Weather Related Modelling and Optimization of Electric Vehicle Integration in Distribution Networks

by

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DEDICATORY

I dedicate this thesis to my beloved family. To my mother, thank you for always believing in me and providing unwavering support. Your love has been the backbone of my journey. To my father, as a doctor, you have saved countless lives. You taught me not to give up. I also wish to thank my girlfriend, Miss Lin, for always being there for me. Your patience and love have brought new meaning to my life.

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ABSTRACT

As climate change becomes increasingly severe, the urgent need to reduce carbon emissions and the push for net-zero emission targets, this has led to the widespread promotion of electric vehicles. However, this transition also presents challenges, such as surges in energy demand, voltage fluctuations and potential threats to the power system equipment from extreme weather events. This thesis aims to systematically address these challenges and proposes approaches and solutions.

Firstly, the thesis proposes the data aggregation method in detail and analyses the real data results in comparison with the Monte Carlo simulation results. It was found that temperature has a significant effect on the driving and charging behaviour of electric vehicles, and the Monte Carlo method demonstrated efficiency and accuracy in bridging the gap between real data, providing an important tool for modelling EV data. Next, in order to reduce the network load pressure and charging cost while increasing the revenue of EV aggregators (EVAs) in providing ancillary services. Then the thesis proposes a scheduling approach to optimise the coordination of EV charging and ancillary services. The approach analyses the participation of EVs in ancillary services on weekdays and weekends, and reveals the impact of risk aversion parameters on the benefits of EVAs. In addition, this thesis evaluates the impact of temperature changes on EV driving and charging behaviours, and proposes a method to quantify the EV hosting capacity of distribution network in different temperature ranges. By integrating temperature data, the thesis reveals the changing of the network under different temperature and highlights the impact of weather factors on network. Finally, the thesis explains the impact of weather factor on power system equipment, and proposes a methodology for weather-related fragility modelling of power system equipment and EV charging point. It can obtain the fragility curves under different weather factors by adjusting the input parameters.

Overall, this thesis makes important contributions in terms of theoretical support and practical approaches. It provides insights for research and practice in related fields.

THESIS BASED PUBLICATIONS

[P1] Wang, Yilu, **Zixuan Jia**, Jianing Li, Xiao-Ping Zhang, and Ray Zhang. 2021. "Optimal Bi-Level Scheduling Method of Vehicle-to-Grid and Ancillary Services of Aggregators with Conditional Value-at-Risk" *Energies* 14, no. 21: 7015.

[P2] **Z. Jia,** D. L. Donaldson and X.-P. Zhang, "Impact of temperature on EV charging and the distribution network," *EVI: Charging Ahead (EVI 2023)*, Glasgow, UK, 2023, pp. 56-60, doi: 10.1049/icp.2023.3126.

[P3] **Jia, Zixuan**, Daniel L. Donaldson, and X-P. Zhang. " Impact of Temperature on the Electric Vehicle Hosting Capacity of Distribution Networks." *7th International Conference on Smart Energy Systems and Technologies (SEST 2024), Torino, Italy, 10-12 September 2024*. (The paper was ranked in the top 50% of all conference papers and is being reviewed for further assessment for publication in SEGAN (ELSEVIER))

[P4] **Zixuan Jia**, Daniel L Donaldson, Emma Ferranti, "Weather-related fragility modelling of critical infrastructure: a power and railway case study," *Proceedings of the Institution of Civil Engineers - Civil Engineering*, vol. 177, no. 5, 2023, pp 50-58, ISSN 0965-089X, https://doi.org/10.1680/jcien.23.00115.

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Nomenclature

$C_i^{bat-rep}$	EV battery replacement fees (£/kWh).
$C_{i,t}^{bat-deg}$	Battery degradation costs (£).
$C_{t,i}^{EV}$	Total EV charging cost (£/MWh).
CA_t^{reg-u}	Power consumption of EVA regulation up (MW). (EV discharging electricity to network)
CA_t^{reg-d}	Power consumption of EVA regulation down (MW). (EV charging electricity to network)
CA_t^{res-r}	Power consumption of EVA responsive reserve (MW).
$CVaR$	Conditional Value at Risk
$E_i^{bat-max}$	EV battery capacity (kWh).
E_i^{Trip}	The amount of energy needed to satisfy the EV's next trip (kWh).
$E_{t,i}^{EV}$	Total charging energy consumption for each EV at *t* (kWh)
$E_{i,max}^{EV}$	The maximum energy that can be charged for each EV (kWh).
$E_{i,min}^{EV}$	The minimum energy that can be charged for each EV (kWh).
EV_{profit}	Profit to EV owners from V2G (£/kWh).
F^{EVA}	Net revenue of EVA in upper-level problem (£/kWh).
$F_{t,i}^{EV}$	Profit of EV owners in lower-level problem (£/kWh).
$MU_{t,i}^{EV}$	Total marginal utility of EV owners (£/kWh).
M_t^k	The tariff offered by EVA to EV owners (£/kWh).
m	Index of EV owners' energy demand blocks.

$P^{a}_{max,t}$	EV maximum additional power consumption at t (kW). (In order to perform the regulation down service, how much can the EV charge rate exceed $P^{EV}_{c,t}$)
$P^{a}_{min,t}$	EV minimum additional power consumption at t (kW). (In order to perform the regulation up service, how much can the EV charge rate low $P^{EV}_{dc,t}$)
P^{res-r}_{t}	Responsive reserve power consumption at t (kW).
P^{EV-max}_{t}	EV maximum power consumption at t (kW). The value is 0 if EV does not plug in.
$P^{EV}_{i,t}$	Total power consumption (exchange power) of battery for each EV at t (kW).
P^{F-ch}_{t}	Final power consumption at t (considering up-regulation, down-regulation and response reserve services) (kW).
$P^{EV}_{c,t}$	EV charging power (kW).
$P^{EV}_{dc,t}$	EV discharging power (kW).
$P^{EV}_{c,t-max}$	Maximum EV charging power (kW).
$P^{EV}_{dc,t-max}$	Maximum EV discharging power (kW).
$EV\_POP_{i,t}$	EV preferred operating point at time t for each EV (kW).
$E^{EV}_{r,t}$	Remaining energy capacity of each EV at t (kWh).
P^{tr}_{max}	Power limits of the substation transformer
p^{reg-r}_{p}	The predicted price of regulation up at t.
p^{reg-d}_{p}	The predicted price of regulation down at t.
p^{res-r}_{p}	The predicted price of responsive reserve at t.
$RegS$	Regulation signal request at t (MW).
$ResS$	Responsive signal request at t (MW).
SOC_{i}	State of charge for each EV.
$SOC_{Init,i}$	State of charge at the initial moment for each EV.

SOC_i^{max}	Maximum state of charge allowed for each EV.
SOC_i^{min}	Minimum state of charge allowed for each EV.
T	Total number of time periods in a day.
t	Time period (h).
t_i^{arr}	Time of arrival at the charging point.
t_i^{dep}	Time of departure from the charging point.
t_i^{EV}	EV charging duration time.
UI	EVA total income (£).
UC	EVA total cost (£).
$u_{t,m}^{EV}$	Marginal utility of EV customer at *m*.
∂	Number of days.
δ_t^{ch}	Electricity market energy price at *t*.
η_i	Efficiency of EV chargers.
ε^{reg-u}	Power consumption of regulation up dispatched expected percentage.
ε^{reg-d}	Power consumption of regulation down dispatched expected percentage.
ε^{res-r}	Powe consumption of responsive reserve dispatched expected percentage.
ξ	Value at Risk.
α	Confidence level.
ρ_s	Probability between profit and the VaR non-negative variable.
η_s	Difference between profit and the VaR non-negative variable.

Chapter 1

Introduction

1.1 Problem Statement

In recent years, electric vehicle (EV) have been growing rapidly due to increased environmental awareness and technological advances [1]. Globally, governments in various countries have introduced policies to encourage the use of EV to reduce greenhouse gas emissions and dependence on fossil fuels. According to statistics, the market share of EV is growing year by year [2]. It is projected that global sales of EV will reach 14 million units by 2023 [3] and the global EV stock will exceed 145 million by 2030 and global EV stock will exceed 145 million in 2030 [4]. With the rapid growth of the EV market, significant adjustments will be needed in environmental policies, the industrial supply chain, energy structures, and equipment.

Traditional charging methods may put great pressure on network during peak hours, such as voltage variations, load variance and power losses [5]. The main research question of this thesis is: How to model and optimize EV integration in distribution networks? This question is based on the common needs of EV owners, charging operators, distribution network planners and charging infrastructure companies. This question is further refined into the following three specific research directions:

1. How can the charging behaviour of large-scale EVs be managed by EV charging operator to meet user demand while relieving the load on the distribution network?

2. How do weather factors such as temperature affect the EV charging behaviours and their maximum hosting capacity in a distribution network?
3. Which equipment faults in power system have the greatest impact on EV charging points under weather factors?

1.2 Motivation

With the increasing global environmental awareness and the pursuit of sustainable development, the integration of EV into the distribution network has become a focus for the advancement of transportation and the implementation of the "smart grid" [5, 6]. As a low-emission vehicle, EV plays an important role in reducing urban air pollution and greenhouse gas emissions (such as carbon dioxide, nitrogen oxide, etc.) [7]. As the world's two largest EV markets, China and the United States have had their greenhouse gas (GHG) and air pollutant emissions from the EV fuel cycle assessed [8]. It was concluded that GHG and air pollutant emissions could be reduced by 60-85% if 80% of EV charging was derived from electricity produced from renewable sources [8]. However, as the number of EVs increases, so does the impact on the network caused by their charging needs [9]. At the same time, during peak hours of EV charging, the residential distribution network can exceed voltage limits [10]. These are challenges that need to be addressed in the development of EVs and distribution network. By optimizing the EV charging behaviours, it is possible to address user demand while avoiding overloading of the power system.

However, weather factors such as ambient temperature can significantly affect the EV driving and charging behaviours. For example, based on real driving data collected on roads in Birmingham, UK, the driving energy consumption (kWh/km) of EVs was found to be twice as high at low temperatures (0 °C) than at moderate temperatures (around 20 °C) [11]. Moreover, the energy consumption of EV air conditioning changes due to extremely hot or cold temperatures, making EV charging energy consumption at extreme temperatures much higher than at moderate temperatures (15-25°C) [12]. This means that the EV driving energy consumption vary significantly under different weather conditions. This will directly lead to changes in EV charging consumption [13].

Weather factors do not only affect the activities of EVs, but also impact power system equipment. Climate change leads to more frequent and intense extreme weather events, including high temperatures, heavy rainfall, flooding and wildfires [14]. For instance, data from the National Centres for Environmental Information [15] indicates that, since 1980, the USA has encountered 372 weather and climate-related disasters, each causing at least 1 billion dollars in adjusted damages, with overall costs surpassing 2.6 trillion dollars. EV Charging points (EVCP) include home-use charging piles, roadside charging piles and public charging stations (containing multiple charging piles) [16]. Any one of these charging posts is considered to be a charging point. Home-use charging piles are installed in user-owned or leased residential premises. This kind of charging pile usually low-power charging devices (~3.5 kW) and mainly used to meet the daily car use need, using nighttime or parking to charge for a long time [17]. Roadside charging piles are installed next to streets or parking lots. They have medium-power charging capabilities (up to 22 kW) and are suitable for short-term parking. The construction of such charging piles is usually promoted by governments or enterprises to enhance the coverage of public charging networks [18]. Public charging stations are set up in public areas such as gas stations, shopping malls or transportation hubs, and are usually equipped with multiple types of charging piles, including fast charging piles and ultra-fast charging piles. Public charging stations have higher power and are suitable for fast charging of vehicles in a short period of time [19]. The normal operation of EV charging points are affected by extreme weather and other emergencies that may cause power system outage. For example, northern California implemented a planned outage in 2019 to prevent hill fires [20]. But it led to difficulties charging EVs on the local power system. Given that nearly half of all EVs in the U.S. are located in California, the unavailability of EV charging points due to power system outages has caused widespread concern. Quantification of the impact of weather on equipment is important to maintain operation in this changing climate. Therefore, assessing the fragility of power system equipment and EV charging points in the event of faults can help to understand and respond to the impact of these events on EV charging.

1.3 Opportunities and Challenges

EV charging presents a number of challenges in distribution network. How to effectively manage EV charging behaviour and assess its impact on the network has become an urgent issue. First, EV not only serve as loads, but also as distributed energy storage resources, participating in electricity markets and ancillary services. In this way, the operating pressure of the network can be relieved. However, different weather factors can affect the energy consumption and charging demand of EV, which in turn has an impact on the operation of the distribution network. Therefore, there is a need to quantify the impact of weather factors on charging behaviour and distribution network hosting capacity. Finally, whether EVs participate in ancillary services or analyse EV hosting capacity under different weather factors, the availability of their charging points must be considered. Unplanned outages due to power system equipment faults can affect the normal operation of EV charging points, thus preventing them from serving EVs. It is critical to quantify the impact of power system equipment faults on EV charging points under different weather factors.

1.3.1 EV participation in the electricity market

A large number of EVs for charging may lead to a sharp increase in the load on the distribution network [10]. Charging 30 million EVs is estimated to require around 100TWh per day and 35GW of additional electricity [21]. However, the promotion of V2G (Vehicle-to-Grid) based technologies have brought new opportunities for the optimal management of power systems [22]. EV participation in the electricity market to provide ancillary services not only improves the load balancing and voltage regulation of the power system, but also optimises energy management system [22, 23]. From the IEA report (Figure 1.1) [24], it is stated that by 2030, 16,000 GWh of energy could be stored in EV batteries globally, which could be actively supplied to the grid at the right time through V2G solutions.

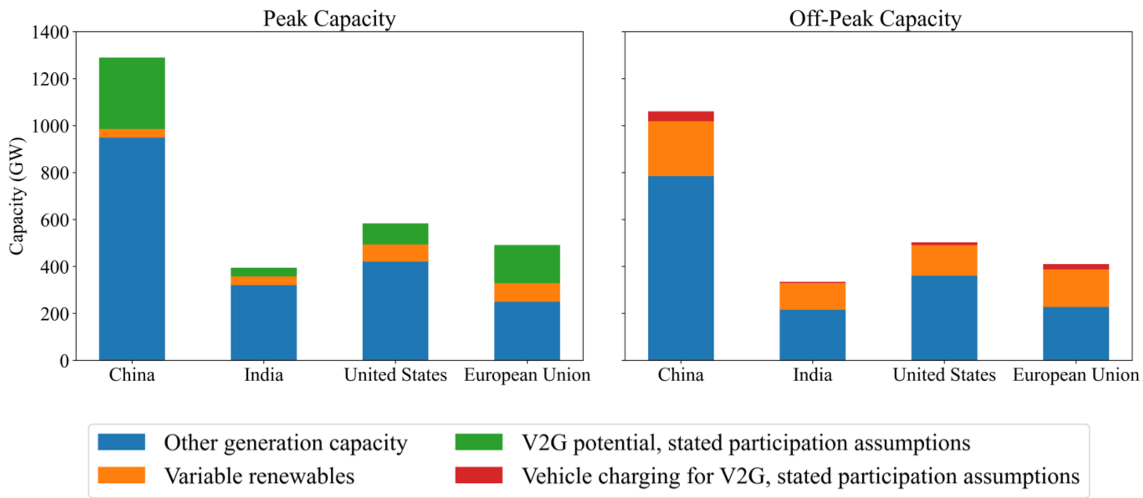


Figure 1.1: V2G potential and the proportion of variable renewable energy capacity relative to total generation capacity requirements in the 2030 Sustainability Scenario [24].

Although there are still challenges to the large-scale application of V2G in practice, the technology is expected to be popularised and used in the future as the technology continues to advance and the related infrastructure is developed. For example, Octopus UK is launching a V2G service in 2023 and has proposed the UK's first V2G tariff [25]. Large-scale EV can be used in the future as distributed energy storage resources to release stored power during peak periods of electricity consumption and to reduce the load on the network, thus avoiding network overloading and frequent start-up of standby generators, and improving the overall energy utilisation efficiency [26-28].

1.3.2 Quantify the EV hosting capacity of the distribution network

The current power system has many challenges in dealing with large-scale EV access, such as the impact on distribution network hosting capacity. The hosting capacity of the distribution network refers to the maximum capacity of the network that can accommodate DER (e.g. EV, PV, wind etc.), without causing problems in the operation of the network or violating power quality standards [29, 30]. The voltage impact of EV charging on the distribution network is particularly important for hosting capacity. Power flows usually unidirectionally in the distribution network. In addition, EV charging can cause significant voltage fluctuations, especially in load-concentrated areas [31, 32]. Keeping voltage amplitudes within limits is one of the key recommendations from the review of the UK Distribution Networks Regulations [33, 34]. Considering the impact of weather factors such as temperature on EV charging behaviour, there has been limited research in quantifying the maximum EV hosting capacity of the distribution network.

1.3.3 Impact of power system unplanned outages on EV charging points

Whether it's participating in ancillary services via V2G or quantifying EV hosting capacity in a distribution network, one key part is essential: EV charging equipment. EVs can be connected to the network only with charging equipment that passes through a charging point. Charging points include home-use charging posts, roadside charging posts and public charging stations [16]. Extreme weather events can cause economic losses due to power outages [35]. In 2016, a severe storm in Australia caused a large outage that affected up to 1.7 million customers [36]. In the same year, a tornado in Jiangsu Province, China caused 135,000 households to lose power [37]. The power system may experience power outages due to extreme weather, which can affect the ability of EV charging points to serve EV users. Most recent studies have focused on the impact of EV charging loads on the power system, lacking the impact of power system outages on EV charging points within their service area. If the impact of unplanned outages caused by equipment faults on EV charging points can be quantified, there will be an opportunity to take precautions in advance to minimise service disruption events during an outage.

1.4 Main Contributions

This thesis analyses the modelling and optimisation of the EV integration in distribution networks, and achieves the following main contributions:

- The first contribution is an optimal bi-level scheduling method for ancillary services provided by vehicle-to-grid (V2G). The significance of the method is that it coordinates the interaction between EV and network. The upper-level model is responsible for optimising the network's operational strategy, while the lower-level model focuses on the charging and discharging behaviour of the EVs. The method is capable of achieving globally optimal solutions in complex multivariate situations. The proposed optimisation method not only significantly reduces the load pressure on the network, but also reduces the cost of the EV charging process and improves the profit of EV aggregator. This contribution led to the publication in [P1].
- The second contribution is a methodology to assess the impact of temperature on EV hosting capacity of distribution networks. The importance of this study is to reveal the critical role of ambient temperature in influencing the charging process of EVs in distribution networks. It is revealed that temperature variations make measurable changes to the EV charging behaviours, which in turn affects the operation of the network. This contribution led to the publication in [P2, P3], which provide an

important reference for network planning and EV charging management for operators in different weather conditions.

- The third contribution is a methodology to quantify the impact of power system outages due to equipment faults on EV charging points within their service area. The importance of this contribution is that it provides an approach to assessing the fragility of power system equipment under different weather factors. The potential impact of different weather factors (e.g. temperature and rainfall) on equipment (e.g. overhead lines, cables and transformers) was revealed through analysis and modelling. Correlation analysis was also used to quantify the correlation between different equipment fault and the affected EV charging points. This contribution led to the publication in [P4].

1.5 Thesis Outline

This thesis is comprised of seven chapters. Chapter 2 provides a comprehensive literature review based on the research question. Chapter 3 proposes the method for modelling and data analysis of EV driving and charging behaviour. Chapter 4 proposes an optimised bi-level scheduling method for ancillary services via V2G. Chapter 5 proposes an algorithm designed to quantify the impact of temperature on EV hosting capacity. Chapter 6 proposes an analytical methodology for assessing the impact of power system equipment failures on EV charging points. Chapter 7 describes the conclusions and future work. The relationship between the chapters is shown in Figure 1.1. They are summarised below:

Chapter 2 reviews and summarises the existing literature relevant to the thesis. Firstly, this chapter provides information on the concept of EV charging behaviour and its impact on the network. Then, the application of V2G technology in ancillary services is summarised. Current research on the impact of EV charging on distribution network hosting capacity is critically reviewed. Finally, the interrelationship between weather factors and power system equipment is assessed. For each area of research, gaps were highlighted.

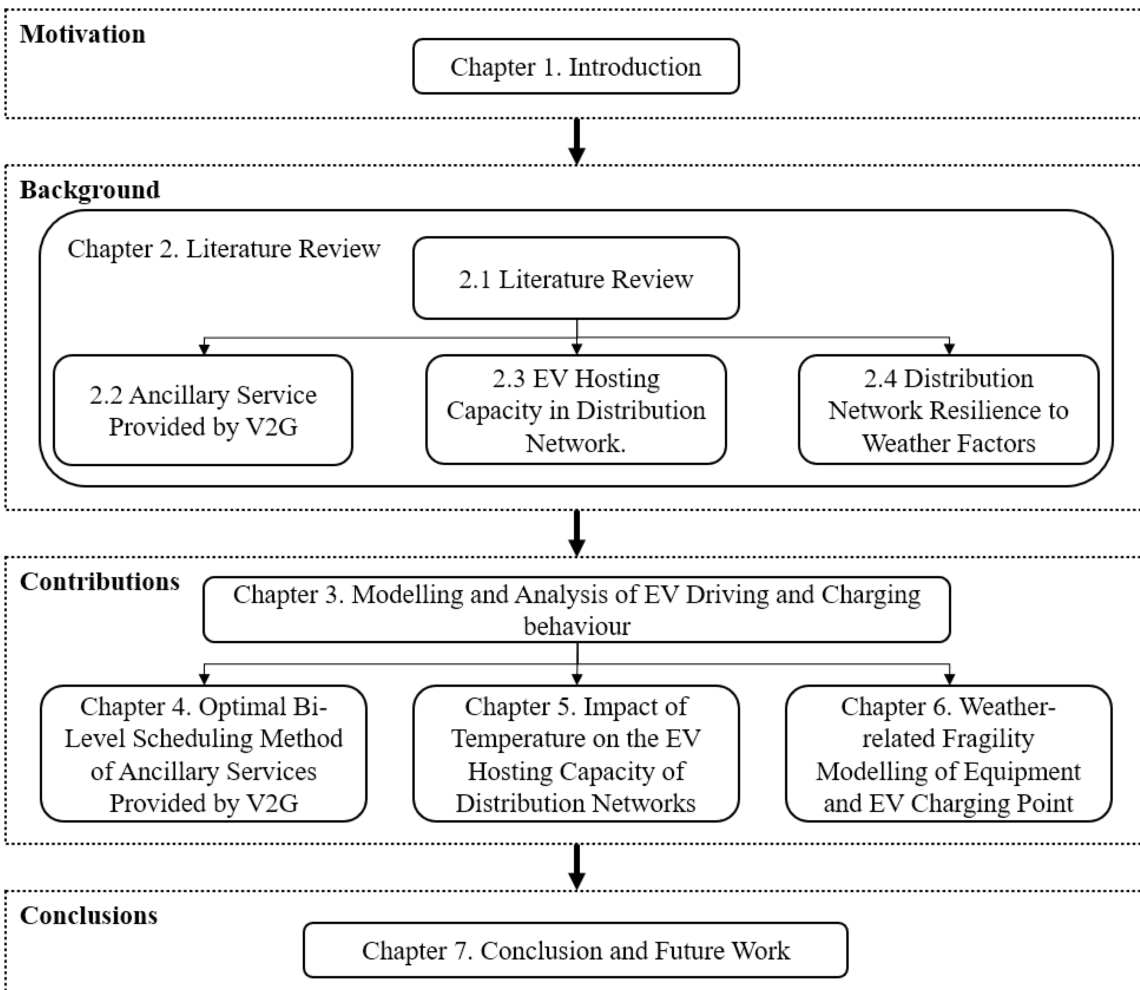


Figure 1.2: Overview of thesis structure.

The method proposed in Chapter 3 begins by discussing the steps of data collection based on the type of data needed to construct the model. Then describes how this data can be used to create profiles. Monte Carlo methods are used to simulate the similarity of EV charging data in terms of trends and characteristics. The final focus is on the impact of ambient temperature on EV driving and charging. Chapter 3 provides the underlying model and data support for analyses in Chapters 4-6.

The method proposed in Chapter 4 aims to reduce the load pressure on the network while providing an additional revenue stream for EV aggregators and EV owners. Case studies are used to demonstrate the feasibility and practicality of the proposed approach. The chapter concludes with a discussion of how the proposed methodology can be used to guide EV participation in ancillary services.

Chapter 5 proposes an algorithm designed to quantify the impact of temperature on EV hosting capacity. Under varying temperature conditions, the algorithm reveals voltage variations in the LV network at different EV penetration rates and determines the maximum hosting capacity. The chapter demonstrates the algorithm's effectiveness through a case study. It concludes by discussing the significance of this method in understanding how EV charging loads affect the distribution network's hosting capacity across different temperature ranges.

The method proposed in Chapter 6 aims to identify and quantify the impact of different equipment failures on the power supply to charging points under different weather factors. Real fault data and EV charging point data verify the feasibility of the proposed method. The chapter concludes with a discussion of the prospects for applying the method in different industries.

Chapter 7 provides the overall conclusions of the work from the research in Chapters 3-6. Applications for future development and discusses further research work are also presented.

Chapter 2

Literature Review

Chapter 1 presents the challenges faced by network in the face of large-scale access to EVs. In order to address these challenges, this chapter not only outlines current research results, but also analyses the existing literature to reveal the research gaps that still exist in this area. Chapter 2 focuses on an overview of research related to electric vehicle (EV) charging in distribution networks, with a particular focus on how EVs can provide ancillary services through Vehicle-to-Grid (V2G), the hosting capacity of EVs in distribution networks, and analyses of power system faults taking into account weather factors. This chapter not only summarises the current state of affairs in these key areas, but also makes clear the contribution of this thesis by comparing it with previous research.

This chapter contains five sections: Section 2.1 explores the emergence of EV charging behaviour and the impact of weather factors on it. Section 2.2 explores the application of Vehicle-to-Grid (V2G) on ancillary services based on EV charging behaviours. Section 2.3 investigates the impact of EV charging on the hosting capacity of the distribution network. Section 2.4 examines the weather-related fragility analysis of power system.

2.1 EV driving and charging behaviours

The rapid increase in EV penetration will lead to an increase in EV charging load, which becomes an important part of the network load [38]. The driving behaviour of EV will determine the EV charging load, and thus the impact on the network [39]. There are many factors that influence EV driving and charging behaviour. However, weather factors can directly affect EV driving and charging behaviours such as driving distance, driving energy consumption, EV charging start time, duration time and charging energy consumption [40-42]. In order to fully analyse and assess the impact of EV charging on the impression of the network, Section 2.1.1 provides an overview of the methodologies and findings related to EV driving and charging behaviours. Section 2.1.2 reviews the impact of weather factors on these behaviours. Section 2.1.3 describes EV charging behaviour impact on the network. This review is crucial for developing strategies to integrate EV into the distribution network.

2.1.1 Modelling EV driving and charging behaviour

The Table 2.1 shows a wide range of literature approaches to modelling EV driving and charging behaviour. Reviewed literature considers basic driving and charging behavioural factors, including EV driving distance, driving energy consumption charging start and end times, duration time, charging energy consumption [40-43]. The authors of [43] used data from more than 2.6 million charging sessions in four major cities in the Netherlands. Key factors affecting charging duration, such as time of day, user type, and city characteristics, were identified through multinomial regression analyses. However, the effect of EV driving behaviour on EV charging energy consumption was not considered. Although the authors of [44] modelled duration and energy consumption by means of earliest start time algorithms, earliest finish time algorithms and integer programming, but did not cover important factors such as cost and location selection.

Table 2.1: Comparison of EV driving and charging behaviour modelling.

Ref.	Behaviours										Model / Method
	Driving distance	Driving energy consumption	EV charging time (Charging start/end time, Duration time)	Charging energy consumption	Number of EV charging per day	EV charging strategy	EV charging power	Costs during the charging process	Selection of EV charging location		
									Residential area	Public places	
[43]			√				√	√	√	√	Statistical model, Multinomial logistic regression
[44]	√		√			√	√				Earliest Start Time algorithm, Earliest Finish Time algorithm, Integer programming
[45]	√	√		√		√	√	√			Weighted bipartite graph,
[46]	√	√	√	√	√	√	√	√		√	Markov chain
[47]			√	√		√	√	√			Nonlinear Programming, Power Map Functions
[48]	√		√	√	√		√				Monte Carlo method
[17]					√		√	√	√		Descriptive statistics, Mixed Logit with a Flexible Mixing Distribution model
[49]	√			√	√	√	√	√		√	Marginal electric distance

The authors of [45] and [46] appear to be more comprehensive in considering the diversity of charging behavioural factors. The choice of charging location (residential areas and public places) is considered. This is essential to optimise the charging infrastructure layout. Meanwhile, nonlinear programming and power map functions have employed in the [47], which are capable of accurately modelling a wide range of variables in the charging behaviour. But none of them consider an important factor, i.e., battery degradation of EVs during V2G. EV participation in V2G causes the battery to charge and discharge [50]. However, this process has an impact on the chemistry and structural stability of lithium-ion batteries [51]. The available power of the battery will gradually decrease, and the charging speed may become slower. Therefore, the battery degradation cost needs to be considered in the EV participation in the V2G process [52].

2.1.2 The impact of weather factor on EV driving and charging behaviour

Weather factors such as temperature directly affect the EV driving distance, EV driving energy consumption per kilometre and charging efficiency, thus changing the EV charging load demand (Figure 2.1) [12, 53-55]. This allows changes in network loads to indirectly affect the operation of the distribution network [53-59].

Weather factors include temperature, rainfall, wind speed, etc [60]. Table 2.2 reviews the literature on EV under the influence of weather factors. The authors in [61] investigated the correlation between different weather factors and daily power for EV charging demand in Leicestershire, Nottinghamshire and the West Midlands, UK. The results showed that the most influential weather factor was temperature. In addition, by analysing the energy consumption of 68 electric vehicles in Aichi Prefecture, Japan, at different ambient temperatures. The authors of [62] found that the most economical energy efficiency was achieved in the range of 22 - 25 °C. The literature reviewed acknowledges the impact of weather factors on EV charging behaviour. Including driving behaviour, charging behaviour. However, there is a lack of assessing the extent of its impact on distribution network. As described in [62], weather factors affect EV driving energy consumption and thus EV charging behaviour. Understanding this relationship is crucial for quantifying the impact of EV charging on the distribution network.

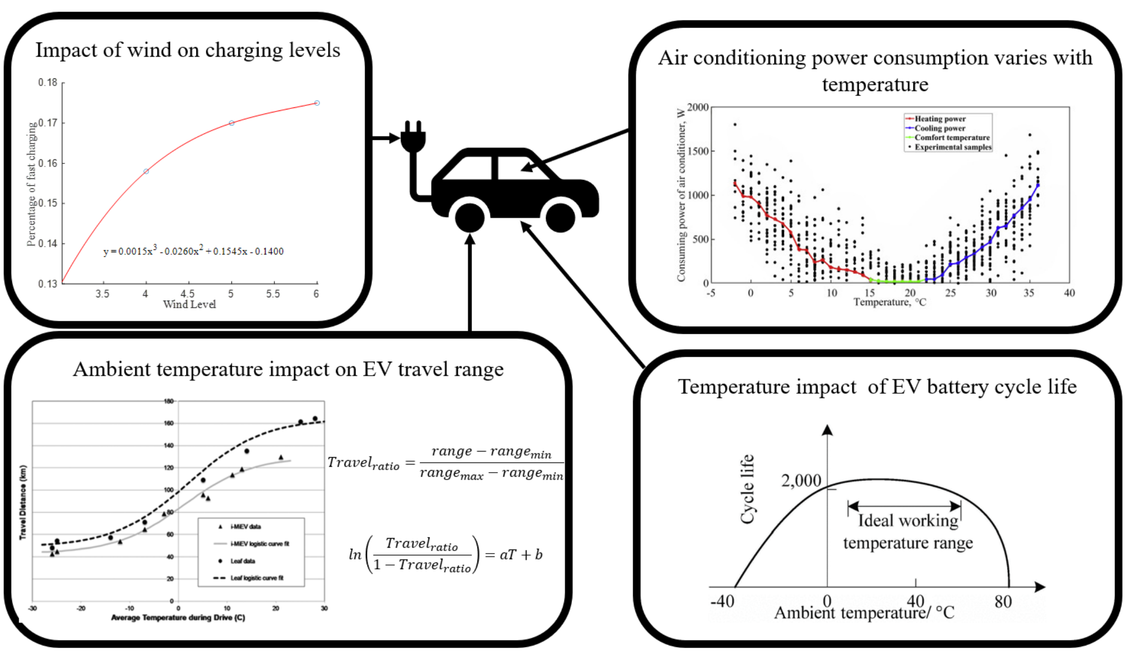


Figure 2.1: Description of the quantification of weather factors on EV performance and charging.

Table 2.2: Literature review on the EV under the impact of weather factors.

Ref.	Weather factor	Research topic	Qualitative finding
[53]	Temperature	Cycle life of the battery.	Lithium-ion batteries can be cycled more than 2,000 times at 25°C, but only 800 times at 55°C.
[12]	Temperature	EV charging demand.	Minimum total charging demand in spring and autumn (0.87~1 TWh), maximum charging demand in winter (1.1-1.26 TWh)
[60]	Temperature	Battery degradation factors	An approximate battery degradation model was obtained by fitting the correlation between battery degradation factors and various parameters such as temperature, driving range, etc.
[61]	Temperature, Wind speed, Rainfall	EV charging demand	Ambient temperature has the greatest impact on EV batteries (absolute correlation coefficient is 19.47%)
[62]	Temperature	EV driving energy consumption, EV charging demand.	In the range of 21.8-25.2 °C, EV driving and charging achieves the most economical energy efficiency.

2.1.3 The impact of EV charging on network

The impact of EV charging on the network is multifaceted (Table 2.3). Firstly, EV can optimise network loads and reduce carbon emissions through smart charging and V2G technologies. Secondly, EV charging may also trigger problems such as network harmonics [63] and load imbalance [64]. More than 2,500 scenarios in Switzerland were analysed and found that public charging can significantly increase the load on the local distribution network by up to 78% during peak hours [65].

Table 2.3: Impact of EV charging on network.

Category	Ref.	Consequence
Positive impacts	[66-72]	Providing ancillary services, increasing revenues for EV owners and aggregators, smoothing network load profiles, integrating renewables, supporting for network renewable energy integration
Negative impacts	[73-75]	EV charging leads to harmonic disturbances. Charging of EVs in low-voltage distribution networks can lead to voltage imbalances. Uncontrolled EV charging power can lead to aging of distribution transformers.

The studies in [66-70] discuss how EVs participating in Vehicle-to-Grid (V2G) provide ancillary services. These services not only offer financial benefits to EV owners but also help mitigate fluctuations in network load. Additionally, the authors of [71] highlight that EVs can contribute to peak shaving by storing electricity during off-peak times and discharging it during periods of high demand. As further noted in [72], EV batteries can serve as mobile energy storage units, storing excess power generated from renewable energy sources such as solar and wind, thereby supporting the integration of these renewables into the network.. However, charging a large number of EV clusters can lead to harmonic disturbances. The increase in harmonic currents may cause damage to network equipment and affect power quality [73]. The authors of [74] propose that uncontrolled fluctuations in EV charging loads accelerate the ageing of electrical equipment and increase maintenance costs.

Table 2.4: Impact of EV charging on the network under weather factors.

Ref.	Weather factor	Consequence
[76]	Cold weather	EV customers have to charge longer. EV charging in cold weather increases harmonics.
[77]	Cold weather	EV will have less range. In colder weather, there is a need for an additional 630 MW of peak power to charge EVs in the UK, compared to what is required under optimal ambient temperature conditions.
[12]	Temperature	The charging load in cold temperatures is much higher than in warm temperatures and hot temperatures.

In the study of the impact of EV charging on the network, the weather factor is recognised as an important external variable [61] (Table 2.4). The authors of [76] study the impact of EV charging on the network in cold weather. In order to meet the charging of 11 million vehicles in cold temperatures, nearly 450 MV of additional power generation are required. However, this research mainly focuses on the harmonic problem. The authors of [77] used Monte Carlo simulations to analyse the impact of cold weather on EV range and network peak power demand. However, the study's data relied on respondents' recollections of travelling during the week, which is subject to a large margin of error. The authors in [12] explored charging loads under different temperature conditions using polynomial models, probability density functions and probabilistic transformation models. EV charging loads modelled by traffic and temperature factors were analysed for Beijing, China. It was shown that charging loads in cold temperatures (~0.87-1 TWh) are much lower than those in warm and hot conditions (1.1-1.26 TWh).

Section 2.1 reviews research on the EV driving and charging behaviour and their impact on the network. It also explores the potential of EVs to alleviate network pressure and support renewable energy integration. However, the positive and negative impacts under different weather factors still requires further research. The subsequent sections will delve deeper into the interaction between EVs and the network, highlighting existing research gaps and presenting the research contributions of this thesis.

2.2 Ancillary services provided by V2G

Vehicle-to-Grid (V2G) technology allows for the bi-directional flow of energy between EV and the network. This enables EVs to both draw power from the network for charging and return stored energy from their batteries back to the network. [78]. Ancillary services include responding to frequency and voltage fluctuations in the network, providing backup power, balancing supply and demand, and improving the overall resilience of the network [29]. EVs can utilize their flexible energy storage characteristics to provide a variety of critical ancillary services to the power system [79]. Therefore, EVs are not only used as a means of transportation, but also as a distributed energy storage device to provide ancillary services and backup power to the network [80].

2.2.1 Application of ancillary services provided by V2G

Renewable energy sources like wind, photovoltaics (PV), and energy storage systems (ESS), which lack large spinning masses, can lead to deviations from the standard system frequency (50-60 Hz) [81]. In response to these challenges, V2G systems provide various ancillary services. These include voltage regulation, frequency regulation, black start capability, reactive power provision, and several other services (as detailed in Table 2.5).

In voltage regulation, [70, 82] show the application of Power-HIL (Hardware-in-the-Loop) testbeds and distributed model predictive control (DMPC). Power-HIL testbeds provide an effective experimental environment to validate control strategies before they are implemented, reducing risks in practical applications [70]. The DMPC method shows strong adaptability and accuracy in voltage regulation and can respond to voltage fluctuations in real time [82]. However, its high complexity and computational requirements may limit its application in large-scale distributed networks. Authors in [83] have explored the application of linear programming and practical deterministic methods to frequency regulation. Linear programming (LP) methods are concise and computationally efficient, but may ignore nonlinear factors. Meanwhile. LP may need to update model parameters frequently to adapt to changing realities. In terms of black-start capability, the "bottom-up" black-start approach provides an effective solution to large-scale outages by enabling gradual restoration of the system from distributed energy sources [84]. Provides an effective solution for large-scale blackouts. Finally, [66, 85, 86] studied spinning reserve services in power system. It can balance the stability of distribution network and the economy of EV owners effectively.

Table 2.5: Ancillary service applications for V2G provided by different countries.

Ref.	Requirements to Participate	Beneficiaries	Model / Method
[70, 82]	Voltage regulation	Distribution network	Power-HIL (Hardware-In-the-Loop) testbed, Distributed model predictive control (DMPC)
[83]	Frequency regulation	Distribution network EV aggregator, EV owners	Linear programming
[84, 87]	Black start capability	Distribution network, Generation	"Bottom-up" black start approach, UCIMG model
[66, 85, 86]	Spinning reserve	Distribution network, EV owners	Linear programming, Three-grid points algorithm, Mixed integer linear programming model

2.2.2 Challenges for ancillary services provided by V2G

Despite the many benefits of the ancillary services provided by V2G, multiple challenges remain. The challenges include the following three main aspects: uncertainty in user charging behaviour, battery degradation and energy loss.

The uncertainty of EV charging behaviour is a significant challenge to be dealt with when V2G is involved in ancillary services, including the availability of EVs and the willingness of EV owners to participate [40, 88]. Firstly, the effectiveness of V2G will be hampered because EV owners may not charge their EVs every day. Analyses show that EV owners charge their vehicles two to three times per week on average, with larger battery capacity EVs requiring more energy per charge and charging less frequently [89]. In order to maximise the ability of EVs to provide electricity services, EV aggregators need to consider the uncertainty of EV availability. Another aspect is that the impact of EV battery degradation due to EV participation in the V2G programme cannot be ignored. Batteries in electric vehicles engaged in ancillary services via V2G may age more quickly than in daily driving [90]. The authors of [52] have proposed a stress-based empirical model to assess the calendar life, cycle life reduction and state of resistance increase of batteries resulting from EV participation in V2G. The simulation results show that the involvement of EVs in V2G to provide ancillary services leads to an average loss of 0.752% of the total battery pack capacity in one year. Then the annual battery degradation cost of different EVs can be obtained based on the EV battery capacity measurement method under V2G introduced in [51]. There are charging or discharging processes during EV participation V2G. Energy losses are incurred at each stage of transmission, conversion and storage of electrical energy [91]. Measurements of combined grid-to-battery-to-grid power losses show that the total unidirectional loss of electrical energy ranges from 12% to 36%, with the main losses occurring in the power electronics used for AC-DC conversion [92].

In summary, while the ancillary services provided by V2G are expected to bring many advantages, there are also multiple challenges and risks. Section 2.2.3 will review how to address these risks.

2.2.3 Risk management

In power systems, risk refers to the potential for unfavourable events or conditions to result [93]. Risks include factors that may threaten the stability, reliability and efficiency of the electricity supply [94]. Risk assessment plays a role in times of peak load, electricity markets and when system security is at risk [95, 96]. Risk management can be used to reduce the adverse effects of the process on system reliability by analysing, evaluating, and controlling the risks of EV participate ancillary service provided by V2G [97].

April 2, 2018 - UK Power Networks has undertaken a project called 'TransPower'. The project examined the network impacts of home, commercial and public charging on V2G and flexibility services [98]. Octopus Energy in the UK, which has joined forces with Nissan to develop V2G, said on February 15, 2024 that it launched the UK's first V2G tariff - Octopus Power Pack [25]. The UK is beginning to gradually implement V2G technology to help balance the network. This means that there will also face different risks with EV participation in ancillary services via V2G in the UK, such as, risks caused by uncertainty in load patterns and charging behaviour. However, existing risk management modelling usually focused on countries or regions with significant EV ownership (China, Germany and USA) or high EV penetration (Norway, Iceland and Sweden) as case studies [4, 99]. There was a lack of realistic modelling based on the local UK electricity power system. Risk management for ancillary services includes developing coordinated EV charging strategies that enable ancillary services provided by V2G to minimise the operating costs of EV aggregators, as well as peak shaving of network loads [100].

2.2.4 Contribution analysis.

A review of the literature on ancillary services reveals that EVs as distributed energy storage devices are capable of providing a variety of ancillary services to the network. However, relatively late development of V2G technology in the UK has resulted in relatively little V2G research based on the UK electricity market and power system context. This current state of affairs reveals an important research gap, namely the lack of research into optimization methods for provision of ancillary services by V2G for future UK power systems and markets.

Therefore, one of the research questions considered and also the first contribution in this thesis is: How can the interaction between EVs and the network be coordinated to achieve a globally optimal solution in the context of the UK power system and electricity market, thereby reducing network load pressure and charging costs, and optimizing the net profitability of participating in the ancillary services process through risk management? Chapter 4 discusses the design and implementation of the methodology in detail. However, due to the lack of V2G data, Chapter 3 simulates the charging behaviour of EVs using the Monte Carlo method. The simulated data is then compared and analysed with real data to validate the accuracy of the simulation method. This validation supports the use of the Monte Carlo method to simulate large-scale EV charging data in Chapter 4.

2.3 EV hosting capacity of distribution network

2.3.1 Analysis of state-of-art research related to EV hosting capacity

As discussed in Section 2.1.2, stakeholders are keen to explore how EV charging impacts their systems and planning policies, as it can greatly influence the operation of the distribution network [101]. In the distribution network, hosting capacity is represented as the maximum quantity of distributed energy resources (DERs) that can be integrated into the network without necessitating major upgrades [102]. EV hosting capacity is a measure of a network's ability to handle growing EV charging demand while maintaining normal functionality. Specifically, it is the maximum level of EVs that can be accommodated without affecting the efficiency, reliability and performance of the distribution network [32]. Previous work developed multiple methods/modelling for calculating the EV hosting capacity in distribution networks for adaptation to different scenarios in different regions. Authors in [103] proposed a real-time smart load management (RT-SLM) control strategy for coordinating EV charging to minimize network power losses and improve the voltage profile. Proper charging strategies can significantly increase the hosting capacity of EVs in residential networks.

Current research on quantifying the EV hosting capacity is based on four main indicators, voltage level, thermal loading, power quality, and protection [104-110]. For example, the voltage of the network decreases when the charging demand of electric vehicles is high. The assessment of thermal loads is particularly important during peak loads to ensure the safety and reliability of the charging infrastructure. The authors of [111, 112] use a deterministic approach based on time series, the worst-case scenario is analysed to obtain an approximation of the hosting capacity. As a method to quantify the hosting capacity, it is relatively simple with small data requirements. However, it cannot cover a wide range of scenarios, the researchers in [113] used stochastic analysis of probabilities in order to achieve this. But the process is computationally long. To compare the contributions and differences more visually between studies, Table 2.6 categorize previous work based on data sources, test networks, and software.

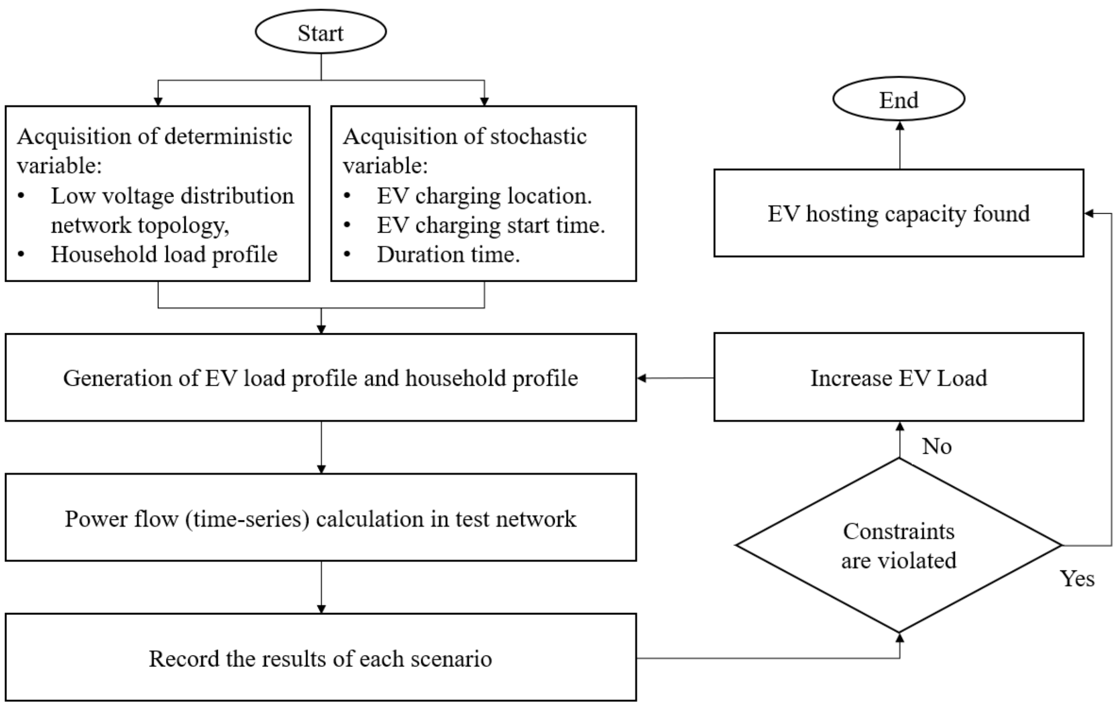


Figure 2.2: Flowchart to calculate the EV hosting capacity of low voltage distribution network [105, 106].

Table 2.6: Review of EV hosting capacity work including data sources, test networks, software/method, consequence, and future work /drawback.

Ref.	Data sources		Test network	Software/ Method	Consequence	Future work / Drawback
	Household load	**EV load**				
[104]	Widén Markov-chain stochastic model.	The Swedish Travel Survey 2006	IEEE European LV Test Feeder.	OpenDSS.	The proposed framework allows for simultaneous evaluation of PV and EV hosting capacity in the same distribution network.	Assessment of hosting capacity for city-scale and non-residential distribution networks.
[107]	Modified IEEE 123-Node DN.	Atlanta Regional Commission (ARC) Metro 2011 metropolitan travel survey archive.	IEEE 123-Node	Matlab, Cplex as a MILP solver.	The concept of "EV charging range" is introduced. This concept is used to evaluate the maximum EV hosting capacity of each node in the distribution network.	Only the voltage deviation within the network was considered as a constraint.
[105]	Brazilian utility.	Probability density function.	75,550 low voltage systems of the Brazilian Electricity Distribution	N/A	Offering insights into strategies for managing systems with high levels of EV penetration.	Considering commercial and industrial customers and did not focus on residential customers with lower loads.
[108]	Salt Lake City utility.	Idaho National Laboratory (INL) EV Project data.	Probabilistic Grid Impact Analysis (PGIA) model.	Monte-Carlo multi-period power flow analysis.	Adding EV charging to the distribution system can cause transformer thresholds to exceed 130%, increasing the risk of overloads.	Incorporate the growth rate of EV and residential solar systems into the influencing factors for future studies.
[109]	Anonymised Victorian smart metre data.	Electric Nation project in the UK.	IEEE 34.	Preston urban network, Hazelbrook rural network.	Quantifying and analysing the constraints of EV hosting capacity in urban and rural areas.	Increasing use of photovoltaic systems should be analysed in more detail.

2.3.2 Contribution analysis

The increase in demand due to EV charging will put a huge strain on the network, especially on the low-voltage distribution network which will be directly affected by changes in EV charging loads. By quantifying EV hosting capacity in low-voltage distribution network, data support can be provided to stakeholders to optimize network planning and scheduling. It also improves the network's responsiveness and adaptability in the face of large-scale EV charging demand.

However, one of the less explored aspects of EV hosting capability is the effect of charging variations on EVs at different temperatures. As described in section 2.1, temperature is the factor that most affects EV driving and charging behaviour. Different EV usage behaviours can lead to variability in EV charging loads. Based on this research gap, this thesis identifies a second research contribution: How can temperature factors be embedded in the assessment of EV hosting capacity of distribution network? The details of how this contribution is achieved are explained in Chapter 5.

2.4 Review of weather-related fragility analysis of power system

As mentioned in Section 1.2 in general, power systems can be severely affected by extreme events [14, 15, 20]. Climate change exacerbates the number and level of extreme events [114]. Resilience assessments are essential to prevent and respond to the impacts of these events on the power system [115]. In particular, the use of fragility curves is a guiding principle in resilience assessment [116]. Section 2.4 begins with a systematic delineation and review of resilience assessments in the power system. It then provides a comprehensive review of how fragility models are used to characterize the likelihood of infrastructure failure under weather conditions. Finally, the research contribution is presented through a discussion of the research gap.

2.4.1 Resilience assessment in power systems

Power system resilience refers to the ability of the power system to restore service quickly after an outage. Such outages can be caused by natural disasters, system overloads, or other disruptions [35]. Resilience involves several key phases: preparation, withstanding the event, adapting to the conditions, and recovery. These phases are illustrated in Figure 2.3 [37, 117-120]. Compared to the traditional power systems performance, resilient systems have a faster response time in the face of outage. Resilience is gaining attention in the power system due to increased climate change and extreme weather events [121].

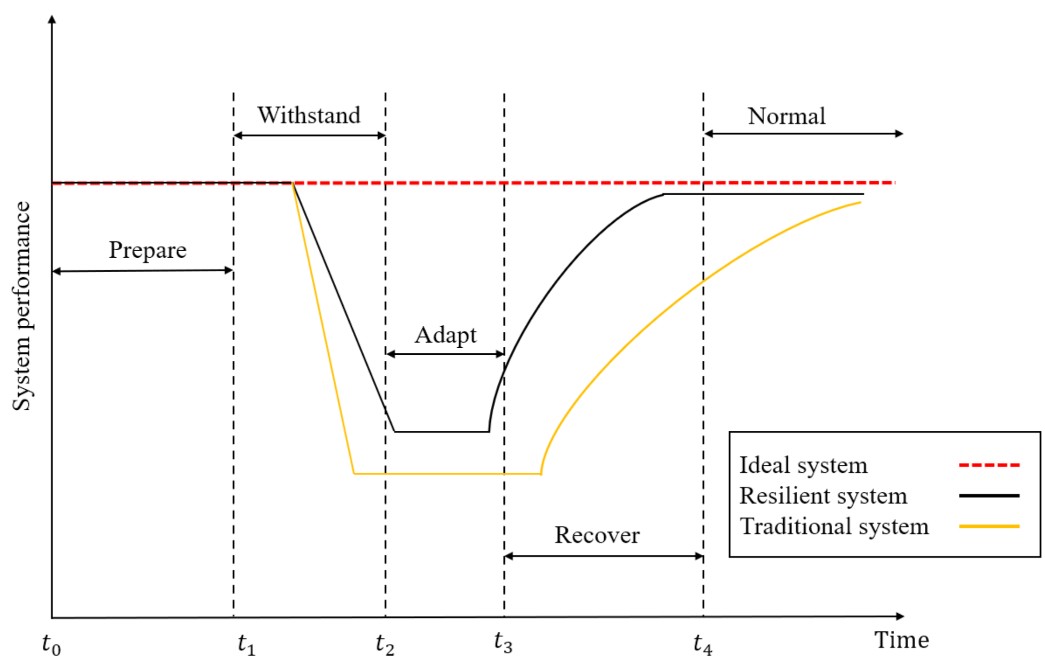


Figure 2. 3: Performance of power system during different phases [37, 117-120].

Overall, the resilience assessment of the power system can be divided based on the timeline of the event, i.e., pre-event, event and post-event [37]. This delineation helps to design and implement resilience strategies more precisely. In order to design and operate resilient power systems, most of the current research is incorporating resilience into planning assessments and operational assessments [122].

In terms of planning assessment, power system resilience is mainly enhanced through short-term and long-term planning. The aim is to increase the system's resilience and ability to recover quickly before an event occurs [122]. Short-term planning focuses on preparatory activities shortly before an event [119], such as weather forecasting and load dispatch optimization. In this phase, to prevent the impacts of upcoming extreme weather events, power system operators may need to adjust generation plans and network configurations based on short-term forecasts. For example, the output of the gensets and the operation of the network are adjusted a day in advance. Minimizing operating costs under worst-case damage scenarios was achieved by testing on the improved IEEE reliability test system and the IEEE 118 bus test system [123]. The authors in [124] enhance resilience through scheduling by using mobile power sources with distribution system. Long-term planning usually involves enhancements to the system hardware, such as increasing the capacity of transmission lines, upgrading substation equipment, and improving the physical layout of the network [119]. This type of approach requires a large capital investment, but can significantly improve the network's resilience to a wide range of extreme events. In addition to upgrades to hardware, long-term planning includes improvements to software and control strategies [125-127].

For operational assessments, this type of assessment focuses on response measures while an event is occurring and recovery strategies after an event has occurred [128]. During an incident, real-time monitoring and rapid response are key, including fault detection, isolation of damaged sections, and rapid restoration of power [129]. Through real-time data analysis, the operations centre is able to quickly identify affected areas and adjust network resources to maintain system stability [130]. Post-incident evaluation focuses on learning from experience. Future planning and operational strategies are improved by analysing why failures occurred and the efficiency of the system response. In addition, Post-incident evaluation also includes an examination of the effectiveness of the recovery operation [130].

2.4.2 Fragility models in resilience assessments

Extreme weather events affect the power system through infrastructure failure or damage, uncertainty in power generation, and changes in demand [131]. In the last ten years, significant progress has been made by both academics and practitioners in comprehending the risks that weather and climate change pose to infrastructure [132]. Multiple studies have worked on predicting infrastructure fault rates related to extreme weather. For example, authors in [133] applied a logistic regression model to predict distribution transformer faults by examining the relationship between weather conditions and historical fault data of distribution transformers. In [134], the authors employed Fuzzy Bayesian

Reasoning to evaluate the climate risks to railway systems, with findings indicating that heavy rainfall and flooding are key climate threats. Additionally, other studies have examined the fragility of infrastructure to specific weather events or disasters, such as earthquakes [115, 135-139].

Table 2.7: Studies on the fragility of power system under different weather factors.

Ref.	**Area**	**Weather factor**	**Objects of the assessment**	**Method**
[140]	UK-wide	Windstorms	Transmission towers	Regression model
[141]	Baton Rouge, USA	Floods	Substation	A systematic stochastic risk-aware decision-making approach
[118]	UK-wide	Windstorms	Overhead lines	Monte Carlo method
[142]	Guangzhou, China	Lighting	Overhead lines	Bayesian network with spatiotemporal

The fragility models can be used to characterize the damage or functional decline of a system or system component in the face of varying degrees of external threats or natural disasters (e.g., heat, floods, storms, etc.) [143]. Fragility models are typically defined based on the relationship between the level of threat (e.g., temperature level, wind speed, etc.) and the level of damage (e.g., length of outage, number of pieces of equipment damaged, etc.). Fragility models can be used to depict the likelihood of failure for specific infrastructure. They can also represent the probability of failure within a region under certain conditions. In the power sector, for example, fragility models have been applied to various extreme events. These include extreme temperatures, flooding, ice storms, lightning, wildfires, and windstorms [115] (Table 2.7).

The authors in [140] use regression model to analyse the impact of storms on power system critical infrastructure. This method is able to predict the impact of future events based on historical data. However, the disadvantage of regression model is that it assumes a linear relationship between the data and is sensitive to outliers. This can lead to limitations in the accuracy of predictions during extreme weather events. A systematic stochastic risk-aware decision-making approach and Monte Carlo method take into account uncertainty and stochasticity in the decision-making process [118, 141]. These approaches are better suited to responding to the complex and uncertain impacts of natural disasters. But these studies lacked the development of thresholds for failure risk management. Authors in [139] used fragility models to examine how wind impacts power system fault rates across different regions. They also developed unified thresholds to aid in fault risk management. As stated in these studies, the most common expression of the fragility model is the Logistic regression (Equation 2.1) and lognormal distribution (Equation 2.2) [118, 144, 145]. Equation 2.1 is particularly appropriate when power systems experience a sharp increase in failures after reaching a specific weather variable. If the fragility analysis between power system failures and weather factors is based on a univariate model, Equation 2.2 can be used to obtain fragility curves. The distributional characteristics of the data need to be considered when choosing between these two methods. Then the expression of the equation for the fragility model and the generic shape are shown below:

$$P(D \geq d|S = s) = {}^{1}\!/_{1\,+\,e^{-(\alpha+\beta\cdot s)}} \tag{2.1}$$

$$P(D \geq d|S = s) = \Phi\left[{}^{(s\,-\,\mu)}\!/_{\sigma}\right] \tag{2.2}$$

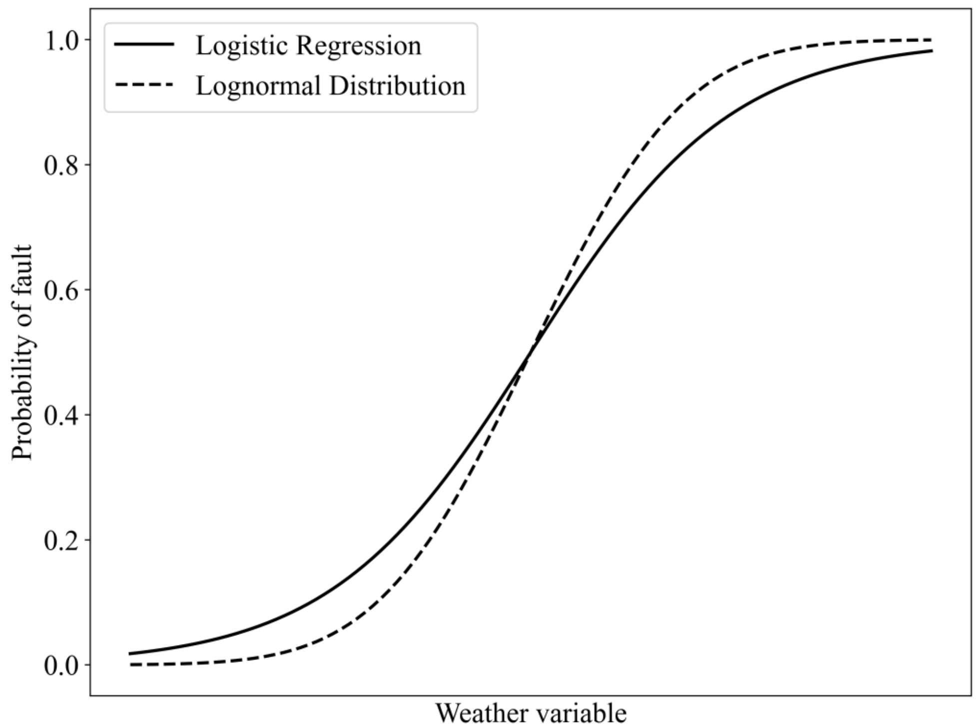


Figure 2.4: Generalized shapes for two fragility curves.

where $P(D \geq d|S = s)$ is probability of fault, s is the weather variable, such as rainfall (mm), wind speed (m/s) and temperature (°C), α and β are the distribution parameters. Φ is the cumulative distribution function of the standard normal distribution, μ is mean and σ is variance.

2.4.3 Contribution analysis

While some progress has been made in understanding the risks faced by infrastructure and its sensitivity to weather and climate change, most weather and climate analysis studies remain limited to specific industry-specific silos. The rapid growth in the number of EVs makes the impression of their charging loads on the network impossible to ignore. Numerous studies have analysed the impact of EV charging on the network and how EV charging can be optimised to reduce the impact on the network. However, EV can only be connected to the network through charger at the charging point [146]. Currently, few studies have examined how extreme weather conditions affect power system equipment and the impact of its faults on EV charging points in the areas served. For example, extreme low or high temperatures can lead to a dramatic increase in load on the local power system, accelerating cable losses and placing additional stress on substations and transmission networks. Power system outage events resulting from these faults may have a direct impact on the ability of EV charging points to provide service [64]. If it is possible to quantify the EV charging points affected by equipment faults during weather factors, there is an opportunity to take precautionary measures in advance. Commonly used fragility curve equations (e.g., Equations 2.1 and 2.2) often do not adequately express the specific impacts of temperature changes on critical infrastructure.

Therefore, one of the research questions considered, which is also the fourth contribution of this thesis is: Which equipment faults have the greatest impact on EV charging points under weather factors? Through analysis and modelling, the potential impacts of different weather factors such as temperature and rainfall on equipment can be revealed. Correlation analysis was also used to quantify the correlation between different equipment faults and affected EV charging points under weather factors. Chapter 6 describes in detail the design of the method and validates it with case study.

Chapter 3

Modelling and Analysis of EV Driving and Charging Behaviour

3.1 Introduction

As EVs are rapidly gaining popularity around the world, their impact on the power system is becoming increasingly significant [88]. EV charging load not only directly affects the load on the network, but will also play a key role in future vehicle-to-grid (V2G) interactions [90, 147, 148]. However, these behaviours are influenced by a number of factors, including the user's driving habits, charging power, and weather conditions (e.g. temperature). Electric vehicle charging level can be divided into Level 1, Level 2, and Level 3 in Europe [149]. The specific data are shown in Table 3.1.

Table 3.1: EV charging levels in Europe [149]

Level	Type	Power (kW)
1	Slow charging	< 3.7
2	Quick charging	3.7 - 22
3	Fast charging	> 22

The aim of Chapter 3 is to provide a foundational understanding for the subsequent chapters by simulating and analysing the driving and charging behaviour of EV. Specifically, this chapter uses the Monte Carlo method to simulate the charging behaviour of EVs. The simulated data is then compared and analysed against real data to validate the accuracy of the simulation method. This validation provides support for the use of the Monte Carlo method to simulate large-scale EV charging data in Chapter 4. The chapter then explores the impact of weather (in particular temperature) on energy consumption during EV travelling. This analysis is critical to understanding the impact of temperature on EV charging behaviour and quantifying the EV hosting capacity in Chapter 5. Finally, this chapter describes the data aggregation method. It is essential to combine and analyse data from various sources for Chapter 6.

The chapter is divided into three sections. Section 3.2 introduces the methodology. Section 3.3 validates the methodology through case study. Section 3.4 summarises the Chapter 3.

3.2 Methodology

3.2.1 Data preparation

1) Profile creation

EV charging data, which usually include time series, are closely related to user behaviour, and this type of data exhibits certain regularities [150]. Much of the current research uses trials to obtain data, which emphasises the importance of using real EV profiles [151, 152].Creating a large amount of EV data is an effective way in studying how large-scale EVs participate in ancillary services via V2G. However, the real data of EV participation in V2G is relatively small.

Authors in [153] [154] have proved the superiority of Monte Carlo method to simulate EV driving and charging data. It is specifically shown in Monte Carlo methods combined with EV driving behaviours can simulate many charging and discharging scenarios to cover a wide range of uncertain EV behaviours, thus providing network planners and operators with a detailed basis for optimizing network operation strategies. Modelling based on the Household Travel Survey (HTS) is a common approach. It can accurately demonstrate the driving and charging behaviour of EVs under different scenarios [155]. The flowchart of the Monte Carlo method to create the EV charging profile is shown in Figure 3.1 [156-158].

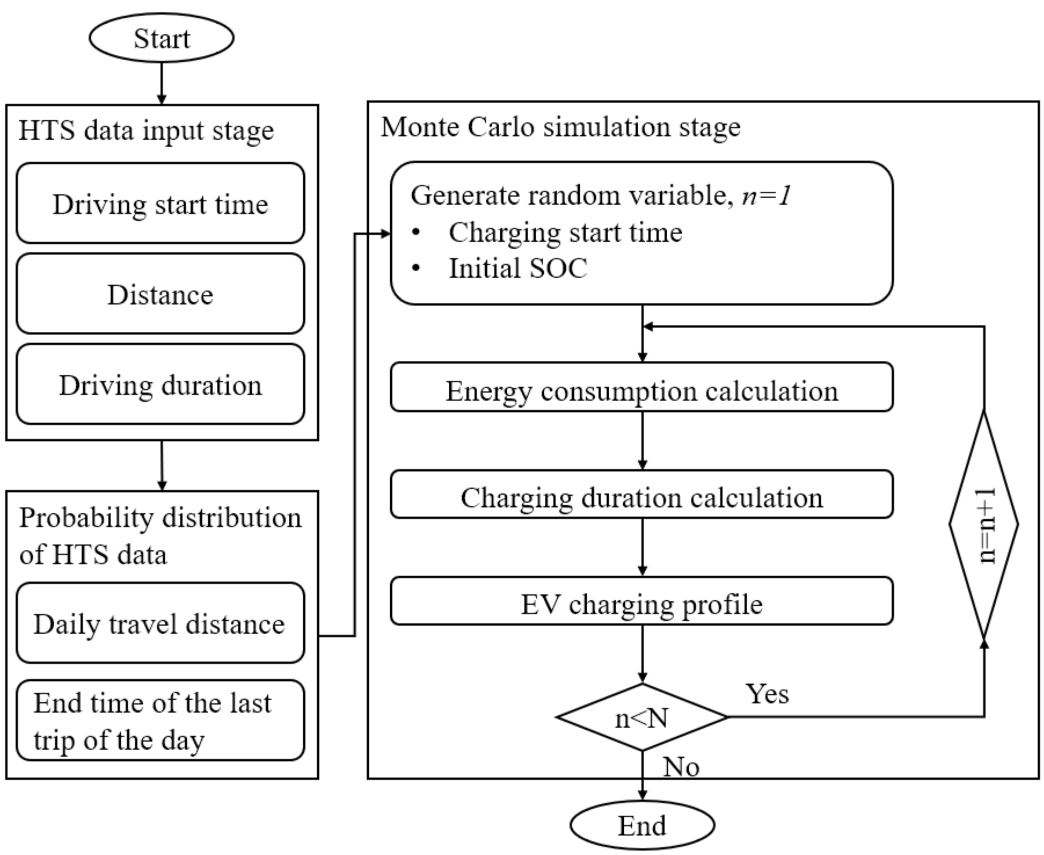


Figure 3.1: Flowchart of Monte Carlo method for creating EV charging profile.

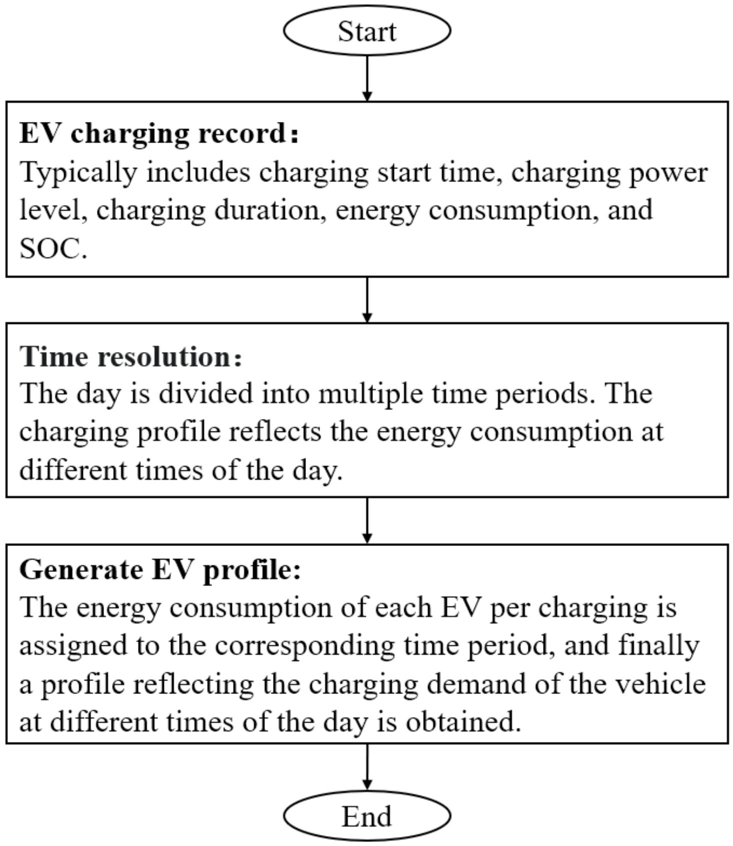


Figure 3.2: Flowchart for creating an EV profile using charging record. Adapted from [P2] and [P3].

The above methodology describes the use of Monte Carlo methods to create an EV charging profile, which is required to cope with the lack of data and the need to simulate a wide range of scenarios. However, there are multiple complexities involved in creating an EV Profile using real data. These factors need to be examined in the context of specific data characteristics. The steps to create a realistic EV profile are shown Figure 3.2.

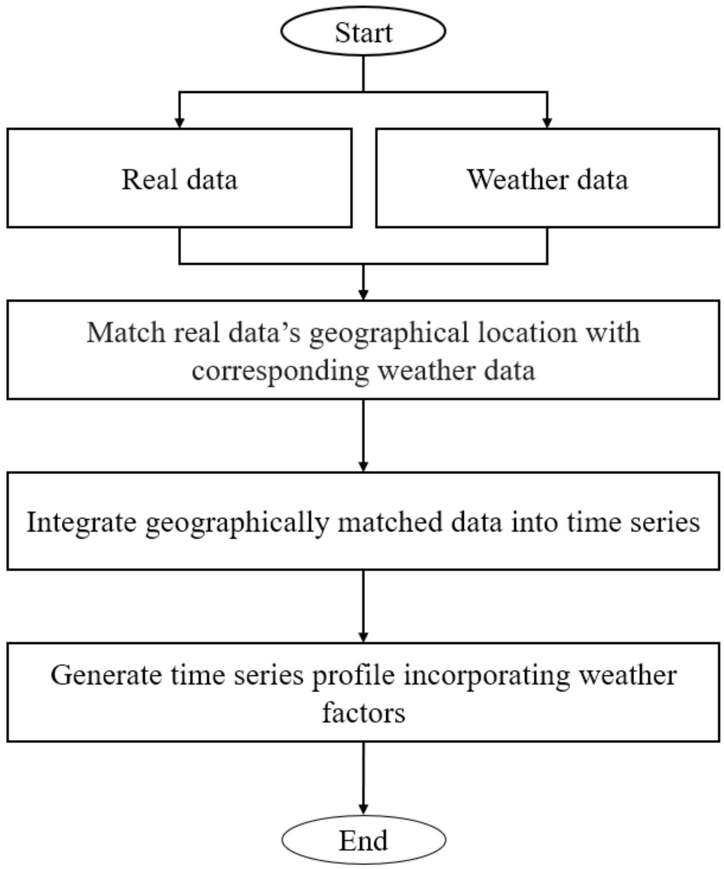


Figure 3.3: Flowchart for data aggregation. Adapted from [P2] and [P3].

2) Data aggregation.

This thesis analyses the impact of EV charging on the distribution network and equipment faults on EV charging points under different weather conditions in Chapters 5 and 6. All of them contain an important factor, the weather factor. Whether it's EV usage ranges, charging points, or equipment, it all includes location, time. The information is spatially associated with the corresponding weather variables. This section combines the real data collected (e.g. EV charging records, device failure data, EV charging points, etc.) with the weather data. As show in the Figure 3.3.

3) Data normalisation.

During the aggregation of multiple types of data, the amount of historical data required may vary significantly due to differences in regions and use cases. For example, the number of EV charging points may not be covered by the primary substation to which they belong. Comparisons based directly on the raw number of faults can lead to inaccurate analysis results. To address this issue, data normalisation is used to ensure comparability between different data.

The main purpose of data normalisation is to eliminate the effects of differences in the size or scale of the data. This allows data sets to be compared and analysed at the same scale [159]. Normalisation allows data from different regions or cases to be mapped to the same range (e.g. between 0 and 1), thus avoiding misleading conclusions due to differences in absolute numbers. Min-Max normalisation is a linear transformation that does not change the shape of the distribution of the data (e.g. skewness and kurtosis of the data) [159]. The relative relationships of the data remain unchanged after normalisation and the distributional characteristics of the original data are preserved. Min-Max normalisation transforms the data into the range [0,1] by the following equation.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3.1}$$

where x is the original data, x' is the normalised data, x_{min} and x_{max} are the minimum and maximum values in the data, respectively

3.2.2 Error Metrics

Root Mean Square Error (RMSE) and Residual Sum of Squares (RSS) are widely used in statistics and data analysis [160]. These metrics can be used to assess the difference between EV charging profile generated by Monte Carlo and real data [161]. These two metrics were chosen because they allow a comprehensive assessment of the accuracy of the modelled data from different perspectives. RMSE is an intuitive and commonly used measure of error [162]. Lower RMSE values indicate a smaller average error in model predictions, which is used in this chapter as a measure of the average deviation of the Monte Carlo simulated profile from the real EV charging profile. RSS provides an overall measure of model fit by calculating the sum of the squares of all simulation errors [163]. Lower RSS values indicate that the simulation results are closer to the real situation in general. The equations for RMSE and RSS are shown below, respectively:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2} \tag{3.2}$$

$$RSS = \sum_{i=1}^{n}(y_i - y_i')^2 \tag{3.3}$$

Where y_i is the real data， y_i' is the simulated data， n is the amount of data

3.2.3 Polynomial regression model

Polynomial regression models can be flexible to accommodate various forms of data [164]. It can model the non-linear relationship that exists between weather variables and

EV driving, charging behaviour. The mathematical equations for the Polynomial regression model are shown below:

$$f = \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots + \beta_n x^n + \varepsilon \tag{3.4}$$

where f represents the dependent variable, x^n represents the independent variable, β_n is the coefficient of the regression equation, representing the weights of the different power terms, ε represents the unobserved random error.

3.3 Case study

3.3.1 EV charging profile modelled by the Monte Carlo method

NHTS provides comprehensive and authoritative travel behaviour data covering driving start times, driving durations, distances, and destinations for all types of vehicles [165]. These characteristics make studies based on NHTS data highly credible and widely applicable, providing a solid database for transportation research, analysis, and policy development [166-168] . Therefore, this section uses vehicle driving data provided by the NHTS as a daily travel characteristic for EVs.

Based on the analysis of the NHTS data (Figure 3.4), it is found that the daily driving mileage of EVs obeys a lognormal distribution (Figure 3.5) whose probability characteristics are expressed by Equation (3. 5). The SOC state of the EV before it is plugged into the charger to start charging is the initial SOC. Assuming that the EV is at 100% SOC before driving, and the EV owner will charge the vehicle immediately after the last trip of the day, the initial SOC can be quantified as Equation (3.6). The probabilistic characteristics of EV charging time (Figure 3.6) can be quantified as Equation (3.7), taking into account the driving behaviours of the EV.

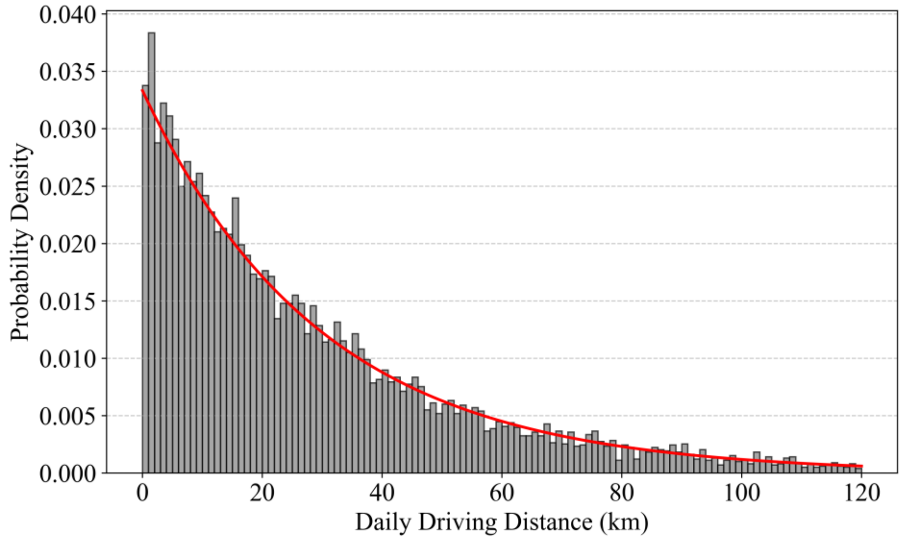


Figure 3.4: Probability density function of daily driving distance.

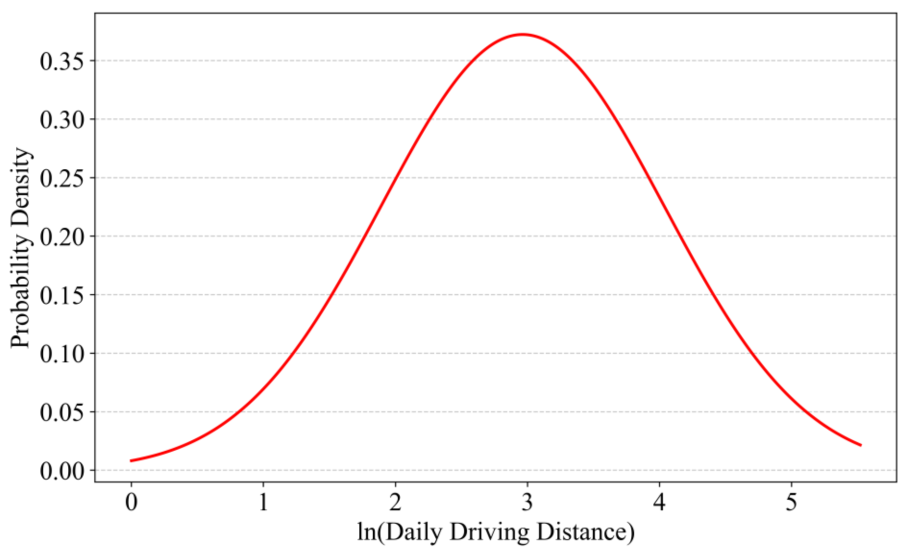


Figure 3.5: Probability density function of lognormal daily driving distance (logarithm).

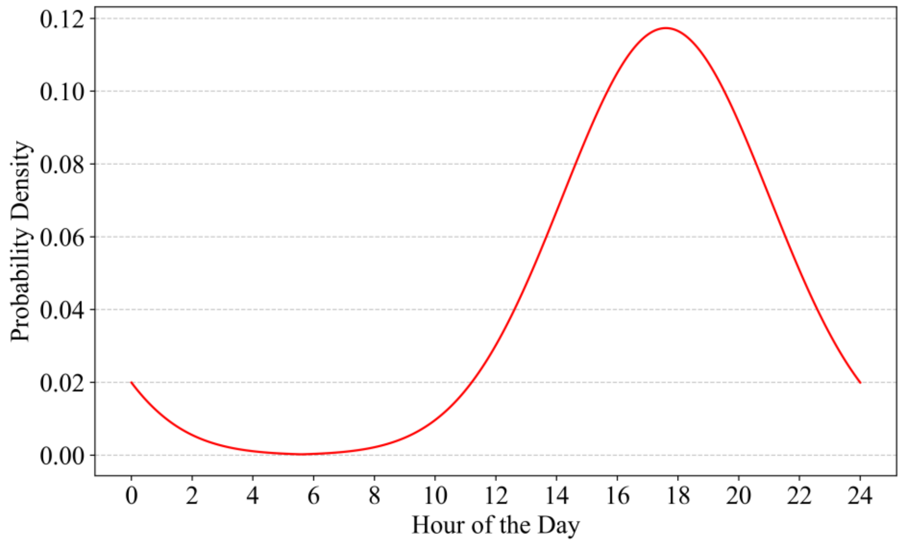


Figure 3.6: Probability distribution of EV charging start time.

$$f_d(x) = \frac{1}{d_{driving}\sigma_{d_{driving}}\sqrt{2\pi}} exp\left[-\frac{\left(ln\, d_{driving}-\mu_{d_{driving}}\right)^2}{2\sigma^2_{d_{driving}}}\right] \tag{3.5}$$

$$SOC_{initial} = \left(1 - \frac{d_{driving}}{D_{driving}}\right) \times 100\% \tag{3.6}$$

$$f_{ct}(x) = \begin{cases} \frac{1}{\sigma_c\sqrt{2\pi}} exp\left[-\frac{(x-\mu_c)^2}{2\sigma_c^2}\right], \ (\mu_c - 12) < x < 24 \\ \frac{1}{\sigma_c\sqrt{2\pi}} exp\left[-\frac{(x+24-\mu_c)^2}{2\sigma_c^2}\right], \ 0 < x < (\mu_c - 12) \end{cases} \tag{3.7}$$

where f_d is EV daily distance (km) , $\mu_{d_{driving}}$ represents mean, $\sigma_{d_{driving}}$ standard deviation, $d_{driving}$ is total driving distance before charging begins, $D_{driving}$ is maximum driving distance of the EV is in 100% SOC, f_{ct} is EV charging time (h), μ_c represent mean, σ_c represent the standard deviation. These parameters determine and adapted from [169, 170].

Charging duration time is determined by 3 factors, namely EV initial SOC, charging power and EV battery capacity. In addition, the charging efficiency can be set according to the requirement.

$$T_d = \frac{C_{battery} \times (1 - SOC)}{P_t^{EV} \times \eta} \tag{3.8}$$

where T_d is EV charging duration time, $C_{battery}$ is battery capacity, P_t^{EV} is charging power at time t, η is charging efficiency.

EV charging behaviour is usually associated with daily usage patterns, most real-time tariffs are usually updated hourly [171]. The 24-hour resolution accurately reflects the volatility and regularity of charging demand [172, 173]. The authors in [174] demonstrate that 10,000 EVs can balance driving and charging behaviour profile. In order to verify the similarity between the Monte Carlo simulated EV charging data and the real data, this section follows the idea in [161, 175]. The simulation results were compared with the charging data of two real projects. These two projects are the "Electric Nation" project [176] and the "My Electric Avenue" project [177]. The average charging load profiles for each project and simulation are shown in the Figure 3.5 with detailed characteristics as follows:

- Electric Nation project [176]: includes 1,200 EVs with daily charging behaviours. Battery capacity range of 33kWh or more and a charging power of 7 kW. Data was recorded from January 1, 2017, to December 30, 2018.
- My Electric Avenue project [177]: includes 215 EVs with daily charging behaviours. Battery capacity of 24 kWh and charging power of 3.5 kW. Data was recorded from August 1, 2013, to July 31, 2015.
- Monte Carlo simulation: The battery capacity is 30kWh, the charging power is 3.5kW, and it simulates the daily charging data of 10,000 EVs. Simulation usually involves a

large number of iterations to produce a distribution of possible outcome values, and as the number of iterations increases, the mean value obtained from a large number of iterations tends to be closer to the expected mean value [178]. The number of iterations for the Monte Carlo method was set to 1000 based on the termination criterion for Monte Carlo simulations[179] and the aggregation of several studies [175, 180].

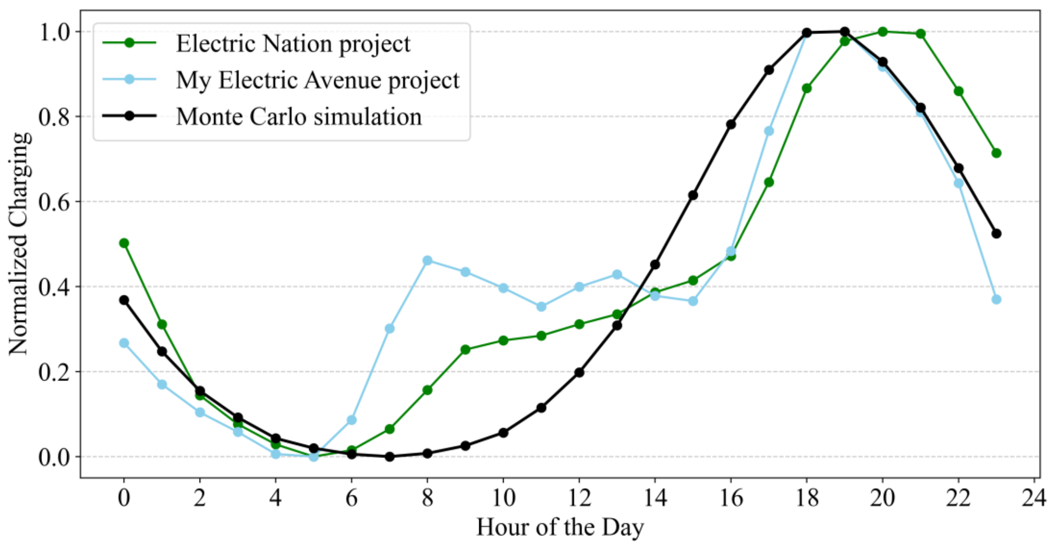


Figure 3.7: The average charging power profiles for simulation and real project.

Table 3.2: Differences between the simulation and real profile.

	RMSE		**RSS**	
	Electric Nation project	My Electric Avenue project	Electric Nation project	My Electric Avenue project
Monte Carlo simulation	0.15	0.41	1.24	4.07

Because of the differences in charging power between the real project and the simulation, a direct comparison does not reflect the consistency between the data. Charging profiles after normalisation the as can be seen from the Figure 3.7. There are differences between the simulated results and the real data. These differences can be assessed in terms of RMSE and RSS [161].

This is reflected in the following aspects: the Monte Carlo simulation profile show a clear peak in charging power during the 18:00 p.m. -22:00 p.m., which almost overlaps with the “Electric Nation” project and is consistent with the trend of the “My Electric Avenue” project. This indicates that Monte Carlo simulation can accurately capture EV charging behaviours during the evening peak hour. During the 0:00 a.m-6:00 a.m., the Monte Carlo simulation profile show lower levels of charging power, which matches the trough hours of the two real projects, suggesting that the simulation methodology is able to reflect lower nighttime charging demand.

The EV data collected by the “Electric Nation project” covers all low voltage networks in the Distribution Network Operator's (DNO) licence area [176], including residential, commercial and public service areas. Smaller error between data normalisation and Monte Carlo simulation. This is demonstrated by the lower RMSE (0.15) and RSS (1.24). The EVs involved in V2G may be at arbitrary locations, but the available data on V2G is rather lacking [22]. By comparing with the Electric Nation project which contains various types of regions EV data, it is demonstrated that the Monte Carlo method can simulate the EV profile under different regions well. This also provides the basis for Chapter 4 to simulate the large-scale EV data using the Monte Carlo method. In contrast, the data from the “My Electric Avenue project” has a larger error value when compared to the load profile from the Monte Carlo simulation, mainly due to the fact that the data from this project shows a new peak between 06:00 and 13:00. The data for the “My Electric Avenue project” comes from EV used by household customers [177]. Concentrating on charging in residential areas.

3.3.2 Effect of temperature on EV behaviour

The charging energy consumption of EV depends on its energy consumption during driving. The daily driving distance of the EV determines the energy consumption during driving [11]. This section provides insight into the relationship between temperature and EV energy consumption per kilometre using polynomial regression models. This section utilizes real EV driving data from the “My Electric Avenue project” [177], along with local maximum temperature data from the UK MET Office [181], to demonstrate the practical relationship between temperature and EV energy consumption. To construct these models, the EV driving profile and weather profile was created following the steps in Section 3.2.1.

Figure 3.8 clarifies the relationship between an EV's driving distance and its energy consumption. Each circular data point represents the energy consumption (in kWh) at a specific driving distance. The colour of the data point changes according to the colour bar on the right, which reflects the corresponding temperature of the EV during driving. The red fit line shows a linear relationship between driving distance and energy consumption, where the Spearman's correlation coefficient is 0.94, which indicates a very strong positive correlation between driving distance and energy consumption. The fitted curve can be expressed by Equation (3.9). This linear fit provides a basic model that can be used to predict the effect of driving distance on energy consumption, even without directly accounting for changes in temperature.

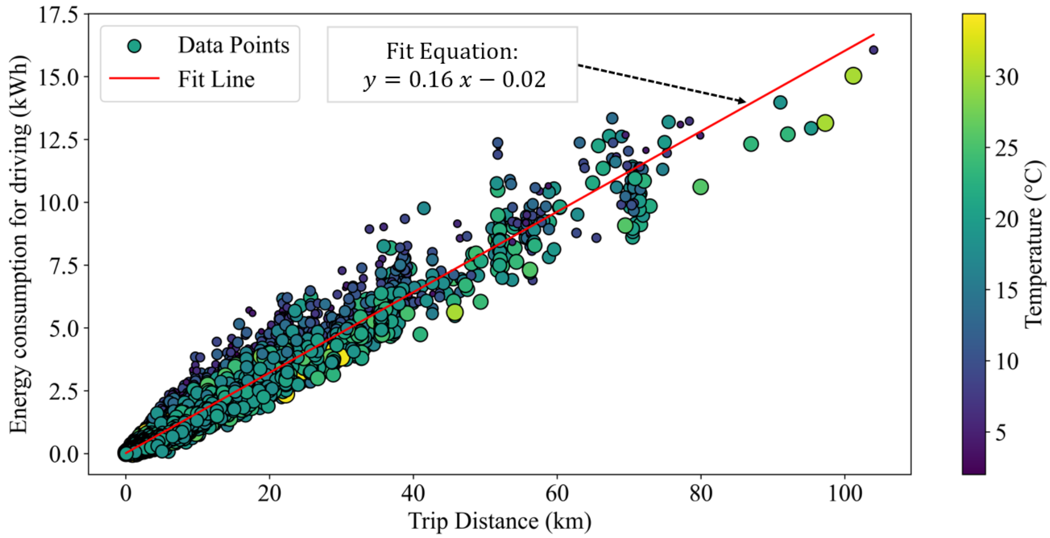


Figure 3.8: Relationship between energy consumption for driving and distance travelled.

$$y = 0.16x - 0.02 \tag{3.9}$$

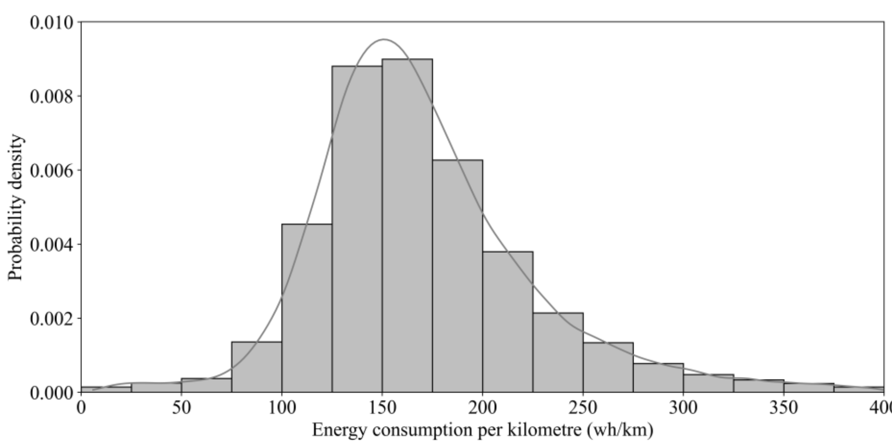


Figure 3.9: Probability of EV energy consumption per kilometre (Wh/km).

Figure 3.9 show the probability density function of the EV energy consumption per kilometre (Wh/km), the statistical characteristics of the energy consumption of the EV in actual operation can be observed. The peak is located near about 150 Wh/km. This value is affected by a number of physical factors, including vehicle speed, acceleration pattern, vehicle weight, air resistance and rolling resistance, etc.

In order to provide a measure of the effect of temperature changes on the energy consumption of EV driving, Figure 3.10 shows the average energy consumption per kilometer (Wh/km) of EVs at different temperatures. The data points represent the average energy consumption at different temperatures, which are fitted by regression function. The results show that there is a significant non-linear relationship between the energy consumption per kilometer of the EV and the temperature: The energy consumption is higher at lower temperatures, decreases rapidly as the temperature increases, reaches a minimum between 15°C and 23°C, and then increases again as the temperature continues to rise.

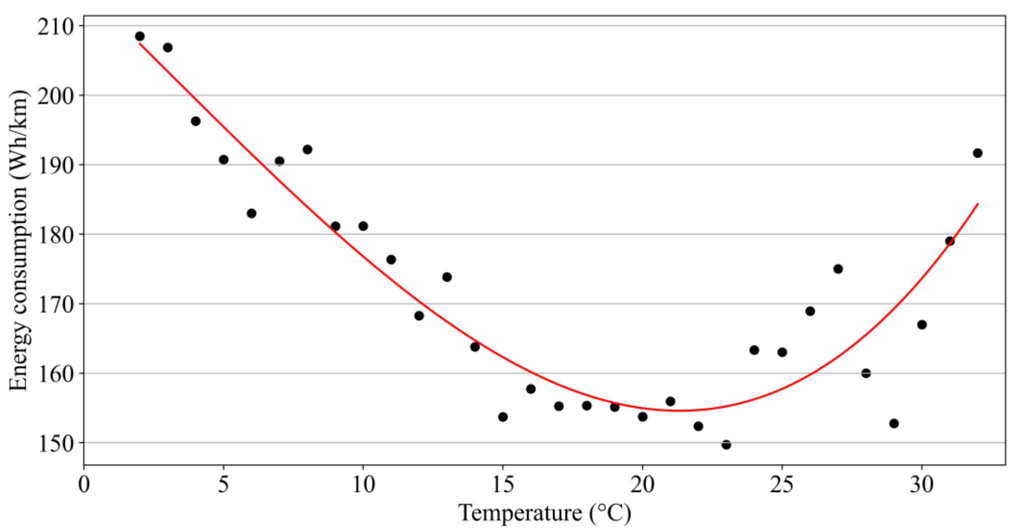


Figure 3.10: Average energy consumption per kilometre (Wh/km) of EVs at different temperatures.

From Figures 3.8 – 3.10 can be observed that in the appropriate temperature range, the driving frequency of the EV is high and the energy consumption per kilometer is relatively low and stable. Under extreme conditions of too low or too high temperatures, the driving frequency of EVs decreases and the energy consumption increases significantly. Comparison of polynomial fit curves on temperature versus energy consumption per kilometer driven from this study and other similar studies are shown in Figure 3.11 [77, 182]. As the plotting of the curve in Figure 3.11 is derived from the regression equation, no normalisation is possible. Although there are differences in specific values, their energy consumption curves show a consistent trend. All three models show a nonlinear U-shaped curve of energy consumption with temperature, i.e., energy consumption increases at very low and very high temperatures. The lowest values of energy consumption per kilometer are all within 21°C -23°C (red dot).

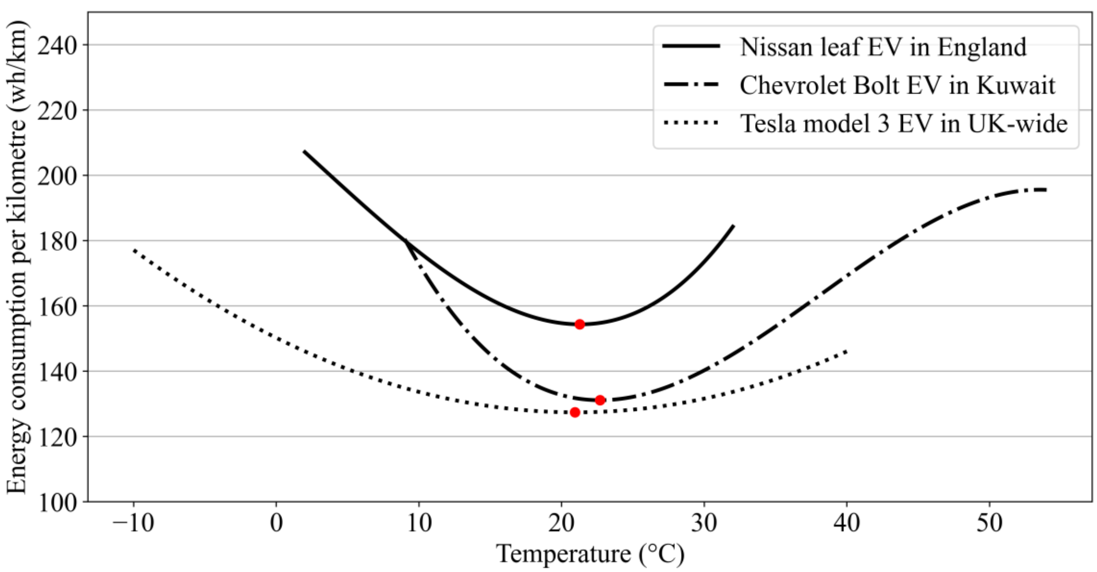


Figure 3.11: Comparison of various studies on EV energy consumption per kilometer as a function of temperature.

While each of these studies provides important insights into the performance of different electric vehicles in a variety of climatic conditions, there are some notable limitations and drawbacks to these studies. For example, while the Chevrolet Bolt case study in Kuwait [182] analyses the effect of temperature on EV driving energy consumption, it does not consider the specific effect of temperature changes on EV charging energy consumption. This is an important omission. Similarly, the case study of the Tesla Model 3 [77], while considering the impact of the EV charging on network power and energy requirements at different temperatures, does not take into account the capacity constraints of the local network at all. This may lead to an incomplete analysis of the feasibility in a real operating environment, as EV charging loads are limited by the hosting capacity of the distribution network.

3.3.3 Discussions

The Monte Carlo simulation method demonstrates large-scale simulation capabilities in simulating EV charging data. By simulating data from 10,000 EVs, the Monte Carlo method is able to cover a wider range of charging behaviours and scenarios, improving the representativeness of the results. Moreover, the Monte Carlo simulation is able to generate corresponding data based on different battery capacity and charging power configurations, which is especially important when the real data is difficult to be fully covered. There is a low error between the Monte Carlo simulated EV charging profile and the real project. This also validates that the Monte Carlo method can be an effective tool for modelling EV data and support was provided for the simulation of a large amount of V2G data using the Monte Carlo method in Chapter 4.

The data for the 'My Electric Avenue Project' comes from electric vehicles used by householders [177], with EVs focussed on charging in residential areas. It is therefore possible to reflect the charging behaviour of EVs in residential areas, in particular the two peaks that occur in the midday and evening hours respectively. In order to be able to further analyse the actual impact of EVs in different regions on the low voltage distribution network in their respective regions. Chapter 5 uses data from the “My Electric Avenue project” to visualise the impact of EV charging on Low-Voltage (LV) distribution network in residential areas.

Comparability between different data sets can be further enhanced through data aggregation and data normalisation. For example, there are differences in charging power, number of EVs tracked, and types of EVs between real projects (Electric Nation, My Electric Avenue, etc.). Direct comparison is not the appropriate method [183]. The focus in Chapter 6 is on the impact of power system equipment faults on EV charging points under different weather factors. This chapter supports the data preparation needed for the analysis in Chapter 6.

3.4 Summary

This chapter present a method to simulate EV charging profile through Monte Carlo and its accuracy is verified. By comparing the simulated data with real EV charging data, this chapter demonstrates the ability of the Monte Carlo method to generate charging data in the presence of insufficient data. This provides a foundation for the future use of Monte Carlo methods in large-scale EV charging data simulations, especially in Chapter 4, where the method will be further applied to larger scale data analyses. In addition, this chapter explores the impact of weather conditions, particularly temperature, on the EV driving energy consumption. Through analysis and discussion, this chapter finds that temperature affects energy consumption during EV driving. This finding will support in Chapter 5 that analyses the effect of temperature on EV charging behaviour and quantifies the EV hosting in distribution networks. Finally, the chapter describes the data preparation, showing how multiple data can be aggregated and data normalised to support the analysis in subsequent chapters. In particular, this method is used in Chapter 6 to present the impact of power system equipment faults on EV charging points under different weather factor.

Chapter 4

Optimal Bi-Level Scheduling Method of Ancillary Services Provided by Vehicle-to-Grid

4.1 Introduction

In power systems, the trend is for more and more vehicles to be connected to the network as the penetration of EVs gradually increases [78]. By involving EVs in the network interaction, bi-directional charging can be achieved. This technology is called Vehicle-to-Grid (V2G) technology [50]. V2G technology not only improves energy utilisation, but also reduces network load while providing an additional revenue stream for EV aggregators (EVA), EV charging stations and EV owners [184]. Therefore, judicious use of the ancillary services provided by V2G can help realise these potential benefits [40]. EVAs are commercial entity that connects EV users and power system operators to participate in the electricity market [184]. The EVA manages the charging and discharging of EVs while also gathering information on the available capacity of EVs connected to the network [185]. When the area covered by EVs in the power system is extensive or the penetration of EVs is high, the entire system requires multiple EVAs [186]. EVA provides flexibility in the operation of electricity markets [187]. However, stochastic aggregation behaviour of EV owners and volatility in electricity market prices can create financial risks for aggregators' operations [188].

Based on above issues, the following research gap is addressed in Chapter 4: How can the interaction between EVs and the network be coordinated to achieve a globally optimal solution in the context of the UK power system and electricity market, thereby reducing network load pressure and charging costs, and optimizing the net profitability of participating in the ancillary services process through risk management? Firstly, the basic concepts of the bi-level scheduling problem are explained in this chapter, including the definitions of the upper-level and lower-level problems and their interrelationships. Secondly, to reduce the complexity of the model, the bi-level scheduling is equated to a linear problem. Subsequently, a profit risk management strategy for EV aggregators is provided to help them effectively manage the profit risk faced in the V2G market.

Section 4.2 details a bi-level scheduling approach to address the uncertainty and profit risk caused by the ancillary services provided by V2G. Section 4.3 describes the application of the above method. Specifically, the application of bi-level scheduling to an actual V2G system is examined and its scheduling results on weekdays and weekends are analysed. In addition, a conditional risk sensitivity analysis is performed. Finally, Chapter 4 is summarised in Section 4.4. The publication [P1] emanates from the research described in this chapter.

4.2 Bi-Level Scheduling Method

As mentioned in Section 4.1, the existence of an EVA is essential for EVs to provide ancillary services to the network. Uncertainty in EV charging behaviour and volatility in electricity market prices can create financial risks for the operation of an EVA. Therefore, a generic bi-level scheduling method is proposed in this section. This method enables the EV to maximise the net revenues of the EV aggregate (EVA), while guaranteeing the benefit of EV users, when they participate in the ancillary services via V2G.

4.2.1 Upper-level and lower-level problem

1) Upper-level problem.

To allow EVs to participate in ancillary services through V2G, EVA receives signals from the energy market, processes them through integrated computing, and then sends charging or discharging signals to the EVs at the charging points [189]. EVs will respond to the signal by adjusting charging or discharging behaviour [190]. This process includes the following services: Regulation-down service is EV charging power from the network when the network power reserve is high and regulation-up service means that the EV provides power to the network. The purpose of both is to ensure load balancing on the network [191].

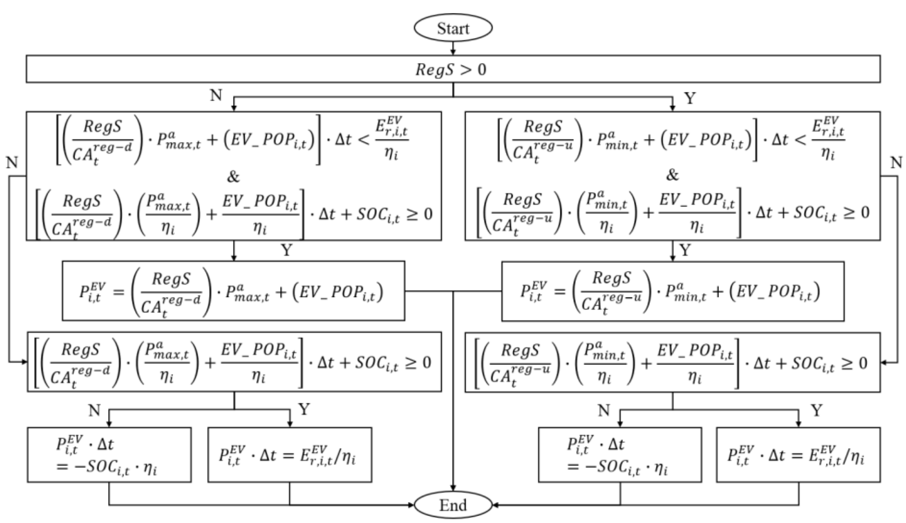


Figure 4.1: Algorithm for calculating EV battery power consumption under regulation services.

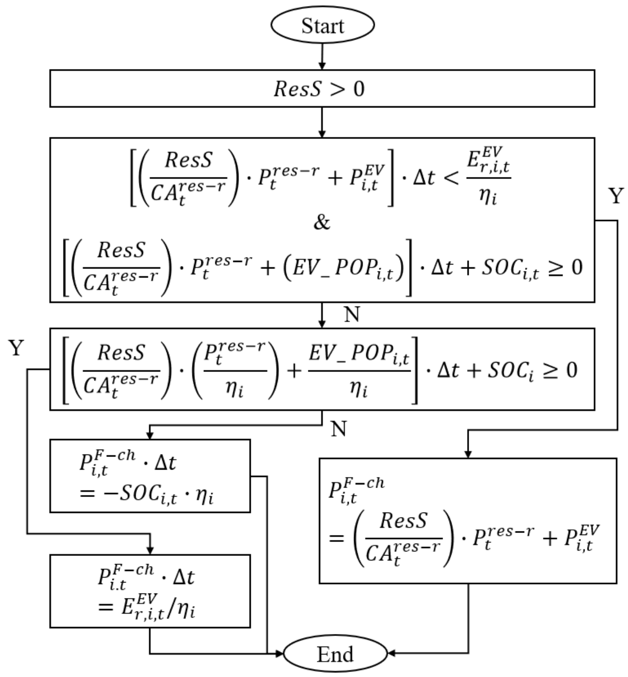


Figure 4.2: Algorithm for calculating EV battery power consumption under responsive reserves services.

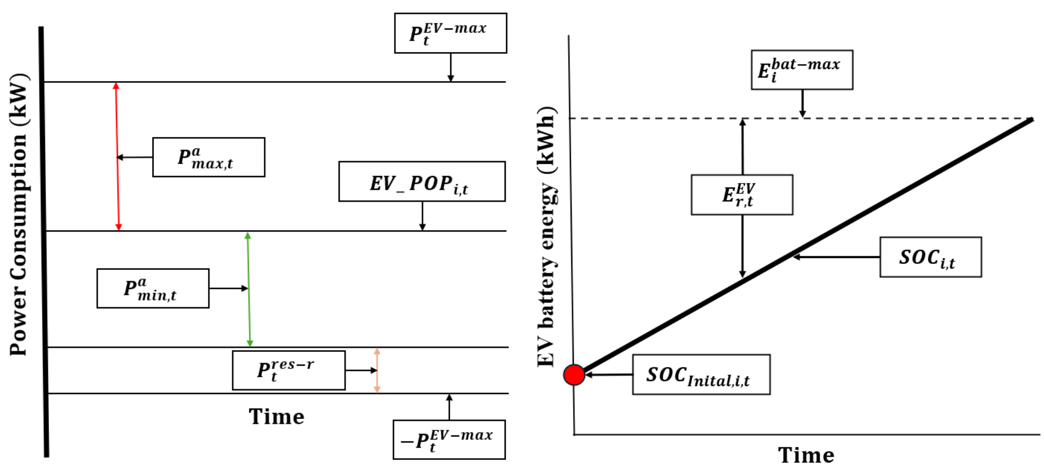


Figure 4. 3: Interpretation and relationship between variables.

The EV must respond to signals received from the system to dispatch energy if capacity for ancillary services is offered. The corresponding EV charging power consumption is obtained by calculating the signal provided by the conditioning service, and the EV charging power consumption is used to calculate the response reserve signal.

The regulation service (Figure 4.1) and the responsive reserve scheduling (Figure 4.2) are independent, but the results of the two algorithms can be combined. Figure 4.3 illustrates the meaning and relationships of each variable.

EVA can provide financial incentives to vehicle owners by maximising profits as they participate in ancillary services. This approach can encourage more EV users to connect their vehicles to the network and participate in the ancillary services market. This financial incentive is a key factor in promoting the adoption of V2G technology and market participation. Therefore, maximising the net revenue of the EVA is defined as the optimisation objective in the upper-level problem. In addition, as reviewed in Chapter 2 - Sections 2.2.2, one of the challenges that EVs face when participating in ancillary services is battery degradation. The degradation costs of EV batteries (Equation 4.9) are also considered in the upper-level problem. The objective function of upper-level problem is expressed as:

a. Objective function: The equations in the upper-level model represent the objective function, which aims to maximize the net revenue of EVA. EVA can provide energy trading services in the distribution network concurrently with EV charging [192, 193]. Equation (4.1) defines F^{EVA} as the EVA net-revenue in the upper-level problem.

$$max\, F^{EVA} = UI - UC \tag{4.1}$$

$$UI = \left[\partial \cdot \sum_{t=1}^{T} \begin{pmatrix} \cdot P_t^{F-ch} + p_p^{reg-u} \cdot CA_t^{reg-u} \\ +p_p^{res-r} \cdot CA_t^{res-r} + p_p^{reg-d} \cdot CA_t^{reg-d} \end{pmatrix}\right] \tag{4.2}$$

$$U\partial \cdot \left(\sum_{t=1}^{T} C_{i,t}^{bat-deg} + \delta_t^{ch} \cdot P_t^{F-ch}\right) \tag{4.3}$$

$$C_{i,t}^{bat-deg} = 0.06 \cdot \left(C_i^{bat-rep} \big/ 5000\right) + \left(1 - \eta_i^2 \big/ \eta_i\right) \tag{4.4}$$

where UI represents the total EVA income and UC stands for the total EVA cost, ∂ is number of days, M_t^k, δ_t^{ch}, p_p^{reg-u}, p_p^{reg-d} and p_p^{res-r} are the tariff offered by EVA to EV owners, electricity market energy price, regulation-up price, regulation-down price and price of responsive reserve within the time period t. $C_{i,t}^{bat-deg}$ *and* $C_{i,t}^{bat-rep}$ are battery degradation costs and EV battery replacement fees. P_t^{F-ch}, CA_t^{reg-u}, $\cdot CA_t^{reg-d}$ and CA_t^{res-r} are final power consumption, power consumption of regulation-up, power consumption of regulation-down and power consumption of responsive reserve within the period *t*. Efficiency of EV charger is represented by η_i.

b. Constraint conditions: In the ancillary services market, the regulation amount refers to the total power deviation allowed from the baseline level, known as the Preferred Operating Point (POP) [194]. This section uses $EV\_POP_{i,t}$ to represent the power consumption of i^{th} electric vehicle at time *t*. The constraints of upper-level objective function are illustrated by Equations (4.5) – (4.15). Firstly, P_t^{F-ch} is defined as shown in Equation (4.5). Equations (4.6) and (4.7) limit the battery's maximum charge during parking time based on its capacity, ensuring that the charge remains positive. At the same time, when the EV departs the charging point, EV remaining capacity in battery must address the subsequent traveling (as shown in Equation (4.8) – (4.11)). The EV charging power from the network and the EV power to the network each hour is constrained by the maximum charge and discharge rates, as outlined in Equation (4.12) – (4.15). These constraints also account for the EV additional power consumption and responsive reserve power consumption at time *t* by the system.

$$P_t^{F-ch} = \left(EV_{POP_{i,t}}\right) + \left(\varepsilon^{reg-d} \cdot P_{max,t}^{a} - \varepsilon^{reg-u} \cdot P_{min,t}^{a} - \varepsilon^{res-r} \cdot P_t^{res-r}\right) \quad (4.5)$$

$$\left(\sum\nolimits_t \left(P_t^{F-ch} * \eta_i\right) + SOC_{Init,i}\right) \le E_i^{bat-max} \quad (4.6)$$

$$\left(\sum_t \left(P_t^{F-ch} * \eta_i\right) + SOC_{Init,i}\right) \ge 0 \quad (4.7)$$

$$\sum\nolimits_{t=1}^{T} \left(P_t^{F-ch} * \eta_i\right) + SOC_{Init,i} \ge 99\% \cdot E_i^{bat-max} \quad (4.8)$$

$$\left(P_{max,t}^{a} + EV\_POP_{i,t}\right) * \eta_i + SOC_{Init,i} \le E_i^{bat-max} \quad (4.9)$$

$$\left(\left(EV\_POP_{i,t} - P_{min,t}^{a} - P_t^{res-r}\right) * \eta_i + SOC_{Init,i}\right) \ge 0 \quad (4.10)$$

$$\left(\left(EV\_POP_{i,t} - P_{min,t}^{a} - P_t^{res-r}\right) * \eta_i + SOC_{Init,i}\right) \ge E_i^{Trip} \quad (4.11)$$

$$EV\_POP_{i,t} \ge -P_{i,t}^{EV-max} \quad (4.12)$$

$$P_{max,t}^{a} + EV\_POP_{i,t} \le P_{i,t}^{EV-max} \quad (4.13)$$

$$P_{min,t}^{a} - EV\_POP_{i,t} \le P_{i,t}^{EV-max} \quad (4.14)$$

$$P_t^{res-r} - EV\_POP_{i,t} + P_{min,t}^{a} \le P_{i,t}^{EV-max} \quad (4.15)$$

where $E_i^{bat-max}$ is maximum battery capacity of the EV. $P_{max,t}^{a}$ and $P_{min,t}^{a}$ is EV maximum / minimum additional power consumption within time period *t*. η_i represents EV charger efficiency. $\varepsilon^{reg-d}, \varepsilon^{reg-u}\ and\ \varepsilon^{res-r}$ represent the expected percentage of power consumption for regulation-down, regulation-up, and responsive reserve scheduling, respectively.

$$0 \le \delta^{ch} \le M_t^k \le M_t^{k-max} \tag{4.16}$$

$$-P_{max}^{tr} \le P_{i,t}^{EV} \le P_{max}^{tr} \tag{4.17}$$

$$0 \le -P_{c,t}^{EV} \le P_{max}^{cf} \tag{4.18}$$

$$0 \le P_{dc,t}^{EV} \le P_{max}^{cf} \tag{4.19}$$

Constraint (4.16) ensures the profitability of the EVA, the charging price (M_t^k) offered by the EVA to the EV owner needs to be greater than the electricity market price (δ_t^{ch}) and be limited to a predetermined range (M_t^{k-max}). Constraints (4. 17) restricts the total power consumption ($P_{i,t}^{EV}$) between the distribution network and the EVA, i.e. the maximum power capacity of the substation transformer cannot be exceeded. Constraints (4.18) and (4.19) limit the EV charging and discharging power through charging facilities. $P_{c,t}^{EV}$ and $P_{dc,t}^{EV}$ stand for EV charging power and EV discharging power.

$$P_t^{F-ch} \cdot \Delta t = E_{t,i}^{EV} \tag{4.20}$$

At the same time, the energy limits for participation in ancillary services have to be considered. Constraint (4. 20) connects the upper level with the lower level by ensuring that the total energy demand of the EV owner is equal to the energy supplied to the EV. E_t^{EV} is total charging energy consumption of the EV.

2) Lower-level problem.

In this lower-level problem, the total profit of the EV user is defined as being obtained by subtracting the original charging cost of the EV from the total marginal benefit obtained by transferring the energy from the EV to the EVA. The method of obtaining marginal utility proposed in [195] has been used in a large number of studies. Therefore, this chapter follows the steps proposed in [195] to obtain marginal utility. The marginal utility of different block of EVs is shown in Figure 4.4.

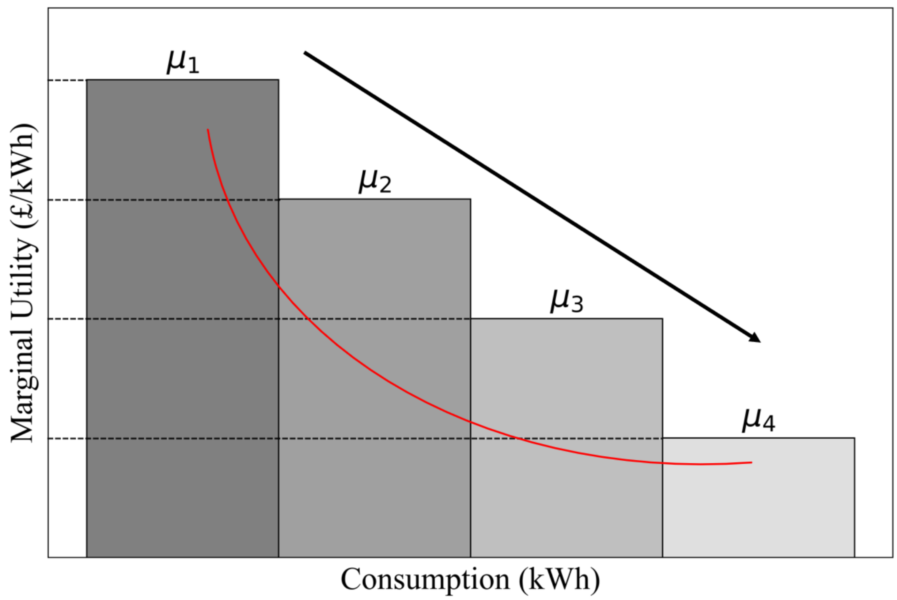


Figure 4.4: Marginal utility block of EV owners.

a. Objective function: In the lower-level model, the profit of EV owners (F_t^{EV}) can be maximized through the following objective function (Equation (4.21)). The total marginal utility ($MU_{t,i}^{EV}$) and total EV charging cost ($C_{t,i}^{EV}$) are shown in Equations (4.22) and (4.23).

$$Max\ F_{t,i}^{EV} = MU_{t,i}^{EV} - C_{t,i}^{EV} \tag{4.21}$$

$$MU_{t,i}^{EV} = \sum_{m=1}^{M} u_{t,m}^{EV} E_{t,i,m}^{EV} \tag{4.22}$$

$$C_{t,i}^{EV} = \sum_{m=1}^{M} M_t^k \, E_{t,i,m}^{EV} \tag{4.23}$$

b. Constraint conditions: Constraints (4.24) - (4.27) correspond to four different marginal utilities ($[\mu_t^1, \mu_t^2, \mu_t^3 \; and \; \mu_t^4]$) and the relationship between the parameters $E_{i,max}^{EV}$ and $E_{i,min}^{EV}$ is also shown by Figure 4.5.

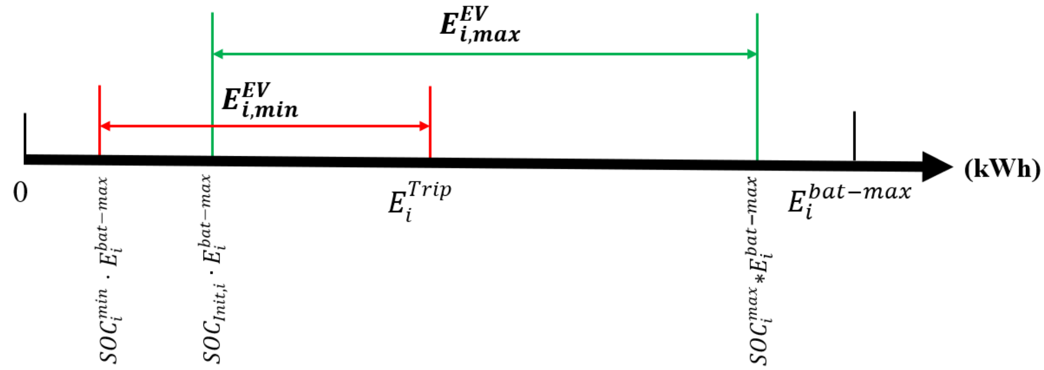


Figure 4.5: Explanation of the difference between $E_{i,min}^{EV}$ and $E_{i,max}^{EV}$.

$$\sum_{t=1}^{T}\left(E_{t,i}^{EV} - E_{i,max}^{EV}\right) \leq 0 \qquad \left(\mu_{t,1}^{EV}\right) \tag{4.24}$$

$$E_{i,min}^{EV} - E_{t,i,m}^{EV} \leq 0 \qquad \left(\mu_{t,2}^{EV}\right) \tag{4.25}$$

$$E_{i,max}^{EV} - E_{t,i,m}^{EV} \geq 0 \qquad \left(\mu_{t,3}^{EV}\right) \tag{4.26}$$

$$E_{t,i,m}^{EV} > 0 \qquad \left(\mu_{t,4}^{EV}\right) \tag{4.27}$$

$$E_{i,max}^{EV} = E_i^{bat-max} \cdot \left(SOC_i^{max} - SOC_{Init,i}\right) \tag{4.28}$$

$$E_{i,min}^{EV} = \; E_i^{Trip}{}_i - E_i^{bat-max} \cdot \left(SOC_{Init,i}\right) \tag{4.29}$$

where $E_{i,max}^{EV}$ is maximum EV energy consumption and $E_{i,min}^{EV}$ is minimum EV energy consumption. SOC_i^{max} and SOC_i^{min} are the maximum and minimum state of charge allowed of the i^{th} electric vehicle, respectively. $SOC_{Init,i}$ is the state of charge at the initial moment of the i^{th} electric vehicle. Figure 4.2 illustrates the meaning of each variable.

For constraint (4.24), the sum of the total energy supplied by the EV over all time is not exceeding $E_{i,max}^{EV}$. This process may continue for a period of time, and the total energy supplied is spread over all units of time. Therefore, the marginal utilities of $E_{t,i}^{EV}$ in this range is set to $\mu_{t,1}^{EV}$. Constraint (4.25) is the sum of the total energy provided by the EV over all time is greater than $E_{i,min}^{EV}$, i.e., this is the portion of energy that can be used to satisfy at least the next trip for that EV. The marginal utilities of $E_{t,\mathrm{i}}^{EV}$ in this range is set to $\mu_{t,2}^{EV}$. Constraint (4.26) is similar to Constraint (4.24), but the difference is that $E_{t,\mathrm{i}}^{EV}$ in Constraint (4.24) is the sum of the energies in the time period used, whereas Constraint (4.27) refers specifically to the total energy in one time period. Then, the marginal utilities of $E_{t,\mathrm{i}}^{EV}$ in this range is set to $\mu_{t,3}^{EV}$. Constraint (4.28) implies that $E_{t,\mathrm{i}}^{EV}$ can be as long as it is greater than 0, and the energy it provides is uncertain. The marginal utilities of $E_{t,\mathrm{i}}^{EV}$ in this range is set to $\mu_{t,4}^{EV}$.

4.2.2 Equivalent bi-level scheduling to single-level linear programming

Variables in the upper-level problem can be considered as parameters of the lower-level problem. However, there are discrete variables in lower-level problem, this is a non-convex problem. Karush-Kush-Tucker (KKT) condition is one of the effective tools for dealing with non-convex optimisation problem [196]. In order to find a globally optimal solution to a bi-level optimisation problem, this method is implemented by splitting the problem [197]. McCormick relaxation is an effective way to convert nonlinear to linear [198]. The proposed method in this section applied KKT condition and combines with McCormick relaxation method to deal with potential nonlinearities in the problem. This process can convert bi-level programming into a single-level linear programming.

The KKT condition can transform a lower-level model into a set of constraints for a higher-level model by introducing a Lagrange multiplier variable. Once converted through the KKT condition, the lower-level model becomes a non-linear constraint set. Therefore, the "linprog" method, which is used to solve single-stage problems, is no longer applicable to the bi-level model. [197]. Given that the Lagrangian function with the Lagrange multiplier results in a non-linear problem, Equations (4.21) to (4.29) can therefore be expressed as:

$$\begin{aligned} L\left(E_{t,\mathrm{ii}}^{EV}, \mu_{v,t}^{1,2,3,4}\right) = \sum_{t=1}^{T} (E_{t,i}^{EV} M_t^k - E_{t,i}^{EV} \cdot u_t^{EV}) + \mu_{t,1}^{EV} \cdot \sum_{t=1}^{T} \left(E_{t,i}^{EV} - E_{i,max}^{EV}\right) \\ + \mu_{t,2}^{EV} \cdot \sum_{t=1}^{T} \left(E_{i,min}^{EV} - E_{t,i}^{EV}\right) + \mu_{t,3}^{EV} \cdot \left(E_{t,i}^{EV} - E_{i,max}^{EV}\right) \\ - \mu_{t,4}^{EV} E_{t,i}^{EV} \end{aligned} \tag{4.30}$$

$$\frac{\delta L}{\delta(d_{v,t}^{EV})} = M_t^k - u_{t,m}^{EV} + \mu_{v,t}^1 + \mu_{v,t}^2 + \mu_{v,t}^3 - \mu_{v,t}^4 = 0 \tag{4.31}$$

$$0 \leq \textstyle\sum_{t=1}^{T} \left(E_{t,i}^{EV} - E_{i,max}^{EV}\right) \perp \ \mu_{v,t}^1 \geq 0 \tag{4.32}$$

$$0 \leq \left(E_{t,i}^{EV} - E_{i,min}^{EV}\right) \perp \mu_{v,t}^2 \geq 0 \tag{4.33}$$

$$0 \leq \left(E_{t,i}^{EV} - E_{i,max}^{EV}\right) \perp \ \mu_{v,t}^{3} \geq 0 \tag{4.34}$$

$$0 \leq E_{t,i}^{EV} \perp \ \mu_{v,t}^{4} \geq 0 \tag{4.35}$$

Equation (4.30) is the Lagrange equation in the lower-level model. Constraints (4.32) – (4.35) are the simplified KKT conditions. Equivalent single-level model of bi-level problem can be obtained by replacing equation (4.21) – (4.27) with (4.31) – (4.35). Constraints (4.32) – (4.35) are complementary conditions to the inequality Constraints (4.24) – (4.27). The complementarity condition $0 \leq E^{EV} \perp \ \mu^{EV} \geq 0$ can be converted into the set of mixed-integer constraints using the Fortuny-Amat transformation [199]. In order to convert the bilinear product of the objective function into a linear product, McCormick relaxation [200, 201] is used in this chapter. According to the McCormick approximation. If $z = a \times b$, where $a \in [a_{min}, a_{max}]$ and $b \in [b_{min}, b_{max}]$, it can be equivalent as four constraints:

$$z \geq a_{min}b + b_{min}a - a_{min}b_{min} \tag{4.36}$$

$$z \geq a_{max}b + b_{max}a - a_{max}b_{max} \tag{4.37}$$

$$z \leq a_{min}b + b_{max}a - a_{min}b_{max} \tag{4.38}$$

$$z \leq a_{max}b + b_{min}a - a_{max}b_{min} \tag{4.39}$$

In addition to the non-linear constraints, the objective function also contains non-linear elements, such as $\delta^{ch}P^{ch}$.

$$UI = \left[\partial \cdot \sum_{t=1}^{T} \begin{pmatrix} z_t^{EV} - \delta_t^{ch} \cdot P_{i,t}^{EV} + p_p^{reg-u} \cdot CA_t^{reg-u} + \\ p_p^{res-r} \cdot CA_t^{res-d} + p_p^{reg-d} \cdot CA_t^{reg-d} \end{pmatrix}\right] \tag{4.40}$$

$$z_t^{EV} \geq M_t^{k-max} \cdot P_{i,t}^{EV} + z_t^{cf} - M_t^{k-max} \cdot P_{max}^{cf} \tag{4.41}$$

$$z_t^{EV} \leq z_t^{cf} \tag{4.42}$$

$$z_t^{EV} \leq M_t^{k-max} \cdot P_{i,t}^{EV} \tag{4.43}$$

$$z_t^{cf} \geq M_t^{k-max} \cdot P_{max}^{cf} + M_t^{k} \cdot P_{max}^{cf} - M_t^{k-max} \cdot P_{max}^{cf-max} \tag{4.44}$$

$$z^{cf} \leq M_t^{k} \cdot P_{max}^{cf} \tag{4.45}$$

$$z_t^{cf} \leq M_t^{k-max} \cdot P_{max}^{cf} \tag{4.46}$$

$$z_t^{EV} \geq 0 \tag{4.47}$$

$$z_t^{cf} \geq 0 \tag{4.48}$$

Replace equation (4.2) with (4.40) and add the constraints (4.41) - (4.48). The Bi-level model can transform into a standard single-level mixed-integer linear programming problem.

4.2.3 Risk management

Section 4.2.2 describes how bi-level scheduling can be equated to single-level modelling. However, risk management of profits is important when developing optimisation strategies for stakeholders. The risk measurement terms related to profit allocation in optimisation models is widely used. Conditional Value at Risk (CVaR) is a risk measure that manages financial risk caused by uncertainty [202-204]. Combining a bi-level optimization model with CVaR ensures that the decision-making process not only considers maximizing the benefits, but also focuses on the impact of potentially extreme adverse outcomes. The mathematical expression of CVaR is as follows.

$$CVaR = \xi - \frac{1}{1-\alpha}\sum_{s=1}^{NS} \rho_s \eta_s \tag{4.49}$$

$$\eta_s + CVaR - \xi \geq 0 \tag{4.50}$$

$$\eta_s \geq 0 \tag{4.51}$$

$$Objective\ function = Max(F^{EVA} - F_t^{EV}) + \beta \cdot CVaR \tag{4.52}$$

where ξ represents VaR, α is confidence level (α =0.95), ρ_s and η_s represent probability and the difference between profit and the VaR non-negative variable. When the profit smaller than VaR, the η_s present difference between them, otherwise, η_s is zero [40]. The parameter β represents risk aversion. As β increases, the aggregator's objective becomes more risk averse. When β is zero, the aggregator's objective shifts to a risk neutral system.

4.3 Case study.

4.3.1 Data preparation

By 2021, there are over 60,000 electric and hybrid vehicles in Birmingham [205]. To alleviate the lack of EV charging points, Birmingham City Council's Cabinet presented the Electric Vehicle Strategy (a 12-year strategy) which aims to build 3,600 electric vehicle charging points across Birmingham by 2030 (Figure 4.6) [206].

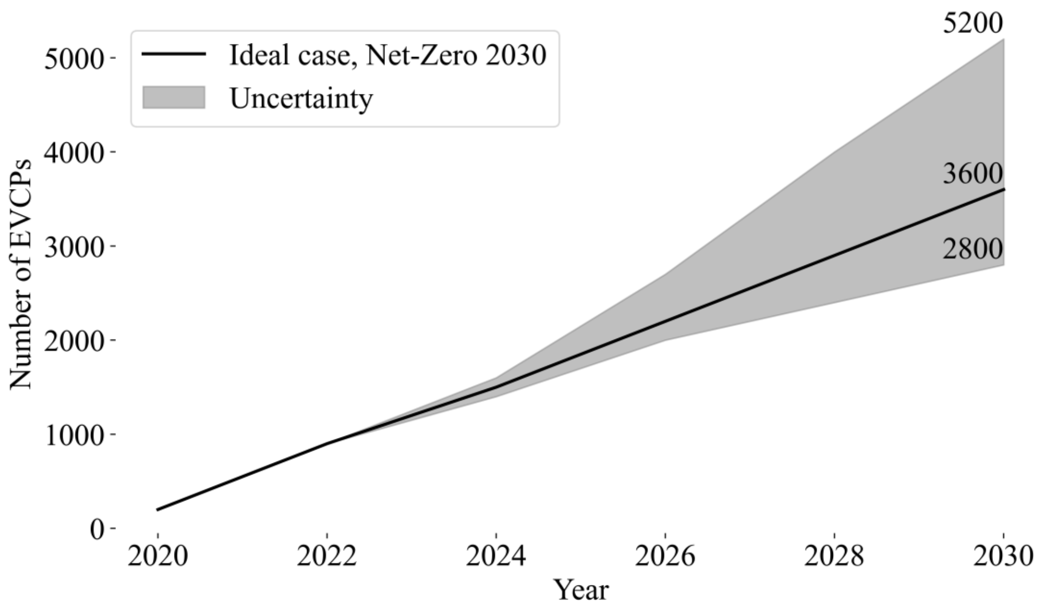


Figure 4.6: Number of EV charging points (EVCPs) expected to be needed in Birmingham [206].

EV charging behaviour is usually associated with daily usage patterns, most real-time tariffs are usually updated hourly [171]. The 24-hour resolution accurately reflects the volatility and regularity of charging demand [172, 173]. The authors in [174] demonstrate that 10,000 EVs can balance driving and charging behaviour profile. In Chapter 3 - Section 3.5, a representative sample of 10,000 EVs was simulated, and the results validate this conclusion. Since the Birmingham government does not track and count such a large amount of EV charging data, a Monte Carlo methodology was used to create an EV charging profile assuming that there are 10,000 EVs in Birmingham that need to be charged in a single day.

In addition, data on the top ten selling models in the UK 2022 and their battery capacities are shown in Table 4.1 [207]. EVs with a battery capacity of less than 50 kWh are classified as short range, 50-70 kWh are defined as medium range versions, and more than 70 kWh are defined as long range [4]. The cases in this chapter contain three models of EVs based on EV battery capacity and market share: 20% Nissan Leaf (39 kWh), 50% Tesla Model 3 (57.5 kWh) and 30% Tesla Model Y (75 kWh), where charge-discharge rate of 90% was selected. EV battery replacement fee is 118 £/kWh [208].

Table 4.1: Top 10 UK EV sales in 2022 [207].

EV model	Percentage of sales (%)	EV battery capacity (kWh)	Categorisation
1. Tesla Model Y	13.3	75	Long range
2. Tesla Model 3	7.1	57.5	Medium range
3. Kia e-Niro/Niro EV	4.2	64.8	Medium range
4. Volkswagen ID 3	3.7	58	Medium range
5. Nissan Leaf	3.4	39	Short range
6. Mini Electric	2.8	28.9	Short range
7. Polestar 2	2.7	75	Long range
8. MG 5 EV	2.6	57.4	Medium range
9. BMW i4	2.5	67	Medium range

European Power Exchange (EPEX SPOT), as one of the largest electricity markets in Europe, provides exhaustive and transparent pricing data, which is suitable for the analysis of electricity market prices [209]. EPEX SPOT provides a comprehensive trading platform for the day-ahead and real-time UK electricity markets. Ancillary services in the

UK are currently managed by National Grid - ESO, but corresponding price information for ancillary services is not yet available. Prices for ancillary services are usually set according to network demand and current electricity market prices [210]. Electric Reliability Council of Texas (ERCOT) provides a suitable case for ancillary services price analysis due to its independent market structure and ancillary services pricing mechanism [211]. Combining data from two different regional electricity markets for analysis may raise questions about data consistency. However, the use of different data enables to demonstrate the applicability of the model in different electricity markets. Therefore, in this case study, the electricity market price is from the EPEX SPOT, ancillary service price is form ERCOT [211] on 11 February 2020 for testing purposes as shown in Figure. 4.7 and the charging tariff provided by EVA is 50 $£/MWh$.

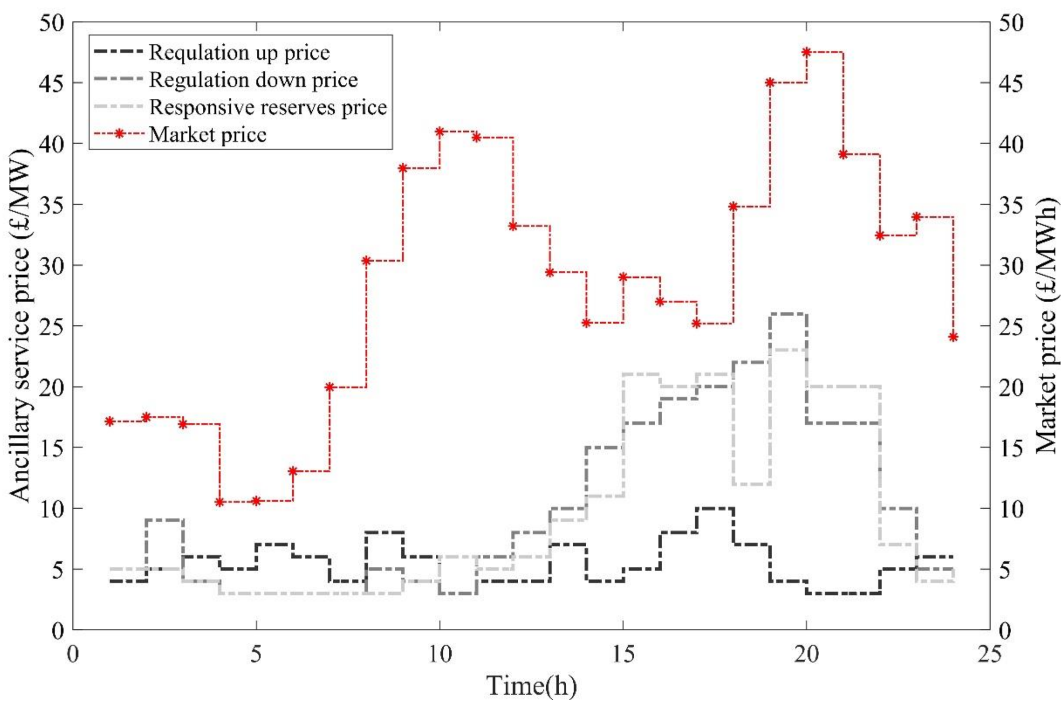


Figure 4.7: Electrical market price and ancillary service price on 11 February 2020.

As shown in Figure 4.7, the electricity price reached its lowest point at 4:00 a.m., with peak prices at 3:00 p.m. and 8:00 p.m. In the subsequent analysis, fluctuations in ancillary service prices and electricity market prices will be combined to explain EV charging behaviours and their effect on EVA's profit.

4.3.2 Application of bi-level service scheduling

This section conducts a bi-level model case study on three different vehicle brands, based on the electricity market price and ancillary service data shown in Figure 4.7. This subsection creates EV charging profiles for these three brands based on the Monte Carlo method steps described in Chapter 3.

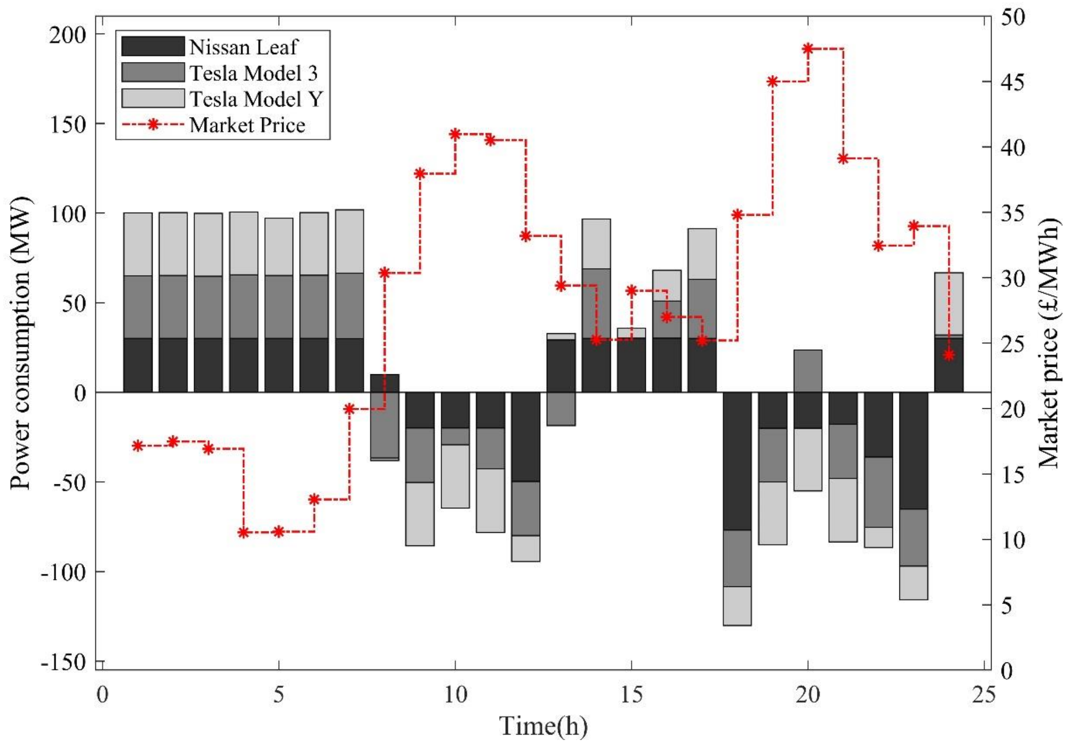


Figure 4.8: EV-POP power consumption under different brands of EV in bi-level model.

Firstly, it is assumed that the charging and discharging behaviour of EVs only considers the electricity price in the electricity market. In this way, it helps to clearly analyse and demonstrate the direct impact of tariff changes on the willingness of EV users to participate in V2G, which is a central economic motivation in understanding and promoting V2G technologies. As shown in the simulation results in Figure 4.8, the EV charging power consumption varies with market price. EV would like to be charged when the hourly market price is in the valley of curve to reduce the charging cost. Conversely, 9.00 a.m. – 11.00 a.m. and 18.00 p.m. – 23.00 p.m., all three vehicles participated in the V2G mode for discharging to gain benefit. This behaviour also relieves the load on the network during this period. The similar power consumption for charging the three types of vehicles further suggests that their charging behaviors are consistent.

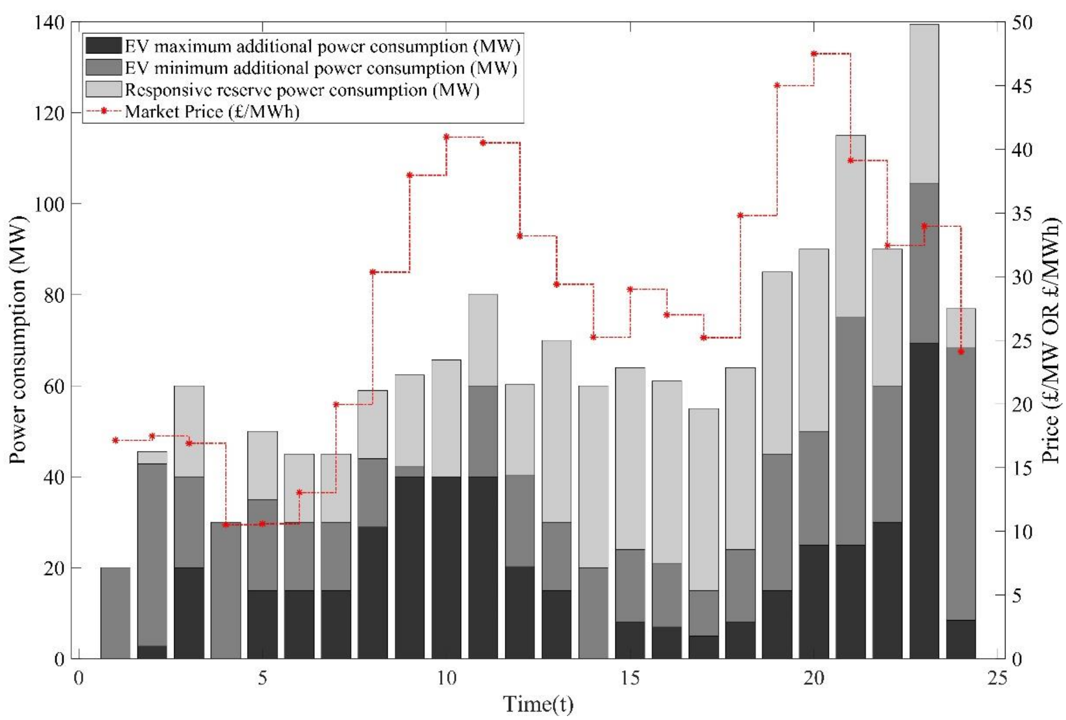


Figure 4.9: Power consumption of ancillary services provided by V2G.

Figure 4.9 presents the results of the EV's maximum and minimum additional power consumption (regulation-down contract limit and regulation-up contract limit) along with the responsive reserve power scheduling. Due to the limited number of electric vehicles parking overnight, the sensitivity is higher at night. A comparison and analysis of Figures 4.8 and 4.9 reveal a general negative correlation between market prices and liquidation behaviours, whereas the relationship between charging behaviours and market prices is positively correlated.

4.3.3 The different result of workdays and weekends

In order to visualise the difference in EV charging behaviour between weekdays and weekends, the EV charging data over a one-year period was divided into two categories: weekdays and weekends in this study. The average value of charging at each time point (e.g., hourly) was calculated to form two sets of representative charging profile. The electricity market prices in Figure 4.10 are taken from EPEX SPOT, cover 11 February 2020 (a typical weekday) and 4 April 2020 (part of the Easter weekend, reflecting holiday effects). The charging prices provided by EVA remain unchanged. This particular weekend has been chosen to explore the particular impact that holidays may have on electricity market prices and EV charging behaviour.

EVA coordinates the EV-POP to maximise profits, Figure 4.10 shows EVA's planning for EV-POP on weekdays and weekends. The average value of electricity prices is higher on weekends compared to weekdays. Considering only the market price of electricity, EVAs will prioritise discharging to make more profit when the electricity market price of electricity is higher and increase charging to reduce the cost of charging when the price of electricity is lower, subject to EV charging requirements. It should be noted that around 15.00 pm, the number of EVs requiring charging and charging power consumption are much higher than that on weekdays even though the electricity market prices were higher on weekends. This is the reason why this section emphasises that EVAs need to satisfy the demand of EV users before they can coordinate EVs to participate in ancillary services.

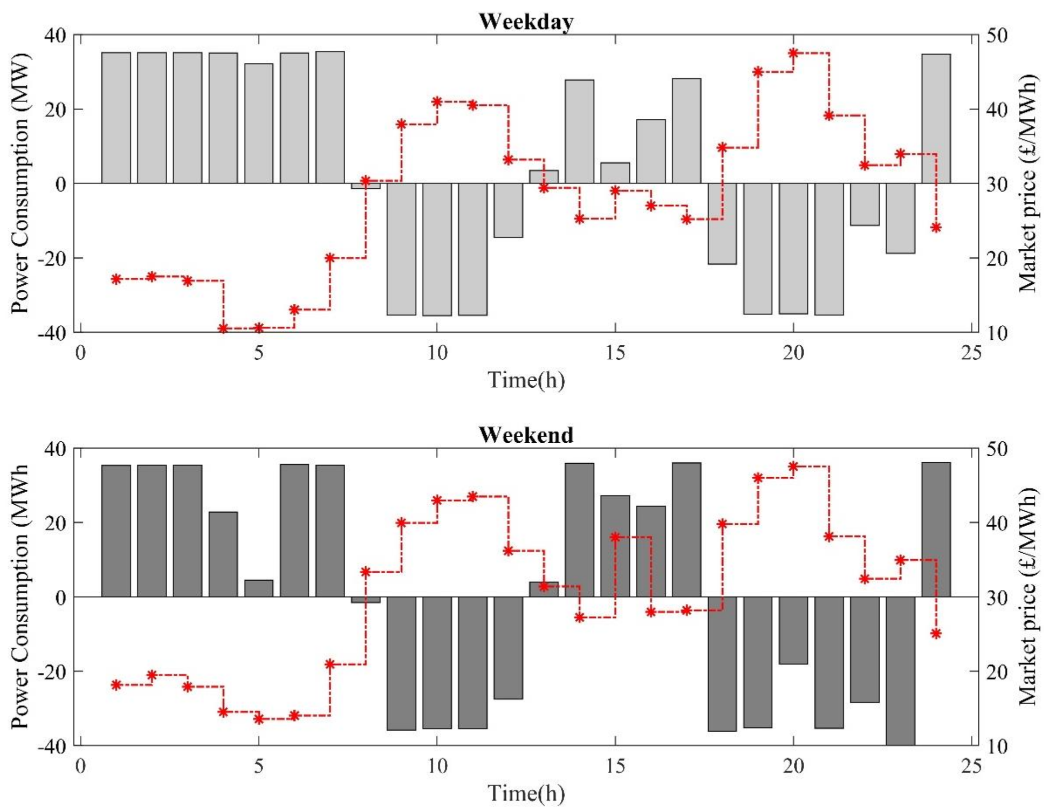


Figure 4.10: EV-POP power consumption on weekdays and weekends.

Assuming the price for the ancillary services do not change, the ancillary services on weekdays and weekends are shown in Figure 4.11. After 14.00 pm, when the response reserve price starts to gradually become greater than the regulation service (regulation-up and regulation-down) price, the response reserve is heavily bid up and only a small amount of regulation service is sold. However, during the peak load period of the network (after 18.00 pm) EVs are involved in regulation service to balance the network load. Before 9.00 am, EVs start a new journey for the day, ensuring that the charge in the EV batteries is at the highest priority level of the expected value, and therefore regulation-up is sold in gradually decreasing quantities.

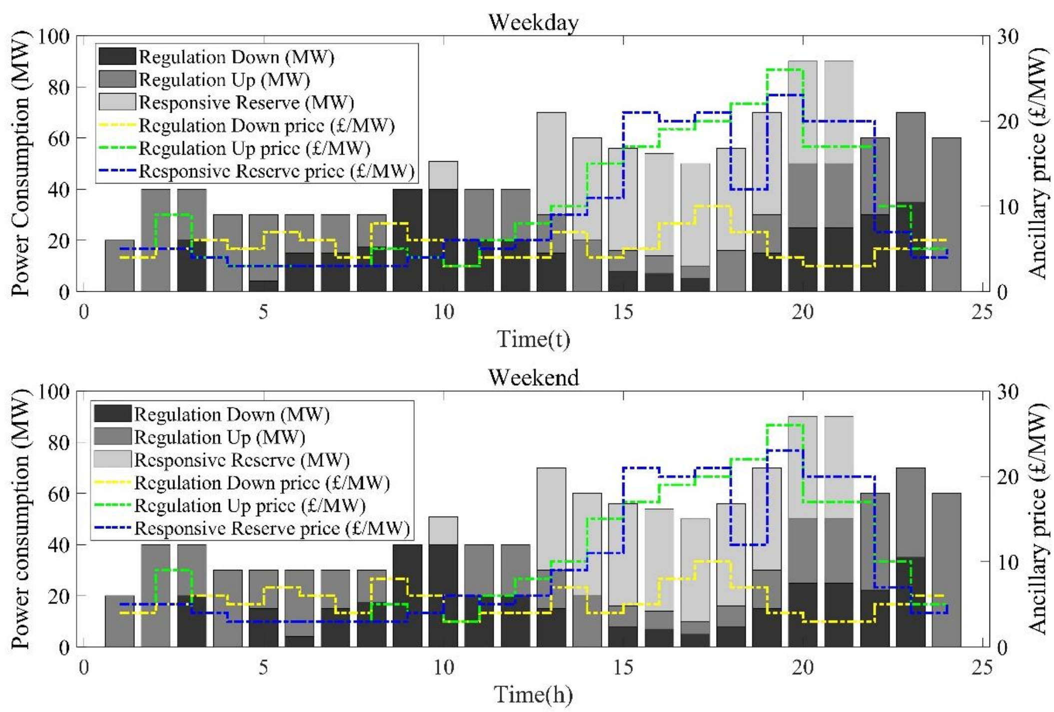


Figure 4.11: Comparison of ancillary service on weekday and weekend.

Figure 4.12 also illustrates the proportions of regulation-down, regulation-up, and responsive reserve on weekdays and weekends. The proportion of responsive reserves increases by about 5% on weekends compared to weekdays. However, aggregators have the flexibility to schedule more dispatchable EVs during the weekends. EVA can earn more profits during weekends than weekdays. This change can be attributed to the fact that aggregators are able to arrange more dispatchable EVs on weekends, so EVA can make higher profits on weekends than on weekdays.

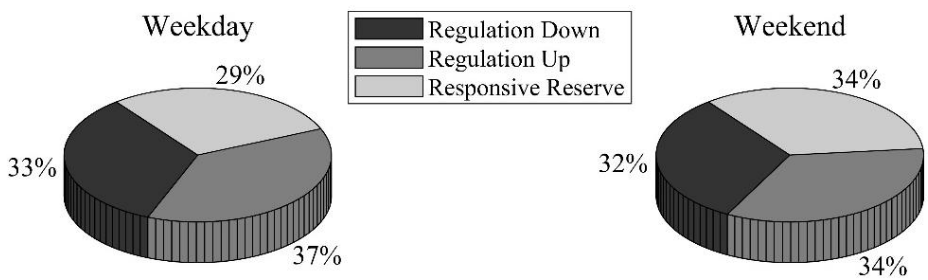


Figure 4.12: Proportion of ancillary service on weekday and weekend.

4.3.4 Conditional risk sensitivity analysis

In this case, the EVA net revenue is maximised considering the EV user profit, and the scheduling of the EVA participation in the ancillary services takes into account the CVaR term. Change the risk aversion parameter from 0.1 to 2.0 and α is set to 0.95 in the objective function.

Figure 4.13 shows the influence of risk aversion parameters on the EVA net revenue. The value of EVA net revenue associated with the risk aversion problem decreases as β increases, i.e., they are negatively correlated. The net-revenue of the EVA is £5238 for risk neutral scheduling ($\beta = 0.1$). The net-revenue of the EVA is only about £1097 when the risk aversion parameter is equal to 2.0. Specifically, a lower risk aversion parameter implies that EVA is willing to take on more risk in pursuit of higher net revenue, whereas a higher risk aversion parameter leads EVA to adopt a more conservative investment strategy in order to minimise potential risks and losses, but this also limits the upper limit of net revenue.

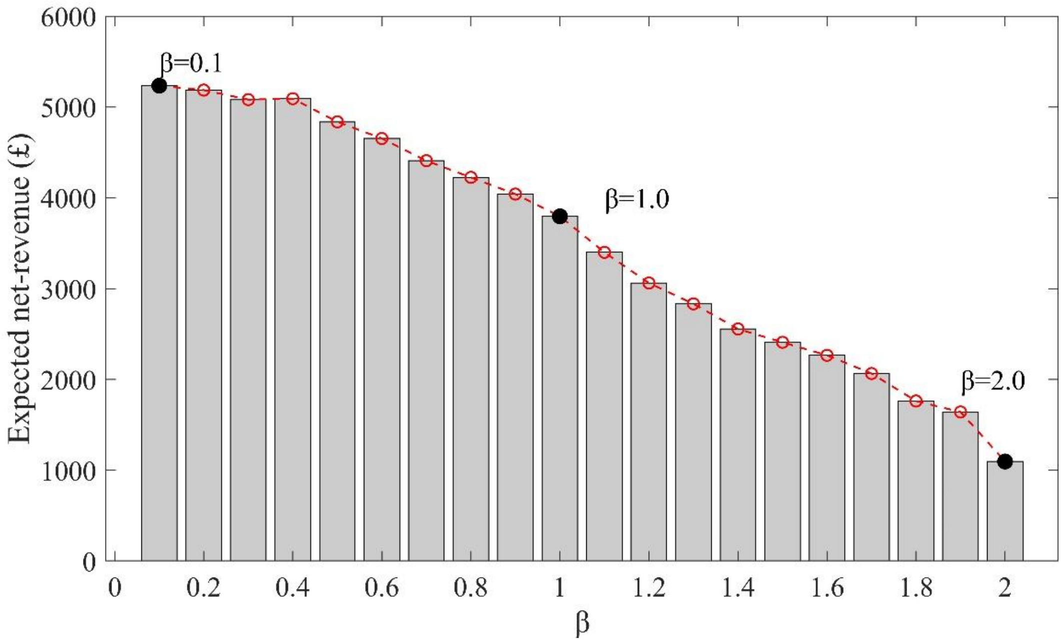


Figure 4.13: EVA net revenue affected by risk aversion parameters.

Considering the effectiveness of such a strategy in adjusting the relationship between risk and net revenue, it is recommended that EVA choose lower risk aversion parameters for its operations within the acceptable risk range. Such an operating strategy not only enhances economic efficiency, but also allows for more profitable opportunities to be found through market volatility. In fact, this choice of balancing strategy is essential to maintain competitiveness and profitability in the electricity market.

4.4 Summary

In this chapter, a bi-level scheduling approach is proposed to optimise the participation of EVAs in the ancillary service scheduling process via V2G for net revenue maximisation.

Firstly, the basic concepts of the bi-level scheduling approach are discussed in detail, including the relationship between the upper and lower problems and their applications in real scheduling. A complex bi-level scheduling problem is transformed into a single-level linear programming problem to simplify the problem-solving process and improve efficiency. In the area of risk management, the conditional value-at-risk (CVaR) methodology has been introduced to assess the dispatch under risk-neutral and risk-averse scenarios.

Using the charging scenario in Birmingham as a case study background, the application of the bi-level scheduling approach proposed in this chapter to real scenarios is demonstrated, and the variability of the scheduling scheme under different weekday and weekend conditions is analysed. Therefore, identifying an appropriate risk coefficient for any aggregator is crucial to balancing profit and risk. Meanwhile, the risk management analysis reveals that EVA can obtain more benefits by choosing a lower risk aversion parameter within the acceptable risk range. This provides an important reference for EVA's actual scheduling decision.

In summary, this bi-level scheduling method proposed in this chapter combines theoretical research and practical application, providing new ideas and methods for service scheduling optimisation in EVA, with theoretical and practical significance. The magnitude of optimization is directly proportional to the number of EVs that can be dispatched. However, the distribution network's capacity limits the number of EVs. Furthermore, temperature variations significantly impact EV users' driving habits, charging behaviours, and charging efficiency, resulting in diverse EV charging profiles. Future research can explore the application of the method in more complex scenarios, such as the comparison and analysis of EV participation in ancillary services under different weather factors, or how to formulate incentive strategies to attract more EV users to participate in V2G planning. This can further improve the theoretical framework and practical application value of scheduling optimisation. Given that holidays may have a particular impact on the market, future studies should consider using more conventional dates for analysis, such as selecting non-holiday weekday and weekend data, or making seasonal and holiday adjustments when analysing the data to ensure the generalisability and accuracy of the results.

In order to successfully implement V2G technology in the UK, a number of measures need to be taken: The widespread adoption of V2G requires government support, especially tax incentives, subsidies and low-interest loans [212]. It is recommended that the UK government establish incentives for EV owners and network operators to encourage widespread adoption of V2G technology. For example, discounts on electricity or rebates on electricity bills should be offered to EV users with V2G capability. Secondly, public acceptance is crucial for the promotion of V2G [184]. It is suggested that in promoting V2G, public awareness of V2G should be enhanced through government-supported publicity campaigns and information education, so that EV owners can understand that they can gain revenue and participate in power regulation through V2G technology, thus enhancing users' willingness to participate.

Chapter 5

Impact of Temperature on EV Hosting Capacity of Distribution Networks

5.1 Introduction

The surge in transportation electrification and the growing adoption of electric vehicles (EVs) offer opportunities alongside challenges for distribution networks [213]. High penetration of electric vehicles can lead to significant increases in distribution network loads, especially during peak charging hour. The low-voltage (LV) distribution network which will be directly affected by changes in EV charging loads [148]. Quantifying the EV hosting capacity of the LV distribution network can provide stakeholders with data to support future optimised network planning and operation. Many studies have examined the performance of distribution network under high EV penetration, but systematic studies of temperature variations on EV hosting capacity are still limited.

Therefore, the following research gap is addressed in Chapter 5: How can temperature factors be embedded in the assessment of EV hosting capacity of distribution network? Firstly, this chapter analyses the effect of temperature on EV usage, including energy consumption per kilometre at different temperatures and charging load profiles at different temperature ranges. Secondly, a methodology is proposed for evaluating the maximum EV hosting capacity at different temperature ranges on the test network. Finally, the scalability and applicability of the proposed method are described.

Section 5.2 elaborates on the algorithm for quantifying the EV hosting capacity. This methodology is distinguished by its scalability and adaptability to case studies conducted in various regions. It furnishes a more exhaustive and precise reference for future assessments of EV hosting capacity and grid planning. Section 5.3 elucidates the practical application of the method and its resultant outcomes. The chapter culminates with a summary in Section 5.4. The publication [P2] and [P3] emanate from the research described in this chapter.

5.2 Methodology

The purpose of this section is to include temperature as part of the EV hosting capacity assessment. To present a proposed methodology for quantifying the impact of EV demand on the distribution network at different temperatures. The methodology consists of two parts:

1) Determining the impact of temperature on EV charging

2) Assessing the EV hosting capacity of the LV network based on temperature.

5.2.1 Impact of temperature on EV charging behaviours

To capture the effect of temperature on EV charging behaviours and evaluate the impact on the distribution network, the first step is to model the EV profile. Then, the EV charging data are clustered based on the energy consumption of the EV charging at different temperatures.

- Collecting EV historical charging data to model EV profile:

This step aims to obtain historical EV charging data to generate EV profiles that contain different charging behaviours for each EV, such as charging start time, power level, energy consumption, etc. Selecting and preprocessing raw data for each charging record is important in ensuring an accurate model. Using historical EV charging data tracked over time, the impact of EV charging loads on the local distribution network can be more precisely analysed. The proposed methodology uses the historical charging data to produce an EV demand profile for each tracked vehicle, where the time resolution is set to every half hour, i.e., 48-time slots in a day. This profile shows the EV charging demand in different time-periods. Each EV's charging energy consumption at different times of the day is allocated to the 48-time slots according to each tracked EV's charging start time and departure time in the charging record. The accuracy of EV charging record is ensured by comparing the battery capacity of each vehicle in the data.

- Divide the temperature ranges:

This section builds upon the approach proposed in [214] to determine the relationship between temperature and EV charging load to inform hosting capacity. The versatility of the method allows analysis of EV charging behaviours in different regions and comparison of the relationship between temperature and charging load. The benefit of clustering is that it reveals patterns and trends in EV charging behaviour under different temperature ranges. This helps planners to understand which temperature ranges cause an increase or decrease in charging load. Algorithm 1 is the approach for partitioning temperature ranges.

- Impact of temperature on EV charging behaviour:

  In order to gain insight into the impact of temperatures on the charging behaviour of EVs, the profiles of the EVs are classified according to the temperature ranges defined in the previous section. Then, within each temperature interval, the average charging energy consumption is calculated for every EV charging record at the same moment. This step results in a typical EV charging profile for each temperature range.

  While a typical value is proposed in this methodology, alternative statistical aggregation methods could be used based on a specific use case, such as a seasonal profile or worst-case scenario. Household electrical loads may also vary by region [215]. For example, colder regions use more electricity in the winter to meet heating needs, while the opposite is true for warmer regions. The steps for household demand profile modelling are similar to those for EV demand profile modelling. It is important to note that the historical data collected for household demand should be consistent with the timeline of the EV charging data, and there is no need to define any penetration rate. Household profiles also vary with temperature. However, as the purpose is to evaluate the EV impact, rather than the influence of temperature on underlying demand, the maximum household profile is selected as the worst-case scenario.

5.2.2 LV distribution network modelling and EV hosting capacity evaluating

Before modelling the low voltage (LV) distribution network, it is essential to gather pertinent data and parameters. This includes information such as the topology of the LV network, cable specifications, transformer characteristics, load data, and performance benchmarks. It's worth noting that standards can differ across countries and regions, with examples provided in Table 5.1. In addition, there are differences in the number of users and the complexity of the network topology in LV distribution networks. A typical LV distribution network is composed of feeders and distribution transformers [216], as illustrated in Figure 5.1. The daily load encompasses residential consumption, EV charging, PV generation, among others. Each feeder comprises multiple three-phase cables catering to customers.

Different EV penetration rates may cause load changes in the LV network, and the impact of load changes on the distribution network is simulated by gradually increasing the EV penetration rate, which allows for assessment of the hosting capacity of EVs in the LV network. For this section, the EV penetration rate for households in residential areas is 0% when none of the households have an EV and 100% when all the households in residential areas have an EV. The metrics used for measurement need to be determined for a given distribution network, e.g., LV network statutory voltage limits, current limits, or losses.

Algorithm 1 Cluster of EV charging profiles by temperature ranges using K-means.

Input: EV charging data, temperature data, Number of clusters K.

Output: Clustered EV charging data based on temperature

Steps:

1. **Data preparation:**

   for each data point i:

$$E_i' = {}^{E_i - \mu_E}/_{\sigma_E} \tag{5.1}$$

$$T_i' = {}^{T_i - \mu_T}/_{\sigma_T} \tag{5.2}$$

   end for

2. **Initialize the centre of mass:** (k=1-10)

$$\mu_k = (\mu_{E,k}, \mu_{T,k}) \tag{5.3}$$

3. **Initiative clustering:**

   repeat until convergence or a number of iterations is reached:

   for each data point i:

   $min\ distance = \infty$

   for each centre k:

$$d_{i,k} = \sqrt{\left(E_i' - \mu_{E,k}\right)^2 + \left(T_i' - \mu_{T,k}\right)^2} \tag{5.4}$$

   if $d_{i,k} < min\ distance$:

   $min\ distance = d_{i,k}$

   assign data point i to cluster k

   end if

   end for

   end for

   for each cluster k:

$$\mu_{E,k} = \left({}^{1}/_{|C_k|}\right) \sum_{(E_i', T_i') \in C_k} E_i' \tag{5.5}$$

$$\mu_{T,k} = \left({}^{1}/_{|C_k|}\right) \sum_{(E_i', T_i') \in C_k} T_i' \tag{5.6}$$

   end for

   if the centres of mass do not change significantly

   stop

   end if

   end repeat

4. **Determine the optimal K-value:**

   for each value of K from 1 to 10:

   execute steps 2 and 3 and calculate SSE for current K:

$$SSE = \sum_{k=1}^{K} \sum_{(E_i', T_i') \in C_k} \begin{pmatrix} \left(E_i' - \mu_{E,k}\right)^2 \\ +\left(T_i' - \mu_{T,k}\right)^2 \end{pmatrix} \tag{5.7}$$

   end for

where E_i' is EV charging data, T_i' is temperature data, $\mu_E\ and\ \mu_T$ are the mean of EV charging load and temperature, $\sigma_E\ and\ \sigma_T$ are the standard deviation of EV charging load and temperature. C_k is cluster, μ_k is the centre mass of the cluster in which it is located. $d_{i,k}$ is the minimum distance of the data point from the centre of mass.

Table 5.1: Voltage tolerance limits in various standards.

Standards	Voltage Limits
AS 61000.3.100-2011 [217]	+10% to -6% at low voltage (230 V)
ANSI C84.1 [218]	Range A: For systems operating at 600V and below, the allowable operating voltage variation is +5% to -5%. For systems operating above 600V, the range is +5% to -2.5%. Range B: For systems operating at 600V and below, the allowable operating voltage variation is +5.8% to -8.3%. For systems operating above 600V, the range is +5.8% to -5%.
IEC 60038:2009 [219]	The 230 V ±10% is a generic all-inclusive range of low voltage.
EN 50160 [220]	95% of the 10-minute root-mean-square (RMS) value of the supply voltage shall be within Un ± 10% for each cycle of the week, and all 10-minute RMS values of the supply voltage shall be within +10%/-15%.

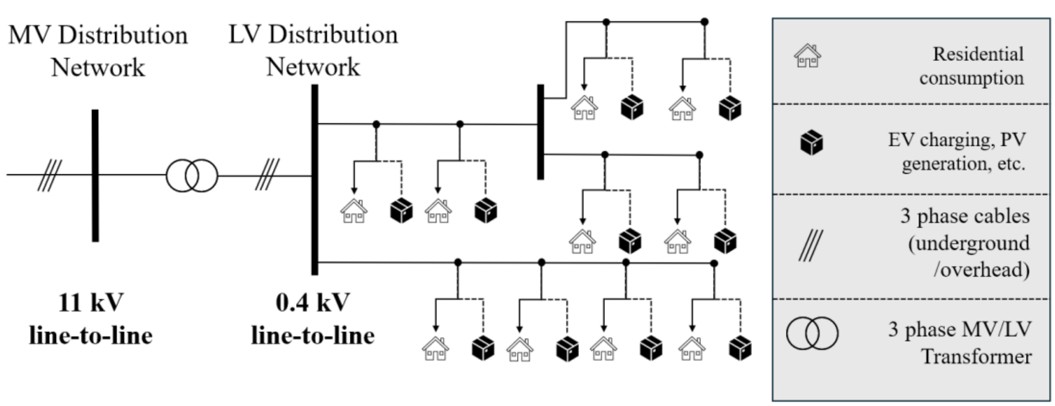


Figure 5.1: Structure of the low-voltage distribution network [216].

A review of existing EV hosting capacity studies shows that most studies use voltage limits as the performance metric and therefore voltage is used for the proposed method [106]. After determining the parameters, profiles, and metrics the hosting capacity assessment is conducted. To evaluate the hosting capacity and respect the voltage limits, the following steps need to be repeated for each temperature range. Each node contains a household load profile and an EV load profile. The penetration of EV in the overall network begins at 0. The overall penetration is measured as the total number of EV in relation to the number of total households.

- **Step 1.** Limitations: Set voltage limit based on the relevant standards.
- **Step 2.** EV profile: Calculate the maximum demand profile of each EV under the selected temperature range.
- **Step 3.** Household profile: Select the maximum household demand profile corresponding to the temperature range. Initialize household load at each node by taking the maximum energy consumption under the selected temperature range.
- **Step 4.** Continue to perform the following steps until the voltage limits are violated: 4.1 Randomly allocate EV to a node on the network; note that a maximum limit of two EVs per household is considered for this analysis. 4.2 Select the EV profile associated with the temperature range and allocate it to each EV. According to the predefined steps, the EV demand profile under different EV penetration rates will be obtained and assigned to node. 4.3 Simulate the power flow in the test network and compare the lowest voltage in each node in the test network with the safety limit. There is only one

voltage in all nodes that violates the limit, it is the hosting capacity of this test network. But if within limits, go to 4.1 and repeat the process.

- **Step 5**. Record the number of EV.

5.3 Case study

5.3.1 Load profiles for different temperature ranges

1) Collecting EV historical charging data to generate EV profile.

In this section, data sourced from a practical EV trial, titled 'My Electric Avenue' [177], have been utilised to analyse the influence of EV loads on the distribution network. Conducted between December 2013 and November 2015 across multiple UK regions, this trial involved 215 participants, each equipped with a Nissan Leaf EV (24 kWh battery) and a 3.5 kW private charger [61]. To accurately quantify the impact of different EV penetration rates on the local LV network in the UK, this section employs an evaluated “Low Voltage Network Solutions (LVNS)” network topology and cable characteristics data that has been completed at the University of Manchester [221], the test network was constructed using the methodology described in [222] for converting the data into a network model. OpenDSS is a power system simulation tool that can be widely used in power system research, especially in voltage control, load flow analysis, etc. It supports timing analysis, parallel computing and multiple control modes, can model different load and distributed power characteristics in detail, and accurately simulate the impact of EVs on the distribution network [223]. This test network implemented using OpenDSS for this work due to the robust testing and open-source nature enabling reproducibility [223].

Figure 5.2: The city or area covered by the "My Electric Avenue" project.

The daily participation of EVs showed fluctuations throughout the trial. Fewer EVs were active at the beginning and end of the trial, while activity increased in the middle of the trial (Figure 5.2). This fluctuation may be related to the trial process, the interest of the

EVs participating, and other factors [224]. Overall, there are 54,652 EV charging data records. The EV charging energy consumption of each tracked EV at different times of the day was assigned to the corresponding 48-time slots based on the charging start time and departure time of each tracked EV.

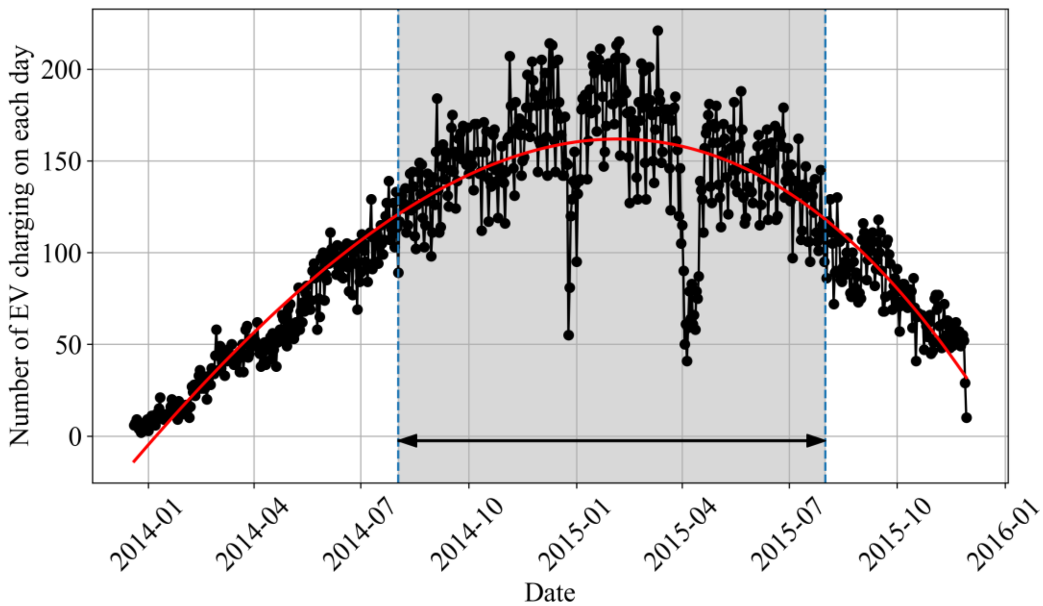


Figure 5.3: My Electric Avenue daily active participants.

2) Collecting temperature and defining temperature ranges by EV charging energy consumption.

The monitored EVs were driven and charged in 59 cities and areas, with temperature data sourced from the Met Office [225]. These areas exhibit significant monthly temperature fluctuations, but share a similar overall trend. To align with each tracked EV, the average maximum temperature on the day of charging is utilised for recording each charging session.

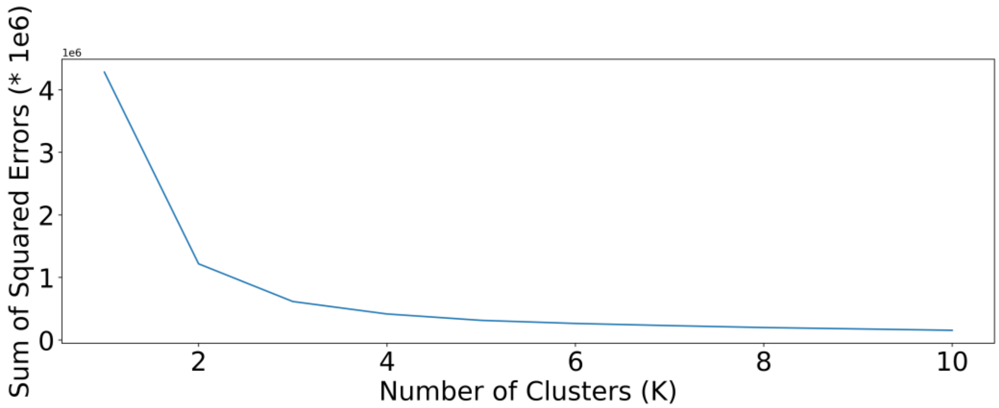


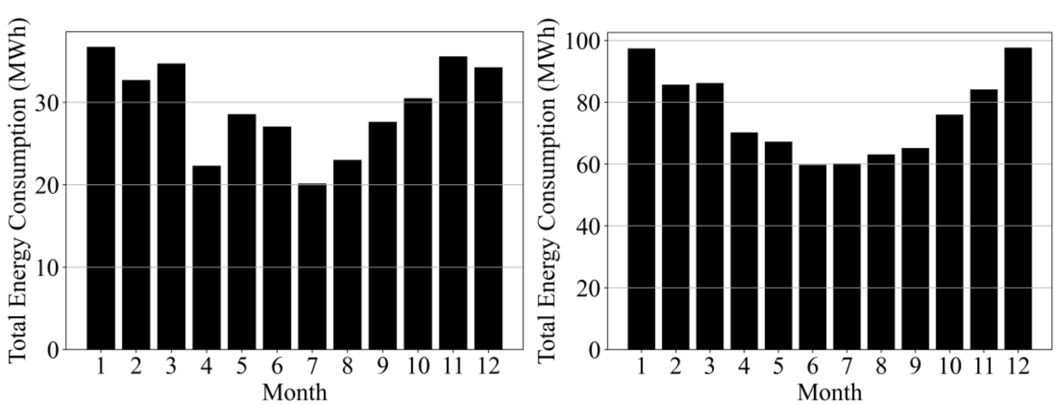
Figure 5.4: Sum of squares of Euclidean (SSE) distances for different K values.

The influence of temperature on EV charging behaviour is scrutinized using the dataset above. The clustering analysis detailed in Section 5.2.1 identifies an optimal K-value of 3, illustrated in Figure 5.4, where the elbow point indicates K = 3. Three different temperature ranges appeared: 2-10 °C, 11-16 °C, and 17-34 °C. Subsequently, EV charging occurrences are categorized based on these temperature clusters.

3) Impact of temperature on EV charging behaviour.

Figure 5.5 (a) summarizes the total power consumption of EV in each month. Notably, the total charging energy consumption is lowest in July, despite July experiencing most of the year's high temperatures. Meanwhile, Figure 5. 6 presents the temperature condition. The results indicate that in the range of 0 to 16 °C, the energy consumption per kilometre of EV decreases as the temperature increases. In the range of 16 to 22 °C, energy consumption remains relatively constant. However, when temperatures exceed 22 °C, energy consumption begins to rise. A polynomial fit to the data yielded the Equation (5.8), which describes the relationship between the average energy consumption of EVs and temperature. This phenomenon shows that the less frequent use of EVs at hot temperatures results in lower total EV charging energy consumption at higher temperatures. However, it also leads to higher energy consumption per charge. During the Easter holiday period in April, people may be more likely to travel. This results in lower total EV charging energy consumption in residential areas in April [226]. To minimize the impact of such special cases on data analysis, EV profiles can be clustered based on the relationship between temperature and EV charging behaviours. This section has used scikit-learn implementation for cluster analysis. K-means++ is an improved initialization method and is the default setting in scikit-learn [227].

In this section, step 2 in the Section 5.2.1 - 2) is employed to generate EV profile for worst-case scenario. By grouping the charging data into three temperature clusters, distinct differences in energy consumption emerge. Notably, when using the maximum load profile for each EV at each temperature as the profile for each EV, the average energy consumption of the EV tends to increase with the temperature increases.



(a) (b)

Figure 5.5: (a) Total EV charging energy consumption per month. (b) Total household energy consumption per month.

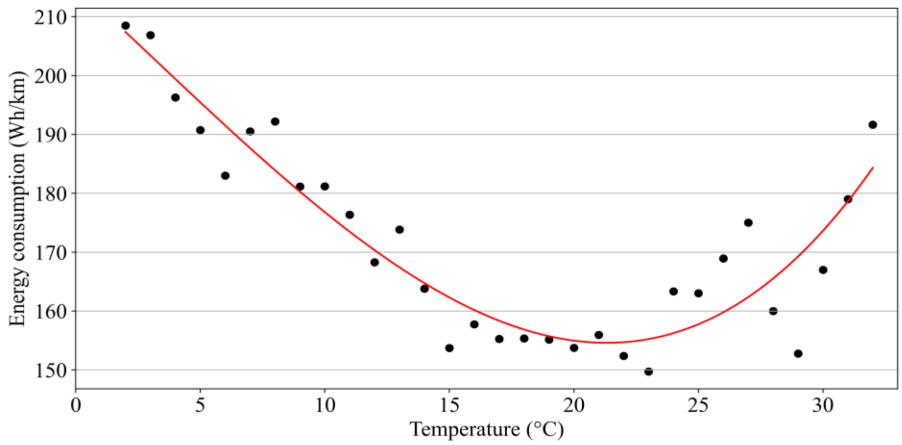


Figure 5.6: Energy consumption per kilometer of EVs at Various Temperatures (Wh/km).

$$E_{ec} = 0.00398T^3 - 0.0358T^2 - 3.89T + 215 \tag{5.8}$$

where E_{ec} represents the energy consumption per kilometer of the EV (in Wh/km), T represents the temperature (in °C).

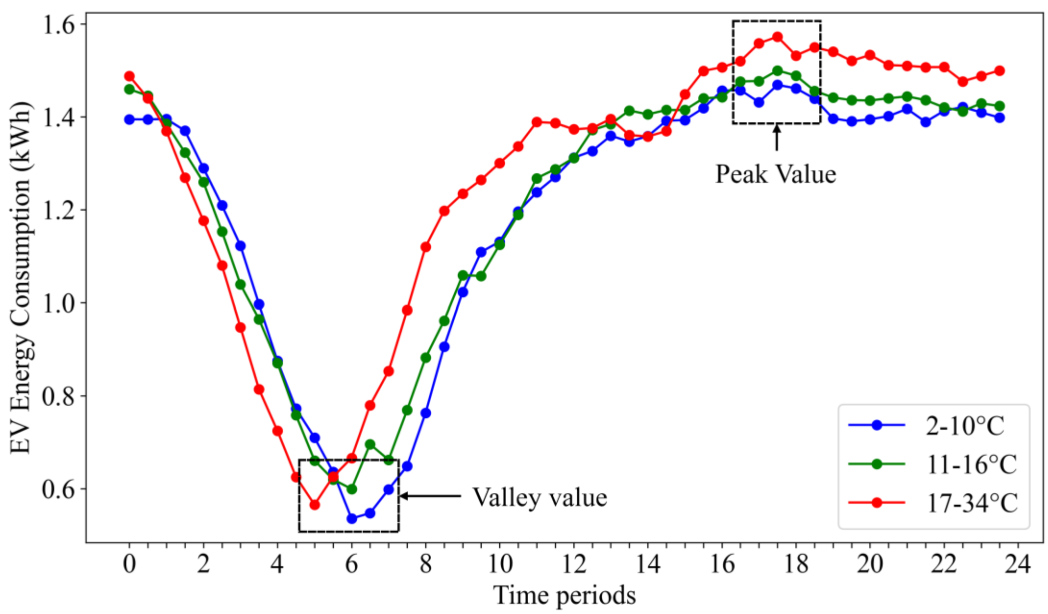


Figure 5.7: Average EV energy consumption for each temperature range within one year (per vehicle/day).

Figure 5.7 illustrates the variation in average worst-case scenario EV energy consumption across temperature for each time-period. The EV energy consumption peaks are observed at around 6.00 p.m. across all temperature ranges, and the valley value is around 6.00 a.m., coinciding with the time most EV users return home and begin charging their vehicles. Conversely, energy consumption reaches its lowest point at around 6 a.m., which aligns with the typical completion of overnight charging [228]. This charging pattern results in a sharp drop in the curves of Fig. 5.7 at 6:00 a.m. A comparison analysis of the average EV energy consumption at different temperature ranges reveals that the average EV energy consumption of EVs in the temperature range of 17-34°C is 7% higher than that of 2-10°C, highlighting the impact of temperature on energy usage of EV charging.

4) Impact of temperature on household profile.

The methodology for analysing the effect of temperature on household energy consumption follows the approach outlined in Section 5.3.1 - 3). Figure 5.5 (b) shows the total household energy consumption per month. Specifically, the overall trend shows lower energy consumption during the warmer months and higher energy consumption in cooler months. This trend highlights the impact of temperature on home energy use. To further validate the impact of temperature on household consumption.

Figure 5.8 shows the average worst-case scenario profile of household energy consumption across various temperature ranges in Bracknell, UK over a year (for each household) [229]. There is a trough at around 4.30 a. m. and a peak at approximately 6.30 p.m. It is observed that temperature affects energy consumption differently for households. As the temperature decreases, the average worst-case scenario household energy consumption rises. This increase is primarily due to the use of heaters in residential areas to increase indoor temperatures during the cold winter months, which in turn leads to higher energy consumption [230].

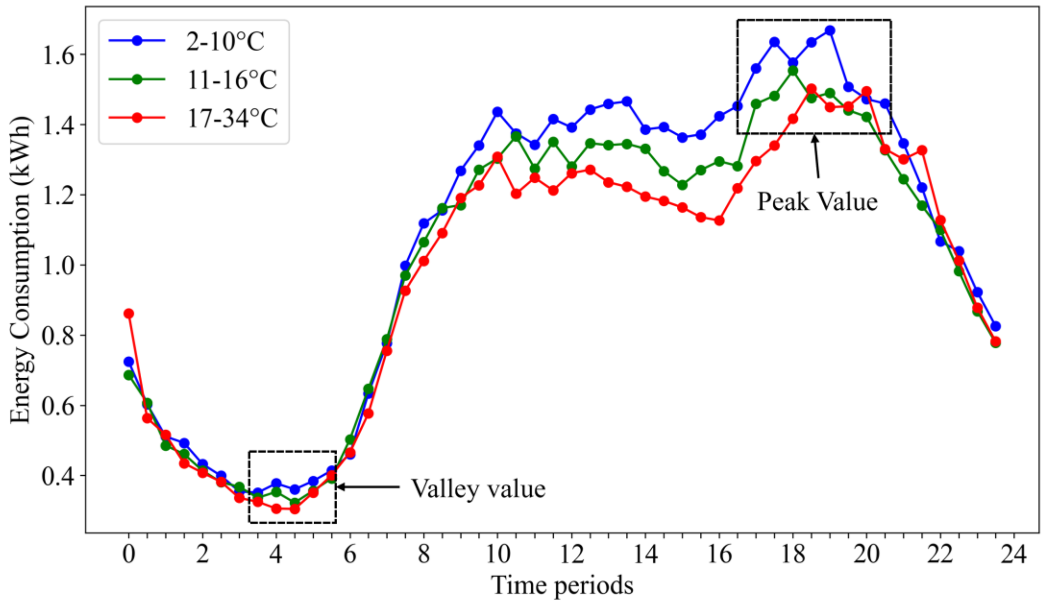


Figure 5.8: Average worst-case scenario household energy consumption for each temperature range within one year (per household/day).

5.3.2 LV distribution network modelling and EV hosting capacity evaluating

1) LV distribution network modelling:

This section quantifies the impact of different EV penetration rates on the UK local LV network. The study utilizes "Network 2-Feeder 1" from the Low Voltage Network Solution (LVNS) [221] and reduces the number of nodes in the test network to the desired number of households (130). The network's technical parameters are shown in Table 5.2, R1 is positive-sequence resistance, X1 is positive-sequence reactance, R0 is zero-sequence resistance and X0 is zero-sequence reactance [221].

Table 5.2: Technical parameters of the network [221].

Line Code of Conductors	**R1**	**X1**	**R0**	**X0**
.007_PSC	3.97	0.099	3.97	0.099
25_SAC_PSC	1.2	0.088	1.2	0.088
25_SAC_XC	1.2	0.079	1.3	0.079
.2c_.007	3.97	0.099	3.97	0.099
2c_.0145	1.903	0.09	1.903	0.09
3c_300_SAC_XC	0.102	0.073	0.594	0.105

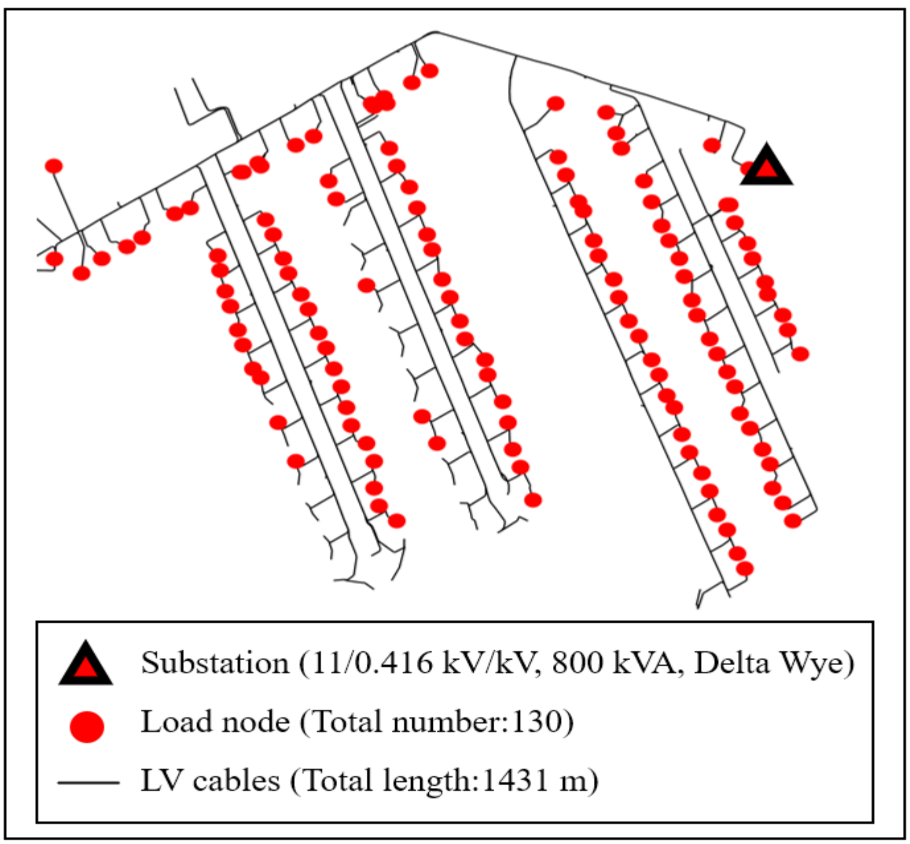


Figure 5.9: Topology of a low voltage test network [221].

In this network setup, 130 nodes represent individual load points, corresponding to 130 households. Additionally, 215 EV profiles are randomly assigned among these households enabling simulation of EV penetration above 100%. Consequently, the load on each node comprises two scenarios: household load alone, and household load combined with EV load with the overall network depicted in Figure 5.9. This structure allows for a detailed analysis of how EV loads affect the local LV network.

2) Evaluation of EV hosting capacity.

In the UK, an electricity supply's declared voltage and tolerance is 230 volts -6%, +10% ([0.94, 1.10] p.u). This gives an allowed voltage range of 216.2 volts to 253.0 volts [231]. Using the temperature range of 2 - 10°C as an example (Figure 5.10), the load of the low-voltage distribution network gradually approaches the voltage limit value (0.94 p.u.) as the penetration rate of EVs gradually increases. This section will focus on analysing and discussing the maximum hosting capacity of the distribution network for EV charging at different temperatures with household demand as the initial load.

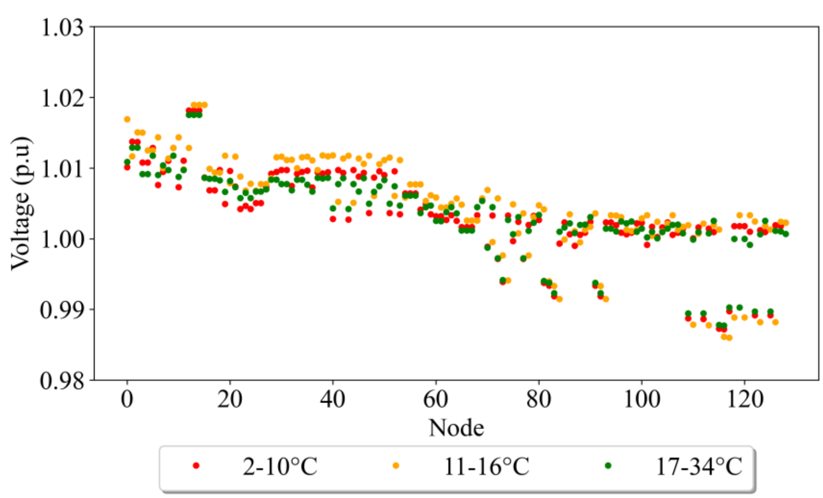


Figure 5.10: Initial voltage value of each node at different temperature ranges.

As described in Section 5.2.1-2). Household profiles also vary with temperature. However, as the purpose is to evaluate the EV impact, rather than the influence of temperature on underlying demand, the maximum household profile is selected as the as the initial load (worst-case scenario) for each node and simulated on the test network as shown in Figure 5.10.

The permissible voltage range is 216.2 V to 253.0 V [232]. Following the steps of Section 5.2.1-2) presented in Section 5.2.3, load profiles in the temperature ranges of 2 - 10 °C, 11 - 16 °C, and 17 - 34 °C were tested on a low-voltage distribution network are shown in Figure 5.11 - 5.13. Using the temperature range of 2 - 10°C as an example (Figure 5.11), the load of the low-voltage distribution network gradually approaches the voltage limit value (0.94 p.u.) as the penetration rate of electric vehicles gradually increases.

Assess the node voltage at 11 - 16°C and 17 - 34 °C using the same procedure. When the EV penetration is 100%, the number of nodes exceeding the voltage limit in the temperature ranges of 2 - 10 °C, 11 - 16 °C, and 17 - 34 °C is 0, 3, and 8, respectively (Table 5.3), and which implies that the hosting capacity of the EVs in the distribution network decreases gradually as the temperature increases (Figure 5.14).

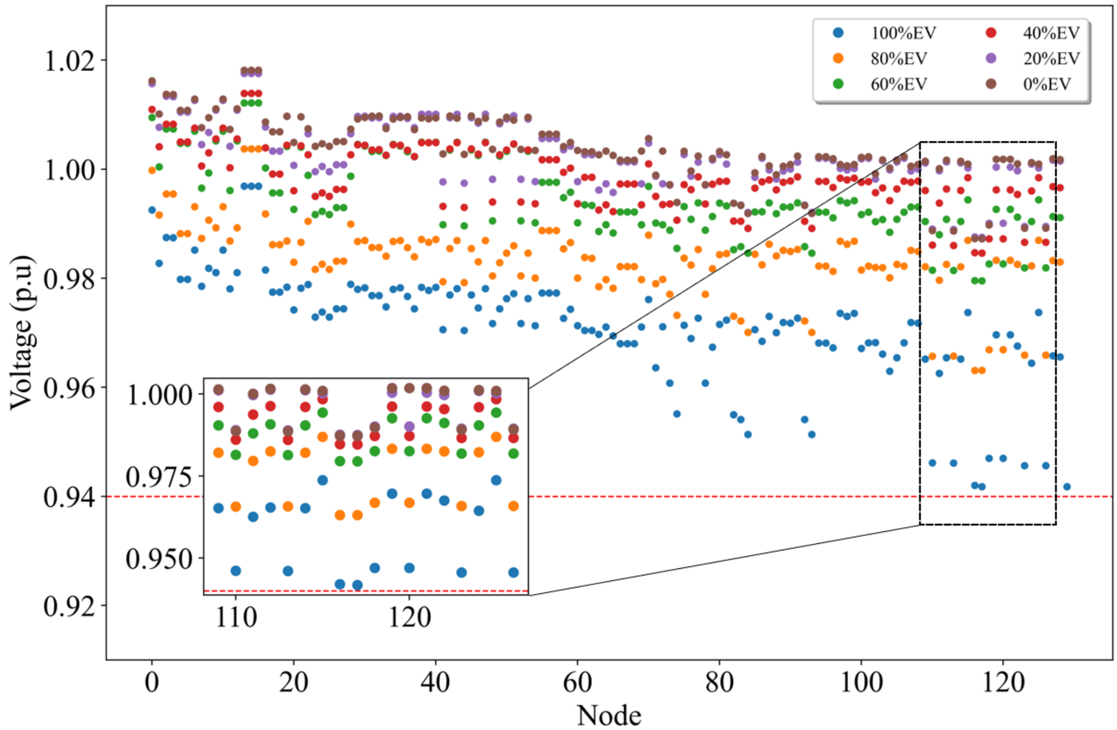


Figure 5.11: Voltage value of each node in the temperature range of 2 - 10°C.

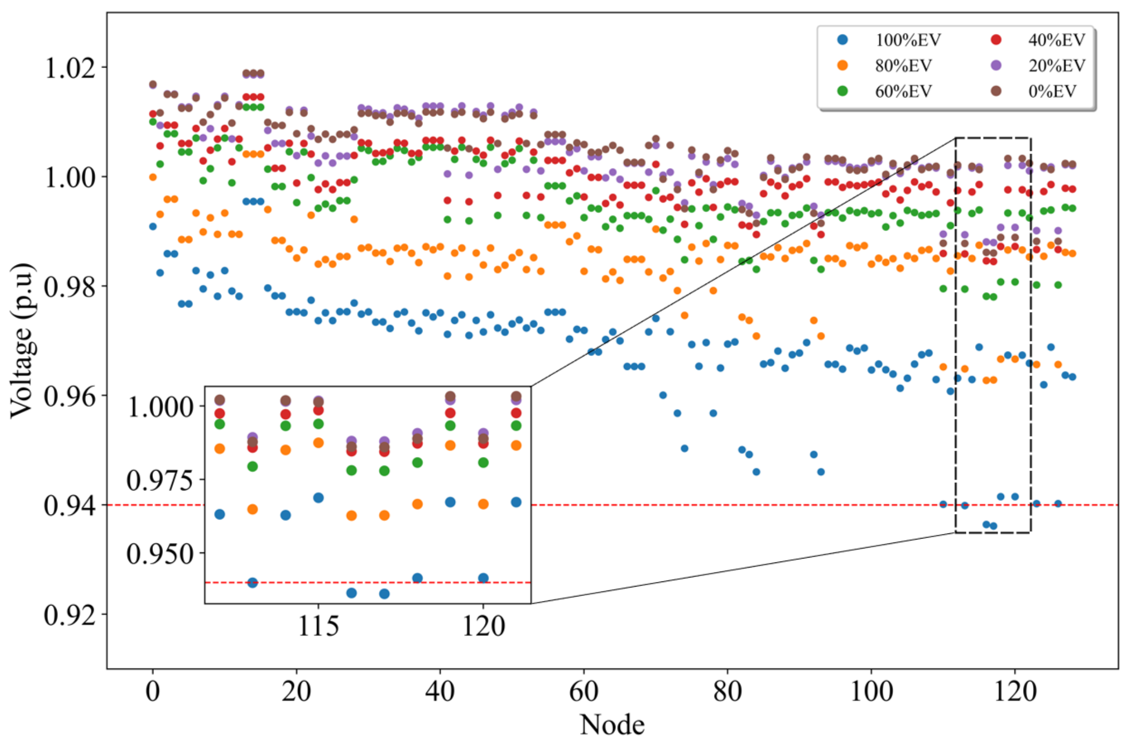


Figure 5.12: Voltage valley value of each node in the temperature range of 11-16°C.

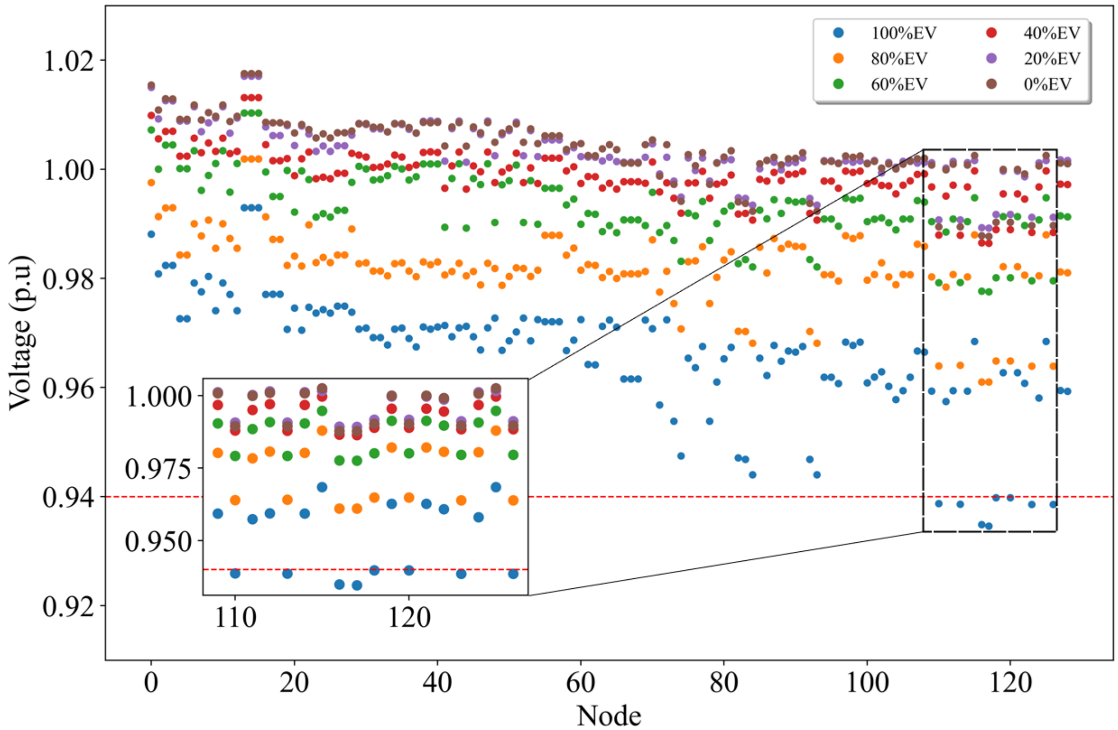


Figure 5.13: Voltage valley value of each node in the temperature range of 17-34°C.

Table 5.3: The voltage curves of different nodes in each temperature range when the EV penetration rate is 100%.

	Number of nodes over voltage limits [0.94 p.u, 1.1p.u]	**Voltage valley (p.u.)**
Initial Load	0	0.9860
2 - 10°C	0	0.9418
11 - 16°C	3	0.9361
17 - 34 °C	8	0.9345

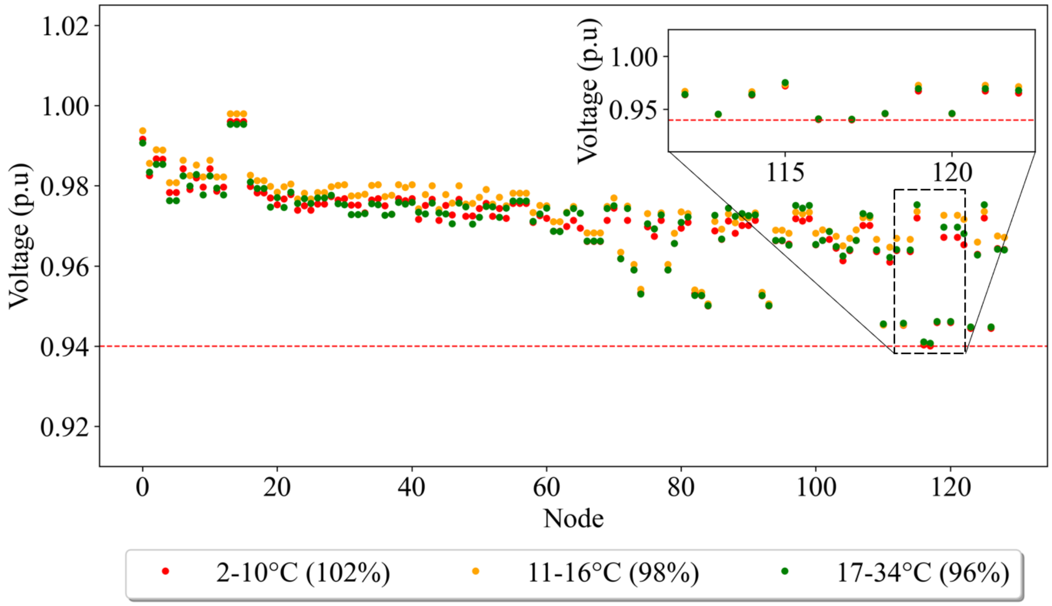


Figure 5.14: Maximum EV hosting capacity of the distribution network for different temperature ranges for each node voltage.

Result shows that temperature affects the EV charging behaviors and different temperatures have varying degrees of impact on the hosting capacity of the UK distribution network. The energy consumption of EVs in the temperature range of 17 - 34°C is 7% higher than that of 2 - 10°C. This suggests that at relatively higher temperatures, EVs may be under greater pressure to consume energy and require users to recharge more often. Meanwhile, EV hosting capacity in the distribution network is maximized at 2 - 10°C, approximately 6% more EV hosting capacity than 17 - 34°C. Considering that the total number of nodes studied was only 130, the difference in EV hosting capacity of 8 EV between 2 - 10°C and 17- 34°C, is quite a large percentage of the overall. This difference in EV hosting capacity between temperature ranges is magnified as the number of network nodes and EV increases.

Although this analysis was conducted on a small portion of the network, similar impacts would be seen across the distribution system leading to further need for infrastructure upgrades that could impede the transition to net-zero. Additionally, as shown in Figure 5.6 EV energy consumption per kilometer is trending upwards after 25 degrees Celsius. This increase in energy consumption means that EVs require more electricity to maintain the same mileage, thus increasing the energy demand across the network. Therefore, with maximum temperatures in the UK increasing year on year [233], the consideration of temperature as part of hosting capacity will grow in importance. The proposed method is scalable and different countries and regions can quantify the effect of temperature on EV hosting capacity by this method. This provides a powerful tool for cross-regional studies to further improve the understanding and analysis of EV hosting capacity of distribution network.

5.4 Summary

As more refined methods of linking temperature to EV demand are created in the future, Chapter 5 provides a pathway to directly account for these changes in distribution network hosting capacity. This paper quantifies the impact of temperature on EV charging behaviours using data from the UK. This observation confirms the existence of measurable changes in the charging behaviour of EVs under different temperature conditions. It is important to have an in-depth understanding of the performance of EVs in other climates or weather and to develop optimized charging strategies accordingly.

The state of the LV test network at different EV penetration rates within each temperature range is revealed by integrating household demand data from local UK settlements and the effect of temperature on EV hosting capacity is quantified. This paper uses the maximum demand of EV and household as the profile (worst-case scenario). The test network can withstand 6% higher demand for EV charging penetration in the temperature range of 2-10°C compared to 17-34°C. This shows that higher temperatures could decrease hosting capacity, leading to overestimation of the network's ability to meet demand under periods of high-loading and adversely impact infrastructure. Furthermore, latent capacity could be unlocked at lower temperatures, supporting grid operators.

Future research could explore the effects of temperature on EV performance and user driving behavior to develop more effective energy management strategies to improve the convenience of charging and energy efficiency of EVs. Policymakers can develop more targeted policies based on the results to promote sustainable energy and EVs. While this study focused on home charging using a 3.5 kW charger, future work could explore the impact of higher power chargers and charging at workplaces or public stations on LV distribution network hosting capacity. Finally, integrating vehicle-to-grid (V2G) and energy storage technologies into the analysis will further enhance the understanding of how to develop a more resilient and flexible distribution network.

Chapter 6

Weather-related Fragility Modelling of Critical Equipment and EV Charging Point

6.1 Introduction

As discussed in Chapters 3 to 5, EVs can provide ancillary services through V2G. However, different weather factors can lead to differences in EV charging loads, which in turn affects the hosting capacity of the distribution network. EVs are connected to the network through charging equipment at charging points. Charging points include public charging stations, roadside charging posts and domestic charging posts [16]. The power demand of an EV charging point (EVP) is limited by the capacity of the local network, and the load management of the network also depends on the charging method of the EVP. Equipment faults in the power system can have a direct impact on the power supply at EV charging points, e.g. large-scale power outages. As shown in the review of existing studies in Section 2.4, several important aspects of the impact of EV charging on power systems have been identified. Most of the studies focus on the impacts of the EV charging side on the power system, such as the impact of EV fast charging on the voltage balance and the impact of EV charging stations on the reliability of the distribution network; however, few studies explicitly assess the fragility of the power system in relation to EV charging points. There is a gap on the impact of outages on EV charging points due to power system equipment faults, which highlights the need for further investigation in this area. Therefore, in this chapter, the following research question is addressed: *Which equipment faults have the greatest impact on EV charging points under weather factors*.

To tackle this gap, Section 6.2 introduces a methodology for the simultaneous assessment of critical equipment vulnerabilities to facilitate joint planning. Section 6.3 applies this methodology in a case study, analysing the impact of weather factors on equipment faults and EV charging points in the North West of England. Section 6.4 discusses the results and Section 6.5 provides a summary of the chapter.

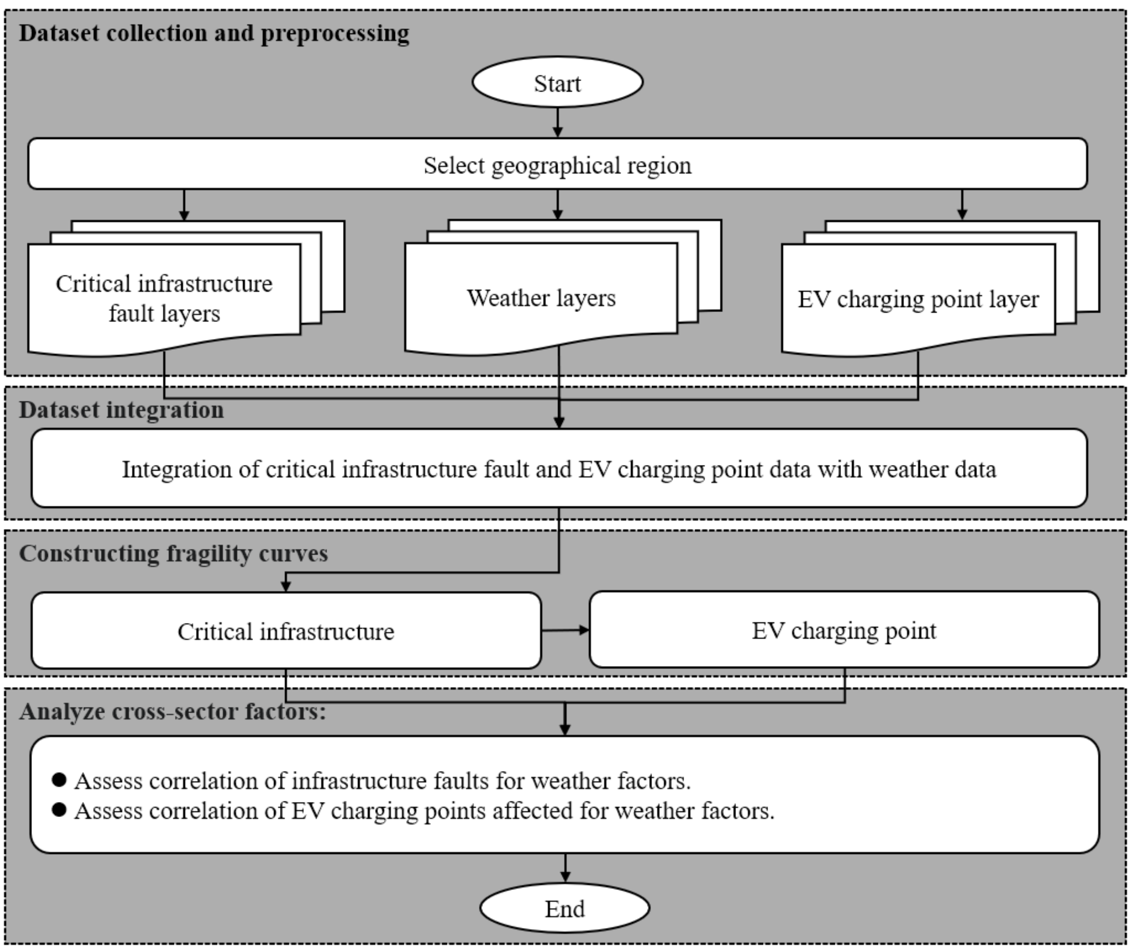


Figure 6.1: Methodology for evaluation of equipment fragility due to weather.

6.2 Methodology

The fragility modelling is designed to analyse and assess power outages caused by power system equipment faults under various weather conditions. The methodology also examines the impact of these faults on charging points (such as those for residential, commercial, and industrial [234, 235]) within the area served. The assessment methodology encompasses several critical stages: data collection and pre-processing, data integration, construction of fragility curves, and correlation analysis. This methodology is summarized in Figure 6.1, with each core step described in detail in the subsequent sections.

6.2.1 Data set collection and pre-processing

Data collection and pre-processing are critical, as the quality of the input data affects the effectiveness of the data-driven approach [159]. This step focuses on selecting a specific region and collecting pertinent historical data to evaluate the impact of regional weather variables on equipment and EV charging points within the area they serve, as outlined in Chapter 3.4. The process primarily utilizes three key data sources: equipment fault data, EV charging points data, and localized weather data. The purpose of collecting these data is to assess the frequency and impact of equipment faults under different weather conditions and to analyse the impact of power outages caused by these faults on electric vehicle charging points. Specifically:

1. The equipment data collection encompasses details such as the primary substation to which it belongs, location of faults, types of equipment, and the timing of faults.

2. The EV charging point data includes its specific location, the service area of the primary substation to which it belongs. This approach is based on the data currently available.
3. Localised weather data is used to analyse the correlation between weather conditions and the frequency of equipment faults and EVP affected.

These data points are then spatially correlated with corresponding weather variables, such as temperature and rainfall, which are chosen based on the climatic characteristics of the area being studied. This methodology enables a detailed analysis of how specific weather conditions influence equipment and EV charging point vulnerabilities and faults within the selected region [236]. The quantity of historical data required varies depending on the region and specific circumstances due to differences in historical fault records and data availability. It is crucial to strike a balance between spatial resolution and data quality during data collection. As per recommendations from the Institute of Electrical and Electronics Engineers (IEEE), longer time-span data can provide more samples [236]. Once the data collection was completed, the data was screened to identify outliers or other extreme values by the method provided by Han et al [159]. These outliers can provide different insights into the network's response under extreme conditions. Given the data characteristics, such as having only one data point for each temperature factor or rainfall amount, a traditional statistical method for detecting outliers, like calculating the median, is not applicable. Instead, these unique data points are treated as outliers due to their isolated nature, offering valuable insights under specific conditions. This approach allows for a more nuanced understanding of the network's resilience and vulnerabilities, particularly in response to rare but critical events. Such data is invaluable for modelling potential future scenarios and enhancing the robustness of equipment against adverse weather impacts.

6.2.2 Integration of data

To successfully integrate the collected data on critical equipment faults and EV charging point with weather data, several key steps must be undertaken. Initially, data on power system equipment faults and EV charging points connected to that power system are combined to align with the temporal resolution of meteorological data. Subsequently, a suitable method must be selected to adjust the weather data to match the spatial resolution of the study area. This integration process involves critical decisions, including the choice between using point-based or gridded weather station data and considering the availability of such data. For example, the authors in [139, 237] used data from various weather stations, typically point-based, are utilized, providing detailed, localized insights. Conversely, the authors in [238] employs gridded weather data, which provides broader spatial coverage and is beneficial for large-scale analyses. Each approach has its advantages and is chosen based on the specific needs of the research, such as the scale of the study area and the precision required in the data analysis.

Utilizing weather information specific to each event location allows for inclusion of data at the highest granularity. This approach is especially pertinent for weather factors with significant spatial variability, such as rainfall, where local conditions can drastically influence the impact on equipment. However, for more localized weather factors like temperature, which can vary dramatically over short distances due to factors like tree shade or urban heat islands, high granularity might not always capture true conditions effectively. Such localized influences can result in discrepancies in data, leading to what might be perceived as false accuracy in the analysis. As authors indicated in [237], while increased granularity can provide detailed insights, it does not always accurately reflect the complex realities associated with asset faults. This highlights the need for careful consideration in choosing the appropriate scale and type of weather data for equipment fragility assessments.

Analyses that employ regional averages can be more effective for decision-making. In this method, the focus shifts from using average values to adopting the maximum values of weather variables. This approach is designed to ensure that localized extreme weather conditions, which are directly associated with equipment faults are considered in the data aggregation [239]. Spatial variations in weather conditions that impact specific assets, such as intense localized rainfall, can be obscured in the averaging process. By focusing on broader regional trends, these departments can make informed decisions that are relevant across larger areas, potentially leading to more efficient resource allocation and better anticipation of equipment vulnerabilities across the region. Equipment faults in the power system can result in outages within its service area, affecting EV charging points within the outage area. The weather data, characterized by these maximum values, is spatially aligned with a time series of equipment faults and EV charging points connected to that power system. This integration creates a comprehensive dataset that encapsulates both spatial and temporal dimensions of weather conditions and their corresponding equipment events.

6.2.3 Fragility curve

To determine the probability of exceeding a specified damage state under a given environmental condition, employing fragility curves is a well-established method [135]. Fragility curves are instrumental for asset stakeholders in estimating, predicting, and responding to the potential number of faults within their service area [115, 139, 238, 240-242]. This model enables the comparative analysis of the performance of multiple equipment networks under identical weather scenarios. The research process will involve an analysis of various weather variables. These variables may be singular, such as wind speed or temperature, or composite, comprising a combination of several weather factors. The construction and analysis of the model will provide an important basis for understanding the fragility of equipment networks under different weather conditions, thus providing data support for optimizing and improving their performance.

The distributions of data point can be showed by the median number of faults frequencies and its associated 95% confidence interval (CI) [239]. The median serves as a robust statistic that remains relatively unaffected by outliers, which can skew results due to their extreme values [243]. These extreme events can disproportionately influence the total fault count, potentially reducing the accuracy of the fragility function. The pronounced effect of outliers on average values renders analyses based on averages less reliable. Thus, employing the median in calculations offers a more accurate representation of the actual fragility of equipment under varying weather conditions. Additionally, it is advisable to plot the fragility curves both with and without the inclusion of extreme values. Although understanding the equipment's response to these extreme events is valuable, the limited number of observations at these extremes might lead to inaccurate conclusions about overall fragility. This lack of data can bias the performance curve towards specific, atypical events. This dual approach, involving both the median and selective inclusion of extreme values, allows for a balanced and precise depiction of equipment fragility across different weather scenarios. This methodology ensures that decision-makers have a clear and comprehensive understanding of equipment resilience, helping to inform more effective management and mitigation strategies.

When converting data points into fragility curves, this study employs a polynomial regression model due to its flexibility in accommodating various forms of data [164]. Polynomial regression models can effectively model the non-linear relationships that often exist between weather variables and equipment faults. The general form of the polynomial regression equation is:

$$f = \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots + \beta_n x^n + \varepsilon \tag{6.1}$$

where f represents the dependent variable, x^n represents the independent variable, β_n represents the coefficient of the regression equation, indicating the weights of the different power terms and ε represents the unobserved random error.

By fitting this polynomial regression to the collected data, one can derive a mathematical model that maps the dependency of equipment fragility on weather conditions, providing a predictive tool to estimate potential equipment faults based on future weather scenarios. However, high-order polynomial regression may run the risk of overfitting and increased model complexity, and it is difficult to interpret the significance of each coefficient. Therefore, this study used second-order polynomial regression. This approach maintains model simplicity and interpretability while still effectively capturing key trends and patterns in the data.

6.2.4 Cross-sectoral impact analysis

After generating separate fragility curves for each equipment, the results need to be visualized and compared for the same time period and weather variables. Plotting these curves allows visual comparisons of shape, magnitude and trend for qualitative assessments. There is also a need to quantitatively assess the relevance of each equipment layer at different weather factors. For this purpose, Coefficient of determination [244] and Pearson correlation coefficient [245] can be used. Coefficient of determination can judge the interpretability of the regression model. The value is between 0 and 1. The closer the value is to 1, the better the regression model explains the data. Pearson correlation coefficient provides an accurate numerical metric, that can help to understand the response patterns of different equipment under the same weather factors. Values range from -1 to 1. The closer the value is to 1 or -1, the stronger the linear correlation between the two variables. Positive values indicate positive correlation, and negative values indicate negative correlation. When using the coefficients of determination, the regression model was first built and R^2 was calculated to assess the explanatory power of the model. If the

R^2 is high, it means that the selected weather factor is highly explanatory of the equipment fault. By calculating the Pearson's correlation coefficient between the number of equipment faults and EVP affected by weather factors, it is possible to identify the significance of different weather factors on the EVP affected by different equipment faults. The combination of qualitative and quantitative assessments allows for a comprehensive analysis of the fragility of various equipment sectors under different weather conditions. This will provide a basis for optimizing the design and management of EV charging point, enhancing its resilience and ability to maintain operation during extreme weather events.

6.3 Case study

For the purposes of this analysis, “Fault” refers to incidents involving the malfunction or breakdown of power system equipment. The number of EV charging points within the coverage area of each primary substation varies. A direct comparison based on the number of faults is not an appropriate way. Therefore, the number of “Faults” needs to be converted to “Fault frequencies” (Number of equipment that faults per day divided by total amount of equipment of that type). “Fault frequencies” can be expressed as fault per equipment within the area covered by primary substation containing the EV charging point. “Outage” denotes a power system outage caused by equipment faults. Equipment fault data, outage events and the area covered by each primary substation are documented by Electricity North West Limited (ENWL) [246]. “Charging point (EVP)” specifically pertains to the entries in the well-established register of public electric vehicle (EV) charging points, which is maintained by the Department for Transport in the UK [247]. There is variability in the number of EV charging points within each primary substation's service area, and a direct comparison of the number of EVP affected" is also not an appropriate way. Therefore, it is also necessary to convert “EVP affected” to “Frequency of EVPs affected”. “Frequency of EVPs affected" can be expressed as the number of EVPs affected by each equipment fault.

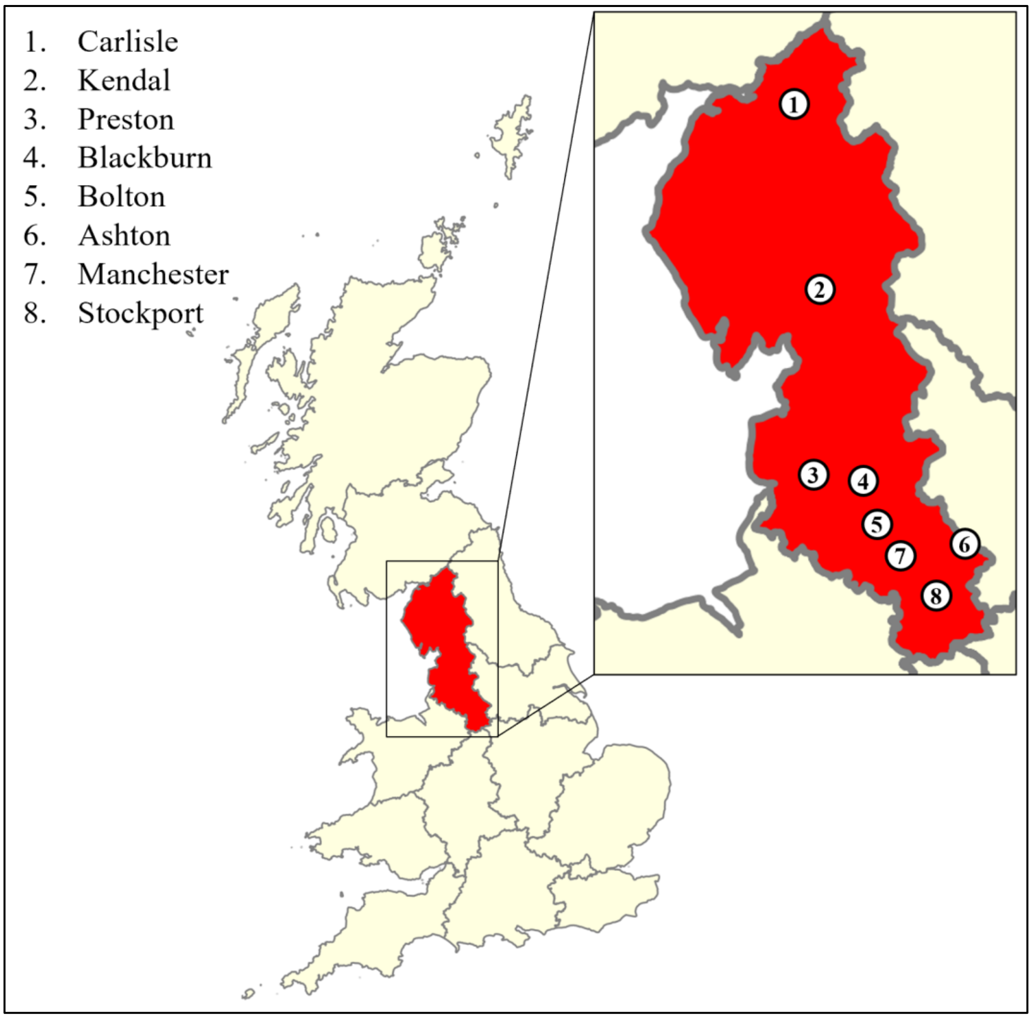


Figure 6.2: Distribution network operator with Northwest of ENWL (show in red) and location of districts used in the analysis [248].

To validate the proposed methodology, this chapter provides a case study of the North West of England, focusing on the equipment in the power system and EV charging point. This DNO region is defined based on the GB DNO License Areas from ESO [248]. As shown in Figure 6.2, the study area covers eight regions in the North West of England - Carlisle, Kendal, Preston, Blackburn, Bolton, Ashton, Manchester and Stockport. It allows for a comprehensive assessment of how equipment faults can impact the availability and functionality of essential services like EV charging. This analysis is instrumental in identifying potential weaknesses in the power supply chain that could affect the broader adoption and reliability of electric vehicles, thereby guiding efforts to improve equipment resilience and ensure service continuity.

Distribution network operators manage the distribution network, which is responsible for delivering electricity from the high-voltage transmission network to residential and commercial premises [248]. Data recorded by ENWL [246] and public EV charging point data from the UK National Charging Point Register (NCR) [247] were collected according to the process outlined in Section 6.2. The data covers all power system fault events within the DNO area of North West of England between January 1, 2013 and December 31, 2022. A total of 97,708 power system fault events and 1,504 EV charging points were considered in this analysis. As the number of new registrations for EV charging points increases incrementally over time, this chapter conducted the data analysis using the total number of EV charging point registrations as of December 31, 2022, as the baseline. This baseline effectively encompasses and accounts for the maximum potential charging demand and load scenarios throughout the period under study.

For the 10-year time periods, 2013-2022, UK Met Office [249] provides climate observations data on a 12km grid over the UK. The data contains daily temperatures and rainfall. In this case study, power system fault data and EV charging point affected resulting from these faults were first aggregated to calculate a daily count. Local authorities, which may lack access to detailed information on specific outages and charge point locations, often rely on such aggregated data [250]. Reflecting this need, the weather data for the region were averaged over the study area to create a single weather series. This series is utilized to compare the performance of regional equipment under varying weather conditions, thereby offering a streamlined yet effective approach for regional planning and response.

6.3.1 Customer impacts of power system outage.

Power system customers are all types of customers who purchase and use electricity services from electricity suppliers, including residential, commercial and industrial customers [234, 235]. For example, for a residential customer who needs electricity for daily needs such as appliances, heating or charging EV. Based on the analysis of charging point information from NCR [247], it was found that EV charging points were constructed in a variety of locations, such as residential areas, commercial public areas, roadsides, etc. This means that when there is a power outage on the power system that causes the customers served to be impacted, the EV charging points contained within those customers are also affected. A power outage in the power system will not only affect the daily lives of residential users, but also disrupt the operations of commercial and industrial users. At the same time, the unavailability of EV charging points will directly affect the travelling and charging needs of EV users. The impact of power system outage on customers depends largely on their nature and magnitude. There are many causes of power system outage. For example, weather factors, internal problems within the power company or third-party causes.

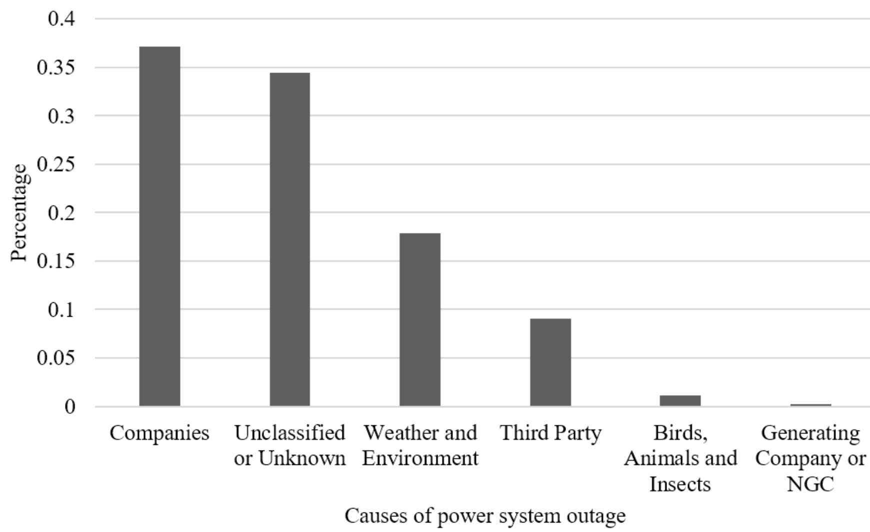


Figure 6.3: Percentage of power system outage due to different causes.

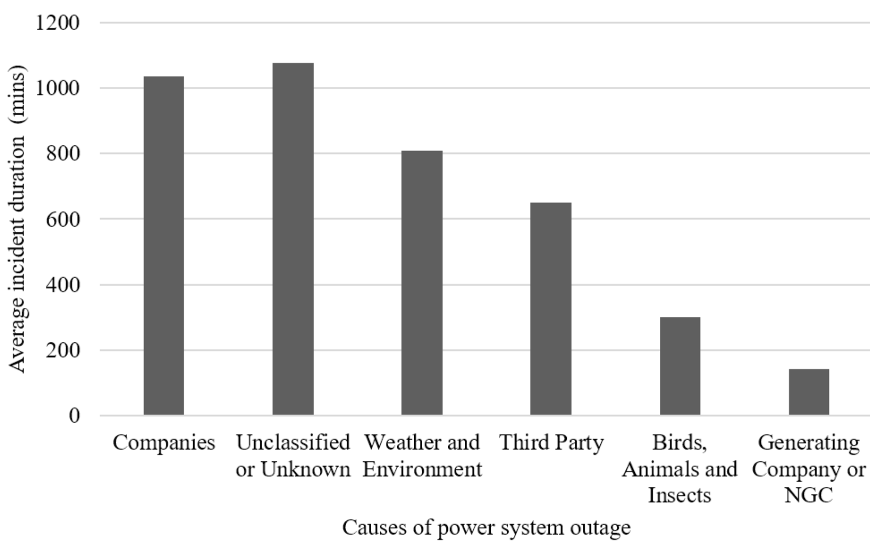


Figure 6.4: Average incident duration for power system outage of different causes.

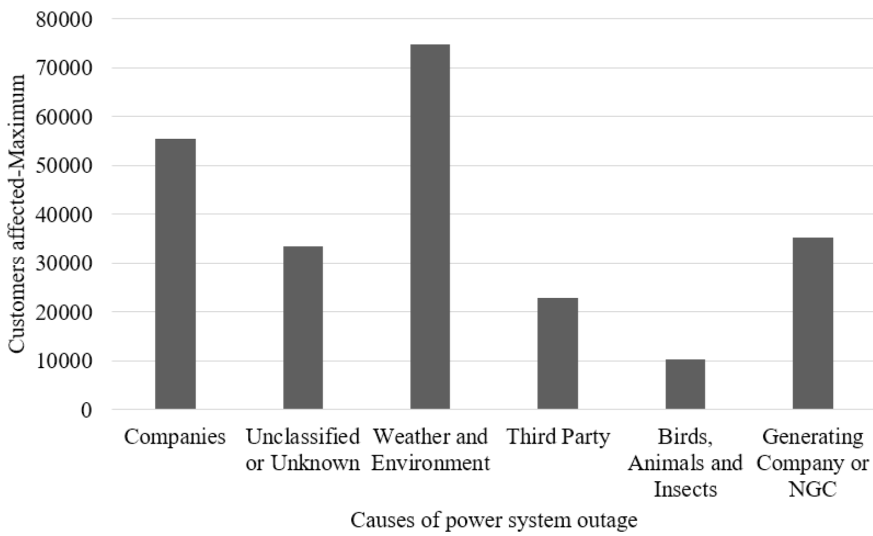


Figure 6.5: Number of customers affected by each cause of outage.

Figures 6.3-6.5 show the percentage of the number of power system outage due to different causes, the average duration of the outage, and the maximum number of affected customers, respectively. Firstly, companies and unclassified or unknown causes account for a larger proportion of the number and duration of outage. The company needs to improve internal operational and management efficiency to reduce human-induced failures. At the same time, further investigation and categorisation of outages with unknown causes, can help to target preventive measures and improve the accuracy and effectiveness of fault management. Secondly, weather and environmental factors have the greatest impact on customers, although they account for a relatively low number of outages. The largest number of customers were affected, and the average duration of outages was long. This shows that weather and environmental have a significant impact on the operation of the power system and require special attention. In order to further explore the impact of the different causes of power system outage on the customers, the Pearson correlation coefficient was used for analysis (Table 6.1).

Table 6.1: Correlation of causes of power system outage and customers affected.

Causes of power system outage	**Pearson correlation coefficient**
Companies	0.26
Unclassified and unknown	0.34
Weather and environment	0.55
Third party	0.23
Birds, animals and insects	0.21
Generating company or NGC	0.23

Table 6.1 shows the highest correlation between weather and environmental factors causing power system outages and the number of customers affected, with a correlation coefficient of 0.55. This suggests a strong positive relationship between weather-related outages and the number of customers affected. That is, as the number of weather-related power system outage increases, the number of customers affected increases accordingly. Extreme weather conditions, such as extreme high or low temperatures, storms, etc., can result in additional power system outages that can affect a wide range of customers. Since EV charging points are typically located in a variety of areas, such as residential,

commercial and public areas, power interruptions in these areas will have a direct impact on the EV charging points and may prevent them from charging EVs.

6.3.2 Impact of weather factors on power distribution equipment fault

Section 6.3.1 analyses the causes of outages on the North West power system in the UK, with weather-related outage events having the highest relevance in terms of their impact on customers. For example, extreme weather conditions can cause equipment such as overhead lines and transformers to fault. These equipment fault can affect the power supply to EV charging points within their service area. Therefore, this section analyses the impact of different weather factors on the various types of equipment in the power system and further explores in Section 6.3.3 which power system equipment fault has the greatest impact on EV charging points.

In power systems, equipment includes: overhead lines, cables, transformers, switchgear, etc [251]. In data analysis, complete and detailed fault information is essential to ensure the accuracy of the results. For data that fails to explain the cause of a specific equipment faults, it is difficult to determine the true cause of the fault and its impact on the system. In contrast, there is data that specifically describes specific information about the faulty device, such as material, configuration, construction, and number of conductors. It is also important to note that while power system outages due to weather and environment are analysed in section 6.3.1, situations such as accelerated line deterioration or wear due to extreme temperatures are classified as other causes. Therefore, this section is based on an initial analysis of the full data, followed by the choice to use only the data containing detailed fault information.

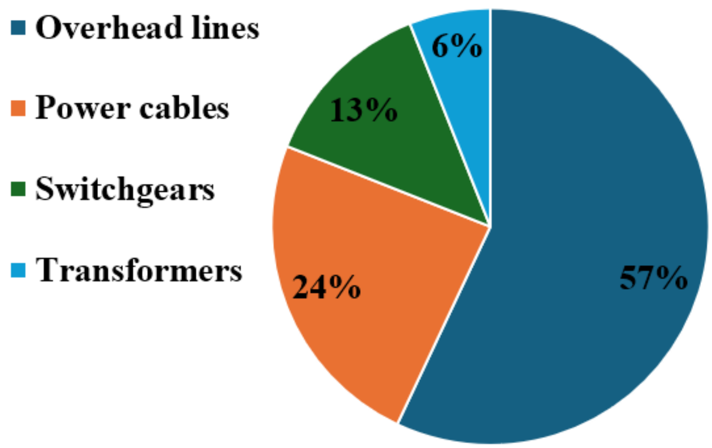


Figure 6.6: Percentage of power system outage caused by equipment.

As can be seen from the Figure 6.6, overhead lines caused 57 % of the power system outages. Overhead lines are exposed to the natural environment and are susceptible to weather factors such as high temperatures, rainfall, storms, lightning strikes, etc., which leads to higher fault rates [252]. This is followed by cables at 24 %. Faults of cable may be due to the effects of ageing, overloading and other internal causes [253]. Switchgear and transformers accounted for 13 % and 6 % respectively. Although relatively rare, their critical role in the power system means that any fault could have a significant impact on the system [254, 255]. Historical weather data were obtained from the UK Met Office HadUK-Grid Datasets, which contain daily temperatures and rainfall [249]. The relationship between faults and weather was quantified by multivariate nonlinear regression of fault frequency and weather parameters (temperature, rainfall).

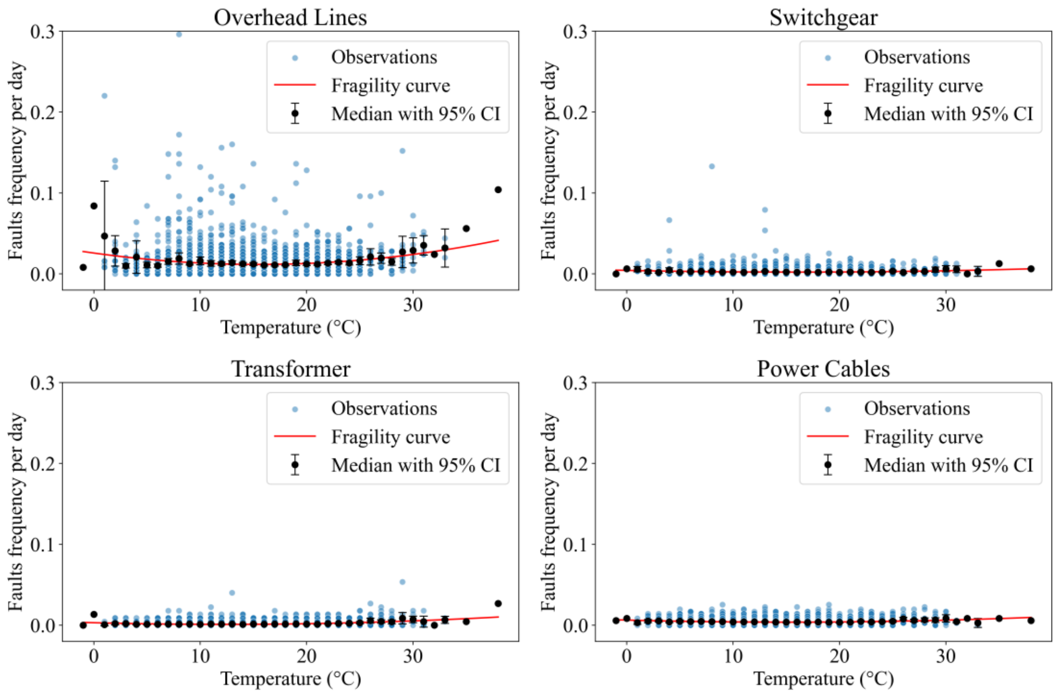


Figure 6.7: Number of fault frequency (blue symbols) and median number of fault frequency with 95% confidence interval (black symbols) recorded for different temperature at all locations (including outliers).

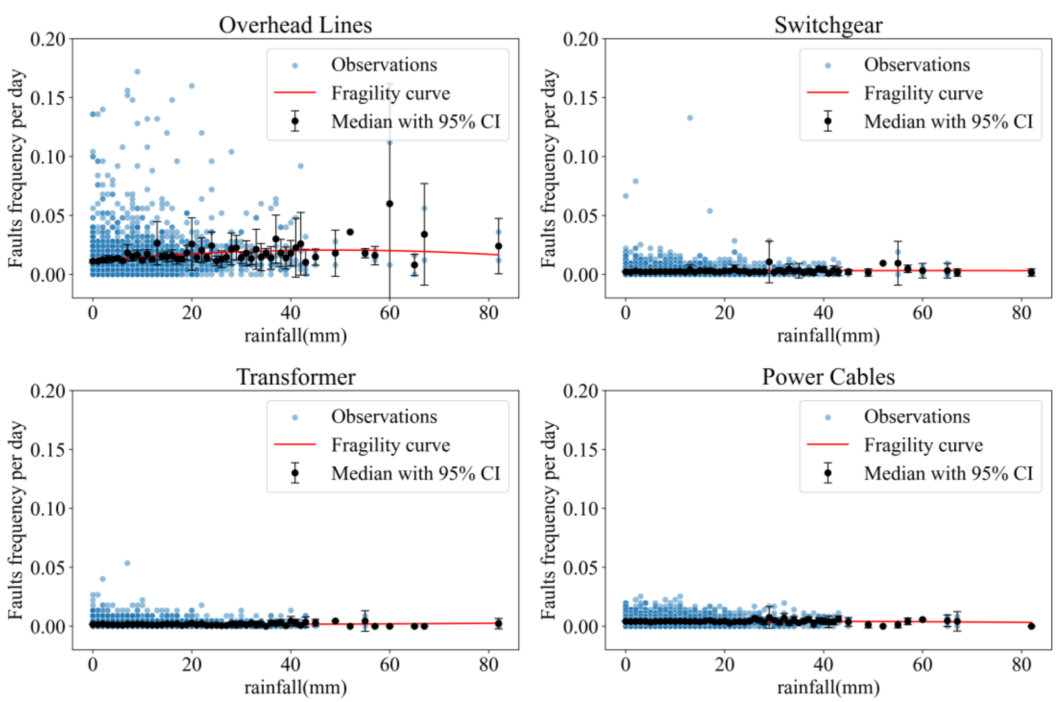


Figure 6.8: Number of fault frequency (blue symbols) and median number of fault frequency with 95% confidence interval (black symbols) recorded for different rainfall at all locations (including outliers).

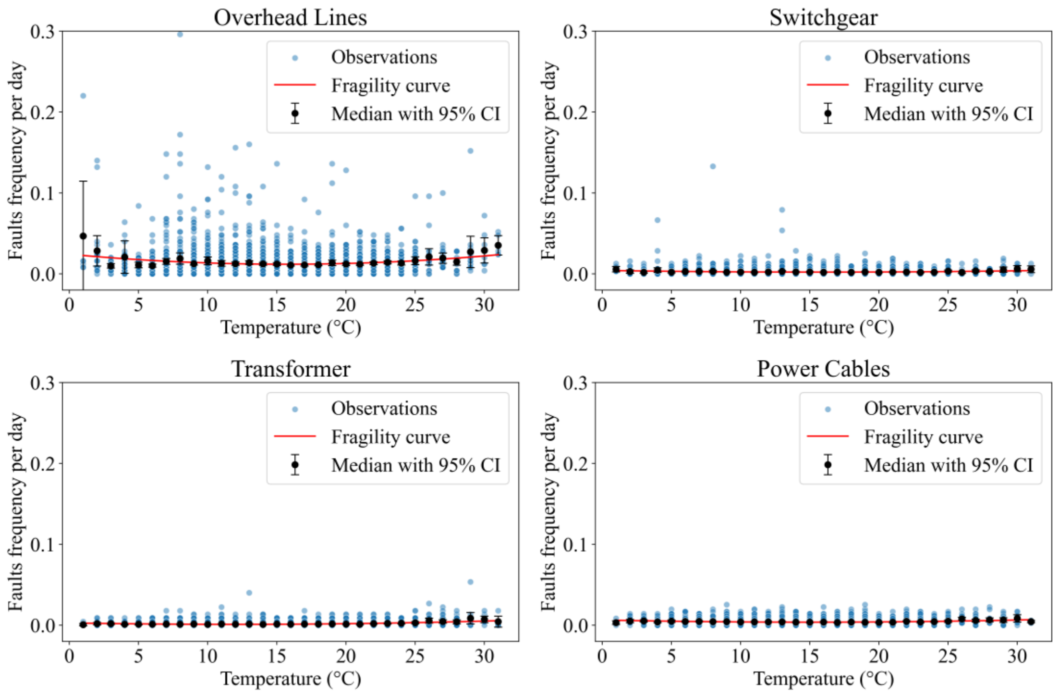


Figure 6.9: Number of fault frequency (blue symbols) and median number of fault frequency with 95% confidence interval (black symbols) recorded for different temperature at all locations (results after removing days with a scarcity of data).

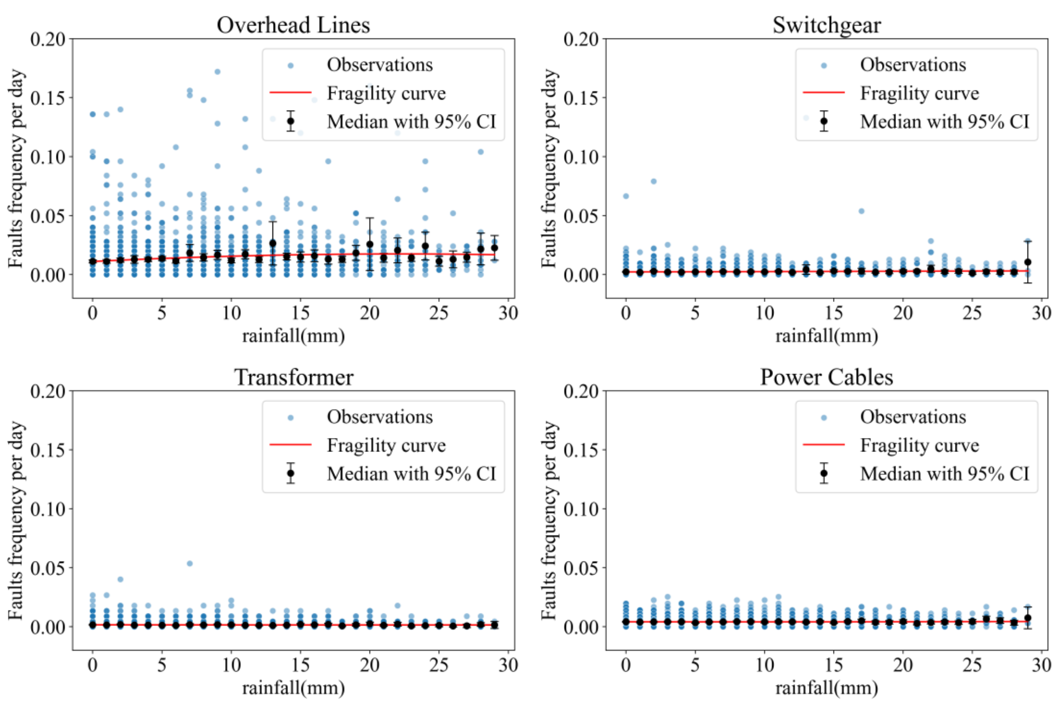


Figure 6.10: Number of fault frequency (blue symbols) and median number of fault frequency with 95% confidence interval (black symbols) recorded for different rainfall at all locations (results after removing days with a scarcity of data).

Figure 6.7 shows the distribution of fault frequencies at different temperatures. It is interesting to note that the fault frequency for each device is concentrated in the 1-31°C range. Below 1 °C and over 31 °C ranges, with an average of only one day's data for each temperature value. Figure 6. 8 shows the frequency distribution of fault for different rainfall amounts. There is a significant decrease in the number of data points when the rainfall exceeds 38 mm. For fault frequencies of transformer and power cables, after a rainfall of more than 29 mm, only one day's worth of data is available for each average rainfall. The scarcity of data at extreme temperatures and high rainfall is illustrated. As a result, data from days with temperatures below 1°C or above 31°C, and rainfall above 30 mm were not used in the analysis. Figures 6. 9 and 6.10 show the results after removing the days with scarce data, respectively. for power system equipment fault under temperature factor and rainfall factor respectively.

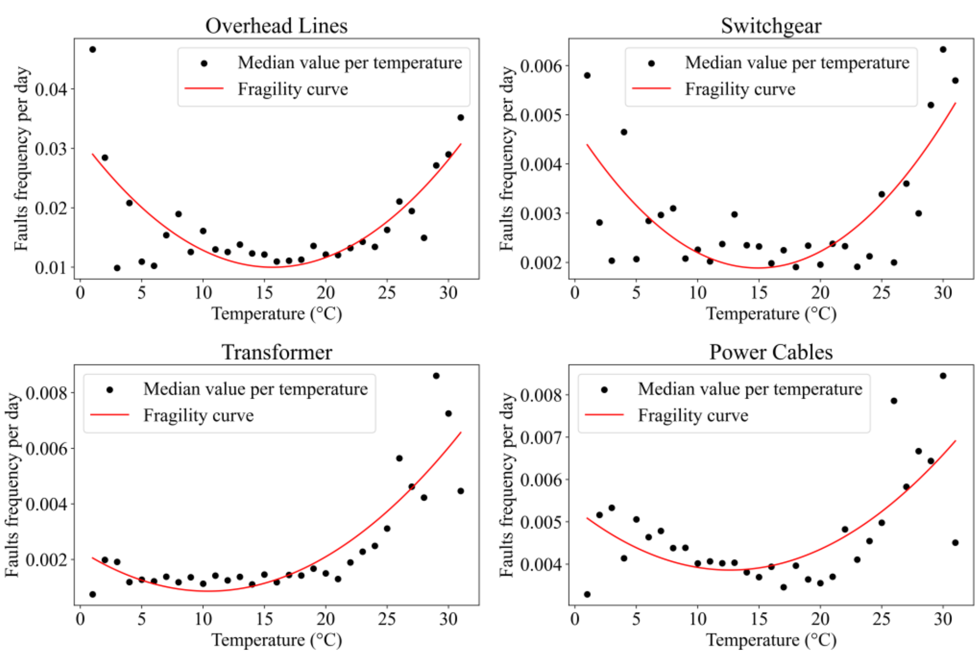


Figure 6.11: Fragility curves of fault frequency for different equipment with temperature.

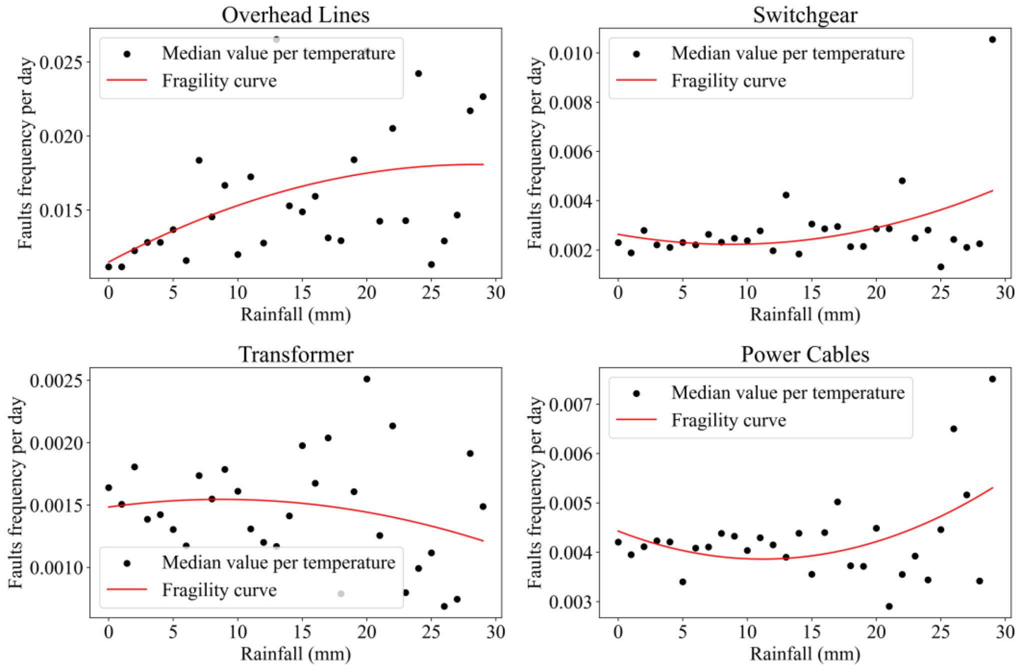


Figure 6.12: Fragility curves of fault frequency for different equipment with rainfall.

Table 6.2: Regression coefficients, Coefficient of determination and Pearson correlation coefficient for fault frequency and weather factor.

		β_2	β_1	ε	R^2	P
Temperature	Overhead line	8.83×10^{-5}	-2.77×10^{-3}	0.032	0.60	0.77
	Switchgear	1.29×10^{-5}	-3.86×10^{-4}	0.005	0.60	0.77
	Transformers	1.35×10^{-5}	-2.81×10^{-4}	0.002	0.77	0.88
	Power cable	9.05×10^{-6}	-2.29×10^{-4}	0.005	0.49	0.70
Rainfall	Overhead line	-8.14×10^{-6}	4.63×10^{-4}	0.012	0.21	0.47
	Switchgear	5.31×10^{-6}	-9.29×10^{-5}	0.003	0.16	0.40
	Transformers	-8.10×10^{-7}	1.42×10^{-5}	0.001	0.05	0.23
	Power cable	4.54×10^{-6}	-1.02×10^{-4}	0.004	0.21	0.46

Figures 6.11 and 6.12 show the fragility curves of fault frequency for different equipment under temperature and rainfall, respectively. For the temperature factor, the fault frequency of all equipment in the power system has the same trend. Below 10 °C, the fault

frequencies rise as the temperature decreases. After 20 °C, the fault frequencies increase as the temperature rises. The fault frequencies caused by the power cable has a weak relationship with temperature, increasing only slightly with increasing temperature after about 20 °C. And there is a significant difference in the power system equipment fault frequencies of under the rainfall factor. Switchgear and power cables share the same trend of increasing the fault frequencies as rainfall increases. Although the overhead line also increases with increasing rainfall, the increase decreases significantly after 17 mm. For transformer, on the other hand, the fragility curve is less interpretable.

Figures 6.11 and 6.12 show that the fragility curves for fault frequencies vary with temperature and rainfall. The fault frequencies of the power system equipment show a minimum value at medium temperatures and an increase at both ends (higher/lower temperatures). Overall, these results show that the fault frequencies fragility curves of equipment have the same trend at different temperatures. This means that different equipment will the number of faults exhibit in similar trends under temperature factors. However, for the rainfall factor, a different trend was found, with only the fault frequencies of the transformer showing a decreasing trend with increasing rainfall. Table 6.2 shows the regression coefficients of the fragility curves for each equipment at different temperatures and rainfall levels. Temperature has a stronger explanatory power for equipment fault frequencies, while rainfall has a weaker effect. Table 7.2 also shows the Pearson correlation coefficients for the observations and the fragility curves. Overall, there is a strong correlation between observations and the fragility model under temperature conditions and a weaker one under rainfall addition.

6.3.3 Impact of power system equipment faults on EV charging points.

As described in Section 6.3.1, EV Charging Points (EVPs) can be placed in many locations, such as residential or public areas. Power system equipment faults can cause widespread outages within the coverage area of the primary substation to which it belongs. Power interruptions at these locations will have a direct impact on the EV charging points and may prevent EV charging. However, as analysed in section 6.2, weather factors affect equipment differently. This also means that these equipment fault can result in different levels of impact on EVPs. This section analyses which equipment fault have the greatest impact on EVP under different weather factors.

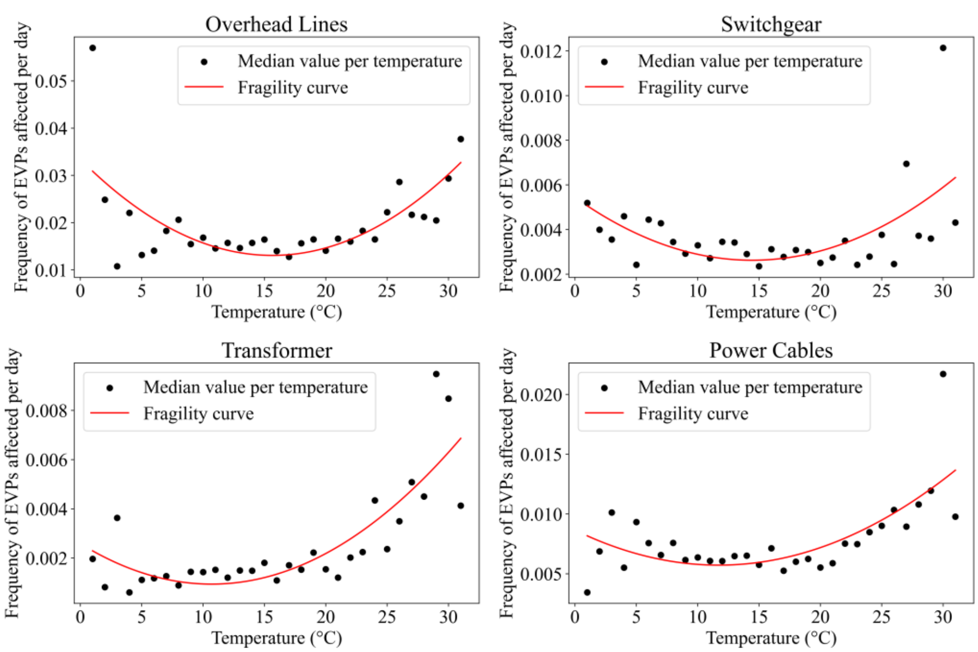


Figure 6.13: Fragility curves of frequency of EVP affected by different equipment faults under temperature.

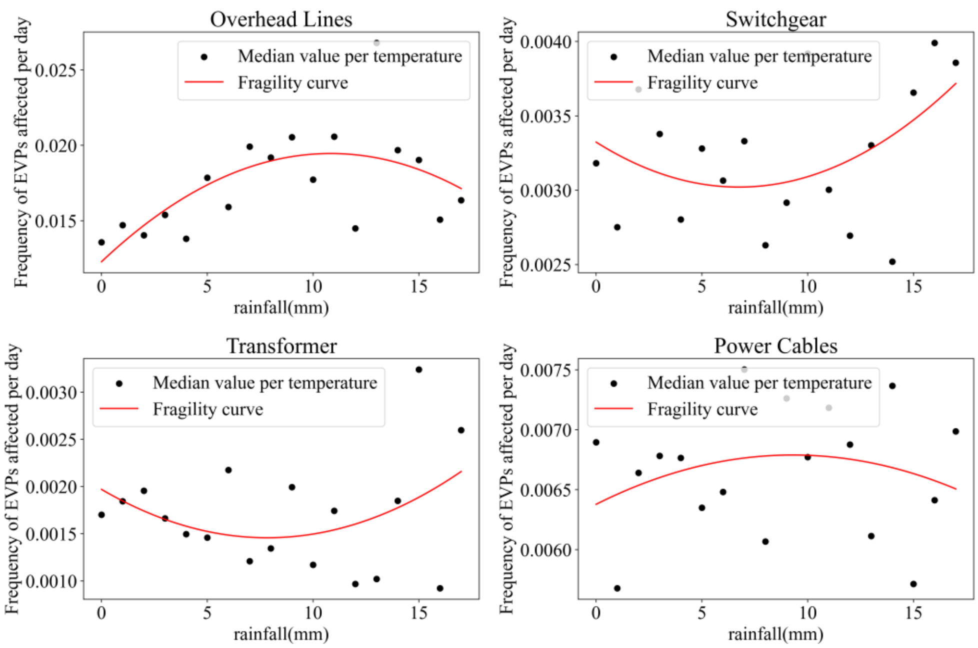


Figure 6.14: Fragility curves of frequency of EVP affected by different equipment faults under rainfall.

Firstly, the faults of power system equipment can result in EVPs being affected in the area it serves. Based on this, the frequency of EVPs affected by each equipment fault can be counted. As described in 6.3.2, due to data scarcity, data from days with temperatures below 1 °Cor above 31 °C and rainfall above 30 mm were not used in the analysis. Figure 6.13 and Figure 6.14 show the frequency of EVP affected as fragility curves to temperature and rainfall factors respectively. The relationship between frequency of EVP affected due to transformer fault and temperature is weak. The strongest relationship between frequency of EVP affected due to overhead lines faults and temperature. In contrast, there is a significant difference in the frequency of EVP affected under the rainfall factor. The frequency of EVP affected due to switchgear and power cables faults have the same trend of increasing frequency of failures with increasing rainfall.

However, the relationship is weaker. The frequency of EVP affected due to overhead line faults showed a strong relationship with rainfall, which increased with increasing rainfall.

Table 6.3: Regression coefficients, Coefficient of determination and Pearson correlation coefficient for frequency of EVP affected and weather factor.

		$\boldsymbol{\beta_2}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\varepsilon}$	$\boldsymbol{R^2}$	$\boldsymbol{P}$
Temperature	Overhead line	8.32×10^{-5}	-2.60×10^{-3}	0.035	0.46	0.69
	Switchgear	1.35×10^{-5}	-3.90×10^{-4}	0.005	0.33	0.58
	Transformers	1.44×10^{-5}	-3.08×10^{-4}	0.003	0.69	0.83
	Power cable	2.13×10^{-5}	-5.00×10^{-4}	0.009	0.50	0.71
Rainfall	Overhead line	-1.50×10^{-6}	2.81×10^{-4}	0.015	0.22	0.47
	Switchgear	1.08×10^{-5}	-2.45×10^{-4}	0.004	0.14	0.38
	Transformers	-1.74×10^{-6}	3.50×10^{-5}	0.002	0.08	0.28
	Power cable	5.33×10^{-6}	-1.44×10^{-4}	0.007	0.10	0.32

Table 6.3 lists the relevant regression coefficients. Temperature has a stronger explanatory power for conditional fragility curves, while rainfall's is weaker. Table also shows the Pearson correlation coefficients for the observations and the fragility modelling. There is a strong correlation between observations under temperature and fragility modelling. In addition, the frequency of EVP affected due to transformer fault is low under the rainfall factor, both in terms of interpretability and correlation between observations and fragility curve.

Figures 6.13 and 6.14 show that the fragility curves for frequency EVP affected differ with temperature and rainfall. The frequency of EVP affected due to the power system equipment fault shows a minimum at medium temperatures and an increase at both ends (higher/lower temperatures). For the rainfall factor, different trends were found, only the frequency EVP affected due to overhead line faults showed a significant increasing trend with increasing rainfall.

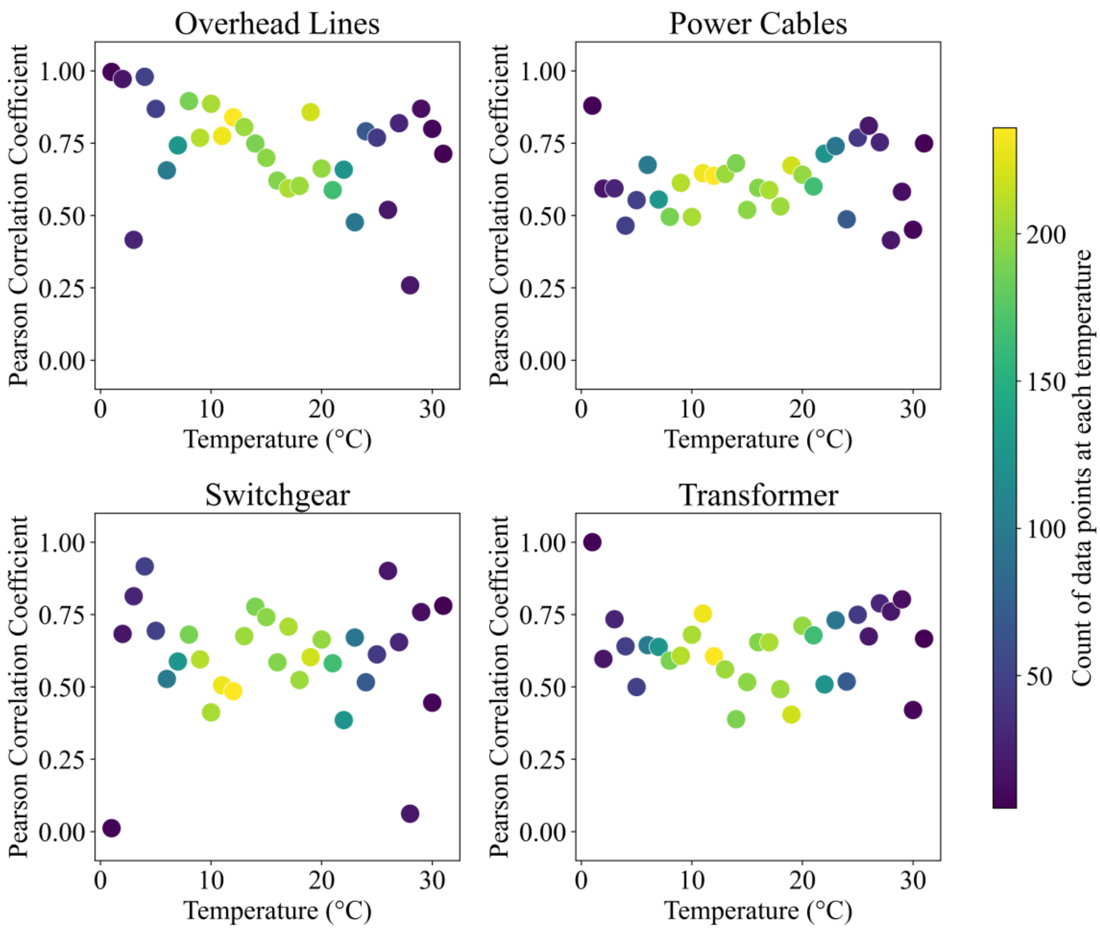


Figure 6.15: Correlation coefficient for frequency of EVP affected and equipment fault frequency for different temperature amounts.

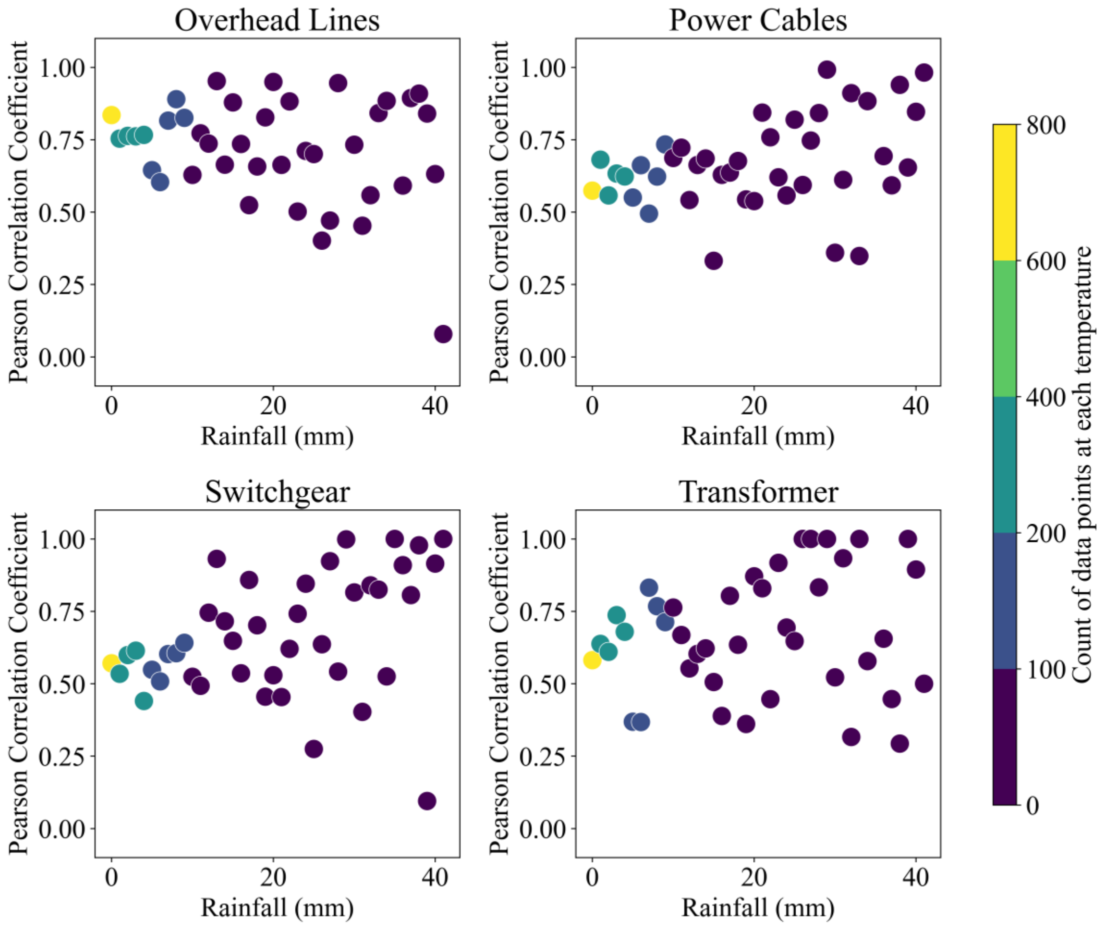


Figure 6.16: Correlation coefficient for frequency of EVP affected and equipment fault frequency for different rainfall amounts.

By Pearson correlation coefficient, Figure 6.15 shows the correlation between the equipment fault frequency and frequency of EVP affected at each temperature. Of the four results, the highest number of data points were found in the temperature range of 10°C to 20°C. However, the correlation between overhead line faults frequency and frequency of EVP affected is highest at low and high temperatures, while the correlation between cable/switchgear and their resulting frequency of EVP affected is more stable over the entire temperature range, with the correlation being 0.5 - 0.75. The correlation between the transformer fault frequency and the resulting frequency of EVP affected is high at low temperatures. Figure 6.16 shows the correlation between the frequency of equipment failures and frequency of EVP affected for each rainfall event using the Pearson correlation coefficient. It can be noticed that the data points are mainly concentrated in the low rainfall range (0-10 mm). Moreover, only the overhead line fault frequency and its corresponding frequency of EVP affected have higher correlation in the low rainfall range, with the correlation being 0.75 - 0.9 below 10 mm.

6.4 Discussion

EVs can provide ancillary services through V2G. Analysing the charging load of electric vehicles can understand their impact on the network. Operators such as EVAs can manage EV charging with coordinated charging strategies to increase profits and reduce pressure on the network. But all of this is dependent on one key point - the EV first needs to be connected to the network via a charging point. The EV charging point serves as a medium for connecting the EV and the network, and it directly affects the interaction between them. Therefore, this chapter analyses the impact of power outages due to equipment faults on EV charging points from power system perspective.

By analysing unplanned outages in the North West region using the proposed methodology, it was found that, there is a moderate to strong positive relationship between weather-related outages and the number of customers affected (Pearson correlation coefficient is 0.55). In order to better understand the relationship between power system outages and their equipment fault, the frequency of power system equipment fault under different weather factors was analysed. Overhead line fault showed high correlation both in temperature factor and rainfall factor. These power system equipment fault can cause EVPs in their service area to be impacted by power system outages. By analysing the fragility curves and correlation between the frequency of EVP affected due to various types of power system equipment faults under different temperature and rainfall, it was found that faults in overhead lines have the greatest impact on EVP affected. EVP affected by transformer fault is the least sensitive to temperature and rainfall, and its fault has a relatively small impact on EVP affected. Therefore, when planning and maintaining EVPs, special attention should be paid to the fragility of overhead lines to weather conditions, and appropriate preventive and countermeasure measures should be taken to ensure the operation of EVPs.

6.4 Summary

Chapter 6 describes a methodology for assessing fragility to multiple weather-related power system equipment faults. The methodology is demonstrated through a case study over a continuous 10-year time period. This case study examines the impact of temperature and rainfall on power system equipment and electric vehicle charging points in the North West of England. For the region, analyses show that weather factors have different impacts on equipment faults. There are also differences in the number of EV charging points affected due to the faults of different equipment. Such events will become more frequent in the future due to climate change.

This chapter only provides a case study of infrastructure in the North West region of the UK, but the methodology is also applicable to the analysis of different sectors in different regions. For example, in [136] , the methodology is used to analyse the fragility of the power and railway systems in the West Midland region of the UK to failures based on weather factors. This work uses weather data provided by the UK Meteorological Office (MET Office) [249], of which only temperature and rainfall have daily records, while other weather data such as wind speed and snowfall lack daily records. Therefore, this work is based on the available weather datasets for analysis. While this work has focused on the impacts of temperature and rainfall on the distribution network and EV charging points, future studies can obtain weather data from different sources in the UK and investigate the fragility of other meteorological parameters such as different climatic indices, wind and other relevant key infrastructure [139, 256].

Chapter 7

Conclusions and Future work

With the rapid growth in the number of EVs, the power system is facing unprecedented challenges. Large-scale EV charging may lead to a surge in network load, increasing the pressure on power supply [257]. Therefore, how to coordinate large-scale EV charging to reduce the pressure on the power system and utilise the flexibility of EVs to support the network has become an important topic of current research.

In the context of large-scale EV access to the network for charging, EVs can be used as distributed energy storage devices to participate in network load balancing, and provide ancillary services to the power system through V2G technology. During the charging process of EVs, several factors can affect their interaction with the network. For example, extreme weather conditions such as high temperatures, low temperatures, and storms can affect EV driving energy consumption and charging demand. In addition, outages due to power system equipment faults can have a direct impact on EV charging and usage, which may result in EV users not being able to charge in a timely manner, thus affecting travel plans. Chapter 7 concludes the research of this thesis and proposes future work.

7.1 Conclusions

In Chapter 3, the modelling and analysis of EV driving and charging behaviours can provide a foundational understanding for subsequent analyses. An important finding in the case study is that the Monte Carlo method proved to be a tool for EV data modelling. Monte Carlo simulation generates EV charging data with a small error from the real data (e.g. Electric Nation project and My Electric Avenue project), which provides support in the absence of real data. Chapter 3 also explores the effect of temperature on EV driving behaviour, and assesses the feasibility of the approach using data from real research projects. The result shows that temperature significantly affects the driving and charging behaviour of EVs. By combining the Chevrolet Bolt case study in Kuwait and the Tesla Model 3 case study in the UK, this chapter validates the non-linear effect of temperature on energy consumption. EV driving energy consumption (Wh/km) shows a U-shaped curve with temperature, increasing at very low and very high temperatures and reaching a minimum in the medium temperature range.

In the context of the UK electricity system and market, optimising the coordination of EVs with the network is essential to reduce network load pressure and charging costs. It is also important to improve the profitability of ancillary services through effective risk management. To address this aim, Chapter 4 presents how charging and ancillary services for EVs are managed. The chapter proposes a bi-level scheduling approach that not only simplifies the complex scheduling problem, but also introduces a conditional value-at-risk (CVaR) approach to assess the EVA revenues under different risk-neutral and risk-averse scenarios. Charging data for 10,000 EVs of different makes in the Birmingham area were modelled by using Monte Carlo methods. This chapter analyses the scheduling options for EV participation in ancillary services under different weekday and weekend conditions.

One of the key findings from the case study was the difference in the dispatch needs of EVs on weekdays and weekends. For example, the percentage of response reservice on weekends is approximately 5 % higher than on weekdays. This means greater scheduling potential for EVA. In addition, choosing a lower risk aversion parameter can result in more revenue for the EVA, within acceptable risk limits.

The hosting capacity of the distribution network limits the number of EVs that can be charged simultaneously in a uniform timeframe. In addition, temperature variations significantly affect the EV driving habits and charging behaviour, leading to a diversity of EV charging profiles. As global warming increases, it will become increasingly important to incorporate temperature changes into considerations of distribution network hosting capacity. Therefore, it is particularly important to understand the impact of temperature variations on the hosting capacity of EVs. Chapter 5 presents a methodology for evaluating the maximum EV hosting capacity on a test network over different temperature ranges. The methodology uses temperature data from the UK MET Office to quantify its impact on the EV charging behaviour in the 'My Electrical Avenue' project. The chapter reveals the impact of different EV penetration rates on the state of the low-voltage test network over various temperature ranges. An important finding is that high temperatures can reduce the hosting capacity of the distribution network, leading to an overestimation of the network's ability to meet demand during periods of high load. Conversely, at lower temperatures, the distribution network can unlock potential hosting capacity to support network operators. The proposed methodology has good scalability and applicability, and can be used in different regions to quantify the impact of temperature on the EV hosting capacity of distribution network, providing a powerful tool for cross-regional studies.

Weather-related faults of power system equipment are becoming more frequent due to climate change. Understanding the risks to power system equipment and its fragility to weather change is necessary for relevant stakeholders. In addition, power system equipment fault (e.g. faults of overhead line, transformer and cable) may affect EV charging point within its coverage area, which in turn may change the charging profile of EV users. Therefore, it is important to analyse the impact of weather factors on power system equipment. Chapter 6 presents a methodology for assessing weather-related fragility modelling of power system equipment and EV charging points. This method combines the impacts of weather on different equipment and the effects of equipment faults on EV charging points. The feasibility of the approach was assessed by analysing the impact of temperature and rainfall on power system equipment faults and EV charging point affected in the North West of England from 2013 to 2022. The results of the study show that extreme temperatures and heavy rainfall have a negative impact on both the power system equipment and the EV charging points. Equipment faults and EV charging point affected in the study area correlate to varying degrees with weather factors. Based on these results, it is recommended that stakeholders enhance power system resilience through increased asset maintenance and improved emergency response capabilities.

The thesis contributes to the field of power system optimisation and management, particularly in the areas of EV participation in ancillary services, hosting capacity assessment and integrated analysis of extreme weather impacts. Firstly, the research in the thesis starts with data collection and simulation modelling, and proposes a comprehensive approach that integrates EV driving and charging data, household demand data, power system fault data, and weather data. And the non-linear impact of temperature on the behaviour of EV is verified. The validity and accuracy of the simulation method in the absence of real EV charging data is also demonstrated through Monte Carlo simulation. Secondly, the thesis further explores how to optimise the scheduling of EVs in the power system. A method is proposed to simplify the complex scheduling problem, and evaluate the scheduling effectiveness under different risk scenarios. Thirdly, it reveals the EV hosting capacity of low-voltage test networks under different temperature conditions. Finally, a methodology for the integrated assessment of infrastructure fragility is proposed to facilitate joint planning of infrastructure.

The research in this thesis demonstrates that EV participation in ancillary services, hosting capacity assessment, and extreme weather factors on power system fault analysis have far-reaching implications of power system operations. Although the focus of this thesis is on modelling and optimization of EV integration in distribution networks. However, the proposed methodology is equally applicable to other types of loads and system evaluations. Considering the overall impact of global climate change on the power system, it has become particularly critical to build a power system that is resilient to future changes. The research results in this thesis provide support for power system planning and operation, and lay the foundation for future research and practice.

7.2 Future work

The research in this thesis provides approaches in EV integration, weather factor impact assessment and power system fault analysis. The following parts suggest possible directions for future research:

- Extended applications of datasets and simulation modelling: The thesis has analysed EV data, power system loads, weather data, etc. based on existing datasets. However, future research should further extend the application of the dataset to validate the applicability and robustness of the model in a wider range of scenarios. At the same time, the combination of machine learning and big data analytics enables deep mining and analysis of huge datasets [258, 259]. For example, machine learning algorithms can identify the complex relationship between EV charging behaviour and power system loads, and predict future electricity demand and charging patterns [260]. This not only improves the predictive accuracy of the model, but also provides real-time decision support. In addition, future research should focus on exploring how datasets from different parts of the globe can be utilised to suit the climatic, economic and social conditions of each location. This will include comprehensive analyses of factors such as EV penetration, charging infrastructure, and energy policies in different countries and regions. Through these extended studies, a more comprehensive understanding of the relationship between EVs and the power system can be achieved, and more adaptive optimisation strategies can be proposed.

- Coordinated EV charging strategy: This thesis proposes methods to optimise the participation of EVs in ancillary services via V2G, providing strong support for current and future power system management. Future research should explore long-term coordinated EV charging strategies to meet the challenges posed by the continued increase in EV penetration, the expansion of charging infrastructure, and the introduction of new technologies [261, 262]. Developing forward-looking optimisation schemes will be key to ensuring stable network operation and maximising efficiency [263]. This includes: (1) Optimise the location and number of charging stations. This will not only reduce the waiting time for EV users to charge. It will also increase the utilisation of charging stations. (2) Dynamic charging time scheduling strategies are developed through EV users' charging behaviours and preferences, combined with network load characteristics. (3) Assess the impact of new technologies (e.g., ultra-fast charging) on the power system. Explore the feasibility and optimisation options of these technologies under large-scale applications. (4) Analyse the effects of different policies and incentive strategies. Propose optimisation recommendations to promote synergistic development of EVs and power systems.
- Long-term impacts of climate change on the power system: By analysing the impacts of extreme weather on the power system, this thesis provides unique insights into understanding the challenges posed by climate change. Future research should focus on the long-term effects of climate change on power system [264, 265].

This includes the impacts of different weather factors on changes in network loads, the need to adjust generation and transmission capacity, and the potential impacts of climate change on power equipment and infrastructure.

- Synergies between EVs and renewable energy: Involvement of EVs as mobile energy storage units in network scheduling can mitigate the instability of renewable energy generation [5, 88]. In addition, to encourage EV users to participate in renewable energy support programmes. The design of incentives and policy frameworks through an assessment of existing market and policy mechanisms.

Appendix

A.1 Information of Electric Vehicles

The following table summarises the key technical parameters of the electric vehicles covered in this thesis, including battery chemistry, battery system type, battery capacity, number of individual cells and maximum charging power.

Table A.1: Technical parameters of different model of EV.

Model of EV	**Battery chemistry**	**Battery capacity**	**Range of travel**	**Energy consumption during driving**	**Charging power (max)**
Nissan LEAF (2013-2018) [266]	Lithium-ion	24 kWh	95-205 km	107-232 Wh/km	46 kW DC
Nissan LEAF (2018-2022) [267]	Lithium-ion	39 kWh	165-355 km	110-236 Wh/km	46 kW DC
Chevrolet Bolt (2019) [182]	Lithium-ion	60 kWh	257-483 km	150-250 Wh/km	46 kW DC
Tesla Model 3 [268]	Lithium-ion	57.5 kWh	300-610 km	94-192 Wh/km	170 kW DC
Tesla Model Y [269]	Lithium-ion	75 kWh	315-635 km	118-238 Wh/km	250 kW DC

A.2 Low- voltage Distribution Network

The test network used in this thesis was adapted from 'Network 2 - Feeder_2' [221]. This network is part of the Low Voltage Network Solutions (LVNS) published by Electricity North West. The LV Network Models folder includes two types of files: text files and MS Excel files. Below is a visual representation of the original "Network 2".

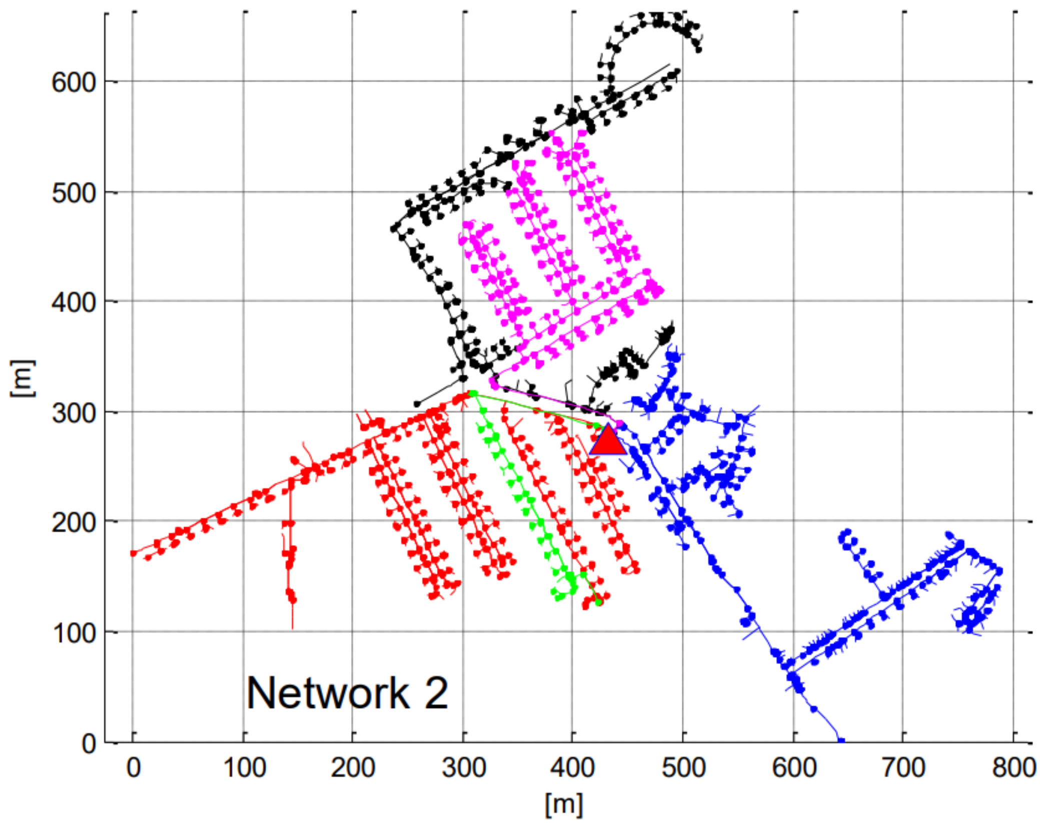


Figure A.1: Visualization of Network 2 [221].

The txt file includes:

1. Master.txt: This txt file reads the data through OpenDSS and gives instructions for execution.

2. Lines.txt: Contains information about all the lines, such as length, units, cable type and the node to which it is connected.
3. Loads.txt: Identifies the bus, load type, load power factor, and load voltage to which each load is connected.
4. Loadshapes.txt: The path where the shape containing the load's power production or consumption is located. Each curve is located in an excel file.
5. Loadcode.txt: Contains network parameters. The names of these conductors are the same as those used in the ‘Lines’ file.
6. Transformers.txt: Includes transformer parameters.
7. Monitors.txt: The location of the monitor. The monitor is used to obtain the voltage, current, active power at its location.

MS Excel files are included:

1. Feeder_Data.xls： Contains information about each line of the network, e.g. source node for each line, end node for each line, distance (in metres) of each line, the phase of each line connection, and whether or not there is a load connected to the end of the line (0 means that no load is connected to the end node, 1 means that a load is connected to the end node). The cable type for each Line.
2. XY_Position.xls： Coordinates of each Node. Each Node has a corresponding ID in this file, which is associated with the “Feeder_Data.xls” file. X represents the X coordinate of the Node. y represents the Y coordinate of the Node.

3. Connectivity_matrix.xls： This file provides information about the connections for each load. “Bus” indicates the bus to which the corresponding load is connected. “Phase” indicates the phase to which the corresponding load is connected.

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