, these include: a reduction in urban pollution levels, a reduction in green house gas (GHG) emissions, improved national energy security (assuming a reduction in foreign oil imports but this must also be weighed against the future resiliency of the electri-

[5] https://www.charinev.org/

cal network) and the potential to operate EVs as an electrical grid asset to facilitate higher penetrations of renewable generation. To date, public charging infrastructure has been deployed as standalone systems with one functional purpose - to charge EVs on demand, when they connect. However, to improve the business case for EV charging infrastructure operators, the additional services that these installations can offer need to be considered while maximising utilisation of the charging asset and grid connection point. During the course of this research the following integrated charging solutions were considered where LVDC could potentially offer a performance advantage, these options are explored in more detail in the subsequent sections:

- **Transmission System Balancing:** The flexible nature of both AC and DC EV charging can permit variable power charging for short durations of time in order to assist wider power system imbalances such as short-term frequency excursions [48]. The market for grid balancing services is rapidly evolving and therefore careful analysis is required to determine the eligible markets based on expected operating characteristics, response time and power rating of EV charging sites.

- **Power Quality Control:** The operation of power electronics associated with DC chargers can provide increased power quality benefits such as re-balancing power across phases [49] and the provision of reactive power support [50]. Therefore, to increase the economic viability of chargers, additional DNO services can be provided in certain locations.

- **Battery Storage and Solar PV:** To interface solar PV and BESS with the electrical grid requires power converters, similar in nature to the EV chargers. Opportunities exist to share grid-tie infrastructure with local BESS and solar PV to provide an additional revenue stream and to exploit off-peak electricity pricing periods [51].

- **Gas Networks:** For High Power Charging sites, where power density is necessary and perhaps the electrical grid infrastructure is constrained, it may prove feasible to integrate gas reciprocating engines or fuel cells with the gas grid to offer both heat and power in an urban environment. This prospect becomes even more compelling as the gas supply reaches higher concentrations of biogas and hydrogen [52].

- **Alternative Distribution Assets:** LVDC can be used to increase the power transfer capabilities of existing cable assets [9] and potentially enable the charging connections of underutilised electrical distribution systems such as street lighting networks and tram/rail distribution systems.

- **Charging Algorithms:** As EVs become increasingly connected, it is possible to levelise the utilisation of charging sites over a regional area by coordinating a collection of EVs to charge at the optimum times and locations based on a series of user, technical and economic constraints [53]. Similar algorithms can also be applied at the charging site level to maximise utilisation of the available charging assets and grid connection, while minimising user inconvenience.

Each of these opportunities are viable but the specific design, sizing and optimal operation still require significant technical work and the collaboration from multiple stakeholders. This thesis offers a number of LVDC charging network topologies that capture these wider energy system benefits and further develops specific concepts into realisable, practical charging options. The intent of this research is to move charging infrastructure development beyond the current "land-grabbing" and "range-confidence" deployment strategies towards a more integrated, adaptive and cost effective approach to EV charging infrastructure.

1.3 Research Objectives

It is self-evident that a significant infrastructure build-out is required to support the advancement in electric transportation but the specific design, strategy and costs are still to be determined. The key question that this thesis seeks to address is can LVDC distribution systems facilitate the deployment of flexible EV charging infrastructure to support the global aim of decarbonising the transport sector. To answer this question the following research objectives were established:

- What future requirements are necessary for LVDC distribution systems to safely and cost effectively implement LVDC charging networks?
- By identifying opportunities where LVDC network topologies can offer greater flexibility for local and national energy infrastructure, how might the associated charging systems help to "de-risk" the use of DC distribution for other related applications?
- What energy management, scheduling and control requirements are necessary to operate LVDC charging infrastructure, either as stand alone systems or also part of an integrated energy system that is sympathetic to wider AC power network constraints?
- To investigate the control and energy management techniques as applied to selected LVDC charging network topologies and establish how they compare against current EV charging infrastructure philosophies.

These objectives have been used to drive the work of this thesis and they will be revisited as appropriate throughout the remainder of this thesis.

1.4 Thesis Contributions

The primary contributions arising from the work of this thesis can be summarised as follows:

1. The first full review of the available LVDC standards and the gaps that exist to safely deploy LVDC public distribution systems; resulting in a journal publication.
2. An energy management solution and network control method for multi-plexed or switching based charging networks was developed and tested in simulation for reconfigurable DC charging networks; resulting in a journal publication.
3. A new optimisation formulation for the development of High Power Charging infrastructure as an integrated energy system has been developed and studied.

4. Utilisation statistics for a network of 200 rapid DC chargers across Scotland are analysed and demand profile curves for specific site classifications have been generated to facilitate energy management modeling, charger scheduling and future infrastructure planning.

5. The concept of a service selection matrix is proposed to assist EV users in evaluating available charging options within both a physical and price constrained power network environment.

The research work of this thesis has produced the following publications and technical reports:

Journal Publications

- Mokoganyana, L., Smith, K., Galloway, S., "Reconfigurable Low Voltage Direct Current Charging Networks for Plugin Electric Vehicles", November 2018, in IEEE Transactions on Smart Grid. DOI: 10.1109/TSG.2018.2883518

- Smith, K., Wang, D., Emhemed, A., Galloway, S. & Burt, G., "Overview of LVDC Distribution System Standards", 31 May 2018, International Journal of Power Electronics. 9,3, p.287-310 14p.

Conference Publications

- K. Smith, L. Hunter, S. Galloway, C. Booth, C. Ross, M. Kellett, "Integrated Charging of EVs Using Existing LVDC Light Rail Infrastructure: A Case Study", 21-23rd May 2019, IEEE Third International Conference on DC Microgrids.

- A. Emhemmed, G. Burt, K. Smith, P. Black, A. Kazerooni, A. Donoghue, M. Eves, "Protection and Earthing Requirements of LV AC and DC Distribution Networks Interfaced by a Smart Transformer", 25th International Conference on Electricity Distribution, Madrid, 3-6 June 2019, Paper no 2002.

- Dong Wang, Abdullah Emhemed, Kyle Smith, Graeme Burt, Jawwad Zafar, Ali Kazerooni, Anthony Donoghue, "Quantification of transient fault let-through energy within a faulted LVDC distribution network", 5-7th February 2019, The 15th IET international conference on AC and DC Power Transmission.

- Smith, K., Galloway, S. & Burt, G.,“Co-location of CHP units for high power charging of battery electric vehicles: a comparison of the fuel efficiency for AC and DC coupled systems”, Aug 2017, IEEE Second International Conference of DC Microgrids, Red Hook, NY:IEEE, P.88-94 7p.

- Smith, K.A., Galloway, S.J., Emhemed, A & Burt G.M., “Feasibility of direct current streeting lighting & integrated electric vehicle charging points”, 6th Hybrid and Electric Vehicles Conference (HEVC 2016), London, 2016, pp. 1-6.

- K. A. Smith, S. J. Galloway and G. M. Burt, “A Review of Design Criteria for Low Voltage DC Distribution Stability”, Universities Power Engineering Conference, Coimbra, 6th-9th September 2016

Industrial Reports

- Smith, K., Emhemmend, A., Burt, G., “LVDC Technical Recommendations”, Scottish Power Energy Networks, LV Engine Project[6]

[6]https://www.spenergynetworks.co.uk/pages/lv_engine.aspx.

1.5 Thesis Overview

The thesis is structured in four main sections which broadly follow the four research objectives: Chapter 2 provides a literature review which encompasses EV battery characteristics, charging equipment classifications, the potential impact of EV charging on the power networks and the opportunities/challenges for LVDC in this context. Chapter 3 presents EV charging demand profiles from Scotland's rapid DC charging network and develops an approach to forecasting the day ahead collective power demand from this charging network. These EV charging demand profiles are applied in the evaluation of LVDC charging systems.

This thesis further classifies charging behaviour beyond the standard slow, fast and ultra-fast charging infrastructure descriptions. As charging infrastructure becomes 'smarter it will be possible to optimise the charging service offered to users according to several power system constraints, one of which is electricity price. Therefore, this thesis proposes that a short duration charge is one that occurs within the wholesale electricity price-trading period (in the UK, this is a 30 minute trading period) and long duration charging occurs over several trading periods. This means long duration charging will be exposed to varying electricity prices and opportunities to optimise the cost of charging exist.

Chapter 4 introduces a short duration charging scenario where little opportunity exists to manage charging according to power prices. This Chapter explores the need for higher power density, distributed generation to meet the desired energy transfer rates of future EV users while minimising power network infrastructure upgrades. A charging infrastructure planning model is presented that can select the optimum combination of charging assets, grid connection sizes and co-located energy assets based on a forecast EV charging demand. In this Chapter 4 charging infrastructure scenario, the option to connect a CHP system to a High Power Charging system is evaluated using the planning model.

Chapter 5 defines long duration charging and goes onto explore the operation of fixed and reconfigurable LVDC charging networks in detail. This charging infrastructure proposal considers one or more centralised rapid DC chargers that are linked to several parking bays by controllable switches. An energy management system is presented which coordinates EV user requirements and several physical electrical infrastructure constraints to minimise the cost of charging for the charging infrastructure operator. Finally, research conclusions are presented in Chapter 6 and opportunities for further work are discussed.

Figure 1.4 provides an overview of this thesis and the core focus of the work in each chapter.

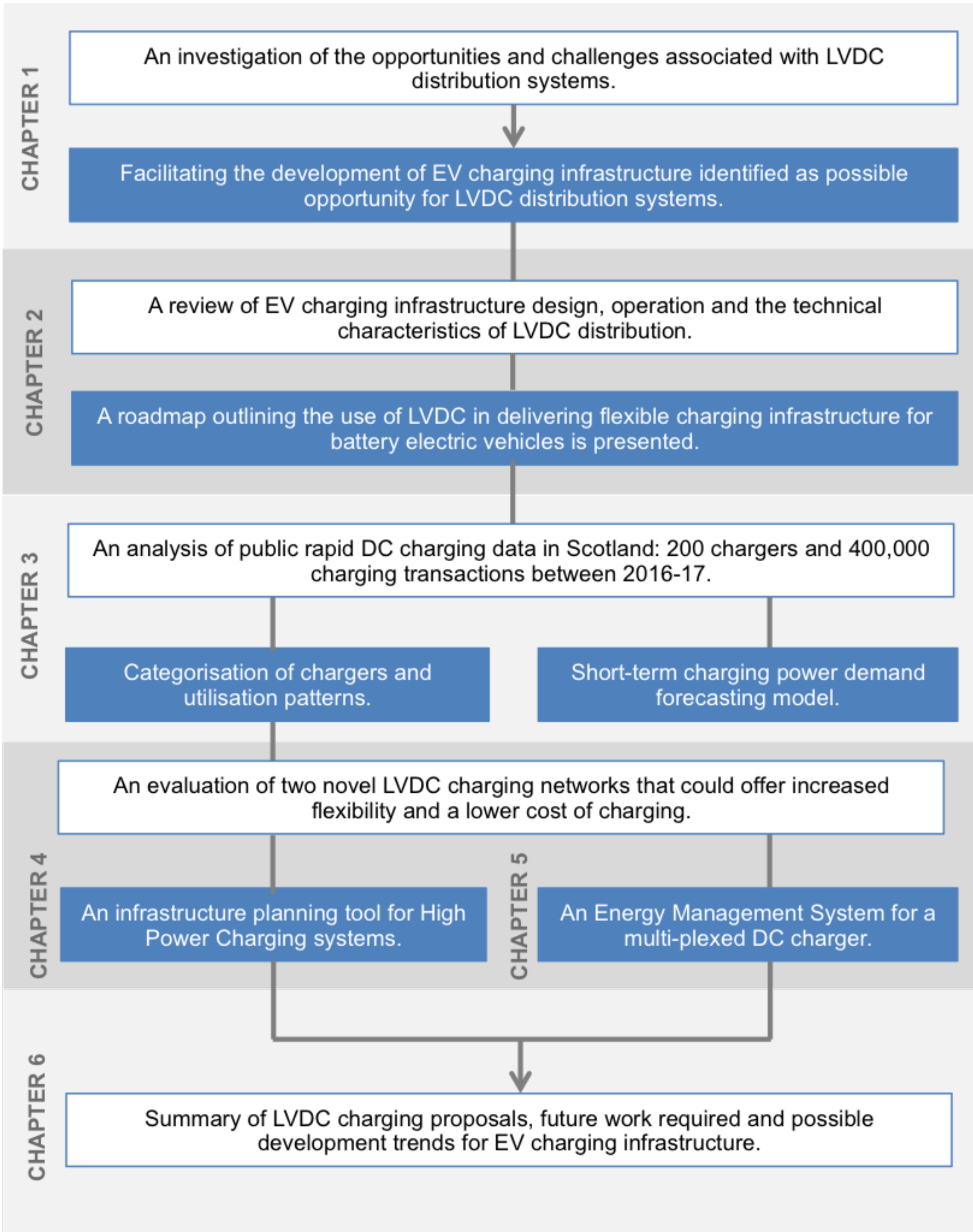


Figure 1.4: Overview of thesis chapters and outputs.

Chapter 2

EV Charging Systems & LVDC Distribution

This chapter provides an overview of the current EV charging equipment terminology, prior or active EV charging research areas and the technical considerations associated with LVDC distribution systems. This informs the modelling work conducted in subsequent chapters. The standard charging solutions presented in literature, and adopted within national/regional policies, are evaluated and alternative LVDC solutions proposed for further development.

2.1 Overview of EV Batteries & Charging Equipment

The development of EV battery technology and the associated Electric Vehicle Supply Equipment (EVSE) are intrinsically linked - the battery technology and onboard power control equipment dictate the requirements from off-board EVSE's in terms of voltage and current transfer levels. However, more recently, EVSE manufacturers are designing charging solutions at a voltage level that is not only compatible with today's EV batteries but has the capacity to increase in voltage level to deliver high power charging solutions to future EVs [54]. It is helpful to understand the available charging standards, EV battery chemistries and alternative charging strategies that are currently under consideration and these will be discussed in the following subsections.

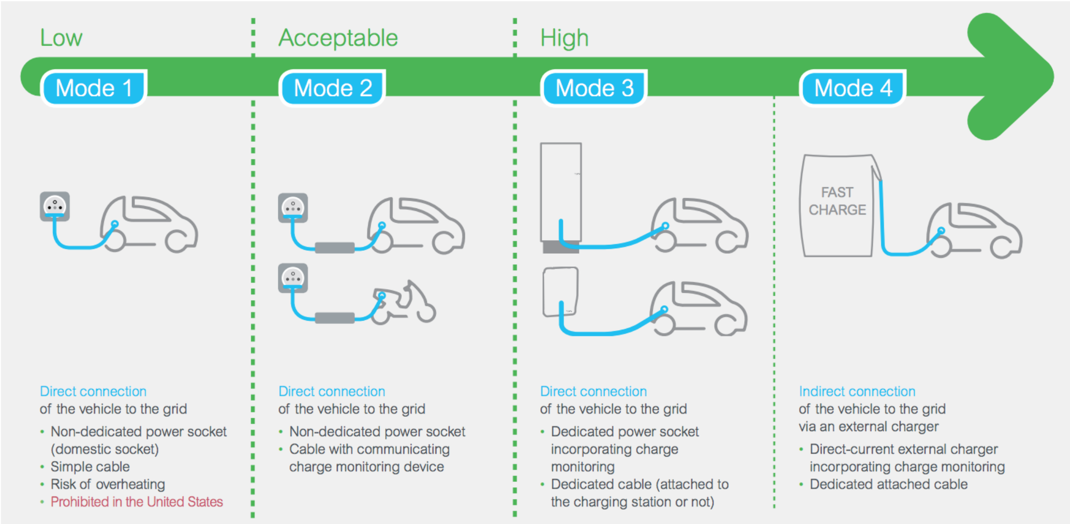


Figure 2.1: Electric Vehicle charging modes [55].

2.1.1 Standard EV Charging Infrastructure

EVSE infrastructure is classified according to IEC 61851 [56] into four modes as illustrated in Figure 2.1. Each of these modes is differentiated by power-level, protection system and communication requirements. Mode-1 is a simple connection to a domestic, single phase socket; in the UK this is generally limited to 13A. Mode-2 also uses a domestic socket but incorporates cable protection and communication with the EV. Mode-3 reaches higher AC power charging, in the range of 7-22kW, with charge monitoring and protection. Mode-4 converts AC grid voltage to a higher DC voltage to enable high power charging and faster servicing of EVs, currently 50kW DC charging is common but power ratings up to 350kW are now being discussed and trialled [54].

There is a classification amongst EVSE charging plugs, Figure 2.2 outlines the primary charging plugs that are in operation around the world. Even with this small variation in type, there is arguably a need to standardise EV charging plugs to reduce the EVSE infrastructure cost and to improve user convenience. The industry working group, CharIN[1], are encouraging European and North American automotive manufacturers to coalesce towards the Combo-2 (CCS) charger for combined AC and DC

[1] https://www.charinev.org/

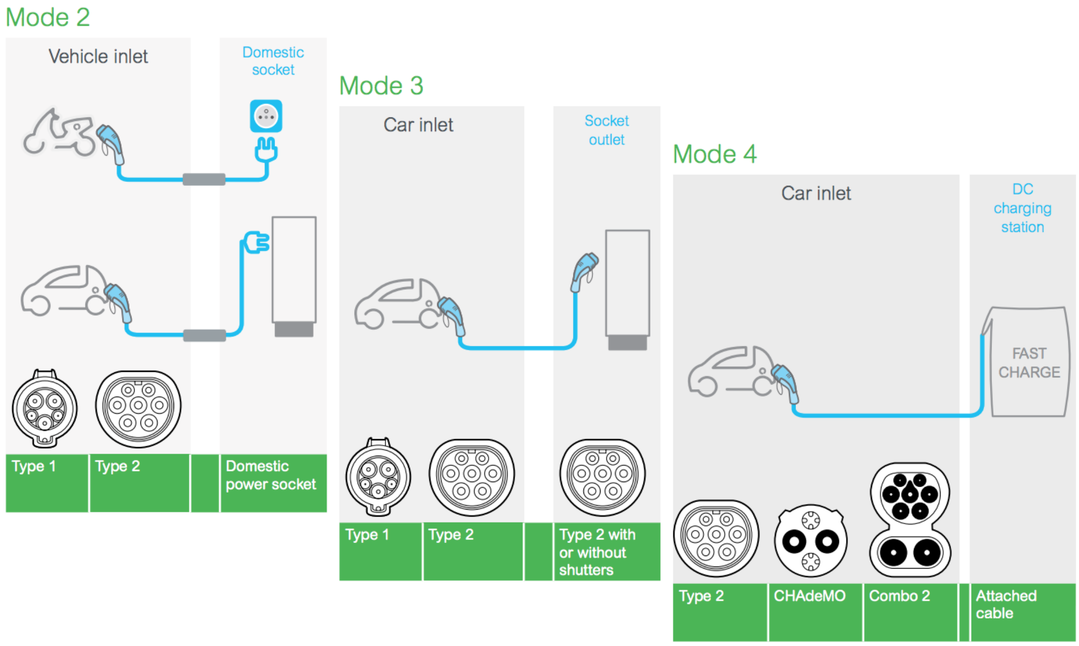


Figure 2.2: Charging plug types [55].

charging from the same plug-head (Mode-2 to Mode-4 charging). This is an alternative to the CHAdeMO ("Charge de Move") plug that was introduced by Japanese automotive manufacturers and both systems are used for Mode-4 charging. The charging cable that connects the EVSE to the EV generally has at least 5 wires: neutral, live, earth, pilot and proximity pilot [56]. The pilot wire provides data communication between the vehicle and the charging station. When an EV connects to a charger, a handshaking process begins through the plug's proximity pilot - which indicates that the EV is connected to the plug - and the pilot wire. This communication process is outlined in IEC 61851 [56] and is used to establish the charging requirements according to the EV battery's needs and to ensure that it is safe to charge prior to commencing.

In addition to the local communication between the charging infrastructure and the EV, there is often communication between the charging point and a centralised management system. The Open Charge Alliance[2] promotes a universal communication system known as Open Charge Point Protocol (OCPP) which enables a centralised management system to access any permitted charge point to monitor transactions and

[2]https://www.openchargealliance.org/

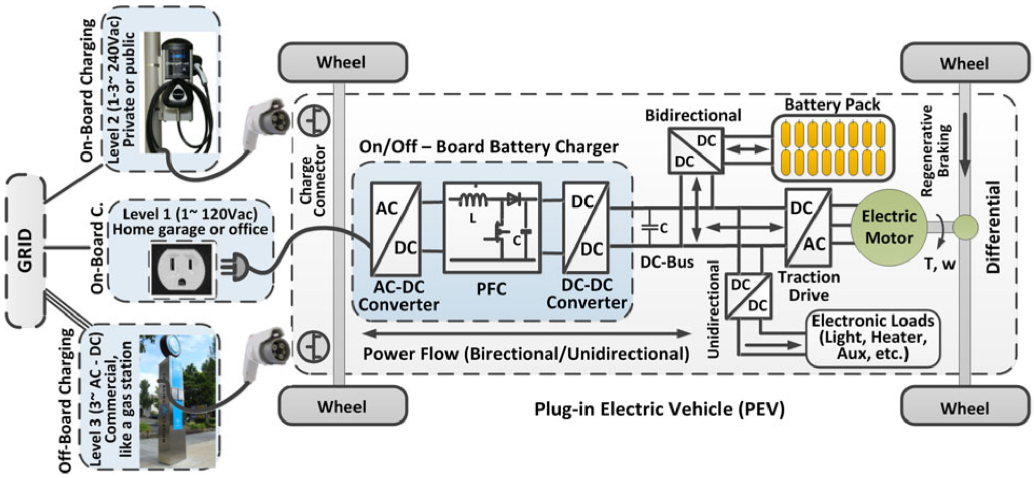


Figure 2.3: EV battery and electrical system [57].

the operational state of the charging infrastructure. This can assist EV users in planning their journey by finding suitable charging points on a common map or the data may be used to inform future infrastructure deployment strategies based on historic charge point usage data.

Figure 2.3 illustrates the electrical power distribution system on an EV. This particular schematic includes an on-board charger to enable a standard AC charging system to charge the DC-based battery. This on-board charger adds cost and weight to the vehicle which could otherwise be avoided or reduced if only DC power was supplied by an off-board charger. As will be described in the following sections, LVDC charging networks can supply DC power at a variety of power levels and in most charging scenarios are more efficient than existing AC charging systems. Therefore, future EV designs may consider removing the on-board rectifier and only utilising DC charging.

2.1.2 EV Battery Technology

To date, EV battery technology has relied heavily on lithium ion batteries (LIB). Lithium is the lightest metal and has a large electrochemical potential which makes it the ideal choice for battery cells [58]. The downside to lithium is that it is inherently unstable as a solid metal and therefore battery cells utilise lithium ions as a more stable charge carrier. A LIB is composed of multiple, mass-manufactured cells, which

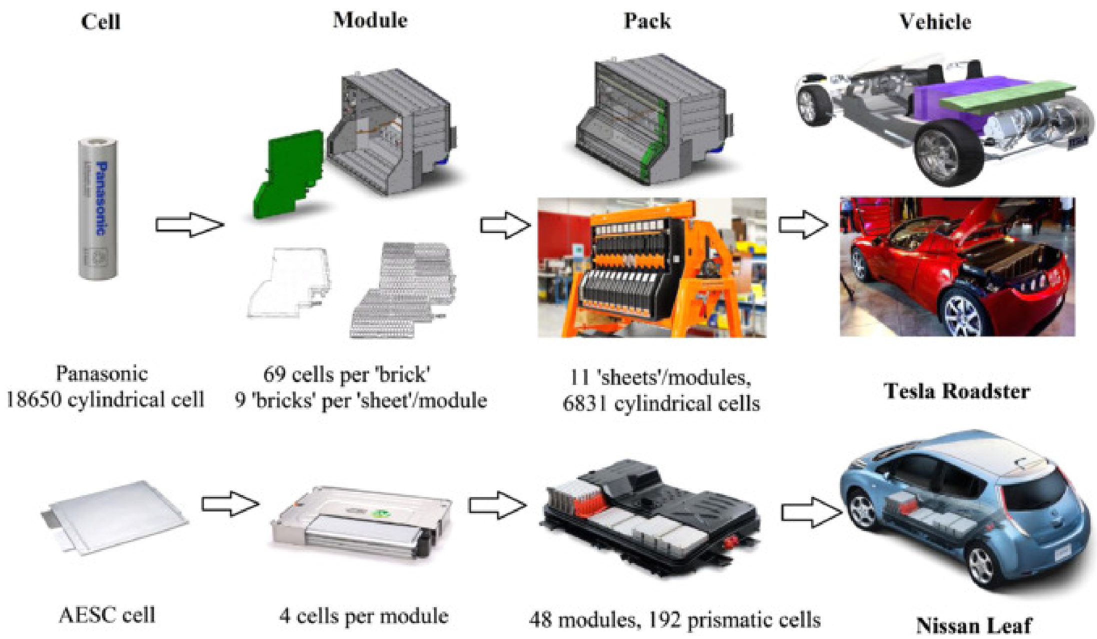


Figure 2.4: Cylindrical and prismatic battery module compositions [59].

can take a cylindrical shape, or as a thin pouch, known as prismatic cells [59]. These cells are then grouped into modules to create power packs with a specific performance characteristic (i.e. voltage and storage capacity) as shown in Figure 2.4.

The basic structure of the battery cells involves an anode (positive), cathode (negative) and an electrolytic fluid that allow the ions to move between the terminals depending on whether the battery is charging or discharging. These three material/chemical components of a battery cell can utilise a variety of periodic elements and structures to create an optimised battery cell for a specific application.

The LIB cells are very sensitive to voltage levels and therefore each module requires control circuitry to prevent over and under voltage conditions from damaging the cells. In addition, the chemical composition of the cells can be affected by environmental temperature. Temperature differences can affect both the real time performance and long-term performance of the cell, most manufacturers will warrant their battery system for a specific operating temperature range [59].

The battery system itself is composed of many battery modules, which contains tens of lithium ion cells. The modules are also likely to contain a temperature sensor,

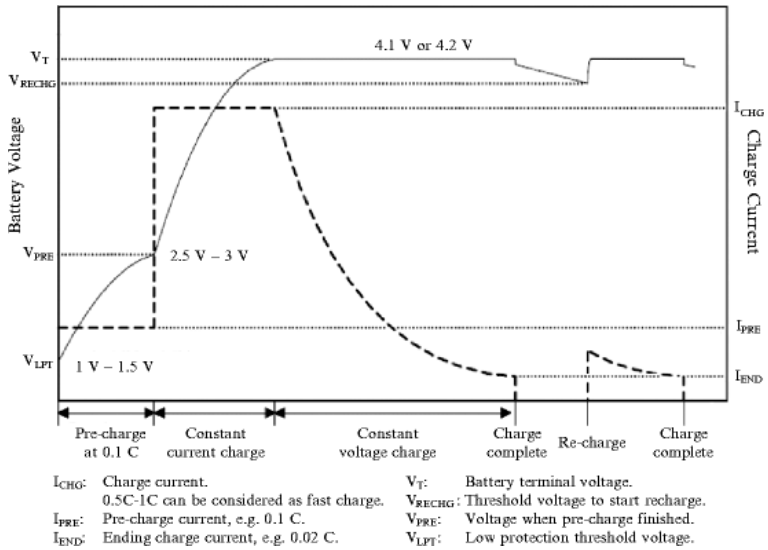


Figure 2.5: EV battery charging voltage and current profiles [60].

voltage converter/regulator and a battery state of charge monitor. The modules require a Battery Management System (BMS) to ensure that a balanced SoC is maintained across all cells - imbalances between cells can reduce the batteries efficiency and storage capacity.

The charging process must therefore be mindful of not only the battery SoC but also the battery's State of Health (SoH) - which is a degradation metric that describes the battery's current condition compared to its original condition, which is directly influenced by temperature, charging cycles and charging power [59]. In HPC scenarios, it may be necessary to implement additional cooling during the charging process, in fact [28] suggests that the charging infrastructure could provide a cooling solution by connecting directly to the BEV's battery cooling system, this reduces the on board cooling equipment weight and cost.

Figure 2.5 demonstrates the voltage and current profiles during a charging process for a single lithium ion battery cell. This technical charging profile influences the charging strategy for both short and long duration EV charging solutions. In a short, high power charging situation, it may not prove beneficial to charge an EV beyond its constant current phase (generally 80-90% SOC) as the charger power output reduces and therefore the charging infrastructure is only operating at a fraction of its available

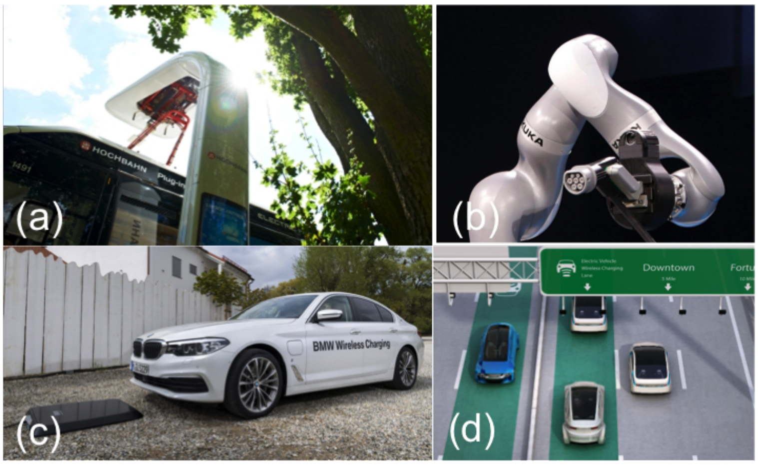


Figure 2.6: Alternative charging infrastructure.

power capacity. For long duration, lower power applications, it may prove feasible for an independent charge point operator to offer a complete charge as the vehicle is likely to be stationary for longer periods of time, however, the diminishing power output beyond the constant current charging should be considered in any optimised energy management system as this will influence the overall time to charge.

2.1.3 Future Charging Infrastructure Trends

Charging infrastructure for EVs is continuing to evolve and novel solutions are being tested by academic researchers and industry to address the specific operational characteristics of not only personal EVs but also buses, ferries and future electric aircraft. Figure 2.6 highlights the most promising of these alternative charging solutions that are under development: (a) represents a gantry charging system for buses that make frequent stops, this is an automated charging solution that uses direct contact charging between the bus and the charging infrastructure [61]; (b) utilises a robotic arm and the same, standard charging plugs currently in operation to charge autonomously driven vehicles [62]; (c) highlights an inductive charging plate that uses wireless power transfer (WPT) to 'wirelessly' charge a vehicle over a short air-gap [63]; finally, (d) uses in-road WPT technology to charge vehicles while on the move [64].

Currently, direct contact charging solutions are the most energy efficient solution for charging EVs, however, significant research work in the area of WPT is ongoing and, in some situations, there is both a technical and economic case for WPT applied to in-road charging of EVs [65] and for battery electric ferries [66]. However, in-road WPT for mass transport applications has a number of practical deployment challenges to overcome such as the coordination between multiple stakeholders, road disruption and the need for EV manufacturers to incorporate both an on-board inductive charging receiver plate and conventional charging plug-in system, adding both cost and weight to the vehicle. Most importantly, the energy efficiency of charging infrastructure should be maximised considering the future volume of electrical energy that will be transferred from the electrical power system to transport. Therefore small inefficiencies in the charging infrastructure will cumulatively result in large absolute energy losses for a national energy system. For example, if 25% of all cars on UK roads were converted to EVs with a battery capacity of 60kWh and on average they charged once per week; every 1% efficiency loss in the charging infrastructure would result in 4.7 GWh of lost energy per week (based on a total of 31.7 million cars on the road in 2016 [67]). This would require a 94MW wind farm with a 30% capacity factor to cover each 1% efficiency loss. As it stands, direct contact charging infrastructure possesses an efficiency that can range between 90-95% (50kW DC charging) [68] whereas low power (3kW) WPT ranges between 80-90% [69].

In the deployment of charging infrastructure now, it is important to consider the future charging technology to ensure that the location and electrical supply to existing infrastructure is 'upwardly' compatible with future charging trends. The use of LVDC charging networks is technically appropriate and adaptable to the various alternative charging solutions that have been identified. The supply of LVDC power to charging solutions depicted in Figure 2.6 (a) and (b) is currently viable and the conversion of an existing LVDC charging network to inductive WPT charging can be achieved by either replacing or incorporating an existing DC/DC charging converter with a DC/AC high frequency converter. Therefore charging infrastructure deployment strategies must consider current and future user trends, the cost to deploy and maintain, and the impact that different charging technologies as well as user behaviour will have on the wider power system.

2.2 EV Charging Impact on Power System

Over the past decade an increasing number of researchers and analysts have turned their attention towards the potential impact that the introduction of EVs will have on the electrical power system [70], [71], [72]. This research effort is timely and necessary to cost effectively adopt EVs and facilitate the required charging infrastructure, however, given the costs and invasive nature of solutions a more holistic understanding of the power network constraints and synergistic opportunities offered by EV charging infrastructure is required. Significant progress has been made to model the impact on existing and future power generation requirements to satisfy the expected peak EV charging capacity, which in the UK does not appear to be an immediate challenge [36]. The impact of EV charging on both distribution and transmission electrical assets is becoming clearer and network operators are beginning to implement management strategies [73], [40]. However, further work is required to identify a national implementation strategy in the UK and elsewhere that ensures the availability of adequate charging infrastructure to meet growing demand at the least cost to energy consumers. The following sub-sections provide an overview of the key power system considerations for the three most common charging locations: low-voltage residential charging; at work charging; public fast charging systems.

2.2.1 Residential Low Voltage Network

Charging at the residential level is considered one of the three primary charging locations for BEV owners [43]. This makes sense considering a residential electricity tariff is likely to offer the lowest cost of energy to the user and the existing energy capacity of EV battery packs requires frequent charging - at home over night and potentially at work during the day. Although, as battery capacity increases the frequency of charging will decrease and if the cost of the residential tariff rises, the desire (or current necessity) to charge at home may diminish. However, it is likely that residential charging will remain an important aspect of EV adoption for some time to come and therefore network operators need to understand the impact that BEV users will have on their network [73].

The primary concern associated with residential EV charging is the concept of 'clustering', whereby a number of residents on the same secondary transformer and/or distribution feeder possess an EV. The demand from charging is likely to occur when for example, each of the EV owners come home from work in the evening, which is already causing the existing evening electricity demand peak [40]. This combined peak may surpass the secondary transformer rated capacity which would cause the main protection fuse to trip and may also occasionally cause the distribution feeder voltage to drop below the low-voltage threshold. Research work and practical engineering field trials have attempted to estimate the point at which EV adoption will begin to cause constraints on the LV distribution network however, as outlined by Putrus *et al.* in [74] this modelling depends on several factors such as the network configuration, charger power ratings, charger phase connections and user behaviour. The work conducted by Bentley *et al.* in [75] offers a flexible Excel based modelling tool using standard electrical engineering equations to assess the impact of EV charging on low voltage networks on a case by case basis.

The largest UK trial of EV user habits was conducted by the 'My Electric Avenue' project which included over 100 participants who were grouped in several geographical clusters and were each provided with an EV for the duration of the trial[3]. The project was funded by the Low Carbon Networks Innovation Funding and lasted 3 years, the project found that over 70% of participants charged their EV at home everyday and that 65% charged their vehicle to full capacity each time. Based on 3.5kW chargers and Nissan Leaf battery capacities of 24kWh, it was found that 32% of LV distribution circuits covered by the trial would require reinforcement when EV penetration reaches 40-70% of households on the same piece of network [76]. An interim EV management solution was therefore trialled to maintain power quality standards and to prevent networks from overloading as an alternative to an established network upgrade

[3]http://myelectricavenue.info/

approach. This involved the use of sensors at the transformer, a micro-controller, power line communication (PLC) and a receiver at each of the customer's households. This trial identified that small pauses or reductions in charging power for certain users could alleviate the temporary constraint on the network without affecting the user's charging requirements. This solution is currently under consultation by Scottish and Southern Energy Power Distribution, who hosted the project on their network, for consideration as a business as usual practice [40].

However, the introduction of EV charging at the domestic level may also offer opportunities for improved power quality where high penetrations of solar PV currently exist, the feasibility of this opportunity is considered in [77]. In these scenarios, if some customers are experiencing voltage rises during daytime hours when the solar power output is high but few people are home. The introduction of residential, 'smart' EV charging can be scheduled to coincide with solar PV output to help regulate network voltages and exploit this local renewable generation. Although, in practice it could be argued that personal EVs will not be parked at home during the weekday but instead at work places and therefore the extent of this residential feeder voltage regulation may be limited.

Further consideration should be given to changing user habits as EV battery capacity increases and more users adopt a 7kW domestic charger as opposed to 3.5kW, this may require longer charging periods to accommodate higher battery capacities and/or larger demand peaks [40]. From a holistic electrical network and energy efficiency perspective, charging of EVs at the domestic level is the most inefficient use of energy, considering the fact that the UK electricity grid looses 1.7% of generated energy through the transmission network and a further 5-8% through the distribution network [78]. Therefore the use of domestic charging in the early stages of EV adoption is a necessity but as public charging stations develop, could these systems offer a more energy efficient and nationally cost effective charging solution that might avoid the need to upgrade residential LV networks?

2.2.2 At Work Charging

For private EV users, at work charging offers an opportunity for optimised energy transfer considering it is likely that the EV will remain stationary for at least 6-8 hours and during daylight hours when solar PV output is at its highest. The work in [79], takes advantage of this situation and describes the control approach for a DC solar PV microgrid that alleviates loading on the wider power network and reduces the carbon content of charging. However, it is also important to consider the operation of fleet vehicles for various commercial and industrial businesses within the 'at work charing' scenario, which may have slightly different charging requirements compared to private EV users[4].

The technical power quality aspects and potential for overloading of transformers and cable assets is equivalent for 'at work charging' as it is for the domestic residential charging scenario. However, the cost to upgrade existing electrical infrastructure to accommodate additional demand from EV charging is more likely to be the responsibility of the local business(es) and is not necessarily socialised across all energy consumers as it would be for any domestic network upgrades. Therefore this may be considered a more equitable charging infrastructure deployment option.

Furthermore, at work charging infrastructure is likely to benefit from more competitive electricity tariffs due to higher elecricity consumption compared to residential households, and the potential to integrate with higher capacity distributed energy resources that may support not only the EV users but also accelerate decarbonisation and energy cost reductions for the business using efficient LVDC charging networks [27]. In addition, overall energy losses are likely to be less than the domestic charging scenario as business parks tend to be located close to secondary substations which limits distribution losses. Where Time of Use (TOU) or flexible energy pricing is considered, the at work charging network can deliver charging services that are optimised based on the user's requirements, cost of energy and carbon content of energy sources [80] [81].

As EV battery capacity increases, the model of charging at home and at work on the same day becomes less necessary. Therefore, considering the advantages that at work

[4]https://data.london.gov.uk/dataset/low-carbon-london-electric-vehicle-load-profiles

charging offers compared to at home charging, it may prove beneficial to consider policy measures that support the development of at work charging over domestic charging.

2.2.3 High Power Charging

Until recently, rapid or fast charging was considered to be public chargers with a power output of 50kW[5] or a Tesla' 'super charger' at 120kW [82] but now charging infrastructure developers are installing chargers that can achieve charging power outputs of at least 350kW. Although, at this time, few EVs can currently accept this power level but these systems are being installed in anticipation of future EV demand [54]. The value of HPC stations is in supporting long distance, national and European wide, travel along the main transportation routes. Both Ionity and Pivot Power are companies actively installing HPC infrastructure and have targeted strategic sites along the busiest motorways. These HPC systems require high voltage electrical grid connections which means less energy is lost in the transmission and distribution process for this charging scenario but the grid connection and capacity payments are substantial (approximately £0.047/kVA of capacity per day)[6]. For example an 11kV connected 1.5MW HPC station will incur an annual capacity payment of £25,732 (on top of energy costs, capital repayments and operational expenses). Therefore high levels of utilisation are required to justify the investment in this infrastructure.

Analysis conducted by National Grid (NG), in the support of long distance EV travel, has identified 50 strategic sites around the UK where 90% of drivers would be within 50 miles of HPC charging infrastructure [83]. Although, on average, almost 70% of UK drivers travel less than 30 miles per day[7], this HPC infrastructure would therefore support longer distance travel in combination with at home or at work charging to support these daily commutes. For these HPC systems a direct connection to the transmission network would ensure a high power capacity (multi-megawatts) and low energy losses but it may not be complementary with intermittent renewable energy.

[5]http://www.aptcontrols.co.uk/apt-security-systems/products/products.asp?product_id=280

[6]https://www.scottishpower.com/pages/connections_use_of_system_and_metering_services.aspx

[7]https://www.statista.com/statistics/513456/annual-mileage-of-motorists-in-the-united-kingdom-uk/

To take advantage of renewable energy will require the use of onsite co-located battery storage infrastructure, as proposed by Pivot Power [36], but this reduces the energy efficiency of charging as the round trip efficiecy of electrical battery storage is in the region of 83-87% but when parasitic loads are considered this reduces to 41-69% [84].

Alternatively, in urban environments where the electrical network is constrained it may prove feasible to utilise the gas grid to provide power and heat through a fuel cell or gas reciprocating engine for an HPC site. Although, this solution has not been considered in a large scale urban environment, it has been reviewed favourably at the residential level [85]. The integration of the gas and electrical network arguably increases energy system resiliency and creates an integrated system that optimises the use of natural gas for both electricity and heating. Furthermore, a well cited US study conducted by the Bonneville Power Administration and the Northwest Gas Association found that the cost of implementing gas networks is half the cost of the equivalent power capacity for electrical networks [86] and, in the near future, the gas grid may be mixed with higher concentrations of hydrogen which further reduces the carbon emissions of such a charging scenario [87].

In summary, the three commonly 'recognisable' charging locations for EV users are considered and the impact that these scenarios may have on the wider electrical network have been highlighted. In line with the focus of this thesis, the use of LVDC distribution in delivering these charging infrastructure solutions will be considered in the following sections.

2.3 LVDC Challenges & Opportunities

Direct current distribution systems have recently been considered as realistic alternatives to existing AC power networks due to a cost reduction and efficiency improvement in power electronic devices [88], [16]. The conversion of rural MVAC networks to LVDC [89], the use of LVDC in last mile LVAC distribution systems for power capacity improvements [9] and the use in onsite microgrid applications [6] have all been trialled in pilot projects but none of them have yet to be adopted as business as usual by distribution network owners and electrical system design engineers. The slow adoption in more complex LVDC distribution systems is arguably due to a lack of available design standards that specify acceptable protection, earthing and safety recommendations. This section introduces a series of use-cases where LVDC distribution can offer an opportunity to either improve the energy efficiency of an EV charging system or reduce the charging infrastructure expense. The technical design and associated challenges that remain to be addressed before these LVDC charging systems can be fully recognised are highlighted and discussed in this section.

For most DC charging systems, it is necessary to interface with the AC grid through a power electronic device and to control voltages or the flow of power to DC loads using a DC/DC power converter. Although power electronic design and control is not the focus of this thesis, it is useful to have a basic understanding of the power converters that may interface with a LVDC network.

The diode bridge rectifier, illustrated in Figure 2.7 converts AC signals into an uncontrolled DC voltage. The diodes conduct in pairs, one from the top one from the bottom. This topology is suitable for power applications up to 500W which require an inexpensive power conversion solution. Single phase diode rectifiers are commonly found in computer power supplies due to their low cost and simplicity but these converters can have a low conversion efficiency of 80% [90], [91], [92]. It is unlikely that these devices will be used to charge EVs due to the lack of controllability but some LVDC networks may contain diode bridge rectifiers, as in the case of a DC street lighting and EV charging system with connected LED street lamps [93].

For DC microgrids that interface with the wider AC network, a Point of Common Coupling (PCC) AC/DC converter is required to supply the DC grid with power when the local generators cannot meet the demand and to export power when generation within the DC microgrid exceeds demand. Most DC networks model a two level, 3-phase bi-directional converter with Insulated Gate Bipolar Transister (IGBT) switches [94], see Figure 2.8, although Metal Oxide Semi-conductor Field Effect Transisters (MOSFETs) could equally be used for lower power applications. Much of the research in this area is focused on switching control strategies to improve power quality on both

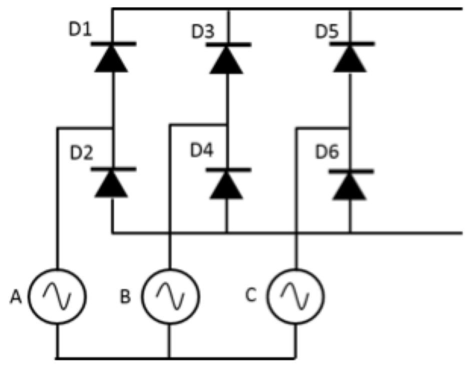


Figure 2.7: Diode Bridge Rectifier for low power DC applications.

the AC and DC sides of the converter and to reduce energy losses [90], [91], [92].

The buck-boost converters depicted in Figure 2.9 can take a variety of forms depending on the application requirements. The buck-boost converter with IGBT switching modules can operate bi-directionally and most DC/DC converters can incorporate isolation transformers [95]. In the case of a full-bridge DC-DC converter, the first stage creates high frequency AC to reduce the mass of the isolation transformer before converting to DC [90], [91], [92]. IGBTs may also be inter-changed for MOSFETs depending on the power level and current blocking requirements. DC converters can also act as protection on LVDC networks by varying the pulse width to limit current during a fault event [11].

This thesis contends (see Chapter 5) that DC/DC converters are required for each EV charging point in a high power, short duration charging scenario. However, longer duration charging scenarios which currently rely on 3-7kW AC chargers could equally be accommodated using a single, centralised AC/DC converter with reconfigurable network switches to direct power to one EV at a time according to an optimised charging schedule.

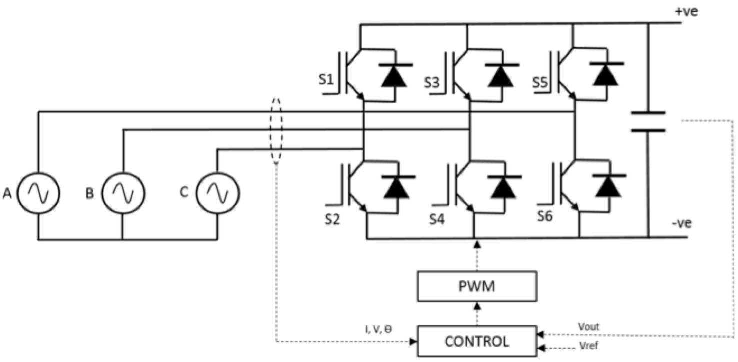


Figure 2.8: 3-phase Voltage Source Converter for rapid DC charging and the interconnection of DC microgrids to the AC network.

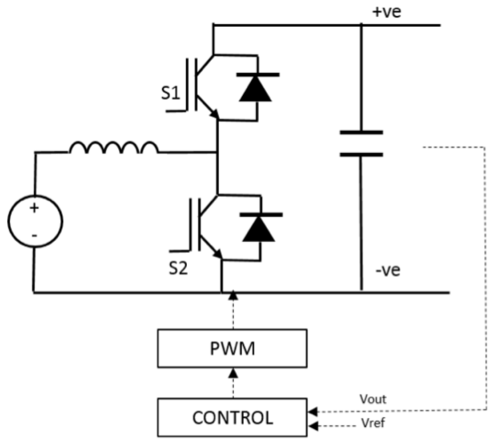


Figure 2.9: DC-DC buck/boost converter to control individual EV charging on a LVDC network.

2.3.1 Enhanced Asset Utilisation

In this thesis, the use of LVDC distribution is considered on the basis that it will improve transformer loading profiles (by meshing multiple secondary distribution transformers), increase the power transfer capabilities of existing cables and increase the utilisation of EV charging infrastructure. As discussed in the previous chapter, the introduction of additional electrical loading from EV chargers on the distribution network may require the replacement of transformers and/or the upgrading of existing cable assets, both of which can cause significant disruption and cost to utilities. However, the application of LVDC networks can optimise the loading on transformers and increase the power

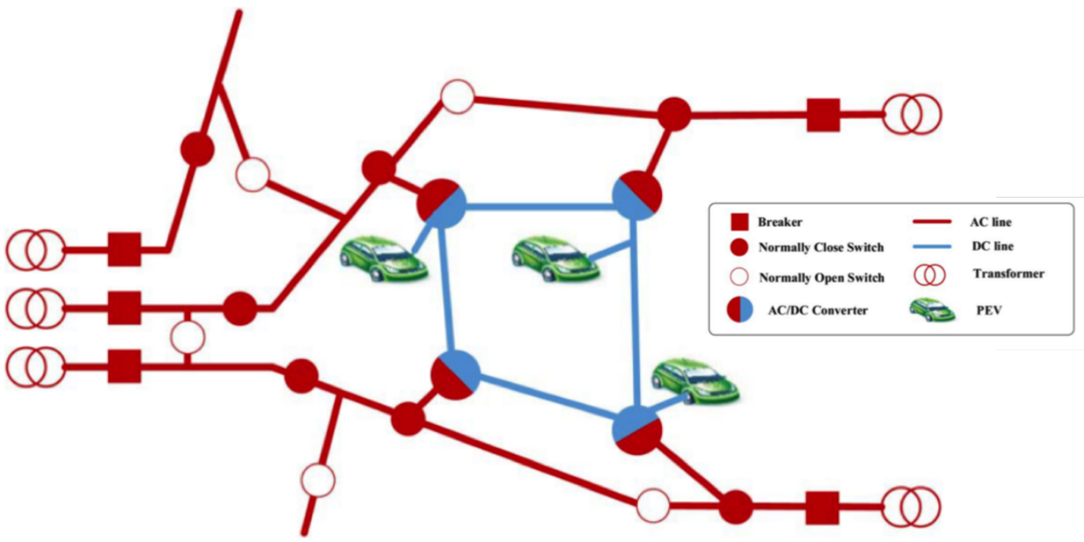


Figure 2.10: MT-LVDC power sharing between distribution transformers [26].

transfer capabilities of existing cable assets, potentially avoiding future infrastructure upgrade requirements.

In [26] the value of LVDC interconnections between transformers is quantified by considering the nubmer of EV charging transactions that can be accommodated with and without an LVDC network - Figure 2.10 illustrates the associated network. By controlling the power flow within the network using an adaptive droop controller a greater number of EV users can be accommodated without affecting the existing AC demand. The implementation of such a system requires careful consideration of the existing transformer loading profiles. Ideally transformers are selected with complementary loading profiles but this will be influenced by the spatial arrangement of the transformers and the associated cost of laying new cable. In practice, the NIC funded, LV Engine project [96] by Scottish Power Energy Networks (SPEN), will be incorporating an element of this transformer load sharing through a LVDC connection. This project provides an appropriate and useful example of a flexible LVDC charging network. However, further work in this area may wish to consider the optimum control solution, protection of the LVDC network and the safety standards for this public LVDC distribution system.

With respect to cable power transfer enhancements, the use of DC as opposed to AC permits power to be transferred at or beyond the peak AC voltage [9]. A DC distribution system can take the form of either a uni-polar system or a bi-polar distribution system, as depicted in Figure 2.11, both configurations have their own advantages and should be selected to meet a specific application. For example, a bi-polar distribution system can generally transfer more power due to a higher voltage difference between the positive and negative terminals but this system will require a more complex power converter than a uni-polar system due to the need to balance loading on both poles of the converter [9]. Currently, there is no standard LVDC voltage for public distribution systems and therefore the voltage level for each configuration is dependent on the load, the insulation properties of the existing cable, the preferred protection solution and allowable system losses [95].

If a uni-polar distribution system is compared with a conventional 3-phase system (a 3-core cable), up to 23.5% more power can be transmitted for the same mass of copper and under the same cooling regime. This is possible since DC distribution can operate at the peak AC voltage level while exerting the same dielectric stress on the cable insulation. From Hodge [12] this is presented formally as:

$$P_{DC} = V_{max} I; \tag{2.1}$$

$$P_{AC} = \frac{1}{\sqrt{2}} \sqrt{3} \cdot V_{max} I cos\theta; \tag{2.2}$$

$$P_{AC} = \frac{1.5}{\sqrt{2}} \sqrt{3} \cdot V_{max} I cos\theta; \tag{2.3}$$

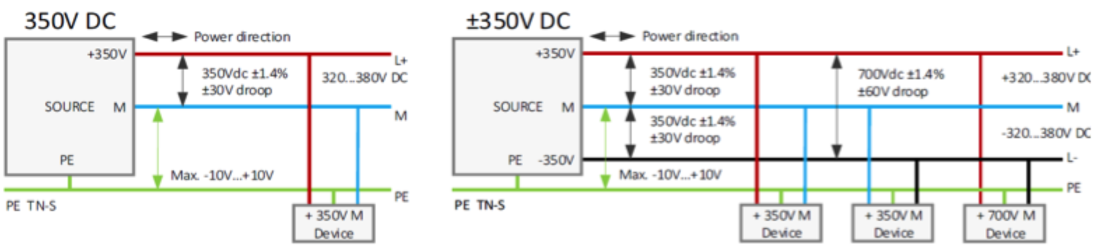


Figure 2.11: Two DC distribution topologies: bi-polar and uni-polar [97].

$$\frac{P_{AC}}{P_{DC}} = \frac{2}{\sqrt{3}} cos\theta; \tag{2.4}$$

In both AC (P_{AC}) and DC (P_{DC}), power is the product of the RMS voltage and current as presented in (2.1). However, in DC systems the RMS values can be equivalent to the peak AC values (V_{max}) and therefore to compare the power carrying capabilities of a uni-polar DC system and a 3-phase AC system, the AC voltage and current must first be multiplied by the inverse of $\sqrt{2}$ to get V_{rms}. The 3-phase line to ground voltage is used for power delivery and therefore the RMS current and voltage levels should be multiplied by $\sqrt{3}$ as in (2.2) and the associated power factor applied ($cos\theta$). It is noted that 3-phase power cables have 50% more copper mass (as only two of the three cable cores are utilised for a uni-polar DC system), and therefore this is reflected in (2.3). The power transmission ratio in (2.4) demonstrates that 3-phase AC power can only transmit 81% of the same power as DC for the same mass of copper and at unity power factor, this means a uni-polar DC distribution system, operating at the peak AC voltage, can transfer 23.5% more power for the same mass of copper.

For certain cables with a high line-line voltage rating the voltage level on a DC system can be increased beyond the peak AC voltage [9]. This further enhances the power transmission of an existing AC cable asset and could offer an alternative solution to early cable replacement due to increased power demand. In the UK, it is common to utilise both 3-core and 4-core LVAC cables as shown in Figure 2.12, with a phase-ground voltage rating of 600Vrms and a phase-phase rating of 1000Vrms [9]. This means the insulation can withstand a peak voltage of 849V phase-ground and 1414V phase-phase, therefore in both cable configurations a bi-polar +/-707Vdc system offers the highest power transfer capacity for existing cable assets.

In general, [9] concludes that existing LVAC cables are heterogeneous in nature, are of different ages and have multiple branches of varying sizes. Therefore converting existing public (DNO owned) LVAC cables to LVDC has a number of practical challenges to overcome and may only be appropriate where the cable integrity is well understood and the cable is of a uniform size throughout the proposed DC network. It is most likely that LVDC distribution will occur on new cable installations to deliver native

Figure 2.12: Conversion of LVAC cables to LVDC 3-core and 4-core bi-polar options [9].

DC power to new DC customers. In this scenario, as depicted in Figure 2.12, a 4-core bi-polar distribution cable is the most appropriate approach to minimise material costs and maximise power transfer capabilities. However, in this case, the mid-point return path would require the use of the earthing sheath around the cable, and it is unknown how this will affect the long-term integrity of the cable. Considering this unknown, perhaps the safer initial configuration for early LVDC deployments is a 3-core bi-polar cable that can utilise a dedicated core for the mid-point return; although, the power transfer capacity of the cable is not optimised.

For specific applications such as street lighting or building-level distribution systems, the power load and cable system is relatively homogenous and therefore the prospect of converting existing underground lighting cables to LVDC may be easier to accomplish [93]. Furthermore, a building with an integrated roof-top solar PV system has to first invert the DC generation to AC before an EV, connected to the building's distribution system, converts the power back into DC to charge it's batteries. A more energy efficient approach is to avoid the AC conversion stage entirely and create a DC 'sub-network' to charge the EV directly as depicted by the 'High Voltage DC Loads' in Figure 2.13 [98]. This paper carefully demonstrates a detailed model of a DC based office building which can yield an efficiency saving of 11.9% to 18.5% depending on the sizing of solar PV and battery storage. In summary, LVDC distribution can can either reduce the cable material requirements or reduce distribution losses compared to equivalent LVAC distribution systems due to higher power transfer rates through cables and fewer power conversion stages. This is a design factor that should also be

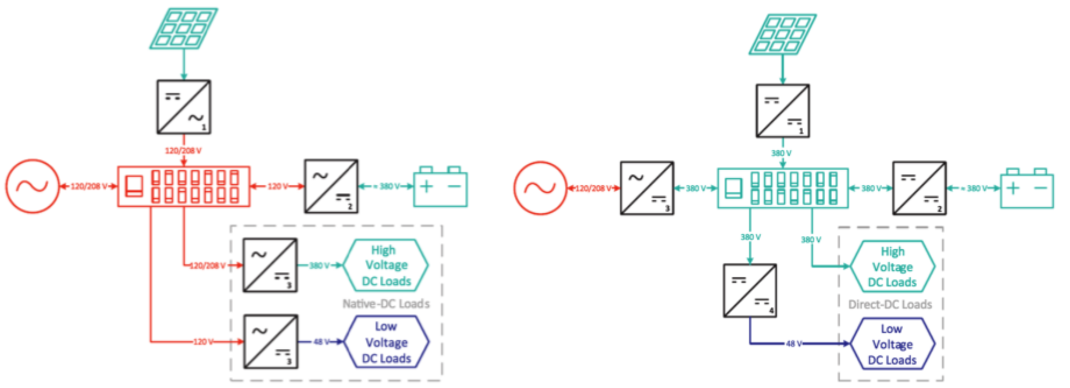


Figure 2.13: Efficiency comparison between AC (left) and DC (right) building level distribution systems.

considered in the implementation of new parking area EV charging networks that may require long cable runs. However, to recognise the potential of these LVDC charging networks will require an update to national electrical design and wiring standards to ensure the networks are adequately protected and safe for public use.

2.3.2 Protection & Earthing Considerations

This section introduces the challenges and possible solutions for the delivery of safe, effective protection and earthing solutions that may be implemented in the case of LVDC charging networks.

DC current is more challenging to break compared to AC due to the absence of a zero crossing point, there is also lower circuit impedance which means fault currents propagate rapidly, and the presence of a smoothing capacitor on the DC side of power converters causes a large current discharge during faults [11]. However, new developments in solid state devices and an enhanced understanding of current dynamics under faulted conditions are providing suitable solutions to this challenge but the selectivity and speed of operation remains an area of research [99], [11]. The design of a DC protection system should in general aim to minimise arcing, reduce component touch voltages, minimise the risk of fire and ensure the protection of downstream loads while also ensuring that any failure to a protection unit itself, fails to open and does not jeopardise the wider protection system. For LVDC distribution systems, the following protective devices may be considered:

- Adapted AC circuit breakers for DC distribution can be utilised on DC networks with voltages up to 325V DC [100]. The arcing effects during operation can be minimised by linking multiple poles of a Moulded Case Circuit Breaker (MCCB) which helps dissipate the energy across open terminals. To utilise an AC breaker such as an MCCB in this case requires a derating of the circuit breaker to reflect the operating conditions of the system [101].

- Circuit breakers on the AC side of the converter may be applied without modification and these will interrupt some faults present on the DC network. This may be a cost effective and reliable solution but it is a blunt protection option that causes the outage of the entire network during a fault condition [11]. This solution is only appropriate where the network is fed by AC sources or the wider AC network. In this case, the DC network may be de-energised momentarily to locate and isolate the fault by opening DC breakers. However, there is still a concern that AC breakers will not act fast enough to prevent fault current damage to power electronic components [11].

- Protective fuses can utilise existing AC fuses for overload and short circuit protection but they must be rated at a lower voltage for DC applications [102]. This is due to a difference in melting and clearing time constants between DC and AC circuits as well as the lack of a zero crossing point for DC which requires a larger air gap and potentially the use of arc splitters to quench the DC arc [102].

- Solid-state circuit breakers (SSCB) offer a promising solution to the low response time and arcing challenges that are present in traditional AC protection devices. Research has focused on the current measurement, control and operation of SSCB which has delivered high performing devices but costs and complexity remain high [11]. The perfect SSCB would operate independently (without central control) and ideally integrate with other devices on the network in order to reduce system costs - such as power converters. According to [103] novel SSCBs should incorporate the following capabilities: short circuit protection, grounding fault protection, arcing faults, mechanical isolation and communication. However, a significant disadvantage to SSCB is their relatively high on-state losses compared to mechanical circuit breakers. Therefore a combination of a mechanical circuit breaker and a SSCB can offer a hybrid solution whereby current flows through the mechanical circuit breaker with low losses under normal working conditions but is diverted through the SSCB during fault conditions. During a fault, this allows the mechanical circuit breaker to operate under a low loading condition and minimises the risk of arcing [104].

- Integrated converter protection may offer the most cost effective and versatile form of protection for DC distribution as the protection control makes use of the existing IGBT modules that compose the main power converter design. This can eliminate additional SSCB from the system and reduce the system losses and complexity [11]. However, in larger LVDC distribution networks a higher level of protection selectivity may be required to avoid disconnecting larger than necessary sections of the network and therefore dedicated protection units, embedded within the distribution network, would still be required. By examining the basic converter topologies in Figure 2.9 it can be seen that the DC/DC converter topology could limit the fault current in the direction of high to low voltage by changing the duty ratio of the IGBT S1. Furthermore Multi-Modular Converters (MMCs) are being widely researched for their use in HVDC applications due to their low on-state switching losses and ability to block fault current by coordinating switching within each module, however, little research on MMCs have taken place in the context of LVDC systems [11].

Currently, a universal protection solution for LVDC distribution does not exist and further research work is needed to develop this inline with the challenges that are set. As such the protection design for LVDC distribution will be application dependent and may incorporate any of the devices summarised above depending on the operational requirements of the power system application. Continued improvements in protection solutions for LVDC will enable tighter tolerances for component ratings and ultimately a more cost-effective power system.

In [105], the available DC grounding solutions and their performance is compared to the existing AC system with respect to public safety. This work offers a useful insight into the design requirements when considering the grounding topology for DC networks however, the grounding system design also has consequences for the technical performance of the DC network such as the presence of neutral voltage shifts when variable speed drives are connected to the DC bus [106] and also the potential requirement for insulation monitoring devices (IMDs).

The selected grounding topology depends on the application, loads, generators and connected AC network. In [107], Kapia et al examine the performance of earthing arrangements for +/-750V LVDC distribution where existing MVAC branch lines have been converted for improved power quality and reliability. They assess both IT (unearthed) and TN (earthed neutral) systems and conclude that although IT systems are considered more complex (due to the need for IMDs), they offer the safest touch voltages during faults. The IT grounding solution for this application requires all aspects of the LVDC network to remain unearthed, this includes: the AC transformer (which steps down MV to LV prior to conversion into DC), DC network and customer AC system. Whereas the earthed TN solution is only recommended in cases where the LVDC network has galvanic isolation from the customer AC network, otherwise a short circuit through ground can occur.

Galvanic isolation of DC power systems is an important aspect to consider when interfacing with an existing AC power system that uses a separate grounding system. The isolation between the two circuits prevents ground loop currents that may be present when the two systems are operating at different potentials. Circuit isolation can be achieved by incorporating a transformer between the input or output of the DC system, however, this can be large and inefficient if operating at the grid frequency of 50Hz. Therefore [108] suggests the use of an isolated DC-DC converter which uses a high frequency transformer to reduce the mass and increase efficiency of the isolation system. Although, the DC-DC isolation converter is more complex and expensive, it recovers the higher costs through long-term efficiency savings.

With respect to EV charging infrastructure, to date, some EV charging infrastructure providers can interface wtih IT/TN/TT earthing configurations [109] but in the Netherlands the use of TN-S earthing has been adopted for EV charging networks and street lighting applications [97]. If widespread adoption of LVDC distribution systems is to take place then standard protection and earthing configurations are required.

2.3.3 Standards & Components

The research work of this thesis has produced a detailed review of international LVDC standards which has been published in [110]. The review has highlighted the international organisations that are actively developing design recommendations for LVDC systems and it has presented the available standards in Table 2.1 with respect to each application's protection requirements, power quality and safety. From this review, it has become clear that stand-alone DC applications have well-defined technical standards, but the technical specifications for more complex, integrated networks that will be found within the built environment and public distribution systems are still evolving. Opportunities therefore exist for academics and industry to assist in the formation of the following standards:

- Voltage harmonisation: standard public distribution voltages are required for street-level, commercial and residential spaces with consideration to allowable voltage tolerances. From this review [110], it is suggested that +/-750 Vdc is considered for street level distribution, +/-200 Vdc (380 to 400 Vdc) is used for building level distribution and a 48 Vdc room-level voltage is established to offer the most likely compatibility with electrical devices while maintaining a safe voltage level.

- Safety: the physiological effects of current on humans are well understood but greater standardisation of allowable touch voltages and acceptable exposure times should be considered. A better understanding of the optimum (safe and economical) earthing configurations for DC distributions systems is required.

Table 2.1: Available LVDC standards [110].

	Application	*Protection criteria*	*Safety*	*Power quality*	*Earthing & Bonding*
LEVEL 1: <120 V	USB	USB-IF (2.0, 3.0, Type-C) BS EN 62680-2-1	USB-IF (2.0, 3.0, Type-C) BS EN 62680-2-1	USB-IF (2.0, 3.0, Type-C) BS EN 62680-2-1	USB-IF (2.0, 3.0, Type-C) BS EN 62680-2-1
	Telecom (48V)	ETSI EN 300 132-2TR 100 283	ETSI EN 300 132-2	ETSI EN 300 132-2	ETSI EN 301 605
	LED Lighting	BS EN 61347 2-13 BS EN 61347-1	IEC 60598-1 IEC 61347-1	BS EN 62384	IEC 61347-1
	PoE	NEC.725	-	IEEE 802.3at	-
EVEL 2: 120-400 V	Residential	-	BS7671 NEC	-	BS7671 NEC
	Building	-	BS7671 NEC	-	BS7671 NEC.250
	Telecom (120 - 400V)	ETSI 300 132-3-1 ITU-TL.12(00-05)	ITU-TL.12(00-05)	ETSI 300 132-3-1 YD/T2378-2011 YD/T2089-2016	ETSI EN 301 605 ITU-TL.12(00-05)
	EV Charging	BS EN 61851-23:2014	BS EN 61851-23:2014	BS EN 61851-23:2014	-
	Data Centre	BS EN 50600-2-2:2014	BS EN 50600-2-2:2014 IEC62040-5-1	BS EN 50600-2-2:2014	ETSI EN 301 605
LEVEL 3: 400-1500 V	Traction	BS EN 50123-7-1 BS EN 50123-1	BS EN 50328 BS EN 50633	BS EN 50328 BS EN 50163	IEC 62128 IEC 60364-4-41
	Public Networks	-	P2030.10 NEC.712	-	NEC.250
	Ship Power	IEC 60092-507 ABYC E11	IEC 60092-507	IEC 60092-101	-
	Solar PV	BS EN 60269-6 BS EN 62548-1	BS EN 62109-1 EC 60364-4-41	BS EN 62109-1	IEC 60364-7-712

- Protection: the provision of performance guidelines for SSCB and DC RCDs is required for the protection of physical assets and life. Special consideration should be given to the interference of power converters and fault current levels on existing building-level protection systems. Furthermore, the operation of protection systems and its impact on fire safety should be considered with respect to stored energy in converters and batteries.

Once these areas are addressed, product manufacturers and electrical system designers will have the confidence to implement public LVDC distribution and the benefits afforded by LVDC can be recognised for not only LVDC charging networks that support battery electric vehicles but also for building-level and isolated microgrid applications.

2.4 Road-map for Flexible LVDC Charging Networks

Based on the review of existing EV charging systems, power network integration challenges and LVDC opportunities, an outline of possible LVDC charging networks is presented in Figure 2.14 that may facilitate the delivery of cost-effective and flexible charging infrastructure that will soon be required. In this figure, the three main charging locations (at home, at work and public HPC stations) are each subdivided into two categories: *long duration* charging and *short duration.* A *long duration* charging solution is one where the EV is stationary for a period of time that is sufficient to enable an optimised charging routine based on power prices, other EV users and local intermittent renewable generation. Whereas *short duration* charging is characterised by the requirement for an immediate request for charge at full-power. This classification also takes into consider the power density requirements for both long and short duration charging.

The short duration charging infrastructure scenarios are envisaged to possess a power capacity between 350kW-2MW+ in scale and therefore the use of solar PV parking canopies will do little to alleviate the local power requirements due to the small area of land that a HPC system would occupy and the resulting low power output from such a PV system in comparison to the overall charging power requirement. The application of onsite energy storage 'buffers' is a worthwhile consideration for both long and short duration charging that could reduce the size of the grid connection and associated capacity payment to the network operator by slowly charging the local battery overnight and discharging to customer's vehicles as required. This is explored as an optimisation problem in [111] and is currently an integrated charging product on offer by Kreisel Electric[8]. Alternatively, the integration of Combined Heat and

[8]http://www.kreiselelectric.com/en/chimero/

Power (CHP) systems that interconnect with the gas grid instead of, or as well as, the electrical network may offer an efficient integrated energy solution for HPC locations, this is considered for lower power EV charging systems in [85] and [112].

In total, Figure 2.14 consists of seven LVDC charging network opportunties that may assist the deployment of EV charging infrastructure by utilising existing electrical grid assets while facilitating integrated energy systems and offering an energy efficient charging process. Three out of the seven LVDC network options have previously been addressed in tangential research areas: the application of 'last-mile LVDC networks' has been considered in [15], [11]; the performance of LVDC building networks is reported in [98], [113]; and the value of MT-LVDC for EV charging is demonstrated in [26]. However, little to no research has considered the feasibility of the remaining LVDC charging network options.

Several research papers have investigated the application of 'fixed' LVDC charging networks that utilise a central AC/DC converter and multiple DC/DC converters at each parking-bay [27], [114]. However, it can be argued that for long-duration charging scenarios this fixed network LVDC charging concept is inefficient and costly. This thesis therefore investigates the concept of a 'reconfigurable' LVDC charging network that efficiently routes power from a centralised AC/DC converter to each parking bay according to an optimised energy management system. The use of this 'reconfigurable' network can also be applied in the conversion of street-lighting networks to LVDC distribution, facilitating higher power and more efficient charging compared to existing AC integrated street-lighting and charging solutions [93].

The connection of HPC systems to existing LVDC light rail networks may offer an alternative connection solution for urban environments where the public electricity network is congested. In Figure 2.14 it is assumed that this will benefit primarily taxis, buses and private EV owners that live and operate within the city limits. In many regions, light rail networks not only traverse a city but the majority rely on a 750Vdc-1500Vdc traction system and therefore the distribution voltage is directly compatible with HPC infrastructure. However, further understanding of light rail operating characteristics is required to identify available capacity and to develop an EV charging

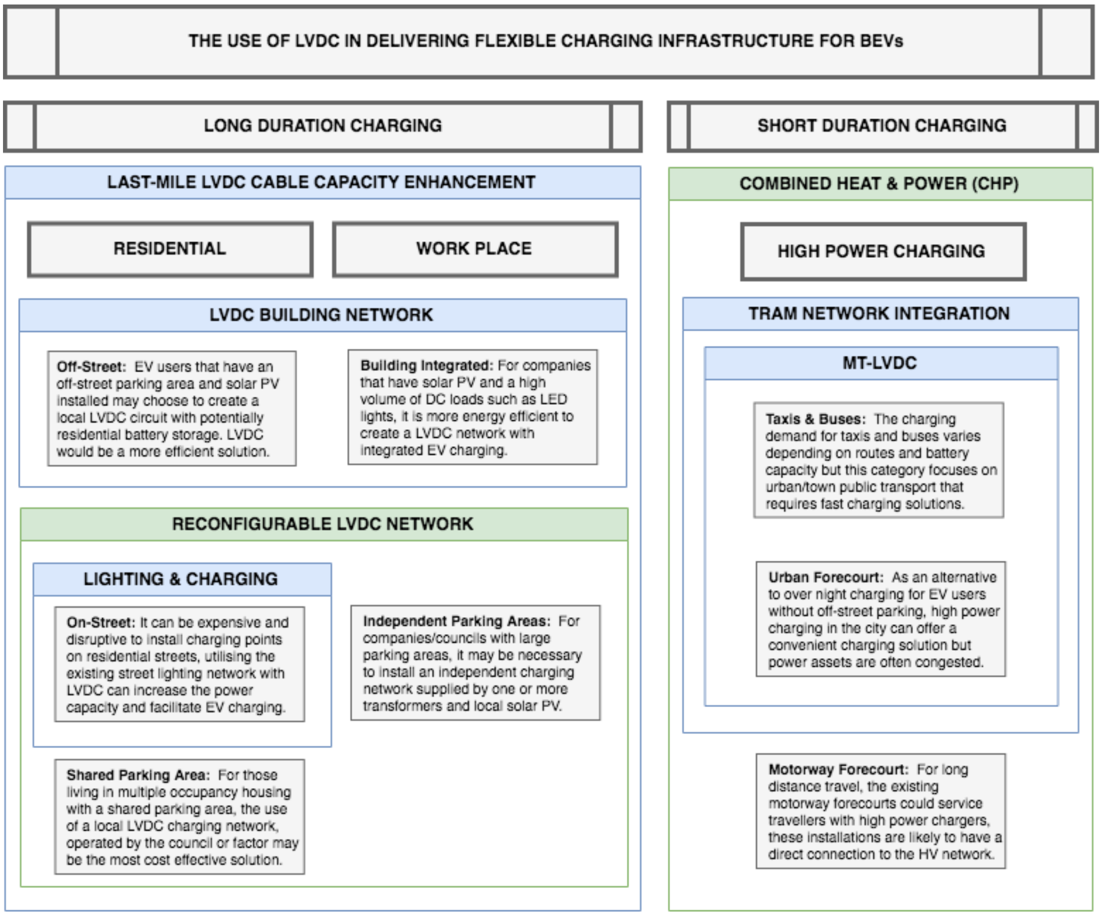


Figure 2.14: The use of LVDC in delivering flexible charging infrastructure.

control solution that can sympathetically integrate with the tram infrastructure.

However, considering the limited research conducted in the area of integrated gas and electrical power networks for the support of EV charging infrastructure, Chapter-4 of this thesis considers the feasibility of co-located CHP systems to provide the necessary power density for 'short-duration' charging infrastructure. Three different CHP technologies connected to both the LVDC charging network and AC distribution system are considered using a high power charging infrastructure optimisation model, developed as part of the work of this thesis. This study is then followed in Chapter 5 by the performance comparison of a 'fixed' and 'reconfigurable' LVDC charging network within the 'long-duration' charging scenario by demonstrating the operation of an appropriate EMS solution for the control of a reconfigurable network. In both cases the focus of the research is on defining the operating characteristics of the LVDC networks, assessing the energy efficiency, cost and the development of an appropriate energy management system (EMS) for the charging networks. To begin these investigations, it is useful to understand EV user charging behaviour and to develop a model of expected arrival rates and energy transferred during each charging transaction within the context of public rapid DC charging infrastructure, this is the focus of the subsequent chapter.

Chapter 3

Modelling the Usage of Rapid DC Chargers

The effective design of charging infrastructure requires an understanding of EV user behaviour and the expected charging requirements for specific locations. The decision to site traditional petrol stations in specific locations has historically depended on vehicle counts, local competition and future traffic forecasts [115]. Similar forward looking demand forecasting is required for the deployment of EV charging infrastructure; not only to ensure that sufficient local demand will be available to justify the investment cost of the infrastructure but also to forecast future power demand for a collection of EV chargers which may be geographically disperse. In the case of charging infrastructure deployment strategies it is clear that many governments and private companies are currently adopting a 'land-grab' and 'consumer confidence' strategy that involves selecting either the lowest cost grid connection sites or areas where future demand for charging is likely to be high, and in the case of the consumer confidence strategy, high-profile chargers are deployed to demonstrate that it is possible to confidently travel throughout a region with an EV [116]. Both approaches could be considered 'push' strategies[1] where governments and early EV manufacturers are encouraging adoption of low emission vehicles by offering free or low cost charging solutions and mitigating

[1]Where an organisation makes their product or sevice visible and easily accessible.

against charging anxiety (a sense of stress felt by an EV user travelling in unfamiliar territory and where the prospect of encountering a charging system is uncertain). As the market for EVs matures, the utilisation at existing charging infrastructure will increase and will precipitate further build-out to meet demand and potentially consolidation as early chargers are found to be uneconomical to maintain. This next generation of chargers will have the advantage of learning from the early pre-commercial deployments but competition amongst CPOs and limited sites will require more intelligent methods of integrating charging systems to the electrical grid and to manage the demand for power competitively. Both of these activities can be supported by analysing charging trends from existing public charging systems to deliver future charging infrastructure that is appropriately sited, sized and controlled to minimise the charging cost to consumers. This is summarised in the proposed charging infrastructure development process of Figure 3.1; where the work of this chapter explores the utilisation of an existing rapid DC charging network and the results from this analysis support the charging system design modelling conducted in Chapter 4. Similar utilisation studies were conducted as part of the Rapid Charge Network deployment in north west England [117] but this network was limited to 74 chargers that were generally under utilised. A larger study of rapid DC charger utilisation was conducted using datasets from Norway and Sweden [118], this research found that one rapid DC charger (150kW) to every 1,000 EVs was sufficient to meet future charging demands and the per kWh charging infrastructure cost was between EUR 0.05/kWh-0.15/kWh. However, neither of these research projects consider the locational variances in rapid DC charging behaviour and the forecasting of day-ahead power demand for the network of rapid DC chargers. This chapter will consider these specific aspects of charging infrastructure development and operation.

This chapter analyses and draws informative trends from two years' (2015-17) worth of charging data (over 250,000 charging events) from Scotland's network of 192 rapid DC chargers. This chapter consists of three sections, firstly an analysis of charging network utilisation provides an insight into representative EV arrival rates and charging energy transactions for specific charger locations. Secondly, a 24-hour power demand forecasting algorithm demonstrates the external variables that can affect aggregate

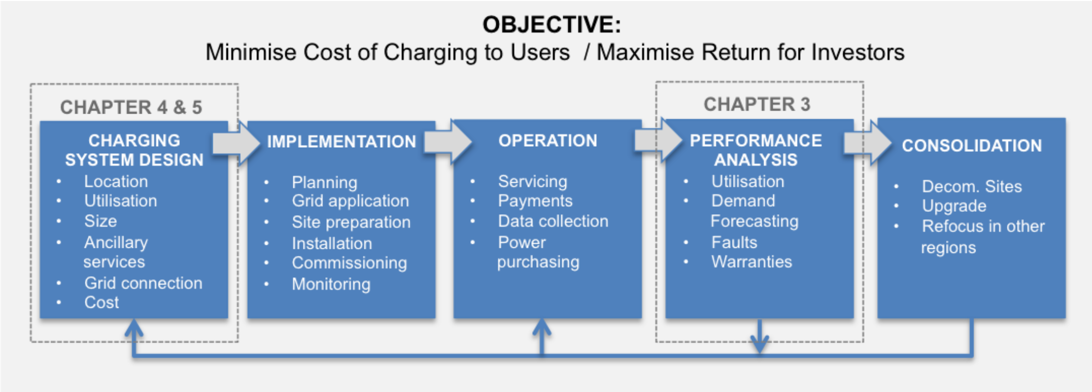


Figure 3.1: Proposed charging infrastructure development process.

charging demand on a daily basis and the value of creating a dedicated energy supply contract for this network of rapid DC chargers is discussed. Thirdly, to explore new LVDC charging network topologies, a charging infrastructure optimisation model is presented in the form of a Mixed Integer Linear Programming (MILP) problem. This model is further developed in Chapter 4 and Chapter 5 to assess the performance of novel LVDC charging networks.

3.1 Charging Network Utilisation

In response to the global societal need to tackle climate change, the Scottish Government has initiated a programme that provides fully-funded rapid DC chargers to a variety of host sites throughout the country with the intention to invigorate the nascent EV market[2]. Since 2013 the Scottish network of rapid DC chargers has expanded to total 192 sites, spanning all areas of Scotland enabling EV drivers to confidently access any region of the country. These charging assets are part of the Charge Place Scotland (CPS) public charging network that is operated and administered by a third party company on behalf of the Scottish Government. Although the individual chargers are owned and maintained by a host site, the CPS network is monitored as an aggregated asset with a central data collection facility.

Scotland is making meaningful steps towards the decarbonisation of its electri-

[2]https://chargeplacescotland.org/

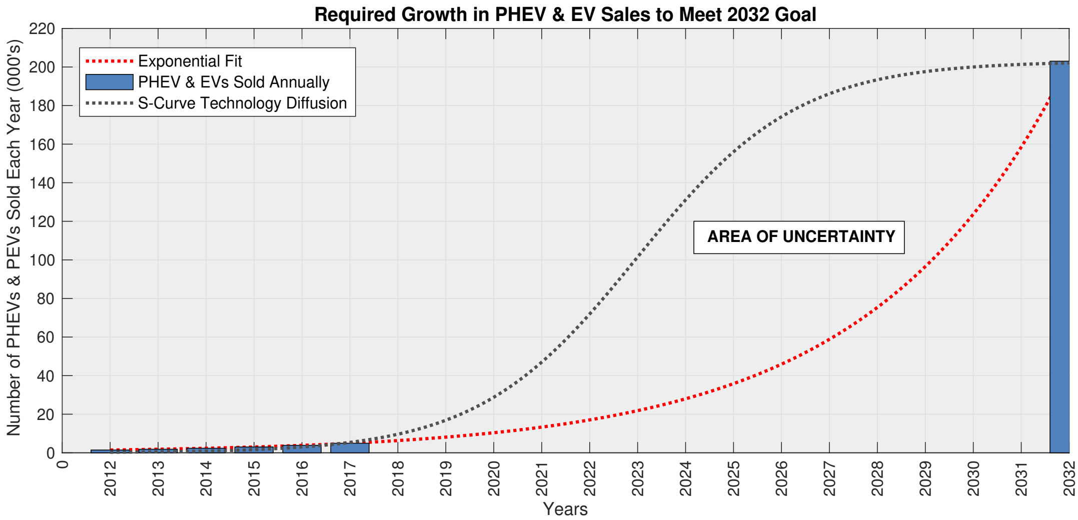


Figure 3.2: Possible Scottish EV sales growth curves from 2017 to 2032 demonstrates trajectory of new car sales necessary to meet 2032 pledge.

cal power sector, 68.1% of gross electricity consumption came from renewable energy sources in 2017 [119]. However, the Scottish Government also recognises the need to accelerate the adoption of lower carbon transport and heating solutions. The 2018 Scottish Energy Strategy [120] announced a 'soft-ban' on the sale of new fossil fuel vehicles in Scotland from 2032 onwards which sets the nation an ambitious challenge to prepare for a future transportation system absent of fossil fuels in a little over a decade.

Current new car sales in Scotland total 203,000 annually, and of this number, 6,000 were considered hybrid electric with 900 full electric in 2017 [121]. To meet the 2032 target will require a 1500% annual growth rate in PEVs from 2017 to 2032 but this growth rate is unlikely to be linear and could follow an exponential rate of adoption or a S-curve that has historically represented the rate of technology diffusion [122], as illustrated in Figure 3.2. Based on a flurry of automotive press releases in 2018 and 2019 [123] [124], it appears that there will soon be a wide selection of EVs for consumers to choose from, but greater consideration may be required in the area of charging infrastructure planning to minimise the transitional cost, to satisfy anticipated charging demand and to capture economic value locally as well as nationally.

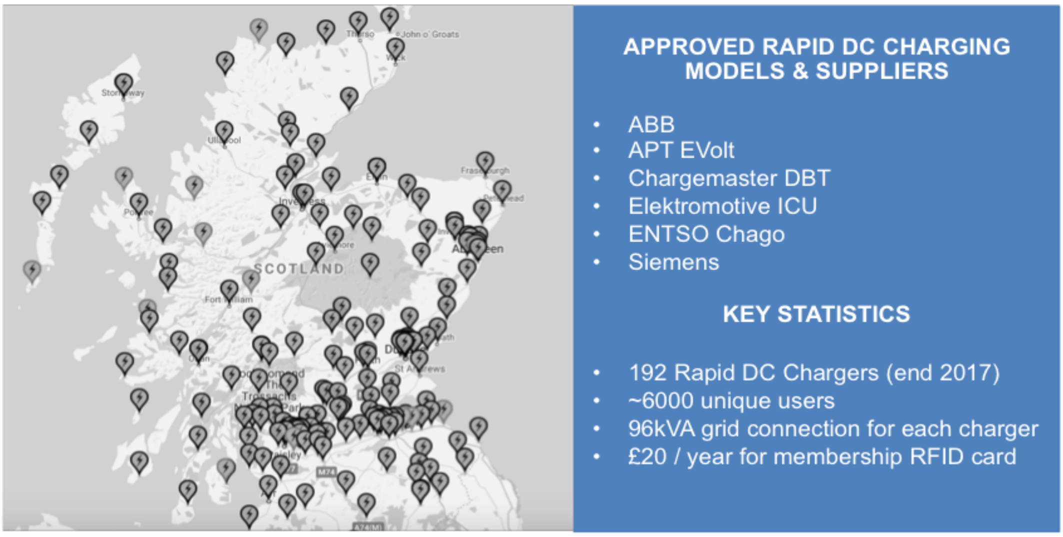


Figure 3.3: Map of Scottish rapid DC chargers (source: zap-map.com). Approved chargers and statistics provided by chargeryourcar.org.uk.

This section classifies the 192 chargers into 8 different locations and examines the utilisation rate and charging behaviour for each class. This analysis can inform future site selection decisions while providing engineers and researchers with real public charging behaviour data to inform further energy system modelling.

3.1.1 The Charge Place Scotland Charging Network

The CPS network is a government organisation that provides funding and oversight for a national network of public EV chargers. The rapid DC chargers within the network can be considered as both destination and en-route charging, with their locations depicted in Figure 3.3. CPS is a technology agnostic network provider, the charging asset itself is selected and owned by the host which is generally a local authority or business that has received funding through CPS. Although funding is contingent upon selecting a charger from the approved supplier list which is also outlined in Figure 3.3. To qualify for the CPS network, the chargers must be Open Charge Point Protocol (OCPP) compliant[3], capable of connectivity, and be able to charge more than one vehicle at once. Most commonly, the connectivity is provided through the 3G communication network and

[3]https://www.openchargealliance.org/

the OCPP is an open standard to enable communication between distributed charging assets and a centralised administrating/operating system.[4]

All chargers are able to charge at a rate of 43kW AC and 50kW DC simultaneously. Therefore a grid connection capacity of approximately 96kVA is required for a 415/230V, 3-phase supply with 138A per phase. In aggregate, the CPS network has a grid connection capacity that is approaching 20MW and therefore opportunities to provide ancillary grid balancing services may become feasible if the cumulative demand profile of the network is well understood and robust forecasting models can be applied.

Users of the CPS network require an access card or must use a mobile application to pay for charging services. This requires registration in advance of arrival at a charging location, there is an annual charge of £20 for a CPS access card but it is free to download and use the mobile application. CPS also offer a pay as you go (PAYG) telephone service for non-members which costs a minimum of £3.50 to use plus any tariff active on the charge point. Host sites cannot administer a charging tariff in the first 1-3 years of operation due to the receipt of public funding for the charging infrastructure, however, after this period the charging tariff can be determined by the local charge point host.

The dataset from the CPS charging network is unique in its size, geographic diversity and data fields that are collected. It presents an opportunity to extract real user statistics for public rapid DC charging that could inform future charging infrastructure decisions within Scotland and internationally. In 2017 there were approximately 6000 unique users of the CPS charging network. Each of their charging transactions are recorded centrally by a contracted 'back-end' data management provider. The available operational data includes the following fields: charge point ID, charging start and end timestamps, energy delivered through each charge, tariff/total cost of charge, connector used and make of vehicle being charged. In total, this data amounts to almost 400,000 charging transactions that have taken place since 2013 and in the following sections this thesis outlines the methodology applied in analysing this data and the conclusions that can be extracted.

[4] Based on an interview conducted with Charge Your Car Ltd.

3.1.2 Locational Classification & Usage

As commonly understood, there are three broad EV charging locations: at home, at work and public charging. However, each of these locations can be further classified, especially in the case of public charging infrastructure. Several research papers consider the geographic coverage of public chargers to ensure sufficient capacity is available to meet the expected utilisation of future EV users but they do not explicitly consider locational differences [125], [54], [126]. In the Rapid Charge Network (RCN) project [117], users of the network were asked their charging location preference[5] but no retrospective analysis of charge point utilisation based on location classes was conducted. Few, if any research activities, have documented the actual utilisation of rapid DC chargers according to specific locational classes. This is what makes the Scottish dataset particularly useful. The location of a rapid DC charger is arguably a key determinant for the pattern of arrivals and energy transactions [43]. Examining the usage of existing rapid DC chargers according to locational classes can inform future deployment locations and charging system design. Therefore this dataset is first classified according to charger locations based on the address of the charger and the host site's primary activity. This highlights the differences in utilisation rates and later allows for the development of locational specific arrival and energy demand patterns.

From the network of 192 chargers, eight locational classifications were identified to examine utilisation rates and differences in EV user arrival/charging patterns. Table 3.1 presents these classifications and the associated number of chargers in each. Within these classes the number of unique users is identified and the total energy delivered from the collection of chargers over the 2017 period is quantified. This information is presented in Figure 3.4.

The boxplots highlight the average number of unique EV users that each charger has received or energy delivered in 2017 (represented by the red line). The top and bottom of the blue plot represents the upper and lower quartiles and the dashed-lines highlight the maximum and minimum number of users or energy delivered for the collection of

[5]User preference was for road-side or service station rapid chargers. Further information about the RCN project is available here: http://rapidchargenetwork.com/index.php

Table 3.1: Classification of Rapid Charger Locations

Index	Class	Qty.	Location Examples
1	Harbour	19	Port facillities and ferry terminals.
2	Park & Ride	26	Peripheral city parking areas serviced by buses or trains.
3	Taxi Rank	9	Taxi waiting areas or depots.
4	Shopping	3	Shopping malls, supermarkets.
5	Public Parking	84	Public 'pay & display' parking areas, multi-story parking.
6	Offices	22	Commercial, schools, universities, hospitals, council offices.
7	Activities	24	Swimming pools, snow sports, museums, music venues, sporting stadiums.
8	Service Stations	5	Traditional fuel stops, rest stops, cafes, restaurants on main roads.

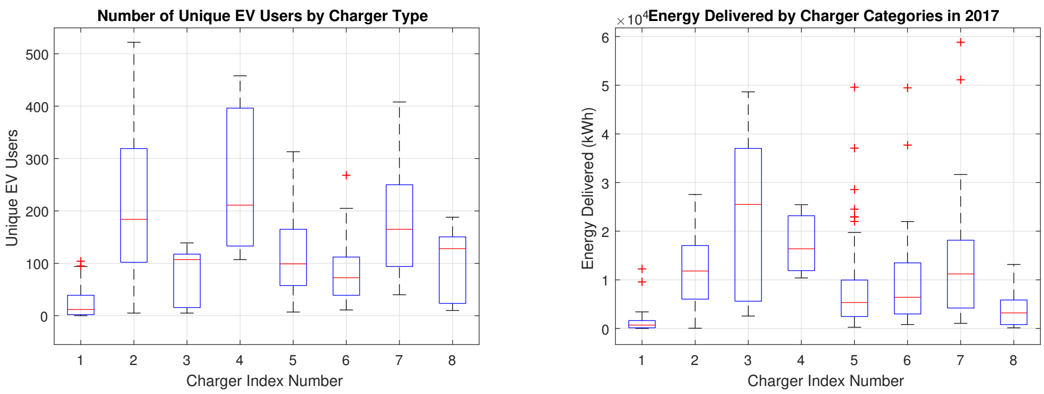


Figure 3.4: Unique EV users (left) and charging energy delivered (right) for each of the 192 rapid DC chargers in 2017 according to specific locational classes.

chargers in each category.

Several useful conclusions can be identified from these plots: it is clear that chargers located in park and ride facilities (Index-2) and shopping locations (Index-4) receive the largest number of unique users and therefore can be considered popular or convenient charging locations but this class does not deliver the most energy. The Taxi Rank charging class (Index-3) delivered the highest volume of energy during 2017 but has one of the lowest levels of unique users. This suggests that the Taxi Rank chargers are highly utilised by a number of regular taxis and indicates the importance of rapid DC charging to support urban taxi fleets. The least popular chargers are located at port facilities and ferry terminals (Index-1) but considering most of the ferry terminals in Scotland are located in remote or rural regions it is to be expected that these charging locations have low utilisation.

For future charging infrastructure development this information allows developers, governments and city planners to select locations that are most likely to receive high utilisation rates to support the long-term charging infrastructure business case. However, this utilisation information does not provide an indication of when EV users visit these sites and how much energy is transferred during each charging transaction. As demonstrated in Chaptert-4 and Chapter-5 of this thesis, this additional information can assist charging system designers in sizing the electrical grid connection, determining the number of chargers required in one location and identifying if any ancillary energy systems can be integrated or electrical grid benefits can be provided at certain times of the day.

3.1.3 Charging Energy & Arrival Models

Background Information

Much of the prior research into modelling arrival rates at public charging points and the subsequent energy transaction has been achieved by monitoring existing traffic flows and then building a model based on the expected utilisation of charger(s). This traffic model, based on either travel statistics or the origin and destination of vehicles, for EV charging demand is is applied in [127], [85] whereas [128] applies random arrival rates at charging stations simply because real charging data is difficult to obtain on a large scale and [129] summarises several other approaches to modelling EV arrival uncertainty. This early work tends to substitute vehicles as electric, with battery capacities based on the proportional sales of early EV models. This approach was adopted by NREL in [130] where utilisation statistics were developed for a rapid DC charger to determine congestion during the day and to consider the integration of renewable energy technology to alleviate the impact on power networks during traditional peak demand periods. A similar approach was adopted in [131] where a model is presented that converts driving patterns from Finnish national travel statistics to anticipated charging patterns but this was limited to low power AC charging and, although days of the week and seasonal characteristics are considered, other factors such as charger locations and weather events are not considered in this model.

However, public EV trials such as My Electric Avenue [76] and How Americans Charge their Electric Vehicles [132] have helped to develop user behaviour models for large-scale residential charging and some public chargers but similar operational data for rapid DC charging is less available, perhaps for two reasons: rapid DC chargers are generally deployed by independent, privately operated companies where the performance data is treated as commercially sensitive and, to a certain extent, the usage of public DC chargers has not received the same research attention that residential charging has due to the perceived, immediate technical impact that high levels of residential charging presents to the low voltage networks.

It is now becoming clearer that rapid DC chargers and HPC systems are likely to play an increasingly important role in future electric transportation infrastructure [54], it is therefore necessary to understand how EV users will interact with these charging systems based on different locations, weather variations and a growing population of EVs in circulation.

Methodology for Analysing Charger Utilisation Data

This sub-section focuses on the locational aspect of rapid DC charging and the associated energy transactions and arrival times. These variables are investigated using a simple frequency analysis with results summarised in histograms for each charger classification. These are generalised into separate probability density functions (PDF) for the EV arrival times and charging energy delivered for each charger classification. From this a better understanding of when charger congestion may occur can be obtained as well as facilitating the development of energy management algorithms that may incorporate optimised charge scheduling and the integration of distributed energy resources (DER) such as solar PV, battery storage and CHP systems [118], [116].

To obtain the results, the dataset was focused on the year 2017 only as it contained the largest collection of installed chargers and a higher demand from charging compared to previous years. The dataset was cleaned to remove spurious charging events (where no energy was delivered) and any outlying energy data points were removed by restricting the energy transferred between 0 and 50kWh (only 0.25% of charging transactions in 2017 were over 50kWh and almost exclusively from Tesla Model S vehicles). In total, 191,621 charging transactions are included in the study. The results are structured in a reference table containing the parameters necessary to re-produce the distributions and a series of plots to demonstrate the closeness of fit between the histogram and selected distribution.

EV Energy Usage and Arrival Timings

The distribution type and associated parameters are presented in Table 3.2 for each of the charging location classifications and for the overall rapid DC charging network in aggregate. The corresponding distributions and histograms are plotted in Figure 3.6 to Figure 3.13.

It is clear that in all charging locations and for the network in general, the charging energy transferred follows a Gamma distribution. The Gamma distribution is characterised by

$$y = P(x|a,b) = \frac{1}{b^{\mathrm{a}}\gamma(a)} x^{(a-1)} e^{\frac{-x}{e^{b}}} \tag{3.1}$$

Where $P(x)$ represents the probability that a charging event will delivery x energy.

The shape parameter a and the scale parameter b are descriptive parameters specific to the gamma distribution function. By using Eq. (3.1) and parameters from Table 3.2, other researchers and engineers can re-produce the distributions for any of the charger locations.

In most of the charging classifications, the charging start times fit a Gaussian distribution, however, in certain cases a uni-modal Gaussian distribution model does not capture all of the features. For example, in Figure 3.5 the red plot illustrates a single Gaussian distribution which misses the early morning EV charging peak that appears to be caused by taxis. However, a more accurate model is represented by the yellow plot which uses a mixture of three Gaussian distributions, formed as a Gaussin Mixture Model (GMM). The standard equations for a uni-modal Gaussian distribution and multi-modal Gaussian distribution are presented in equations (3.2) and (3.3) respectively.

$$y = P(x|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{3.2}$$

Where $P(x)$ represents the probability of a charging event beginning at time x given the mean μ and the variance σ of the distribution. For multi-modal Gaussian distributions it is necessary to know the mean and variance for each Gaussian distribution as well as the number of Gaussian components K percentage that each distribution contributes to the final GMM.

$$y = P(x|\mu_i,\sigma_i) = \frac{1}{\sqrt{(2\pi)^K|\sigma_i|}} exp^{(} - \frac{1}{2}(x-\mu_i)^T\sigma_i^{-1}(x-\mu_i) \tag{3.3}$$

For each of the charging categories presented in Figures 3.6 to 3.13, Table 3.2 contains the a and b values for the energy transaction gamma distribution and it is stated whether the Gaussian distribution of the charging start times is uni-modal or multi-modal and the corresponding σ and μ values for each.

The resulting probability distribution functions for the time at which charging initiates and the energy transfer for each transaction is displayed in Figure 3.5 for the charging network in aggregate and then, by examining the eight charger classifications,

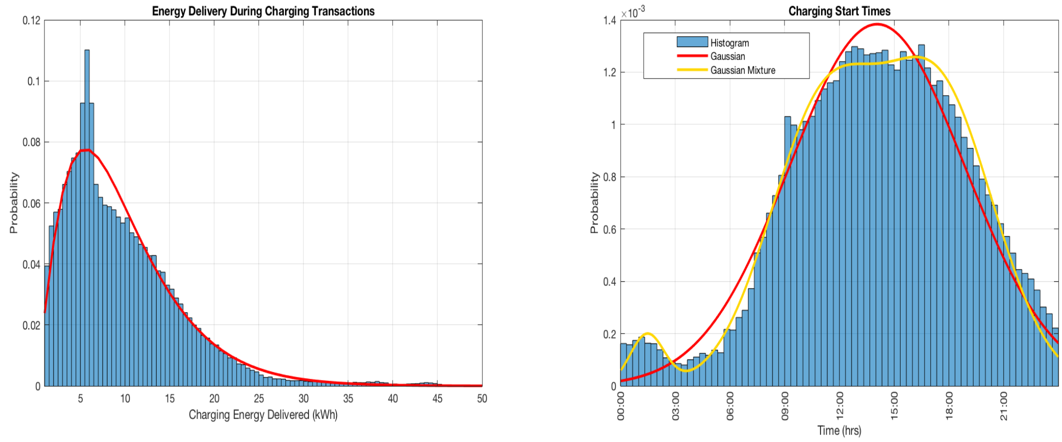


Figure 3.5: Charging energy delivered and start time for all charging events that took place in 2017.

it is possible to see the underlying composition of this aggregated profile in Fig 3.6 to Figure 3.13.

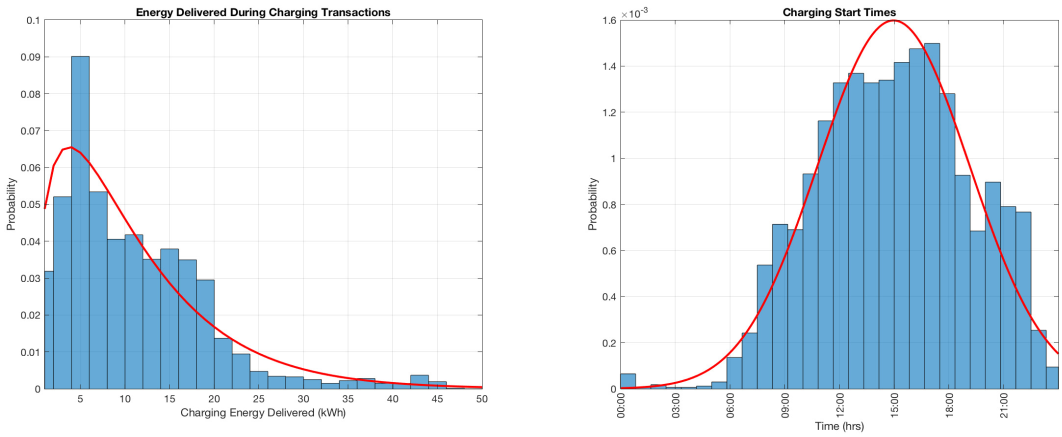


Figure 3.6: Index-1: Harbours & Ferry Terminals.

Table 3.2: Parameters for Gamma, Gaussian and Gaussian Mixture Models.

	Fig.	PDF	a	b	µ	σ	Mix
Aggregated Chargers	3.5	Gamma	2.30	4.20	-	-	-
	3.5	Gaussian	-	-	844.20	288.40	-
	3.5	GMM	-	-	[762.13, 1202.98, 950.49, 597.93, 87.69]	[37569, 14873, 21287, 26199, 3116]	[0.3050, 0.1883, 0.2728, 0.2062, 0.0274]
Ferry Terminals	3.6	Gamma	1.51	7.34	-	-	-
	3.6	Gaussian	-	-	898.04	249.69	-
Park & Ride	3.7	Gamma	1.94	5.37	-	-	
	3.7	Gaussian	-	-	860.90	268.57	
Taxis	3.8	Gamma	2.18	3.10	-	-	-
	3.8	Gaussian	-	-	804.36	334.09	-
	3.8	GMM	-	-	[1235.43, 565.74, 74.60, 892.96]	[13896, 44991, 1779, 30241]	[0.1877, 0.3680, 0.0396, 0.4045]
Shopping Areas	3.10	Gamma	1.55	6.50	-	-	-
	3.10	Gaussian	-	-	880.79	234.02	-
	3.10	GMM	-	-	[864.51, 672.36, 1077]	[50274, 11774, 20416]	[0.3674, 0.2919, 0.3407]
Public Parking	3.11	Gamma	1.57	6.33	-	-	-
	3.11	Gaussian	-	-	854.2765	267.8038	-
Office Parking	3.12	Gamma	1.97	4.59	-	-	-
	3.12	Gaussian	-	-	812.1931	309.1520	-
Activities	3.13	Gamma	1.80	6.06	-	-	-
	3.13	Gaussian	-	-	859.0887	289.2148	-
Service Stations	3.14	Gamma	1.82	6.43	-	-	-
	3.14	Gaussian	-	-	849.773	245.1855	-
	3.14	GMM	-	-	[514.37, 879.25, 886.50]	[320.45, 4486.90, 65236]	[0.089, 0.509, 0.402]

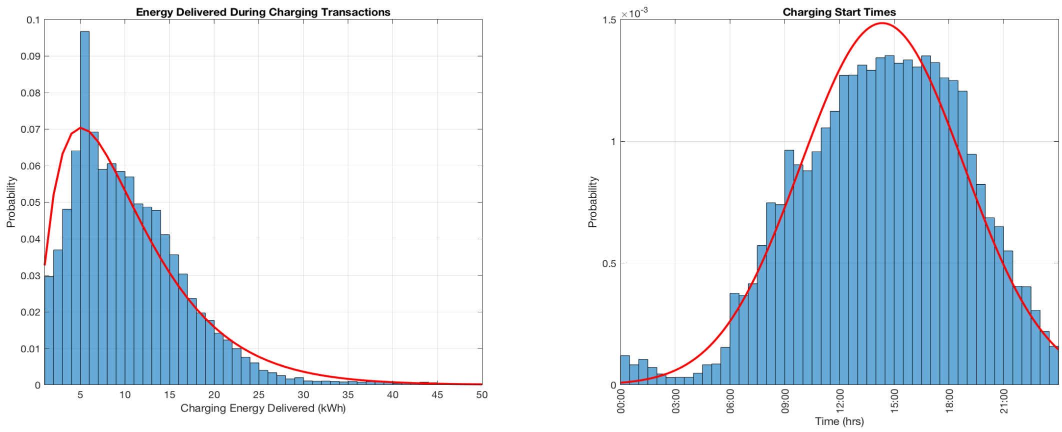


Figure 3.7: Index-2: Park & Ride facilities.

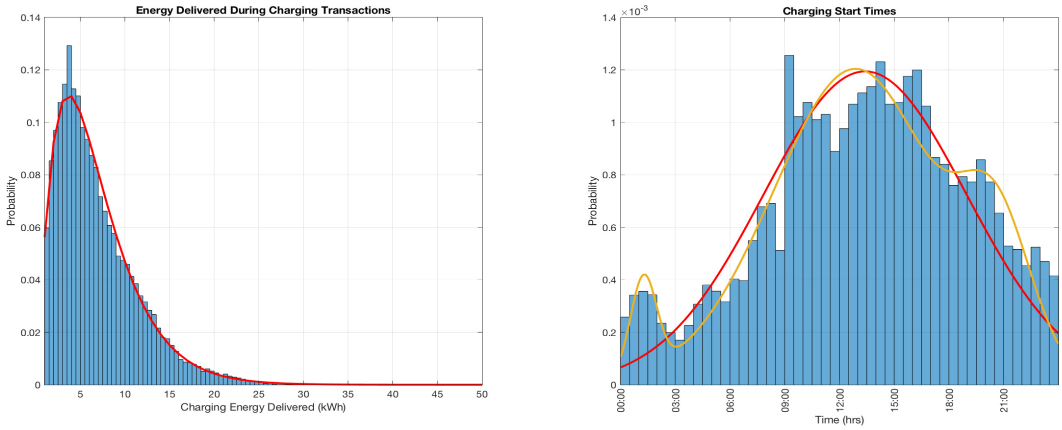


Figure 3.8: Index-3: Taxi rank chargers.

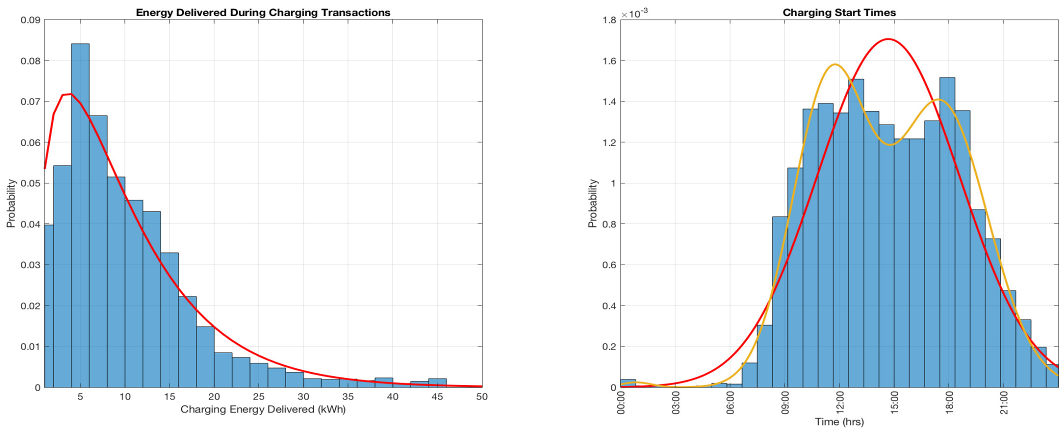


Figure 3.9: Index-4: Shopping Areas.

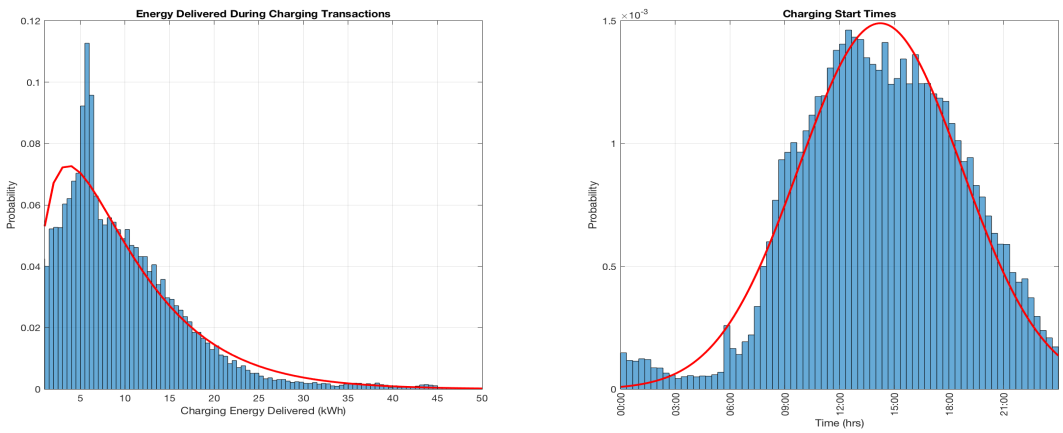


Figure 3.10: Index-5: Public Parking Areas.

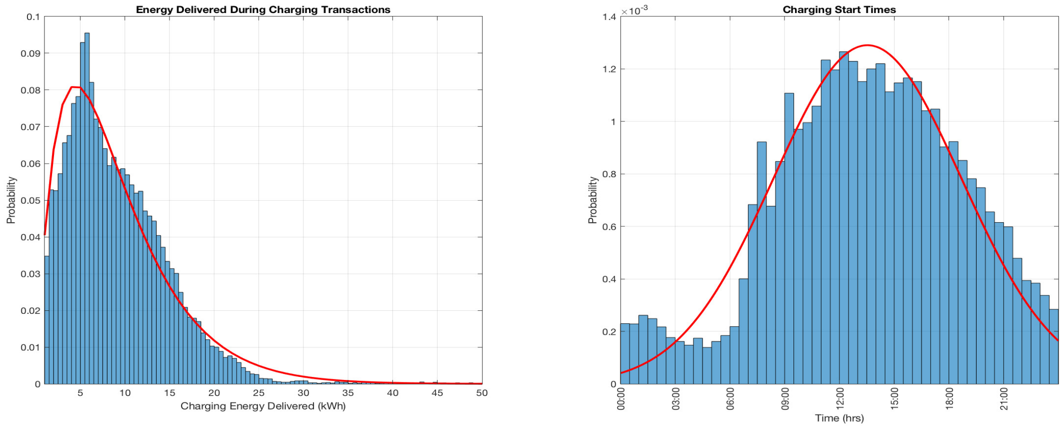


Figure 3.11: Index-6: Office Parking Areas.

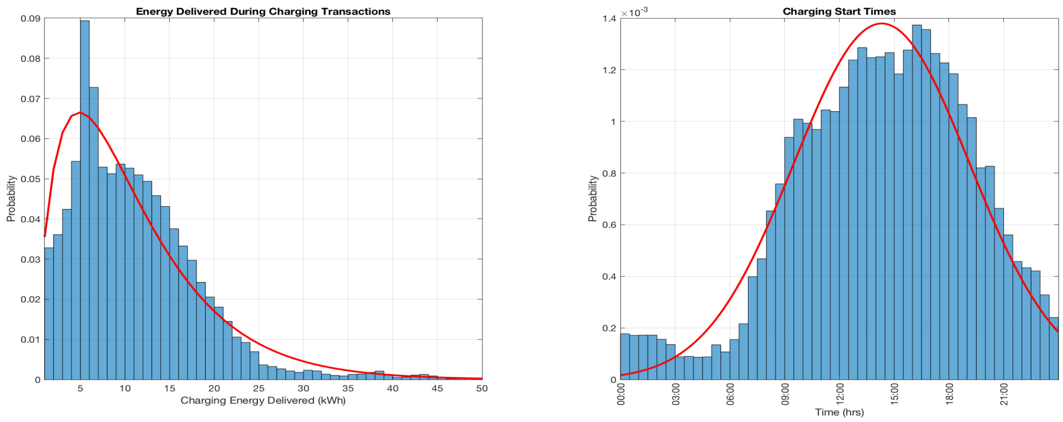


Figure 3.12: Index-7: Activities.

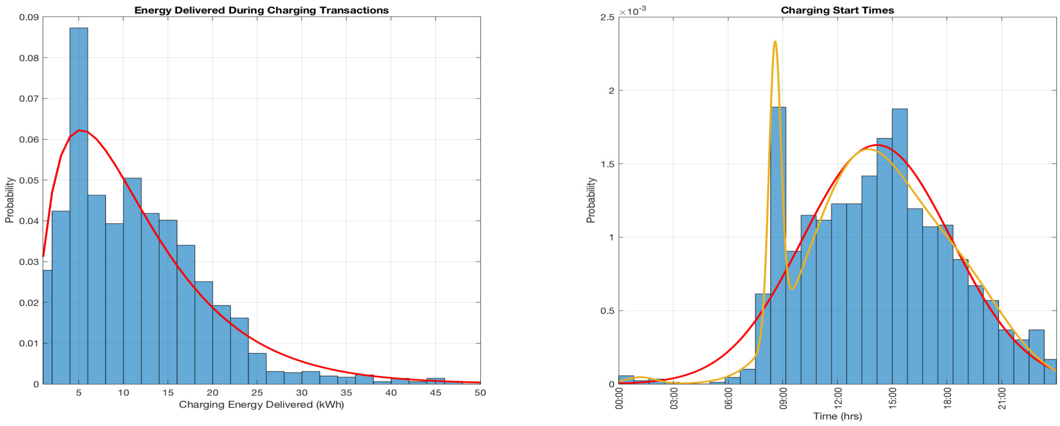


Figure 3.13: Index-8: Service Stations.

Discussion

The analysis of EV arrival rates at charger locations and the corresponding charging energy delivered, demonstrate that there is not only distinct differences between charger locations but also general differences between prior modelling of EV charging activity compared to the actual usage statistics. These differences are noted as follows:

- In each charging classification the charging energy delivered follows a Gamma probability distribution function which is similar to what was found in the examination of Swedish and Norwegian rapid charging stations, although the authors record the charging duration rather than energy delivered [118]. What is clear from the Gamma models in this thesis is that the peak is not always captured in the model and therefore applying the distributions to future models may underestimate the most frequent energy level transactions.

- This Scottish dataset demonstrates that EV arrival rates at chargers do not follow a simple Gaussian distribution but are often comprised of several Gaussian distributions in a 24-hour period. For certain charger locations, it is therefore necessary to model arrival patterns in such a way as to capture a range of peak periods, one approach is to use a Gaussian Mixture Model (GMM). This is different than the findings reported in other rapid DC charging studies [118], [117] where arrival rates are reported as a single Gaussian model for the general classification of rapid DC chargers.

- The EV arrival times and energy transactions for Ferry Terminals and Park & Ride facilities (see Figure 3.6 and 3.7) results in a single Gaussian distribution as this dataset does not demonstrate significant charging activity at night and only limited effects during commuting times for these rapid DC charger locations.

- The taxi charger classification (which are chargers either owned by a taxi company or are regularly used by taxis) experience a series of charging peaks during a 24 hour period and the arrival behaviour can best be described using a GMM (see Figure 3.8). There is a clear secondary charging peak after mid-night, which is also more pronounced on Friday and Saturday nights due to late night activities. There are also local maximums at post-commuting times i.e. immediately after 9am and 6pm. As electric taxi penetration increases, will post-commuting charging peaks become more developed and does this correspond with the existing daytime re-fuelling periods for ICE taxis?

- Chargers located in shopping areas also experience multiple local maximums which can be better described using a GMM (see Figure 3.9). Public Parking Areas (Figure 3.10), Office Parking Areas (Figure 3.11) and chargers located at places of leisure Activity (Figure 3.1.3) broadly follow a Gaussian distribution for charging start times with some minor charging activity in the early morning which may be the result of local electric taxis operating within the area.

- Although the service station category only totals 5 chargers in this data set, a demand profile is emerging which may prove useful in the modelling and analysis of HPC systems, such as the projects currently being implemented by Ionity[6] and Pivot Power[7]. Figure 3.13 illustrates a high utilisation period during the morning commuting period.

[6]www.ionity.eu
[7]www.pivot-power.co.uk

- It is important to note that the charging start times are likely to remain similar for some years to come as they are strongly dictated by user behaviour, however, the energy delivered during the charging transactions model is more technically dependent than behaviour dependent. Therefore, as EV battery and charging power capacity increases, the energy transferred during each transaction is also likely to increase and the peak of the Gamma distribution will move to the right of the chart.

3.1.4 Summary

From the Charge Place Scotland network of rapid DC chargers [8], the utilisation statistics, arrival times and charging energy delivered have been investigated to provide useful metrics for the assessment and planning of future charging infrastructure deployment. This information provides a meaningful input to the modelling work conducted in Chapter 4. However, this dataset can also be applied towards the development of power demand forecasting models to support the operational management of a rapid DC charging network. The following section therefore outlines a basic forecasting approach and examines a series of variables that can affect the aggregate power demand of a rapid DC charging network.

3.2 Forecasting Rapid DC Charger Power Demand

As the adoption of EVs increases, the demand for electrical power from charging infrastructure will become a more meaningful contribution towards an energy supplier's overall customer energy demand. Energy suppliers such as Ovo Energy[9], Ecotricity[10] and Good Energy[11] already offer dedicated EV tariffs at the residential level but rapid DC chargers and future high power chargers (50kW+) will require a commercial energy supply contract, the structure and operation of which may vary between infrastructure owners. In both energy customer cases, it will become increasingly important

[8] https://chargeplacescotland.org/
[9] https://www.ovoenergy.com/ev-everywhere
[10] https://www.ecotricity.co.uk/for-the-road/at-home-and-on-the-road
[11] https://www.goodenergy.co.uk/media/11638/ev-tariff-faqs-2017.pdf

for electricity suppliers to understand how external or exogenous variables affect EV user behaviour so that accurate power demand forecasting can be achieved to ensure sufficient power generation is procured at an economically favourable price.

In the U.K., the electricity market is deregulated and consists of several independent entities, which can generally be classified as generators, physical distribution/transmission networks and energy suppliers[12]. There is also an appointed organisation that ensures the electricity system maintains a state of balance between electricity demand and generation but ultimately, the risk of electricity imbalance is carried by the energy suppliers who must ensure that for any half-hour period of the day, they have procured sufficient generation to meet the expected demand from their energy customers. Any difference between customer demand and procured generation incurs a financial penalty, therefore demand forecasting models play an important operational role for energy suppliers.

The introduction of electric transportation systems introduces a new electricity demand variable into the forecasting models for energy suppliers. At this early stage of EV adoption, the full characteristics of EV power demand from user charging actions is still unclear but through pilot projects such as My Electric Avenue [76], greater understanding of user charging behaviour at the residential level is beginning to inform both electricity network design decisions and energy supplier demand modelling. However, not all charging will take place at home, over night, and there is a growing argument that centralised high power charging infrastructure is required to enable mass adoption of EVs, especially for users without off-street parking [54], [133]. It is therefore useful to examine the charging behaviour of rapid DC chargers and to determine the idiosyncrasies of daily power demand profiles so that energy suppliers and potentially charging network operators can cost effectively procure generation and deliver a profitable service at the least cost to EV users.

Power demand forecasting is a wide and well established research field with many forecasting methodologies available, where the most common approaches summarised in [134]. In the power industry, short-term, medium-term and long-term forecasting

[12]https://www.elexon.co.uk/about/

is required to determine hourly/daily variances in power demand, seasonal changes in demand and growing/declining demand over a number of years. For EV charging infrastructure, all three forecasting horizons are necessary:

- there is the short-term need to forecast power demand on a daily basis to ensure sufficient generation is procured to meet the demand from public chargers;
- there is a medium-term forecasting requirement to incorporate renewable generation and seasonal changes in EV user behaviour;
- and then a long-term forecasting solution is required to determine the charging infrastructure requirements to meet future EV demand.

The purpose of this forecasting section is to develop an appropriate forecasting model that can accurately forecast the short-term, day-ahead, power demand of the Charge Place Scotland network of 192 rapid DC chargers. An accurate forecasting model not only assists energy suppliers but can also provide a useful input into charging network energy management systems. In respect to this thesis, the charging power demand forecasting work can be applied to further enhance the daily energy management system proposed in Chapter 5 and more generally this work offers an insight into the variables that could influence the future charging demand from public rapid DC chargers.

3.2.1 Background Review & Methodology

This forecasting section of the thesis organises the CPS charging data for further analysis, reviews appropriate forecasting models and builds on a baseline auto-regressive model by considering several dependencies and exogenous variables. The final model is trained and evaluated using two months of charging transactions from Scotland's rapid DC charging network in 2017. The performance evaluation of the model is considered based on the Root Mean Square Error (see Eq. 3.22), Mean Absolute Error (see Eq. 3.9) and the economic performance of the model using actual balancing and settlement prices during the two-month study period.

This study assumes that a large public rapid DC charging network (like the CPS network) either wishes to purchase electricity on the wholesale market themselves or from a commercial energy supplier to achieve more competitive pricing. This requires an understanding of the charging network's average power demand during each half-hour period of the day, as this is the period of time in which the wholesale electricity markets trade[13]. Figure 3.14 illustrates the repeating daily power demand profiles for the CPS charging network, in half-hour periods, during the first week of January 2017.

Based on the repeatability of the power demand profiles, and the similarity to other electricity demand forecasting approaches, it is useful to consider an Autoregressive Integrated Moving Average (ARIMA) model which has previously been applied to the forecasting of EV charging in [127], [135], [136]. These EV power demand forecasting models offer useful contributions in demonstrating the value of ARIMA forecasting approaches, however the work in [127] and [135] rely on traffic statistical data to create estimated charging demand models and none of them consider rapid DC chargers, weather related dependencies or EV battery capacity trends. Other studies in Sweden and Norway have rapid DC charging datasets of a similar size to the CPS network [118] and consider the utilisation of chargers but not the forecasting of DC charging demand. In the UK, the Rapid Charge Network has a total of 74 rapid DC chargers, the operational data has been shared for research purposes and used in prior utilisation studies but not in forecasting models [117]. The CPS charging data is the most comprehensive UK dataset for rapid DC chargers that the author has found to date and it therefore offers a unique insight into the operational characteristics of a national rapid DC charging network due to the number of charging transactions and geographic diversity of chargers.

3.2.2 Selecting a Forecasting Model

The forecasting of public rapid DC charging is a relatively new area of research and therefore it is appropriate to begin analysing the data using a basic forecasting model to understand the dependencies and impact of variables such as day of the week, weather events and battery capacity of EVs. The development of the forecasting model presented in this section follows similar electricity demand and price forecasting models

[13] https://www.elexon.co.uk/knowledgebase/about-the-bsc/

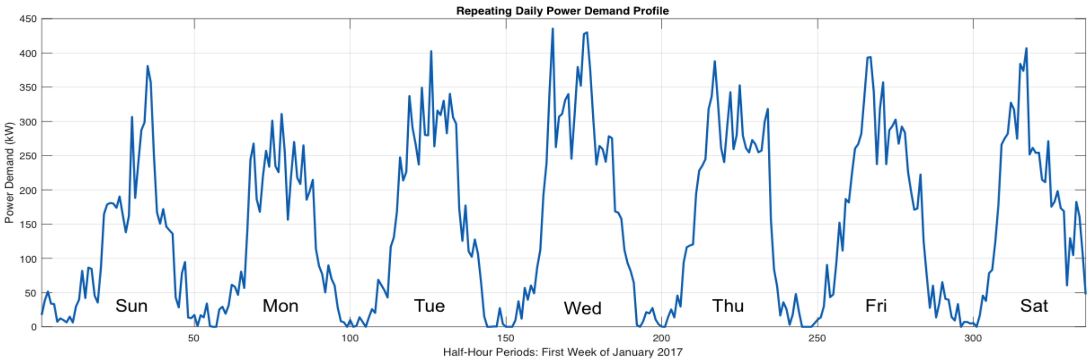


Figure 3.14: Repeating daily power demand profiles for the collection of 192 rapid DC chargers in Scotland.

outlined in [137] and [138].

To determine the most appropriate model for the charging demand data, it is useful to consider plots of the autocorrelation function (ACF) and partial autocorrelation function (PACF) for a sample of the time series. Figure 3.15 illustrates the ACF and PACF for 1000 half-hour periods, which is equivalent to three weeks of half-hour power demand data from the the charging network. The ACF plot describes the level of correlation between the charging power demand at two different points in time but this can be influenced by a dependency on the values between these points in the time series, therefore the PACF plot removes any confounding dependencies. According to [139], a positive correlation at a lag of 1 in the ACF plot and a PACF plot that cuts-off quickly towards 0, indicates that the time series data can be predicted with the use of Auto-Regressive (AR) terms in the forecasting model. The number of AR terms applied in the model can be determined from the PACF plot by examining the number of maximums in the data. From Figure 3.15 it can be seen that a positive maximum occurs at a time lag of 48 and 336 half-hours (one day and one week prior). It could be argued that two weeks prior (672 half-hours) offers another appropriate time lag, but for the purpose of this investigation the model will be limited to two AR terms.

The proposed AR model can therefore be expressed as,

$$\hat{P}_t = \sum_{i=1}^{q} \beta_i p_{t-i} + \sum_{j=1}^{r} \omega_j W_j + \varepsilon_t \tag{3.4}$$

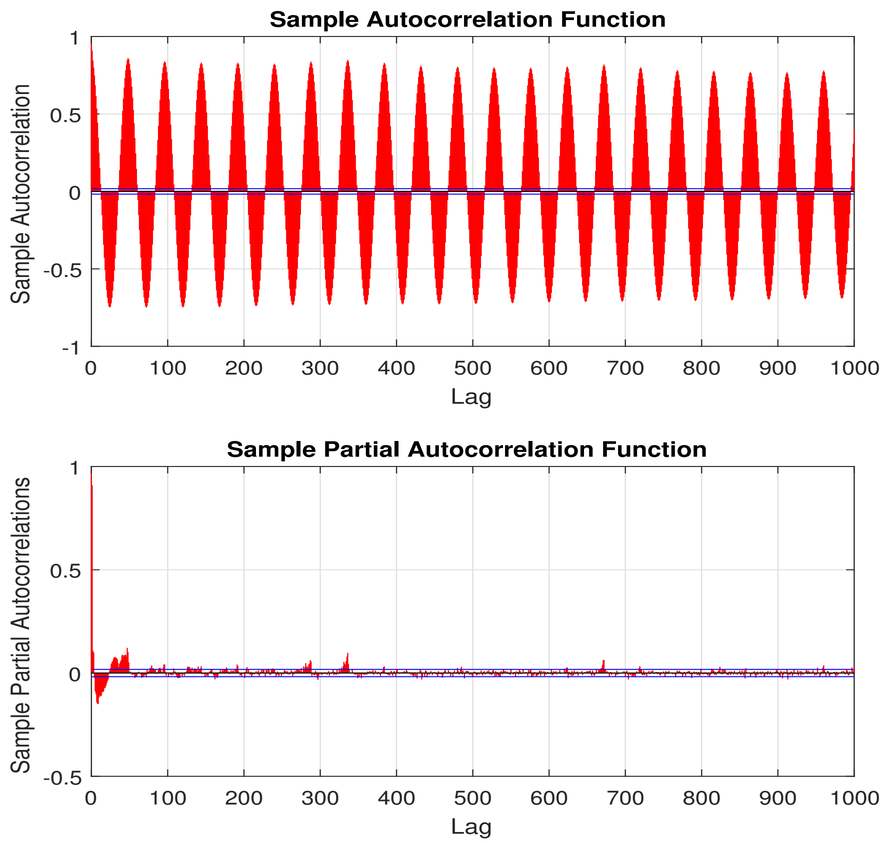


Figure 3.15: Autocorrelation and Partial Correlation over a duration of 500 hundred hours to determine repeating patterns in the charging power profiles.

Where $\hat{P}_t$ represents the predicted power demand during a half-hour time step and β_i is the linear regression coefficient for each of the lagged values from i to q. The number of independent or exogenous variables under consideration can be represented by W_j with indexes j to r, and where ω_j is the coefficient for each of the exogenous variables. Finally, an error adjustment, ε_t, is applied at time t.

External predicting values such as temperature, rainfall and total battery capacity of EV users, may all contribute towards an improved power demand forecast. However, these exogenous variables are selected *a priori* and therefore their contribution to the accuracy of the forecasting model should be individually assessed.

3.2.3 Day of the Week Dependency

Before introducing each of the exogenous variables, it useful to investigate variations of the daily power demand curve according to each day of the week to determine if any specific day of the week dependencies exist. Figure 3.16 illustrates the average power demand profile for the collection of chargers during 2017 according to day of the week.

From these demand profiles it is clear that Saturday and Sunday have a distinct demand profile that is separate to the week days. During the weekend, a higher demand for charging occurs at night (most likely from taxi charging) and a lower demand for charging in the morning occurs as there is perhaps less commuting traffic at the weekend. Furthermore, the peak charging power for the week occurs on a Friday which is distinct from the other days of the week.

Based on these observations, three separate index days (d) are created for Monday to Thursdays, Fridays and Saturdays/Sundays, which are grouped in a set (B) to represent days that have distinct demand profiles (or weekly 'seasonality') and which may be used to enhance the accuracy of the forecasting model. This day of the week dependency is incorporated into the forecasting model by introducing a dummy variable $D_d(t)$, where:

$$D_d(t) = \begin{Bmatrix} 1, D(t) = d \\ 0, D(t) \neq d \end{Bmatrix} \tag{3.5}$$

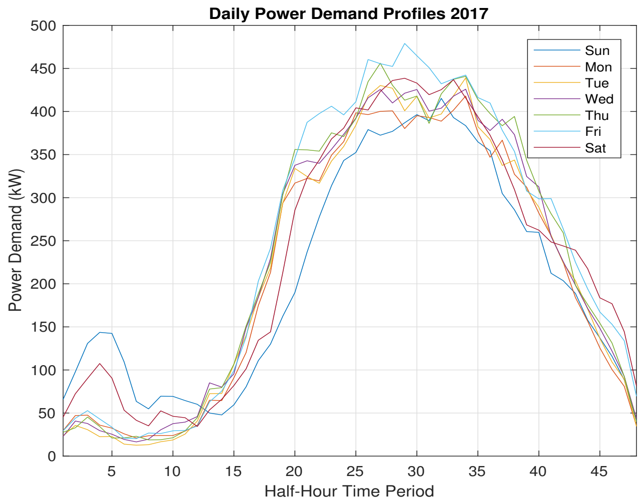


Figure 3.16: Daily demand profiles for Scotland's Rapid DC Charging Network.

The day of the week dependency is therefore incorporated into this charging demand forecasting model in the same manner as day-ahead electricity price forecasting in [138] and the EV charging power demand model now takes the form:

$$\hat{P}_t = \sum_{k \in A} \beta_k p_{t-k} + \sum_{d \in B} \phi_d D_d(t) + \sum_{j=1}^{r} \omega_j W_j + \varepsilon_t \tag{3.6}$$

Where A=$\left\{48, 336\right\}$ represents the regressive relationship indexes for the number of half hourly periods in a day and a week prior and B=$\left\{Mon - Thur, Friday, Saturday, Sunday\right\}$ represents the weekly seasonality indexes.

3.2.4 Weather Variables

Here weather is consdiered an exogenous variable (W_j) of the model. Based on traditional power demand forecasting, weather variables have an important influence on forecasting models [137], [138], and it is assumed that this will also be the case for EV charging demand from public, rapid DC chargers, as prior studies have documented that the energy consumption of EVs increases in cooler and warmer weather [140]. It is logical to consider that temperature will influence EV energy requirements on any given day; as the temperature reduces, more heating is required within the vehicle and therefore the battery will become depleted faster and the converse is also true, in warmer temperatures more cooling is required within the vehicle and therefore more frequent charging will be necessary. There are also battery chemistry changes that occur at varying temperatures which will affect the EV energy requirements [140]. In fact the combination of in-cabin heating on cold days and the change to internal battery resistance has reportedly reduced EV range by up to 40% [140].

It is hypothesised that precipitation will also impact EV energy consumption and the collective charging demand, especially if there are a large number of electric taxis operational within the EV population. From a practical perspective, when it rains, it is more likely that EV users will leave their bike at home and drive to work, while pedestrians will be more inclined to order a taxi rather than walking [141]. However, it could also be the case that EV energy usage *reduces* due to slower, more economical driving when it is raining[14].

To help identify the relationship between rapid DC charging demand and temperature or rainfall requires the collection of reliable weather data. The required time resolution for both rainfall and temperature data remains an open discussion but in other electricity demand forecasting work hourly air temperature is applied [138]. For EV charging demand forecasting less granularity in the data may be acceptable as the impact of a weather event on charging demand may occur several hours later. However, heavy rainfall during one period of the day may cause a higher demand in charging a number of hours later (consider taxi operations). Also, cold morning commutes will deplete the EV battery faster and potentially increase demand for charging later in the day.

One of the challenges associated with weather related data is the selection of a suitable observation station, as the chargers in this dataset are located across Scotland and there will inevitably be some weather variance between regions. An operational demand forecasting model will require the input of weather data from a selection of weather stations across the charging network's operating region. For the work of this

[14]https://ops.fhwa.dot.gov/weather/q1_roadimpact.htm

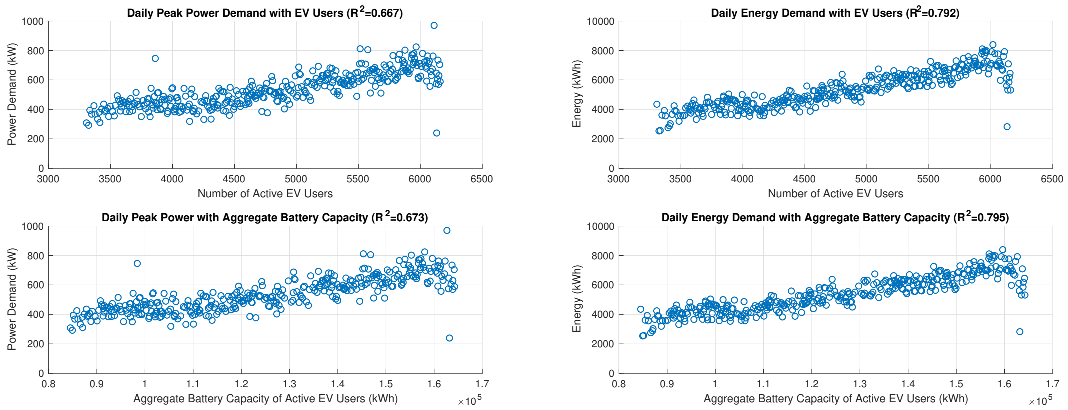


Figure 3.17: Comparison between Number of EV Users and Aggregate Battery Capacity of EVs.

thesis, however, a weather station located at Carse of Gowrie[15], in central Scotland, was selected based on the long term quality and reliability of the rainfall and temperature measurements but also due to its proximity to the city of Dundee where it is known that a large number of electric taxis are in operation.

3.2.5 EV Users vs. Battery Capacity of EV Users

To examine the relationship between weather variables and the charging demand from the collection of rapid DC chargers, it is necessary to normalise the charging demand data due to the growth in utilisation of the charging network (as more EV owners are using the network as EV adoption increases). This can be achieved according to either: the growth in unique users of the charging network; or the aggregate battery capacity of these registered charging network users. The CPS charging dataset contains a unique user ID for each charging transaction and also the user's model of EV. It is therefore possible to attach the battery capacity for each unique user of the network by looking-up the specifications of the user's EV model. Table 3.3 presents the range of EV models that used the CPS rapid DC charging network, their battery capacity and the number of users of each model in 2016 and 2017. Using this information, the cumulative number of unique users and cumulative battery capacity of these users for

[15] http://wow.metoffice.gov.uk/

each day of 2017 can be created.

The linear relationship between the daily peak power and daily energy demand in 2017 according to the number of active EV users and the aggregate battery capacity is presented in Figure 3.17. Based on an evaluation of the R^2 values of these relationships, there is a marginal improvement in the correlation of both the peak power demand (+0.6% improvement) and daily energy usage (+0.3% improvement) when the aggregate battery capacity is considered compared to the number of active EV users. Considering this marginal improvement, the cumulative battery capacity of the network is used to normalise daily temperature and rainfall data in the forecasting model.

The weather dataset from the Carse of Gowrie offers the average temperature and the cumulative rainfall over a 24 hour period. Figure 3.18 illustrates the direct relationship between temperature and energy demand as well as the temperature and normalised daily energy demand based on the battery capacity of registered users. Although this dataset only contains 365 data points (365 days in 2017), the normalised relationship between daily charging energy demand and temperature appears to follow similar electricity demand and temperature models [142] - where the charging demand increases as the temperature cools and also increases as the temperature warms. The line of best fit is represented as,

$$E_{norm}(T) = 0.000026T^2 + 0.00052T + 0.045 \tag{3.7}$$

and during the evaluation of the ARX forecasting model developed in this thesis (see section 3.2.7) both the daily temperature (T) and the transformed temperature, based on the quadratic relationship to the normalised energy demand (E_{norm}) are tested as exogenous variables.

The same approach can be applied to the cumulative rainfall data but in this case a relationship between rainfall and daily energy demand is less clear. Figure 3.19 presents the relationship between rainfall and daily energy demand compared (left) with normalised energy demand according to aggregate battery capacity of the EV population (right). In the absence of a strong relationship between charging network

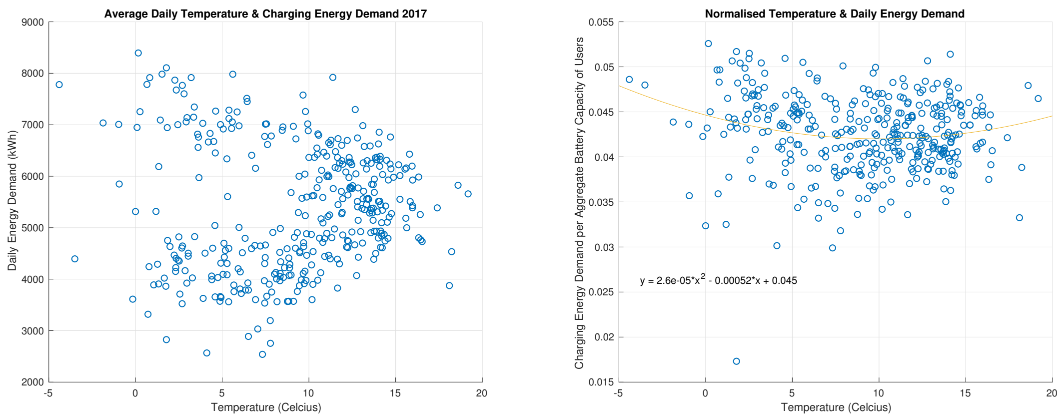


Figure 3.18: Temperature relationship with daily charging energy demand (left) and normalised daily charging energy demand according to cumulative EV user battery capacity of the network (right).

energy demand and rainfall, no transformation to the rainfall data is applied but (R_{mm}) is incorporated as an exogenous variable and the value of its inclusion on forecasting accuracy is assessed.

3.2.6 Performance Evaluation

The charging network power demand forecasting model therefore has seven elements or predictors to evaluate: two autoregressive components ($\beta_1 P_{t-48}$ and $\beta_2 P_{t-336}$), a day of the week dependency ($\phi_d D_d(t)$), temperature ($\omega_1 T(t)$), temperature transform ($\omega_1 T_{adj}(t)$), rainfall ($\omega_2 R_{mm}(t)$) and aggregate network battery capacity ($\omega_3 EV_{cap}(t)$). The aim of this study is to assess the performance that each of these predictors have on the accuracy of the 24 hour ahead power demand forecast. To conduct this study requires one or more evaluation metrics. In this case the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are used to compare the performance of each forecast and these are expressed as:

$$RMSE = \sqrt{\sum_{i=1}^{n} (P_t - \hat{P_t})^2 \frac{1}{n}} \tag{3.8}$$

Table 3.3: EV Users from Charging Transactions

EV Model	2016 Users	2017 Users	Battery Capacity (kWh)
Aixam Mega City Electric	9	10	3.24
Audi e-tron	40	69	95
BMW 225xe	4	21	7.60
BMW 330e	23	73	7.60
BMW 333e	8	9	7.60
BMW X5 40e PHEV	6	16	9
BMW i3	98	220	27.20
BMW i3 EREV	104	202	27.20
BMW i8	7	13	11.60
Citroen Berlingo	1	3	22.50
Citroen C-Zero	18	28	14.50
Ford Focus Electric	1	2	33.50
Kia Soul EV	9	30	27
Mercedes-Benz B Class	5	13	28
Mercedes-Benz C350E	44	90	6.20
Mercedes-Benz SLS AMG E-Cell	3	6	48
Mitsubishi Outlander PHEV	842	1391	9
Mitsubishi i-MiEV	10	16	16
Nissan E-NV200	63	108	38
Nissan LEAF	1160	2212	24
Peugeot iOn	30	50	15
Porsche Cayenne E-hybrid	6	11	10.80
Renault Kangoo ZE	2	4	31
Renault Kangoo ZE Van	8	15	31
Renault ZOE	426	699	22
Reva G Wiz	1	2	16
Tesla Model S	284	555	85
Toyota Prius Plug-In Hybrid	4	9	3.20
Vauxhall Ampera	11	20	16
Volkswagen Golf GTE	46	103	8.70
Volkswagen e-Golf	8	15	32
Volkswagen e-Up	1	1	18.70
Volvo V60 D6 Twin Engine	6	21	11.20
Volvo Volvo XC90 T8 Twin Engine	7	28	10.40
Smart Fourtwo Ed	2	4	17.60
BMW 530e	0	1	9.20
Kia Optima	0	7	9.80
Peugeot Partner	0	4	22.50
Renault Fluence Z.E.	0	1	22
Tesla Model X	0	69	85
Tesla Roadster	0	1	53
VW Passat Estate GTE	0	8	9.90
Total Identifiable Users	**3306**	**6160**	
Total Battery Capacity	**84,514 kWh**	**164,240 kWh**	

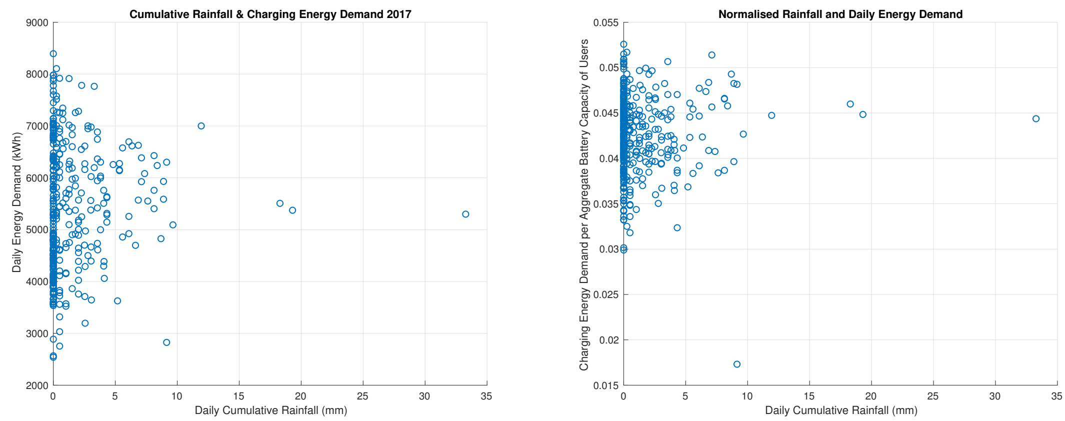


Figure 3.19: Rainfall relationship with daily charging energy demand (left) and normalised daily demand according to cumulative EV user battery capacity of the network (right).

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|\hat{P}_t - P_t\right| \tag{3.9}$$

where n is 48 half-hourly periods, $\hat{P}_t$ is the predicted power demand and P_t is the actual power demand.

Prior to performing this study it was necessary to 'clean' the data to ensure only charging transactions with a user ID and identifiable EV model are included in the sample. This enables an accurate daily recording for the number of active users and the total battery capacity of the user's EVs, Table 3.3 highlights the number of active users at the end of 2016 and 2017 according to the EV type and the associated battery capacity for each EV. It is interesting to note that the number of unique users and the total battery capacity of the population almost doubles over the course of 2017. From these users, 204,229 charging events were recorded in 2017 but this reduced to 136,736 charging events that are directly attributable to specific users with a definite EV type and battery capacity.

The first nine months of 2017 are used to 'train' the ARX model before being tested as an operational forecasting algorithm for the months of October and November 2017. The month of December is omitted as it contains a number of holidays or special events which introduce anomalies, this can be seen in Figure 3.20 where the daily energy

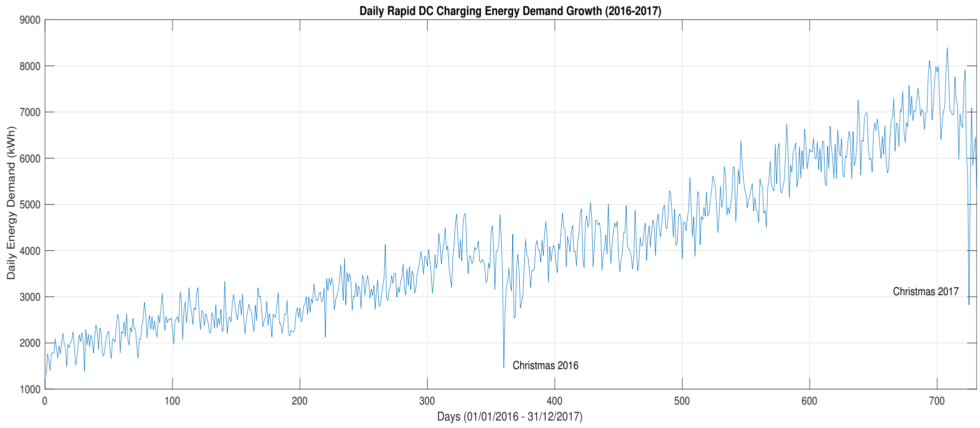


Figure 3.20: Scotland's rapid DC charging network daily energy demand growth across 2016-17.

demand trend across 2016 and 2017 is presented with significant charging demand reductions on Christmas day. It is acknowledged that there are methods available to incorporate 'special dates' into a forecasting model, however, it is not considered necessary for this early study.

3.2.7 Rapid DC Charger Power Demand Forecasting Results

The results of the performance evaluation of the developed forecasting model for the CPS network of rapid DC chargers are presented in Table 3.4. Each component of the ARX model is evaluated individually and if there is a reduction in error compared to the prior trial, then the variable is adopted as part of the model and then the next variable is subsequently tested. Each of the trials are documented with an ID number (1-7) which is also referenced in Table 3.5, Figure 3.21 and Figure 3.22.

An economic evaluation of the forecasting model is also conducted by examining the total energy cost over the testing period (1/10/2017-30/11/2017). The total energy cost presented in Table 3.5 is the real operational energy and balancing cost that a dedicated public DC charging energy supply company would incur. This is presented according to a base energy price of £0.04/kWh and exposure to a System Sell Price (SSP) and System Buy Price (SBP) for each half-hourly settlement period.

The SSP and SBP are set by the UK's system balancing mechanism[16], which is administered by Elexon, for every half-hourly settlement period each day. The SSP is the price paid to energy suppliers that have over procured energy prior to the half-hourly settlement period and are therefore in an 'overbought' position and must sell their excess energy at the SSP rate for that period. The SBP is the opposite, where the supplier is in a deficit for a half-hourly period and therefore must purchase energy at the SBP rate for that period [143]. The SSP and SBP rates for each half-hourly period during the out-of-sample testing are presented in Figure 3.23 and subsequently incorporated into the total energy cost calculation of Table 3.5. It is noted that there is now a single price for SSP and SBP in each half-hour period[17].

Through examination of the results, it is clear that from model ID-3 onwards few improvements are recognised in both the financial cost of energy and in the model errors. Therefore, at this point in time, the incorporation of temperature and rainfall variables does not improve the performance of the forecasting model. Although, through a process of regularization, where the best of the 7 models are used for each of the half-hour periods, it appears that the incorporation of rainfall data improves the model between 8pm and mid-night. Furthermore, using the quadratic temperature transform (3.7) to predict daily energy demand is more accurate than using temperature alone.

As utilisation of EV charging networks increases, it is likely that exogenous variables such as temperature and rainfall will begin to play a role in the forecasting of charging energy demand. However, at this time and with this weather dataset only a weak emerging relationship between temperature and daily energy demand can be identified and the incorporation of rainfall data may generate a marginal forecasting improvement during the evening hours. Therefore, the most cost effective ARX model is presented as,

$$\hat{P}_t = \beta_1 p_{t-48} + \beta_2 p_{t-336} + \sum_{d \in B} \phi_d D_d(t) \tag{3.10}$$

If this forecasting model was utilised to procure electricity for Scotland's rapid DC

[16] https://www.elexon.co.uk/knowledgebase/what-is-the-balancing-mechanism/

[17] https://www.elexon.co.uk/operations-settlement/balancing-and-settlement/imbalance-pricing/

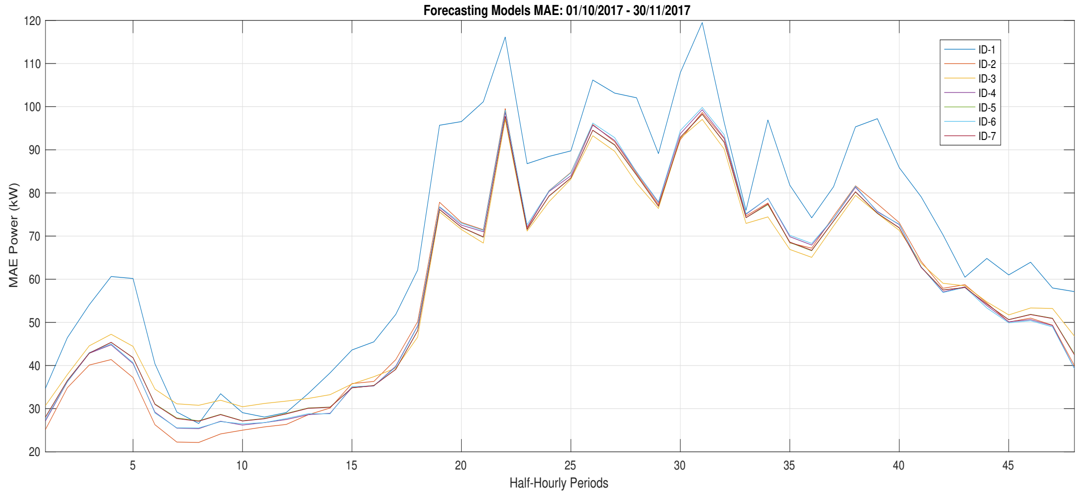


Figure 3.21: Mean Absolute Error results for a ARX model with seven different variations.

Table 3.4: ARX Forecast Model Results

ID	Model Description	Notation	MAE	RMSE
1	AR component using data from prior day	$\beta_1 P_{t-48}$	16.82	69.77
2	AR component expanded to include prior week	$\beta_2 P_{t-336}$	9.22	58.04
3	ARX day of week dependency	$\phi_d D_d(t)$	1.77	59.09
4	ARX adjusted to include temperature	$\omega_1 T(t)$	10.59	58.42
5	ARX adjusted to include temperature transform (E_{norm})	$\omega_1 T_{adj}(t)$	5.46	58.47
6	ARX adjusted to include rainfall	$\omega_2 R_{mm}(t)$	10.90	58.56
7	ARX adjusted to include EV battery capacity	$\omega_3 EV_{cap}(t)$	5.78	58.47

charging network, between the period of 1st October 2017 to 30th November 2017, the total cost of energy would have been £16,684 (ID-3); whereas the perfect forecast or baseline energy cost would have been £16,668, as presented in Table 3.5.

3.2.8 Summary

This section has presented an autoregressive forecasting model (Eq. 3.10) for the day-ahead power demand forecasting of 192 rapid DC chargers located throughout Scotland. Little research work to date has considered this subset of charging infrastructure nor attempted to apply a general power demand forecasting model for the aggregate demand of a rapid DC charging network. This forecasting work is therefore an early insight into

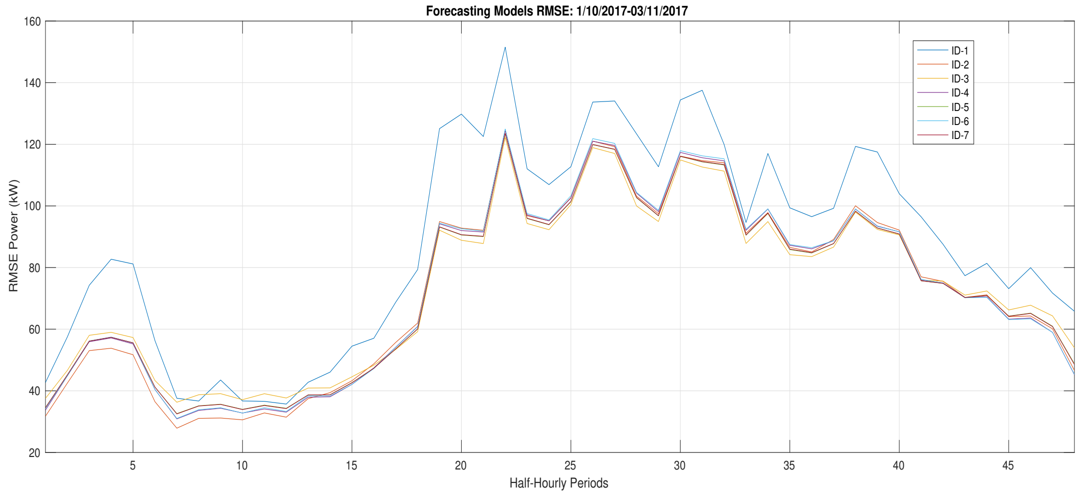


Figure 3.22: Root Mean Square Error results for the ARX model with seven different variations.

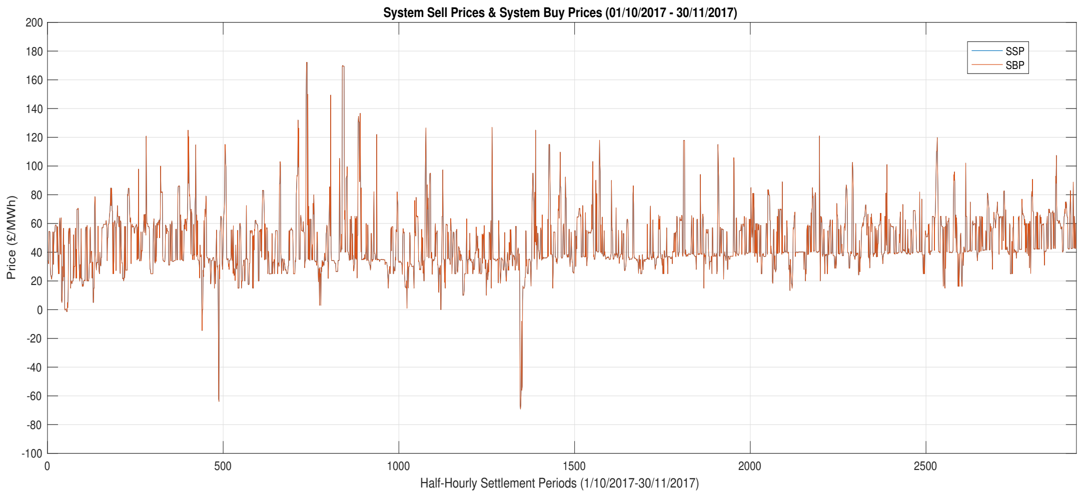


Figure 3.23: Exelon System Sell Prices and System Buy Prices during out of sample testing period. Note, SSP and SBP rates are equivalent.

Table 3.5: Energy Position Assessment During Out-of-Sample Period (kWh)

Position	1	2	3	4	5	6	7
Overbought (kWh)	38758	35733	44553	35013	38806	34892	38,571
Underbought (kWh)	63388	49234	41957	50514	46794	50844	47,037
Energy Procured (kWh)	392080	403210	419300	401210	408720	400,750	408,240
Total Energy Cost	£16,968	£16,777	£16,684	£16,806	£16,761	£16,808	£16,765

the emerging power demand from a national rapid DC charging network and several areas for further work exist as utilisation of this charging network increases.

The physical behaviour and energy consumption of EVs in varying weather conditions is discussed. A weak relationship between temperature and energy demand is emerging but it failed to provide an improvement in overall forecasting accuracy at this time. Additional work in this area may consider the collection of weather data from multiple stations throughout the charging network region and the classification of chargers by location (potentially also including AC low power chargers within the network) to determine if certain chargers experience greater utilisation under varying weather conditions. Further consideration should also be given to wider seasonal patterns and holidays. This work enhances the understanding of rapid DC charger usage patterns and may help charging operators procure power more competitively as well as inform other energy management strategies, as outlined in Chapter 4 and Chapter 5.

The final section of this chapter provides the optimisation methodology and modelling assumptions that are applied in the evaluation of two, novel LVDC charging networks that rely on the EV usage patterns presented in this chapter to inform their infrastructure planning and energy management strategies.

3.3 LVDC Charging System Modelling Using MILP

The prior sections of this chapter have introduced the charging behaviour and utilisation of public rapid DC charging systems. However, the development and evaluation of new LVDC charging topologies requires a methodology in which to model the charging networks and to compare their performance in terms of cost, efficiency and scalability against existing/alternative solutions. This thesis presents two LVDC charging network optimisation models that are formulated using the same Mixed Integer Linear Programming (MILP) structure. This section therefore introduces this structure and the notation adopted within these models.

With a broader respect to public EV charging infrastructure development and operation, the application of optimisation methods can, and have, been used to address the following problems:

- A Partical Swarm Optimisation (PSO) model is applied in [144] to determine the optimum siting and combination of slower, parking-lot charging and rapid DC charging across a city in China to minimise the social cost of developing charging infrastructure. Although EV demand and the effect of temperature variation on charging requirements is considered, the work does not incorporate multiple infrastructure options nor does it consider the optimal sizing of charging infrastructure based on future utilisation rates due to EV demand growth.

- The sizing and siting of charging infrastructure in terms of the number of charging plugs and grid connection capacity is addressed in [145]. The objective function in this scenario is a Mixed Integer Non-Linear Programming (MINLP) problem that is solved using a combination of a Genetic Algorithm (GA) and PSO. However, this work does not take into consideration the growth of EV charging demand and the economic impact of varying grid connection options or distributed energy resources.

- The control of chargers to maintain power quality on the wider AC distribution network is explored in [146]. By using a MILP model the authors demonstrate that coordinated EV charging can balance the loading across three phases of the LV distribution network and ultimately improve the voltage profiles for the network.

- The scheduling and power control of chargers to maintain stability on a fixed LVDC charging network is explored in [27]. This problem assumes a parking-lot based charging system with one centralised AC/DC converter and a DC/DC charger at each parking-bay. In Chapter-5, it is demonstrated that a reconfigurable charging network can avoid the stability challenges of the fixed LVDC charging network and reduce the infrastructure requirements.

- The optimal scheduling of chargers to minimise electricity costs or to maximise consumption from optimally sized, co-located, renewable energy resources is investigated in [80]. The charging system design approach considers solar PV and battery storage but does not consider wider AC grid constraints such as grid connection options, transformer loading profiles or a growth in EV demand over time.

There are several optimisation methods that have been applied to charging infrastructure operational problems. However, the final selection and model formulation depends on the complexity of the problem under study, the required solving time and the physical characteristics of the modelled parameters. The use of linear programming (LP) delivers a global optimum solution but in more complex problems, this can require the linearisation of non-linear physical parameters and careful consideration of the model formulation to avoid generating an unmanageable number of problem variables [147].

With increasing computational power and methods to linearise non-linear constraint functions, LP optimisation remains a versatile and widely understood operational research tool [147]. In the case of infrastructure planning or expansion planning problems, where a decision is required to invest or install infrastructure, the application of discrete, integer decision variables can be applied, this converts an LP problem into an integer linear programming problem and, where the problem contains a mixture of continuous and discrete variables, it becomes a Mixed Integer Linear Programming (MILP) problem.

3.3.1 Structuring MILP Problems

The general MILP problem formulation can be described as,

$$J = min \sum_{k=1}^{n} c_k^T x_k \tag{3.11}$$

Subject to equality and inequality constraints:

$$\sum_{k=1}^{n} a_{i,k} x_k = b_i \quad (i = 1, 2, ..., m), \tag{3.12}$$

$$x_k \geq 0 \quad (k = 1, 2, ..., n), \tag{3.13}$$

$$x_k \ integer \ (for \ some \ or \ all \ k = 1, 2, ..., n). \tag{3.14}$$

where the objective function J can be minimised or maximised according to several equality and inequality constraints. The objective function in Chapter-4 is to maximise the Net Present Value (NPV) of the charging infrastructure over the investment lifetime of the project subject to electrical grid capacity restrictions, available charger sizes, CHP capacity limitations, linearised part-loading efficiency curves of the CHP systems, and the predicted charging power demand from a large group of electric taxis. Whereas the objective in Chapter-5 is to minimise the charging energy cost for a multi-plexed network of rapid DC chargers that is subject to transformer power and user time constraints.

3.3.2 Solving the MILP Problems

In both charging infrastructure modelling scenarios, the MILP problem is solved using a six stage process to identify and refine the optimal solution[18]:

1. The problem size is first reduced using Linear Programme Preprocessing, which eliminates any unnecessary variables or constraints and reduces the sparsity within the equality and inequality matrices.

2. A Linear Programming solution is obtained by relaxing the integer constraints.

3. Mixed Integer Preprocessing is then conducted by analysing the linear inequalities and determining if the problem is infeasible prior to removing any redundant inequalities, strengthening inequalities or fixing integer variables.

4. Cut Generation is then tried to further enhance the LP relaxation of the mixed-integer problem by identifying regions where the LP relaxations are closer to integer solutions.

[18]https://uk.mathworks.com/help/optim/ug/mixed-integer-linear-programming-algorithms.html

5. Hueristics can be applied to identify the upper bound of the objective function prior to beginning the branch and bound approach.

6. The optimal solution is identified using the branch and bound method which generates a series of sub-problems from the 'root' upper-bound and lower-bound solution with the intent to improve upon this solution while conforming to the problem's integer constraints. At each branch, two 'nodes' (or possible solutions) are explored, if either of the solutions offers an improvement from the previous node then another branch is created and further nodes explored. This process continues until the lower and upper-bound solutions are within a specified relative gap tolerance.

In both Chapter 4 and Chapter 5 the practical problem is first introduced and the model structured according to the MILP formulation. Several scenarios are simulated which require the use of charging energy demand models as outlined in Chapter 3. This work presents two useful models for charging infrastructure developers that can assist the development of cost effective, flexible charging infrastructure.

3.3.3 Adopted Notation

The following notation is employed in formulating the LVDC charging infrastructure models that are presented in Chapter-4 and Chapter-5.

Table 3.6: Notation: LVDC Charging Infrastructure Optimisation

d	Index for days within charging energy demand profile.
f	Index for electrical grid capacity options.
g	Index for EV charger power capacity options.
h	Index for CHP power efficiency levels.
i	Index for EV arrivals.
k	Index for EV chargers.
γ	Index for linear power boundaries in CHP model.
ϕ	Index for charging power level.
Ω_F	Set of electrical grid capacity options.
Ω_G	Set of EV charger options.
Ω_H	Set of CHP efficiency levels
Ω_Γ	Set of linear power boundaries.
Ω_N	Set of EV arrivals.
Ω_L	Set of charging power levels.
Ω_M	Set of EV chargers.
Ω_T	Set of time intervals.
η_i	Charging efficiency (50kW rapid charger).
η_{dc}	DC/DC Charger efficiency.
η_{acdc}	AC/DC grid converter efficiency.
EHR	Electric Heat Rate of a CHP system.
HPR	Heat to Power Ratio of a CHP system.
C^x	Capex cost of electrical grid connection.
$C^e(t)$	Cost of energy over time interval t.
Δt	Time step.
E_i	Total energy supplied to ith EV.
E^{grid}_{cost}	Per kWh cost of electricity from grid (including CO_2 cost).
E^{cap}	EV battery energy capacity (kWh).
G^{grid}_{cost}	Per kWh cost of gas from grid (including CO_2 cost).
$P^{gas}(t)$	Rate of gas consumption in CHP (kW).
$P^{th}(t)$	Rate of useful thermal output from CHP (kW).
I_0	Initial infrastructure investment in year one.
$\mu_i(t)$	Availability status of ith EV.
$P_{ev}(t)$	EV charging power delivered during each time step.
$P^e_{grid}(t)$	Electrical power supplied by AC grid during each time step.
$P^e_{chp}(t)$	Electrical power supplied by CHP during each time step.

Table 3.7: Continued Notation: LVDC Charging Infrastructure Optimisation

P^{ex}	Electrical export capacity of grid connection.
P^{cap}_{grid}	Capacity of grid connection and power converter.
P^{cap}_{chp}	Electrical capacity of CHP system.
$P^{cast}_{d}(t,y)$	EV power demand forecast.
P^{cgr}_{g}	Vector of charger rated power capacity levels.
$P^{max}_{net}(t)$	Maximum power available from AC network over time interval t.
$P_{i,k}(t)$	Power flow from ith EV to kth charger over time interval t.
$P^{rat}_{k}(t)$	Charging power rating according to EV SOC.
$P^{\phi}_{i,k}$	Charging power level.
P^{UB}_{γ}	CHP electrical power upper boundary for γ efficiency region.
P^{LB}_{γ}	CHP electrical power lower boundary for γ efficiency region.
ψ	HPC operating expense multiplier, as a percentage of charging revenue.
q	Binary investment state for CHP option.
R^{ev}	Revenue from EV charging per time step (r_{ev} per unit).
R^{th}	Revenue from heating services per time step (r_{th} per unit).
R^{ex}	Revenue from CHP exports per time step (r_{ex} per unit).
r	Discount rate.
R^{net}	Net revenue from charging station.
$N_g(y)$	Integer value for charger types deployed in each year.
$H_g(t)$	Integer variable for active chargers during time intervals.
S_p	Number of available parking/charging spaces.
S^{ini}_{i}	Initial ith EV SOC (kWh).
S^{fin}_{i}	Final ith EV SOC (kWh).
S^{1}_{i}	Start of constant voltage charging (kWh).
S^{ln}_{i}	Lower SOC level for SOC step n.
S^{un}_{i}	Upper SOC level for SOC step n.
$S_i(t)$	SOC of ith accumulating over time tth interval (kWh).
t^{a}_{i}	Time of arrival for ith EV.
t^{d}_{i}	Time of departure for ith EV.
$u^{\phi}_{i,k}(t)$	Binary variable denoting power level state of charger output.
$u_{i,k}(t)$	Binary variable representing control state for ith EV and kth charger over time interval t.
u_f	Binary state for fth electrical grid capacity option.
u_{γ}	Binary variable for active CHP efficiency boundary.
y	Number of years that charging infrastructure is operational.
Y^{ehr}_{γ}	EHR y-axis intercept for γ efficiency boundary.
Y^{hpr}_{γ}	HPR y-axis intercept for γ efficiency boundary.
X^{ehr}_{γ}	EHR power conversion multiplier for γ efficiency boundary.
X^{hpr}_{γ}	HPR power conversion multiplier for γ efficiency boundary.

3.4 Chapter Summary

This chapter has examined two years worth of operational charging transactions for a public EV charging network totalling 192 rapid DC chargers. From this operational data, two useful studies were performed: the development of locational based charging models and an early, day-ahead, power demand forecasting model for the collective charging network. This work broadly addresses some of the challenges associated with the development of economically viable EV charging infrastructure. For example, the locational based charging models indicate the most frequented charging locations and offer an arrival rate and energy utilisation model for each of the charging locations which can assist the planning and feasibility assessments for the siting of future charging infrastructure deployments. It was found that the PDF charging energy transactions follows a Gamma distribution for all charging locations and that a Gaussian Mixture Model can more accurately describe EV arrival times at rapid DC chargers for certain locations as opposed to a single Gaussian distribution.

The forecasting model highlights the opportunity to operate the CPS network, and other, public charging networks under a collective energy supply contract, while offering an insight into the emerging relationships between daily charging demand and days of the week, as well as the impact of weather variables on charging demand. It was found that a similar charging demand profile is followed between Monday to Thursday but Friday, Saturday and Sunday have their own distinct demand profiles. A later charging peak on Fridays was found and higher charging demand in the early hours of Saturday and Sunday is present; with a lower demand for charging during the weekend mornings. The exact cause of these differences in collective charging power demand cannot be fully determined but it is likely that electric taxis are the cause of the weekend, early morning demand peaks and that fewer commuters on the weekends reduces the morning demand for charging. Although the physical impact of weather variables on EV energy demand is theoretically understood, the practical impact of temperature and rainfall on charging demand currently has a weak emerging relationship according to this dataset. However, using the aggregate EV battery capacity of the charging network users offers a more accurate normalisation of weather data compared to the number of EV charging network users alone.

This charging demand data is utilised in Chapter 4 and discussed in Chapter 5 as the input into similar charging infrastructure design and control optimisation problems. The selected optimisation method and notation has been presented in this chapter and the detailed problem formulations are fully developed and discussed in the following two chapters.

Chapter 4

Short Duration EV Charging

This chapter focuses on developing a LVDC charging infrastructure planning model for the optimum deployment of high power charging (HPC) assets where the EV user expects a short duration charging service. In this thesis, short duration EV charging takes place within the half-hourly balancing and settlement period and could be considered the most similar to existing refuelling services experienced by ICE vehicles. To deliver this level of service requires a power density of several hundred kilowatts per charging point and therefore, collectively, a charging station consisting of three or more chargers will require a grid connection capacity in excess of one megawatt [148], [149]. Although several automotive manufactures[1] [2] have indicated that future vehicles will accept 800-1000V DC charging at a power rate of 350kW, it remains to be seen how their vehicle batteries will peform at these higher charging levels. Without significant battery technology and chemistry improvements, it is widely understood that charging rates of this magnitude will accelerate battery degredation and create safety challenges [133], [150], [151]. However, the US Department of Energy (USDoE) believe that HPC stations are critical to ensuring mass adoption of EVs and the US Advanced Battery Consortium has set a target of developing batteries capable of an 80% pack charge capacity within 15 minutes by 2023 [152]. Therefore the work in this chapter acknowledges the current battery limitations with respect to high power charging rates

[1] https://www.chargepoint.com/blog/charging-porsche-taycan-fast-charging-and-more/
[2] https://electrek.co/2019/06/11/tesla-model-3-vs-audi-e-tron-350kw-charge-off/

but anticipates that the competitive drive for lower cost, higher energy capacity and faster charging batteries is likely to deliver a suitable battery technology in the future.

Depending on the location of the proposed HPC station, the electrical grid may require significant reinforcement to deliver this power capacity [54]. An alternative solution to electrical grid reinforcement pursued in this thesis considers the feasibility of incorporating the gas grid to support the charging power density and energy requirements of HPC stations. This option is particularly interesting when demand for low-grade heat is within the vicinity of the proposed charging station. In this scenario, a combined heat and power (CHP) gas reciprocating engine or fuel cell may then satisfy a portion of the charging station's electrical demand while providing thermal power to local customers. To investigate this opportunity, this chapter presents a charging infrastructure planning model that maximises the Net Present Value (NPV) for the charging infrastructure developer based on several practical constraints and a multi-year charging energy demand forecast. The model is used to compare the NPV of the charging infrastructure with and without three different CHP technologies that are connected to both the DC charging bus and the low voltage AC grid.

The chapter is structured in four sections, where Section 4.1 introduces the concept of integrated energy systems, the potential value of several CHP options and their interconnection requirements to a LVDC charging network. Section 4.2 outlines the model formulation and assumptions necessary to solve the integrated charging infrastructure planning problem. Section 4.3 applies the model to the City of Edinburgh taxi population to determine the HPC infrastructure necessary to satisfy varying levels of future electric taxi charging demand. Finally, Section 4.6 comments on the accuracy of the model, the impact that a CHP system connected to the LVDC charging network has on the overall charging energy efficiency and the additional work required to expand this model to a practical planning tool.

4.1 Charging Infrastructure as an Integrated Energy System

The proposed HPC system to be studied in this thesis can be classified as an integrated energy system (IES), in that it combines the gas grid and power network to deliver energy services for transport, heating and electrical generation. Other IES research work has also considered the nexus of gas grids, power networks and heating but in other end-use demand applications such as the optimisation of building energy consumption [153], microgrid systems for islands or small regions [154], and national, whole system energy studies have investigated the convergence of multiple energy vectors to identify synergies and mutual benefits between the traditionally disconnected energy sectors [155]. Thiem [156]considers a detailed design solution to minimise the LCOE for building-level energy use cases according to varying daily energy demand profiles and non-linear part-load power efficiency curves for generators and power converters. Their problem formulation is robust and detailed but it assumes fixed infrastructure deployment in the first year of the investment model and does not consider growth in energy demand and future infrastructure investment requirements necessary to meet the predicted demand growth. For EV charging systems, this is an essential component of any infrastructure planning work as there is a need to provide charging services early in the adoption of EVs but this initial infrastructure may be required to rapidly scale depending on the rate of EV adoption. Any charging infrastructure planning model is therefore heavily reliant on the 'charging resource assessment' (i.e. the EV energy demand forecast), in the same manner that wind and solar energy projects require site specific resource assessments [157] and power network operators forecast long-term energy demand to determine future infrastructure investments [158].

In [159], the authors outline a multi-energy system expansion planning method that also utilises a mixed integer linear programming (MILP) optimisation approach and linearises the energy demand curves according to the Douglas Peucker algorithm - this technique decomposes a non-linear function into a series of linear equations that best approximate the non-linear curve, according to a desired number of sections. This

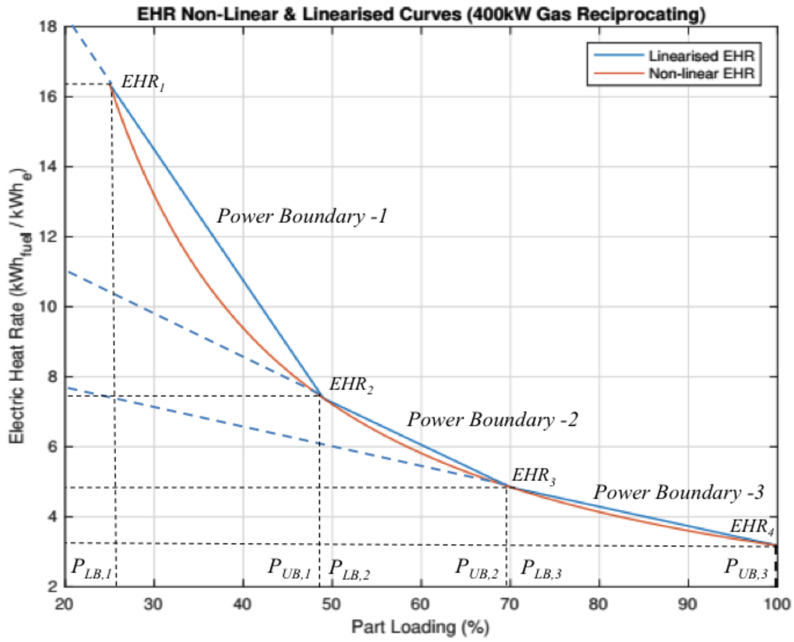


Figure 4.1: Linearised electric heat rate for a 400kWe gas reciprocating engine.

is demonstrated in Figure 4.1 for the electric heat rate of a 400kWe gas reciprocating engine that uses three linear 'power boundaries'. To adequately model an integrated gas CHP charging system it is necessary to account for part-loading efficiency of the CHP unit and the power electronic devices that convert grid AC power to high power DC outputs for charging which have a non-linear efficiency curve.

Through lessons learned from the deployment of early rapid DC chargers, it is becoming increasingly clear that achieving the required electrical grid capacity for high power charging systems is likely to pose an economic and technical challenge [54]. Therefore, to reduce the electrical network upgrade infrastructure costs it may prove necessary to consider alternative power sources that can deliver the required charging power on demand. These solutions may include: gas CHP systems located in urban environments, stationary energy storage buffers fed by existing power infrastructure and the interconnection to alternative electrical distribution assets such as rail/tram networks that may possess spare power capacity at certain times.

Electrical manufacturers such as Siemens, ABB, Enercon and Tritium are all developing high power chargers that can output up to 350kW at 700-900Vdc [148], [160]. Infrastructure developers such as Pivot Power and Ionity are expanding national networks through the UK and Europe that connect HPC stations directly to the transmission grid at motorway service stations to facilitate long distance travel [149]. However, little consideration has been given to urban HPC stations where, in the UK, a large population live without off-street parking (approximately 30%) and will therefore be required to charge at public charging facilities [161]. An additional characteristic of urban charging infrastructure is that power networks in these environments can often be congested and additional demand from EV charging will necessitate substantial network upgrades [162]. It is also worth considering the security of the wider energy system as transport becomes partially or wholly reliant on electricity networks - can the gas grid offer additional energy resiliency?

By building on the approaches in [159] and [156] a MILP expansion planning formulation for a HPC station where the grid connected power converter efficiency and part-loading fuel consumption of CHP plants can be linearised will be developed as part of the work of this thesis. This type of formulation considers the whole system energy efficiency and the optimum deployment of energy assets (chargers, grid connection capacity, CHP type) that will maximise the Net Present Value (NPV) for the charge point operator (CPO). Prior to formulating the infrastructure planning model it is useful to contextualise the problem and describe the emergence of existing HPC stations, the integration options available for CHP solutions and the wider modelling assumptions. The concept of combining power and gas networks to supply a HPC system therefore becomes a worthwhile consideration from an infrastructure investment cost, energy efficiency and energy system resiliency perspective.

4.1.1 Integrated EV Charging with CHP Systems

Installing a stand-alone CHP system or a HPC station arguably requires complex techno-economic modelling, while the concept of integrating these two independent systems only increases the challenge. The modelling approach in this chapter therefore first considers the sizing of a standalone, grid connected HPC station and then

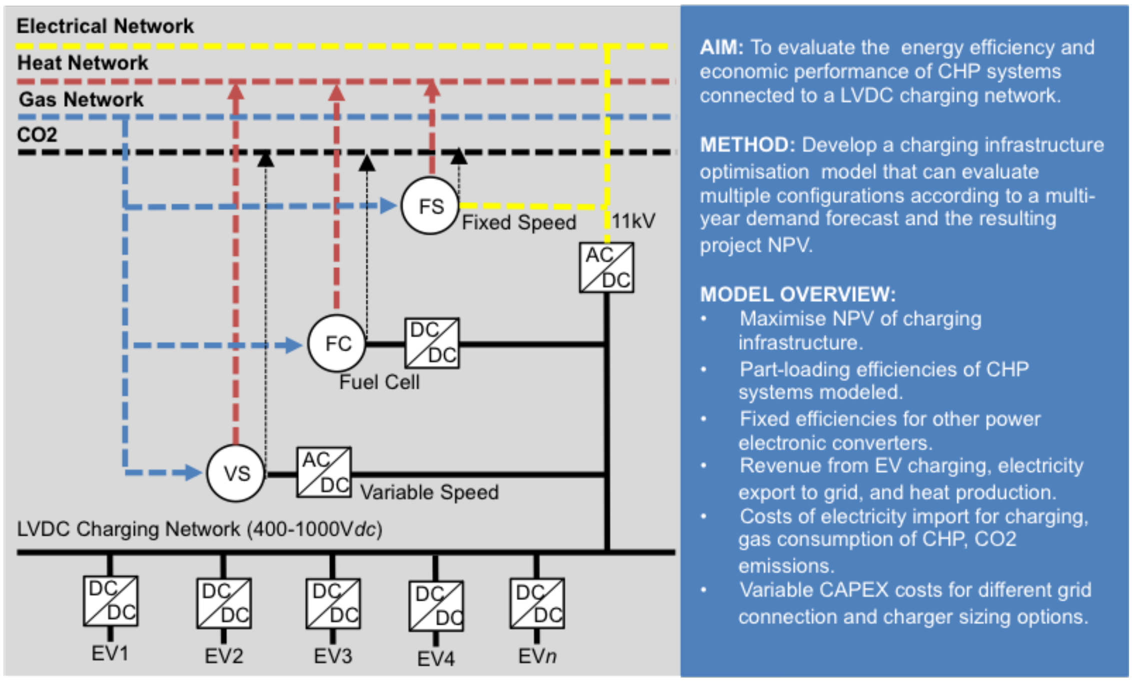


Figure 4.2: Network topologies under consideration within the optimisation model.

subsequently the interconnection of three different CHP solutions and their effect on the NPV of the project is evaluated. Figure 4.2, outlines the proposed concept with three different CHP integration options that allows for the evaluation of LVDC and LVAC connected CHP units. The scale, system components and project costs can all be incorporated into a optimised design process that is outlined and tested in this chapter.

Other integrated charging solutions have been considered in literature and implemented in practice such as the use of stationary batteries to connect lower power grid connections while still providing high power charging services [163]. Furthermore, the integration of stationary battery storage with EV charging can be accomplished efficiently on a single DC bus [164]. Other papers outline the integration of solar PV charging, battery storage and EV charging however, while this has a place for longer duration charging, it is unlikely to offer value for HPC stations in urban environments [51], [130]. This is because the power to area ratio is too low for solar PV to offer any meaningful contribution to the power or overall energy requirements of the charging station where land area is a constraint (e.g. a 1MW solar PV system requires 3-5 acres of land [165], whereas only 3x350kW charger parking bays require over a megawatt of electrical power capacity when all are in use).

The use of Combined Heat and Power (CHP) systems as part of a wider integrated energy solution is not new. It has been adopted as an efficient use of fossil fuels for power generation in Scandinavian countries for decades and has recently seen a renaissance in the UK and internationally, as governments make a concerted effort to decarbonize heating and electricity production [166]. Although, little research work has considered the use of CHP systems as a power capacity enabler for electric transportation systems, this concept therefore links gas networks, power networks heating networks and transport systems into one integrated project.

CHP systems can take many forms and sizes, however, they are generally associated with small to medium scale distributed generators (1kWe-10MWe) such as diesel or gas reciprocating engines, gas turbines and more recently the use of fuel cells [166]. Larger, centralized thermal power plants such as coal and nuclear can also operate as heating plants but are generally subject to higher installation costs due to their distance from population centres and the associated heating loads [167]. The most common urban area CHP systems utilize gas reciprocating engines that can range from a few hundreds of kilowatts up to multi-megawatts and are generally installed for on-site building or campus generation and thermal loads or connected to a wider district-heating network (DHN) [168]. Gas reciprocating generators are more appropriate for sub-10MW applications compared to gas turbine solutions and for that reason gas turbines are excluded from this analysis [169], as HPC stations are currently being installed with a capacity of 1-3MW[3].

The great majority of gas reciprocating engines, acting as distributed generators, operate at a fixed speed, where the connected generator is electrically synchronized with the national/regional grid frequency. Although more recently the use of variable speed gas and diesel engine-generator sets (gensets) have been investigated and the fuel efficiency benefits documented for small-scale building level systems and larger marine

[3]https://ionity.eu/

power system applications [170], [171]. It is therefore worth considering the use of variable speed gensets for distributed generation applications, especially in conjunction with intermittent renewable generators or highly varying loading profiles; as this causes the generator to operate under a part-loading, lower energy efficiency state for extended periods of time.

Conventional gas reciprocating gensets operate at a fixed rotational speed, which is determined by the generator topology and grid frequency [172]. The engine maintains a fixed speed regardless of the electrical load on the generator. This is appropriate for base-load power generation applications or for peaking plants where maximum power output is required for set periods of time. However, under part-loading conditions, particularly under 50% loading, the fuel efficiency of the gensets drop markedly. This is illustrated in Figure 4.10 and extensively modelled for commercial engines in [172].

A variable speed reciprocating genset enables the engine to operate at its optimum speed and therefore fuel consumption for a specific loading condition. This is achieved by either decoupling the generator output from the AC grid using power electronic equipment or by varying the magnetic field on the generator rotor exciter for doubly fed induction generators (DFIGs). In the case of a LVDC charging network, a variable speed CHP engine may interface directly with the DC bus, which can increase the fuel efficiency of the engine but may also reduce power electronic efficiency losses compared to a fixed speed CHP engine that is connected to the AC grid. These two interconnection options are illustrated in Figure 4.2, where a third CHP solution is also depicted, the use of a fuel cell.

The development of fuel cell technologies has been on-going for a number of decades, however, their applications remain limited to niche areas such as data centres, telecoms and some large retail warehouses [173]. Potential applications for fuel cells exist within utility power systems, transportation and portable electrical devices but the capital and operating costs remain higher than alternative power solutions. Lower emissions and higher electrical efficiency are the primary advantages of fuel cells over traditional gas reciprocating engines. In some cases fuel cells may provide a more favourable economic solution in urban environments where strict emission regulations are enforced [174].

Based on the early development of HPC stations and the operational experience with these three CHP systems, this chapter considers the following questions:

1. Can CHP systems improve the overall NPV of a HPC station?
2. Should a CHP system be connected to the DC charging network or on the AC input side to the charging system?
3. In what situations should a co-located CHP system be installed?

Three possible CHP connection options are presented in 4.2: a fuel cell (FC) and variable speed (VS) gas reciprocating engine connected the LVDC network and a fixed speed (FS) gas reciprocating engine connected to the AC side of the grid-tie converter which support several DC/DC chargers connected to the LVDC network. With appropriate cost assumptions, the HPC planning model that is developed in this thesis can determine the scenarios in which a co-located CHP system is desirable and furthermore, which of the three CHP topologies offers the highest NPV for the infrastructure owner.

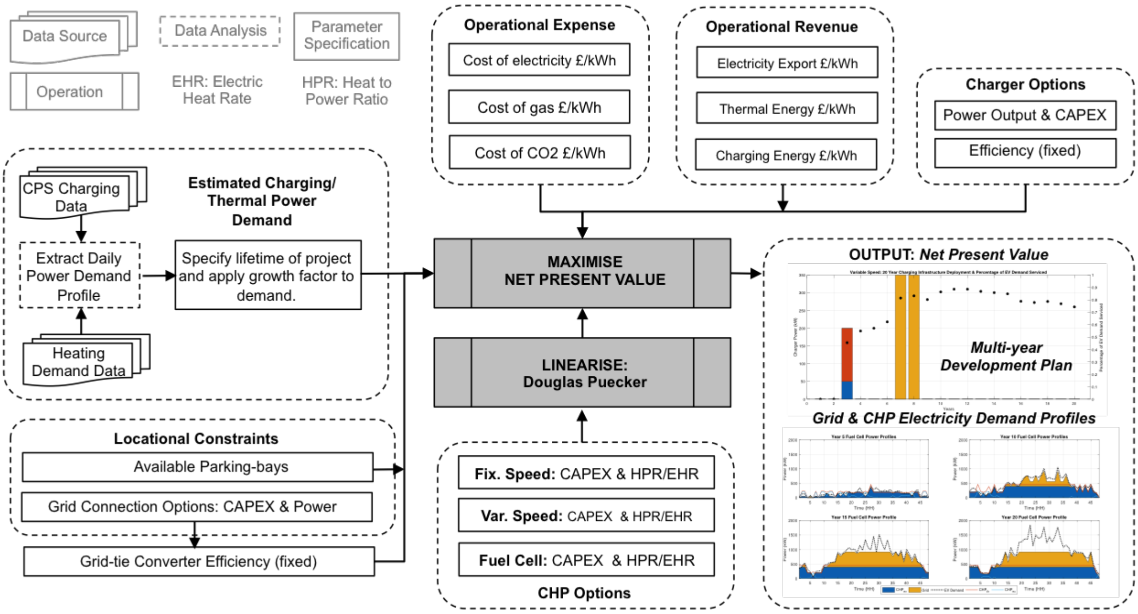


Figure 4.3: Inputs and results from HPC charging infrastructure optimisation.

4.2 Model Formulation for HPC Infrastructure Planning

This section outlines the problem structure and formulation as a MILP problem according to the methodology presented in Chapter-3. The objective function is described and the required equality and inequality constraints are presented. The notation defined in Table 3.7 of Chapter-3 is employed for indices, sets, parameters and variables in the optimisation model.

Figure 4.3 highlights the model inputs and outputs for an HPC optimisation: the model requires the user (a charging infrastructure developer or designer) to provide an average daily charging power demand profile for the HPC station and a specified number of parking-bays that the proposed HPC station location can accommodate. It is also assumed that the developer desires to evaluate several electrical grid connection options which have varying capital costs depending on the desired power capacity. A choice of chargers with varying power outputs can also be stipulated and the associated cost of each charger incorporated. Although several co-located energy assets could be evaluated using this model, such as: stationary battery storage, super-capacitors or solar PV and wind energy; in this case, the cost and operational characteristics of three CHP systems are specified for evaluation.

This problem can be described as multi-objective, in that it is desired to minimise charging infrastructure costs, while maximising the charging energy delivered to a population of EVs and minimising the carbon dioxide emissions from the HPC station by considering the carbon content of grid electricity and the carbon emissions from a co-located CHP system. These objectives are embodied in the Net Present Value (NPV) calculation of the HPC infrastructure investment. The NPV of an HPC station depends on the net revenue of energy sales from EV charging, electricity exports to the grid and any CHP heating activities minus the cost to purchase grid electricity/gas, plus the operating costs of the assets and the energy conversion losses within the system. In this model, the net revenue is calculated on an annual basis and discounted back to the present day value according to a discount rate r which is stipulated based on the developer's historic investment returns or financing interest rates. The initial capital infrastructure investment is captured in year-1 of the investment analysis (I_0), this represents the starting infrastructure necessary to begin servicing the predicted charging demand from a nascent population of EVs.

However, future infrastructure investment is also considered, such as additional chargers or the introduction of a CHP system when sufficient demand for charging might justify this investment. These expansion options are captured in the net revenue calculation for the year in which the capital investment is made. If the overall project investment analysis results in a positive NPV, then it is a worthwhile alternative to other investment options for the organisation, and the highest NPV out of a number of similar options may offer the best design/configuration to take forward for development. NPV is expressed formally as:

$$NPV = \sum_{y \in \Omega_{\mathrm{Y}}} \frac{R^{net}}{(1+r)^y} - I_0 \tag{4.1}$$

The NPV calculation for this problem can be expressed as follows and it is desired to maximise this function:

$$J = \max \sum_{y \in \Omega_{\mathrm{Y}}} \sum_{d \in \Omega_{\mathrm{D}}} d(\sum_{t \in \Omega_{\mathrm{T}}} (R^{ev}(t) + R^{ex}(t) + R^{th}(t))\Delta t - (C^g(t) + C^e(t))\Delta t) - C^x(y) \tag{4.2}$$

Here J is the objective function and 4.2 represents a simple revenue-cost model, where R^{ev}, R^{ex} and R^{th} represent the revenue opportunities from EV charging, CHP electrical export to the grid and CHP thermal revenue from waste heat respectively. The net revenue for each time step is calculated by deducting the gas cost C^g and electricity cost C^e. Each of the net revenue components are described as follows:

$$R^{ev}(t) = P_{ev}(t)(r_{ev} - \psi r_{ev}) \tag{4.3}$$

$$R^{ex}(t) = P^{ex}_{chp}(t) r_{ex} \tag{4.4}$$

$$R^{th}(t) = P^{e}_{chp}(t) \eta_{hpr} r_{th} \tag{4.5}$$

$$C^e(t) = E^{grid}_{cost} P^e_{grid}(t) \quad where; \quad P^e_{grid}(t) = \frac{1}{\eta_{dc}} \frac{1}{\eta_{acdc}} P_{ev}(t) - P^e_{chp}(t) \tag{4.6}$$

$$C^g(t) = G^{grid}_{cost} P^{gas}(t) \tag{4.7}$$

The cost of electricity C^e (Eq. 4.6) considers both the DC/DC charger efficiency and the grid connected AC/DC converter efficiency. The gas cost (Eq. 4.7) requires the rate of gas consumption $P^{gas}(t)$ which is a function of the electrical output of a CHP system. Both $P^{gas}(t)$ and the thermal power output from a CHP system $P^{th}(t)$ are defined later in Eq. 4.21 and Eq. 4.22. In this analysis it is assumed that a district heating network (DHN) or building has the capacity to absorb all thermal power from any CHP system at a fixed price per kWh, therefore no varying thermal demand profile is considered in the case studies. The cost of carbon dioxide is incorporated into C^e and C^g as a portion of the unit cost of energy (kWh) from the electrical grid (E^{grid}_{cost}) or gas grid (G^{grid}_{cost}).

The charging infrastructure capital (C^x) expenses are incorporated on an annual basis. This considers the grid connection cost, any additional chargers and the decision to implement a CHP plant. The operating expense of the charging system is integrated into the charging revenue calculation by assuming a variable operating expense that increases as usage of the HPC station increases. A percentage multiplier is therefore applied (ψ) to the per kWh charging tariff to represent the percentage of charging revenue that is allocated for operation and maintenance of the system. Finally, the daily energy revenue is multiplied by the number of days d that the charging power demand profile is applicable. There can be multiple charging power demand profiles in the set Ω_{D} which can correspond to seasonal changes or day of the week differences in daily charging power demand curves.

The objective function (Eq. 4.2) is subject to several practical constraints:

Charging Power Output is within EV Forecast Power Demand

The sum power output of all active chargers during time interval Δt in any given year should not exceed the forecast power demand for the same time period based on the average daily demand profile for the set of days under consideration (Ω_D), thus

$$P_{ev}(t) \leq P_d^{cast}(t), \forall t\ \forall y; \tag{4.8}$$

It is assumed that each of the deployed EV chargers is either off or at full power, therefore the total charging power output in any time interval can be defined as;

$$P_{ev}(t) = \sum_{g \in \Omega_G} P_g^{cgr} H_g(t), \forall t\ \forall y; \tag{4.9}$$

where P_g^{cgr} represents the rated charging power output for any of the available chargers in set Ω_G. $H_g(t)$ is an integer variable that indicates the number of specific chargers that are active during a time interval. The number of active chargers (H_g) in each time interval should not exceed the cumulative number of installed chargers (N_g),

$$\sum_{g \in \Omega_G} H_g(t) \leq \sum_{y \in \Omega_Y} \sum_{g \in \Omega_G} N_g(y), \forall t\ \forall y; \tag{4.10}$$

and the cumulative number of installed chargers should not exceed the number of available parking spaces (S_p).

$$\sum_{y \in \Omega_Y} \sum_{g \in \Omega_G} N_g(y) \leq Sp, \forall y; \tag{4.11}$$

Constraints (4.8) to (4.11) capture the restrictions that arise from the available charging infrastructure.

Available Electrical Power Capacity

Over each time interval and for every year, the electrical power imported from the power network and supplied by any co-located CHP system must not exceed the rated electrical capacity of each power supply asset. For any time period, it is necessary to know the number and size of chargers that are installed, the grid connection capacity and whether the CHP system is selected as desirable. The following inequalities link the annual asset investment decision variables to the electrical power supply constraint during each time interval of the supplied EV energy demand profile:

It is desired to select only one of the grid connection options (u_f) that is the preferred size to supply the charging network with power and enable power export from any CHP option for the duration of the investment period,

$$\sum_{y \in \Omega_{\mathrm{Y}}} \sum_{f \in \Omega_{\mathrm{F}}} u_f \leq 1, \ \forall f \ \forall y \tag{4.12}$$

and when selected the electrical power delivered by the grid to the charging system should not exceed the selected grid capacity.

$$P^{e}_{grid}(t) - P^{grid}_{cap} u_f \leq 0, \ \forall t \tag{4.13}$$

The electrical power supplied by the CHP must be within the rated electrical capacity of the CHP system and can only be incorporated into the model when the cumulative sum of the binary investment variable q is equal to 1. This allows the model to determine in what year of the project a CHP system is best deployed.

$$P^{e}_{chp}(t) - P^{chp}_{cap} \sum_{y \in \Omega_{\mathrm{Y}}} q \leq 0, \ \forall t \tag{4.14}$$

The export of electrical power from the CHP system should not exceed the selected grid capacity connection and should also be within the rated electrical capacity of the selected CHP system:

$$P^{ex}_{chp}(t) - P_{grid} u_f \leq 0, \ \forall t \tag{4.15}$$

$$P^{ex}_{chp}(t) - P^{chp}_{cap} q \leq 0, \ \forall t \tag{4.16}$$

Constraints (4.12) to (4.16) capture the power capacity of the available grid connection options under consideration and define the CHP maximum electrical power output while ensuring any electrical export from the CHP system remains within the selected grid connection power capacity.

Linear Efficiency Restrictions

The grid connection converter, the EV chargers and any CHP option will be subject to varying energy efficiency profiles depending on the electrical power loading on the charging system at any moment in time. In practice, each converter and CHP system will possess a part-loading efficiency curve i.e. when the power loading reduces, the efficiency of the electrical device also reduces. However, it is assumed that the DC/DC charger for each EV parking-bay has a fixed efficiency level as the model considers the charger to be either off or at full power. For simplicity, and to focus on the CHP operational scenarios, it is also assumed that the grid tie converter has a fixed efficiency. The non-linear, part-loading, efficiency curves of the CHP options are linearised according to the Douglas Peucker algorithm [159]. This approach separates the non-linear curve into a series of best-fit linear gradients which can then be applied as efficiency multipliers depending on the allocated electrical power supply for the CHP system at each time step. The multiplier selection is established according to a series of power level boundaries and binary decision variables, as follows:

There are two metrics that vary depending on the CHP electrical part-loading condition of a CHP system. This is the Electric Heat Rate (EHR) and Heat to Power Ratio (HPR) [172]. The EHR determines the gas input energy required to produce one kWh of electrical energy, and the HPR represents the ratio of thermal energy generated for every one kWh of electrical energy produced. The objective function requires the EHR to determine the fuel cost at each time step and the HPR is required to determine the waste heat revenue, both of which are a function of the electrical output from the CHP system.

The electrical power output from the CHP system must therefore be bounded within one of the linear efficiency regions identified by the Douglas Peucker algorithm. A series of upper power boundaries (P_{γ}^{UB}) and lower power boundaries (P_{γ}^{LB}) can be used to define the different part-loading operating regions as defined in Eq. 4.17 and Eq. 4.18. The corresponding linear multipliers for each region can then be used to convert the CHP electrical power output $P_{chp}^{e}(t)$ to the thermal power output $P^{th}(t)$ and gas power input $P^{gas}(t)$:

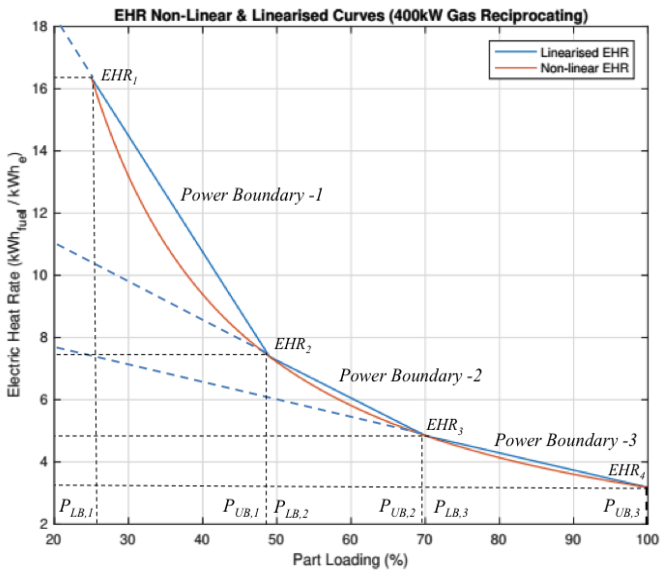


Figure 4.4: Annotated linearised EHR curve with power boundaries to determine gas power input and thermal power according to electrical CHP output.

$$P^{e}_{chp}(t) - \sum_{\gamma \in \Omega_{\Gamma}} P^{UB}_{\gamma} u_{\gamma} \leq 0 \ \forall t \tag{4.17}$$

$$\sum_{\gamma \in \Omega_{\Gamma}} P^{LB}_{\gamma} u_{\gamma} - P^{e}_{chp}(t) \leq 0 \ \forall t \tag{4.18}$$

Figure 4.4 is annotated to illustrate the calculation of the gas power input and thermal power output based on the electrical power of the CHP system. From this figure, it can be seen that the original non-linear EHR curve has been linearised into three sections/regions (for all case studies, three regions are used however, more can be applied and this will increase the accuracy of the linearised model but also increase the size of the optimisation problem). To determine $P^{gas}(t)$ and $P^{th}(t)$ from $P^{e}_{chp}(t)$ it is necessary to identify the conversion multiplier and y-intercept for each power boundary. The conversion multiplier is defined byX^{ehr}_{γ} or X^{hpr}_{γ} and is calculated according to

$$X^{ehr}_{\gamma} = \frac{EHR_{\gamma} - EHR_{\gamma+1}}{|P^{LB}_{\gamma} - P^{UB}_{\gamma}|} \tag{4.19}$$

It is also necessary to identify the y-intercept (Y_{γ}^{ehr}) for each linear power boundary region:

$$Y_{\gamma}^{ehr} = EHR_{\gamma} + P_{\gamma}^{LB} X_{\gamma}^{ehr} \tag{4.20}$$

The gas input power and thermal output power is therefore represented by the following:

$$P^{gas}(t) = P_{chp}^{e}(t) \sum_{\gamma \in \Omega_{\Gamma}} u_{\gamma}(Y_{\gamma}^{ehr} - P_{chp}^{e}(t) X_{\gamma}^{ehr}),\ \forall t \tag{4.21}$$

$$P^{th}(t) = P_{chp}^{e}(t) \sum_{\gamma \in \Omega_{\Gamma}} u_{\gamma}(Y_{\gamma}^{hpr} - P_{chp}^{e}(t) X_{\gamma}^{hpr}),\ \forall t \tag{4.22}$$

where,

$$\sum_{\gamma \in \Omega_{\Gamma}} u_{\gamma} \leq 1\ \forall t \tag{4.23}$$

and u_{γ} is a binary integer variable that indicates the operating power boundary according to $P_{chp}^{e}(t)$ and enables the selection of the appropriate power boundary conversion multipliers and y-intercept values.

Therefore constraints (4.17) to (4.23) describe the linear efficiency regions for a CHP system and the corresponding EHR and HPR multipliers to derive the gas power consumption and thermal generation for each time step, according to the electrical power output of the CHP system.

Electrical Power Balance on DC Bus

The integrated energy charging system is driven by the demand from the EV chargers, the output power demand is based on the full rated capacity of each charger but the efficiency of each charger must be taken into consideration to determine the total electrical energy required on the DC bus. The DC bus electrical energy may be supplied by the electrical grid or a CHP system. Therefore it is necessary to ensure that the electrical power supplied to the DC bus from the AC power network or CHP system is equal to the power demand from all connected EV chargers and the allocated CHP export power to the AC grid. This can be described formally as:

$$\frac{1}{\eta_{dcdc}} \sum_{g \in \Omega_{\mathrm{G}}} P_g^{cgr} H_g(t) - P_{grid}^{e}(t) - P_{chp}^{e}(t) + P_{chp}^{ex}(t) = 0, \forall t \tag{4.24}$$

This section has introduced the objective function for the HPC infrastructure optimisation and the practical constraints associated with electrical network connections and operating characteristics for CHP systems. The following section will apply this model to specific case study scenarios.

4.3 HPC Infrastructure Case Study Parameters

This section introduces the operating parameters and assumptions for each of the model components prior to investigating two case studies in Section 4.4 and 4.5. The case studies are considered from the perspective of a charging infrastructure developer, which may be either a private or public entity. A developer may recognise the need for an urban charging system to meet the growing demand from electric taxis, private vehicles and buses. However, the developer may wish to consider the future charging demand and to decide on the location, the number of chargers, the charger power capacity, the grid connection capacity and whether any co-located energy assets could economically support the charging system.

These case studies therefore assume that an area of land is available which may host a number of parking bays and charging point connections. Prior to performing the infrastructure optimisation process it is necessary to identify the charging system components and state the operating assumptions of each. In this infrastructure assessment, the aim is to identify the optimum combination of energy sources (grid electrical capacity and CHP requirements) and power capacity of chargers to meet a predicted EV charging demand at the least cost to users over a fixed period of time.

The case study parameters are defined and modelled as follows:

4.3.1 Taxi EV Charging Energy Demand

In both case studies, it is assumed that the charging infrastructure will have a lifetime of 20 years and therefore the model requires an estimated charging power demand forecast for up to 20 years into the future. This section outlines the approach and charging power demand profiles used in these case studies.

The City of Edinburgh has a total of 3,118 taxis (1,716 Hackney carriages and 1,802 private hire cars) [162]. Three different electric taxi growth s-curves are presented in Figure 4.5 to highlight a high rate of electric taxi adoption, a base case and low rate of adoption case. For the high rate of adoption case, it is assumed that within 20 years all taxis have converted to electric and within 25 and 30 years for the base case and low case scenarios respectively. The Energy Savings Trust estimates in their infrastructure report for the City of Edinburgh that 623 electric taxis will be operational in Edinburgh by 2023 [162], this estimate is between the base and high forecast estimates of Figure 4.5.

However, variables such a fleet replacement rates, government incentives and the availability of affordable EVs will all impact the uptake of electric taxis, but for the purpose of this analysis; the low, base and high rates of adoption curves are used to develop charging power demand forecasts and to assess the associated charging infrastructure requirements necessary to service a portion of this charging demand and to demonstrate the varying charging infrastructure requirements for each forecast.

Using the taxi specific multi-modal probability density function presented earlier in this thesis, it is possible to generate daily power demand profiles for the electric taxi population based on the number of electric taxis in circulation in any year. Three different power demand profiles were generated based on the predicted rate of adoption cases in Figure 4.5. Each power demand profile was generated by sampling from the taxi arrival rate probability distribution function and attaching a selected energy transaction from the Gamma distribution of charging transactions.

The charging energy transaction was scaled by 50kW (the charging capacity of existing rapid DC chargers) to determine the charging duration for each transaction. These two metrics combined provide the charging start and end times. A 50kW charging

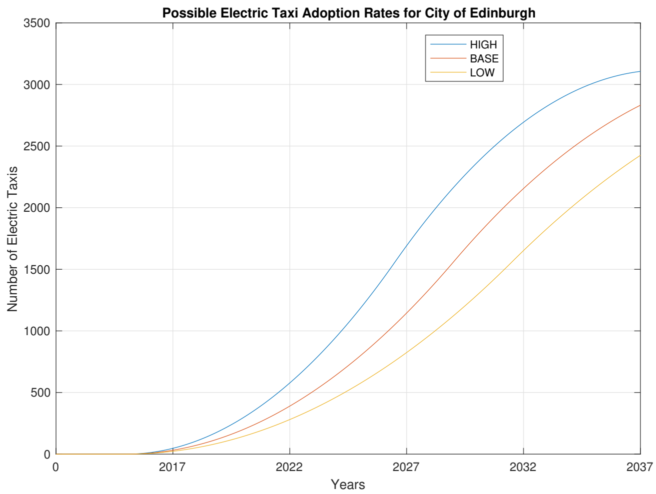


Figure 4.5: Estimated growth in registered electric taxis in the City of Edinburgh over a 20 year period.

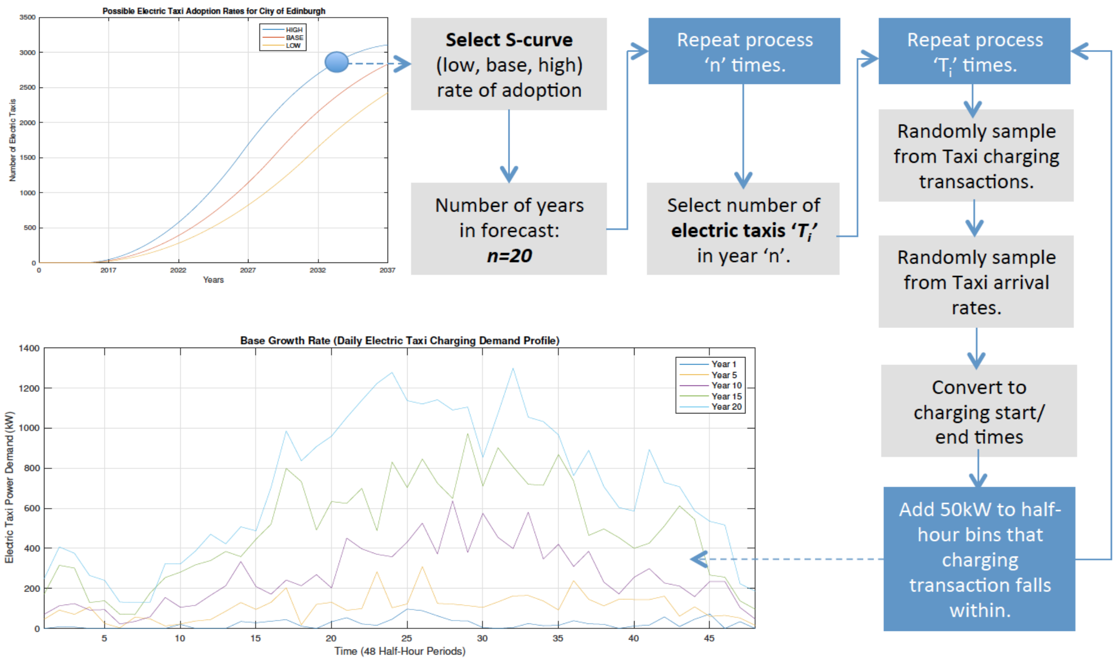


Figure 4.6: Taxi average daily half-hour power demand profiles generated from rate of adoption forecast and real taxi charging utilisation statistics.

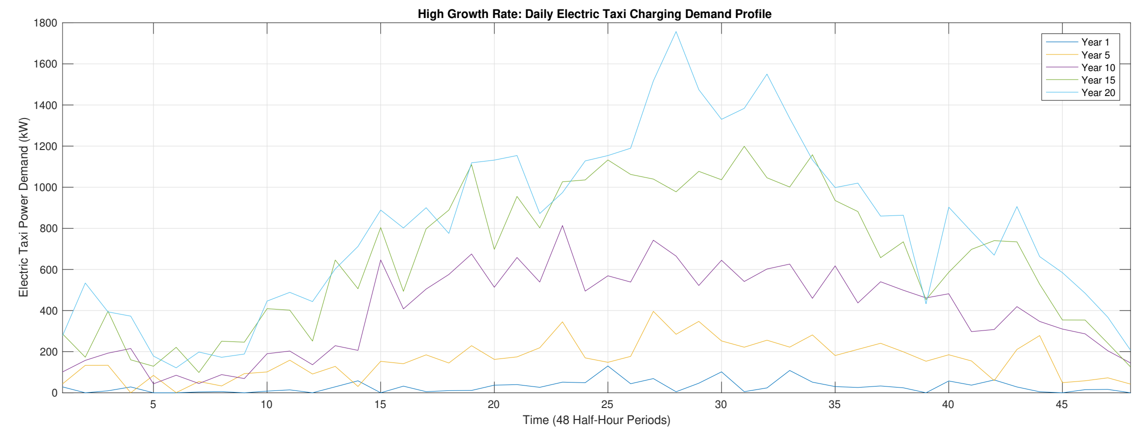


Figure 4.7: Estimated daily demand profile for high-growth in registered electric taxis in the City of Edinburgh over a 20 year period.

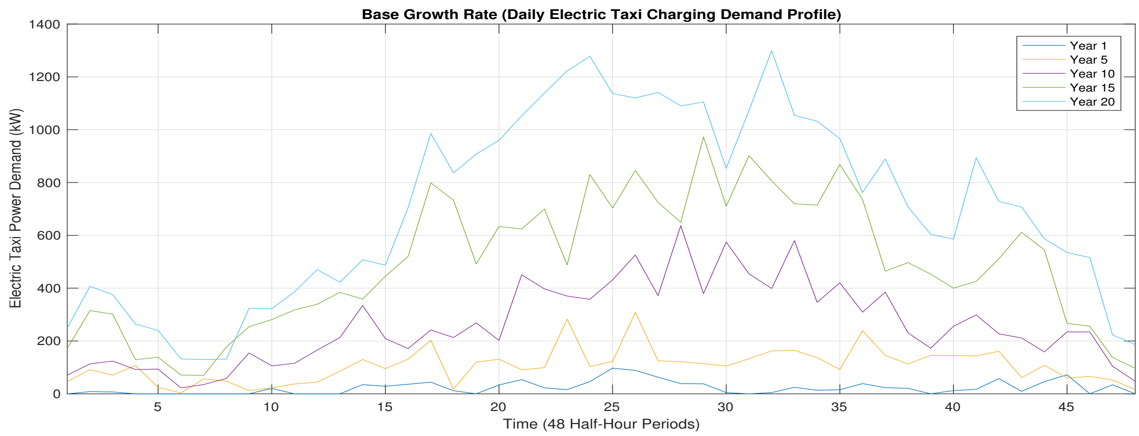


Figure 4.8: Estimated daily demand profile for a baseline-growth in registered electric taxis in the City of Edinburgh over a 20 year period.

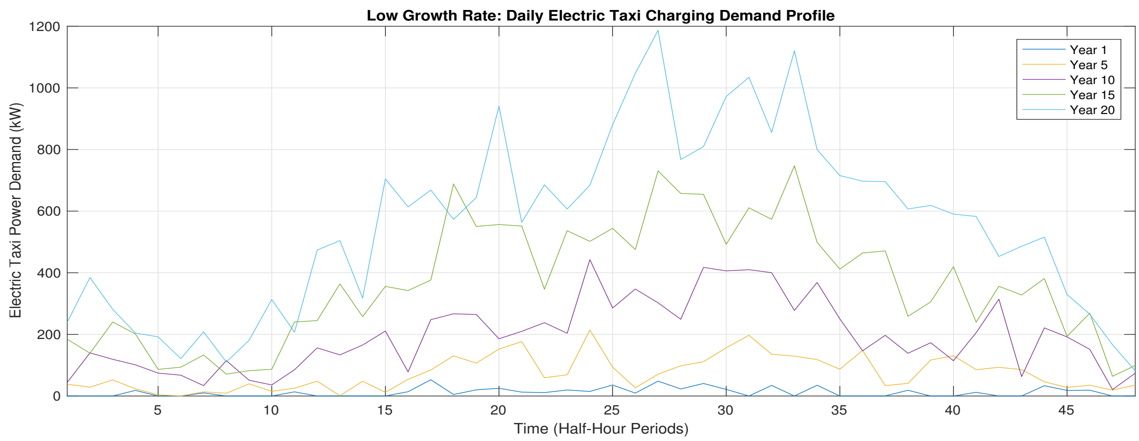


Figure 4.9: Estimated daily demand profile for a low-growth in registered electric taxis in the City of Edinburgh over a 20 year period.

demand is then allocated to half-hourly bins that fall within the charging start and end times. This process was repeated according to the number of electric taxis estimated to be in circulation for each year of the 20 year horizon. Figures 4.7,4.8 and 4.9 illustrate the power demand profiles according to the predicted uptake of electric taxis. These three profiles are used to determine the HPC charging infrastructure requirements in each case study based on the best available charging demand data at this time.

4.3.2 Power Converters

In this model the power electronic converters refer to the DC/DC charger at each of the parking bays which controls the power flow from the HPC DC-bus to each of the charging vehicles. The grid-tied AC/DC converter is sized to meet the peak demand from the cumulative installed DC/DC chargers. It is assumed that the DC/DC chargers are uni-directional as the EV users are expecting a quick charge and therefore no V2G facility is required.

In practice, the grid-tied converter may be bi-directional where a variable speed generator or fuel cell are directly connected to the DC-bus of the charging station. In this case, the generators can also export electrical power to the grid when there is a thermal demand or the economic conditions are favourable. Furthermore, the grid-tied converter and DC/DC chargers are likely to experience non-linear power efficiency curves and these may be incorporated into the optimisation model if a more detailed study is required. However, the part-loading characteristics of the CHP systems under study will have a larger impact on overall energy efficiency. This has therefore taken priority over the part-loading efficiencies of the power electronic converters.

4.3.3 Electrical Grid Connection Options

The HPC optimisation model is structured to allow the selection of one grid connection from multiple options. In practice, this may arise when a DNO has to perform reinforcement work to a site and there are capital costs associated with a capacity option. Or perhaps the developer is considering multiple sites with different grid connection costs. This takes into consideration the future EV charging demand forecast and therefore identifies the optimum grid connection capacity to deliver the highest NPV for the charging station owner over a specified investment period.

In addition to the cost of electricity, the model considers the cost of carbon dioxide emissions from each energy source (either grid or CHP electricity). In the UK, the carbon content of electricity varies with time depending on the proportion of renewable generation but in this case study an approximate figure of 307g/kWh is used based on research conducted in [175]. With this carbon intensity figure, it is necessary to assign a cost of carbon per kWh of grid electrical and gas energy consumed. The average cost of carbon in the UK is £24.00 / tonne [176]. This puts the carbon cost per kWh of grid electricity at £0.0074/kWh. While burning one kWh of natural gas results in 181g/kWh of carbon dioxide at a cost of £0.0043/kWh [177](converted from lbs of CO2/MBtu to g/kWh).

4.3.4 Gas Grid Connection Points

The cost of connecting either a FS, VS or FC CHP system to the gas grid will depend on the availability of capacity in the vicinity of the proposed HPC station and is generally characterised by the desired gas pressure and maximum expected flow rate [178]. In this case study it is assumed that the same gas connection cost will be required for all three CHP systems and is therefore incorporated into the capital installation expense for the units.

The use of power to gas (wind power to hydrogen) is already economically viable in some niche applications but will become industrially viable within the next 10 years if current cost trends continue [52]. If this electrically generated hydrogen or biogas is injected into the existing gas grid, the carbon content of this proposed charging solution will reduce. The primary value of a gas CHP solution over the standard electrical grid connection is the local production of electrical power and the additional energy efficiency benefit that waste heat usage can bring which large scale, centralised gas CCGT systems or steam power plants struggle to provide due to proximity to heating demand and the associated cost of planning and implementing a wider DHN. Furthermore, the utilisation of the gas grid to power independent HPC stations may enhance the resiliency of the transportation and wider energy sector as it moves towards greater electrification.

In reality, it is likely that additional constraints will be required to characterise the CHP systems, such as minimum power generation threshold, start-up time, minimum operational time, cool-down period and minimum off-time [178]. However, in the following case study simulations, it is assumed that the CHP systems can ramp from zero to their rated electrical capacity within the modelled time step. A minimum power constraint of 100kWe is applied for all CHP options and the maximum power under consideration is 400kWe. This power range is dictated by available fuel cell operational performance data as there is currently limited commercial options available for fuel cells compared to gas reciprocating engines.

4.3.5 Fixed Speed Gas Reciprocating Engines

Gas reciprocating generator sets can be characterised by their Electric Heat Rate (EHR) and Heat to Power Ratio (HPR). The EHR is the ratio of electrical energy to fuel input, since the model is driven by the demand for electrical energy, the EHR is used to determine the fuel input requirements necessary to meet the electrical demand. The HPR is the ratio of useful heat production to electric power output. The part-loading characteristics of gas reciprocating engines are documented in [172], the specific EHR and HPR parameters for a 400kWe system are presented in Table 4.1. The part-loading function,

$$f(x) = cax^b \tag{4.25}$$

has three parameters (a,b,c) which vary depending on whether the HPR or EHR is being modelled as well as the type and size of gas reciprocating engine. The detailed efficiency modelling conducted in [172] uses the part-loading percentage ($P^{chp}_{e-out}/P^{chp}_{e-cap}$) as the x variable. In all three EHR and HPR models, x ranges from 25% part-loading (100kWe) to 100% full-loading (400kWe) - this is expressed in Table 4.1 as 25:1:100, meaning the x-axis increments in 1% part-loading points from 25% to 100%.

Table 4.1: EHR and HPR part loading equation parameters for a 400kWe fixed speed gas reciprocating CHP system

	a	b	c	x(%)
EHR	227.9	-1.182	11000	25:1:100
HPR	6.399	-0.4048	1.60	25:1:100

Table 4.2: Linearised EHR values according to Douglas Peucker algorithm and corresponding HPR values using the same part loading bounds in a fixed speed scenario.

	P_1^{LB}	P_2^{LB}	P_3^{LB}	P_3^{UB}
Part Loading (%)	25	49	70	100
kWhf/ kWhe	16.35	7.38	4.84	3.17
kWth/kWe	2.78	2.37	2.06	1.58

The EHR is necessary to determine the fuel input to the CHP system based on the electrical demand, and the HPR relies on the electrical demand to determine the quantity of useful thermal power. However, if both the EHR curve and HPR curve are linearised independently (using the Douglas Peucker algorithm), they encounter different part-loading efficiency regions. To conform with the current MILP problem formulation it is necessary to correlate both the EHR and HPR within the same part-

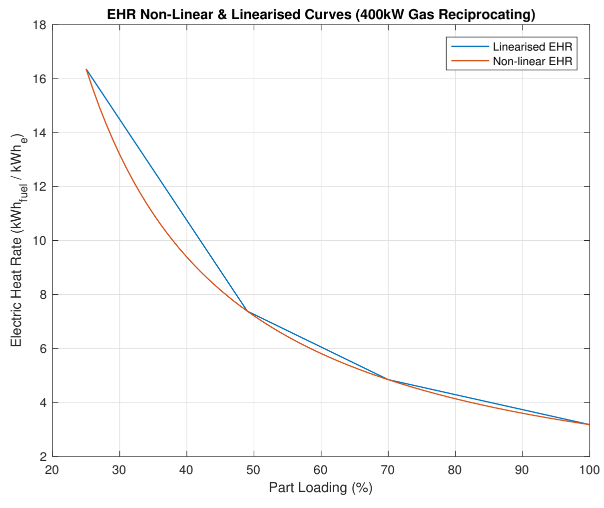


Figure 4.10: Non-linear and linearised EHR according to the Douglas Peucker algorithm with three efficiency regions.

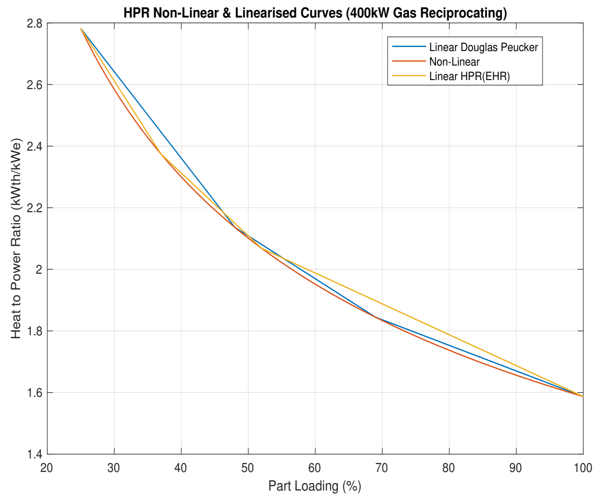


Figure 4.11: Non-linear and linearised HPR according to the Douglas Peucker algorithm with three efficiency regions. The model uses the linear model based on the same EHR part-loading regions.

loading region. Figure 4.10 illustrates the non-linear EHR curve according to Eq.4.25 with the accompanying Douglas Peucker linearised curve (using three linear regions). Table 4.2 presents the part-loading 'bounds' for the three efficiency regions at 25%, 49%, 70% and 100%. To simplify the model formulation, it is important that these same part-loading bounds are applied to the HPR linearisation curve to ensure a single efficiency multiplier is used for each of the part-loading bounds. Figure 4.11 presents the non-linear HPR curve according to the input parameters in Table 4.1. The corresponding Douglas Peucker linearised EHR curve is illustrated alongside the proposed HPR linear curve using the same EHR part-loading bounds.

4.3.6 Variable Speed Gas Reciprocating Engines

Diesel powered variable speed gensets have previously been considered and deployed in microgrid applications to dynamically respond to intermittent renewable energy generation and in diesel-electric transportation systems [171], [179]. However, little research exists on the use of large (400kWe+) variable speed gas reciprocating engines and their associated efficiency improvements under part-loading conditions compared to fixed speed gensets. Tecogen, a commercial manufacturer of 100kWe variable speed gas reciprocating engines claims high efficiency values and a turn-down ability to 10% of rated electrical load [180], [181] and a sophisticated simulation model of a 28kW gas reciprocating CHP system for an onsite building energy application is presented in [170] where efficiency improvements are demonstrated compared to an equivalent fixed speed system.

For the most part, small-scale variable speed reciprocating gensets tend to use Permanent Magnet Synchronous Generators (PMSG) [181]. However, larger gas reciprocating gensets use conventional synchronous generators (SG) due to the cost, weight and supply chain monopoly of rare earth metals [170]. Much research and development exists on variable speed generation within the wind industry as it is an operational necessity to convert variable rotational speeds to match ac grid power quality and effective solutions exist for PMSGs and DFIGs [182]. For utility scale gas reciprocating generators, there is little desire to operate generator units at part loading and therefore limited research exists within this area.

To develop a 400kWe variable speed gas reciprocatng model that is suitable for this thesis it is necessary to extrapolate from the existing studies that focus on smaller scale gas and diesel variable speed generators and make some assumptions on the behaviour of larger variable speed gas reciprocating engines. Based on the approach outlined in [183], an adjustment is applied to the non-linear part loading EHR curve of the fixed speed, 400kWe gas reciprocating engine. This results in the EHR, HPR and linearised Douglas Puecker curves in Fig 4.12. The efficiency boundaries and corresponding multipliers used in the HPC optimisation model are presented in Table 4.4. Since limited information is available on the HPR for variable speed gas reciprocating engines, the same HPR parameters (a,b,c) from the fixed speed part-loading curve are applied to the variable speed model while using the same part-loading regions identified for the variable speed EHR curve.

4.3.7 Fuel Cells

The third integrated CHP solution considers the use of fuel cell. The fuel cell selected for evaluation within the subsequent case studies is a 400kWe Doosan Purecell. This was

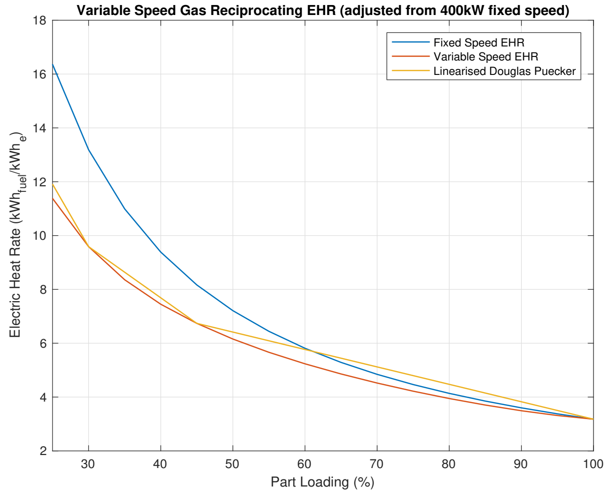


Figure 4.12: Non-linear and linearised variable speed EHR according to the Douglas Peucker algorithm with three efficiency regions.

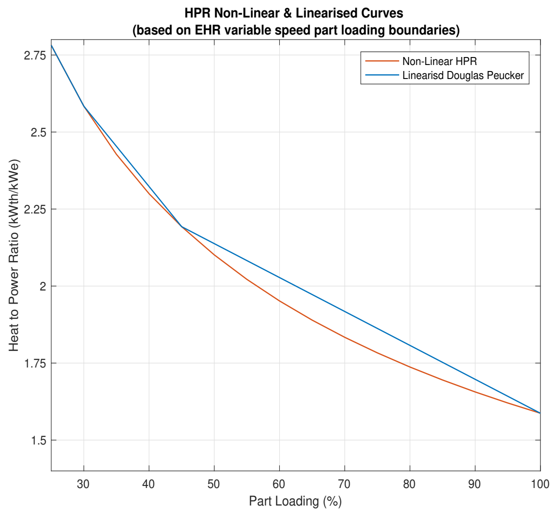


Figure 4.13: Non-linear and linearised variable speed HPR according to the Douglas Peucker algorithm with three efficiency regions.

Table 4.3: Linearised variable speed EHR values according to Douglas Peucker algorithm and corresponding HPR values assuming the same part loading bounds

	P_1^{LB}	P_2^{LB}	P_3^{LB}	P_3^{UB}
Part Loading (%)	25	30	45	100
kWhf/ kWhe (EHR)	11.90	9.59	6.74	3.18
kWth/kWe (HPR)	2.78	2.58	2.19	1.59

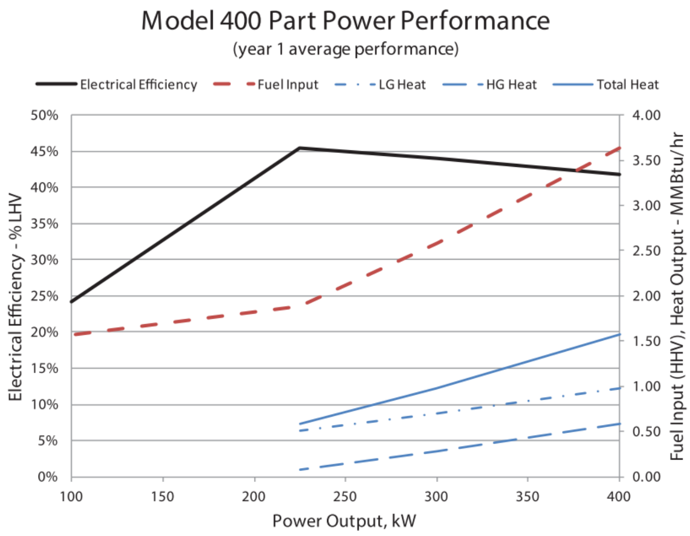


Figure 4.14: Part loading power performance for a Doosan 400kWe fuel cell [184].

selected based on the availability of operational performance data which can provide a similar EHR and HPR metric for comparison with gas reciprocating engines [184]. Although other fuel cell systems are under development such as Bloom Energy's solid oxide fuel cell[4] and Fuel Cell Energy's molten carbonate fuel cell[5], the model of the Doosan Fuel Cell has the most publically available operational data, as outlined in [184], and it is capable of both electrical power and heating. The performance metrics are presented in Figure 4.14 where the EHR is already linearised in two intervals (100kWe - 225kWe and 225kWe to 400kWe). The HPR is estimated based on the total available heating output and is extended at the same heat rate to include 100kWe-225kWe, which is absent in the performance chart but necessary for the HPC optimisation problem formulation in this thesis.

[4]https://www.bloomenergy.com/
[5]https://www.fuelcellenergy.com/

Table 4.4: Fuel cell part loading boundaries and associated EHR and HPR values from [184]

	P_1^{LB}	P_2^{LB}	P_2^{UB}
Part Loading (%)	25	56.25	100
kWhf/ kWhe	4.17	2.22	2.38
kWth/kWe	1.76	0.78	1.14

4.4 Case Study 1: Charger Allocation for Edinburgh Taxis Demand

In this section, the first case study is used to assess the results from the HPC optimisation model by considering only the allocation of chargers and the selection of a grid capacity option according to the charging power demand profiles of electric taxis presented in Figures 4.7 to 4.9.

This case study relies on several infrastructure and energy cost assumptions that may not be readily available or can vary on a site by site basis, such as the cost to reinforce a grid connection point. The charger infrastructure model assumptions are therefore a combination of informed parameters based on UK electricity prices, EV charging rates and electricity carbon cost. While the charger cost and grid connection cost assumptions are best estimates based on work in [54]. The case study parameters are presented in Table 4.5 and the HPC optimisation model is solved using the methodology detailed in Chapter 3.

4.4.1 Results: Charger Allocation for Edinburgh Taxis Demand

The case study parameters are applied to all three taxi charging demand scenarios (low, base, high charging demand forecasts). In all demand scenarios, the HPC optimisation model selects the 1200kW grid connection option as the optimum electrical grid capacity to maximise the project NPV. The resulting NPV for the low, base and high demand forecasts are £1,243,600, £1,840,700, and £2,476,800 respectively. Although the investment case in all three growth forecasts appears favourable, these results will vary on a case by case basis depending on the practical study parameters for a specific site. More

Table 4.5: Model assumptions for single electrical grid connection charging infrastructure assessment.

Parameters	Values
Available parking bays	[4]
Grid connection capacity options (kW)	[500, 1200, 2000]
Cost of grid connection options (£)	[75,000, 150,00, 250,000]
Charger capacity options (kW)	[50, 150, 350]
Cost of charger options (£)	[10,000, 25,000, 50,000]
Cost of electricity	£0.010/kWh
Charging cost	£0.25/kWh
Annual OPEX (10% of charging revenue)	£0.025/kWh sold
Carbon cost	£0.0074/kWh
Demand profile time step	30 minutes
AC/DC grid converter efficiency	96%
DC/DC charger efficiency	98%
Discount rate	8%

generally, these results demonstrate the ability of the model to optimally select the best combination of chargers and grid connection options based on a multi-year EV energy demand forecast. These input variables represent the basic infrastructure requirements that a developer or local authority must consider in the process of deploying charging infrastructure.

The results are presented in Figures 4.15-4.17, where the type and number of EV chargers are represented by the bar chart and the percentage of taxi EV charging demand serviced is plotted as a dot on the secondary y-axis for each year.

The three infrastructure charts demonstrate the optimum deployment of chargers for each electric taxi demand forecast in Edinburgh. It can be seen that the low growth case scenario selects two 50kW chargers, one 150kW and one 350kW charger, however, both the base and high growth rate scenarios select one 50kW, one 150kW and two 350kW chargers. In the high growth scenario the installation of each 350kW charger is brought forward by two years and three years respectively, indicating the higher demand for charging earlier in the investment period. The percentage of EV charging forecast demand that is met by the deployed infrastructure is primarily determined by the number of available parking spaces (the spatial restrictions) as this controls the number of chargers that can be installed. The model must then find the best combination of chargers, grid connection and the associated investment years to maximise the NPV of the project over a 20 year period.

In these scenarios, the project costs and EV demand forecast are sufficient to economically support a HPC station and it is found to be viable to deploy at least one charger from year 1 of the project. However, in other cases, the charger infrastructure model may determine that it is advantageous to delay the investment until the charging demand can support the project costs. The charger infrastructure model could therefore be used to determine the additional government financial support necessary to deliver a viable project in an area that may have a low EV charging demand during the early years of the investment - this support may be structured as capital support (as is currently the approach for charging infrastructure in Scotland) or subsided electricity. For example, Figure 4.18 illustrates the infrastructure deployment results if the low growth case demand is reduced by 20%. In this scenario, the model delays the infrastructure (grid connection and the first 50kW charger) by one year due to the low demand in the first year of the project. To economically deliver a charging service in year 1, the capital cost of the grid connection must be subsidised by £800 in this scenario.

4.4.2 Discussion: Charger Allocation for Edinburgh Taxis Demand

Two aspects that are not incorporated in this model but should be in practice are the capacity payments (either for the electrical network or gas grid), these payments reserve a specific capacity from the network to support the charging station's operating requirements. Furthermore, amortisation of assets and useful lifetime is not considered in the economic model. The model does not discount the grid connection cost nor the CHP capital costs (included in subsequent scenarios) as it was found to artificially reduce these asset costs and push the investment further into the future however, the capital cost of chargers are discounted to the present value to consider the scalable deployment of these assets over a number of years.

The infrastructure requirements and investment results are heavily reliant on the

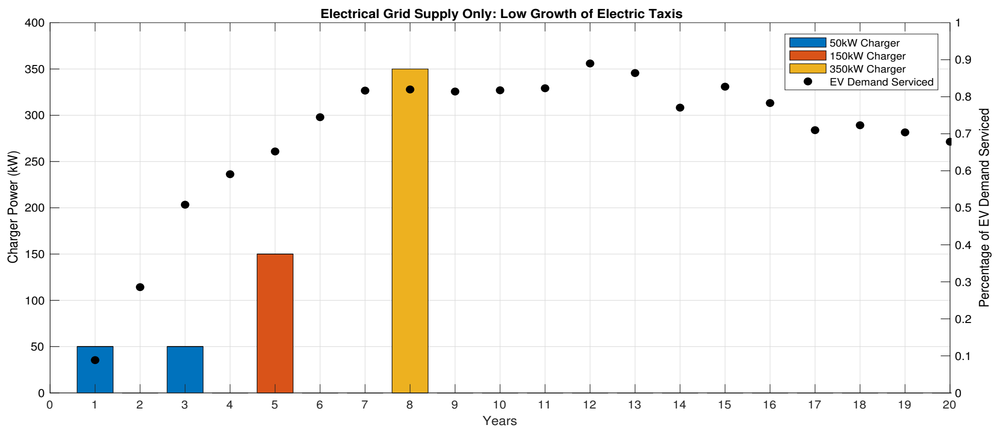


Figure 4.15: Charging infrastructure requirements and percentage of EV energy demand serviced for a low growth rate of electric taxis in Edinburgh.

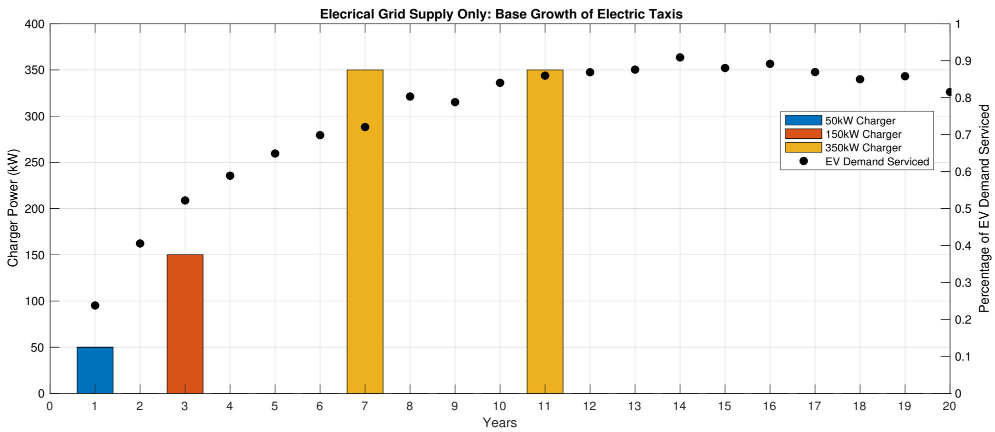


Figure 4.16: Charging infrastructure requirements and percentage of EV energy demand serviced for a baseline growth rate of electric taxis in Edinburgh.

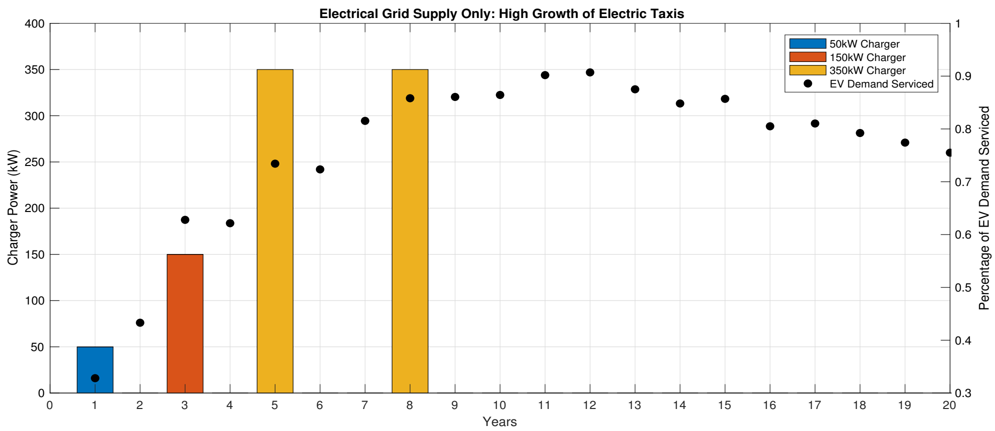


Figure 4.17: Charging infrastructure requirements and percentage of EV energy demand serviced for a high growth rate of electric taxis in Edinburgh.

EV charging demand forecasting model. In these scenarios, the charging demand model is specifically addressing the taxi charging population in Edinburgh and it is based on charging patterns at rapid DC taxi chargers throughout Scotland between 2016 and 2017 as outlined in Chapter 3. Therefore, it should represent the best estimate of taxi charging behaviour at this point in time, however, the average charging energy demand from the forecasting model is approximately 7.2kWh per taxi per day. Intuitively, this appears lower than expected. In 2016 the majority of taxi operators drove over 20,000 miles [185] which corresponds to a daily mileage of 54.8 miles. The 2015 Nissan Leaf, a common EV used by taxi operators, has a battery capacity of 24kWh with an energy economy of 3.5 miles/kWh, therefore a Nissan Leaf taxi would require 15.7 kWh to drive 54.8 miles each day, this is approximately double the charging energy delivered in these simulated forecasts. This indicates that the taxi operators in this sample do not solely rely on the rapid DC chargers but also charge at home and use the rapid chargers as a 'top-up' while on duty.

Through the development of this case study the basic functionality of the HPC optimisation model with respect to charger allocation and grid capacity selection has been demonstrated. The second case study evaluates the incorporation of three different CHP systems, by considering any improvement or reduction in the NPV found in this

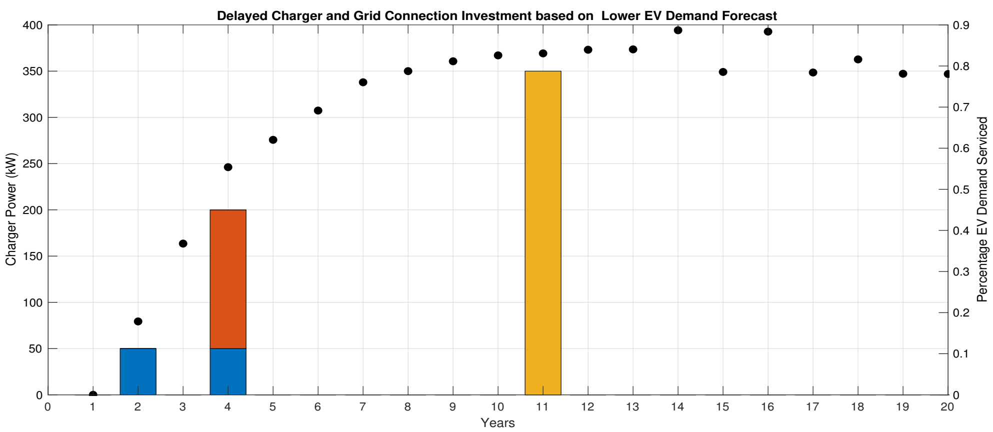


Figure 4.18: Charging infrastructure requirements and percentage of EV energy demand serviced for the low growth scenario, where a 20% demand reduction is applied to demonstrate the delayed investment decision.

first case study.

4.5 Case Study 2: Evaluation of CHP options

The integrated CHP assessment is conducted using the taxi charging power demand profiles from the high growth rate scenario in Figure 4.7, with generalised equipment costs applied from industry and manufacturer reports presented in Table 4.7. The aim of this case study is to demonstrate the ability of the charger infrastructure model to determine the preferred year to install a CHP system and the opportunity to evaluate the NPV for each of the CHP scenarios. This case study compares the performance of three different CHP options: a traditional fixed speed (FS) gas reciprocating engine, a variable speed (VS) gas reciprocating engine and a fuel cell (FC). This modelling approach may assist charging infrastructure developers in evaluating not only the viability of an integrated CHP and charging system but also the capital cost premium that may be applied to a variable speed gas reciprocating engine or a fuel cell which is interfaced with the DC bus of the charging system. This may be compared to a more conventional fixed speed gas reciprocating engine that is connected to the AC side of the HPC station - as illustrated in Fig 4.2

The decision to install a CHP system instead of, or in addition to, an electrical grid connection depends on the capital cost of the grid connection itself, the cost of electricity, the cost of natural gas, the capital cost of the CHP project, the price per unit of heat from the CHP plant and the efficiency of the CHP system at different part loading conditions. The same model parameters from Table 4.5 are kept constant within this CHP scenario but the additional parameters in Table 4.7 are incorporated. The charger infrastructure model is structured to evaluate one CHP option at a time, with the specific EHR and HPR values updated according to data presented in sections 4.3.5 to 4.3.7.

The gas reciprocating generator capex costs are taken from a U.S. Enivronmental Protection Agency (EPA) report [186] that presents a catalogue of CHP technical and cost parameters. In a practical context, it is likely that the equipment cost will vary

Table 4.6: Model assumptions for CHP system evaluation [186], [187].

Parameters	Values
Electrical power capacity	400kW
Plant cost: Fixed speed	£873,570
Plant cost: Variable speed	£873,570
Plant cost: Fuel cell	£950,000
Cost of gas	£0.04/kWh
Heat revenue	£0.05/kWh
Export revenue	£0.05/kWh
Export constraint	200kW
Carbon cost per kWh of gas consumed	£0.0043/kWh

between the CHP systems but the project development and integration costs are likely to remain similar. The electrical capacity of the CHP options under consideration have been restricted based on the availability of technical information for fuel cells, the largest fuel cell with sufficient publicly available technical specifications is the 400kW Doosan Purcell. Therefore the FS and VS gas reciprocating engines are specified based on a 400kW electrical output.

As outlined in [186] the CHP project costs amount to \$1049/kW installed (or £807/kW), which totals £322,800 for each 400kW system. The closest equipment cost estimate for a fixed speed 400kW gas reciprocating engine is £550,770 which generates a total project cost of £873,570. The same cost estimate is applied in both the fixed and variable speed cases due to limited experience and economic information on variable speed gas reciprocating engines. Although, it is acknowledge that additional power electronic equipment and associated costs will be necessary for the integration of a 400kW variable speed gas reciprocating engine to the DC charging bus of a HPC station. However, by examining the NPV for both the fixed and variable speed generator cases, the difference in value will provide an indication of the allowable cost premium for a variable speed generator compared to a traditional fixed speed system.

A detailed manufacturing study of proton exchange membrane (PEM) and solid oxid fuel cell (SOFC) systems is presented in [187]. This study provides manufacturing cost data for 100kW and 250kW systems at varying volumes of serial production. Although the technical performance parameters used in the fuel cell model are from a Doosan phosphoric acid fuel cell (PAFC) system, the cost estimates from the manufacturing study are the closest commercial estimates that could be obtain at the time of this study. The per kW equipment cost of a 250kW PEM system at a production volume of 1,000 units per year was estimated to be \$2040 (£1570). Using this estimate, an installed 400kW fuel cell system cost of £950,000 is applied to the model.

In all CHP system cases, the energy demand is electrically led and therefore it is assumed that waste heat is dissipated into a district heating network or building at a fixed price. Additional revenue may be generated by exporting power from the CHP system, through the grid connection point at a lower per unit value than the charging service. In reality, both the heat supply and local demand for electrical power may be constrained by additional demand profiles, however, these have been omitted in this study for simplicity within confines of the model requirements. The export of power from the CHP system requires the consideration of additional power converter losses for the variable speed and fuel cell systems, which are directly connected to the DC charging bus. These losses are taken into consideration within the charger infrastructure model by applying the HPC grid-tie converter efficiency to all CHP electrical power exported to the AC grid. Finally, a power export constraint is applied to the CHP systems, which may vary depending on local distribution system constraints and the associated cost of the export connection, in these simulations the power export is limited to 200kW.

4.5.1 Results: Evaluation of CHP Options

In this section, the HPC optimisation results from three different CHP solutions are presented. It is important to emphasise that this is not a detailed project feasibility assessment but instead a demonstration of the modelling approach developed as part of the work of this thesis that may be applied to specific case studies where detailed grid connection arrangements and equipment costs are understood. From Figures 4.19 to 4.21, the recommended charging infrastructure is presented for each of the CHP system options. Based on the cost assumptions and the linearised EHR and HPR metrics, the fuel cell solution offers the highest NPV out of the three options. If the capital cost is held constant at £873,570 for all three CHP options, the project NPV with an integrated FC is £296,000 higher than the FS option, this means a FC project can cost up to £296,000 more than a traditional gas reciprocating CHP system and still result in an equivalent NPV. This is due to the FC's superior electrical efficiency. However, in reality, the FC may possess higher operating costs compared to gas reciprocating systems and this should be factored into a project specific commercial model. The difference between the FC and gas reciprocating CHP systems is more pronounced when the electrical grid connection is removed from the model. This requires the CHP system to follow the EV charging demand profile and therefore the generators will experience longer durations of operation under part-loading, the results of this scenario are presented in Table 4.8, where the NPV difference between the FC and conventional FS gas reciprocating engine increases to £1,367,950 over the 20 year period.

To validate this case study, Figure 4.22-4.24 present the forecast EV charging demand and generation profiles over an average 24 hour period in years 5, 10, 15 and 20 of the project. These charts depict the EV forecast demand (dashed black line), the CHP electrical contribution to the EV charging system (dark blue area), the additional grid electrical contribution (orange area, stacked on top of the CHP electrical contribution), the CHP electrical exports (light blue line) and the CHP heat generation (dark orange line). From these charts, it is clear that the CHP electrical contribution and grid contribution do not exceed the EV charging electrical demand, as specified in the constraints.

The primary difference between the three CHP scenarios occurs in the first 5 years of the project, where the EV charging demand is low. In the FC scenario, the EV demand is met almost entirely from the FC system without electrical grid support due to its low EHR under part-loading compared to the FS and VS systems. In all cases, as the EV charging demand increases, the CHP electrical output first maximises its contribution to the charging bus and then exports the remainder.

In theory, the value of a VS and FC system compared to a FS gas reciprocating engine is their improved fuel efficiency under part loading conditions. However, this analysis demonstrates that the FS system has a higher NPV than the VS system when a electrical grid connection is available, this is for two reasons: the price applied to the

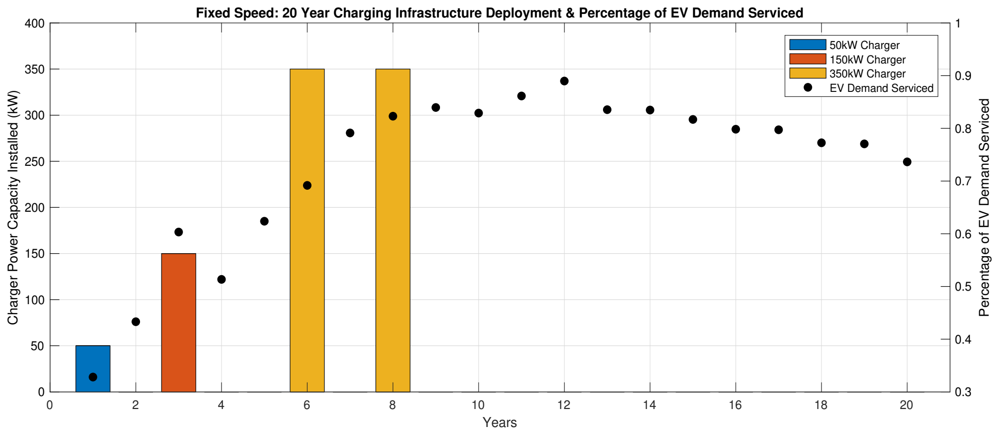


Figure 4.19: Charger infrastructure deployment and percentage of EV demand serviced for the Fixed Speed scenario.

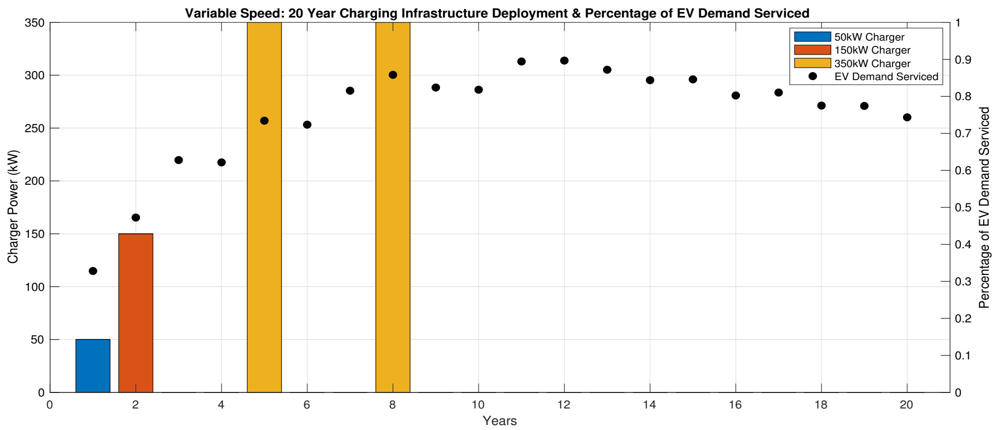


Figure 4.20: Charger infrastructure deployment and percentage of EV demand serviced for the Variable Speed Gas Reciprocating scenario.

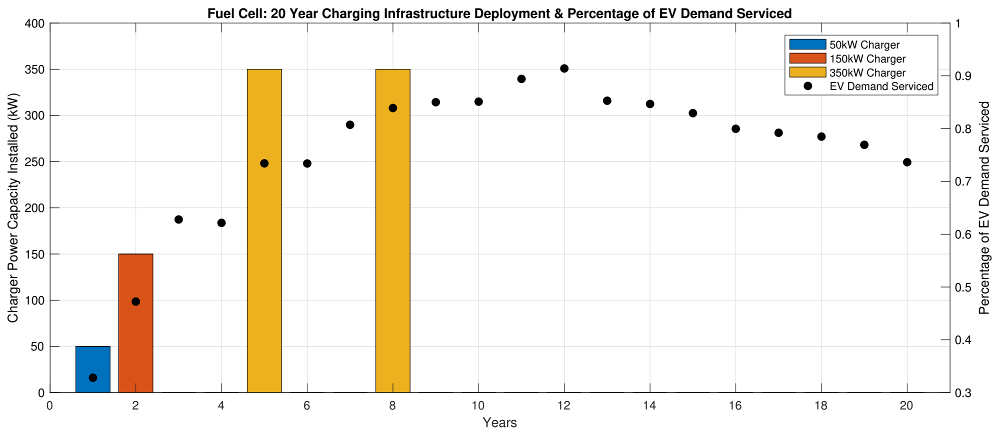


Figure 4.21: Charger infrastructure deployment and percentage of EV demand serviced for the Fuel Cell scenario.

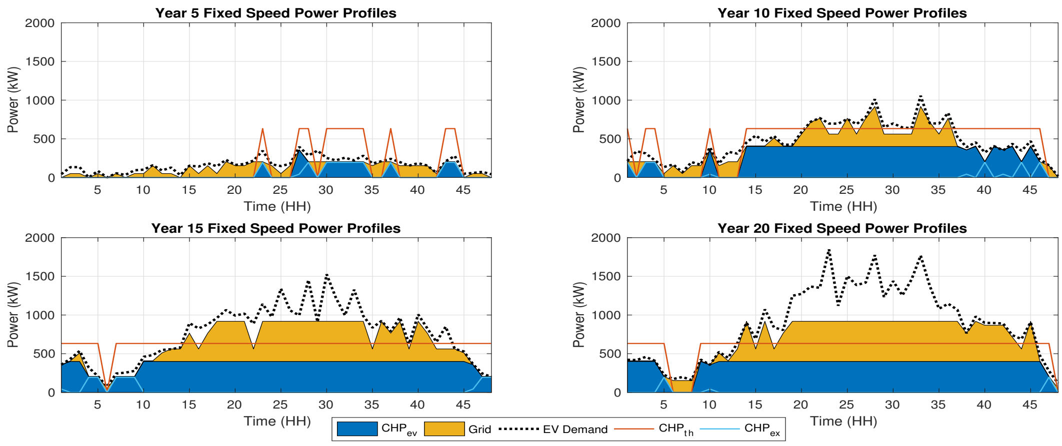


Figure 4.22: Daily power generation and EV demand profiles for years 5, 10, 15 and 20 with a fixed speed gas reciprocating CHP system.

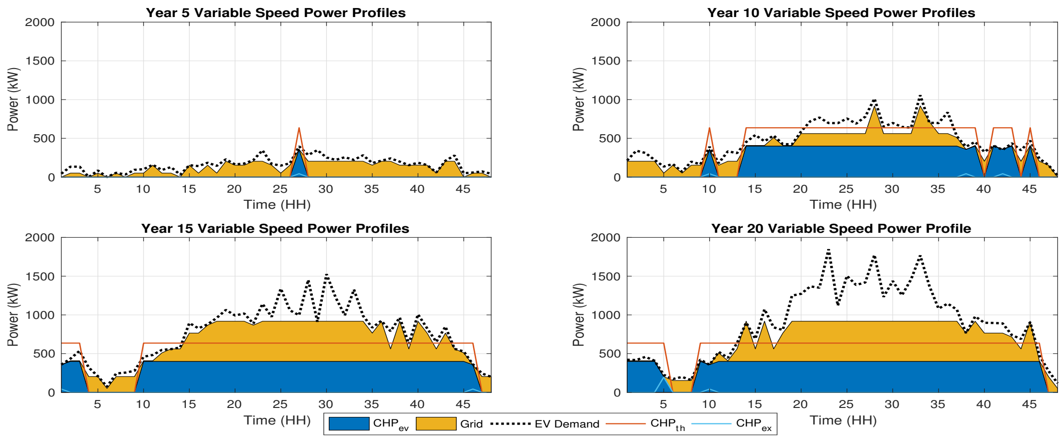


Figure 4.23: Daily power generation and EV demand profiles for years 5, 10, 15 and 20 with a variable speed gas reciprocating CHP system.

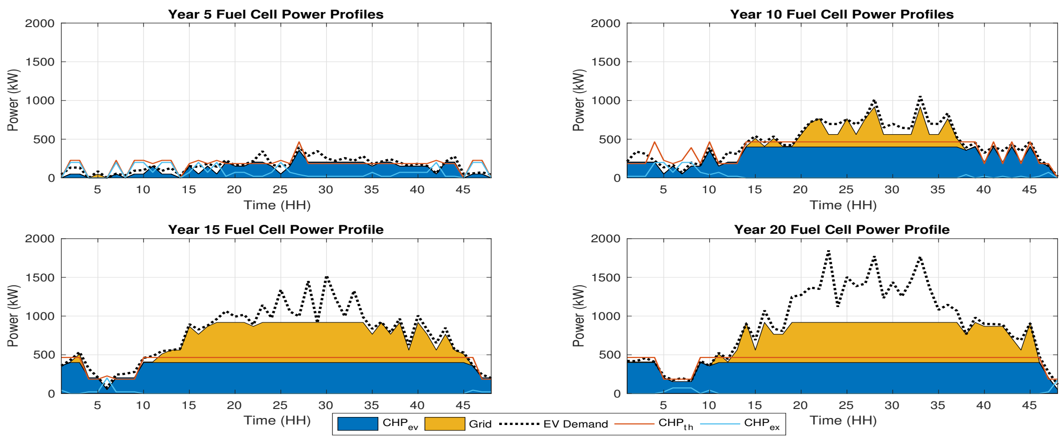


Figure 4.24: Daily power generation and EV demand profiles for years 5, 10, 15 and 20 with a fuel cell CHP system.

'waste' heat means that a less electrically efficient CHP system can generate additional waste heat and associated revenue; and the model optimises the generating periods for the CHP systems based on the available EV demand (thus minimising the periods spent operating in an inefficient part-loading region). Therefore a different set of results is obtained if the price of heat is reduced and the electrical grid connection is removed. Table 4.8 presents the results based on stand alone CHP systems without an electrical grid connection.

In this stand alone operational scenario, the VS CHP option results in a higher NPV than the FS, with a price premium of approximately £134,000 compared to a FS CHP system. In both cases, the CHP and charging infrastructure investment is delayed to year 3 due to the low EV charging demand in the early years of the forecast. Whereas, due to the fuel cell system's higher electrical efficiency under a lower charging demand, the fuel cell and charging infrastructure are deployed from year 1.

The fuel cell energy generation profiles are presented in Figure 4.25, where the FS and VS systems follow similar profiles but with higher gas consumption due to longer periods under part-loading conditions. The charging infrastructure assessment charts for all three stand alone CHP options are presented in Figure 4.26 to 4.28, which demonstrates the delayed charging infrastructure deployment in the VS and FS cases due their higher operating costs at lower charging demand levels.

4.5.2 Discussion: Evaluation of CHP Options

This second case study has considered the co-location of CHP systems with a HPC station. The study has demonstrated that the HPC optimisation model developed in this thesis can incorporate on-site generating assets and determine in what scenarios they present an appropriate alternative to a standard electrical grid connection. This work may be extended to consider not only CHP systems but also the sizing of co-located battery storage at HPC stations to maximise the NPV for the charging infrastructure developer.

Although this analysis indicates a positive economic case for all three CHP options (with and without an electrical grid connection), the fuel cell CHP scenario offers

Table 4.7: Results of Grid Connected CHP System Trials.

Scenarios	NPV
VS original parameters	£2,163,200
FS original parameters	£2,213,000
FC original parameters	£2,458,700
FC capex equal to VS & FS	£2,509,000
Cost of gas	£0.04/kWh
Heat revenue	£0.05/kWh
Export revenue	£0.05/kWh
Export constraint	200kW
Carbon cost per kWh of gas consumed	£0.0043/kWh

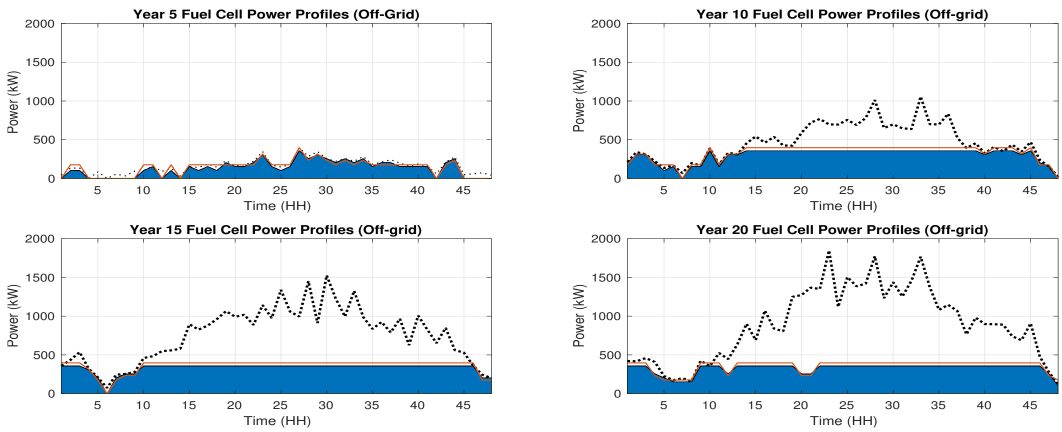


Figure 4.25: Daily fuel cell power generation and EV demand profile for years 5, 10, 15 and 20. This scenario considers only the CHP option, without an electrical grid connection.

greater financial value compared to the gas reciprocating options and should be considered in an integrated charging project, where a direct connection to the DC charging bus reduces the electrical conversion losses. However, the application of a variable speed gas reciprocating engine, interfaced to the DC bus of the charging network is not a clear decision. The value of a variable speed engine compared to a fix speed engine depends on the grid export and thermal revenue in each scenario as well as the defined part-loading characteristics for the engines.

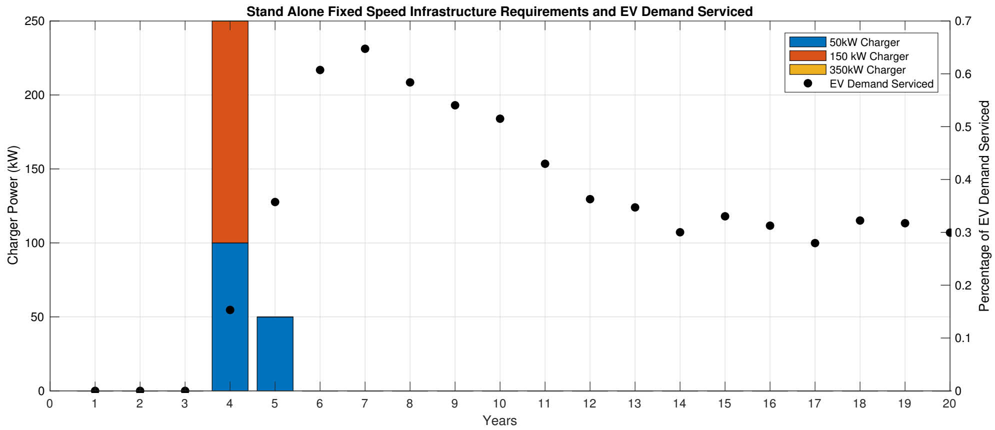


Figure 4.26: Charger infrastructure deployment and percentage of EV demand serviced for the stand alone Fixed Speed scenario.

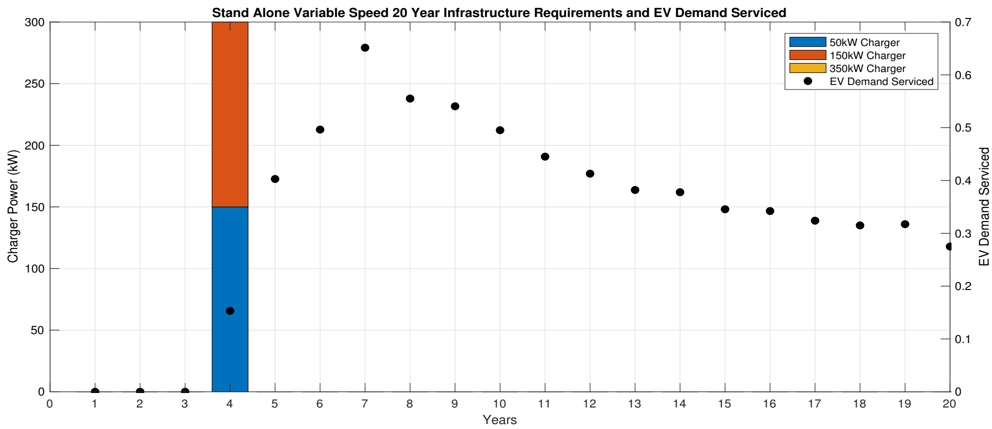


Figure 4.27: Charger infrastructure deployment and percentage of EV demand serviced for the stand alone Variable Speed Gas Reciprocating scenario.

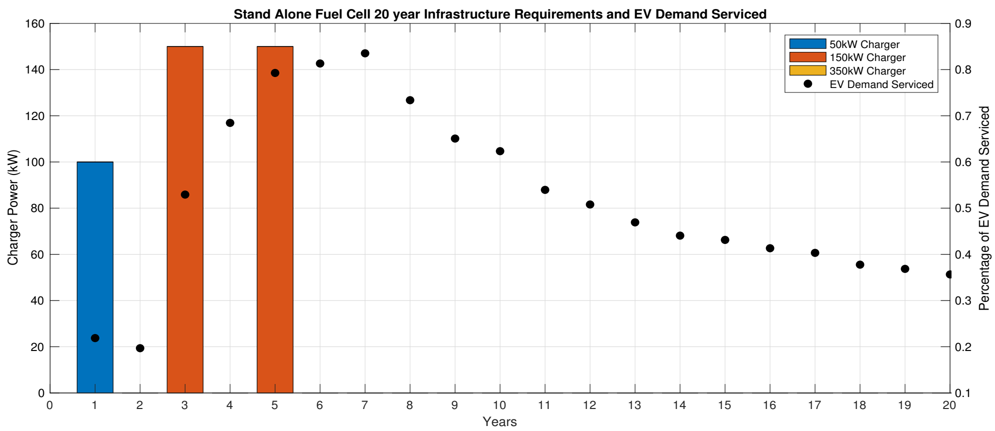


Figure 4.28: Charger infrastructure deployment and percentage of EV demand serviced for the stand alone Fuel Cell scenario.

Table 4.8: Results of Stand Alone CHP System Trials.

Scenarios	NPV
Stand alone VS	£444,270
Stand alone FS	£310,350
Stand alone FC	£1,595,900
FC capex equal to VS & FS	£1,678,900
Cost of gas	£0.04/kWh
Carbon cost per kWh of gas consumed	£0.0043/kWh

4.6 Chapter Summary

The work of this chapter has provided an infrastructure optimisation model that may be applied to the evaluation of HPC system infrastructure options. Specifically, the integration of gas and electricity networks offers a three-fold opportunity: a reduction in electrical grid connection requirements, a source of low carbon heat and the potential for enhanced energy system resiliency. A planning model such as this can support municipal planners and commercial charging system developers in identifying the optimum energy sources and infrastructure requirements for any desired charging location.

The use of a LVDC charging bus for a HPC system is a natural choice, as the charging voltage must be tailored to suit different EV battery requirements and to enable the delivery of high power charging services. However, the use of a LVDC distribution system in this case also allows for the integration of 'native' DC distributed generation such as fuel cells, stationary battery storage and the connection of variable speed gas reciprocating generators. Each of these power system assets can interface with the LVDC charging network through a more energy efficient and less complex electrical connection.

The developed HPC optimisation approach successfully provides the capability for the comparison of CHP systems as well as stand alone chargers and several electrical grid connection options simultaneously. The model converts non-linear efficiency curves to linear efficiency regions using the Douglas Peucker algorithm, enabling the model to consider the part-loading characteristics of CHP systems and power converters. From the case studies presented in this chapter, it is clear that the EV charging demand forecast is the primary input to the model, from which the infrastructure requirements are assessed. The incorporation of a CHP system improves the project's NPV by reducing the size of the electrical grid connection that is required to support the allocated HPC chargers and it offers an additional revenue opportunity through the sale of waste heat. The higher electrical efficiency of the fuel cell CHP option offers the highest NPV in the modelled case studies and in practice the charger infrastructure model developed in this chapter can be used to determine the acceptable cost premium of each generating asset against a base case scenario.

Although the investment period considered in this analysis is over 20 years, in reality it is likely that the power electronic converters within the EV charging units will require replacement before year 15, which is in line with current solar PV inverters [188]. Therefore, future iterations of this planning tool should incorporate a component lifetime variable within the optimisation problem to reflect replacement costs during the overall investment period. A replacement cost variable would increase the overall infrastructure costs during the investment period and may delay the recommended installation year for chargers or reduce the number of deployed chargers to ensure a higher utilisation.

Finally, in a practical context the recognised charging rates associated with a 350kW charger will likely have an adverse impact on the battery state of health and overall useful lifetime of the battery pack [151]. Further research and development work is required to produce batteries that are better suited to higher charging rates [152]. In addition, careful control of the charging process will likely include reduced power charging as battery state of charge increases and monitoring of battery temperature during the charging process. Future modelling and planning of HPC infrastructure should therefore consider lower grid capacity connections as it is unlikely that a collection of several chargers will all require their peak power demand at the same time.

The next chapter considers the case of long duration charging and addresses the need for optimised charging schedules, user interfaces and principles of access for a reconfigurable LVDC charging network.

Chapter 5

Long Duration EV Charging

As an alternative to the high power charging systems discussed in the previous chapter, a long duration charging service may be appropriate when EV users are parked for an extended period of time. This thesis describes the difference between short duration and long duration charging as those EVs that require an immediate charge within a 30 minute period and those that do not. This time period is the same length as a trading block in the balance and settlement market for the UK power system. Therefore a high power charge is likely to be required to deliver a short duration charging service, but for EV users that can wait for multiple 30 minute periods, an optimised charging solution can be provided that considers electricity pricing and wider power system constraints.

This chapter considers long duration charging scenarios, it proposes a LVDC reconfigurable charging network for plug-in electric vehicles and presents a functional EMS that is capable of planning and operating the charging network to minimise charging cost and to facilitate progressive infrastructure deployment based on EV demand. The charging network considered is connected to the main AC grid through one or more centralised AC/DC converters that supply power to EVs connected to the DC side of the converters.

The EMS is taken to accommodate multiple parking bays, charging sources, AC constraints, non-linear EV battery loads and user charging requirements with a novel approach to managing user inconvenience. An inconvenience model is presented to account for 'human' effects related to the presence of user flexibility i.e., an allowance on charging time or battery SOC, providing the capability to increase asset utilisation and enable access for additional network users. Through a series of case studies, the reconfigurable network and EMS demonstrate the capacity to achieve savings over fixed AC and sequential DC charging systems.

This chapter is structured as follows. Section 5.1 introduces the differences between a 'fixed' LVDC charging network and a 'reconfigurable' charging network. Section 5.2 provides an overview of the prominent EV charging configurations for long-duration charging solutions and the advantages that a reconfigurable DC charging network can offer. Section 5.3 presents the formulation of an EMS for the reconfigurable network with a representation of user charging inconvenience. Section 5.4 introduces a series of case studies in which the control strategy and reconfigurable charging network are evaluated.

5.1 Fixed DC Charging Network Limitations

This thesis has contributed towards the growing body of research that identifies LVDC charging networks (400-1500 Vdc) for PEVs as offering improved renewable energy integration by using fewer power conversion stages, enhanced network controllability due to the absence of reactive power and higher power charging compared to the existing AC charging solutions [27], [26], [189], [190]. However, the implementation of such charging networks are likely to require the use of DC/DC converters at each parking bay to control the charging power flow and voltage for each vehicle. This adds an additional cost to enable charging for each parking bay and can introduce voltage stability challenges that would need to be addressed in the design and operation. Furthermore, a centralized AC/DC converter, connecting the EV charging network to the wider AC grid, and associated distribution cables will be over sized to match the simultaneous demand from multiple vehicles. Such DC charging networks will operate well as high power chargers in locations with frequent vehicle turnover such as dedicated charging stations in urban or motorway environments [149]. But, under low utilization rates, a centralised converter will operate under part-load with lower power conversion efficiencies and the oversized, fixed cable, will result in higher implementation costs [191].

In this thesis a LVDC charging network that does not require DC/DC converters at each parking bay is considered for longer duration EV charging scenarios such as work place, urban and residential overnight charging. This takes advantage of the rapid start-up and shut-down properties of existing fast DC chargers [192] to reconfigure the charging network in a de-energized state. Power is routed to connected vehicles according to an optimised EMS solution. The EMS model considered in this thesis includes constraints related to single charger to EV pairings that are capable of varying power output over time, charging characteristics of lithium ion batteries and a temporal transformer loading constraint. User inconvenience is defined and presented as a service selection matrix, enabling the user to choose between desired SOC level, parking time and cost to charge, which reflects the anticipated constraints on the charging network at any moment in time. Like the work of Chapter 4, this is formulated as a MILP problem. The reconfigurable network is compared to the fixed DC charging networks discussed in prior literature and the AC charging systems currently being deployed. The solving speed and associated infrastructure costs for each solution are considered, which leads to a charging infrastructure deployment philosophy for long duration charging locations, that can be summarised as follows:

1. Deploy minimal infrastructure (i.e. one charger and many plug-in points, controlled by this proposed reconfigurable network model),

2. Monitor utilisation of charger,

3. Exploit user flexibility to maximise energy delivery based on the proposed user inconvenience model (this approach allows the user to choose from several service options based on their own flexibility in advance of charging commencing),

4. Deploy additional chargers when the level of user inconvenience is unacceptable,

5. Upgrade public electrical network assets when charging demand is frequently curtailed.

Overall, this approach, as proposed by the work of this thesis, challenges the conventional, low-power AC charging systems that are deployed in parking areas for long duration charging by demonstrating the modularity, operation and economy of a reconfigurable LVDC charging network. Although, with optimised LVDC charging infrastructure comes the issue of user inconvenience i.e. the ability of the network to reliably service the charging requirements of users as utilisation increases. The cost penalty frequently applied in other charging coordination problems to represent unmet charging requirements does not clearly capture user preference and flexibility therefore an alternative approach is also proposed [141], [144], [193].

5.2 Long Duration EV Charging Networks

An illustration of the standard AC charging network layout for parking areas and the fixed LVDC charging systems that have been discussed in prior literature [27], [26] is shown in Figure 5.1. Both the cables in each case and the converter in the LVDC case are sized to meet the peak charging demand when all EV charging spaces are occupied; this results in an over designed network when occupancy of charging points is less than 100%. This chapter proposes a reconfigurable DC charging network that can be considered a hybrid solution between the existing AC charging systems and the fixed LVDC charging network presented in Chapter 4. The concept of long-duration charging is determined by user expectations and parking requirements, the locational scenarios considered in this chapter are: residential over-night charging, at work charging and urban parking areas where the EV user is not expecting an immediate charging service but instead a flexible service can be offered to meet user charging requirements within electrical network constraints. This thesis contends that long-duration charging scenarios can possess greater flexibility by incorporating centralised, higher power rated chargers that can deliver an immediate charge to users if requested but can also accommodate the charging requirements of several EVs over an extended period of time according to an optimised charging schedule.

The classification of EV charging infrastructure used in this chapter is outlined

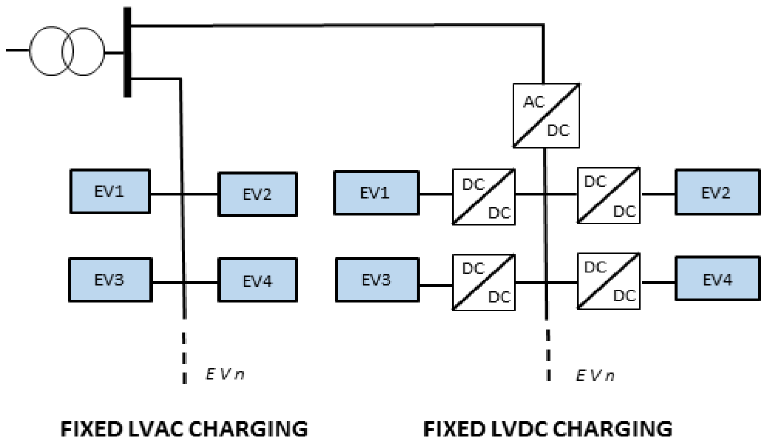


Figure 5.1: Comparison between fixed AC and DC charging networks.

in [194] and was previosly introduced in Chapter 2. Existing parking area charging systems generally use Mode-1 & 2 AC charging that provide up to 32A single phase current. They connect directly to the AC low voltage network with a dedicated charge controller and protection. This system is perceived to be simple and cost effective. Most EVs have an AC charging capability, although their charging speed is limited. The fixed LVDC charging network utilizes DC/DC converters at each parking bay to control the charging process from a centralized AC/DC converter.

This proposed reconfigurable charging network topology relies on a standard fast DC charger that is networked to parking bays with controllable switches at each bay as shown in Figure 5.2. A network control algorithm collects EV data and optimizes the charging sequence based on user requirements and overall cost of energy delivered. This system reduces costs and increases asset utilization compared to existing charging solutions. Practical applications include: phased infrastructure deployment for public parking areas, the conversion of existing street-lighting networks to integrated DC charging [93] and multi-plexing of existing rapid DC chargers with high demand [195].

As EV ownership rises, it may be necessary to increase the size of the charging network and upgrade grid assets such as the distribution transformer. As the network scales, a design trade-off occurs between available computational power to solve the optimization problem and the physical size of the charging network. In larger parking

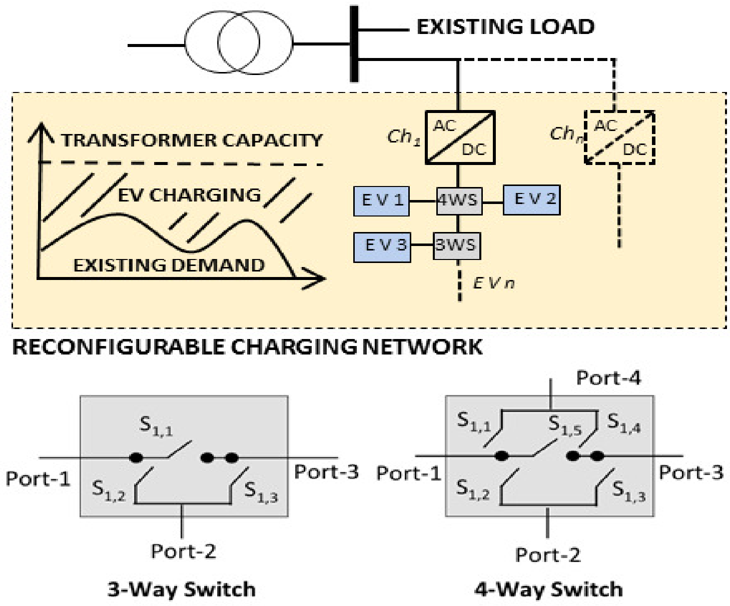


Figure 5.2: Reconfigurable network, interfaced with secondary transformer and proposed switching configuration.

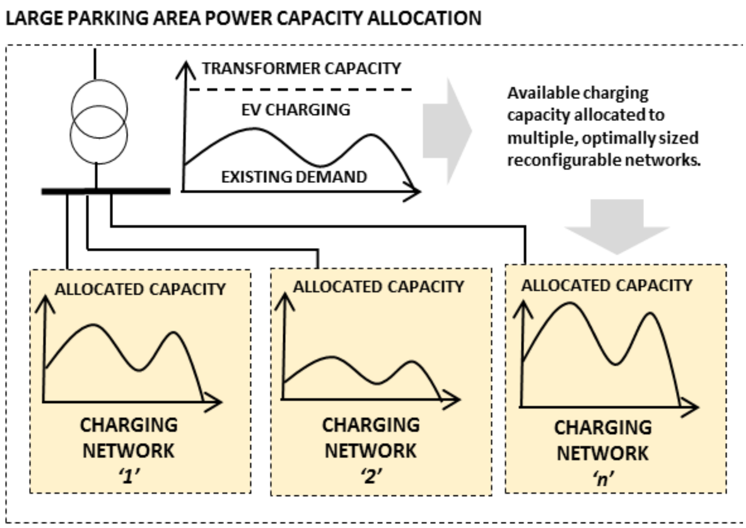


Figure 5.3: Heuristic allocation of transformer capacity for large parking areas.

area scenarios (50+ parking-bays), it may therefore be necessary to create multiple sub-charging networks with their own allocated power capacity profile from the shared transformer. The coordinated allocation of power capacity can be achieved using a number of formal heuristic methods as indicated in Figure 5.3.

The reconfigurable aspect of this charging network circumvents some of the technical and standard limitations associated with DC distribution systems which are summarized in Chapter 2 [13]. For example with the topology, fully depicted in Figure 5.4, there is no requirement to interrupt DC current since the network is reconfigured offload and the instability challenges associated with constant power loads is mitigated as only one EV is charged from a dedicated source at any moment in time [23], [196]. Furthermore, in a reconfigurable network, the cables are sized for the maximum power of a single charger and not for the peak output power of multiple chargers, as is the case in a fixed LVDC charging network or standard AC network. A variety of existing switches and communication systems are commercially available which can be employed to operate the reconfigurable network. However, a failed switch could potentially block charging of other connected vehicles located beyond the point of failure unless specific provision is made to account for such a situation. Therefore, if the central switch ($S_{1,3}$ and $S_{1,5}$ in the reconfigurable diagram of Figure 5.2) should fail closed and the remaining switches open, to allow charging access to parking bays beyond the failed switch and therefore the continued supply of charging services beyond the failure point.

With existing EV charging schemes not extending beyond 100 parking bays at the upper end [197], this reconfigurable DC charging network considered in this thesis (covering up to 50 EV's) is suitable to current practical deployments but it could also be replicated many times over to accommodate future, larger parking areas without adversely affecting the solving speed of the EMS. In this case a zonal approach to charging is envisaged that would help manage the demand in line with the available capacity of secondary distribution transformers by allocating a portion of the available power capacity to each of the reconfigurable charging zones (as illustrated in Figure 5.3).

Regardless of the parking area size, to effectively operate a reconfigurable DC net-

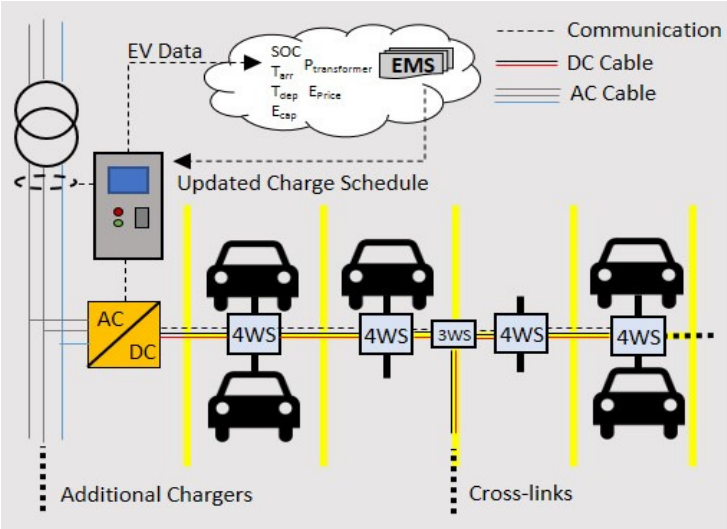


Figure 5.4: Overview of a reconfigurable DC charging network.

work (Figure 5.4) requires an EMS solution that can optimally manage the interaction between the chargers and EVs according to user requirements and within specified system constraints. The mathematical model of the EMS developed in this thesis is described. Here the EMS performs network reconfiguration, charger power level selection and manages user inconvenience.

5.3 Modelling & Control of a Reconfigurable DC Network

The technical challenge relates to the wide and varied EMS-based solutions but it must comply with the resultant constraints (e.g. EV and charger switching requirements). The following section introduces the problem formulation for the EMS. This is defined in three parts, firstly the governing equations that captures the 'switching' of EV charging and associated grid constraints. Secondly, a specific modelling component related to the development of temporal allocation of power from EVs. Together these two problems can be formulated as a binary MILP. This optimization approach readily enables the consideration of discrete switching actions, which are essential to the operation of a reconfigurable network, and could not otherwise be modelled efficiently in linear programming or non-linear programming problems. Lastly, the user inconvenience model that is intrinsic to the work of this thesis is developed. This is solved in line with the outputs of the MILP.

5.3.1 EV-Charger Switched Model

The task of the EMS is to identify the optimum scheduling pattern between chargers and EVs that minimises the charging costs according to the system constraints. The following sections detail the modelling approach, which has been structured as a MILP problem that can be solved using the branch-and-bound method within Matlab or other commercial solvers [198]. The MILP problem may be applied as either a network planning tool — to determine the minimum charging infrastructure requirements that will satisfy EV user demands — and as a near real-time energy management system. The EMS operates in near real time in the sense that each schedule update is completed within the stated time step.

The model is formulated to determine the optimal switching sequence for minimizing the total energy cost. Let $u_{i,k}(t) \in [0, 1]$ denote the binary control state for ith EV and kth charger pair over time interval t. The objective function is expressed as;
Problem P1 (Whole Optimisation Model),

$$J = \min_{u_{i,k}(t)} \sum_{t \in \Omega_{\mathrm{T}}} \sum_{i \in \Omega_{\mathrm{N}}} \sum_{k \in \Omega_{\mathrm{M}}} P_{i,k}(t) u_{i,k}(t) C^{\mathrm{e}}(t) \Delta t, \tag{5.1}$$

where $P_{i,k}(t)$ is the power flow from ith EV to kth charger over time interval t, $u_{i,k}(t)$ is the binary variable representing the control state from the ith EV and kth charger over the time interval, and $C^{\mathrm{e}}(t)$ is the cost of energy over the time interval. This is subject to the following constraints:

Exclusive EV charging

A charger is only allowed to charge one EV at a time,

$$\sum_{i \in \Omega_{\mathrm{N}}} u_{i,k}(t) \leq 1, \ \forall k, \forall t; \tag{5.2}$$

and an EV must only receive power from single charger at a time,

$$\sum_{k\in\Omega_{\mathrm{M}}} u_{i,k}(t) \leq 1,\ \forall i, \forall t. \tag{5.3}$$

Temporal Grid Capacity

Over each time interval, the total power consumed by the charging network must not exceed available grid capacity,

$$\sum_{i\in\Omega_{\mathrm{N}}}\sum_{k\in\Omega_{\mathrm{M}}} P_{i,k}(t)u_{i,k}(t) \leq P_{\mathrm{net}}^{\max}(t),\ \forall t. \tag{5.4}$$

Energy Requirement

The energy supplied over the charging period must be equal to the energy required by the EV,

$$\eta_i \sum_{t\in\Omega_{\mathrm{T}}}\sum_{k\in\Omega_{\mathrm{M}}} P_{i,k}(t)u_{i,k}(t)\Delta t = E_i,\ \forall i, \tag{5.5}$$

$$E_i = (\mathrm{S}_i^{\mathrm{fin}} - \mathrm{S}_i^{\mathrm{ini}}). \tag{5.6}$$

Where $\mathrm{S}_i^{\mathrm{fin}}$ and $\mathrm{S}_i^{\mathrm{ini}}$ are the final and initial SOC of the ith EV at time $t = \Delta t$. The SOC of each EV accumulates over time,

$$S_i(t) = S_i(0) + \eta_i \sum_{\tau\in\Omega_t}\sum_{k\in\Omega_{\mathrm{M}}} P_{i,k}(\tau)u_{i,k}(\tau)\Delta t,\ \forall i, \tag{5.7}$$

where $\Omega_t = [0, t)$ and η_i is the charger efficiency.

$$S_i^{\min} \leq S_i(t) \leq S_i^{\max},\ \forall i, \forall t. \tag{5.8}$$

The formulation, (5.1)–(5.8), represents EV-charger switching control in terms of linear functions of variable $u_{i,k}(t)$, forming a MILP problem. Next, a dynamic model to control power output and allocate charging intervals is introduced within the same MILP structure.

5.3.2 Power Control and Interval Allocation

The charging system must be able to determine appropriate power outputs given a multitude of network configurations and charging requirements. EV-charger switch control and power level states are linked as follows:

$$u_{i,k}(t) = \sum_{\phi \in \Omega_{\mathrm{L}}} u^{\phi}_{i,k}(t)\mu_i(t), \tag{5.9}$$

$$\sum_{\phi \in \Omega_{\mathrm{L}}} u^{\phi}_{i,k}(t) = 1, \tag{5.10}$$

each EV is available to charge during the interval between its times of arrival and departure,

$$\mu_i(t) = \begin{cases} 1, & t^{\mathrm{a}}_i < t < t^{\mathrm{d}}_i; \\ 0, & \text{otherwise.} \end{cases} \tag{5.11}$$

For every $u^{\phi}_{i,k}(t)$, there is a corresponding power level, $P^{\phi}_{i,k}$. Therefore,

$$P_{i,k}(t)u_{i,k}(t) = \sum_{\phi \in \Omega_{\mathrm{L}}} P^{\phi}_{i,k} u^{\phi}_{i,k}(t)\mu_i(t). \tag{5.12}$$

The charging profile for lithium ion batteries is adapted from typical characteristics to make it suitable for the MILP formulation [154], [199]. The typical and stair-step charging profiles are shown in Figure 5.5, thus

$$P_{i,k}(t) = \begin{cases} P^{\mathrm{rat}}_k, & \mathrm{S}^{\mathrm{fin}}_i \geq \mathrm{S}_i(t); \\ \frac{P^{\mathrm{rat}}_k (100 - \mathrm{S}_i(t)/E^{\mathrm{cap}})}{(100 - \mathrm{S}^1_i/E^{\mathrm{cap}})}, & \text{otherwise.} \end{cases} \tag{5.13}$$

$$S^{(ln)}_i \leq S_i(t) \leq S^{(un)}_i, \tag{5.14}$$

where $P_{i,k}(t) \leq P^1_{i,k}$ if $S^{(l1)}_i \leq S_i(t) \leq S^{(u1)}_i$,
$P_{i,k}(t) \leq P^2_{i,k}$ if $S^{(l2)}_i \leq S_i(t) \leq S^{(u2)}_i$ and so forth.

In summary, the problem formulation, (5.1)–(5.14), describes a MILP model to optimise switching links between EVs and chargers with varying power supply. The

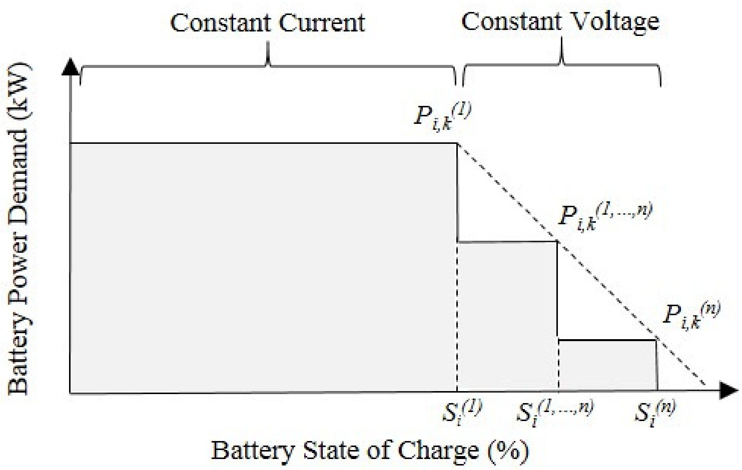


Figure 5.5: Stair-step charging profile approximation.

optimisation model is perfectly suited to reconfigurable networks such as the network illustrated in Figure 5.4. However, given some user inputs or congested networks a feasible solution may not exist. In this case, the output of the optimisation routine will be"infeasible", even though it may be possible to amend the user's requirements. The following section extends the above model to effectively characterise flexible users.

5.3.3 Managing User Inconvenience

There will be occasions when the charging network cannot deliver the preferred charging service for the joining EV user due to a congested charging schedule or constraints on the AC distribution network. This represents a user inconvenience scenario as the user cannot receive their desired SOC level within their parking time. Previous EV charging coordination papers propose a cost penalty to the CPO for failing to meet the user's desired SOC before the user departs the charging network [154], [200]. This penalty approach enables the EMS to identify the least cost charging schedule for the group of EVs by inconveniencing some users and penalizing the CPO for doing so. However, in a practical charging context, the proposed EMS in this thesis can provide the user with an upfront charging service selection that guarantees a specific service in advance of charging.

The flow chart in Figure 5.6 demonstrates that a selection matrix is composed of m

SOC levels and n parking times. The EMS generates $m \times n$ optimisation results based on the joining EV parameters and a 'rolling-schedule' for the network which includes the temporal transformer loading and utilisation of each charger. Each instance within the rolling-schedule relies on the solution to the following problem.

In the formulation, the notation x' denotes variables for the new EV arrival.

Problem P2 (User Inconvenience Model).

$$\min_{u'_k(t)} \sum_{t\in\Omega_{\mathrm{T}}} \sum_{k\in\Omega_{\mathrm{M}}} P'_k(t)u'_k(t)C^{\mathrm{e}}(t)\Delta t + J, \tag{5.15}$$

subject to

$$u'_k(t) \leq 1 - \sum_{i\in\Omega_{\mathrm{N}}} u_{i,k}(t),\ \forall k, \forall t, \tag{5.16}$$

$$\sum_{k\in\Omega_{\mathrm{M}}} u'_k(t) \leq 1 - \sum_{k\in\Omega_{\mathrm{M}}} u_{i,k}(t),\ \forall i, \forall t, \tag{5.17}$$

$$\sum_{k\in\Omega_{\mathrm{M}}} P'_k(t)u'_k(t) \leq P^{\max}_{\mathrm{net}}(t) - \sum_{i\in\Omega_{\mathrm{N}}} \sum_{k\in\Omega_{\mathrm{M}}} P_{i,k}(t)u_{i,k}(t),\ \forall t, \tag{5.18}$$

$$\eta' \sum_{t\in\Omega_{\mathrm{T}}} \sum_{k\in\Omega_{\mathrm{M}}} P'_k(t)u'_k(t)\Delta t = E', \tag{5.19}$$

$$S'(t) = S'(0) + \eta' \sum_{\tau\in\Omega_t} \sum_{k\in\Omega_{\mathrm{M}}} P'_k(\tau)u'_k(\tau)\Delta t. \tag{5.20}$$

Note that the dimension of Problem P2 is smaller than that of the whole optimisation model (Problem P1) because it determines the potential charging schedule for the latest EV to join the network rather than the entire network simultaneously. The rolling-schedule is updated every time step with an optimisation of the whole system (Problem P1), which takes into consideration both the newly arrived EVs and any EVs that have departed before their scheduled charge has completed. However, as the utilization of the charging network increases, with the diffusion of EV ownership, there will be occasions when even the user selection matrix cannot offer all services due to congestion caused by a limited number of centralized DC chargers or a power constraint on the secondary distribution transformer. If this scenario arises frequently, it

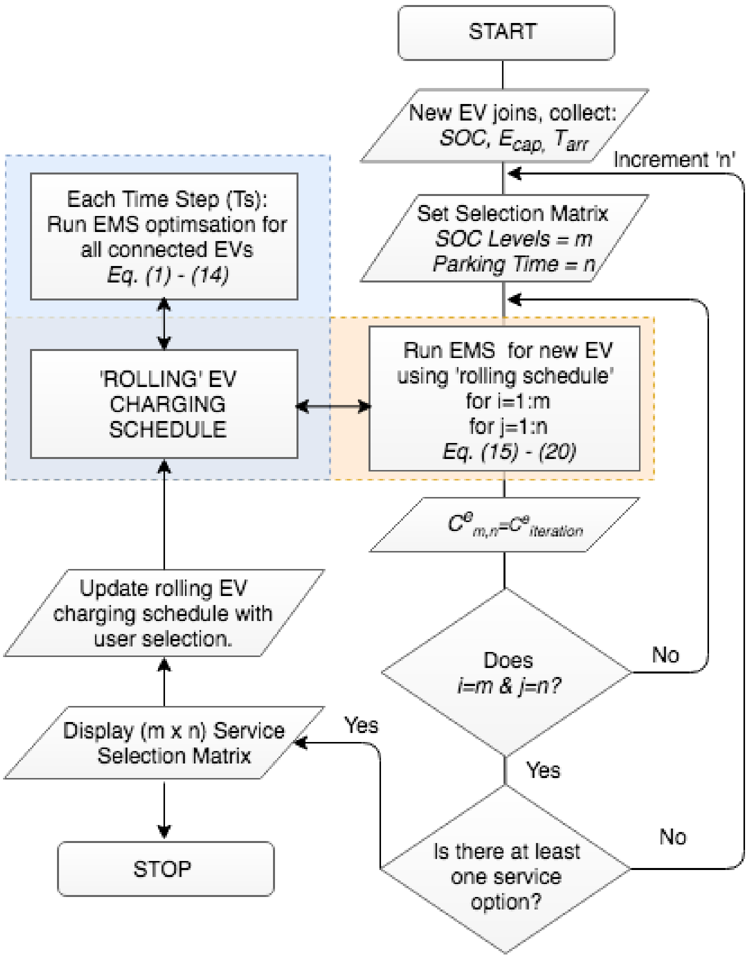


Figure 5.6: Generation of the rolling-schedule and service selection matrix to manage user inconvenience.

is an indication to the charging network operator that it is time to install an additional DC charger or to issue a request to the Distribution Network Operator to increase transformer capacity.

5.3.4 Economic Analysis

To enable the feasibility of a reconfigurable DC charging network to be compared to the standard AC charging systems that are currently being installed for long-duration charging solutions, an assessment of net present value (NPV) for each investment is considered:

$$NPV(j, N) = \sum_{y=0}^{N} \frac{R_y}{(1+j)^y}. \tag{5.21}$$

As outlined in (5.21), the NPV is composed of: the net annual revenue which is the product of the charging price and energy delivered to EVs minus the annual cost of energy to service the EV charging demand (R_y); the investment discount rate (j); the time period in which revenue is generated (y); and the total number of periods in which the investment is evaluated (N). This analysis does not take into account annual servicing and administration costs or installation costs, it is assumed that these costs will be similar in both cases.

The economic model and preceding optimisation model are applied to the planning and operation of EV charging networks in the next section.

5.4 Reconfigurable LVDC Case Studies & Simulations

The performance of the developed EMS is assessed as both a network-planning tool and as a near real time network controller. In both applications, three practical deployment environments are simulated in which a reconfigurable LVDC charging network may prove beneficial. These include work place parking, urban parking lots and residential overnight parking. These cases were identified as the most appropriate charging locations in an expansive study of electric vehicle ownership and user habits in the United States [132].

5.4.1 EV Charging Network Case Study Parameters

To test the EMS it is necessary to develop a set of input parameters that simulate the expected arrival/departure times of vehicles at each location and the associated SOC for each EV, these are outlined in Table 5.1 based on similar approaches from [94] and [199]. The rapid DC charging data from Chapter 3 is not appropriate to use in these case studies, as the chargers in the Charge Place Scotland Network are predominantly used for short-duration charging. In fact, of the charging events in 2017, 65% were less than 30 minutes and 93% were less than 60 minutes. The case studies presented in this

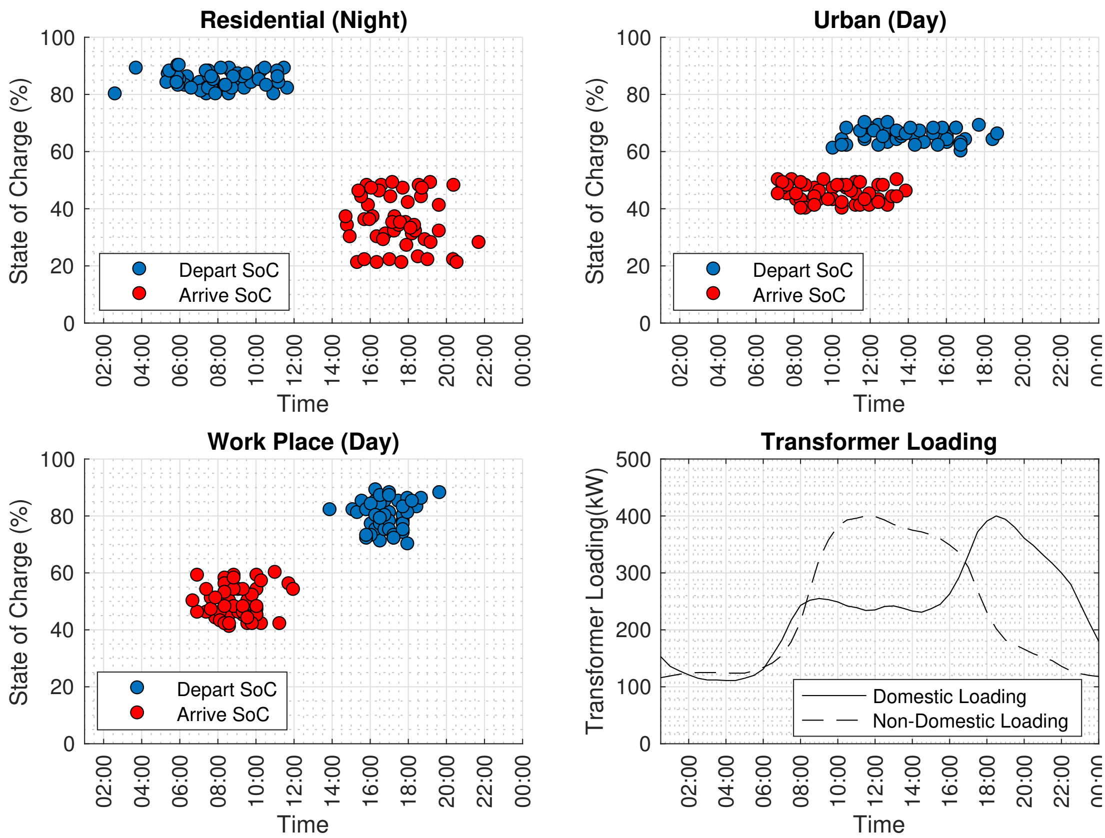


Figure 5.7: Arrival time, departure time and state of charge probability distributions for each case study location.

chapter use the same power rating of DC charger as that used in the CPS network, however it is intelligently managed to schedule charging to EV users that may be parked for several hours. Therefore the arrival times and energy consumption of these users will be different than the data reported in Chapter 3.

Further to the EV arrival and SOC data, realistic secondary distribution transformer loading profiles and TOU pricing are required to simulate real-life constraints on the charging network. In each charging location, a set of 50 EV charging parameters are generated, as depicted in Figure 5.7. From this set of 50 parameters, each simulation randomly selects a subset of EVs as the input parameters for the EMS.

In practical deployment scenarios, it is likely that the charging network will connect to an existing secondary distribution transformer and therefore the EMS must

Table 5.1: Arrival & Departure Probability Distributions

Location	Arrival/Departure Times	Arrival/Departure SOC
Work Place	Normally distributed around 09:00 for arriving EVs and normally distributed around 17:00 for departing EVs, both with a 1 hour variance.	Uniform distribution with an arrival SOC between 30-40% and a departure SOC between 70-80%.
Residential	Normally distributed around 17:00 for arriving EVs and normally distributed around 08:00 for departing EVs, both with a 1 hour variance.	Uniform distribution with an arrival SOC between 20-50% and a departure SOC between 85-100%.
Urban	Uniformly distributed between 09:00 to 17:00.	Uniform distribution with an arrival SOC between 40-50% and a departure SOC between 60-70%.

be sympathetic to the existing loading conditions on said transformer. Two loading profiles from Elexon's demand classification system are utilised [201] (Elexon is the organisation that manages Great Britain's transmission system balancing). The winter demand profile for a Domestic Class-1 profile is used for the Residential charging scenario and the winter demand profile for a Non-domestic Class-3 profile is applied to the Urban and Work Place charging scenarios. In both cases the winter profile is selected to simulate the worst case loading condition and in each charging scenario, the loading profiles are scaled to suit a 500kVA distribution transformer capacity.

It is unclear as to whether commercial EV charging infrastructure operators will possess the ability to access wholesale electricity prices, perhaps this will occur when an operator reaches a certain scale and/or V2G aggregation becomes commercially viable. In the meantime, it is likely the operator will be subject to standard energy supplier tariffs, either flat-rate or TOU prices. In the UK, TOU tariffs are not commonly used, however, the closest available tariff is the Economy 10 tariff offered by SSE [202]. This tariff is available in many regions throughout the UK but prices vary according to location. It provides 10 hours of off-peak energy pricing during the day at a rate of £0.1162/kWh and 14 hours of peak pricing at £0.1979/kWh for the distribution zone located around the city of Glasgow, Scotland [202]. The Economy 10 tariff is applied as the energy pricing parameter for all charging scenarios, this is compared against a standard flat-rate tariff of £0.164/kWh that is offered in the same geographic region.

5.4.2 Case Study 1: EMS Validation

Figure 5.8 demonstrates the charging schedule for five EVs connected to a charging network with two, 50kW rapid DC chargers and using test EV input parameters from Table 5.2. It is clear from the characteristics for EV-2, that Charger-1 and Charger-2 operate independently and only one EV is charged from each charger at any moment in time. In this test scenario, and in further investigations, the EMS can select one of three different charging power levels (10kW, 30kW and 50kW). These power levels enable a scaled reduction in power when the EV battery surpasses its constant current charging threshold, however, these variable power levels can also be utilized during the charging routine to meet the user requirements at the least cost and within the available power capacity of the transformer (Figure 5.9). Additional power levels can be incorporated to offer increased power control but this must be balanced against the increased computational complexity that would result.

In the five EV and two charger test network a time step of 30 mins is adopted, this is an appropriate starting point considering the energy market balancing and settlement process is conducted in half-hourly periods [201]. A smaller time step will increase the computational time but improve the accuracy of the charging cost and although this is desirable the 30 minute period was considered a reasonable trade-off. For completeness, Table 5.3 demonstrates the effect of varying time steps on the optimization solving speed and the cost to charge a representative sample of 25 EVs and 50 EVs with four chargers and five chargers respectively. To achieve reasonable solving speeds for the 50 EV network, it is necessary to limit the time horizon to the most relevant time periods rather than consider an entire 24-hour period. In all scenarios the EMS solves within the allocated time-step. In these simulations and subsequent scenarios, Matlab is used to perform the EMS optimization process on a 3.4 GHz Intel Core i7 processor.

The solution times and network scale are appropriate for the desired applications -

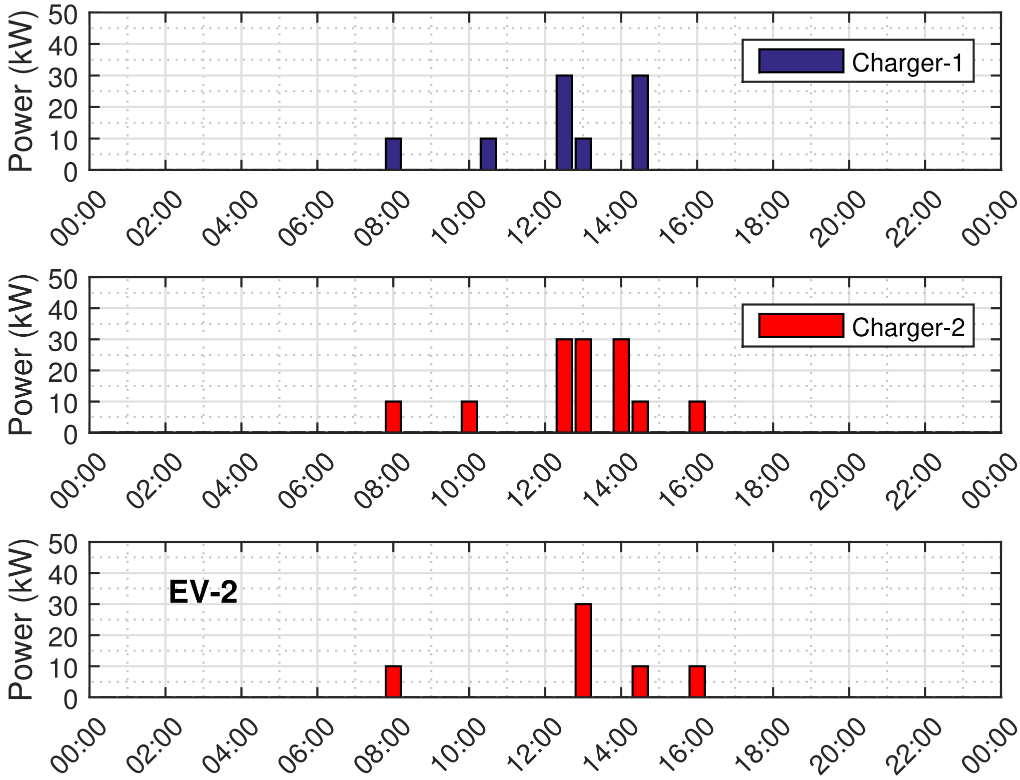


Figure 5.8: Overall charging characteristics for the five-EV, two-charger system and an individual characteristic for EV-2.

long duration charging (> 15 minute parking time) and the integration of charging infrastructure into existing electrical network infrastructure with minimal initial upgrade requirements. Larger parking areas may contain multiple separately controlled reconfigurable networks or one continuous network that is controlled by a more powerful cloud based processor, as depicted in Figure 5.4. The size of each charging network is dictated by the physical limitations of cable runs, allowable voltage drops and acceptable computational complexity.

5.4.3 Case Study 2: Charging Infrastructure Performance

This study demonstrates the EMS as an infrastructure planning tool and highlights the value of an optimised reconfigurable DC network compared to a reconfigurable DC

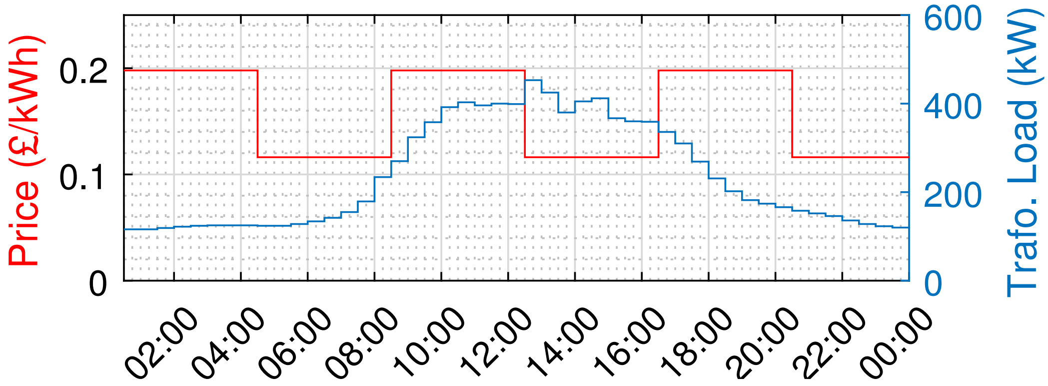


Figure 5.9: TOU pricing and transformer load.

Table 5.2: Input Parameters for 5EV×2 Charger Network

E_n	kWh_{start}	kWh_{end}	$T_{arrival}$	T_{depart}
EV_1	20	50	10:00	15:00
EV_2	30	60	08:00	17:00
EV_3	40	50	09:00	11:00
EV_4	20	40	07:00	15:00
EV_5	20	40	05:00	13:00

Table 5.3: Solving Time Comparisons: 4CH x 25EV and 5CH x 50EV.

		Work Place		Urban		Residential	
Network	Δt	Time(s)	Cost(£)	Time(s)	Cost(£)	Time(s)	Cost(£)
4CHx25EV	15	151	£51.71	142	£34.13	170	£83.29
	30	28	£54.16	12	£36.15	21	£83.49
	60	4	£68.28	5	£43.53	5	£86.24
5CHx50EV	15	321	£127.54	10	£78.33	537	£211.94
	30	31	£129.00	7	£78.12	396	£190.87
	60	9	£127.58	1	£88.16	116	£177.13

network that charges vehicles sequentially upon arrival, and the existing AC charging networks that charge EVs immediately upon connection to the network. The parameters used in this analysis are presented in Table 5.4. The charging price is set to £0.25/kWh which is similar to pricing offered by commercial operators [203]. The 50kW DC and 7kW AC chargers are priced according to [204] and [205]. The cable cross sectional area (CSA) was calculated according to BS7671 standards. The DC

Table 5.4: Simulation Parameters for Case Study 2

Parameter	Value
Number of EVs	50
EV Battery Capacity	60 kWh
Power Rating DC Charger	50 kW
Number of DC Chargers	5
Power Rating of AC Chargers	7 kW
Charger η for both AC & DC	100%
Simulation Time Step	30 minutes
Simulation Time Period	24 hours
Power Level 1: 0-90% SOC	50kW
Power Level 2: 90-95% SOC	30kW
Power Level 3: 95-100% SOC	10kW
Assumed Investment Period	10 years
Discount Rate	5%
Charging Price	£0.25/kWh

cable has 3-cores and the AC cable 4-cores [206], both cables are copper conductors, XLPE insulated and Steel Wire Armored (SWA). It was assumed that all parking bays are within 100m of a centralized 50kW DC charger with a maximum acceptable voltage drop of 3% was to be maintained.

In the first instance, it is desirable to compare the performance of the LVDC reconfigurable charging network against established charging solutions in order to quantify the benefit it brings. The baseline charging network (*AC Uncontrolled*) uses a standard 7kW AC charger supplied to each parking-bay, this represents the existing charging infrastructure planning theory for extended-stay parking areas. This is compared to a reconfigurable DC charging network (*DC Uncontrolled*) that charges EV's in sequential order (first come, first served). Both methods are compared against the proposed EMS controller (*DC Controlled*) presented in Section 5.3. The simulations are performed in three charging location scenarios: work place, residential and urban areas. The resulting charging demand profiles on the secondary distribution transformer are displayed in Figure 5.10.

In each charging scenario the 7kW AC charging network and 50kW DC sequential charging system either approach or surpass the 500kVA capacity of the distribution

Table 5.5: Service Cost Comparison of Charging Scenarios for 5 Chargers & 50 EVs

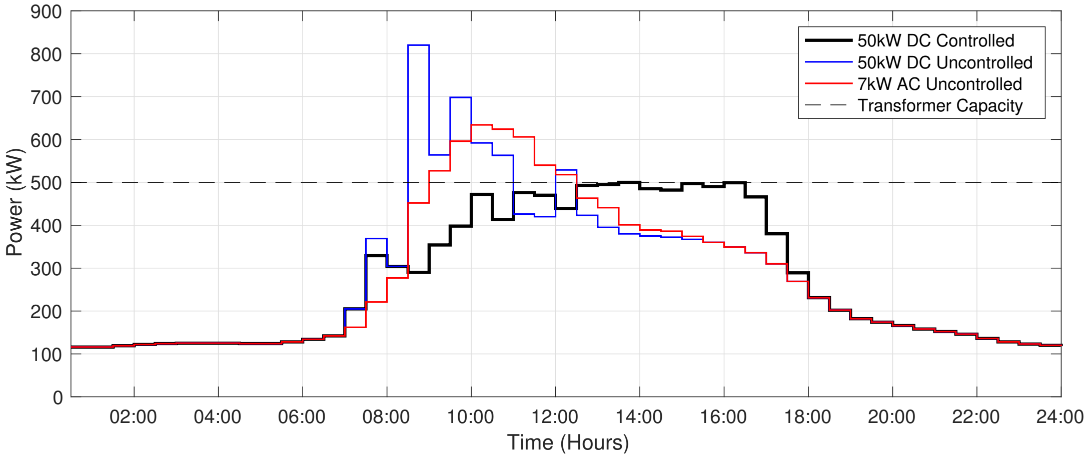
Location	50kW DC Optimized	50kW DC Sequential	7kW AC	Flat Tariff
Urban	£86.10	£185.46	£99.48	£102.50
Work Place	£128.94	£188.72	£172.93	£152.52
Residential	£182.06	£182.70	£246.78	£246.00

transformer, whereas the optimised EMS ensures the charging schedule for the reconfigurable DC network remains within the power limit constraint of the transformer and maximizes energy delivery during the off-peak pricing periods for every scenario. Table 5.5 highlights the charging costs associated with servicing 50 EVs at each location. As expected, the optimized EMS charging schedule has the least expensive charging cost in all scenarios.

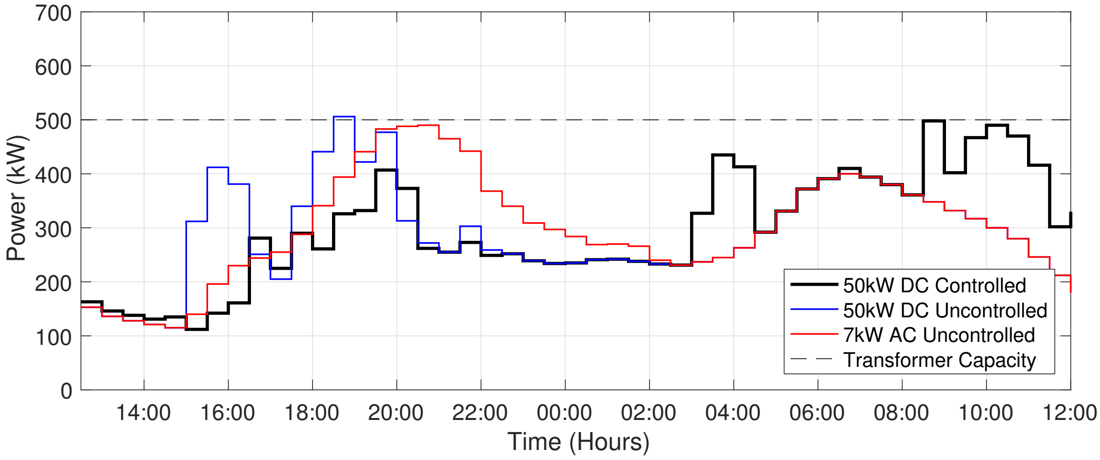
Table 5.6 considers the cost implications of reducing the number of chargers from five, 50kW chargers, to four and increasing to six chargers. It is clear that increasing the number of chargers has no affect on the daily cost of energy but reducing the number of chargers to four marginally increases the daily cost of energy. Despite the daily cost increase the NPV of the charging infrastructure over a 10 year period with a 5% discount rate is significantly higher for a four charger system, compared to a five charger system and higher still compared to the normal AC charging infrastructure that is currently deployed, indicating a superior investment opportunity. It should be mentioned that the annual revenue remains constant across all scenarios as this is an infrastructure assessment analysis that assumes the same forecasted number of EVs, arrival rates and charging requirements across all four scenarios. The EMS optimisation approach is applied as a planning tool to determine the minimum number of chargers necessary to meet the forecasted EV charging demand.

5.4.4 Case Study 3: Service Selection Matrix

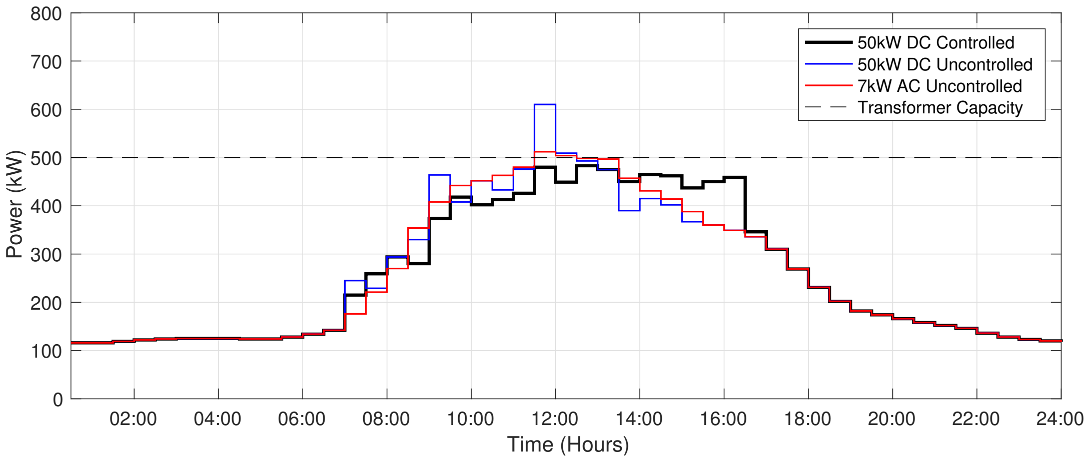
The EMS can equally be applied to the near real time energy management of the charging network. The reconfigurable DC charging network is designed to maximize the utilization of the fixed infrastructure and as a result the network will naturally become



(a) Work Place charging profiles for 50 EVs.



(b) Residential charging profiles for 50 EVs.



(c) Urban charging profiles for 50 EVs.

Figure 5.10: Transformer loading for 50 EVs and different charging coordination methods.

Table 5.6: Infrastructure Assessment for 50 EVs

Design Parameter	4x50kW DC	5x50kW DC	6x50kW DC	50x7kW AC
Daily Energy Cost	£129.43	£128.94	£128.94	£172.93
Annual Energy Cost	£32,357	£32,235	£32,235	£43,232
Charger Cost	£80,000	£100,000	£120,000	£17,850
Peak AC Power	200kW	250kW	300kW	350kW
Cable Capacity	50kW	50kW	50kW	350kW
Cable CSA	50mm^2	50mm^2	50mm^2	240mm^2
Cable Cost	£916	£916	£916	£6,180
Annual Income (£0.25/kWh)	£58,125	£58,125	£58,125	£58,125
10 Year NPV	£112,436	£94,285	£75,238	£86,752

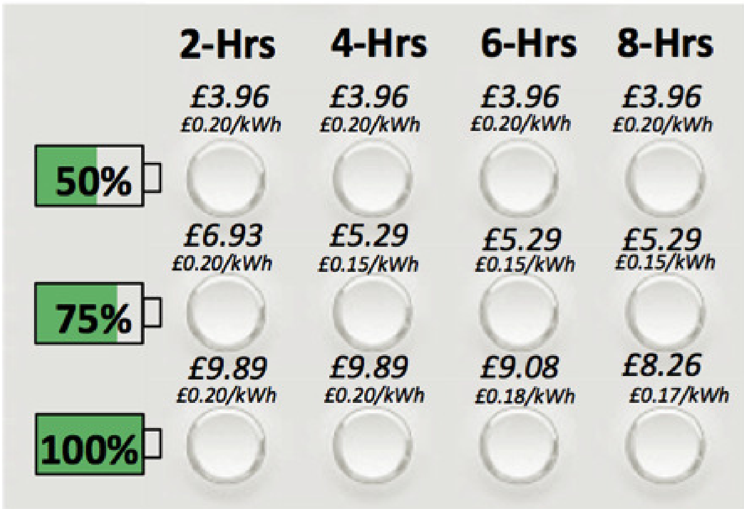


Figure 5.11: EV charging service selection matrix

constrained as EV utilization increases due to limitations on charger power output capacity, available headroom on the distribution transformer and volatility in energy prices. It is therefore necessary to offer the EV user a selection of charging services that take into consideration the existing charging schedule and future constraints. This permits the user to select the most appropriate departure SOC, departure time and price for the service. In line with existing pay in advance parking system arrangements in the UK - the driver selects and pays for a fixed period of time on arrival in the parking area and no compensation is available if they vacate before the pre-paid period elapses. The EMS and selection matrix presented in this thesis follows this established practice and therefore, if a user returns prior to the agreed charging completion time, there will be no cost re-adjustment, however, the additional charging capacity made available by the early-to-depart EV will be incorporated in the next optimization step.

To produce these charging service selections, the online EMS algorithm must generate multiple service options based on the EV's SOC upon joining the network, the EV battery capacity and the existing network charging schedule. From a practical perspective, the user selection matrix could be generated between the time the user plugs into the network and walks over to a centralised payment kiosk or the user may be able to wait longer, perhaps for a charging notification and payment to appear on the user's mobile device. The EMS should therefore be able to provide an immediate service option while continuing to improve the accuracy and expand the user options, prior to the user making a selection.

A user-selection matrix from simulated results is presented in Figure 5.11 that offers the EV owner three different SOC levels and four different parking time options. The costs for each charging service option represent the direct energy cost to the CPO. To generate the service selection matrix requires twelve, independent optimization runs with discrete combinations of SOC and parking time. The results in Figure 5.11 are from two 50kW DC chargers networked to twenty-six EV parking bays at a work place parking area. In this scenario, the selection matrix is the result of a whole network optimization and demonstrates that the network can accommodate all service options for the 26th EV, however, from Table 5.3 it is clear that this matrix generation approach takes over five minutes to produce using 30 minute time steps. From a practical implementation perspective, the rolling-schedule optimization can generate the service selection matrix in less than 5 seconds. Although this approach is more practical in solving speed, it can result in fewer available service options than the slower, whole network optimization. In this congested network scenario the 'rolling-schedule' can only accommodate the 26th EV if it remains parked for at least 9 hours. However, if the user can wait an extra 50 seconds prior to making their service selection, the EMS continues to refine the service options by generating a service selection matrix based on the 60 minute time step as outlined in Table 5.3. Then once complete, and if time permits, the EMS can move onto the 30 minute time step with the resulting matrix in Figure 5.11. This tiered approach to the selection matrix balances the operational need for rapid service options against the optimal network solution and computational time constraints.

The selection matrix scenario in Figure 5.11 represents the service costs for a twenty-sixth EV to join the network at 9am and with a starting SOC of 10kWh. As expected, the overall service cost for each SOC level reduces as the parking time increases. However, the per unit tariff rate varies widely across the service options therefore both the unit rate of energy and the total service cost should be provided so that the user may choose their preferred option. The best economic choice for the EV user in this scenario is a 4-hour parking time with a 75% SOC on completion. The 50% SOC rates appear higher because the highest power level is not being used as it would supply more energy than required (this charging service option requires 20kWh but a 50kW power level would deliver 25kWh during the allocated 30 minute time-step). Thus less energy is supplied during off-peak periods for this service option as the lower power levels 30kW and 10kW must be used according to the model's SOC and power level constraints, (5.12)–(5.14). Using a lower time step, e.g. 15 minutes, will improve the results but another factor plays a key role: although the use of the 30-minute time step makes the results 'suboptimal', it is of course more computationally efficient (Section 5.4.2). Despite this solution, the proposed charging system still delivers a lower daily charging cost and NPV in comparison to a *first come, first served* charging pattern for conventional AC charging systems. It is also important to note that the EMS is minimizing the cost for the charging network operator and not the price for the connecting EV, therefore each of the available service options are presented in the context of independent charging schedules. This means the 26th EV must pay the difference between the previously agreed charging cost for the original 25 EVs and one of the new charging network cost options based on the newly optimised charging schedules for 26 EVs in the user selection matrix.

It is intuitive to offer a reduced charging cost to an EV user that is connected to the network for a longer duration, as this allows the EMS to charge the vehicle at the lowest prices and schedule it around more time urgent EV users. However, this is in contrast with conventional parking-lot pricing strategies where a vehicle owner will pay according to the time spent occupying a parking-bay. It is perhaps then important to state that this service selection matrix only presents the cost of energy and assumes there is no additional cost to park an EV for longer durations.

5.5 Summary & Evaluation of Proposal

A reconfigurable LVDC charging network for plug-in electric vehicles along with an EMS controller are developed. The results of the model have interesting implications for charging network design and operation. Specifically, despite the use of fast DC chargers being more capital intensive than conventional AC equivalents, and their adoption to date being limited, this should not be considered a deterrent to their use because they can have comparable or even lower overall costs in the long term. For this to be realised, a network of DC chargers must be deployed optimally, with three main factors influencing design and operation costs. These are the total number of chargers, network configurability and energy management.

As demand grows, operators should consider taking advantage of user flexibility before upgrading their networks, while further work could demonstrate the value of incorporating stationary battery storage with local renewable energy resources. The inconvenience technique within the modelling work of this thesis enables operators to create charging offers that can be easily interpreted by those with flexible time or SOC requirements and are tailored to the current network utilisation level. This is a mutually beneficial approach, providing additional revenue for operators and access for new EV arrivals in congested charging networks.

Further enhancements to the Energy Management System might consider the inclusion of optimum battery state of health for the connected EVs. It is understood that battery degradation accelerates with higher charging rates and with a higher average state of charge [151]. Both of these battery health metrics could be included within the optimisation model to minimise battery degradation across the EV users.

Chapter 6

Conclusions & Further Work

The primary aim for the work of this thesis was to investigate the viability of public LVDC distribution systems and to assess the opportunities as well as the challenges that are necessary to overcome before widespread adoption can occur. As part of this process, the opportunity to apply LVDC distribution systems in the area of EV charging infrastructure was identified as a low risk application with potential commercial advantages compared to the incumbent LVAC distribution system. This chapter offers several conclusions, revisits the objectives established at the beginning of the thesis and discusses areas for further work based on the research presented in this thesis

It is fair to say that in the last few years, EVs have become a real proposition for mainstream consumers and the development of charging technology has advanced from 50kW DC chargers to the installation 350kW high power chargers and multi-megawatt charging hubs (where four or more 350kW chargers are installed; such systems are being developed by companies like Ionity throughout Europe but few vehicles are currently available to take advantage of these high power chargers). For energy network operators and policy makers, the proposition of EV adoption is no longer a question of 'what will we do *if* this happens' but more of a question of 'what will we do *when* this happens'.

To study the application of LVDC systems in the realm of EV charging infrastructure, a classification system was proposed that enabled two recognisable but distinct challenges to be accounted for - short duration and long duration charging. Short-duration charging assumes that power will be delivered immediately and if there is a constraint on the delivery of power, the available power will be shared amongst the chargers according to a principles of access philosophy and absent of a temporal control aspect. Long-duration charging has greater flexibility to identify the optimum charging schedule based on a series of physical network and user constraints. Based on the work of this thesis, it is proposed that a time classification is applied according to the half-hourly settlement period and power trading unit. Therefore a short duration charging service, as considered in this thesis, occurs within the immediate 30 minute period that the user connects to the charging network, whereas a long duration charging service may extend over several half-hourly periods depending on the user requirements. In a short duration charging scenario it is necessary to consider power density and there is less concern around varying charger power output, as the user expects a full charge in the shortest period of time. Whereas long duration charging solutions may vary the charging power to accommodate wider AC system constraints, fluctuating energy prices and the constant current charging curve that is indicative of lithium ion battery charging.

This thesis provides four main outputs for charging infrastructure developers, distribution network operators and policy decision makers, these include:

1. LVDC Distribution Standards and Design

A systematic evaluation of international LVDC standards was conducted which determined that although some gaps in earthing, protection and wiring regulations exist there are precedents available from other stand-alone DC distribution applications (such as solar PV systems, tram/rail power systems and telecommunications) which may be applied towards the standardisation of a public LVDC distribution system. This thesis therefore concludes that the technical capabilities are present to deliver more sophisticated public LVDC charging infrastructure such as the schemes outlined in Chapter 4 and Chapter 5, as well as dedicated DC charging networks that may mesh two or more secondary substations. However the commercial case and associated risk of changing from an incumbent LVAC system to LVDC distribution presents a barrier for wider adoption. Although, the work of this thesis has demonstrated that the use of LVDC can reduce the capital expense of projects and increase the overall system energy efficiency. Therefore LVDC distribution should perhaps be viewed as a 'tool' that power network operators may deploy to enhance the performance of their assets in specific scenarios. This opportunity is being investigated by Scottish Power Energy Networks in their ongoing LV Engine project [96] and by other network operators in Korea [89] and Finland [88]. The standards research work of this thesis has supported the development of technical recommendations for LVDC street lighting and EV charging networks as part of the LV Engine Project.

2. EV Charging Demand Forecasting

The early charging performance data from the Charge Place Scotland network of rapid DC chargers presented in Chapter 4 offers a timely insight into the emerging charging trends that may influence the location and operation of future charging infrastructure. This thesis has identified that the arrival pattern at certain rapid DC chargers (taxi, service station and shopping centres) can best be expressed with multi-modal Gaussian distributions and the pattern of charging energy transactions at these sites follows a gamma distribution. These findings will assist researchers and engineers in developing appropriate EV demand models for infrastructure planning and energy management modelling.

3. Short-duration Charging

This thesis has highlighted that the build-out of EV charging infrastructure presents an opportunity to consider more integrated energy systems that can combine electricity, gas, heating and transport. In considering short-duration charging systems, the power density requirements were outlined. Early companies active in this space [149], [54] have recognised the need to connect to the transmission system to deliver energy to motorway HPC infrastructure efficiently but urban environments may also benefit from HPC stations where the electrical infrastructure may be more costly to access. In Chapter 5 this thesis has therefore explored the concept of an integrated CHP and charging solution for urban environments, such as a charging hub adjacent to a community tower block. In this case, the incorporation of a LVDC charging network enables the comparison of variable speed gas reciprocating engines and native DC fuel cells with a standard fixed speed engine.

4. Long-duration Charging

In this thesis, the application of LVDC charging networks to long duration charging scenarios (charging events in excess of 30 minutes) considers the use of a higher power DC charger (50kW+) multi-plexed to several EV plug-in points. The operation of the mutli-plexed charging system enables 1:1 pairings between the rapid charger and several different EVs over an extended period of time. The scheduled pairings depend on the AC system constraints, electricity prices and user preferences. The control approach developed in this thesis can be applied as either a design tool or a real-time controller. Through this work, in Chapter 5, the concept of user inconvenience was investigated by developing a user selection matrix which enables the EV user to select their preferred charging service upfront based on their sensitivity to price and available parking time.

This reconfigurable DC charging network, considered and studied in this thesis, may be applied in work place parking areas where users are parked for several hours and for on street charging where the use of existing street lighting cables may limit the power transfer at any moment in time. The charging control algorithm can route power to individual EVs according to several defined power network constraints. This approach reduces the upfront infrastructure costs and maximises the utilisation of the charging assets prior to deploying additional chargers. Overall, this approach offers a higher NPV compared to the deployment of 'standard' 7kW AC chargers at each parking bay.

6.1 Future Work

This thesis has tackled four separate but complementary themes that work together to deliver appropriate, cost effective EV charging infrastructure. In each theme, further work should be conducted to enhance the collective understanding of LVDC distribution systems and the development of scalable charging infrastructure, this can be summarised as follows:

6.1.1 LVDC Distribution Standards and Design

To enhance the commercial opportunity and reduce the risk associated with LVDC distribution systems, greater understanding of power converter lifetimes is required. Furthermore, an understanding of any accelerated cable ageing effects that may occur where existing LVAC cables are converted to operate under a LVDC distribution regime will help to inform the practical viability of this proposal. This understanding may also lead to the development of specific LVDC cables. This enhanced understanding of converter and cable performance over extended time periods will reduce the risk associated in developing LVDC charging infrastructure.

6.1.2 EV Charging Demand Forecasting

The operational data from the Charge Place Scotland network of AC and rapid DC chargers has been used to inform future charging infrastructure deployment in this thesis. But despite it being 'real' usage there are particular aspects of the usage patterns - geographical, dispersion and cost (currently free charging) - that do not make it a fully representative data set and therefore universally applicable.

This thesis focussed specifically on the rapid DC charging data, however, a similar approach may be applied to the larger number of 7kW and 22kW AC chargers throughout the network. Further work may build on the demand forecasting models to consider not only day ahead power demand but also medium term and longer term trends to ensure that charging infrastructure is deployed appropriately.

Alternative forecasting techniques may be applied to the charging utilisation data such as the use of Artificial Neural Networks which may identify more subtle relationships between charger usage and a variety of exogenous variables. The application and correlation of weather related data may also be improved by using weather forecasts rather than hindcasts; since an operational demand forecasting algorithm must rely on day ahead weather predictions. However this is performed, there is value in going beyond the work of this thesis to consider forecasting models for both 'short duration' and 'long duration' charging infrastructure.

6.1.3 Short-duration Charging

Although it is not quantified in this thesis, it is likely that the integration of gas and electrical networks for the provision of charging services will improve the overall energy/transportation system resiliency. Further work might attempt to address this axiom by considering the energy security of the current fossil fuel based transportation system and how this may change as transportation moves more towards electrification. This could consider the opportunity to inject higher concentrations of biogas or hydrogen into the gas network and whether there is spare power capacity within the gas network that may be more cost effective to exploit than alternative upgrades to the electrical networks.

6.1.4 Long-duration Charging

Further work in the area of user inconvenience and principles of access could offer additional flexibility to long duration charging assets. It appears that the technical controllability of chargers is available and possible but more research work could be done to improve upon the user interaction with charging systems. In contrast to a short duration charging service, where the only option is an immediate charge, the user of a long duration charging system may have a variety of charging options to choose from. The speed at which these options are generated and the manner in which they are displayed is an area for further development. Furthermore, the delivery of a practical demonstration of the reconfigurable network in a laboratory environment and then moving to a pilot implementation project would be useful and possible next steps.

6.1.5 Closing Remarks

The research work of this thesis has found that an integrated EV charging infrastructure strategy should consider the whole energy system landscape, the integration of multiple energy vectors, the efficiency of charging systems based on their grid connection location and overall fairness to energy consumers. The application of LVDC distribution systems can facilitate the implementation of scalable charging infrastructure by delivering power dense charging applications, efficiently integrating distributed generators and reducing charging infrastructure costs.

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