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University
of Glasgow

**Exploring the Use of Agent-based Models for Electric Vehicle Driver
Behaviour Simulation**

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**A thesis submitted as fulfilment of the requirements for the degree of Doctor of
Philosophy**

School of Social and Political Sciences

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Abstract

With the rapid expansion of public electric vehicle (EV) charging infrastructure, the network has progressed beyond its early deployment stage, but remains far from achieving the maturity of conventional refuelling systems. Despite the increasing number of public chargers, many drivers still have difficulties finding available chargers at convenient locations or facing long waiting time before charging. It is important to better understand the charging demand of EV drivers for the sustainable placement of future public chargers.

The aim of this research is to explore the driving and charging behaviours of EV drivers, estimate the spatial distribution of their charging demand, and identify optimal locations for future public chargers in Great Britain (GB). The research first explores the usage patterns of existing public charger network and quantifies their relationships with various contextual factors using spatial regression models. To move beyond these observed charger usage patterns and explore the individual-level behaviours that generate the charging demand, an Agent-Based Model (ABM) is then developed to simulate the driving and charging behaviours of EV drivers across GB. Building on the rule-based ABM, the research further improves the predictive accuracy of the agents by introducing an agent-based reinforcement learning model. The model can capture how EV drivers adaptively learn and adjust their behaviours through repeated exposure to the changing environment, and more closely reflect human decision-making processes. Finally, the research developed a simulation-optimisation framework to integrate complex individual-level driver behaviours with system-level spatial location optimisation. Based on the charging demand generated by the simulation models, a spatial optimisation model is developed to find the optimal locations of future public chargers. The agent-based RL model is then re-implemented to explore how EV drivers respond to the expanded infrastructure network and adjust their charging behaviours accordingly.

The results provide granular estimates of the spatial distribution of charging demand across GB, and the proposed framework offers a new perspective for behaviour-aware planning of public EV charging infrastructure. The simulation-optimisation framework can also be applied to other case study areas and contribute to more sustainable charging network planning.

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List of Publications

Journal Articles

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Author Declaration

I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

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Chapter 1

Introduction

1.1 Introduction to the Research

The transition from conventional vehicles to electric vehicles (EVs) can significantly reduce global greenhouse gas emissions and air pollution (Métais et al., 2022; Unterluggauer et al., 2022). Large-scale rollout of EVs has become an important strategy for many countries to mitigate carbon emissions in the transport sector (Calvillo and Turner, 2020). In the UK, over 86,000 public chargers were installed as of October 2025 (Department for Transport, 2025b). However, despite this expansion, many EV drivers still have difficulty finding available public chargers at convenient locations and times. Insufficient and unevenly distributed public charger provision remains a major constraint on further EV adoption (Prakhar, Gupta and Jaiswal, 2025). To develop a more sustainable charging network and encourage greater EV uptake in the long term, it is important to gain deeper insights into the charging and driving behaviours of EV drivers, as well as the spatial and temporal distribution of charging demand.

One of the key challenges of modelling EV driver behaviour lies in adequately representing the heterogeneity and autonomy of drivers when exploring their decision-making processes and estimating their charging demand. Among the different categories of EV users, private EV drivers pose the greatest modelling challenge. The availability of high-resolution trajectory data for these drivers in the UK remains limited due to the relatively early stage of EV adoption and data privacy concerns. As a result, it is difficult to investigate their charging behaviours empirically in most case study areas. Meanwhile, unlike commercial fleets, which typically operate under predetermined schedules and fixed routes, private EV drivers show greater behavioural complexity. Their charging and driving decisions are shaped by interactions with the built environment and other EV drivers, as well as their psychological features, such as range anxiety, bounded rationality, and learning ability. An effective methodological framework must be developed to capture these behavioural complexities to enable more accurate estimation of the charging demand distribution.

Agent-based modelling (ABM) shows considerable promise in addressing this challenge. ABMs are composed of autonomous agents that interact with one another and their environment. In ABM, the global behaviour of the system is not explicitly defined but emerges from the self-organised local interactions between agents (An, 2012; An et al., 2021; Bonabeau, 2002a; Railsback & Grimm, 2019). ABM can thus capture the heterogeneous charging and driving decisions of EV drivers and enable a more accurate estimation of charging demand.

Despite these advantages, rule-based ABMs are often criticised for their limited capacity to capture the adaptability and bounded rationality of private EV drivers. This limitation constrains the accuracy of charging demand predictions. RL-trained agents offer a promising pathway to address this behavioural modelling challenge (Brearcliffe and Crooks, 2021). Unlike rule-based agents, RL-trained agents can provide a more realistic representation of adaptive behaviour by learning decision strategies through repeated interactions with their environment (Sutton and Barto, 1998; Malleson et al., 2022). However, the application of agent-based RL to simulate private EV charging and driving decisions remains underexplored. There is a need for an agent-based RL model that effectively simulates the charging and driving behaviours of private EV drivers.

Additionally, a further research gap lies in the location optimisation of future public chargers. Existing studies on public charger optimisation typically end at the optimisation stage. There has been limited evaluation of the effectiveness of optimised charger placements, particularly in terms of how drivers adapt their behaviours in response to the newly proposed chargers. Given the rigid nature of charging infrastructure, inappropriate placement decisions are too costly to correct once implemented. This makes it challenging to conduct realistic real-world experiments to evaluate optimisation outcomes. As a result, validating the effectiveness of optimised charger locations within the modelling process is crucial for assessing their practical value. There is a need to develop an integrated simulation-optimisation framework that optimises future public charger locations while explicitly evaluating the subsequent adaptive responses of EV drivers.

This thesis addresses these gaps by progressively moving from rule-based ABM to RL-trained ABM to simulate the charging behaviours of private EV drivers and estimate the spatial distribution of charging demand. Building on this foundation, this thesis proposes an integrated simulation-optimisation framework that identifies optimal locations for future

public chargers while explicitly accounting for drivers' adaptive behavioural responses to infrastructure expansion. The model is applied to Great Britain (GB), where the national-scale road and charging network allows both intra- and inter-city travel to be explicitly modelled.

1.2 Aims and Objectives

The overall aim of this research is to explore the driving and charging behaviours of EV drivers, estimate the spatial distribution of charging demand, identify optimal locations for future charging infrastructure, and evaluate how drivers respond to the newly proposed chargers. To achieve this, the following objectives are defined:

1. Review and discuss the literature on EV driver behaviour and existing modelling techniques to identify the key factors shaping the driving and charging behaviours of private EV drivers, evaluate how these behaviours have been represented in existing models, and identify methodological research gaps.
2. Analyse the usage patterns of the existing public charger network and quantify their relationships with contextual factors using spatial regression models.
3. Design and implement a rule-based ABM and an RL-trained ABM to simulate the charging and driving behaviours of EV drivers and estimate the spatial distribution of charging demand.
4. Develop an integrated simulation-optimisation framework that identifies optimal locations for future public chargers and evaluates how EV drivers adapt their charging behaviours in response to infrastructure expansion.
5. Critically reflect on the research findings and assess the effectiveness and limitations of the proposed models in capturing EV driver behaviours and informing public charger placement decisions.

This thesis makes both methodological and empirical contributions. The methodological contribution lies in the modelling pipeline that progresses from a national-scale rule-based ABM to an RL-trained ABM to simulate the charging behaviours of private EV drivers, and its integration into a bidirectional simulation-optimisation framework for public charger placement. This modelling framework is transferable and can be applied to other geographical areas or infrastructure scenarios subject to data availability. The empirical contributions of this thesis include the observed public charger usage patterns and their

associations with contextual factors, the simulated charging demand distributions across GB, and quantitative findings on drivers' adaptive behavioural responses to infrastructure expansion.

1.3 Organisation of the thesis

Chapter 2 reviews the literature on EV driver behaviour, exploring how driving and charging decisions are shaped by a complex interplay of built environment, social interactions, and cognitive factors. The chapter begins with an overview of the evolution of transport electrification and the growth of EV markets. It then reviews empirical studies on how EV driver behaviour is shaped by the built environment and interactions with other drivers. Following this, it reviews the intrinsic behavioural characteristics of EV drivers, such as range anxiety, learning ability, and bounded rationality. These factors establish the foundations for the EV driver simulation models.

Table 1.1 The organisation of the thesis with respect to the research objectives.

Objectives	Chapters
Review and discuss the literature on EV driver behaviour and existing modelling techniques in order to identify the key factors shaping the driving and charging behaviours of private EV drivers, evaluate how these behaviours have been represented in existing models, and identify methodological research gaps.	2: Understanding Electric Vehicle Drivers 3: Modelling Electric Vehicle Drivers
Analyse the usage patterns of the existing public charger network and quantify their relationships with contextual factors using spatial regression models.	4: Exploring the Factors Associated with Public Charger Usage in Great Britain

Design and implement a rule-based ABM and an RL-trained ABM to simulate the charging and driving behaviours of EV drivers and estimate the spatial distribution of charging demand.	5: Using Agent-based Models to Simulate the Electric Vehicle Driver Behaviours in Great Britain 6: Replicating the Behaviour of Electric Vehicle Drivers Using an Agent-based Reinforcement Learning Model
Develop an integrated simulation-optimisation framework that identifies optimal locations for future public chargers and evaluates how EV drivers adapt their charging behaviours in response to infrastructure expansion.	7: An Integrated Simulation-Optimisation Framework for Future Public Electric Vehicle Charger Deployment
Critically reflect on the research findings and assess the effectiveness and limitations of the proposed models in capturing EV driver behaviours and informing public charger placement decisions.	8: Conclusion

Chapter 3 reviews existing methods for modelling EV driver behaviour and identifies their limitations. It first reviews statistical and analytical approaches and highlights their limited ability to represent individual decision-making processes and interactions. The chapter then reviews computational modelling approaches that address these limitations. Rule-based ABMs are identified as a suitable framework for representing private EV drivers as autonomous decision-makers, but they are limited in capturing the adaptive and cognitive complexity of human behaviour. The agent-based RL model is presented as an improvement over these methods, though its application to private EV driver simulation is limited.

Chapter 4 develops spatial regression models to explore the relationships between public charger usage rates and contextual factors in three case study regions: Greater London, Greater Manchester, and the Central Belt of Scotland. The results show substantial regional variation in public charger usage patterns and underline the importance of region-specific strategies for public charger deployment.

Chapter 5 develops a rule-based ABM to simulate the driving and charging behaviours of EV drivers and their demand for public chargers. The model is validated against real-world

charging session data and provides insights into heterogeneous charging decisions of drivers with different trip characteristics.

Chapter 6 proposes a multi-stage agent-based RL model that accounts for the adaptability and bounded rationality of private EV drivers when making driving and charging decisions. The model is validated against real-world charging session data. The simulated charging demand is spatially analysed to identify critical areas where EV drivers consistently experience low SOC levels and have limited access to public chargers.

Based on the RL-based ABM developed in Chapter 6, Chapter 7 introduces an integrated, bidirectional simulation–optimisation framework to identify optimal locations for future public chargers and evaluate drivers’ behavioural responses to infrastructure provision changes. The results show how private EV drivers adapt their charging behaviours in response to the charging network expansion.

Finally, Chapter 8 concludes the thesis. It discusses the contributions and limitations of the research and identifies directions for future research.

Chapter 2

Understanding Electric Vehicle Drivers

2.1 Introduction

One of the main objectives of this research is to develop an ABM to simulate the charging and driving behaviours of private EV drivers. To accurately represent these behaviours, it is important to develop a thorough understanding of the complex behaviours of EV drivers. This chapter will review the contextual factors and cognitive characteristics that shape EV driver behaviour and that should be considered in behavioural modelling. Section 2.1.1 will introduce the historical evolution of electrified transport systems. Section 2.1.2 will then introduce the evolution of research on EV driver behaviour in the context of changing EV adoption rates. Section 2.2 will discuss the contextual factors that influence EV driver behaviour, while Section 2.3 will focus on the cognitive characteristics of EV drivers when making driving and charging decisions. Section 2.4 will summarise this chapter.

2.1.1 Transport Electrification

EVs are not a new invention and the first EV was invented in the 19th century. EVs held a substantial share of the automobile market in the early 1900s, particularly in the U.S. In 1900, among 2,370 automobiles in the major metropolitan areas in the U.S., 1,170 were steam-powered, 800 were electric, and only 400 were gasoline-powered vehicles (Sulzberger, 2004). At that time, EVs were generally slower and constrained by unreliable batteries that offered limited energy storage, required frequent maintenance, and added considerable weight to vehicles. Nevertheless, much as today, EVs were quieter, cleaner, and easier to operate than steam- and gasoline-powered vehicles. As a result, despite their limitations, EVs gained some popularity in the early 1900s, with around 20,000 electric passenger cars operating in the U.S. and around 1,600 in Europe (Santini, 2011).

The early prominence of EVs was, however, short-lived. From around the 1910s to the 1920s, EVs were gradually phased out from the commercial market as a result of several transformative developments favouring gasoline-powered vehicles. These included Henry Ford's introduction of the assembly line for the affordable Model T, declining gasoline

prices following crude oil discoveries in Texas, and the rapid expansion of the intercity road network, which increased demand for vehicles with longer driving ranges (US Department of Energy, 2014). Consequently, many manufacturers discontinued EV production, and the automobile industry entered an era of gasoline dominance that persisted for nearly a century. A comprehensive review of the historical dynamics of the EV technology and markets can be found in Mom (2013).

The modern resurgence of EVs can be traced to the energy crisis of the 1970s, particularly the OPEC oil embargo, alongside growing environmental awareness in subsequent decades. From the late twentieth century onwards, alternative fuel vehicles, such as hydrogen fuel cell vehicles, natural gas vehicles, and EVs, began to be considered as a promising technology for low-carbon transport. Early policy interventions played a critical role in the shift to EVs, including California's Zero Emission Vehicle mandate (Collantes and Sperling, 2008) and Norway's EV incentive programme introduced in the 1990s (Mersky et al., 2016). In the UK, the government-sponsored PowerShift programme was established in 1996 and provided grants to support the conversion of new and nearly new vehicles to cleaner fuels (Brevitt, 2025). During this period, research on EVs primarily focused on technological and engineering aspects, such as battery capacity and vehicle design. Key technological milestones included the commercialisation of lithium-ion batteries by Sony and Asahi Kasei in 1991, the launch of the first mass-produced hybrid vehicle, Toyota Prius, in 1997, and the introduction of the Tesla Roadster in 2008, which became the first production EV to exceed a driving range of 200 miles per charge (Collantes and Sperling, 2008).

As EV technology matured and market penetration increased, research attention expanded beyond engineering challenges to encompass EV market diffusion and consumer adoption. Studies began to explore EV consumer behaviours to identify the conditions under which individuals choose EVs over conventional vehicles (Li et al., 2017). Much empirical research has highlighted the role of socio-demographic factors such as age, gender, educational level, and income in shaping adoption decisions (He, Sun and Luo, 2022). Early adopters have often been characterised as middle-aged, well-educated, higher-income individuals, particularly those working in technical professions (Plötz et al., 2014; Hardman, Shiu and Steinberger-Wilckens, 2016). Adoption has also been associated with higher levels of environmental concern (Dong et al., 2020), anticipated financial benefits from lower electricity prices (Dumortier et al., 2015), and normative motivations (e.g.

perceiving EV adoption as the right thing to do) (Noppers et al., 2014; van der Kam et al., 2019). Beyond individual characteristics, infrastructure availability has also been identified as a critical determinant of EV adoption (He, Sun and Luo, 2022). This is closely related to the widely discussed ‘Catch-22’ problem in EV diffusion (Shi et al., 2021): consumers are reluctant to purchase EVs if there is insufficient provision of public chargers, while operators are reluctant to invest in new chargers without sufficient demand to make it profitable. Within this context, many studies on public charger location optimisation have emerged to support efficient and equitable charger deployment, thereby facilitating EV adoption (Kchaou-Boujelben, 2021). These optimisation studies will be discussed in more detail in Chapter 7.

As EV adoption becomes more widespread, the population of EV drivers continues to grow, and research focus has increasingly shifted from adoption decisions to the everyday driving and charging behaviours of EV users. These works seek to understand how EV owners actually use their vehicles and interact with charging infrastructure. Meanwhile, the characterisation of EV users during this stage has evolved from a relatively homogeneous group of early adopters to a more heterogeneous population, differentiated not only by socio-demographic attributes but also by diverse preferences, habits, and behavioural patterns. These features will be discussed further in Section 2.1.2.

It should be noted that the remainder of this literature review will focus specifically on private EV drivers. The behavioural patterns of private EV drivers differ from those of EV fleets such as taxis or freight vehicles, and behavioural insights from one group may not be directly transferable to another (Zhan et al., 2025). Private EV drivers travel to complete daily activities related to work, home, and leisure. In contrast, freight EVs operate under fixed operational schedules and routes and often use predetermined charging locations, while ride-hailing EVs are heavily influenced by stochastic passenger requests (Yang et al., 2025). This research will focus on the behavioural modelling and charging demand estimation of the private EV drivers, whose driving and charging decisions are jointly shaped by the built environment, social interactions with other drivers, and individual travel plans and preferences.

2.1.2 Heterogeneous EV Drivers

Besides research on EV technology and consumer adoption, a substantial body of literature has explored EV drivers' driving and charging behaviours after adoption. Early studies primarily used vehicle trials and stated-preference surveys to understand EV driver decision-making, while initial charging demand mapping often relied on aggregated statistics. More recent empirical research has increasingly used GPS trajectory data and charging session records to analyse driving and charging patterns at finer spatio-temporal resolutions. Across different data sources, studies have consistently found that EV driver behaviours differ substantially from those of conventional vehicles, due to factors such as limited vehicle range, longer refuelling times, and the availability of home, workplace, and public chargers (Franke and Krems, 2013; Bunce, Harris and Burgess, 2014).

Important early insights into EV driving and charging behaviour were generated through vehicle trial programmes conducted in the late 2000s and early 2010s. Featured trials include the UK's Ultra Low Carbon Vehicle Demonstrator Trial (Burgess et al., 2013), the MINI E Trial conducted in Berlin (Cocron et al., 2011), and the EV Project in the US (Smart and Schey, 2012). These trials provided some of the earliest real-world evidence on EV usage during the early adoption phase, particularly in terms of how drivers adapt daily travel schedules to vehicle range constraints, experience range anxiety, and make trade-offs between home and public charging options.

As EV adoption expanded, the profile of EV adopters has diversified beyond the early adopter groups to include a wider range of users with varied socio-demographic characteristics and behavioural features. As mentioned in Section 2.1.1, empirical studies have often characterised early EV adopters as middle-aged, well-educated, higher-income individuals, particularly those employed in technical professions (Plötz et al., 2014; Hardman, Shiu and Steinberger-Wilckens, 2016). However, as EV markets mature and adoption spreads beyond these initial groups, the EV driver population has become increasingly heterogeneous. This growing diversity challenges the generalisability of behavioural insights derived from early EV trials that focused on early adopters. For example, early research found that EVs were predominantly used for everyday short-distance trips (Burgess et al., 2013). This finding may reflect the tendency of early adopters to own multiple vehicles, using EVs as secondary cars while retaining conventional vehicles for longer-distance journeys (Hardman, Shiu and Steinberger-

Wilckens, 2016). In contrast, more recent EV users are increasingly likely to rely on EVs as their sole household vehicle, including for long-distance travel that approaches or exceeds the vehicle range, thereby leading to different driving and charging behaviours (Hu, Dong and Lin, 2019). Additionally, heterogeneity in EV driver behaviour is also evident in drivers' perceptions of range anxiety. Franke and Krems (2013) introduced the concept of 'comfortable range', referring to the psychological safety buffer that drivers maintain to avoid stress. They found that users typically use only 75-80% of available battery range. Rauh et al. (2015) subsequently demonstrated that this safety buffer decreases as drivers accumulate experience and become more comfortable operating at lower SOC levels. However, as the EV driver population has diversified and EV technologies have advanced to offer a broader range of vehicle models, range anxiety alone is no longer sufficient to explain observed charging behaviours. More recent studies have identified patterns such as 'procrastinated charging', whereby some EV users consistently delay charging until battery levels become critically low (Khaleghikarahrodi and Macht, 2024).

Taken together, these findings indicate a clear evolution in EV driver behaviour, from relatively homogeneous patterns observed among early adopters to increasingly diverse behaviours as EV adoption has broadened. Large-scale empirical studies have further confirmed that EV driver behaviours are far more varied and nuanced than early research suggested. Helmus et al. (2020) analysed 4.9 million charging transactions and showed that observed charging patterns deviate substantially from expected behaviours, revealing subtle but important distinctions across individual drivers that need to be captured. Similarly, Hajhashemi et al. (2024) identified distinct charging style classes, each associated with different socio-demographic profiles, charging needs, and behavioural preferences. These studies further highlight the importance of explicitly accounting for user heterogeneity in both computational modelling of EV drivers and charging infrastructure planning, a challenge that directly motivates the model design of this research.

2.2 EV Drivers and the Environment

To accurately model EV driver behaviour, it is important to explore how driving and charging decisions are shaped by a complex interplay between contextual factors and

individual behavioural characteristics. Existing reviews suggested that EV driver behaviour is influenced by multiple interacting factors (Perlaviciute and Steg, 2014; Shariatzadeh, Lopes and Henggeler Antunes, 2025). Some factors arise from drivers' own attributes and others from the physical and social environments where EV drivers drive and charge. This section will explore how contextual factors, particularly the built environment and social interactions, influence EV drivers' driving and charging decisions. This can inform the variable selection and simulation model design in Chapter 4, 5, and 6. The behavioural characteristics intrinsic to EV drivers themselves will be reviewed separately in Section 2.3.

2.2.1 Built Environment

The built environment is important in shaping travel behaviours (Ewing and Cervero, 2010). Compared to conventional vehicles, in the context of EVs, these influences take on additional complexity, yet remain a critical determinant of EV drivers' driving and charging behaviour (Liu and He, 2025). In this section, two factors that have been most widely discussed in previous research as shaping EV drivers' charging and driving behaviours are examined: the home and workplace chargers and the public charging network.

Home and Workplace Chargers

Charging activities can occur at home, at workplace, or at public locations. Most studies on EV charging behaviour assume that drivers either have access to charging at their primary destinations such as home or work, or rely on public charging stations during travel (Guo et al., 2022). Although this research focuses on modelling demand for public chargers, it is still important to acknowledge the role of home and workplace charging, as both remain dominant sources of charging provision for private EV drivers (Hardman et al., 2018).

Access to home charging has consistently been identified as one of the most influential factors in EV adoption. Early surveys indicate that access to home charging strongly shapes EV adoption decisions (Bailey et al., 2015). A recent survey by Hardman et al. (2024) found that drivers value home charging due to its convenience and lower cost compared to public charging. Around 35% of EV buyers would even consider switching to a conventional, hybrid vehicle if home charging were unavailable (LaMonaca and Ryan,

2022). Home charging is also favoured because of its flexibility and ease of scheduling (Chakraborty et al., 2019). However, access to home charging is unevenly distributed across the population. Home chargers can typically only be installed by households living in detached or semi-detached houses with off-street parking spaces (LaMonaca and Ryan, 2022). In the UK, around 70% of households have access to off-street parking, suggesting substantial potential for home charging, but this proportion drops to approximately 30% in dense urban centres, largely due to the prevalence of flats and apartments without private parking (LaMonaca and Ryan, 2022; Lusk, Li and Liu, 2023).

Workplace charging therefore plays a critical complementary role (Wu, 2018), particularly for apartment residents (Chakraborty et al., 2019). This thesis defines workplace charger as those restricted to employees and not open to the general public. It is a well-suited charging option due to the long parking durations during the daytime (Liu et al., 2023). Research also suggested that some charging demand may shift from home to workplace locations as workplace charging networks expand, particularly when workplace charging is free of charge (Wu, 2018). Despite its appeal, zero-cost workplace charging has been criticised for being financially unsustainable in the long term and for contributing to congestion at charging points. Evidence indicates that perceived congestion at workplace chargers may even discourage some drivers from using EVs for commuting purposes (Nicholas and Tal, 2015).

Public Charging Infrastructure

Despite the importance of home and workplace charging, literature consistently highlights the critical role of public charging infrastructure. In this thesis, the term public charger refers to any charging point located in a publicly accessible location and available for use by all EV drivers. Studies have argued that the density and distribution of public chargers significantly affects both EV adoption rates and charging patterns (Hardaway et al., 2025). Although empirical surveys suggest that public chargers only represent approximately 5–10% of total charging events for most EV owners, LaMonaca and Ryan (2022) argue that such evaluation based on charging frequency may underestimate their importance. Even when most charging needs can be met at home, drivers still take public chargers as a safety net to provide reassurance that charging is available when needed and can help to overcome range anxiety (Kley, Lerch and Dallinger, 2011). EV trials have shown that many drivers consider public charging as essential, even though most of them can

complete their trips without a public charger (Azadfar, Sreeram and Harries, 2015). Particularly, public charging infrastructure is important for EV drivers living in dense urban areas where private charging is limited (Guo et al., 2022), and for supporting those with long-distance travel demand (Hu, Zhou and Lu, 2025). Given their importance, public charging networks affect EV drivers in various ways. This section focuses on four widely discussed features: charging speed, charging price, parking fees, and charger accessibility.

Public chargers differ substantially in charging speed and price. The classification of charger types differs across academic, geographical, and policy contexts (LaMonaca and Ryan, 2022; Zhang et al., 2025). In this section, we summarise the commonly used UK power-based classification. Traditionally, chargers have been categorised as slow (2–6 kW), fast (7–22 kW), rapid (25–100 kW), and ultra-rapid (>100 kW). A recent update by the Department for Transport (2024) proposes revised categories: 2–8 kW and 8–49 kW (both considered slow), 50–149 kW (fast), and ≥ 150 kW (ultra-fast). Compared to home and workplace charging, one of the primary advantages of public chargers is their higher charging speed. Survey-based studies indicate that while EV drivers generally show limited willingness to pay for public charging, they are highly sensitive to charging duration, and are willing to pay a premium for fast public charging options (Wen, MacKenzie and Keith, 2016; Globisch et al., 2019). Fast chargers are particularly preferred by EV drivers undertaking long-distance travel (Andrenacci and Valentini, 2023). Nevertheless, slow chargers remain an important component of the public charging network and are often preferred when vehicles are parked for extended periods (LaMonaca and Ryan, 2022).

Public charging typically combines parking and charging services, and the cost of a charging session typically includes both energy fees and parking charges (Latinopoulos, Sivakumar and Polak, 2017). Compared to refuelling conventional vehicles, EV charging prices are more complex and vary widely across locations, charger speed, and pricing schemes adopted by operators (Limmer, 2019; Visaria et al., 2022). While studies generally find that EV drivers prefer to minimise charging costs, price sensitivity varies considerably across user groups (Ge, MacKenzie and Keith, 2018; Wang, Yao and Pan, 2021). Additionally, EV drivers' willingness to pay may increase under conditions of high planning burden, uncertainties of dynamic pricing, or urgent charging needs when SOC levels are low or range constraints are binding (Latinopoulos, Sivakumar and Polak, 2017; Dorcec et al., 2019).

Parking fees associated with charging are also important in shaping charger usage. Higher parking fees have been found to have a negative effect on public charger usage (Luo and Wang, 2025). Consistent with general parking behaviours, parking durations tend to be shorter in paid parking areas than in free ones (Langbroek, Franklin and Susilo, 2016; Wolbertus, Kroesen, van den Hoed and C. G. Chorus, 2018). However, Zhang et al. (2025) found that in some contexts, plug-in durations far exceed the time needed to deliver the consumed energy. This suggests that EV users may treat charging points primarily as parking spaces rather than charging facilities. This behaviour is particularly evident at locations where parking at charging stations is free (Wolbertus and van den Hoed 2018).

Another key factor influencing public charger behaviour is charger accessibility and availability. Accessibility is a well-established concept in transport research, used to assess the relationship between travel demand and the spatial distribution of infrastructure supply (Tahmasbi et al., 2019). Many studies have evaluated EV charging accessibility in terms of physical reachability and equity (Falchetta and Noussan, 2021; Esmaili et al., 2024; Peng et al., 2024; Mehdiabrizi et al., 2025). While equity-related discussions are deferred to Chapter 8 as prospective future work, this chapter focuses on physical accessibility, which is defined as drivers' opportunity to reach charging stations within reasonable travel distances or times (Falchetta and Noussan, 2021; Li, Luo and Song, 2022). Recent advances have moved beyond fixed buffers around origins and destinations to route-based accessibility metrics that account for chargers reachable along the actual travel path (Mehdiabrizi et al., 2025). Studies have shown that drivers' charging decisions are strongly influenced by convenience (Azadfar, Sreeram and Harries, 2015). When selecting chargers, they place high value on minimising detour time and tend to avoid substantial deviations from planned routes (Visaria et al., 2022), particularly during long-distance travel (Ge and MacKenzie, 2022). Wang et al. (2024) further show that EV drivers value the density of chargers along routes. When charger density is low, drivers may act in a 'survival mode' and attempt to reach the destination without charging enroute and only stopping when sufficient or redundant charging opportunities are available (Ge and MacKenzie, 2022). Additionally, accessibility measured in travel time and distance should be considered together with charger availability, which depends on real-time occupancy created by other EV drivers and is observable through information systems. This aspect will be discussed in more detail in Section 2.2.2.

2.2.2 Social Interaction

As EV adoption increases, competition for public charging resources has become an important factor influencing driver behaviour. Unlike the refuelling of ICE (Internal Combustion Engine) vehicles, which typically takes a few minutes and rarely results in significant queueing, EV charging requires vehicles to occupy charging points for extended periods. This extended dwell time changes the way of refuelling and creates potential congestion and long queues at charging stations. Helmus and Wolbertus (2023) summarise public charging stations as non-excludable and subtractable: they are open to everyone, but their use reduces availability for others. Unlike fleet drivers who follow controlled work schedules (Hu et al., 2016), private EV drivers operate in a highly uncertain and decentralised environment. They are individuals who make independent decisions. They also have limited communication with and information on other drivers' decision-making processes. As a result, a social dilemma is created: drivers acting rationally to secure charging opportunities for themselves may collectively produce inefficient outcomes, such as excessive queueing and congestion. EV driver decisions are therefore directly influenced by the behaviour of other drivers. Such interactions occur both before arrival at charging stations, through shared information accessed via digital platforms, and upon arrival, when drivers compete for access to limited charging infrastructure.

Interaction through Digital Platforms

Digital platforms play a central role in mediating indirect social interaction among EV drivers. As mobile applications provided by charger operators and aggregators have become increasingly widespread (Ha et al., 2021), drivers interact through a shared information environment that they collectively create and consume. Such an environment is not static: when drivers arrive at, occupy, or depart from charging stations, their actions update the availability status that becomes visible to other users. Drivers routinely access these platforms to search real-time availability status (e.g. in use, available, or out of service) and adjust their charging choices accordingly. Charger availability can also change when a driver is driving to it, and a driver can reassess whether to continue to that station or divert to another one. Tian et al. (2018) also show that drivers tend to prefer selecting stations with shorter expected waiting times rather than simply choosing the nearest charger. Additionally, drivers also interact through shared information on charging experiences. Studies analysing user reviews of public chargers indicate that the online

reviews on reliability and user satisfaction can influence drivers' charging station choice (Asensio et al., 2020; Wang et al., 2025).

Competition at charging stations

Direct interaction among EV drivers occurs through competition for chargers at stations. This competition often manifests as queueing, where drivers wait for chargers to become available and incur waiting delays (Jung et al., 2014). As EV usage increases, mismatches between charging demand and infrastructure supply can result in substantial queues and prolonged waiting times (Huang and Kockelman, 2020). Recent studies suggest that 'charging anxiety', which refers to concerns about whether a charger will have queues or be reliable upon arrival, may increasingly replace range anxiety as a primary concern among EV drivers (Hanig et al., 2025).

Beyond queueing, drivers show other kinds of impatience-driven behaviours at charging stations. Tian et al. (2018) found that EV drivers are less tolerant of waiting time than of charging time itself. Consequently, drivers may 'balk', choosing not to join the queue and instead rerouting to another station, or 'renege', leaving the queue after waiting for some time due to impatience (Ha et al., 2021; Lai et al., 2023; Varshney et al., 2025).

Chattopadhyay and Kar (2024) further found that providing drivers with real-time information on expected waiting times can substantially reduce such impatience-related behaviours. However, while this information is frequently incorporated into research models, it remains largely unavailable on most real-world charging platforms.

Finally, competition at public charging stations is further complicated by the dual function of many charging locations as both parking and refuelling spaces (Wolbertus et al. 2018). Consequently, an overstaying problem emerges, whereby an EV continues to occupy a park-and-charge spot even after the vehicle is fully charged (Biswas, Gopalakrishnan and Dutta, 2016). Wolbertus and van den Hoed (2018) describe this behaviour as 'charging station hogging', while Caperello et al. (2013) define it as a 'charging etiquette' issue. Empirical analyses show that plug-in durations frequently exceed the time needed to deliver the required energy, indicating that chargers are often used primarily as parking spaces rather than for charging (Zhang et al., 2025). This behaviour exacerbates availability problems, particularly in dense urban areas with limited parking and high reliance on kerbside charging by households without private parking (Wolbertus et al.

2018). Additionally, local policies that offer free parking at charging locations, while potentially accelerating EV adoption, may unintentionally intensify overstaying and congestion and reduce charger availability (Wolbertus, 2020).

2.2.3 Summary of the Contextual Factors

Table 2.1 Contextual factors influencing EV driver behaviours

Category	Factors	References
Home and workplace charger	Home charger availability	(Hardman et al., 2018)
	Workplace charger availability	Wu (2018) ; Nicholas and Tal (2015)
Public charging infrastructure	Charging speed	Globisch et al.(2019); Wen et al., (2016); Andrenacci and Valentini (2023); LaMonaca and Ryan (2022)
	Charging price	Visaria et al. (2022); Ge et al. (2018); Y. Wang et al. (2021a)
	Parking fee	Pan et al.(2019); Langbroek et al. (2016); Wolbertus et al. (2018b); Zhang et al. (2025)
	Charger accessibility	Ge and MacKenzie (2022); X.-H. Sun et al. (2016); Visaria et al. (2022); Ge and MacKenzie (2022)
Social Interaction	Interaction through Digital Platforms	Ha et al. (2021); Asensio et al.(2020); Wang et al. (2025)
	Competition at charging stations	14/09/2026 09:33:00Wolbertus and van den Hoed (2018)

To summarise, Section 2.1 introduced the broader process of transport electrification and the evolution of EV drivers from early adopters to an increasingly heterogeneous user population. Section 2.2 then reviewed how EV driver behaviours are shaped by the built environment and social interactions among drivers. These factors will be considered in the

models in Chapter 4 – 7. Table 2.1 summarises the factors discussed in Section 2.2 and the associated literature.

2.3 Complex Behaviours of Electric Vehicle Drivers

The previous section explored how the built environment and social interactions with other drivers shape EV drivers' charging and driving behaviours. These contextual factors primarily inform the formulation of the simulation environment in Chapters 5 to 7. This section shifts the focus from external context to the intrinsic behavioural characteristics of EV drivers themselves. The behavioural features reviewed will provide the conceptual basis for agent design in the simulation models. Three key behavioural characteristics of EV drivers will be discussed in Sections 2.3.1 to 2.3.3: bounded rationality, learning ability and adaptability, and range anxiety.

2.3.1 Bounded Rationality

Neoclassical economics typically assumes perfect rationality of homo economicus (Mill, 1844). Under this assumption, a self-interested individual has complete information about the options, perfect foresight of the consequences and future states, and is capable of solving complex optimisation problems to maximise expected utility (Savage, 2012; Gigerenzer, 2020). Herbert Simon challenged this assumption by arguing that neoclassical economics paid insufficient attention to how people actually make decisions, and introduced the concept of 'bounded rationality' (Simon, 1955, 1956). Rather than assuming perfect optimisation, bounded rationality recognises that human decision-making is constrained by limited cognitive capacity, incomplete information, and time pressures (Simon, 1955):

‘Broadly stated, the task is to replace the global rationality of economic man with the kind of rational behaviour that is compatible with the access to information and the computational capacities that are actually possessed by organisms, including man, in the kinds of environments in which such organisms exist’ (Simon, 1955)

A key implication of Simon's bounded rationality is to study how individuals make decisions under uncertainty, rather than assuming behaviour can be explained by as-if expected utility maximisation (Gigerenzer, 2020). The concept has been widely applied in

transportation research to explain observed driver behaviours that deviate from predictions of classical utility theory (Schwanen and Ettema, 2009; Zhou et al., 2014; Tang, Huang and Shang, 2015; Hu, Dong and Lin, 2019).

EV drivers operate within a distinct decision-making context compared to conventional vehicle drivers, though both show planning-oriented behaviour and bounded rationality. On the one hand, EV drivers are ultimately concerned with minimising time costs and travel expenses (Wang et al., 2024; Yang et al., 2020). However, this utility formulation varies by individuals depending on their idiosyncratic preferences and the situational context (Daina, Sivakumar and Polak, 2017a). They show forward-looking behaviours, plan driving and charging activities in advance (Thorhauge, Rich and Mabit, 2024), and have perceived risks of unanticipated vehicle use and uncertainties in vehicle range predictions before departure (Daina, Sivakumar and Polak, 2017a). When choosing among charging alternatives, drivers tend to favour more direct routes and options associated with lower charging time and cost (Wang, Yao and Yang, 2024). Empirical analyses of charging events and user preference surveys further indicate that EV drivers tend to pair charging with other daily activities, particularly at trip destinations rather than in the middle of a trip (Pan et al., 2020; Mahlberg, Desai and Bullock, 2023).

On the other hand, EV drivers' decision-making remains constrained by bounded rationality (Yang et al., 2020). Charging decisions are influenced by psychological factors such as risk aversion and limited confidence in battery performance (Wang, Yao and Yang, 2024). The most widely discussed concept related to this is range anxiety, which will be discussed in more detail in Section 2.3.2. Additionally, drivers face planning and cognitive burdens when evaluating multiple charging options and may show a 'myopic behaviour' (Latinopoulos, Sivakumar and Polak, 2017). Empirical studies have found that EV drivers often rely on habitual charging patterns based on prior experience and convenience, rather than systematically evaluating all feasible charging stations (Guo et al., 2022; Pellegrini, Cherchi and Rose, 2025; Shariatzadeh, Lopes and Henggeler Antunes, 2025). Such habits emerge through repeated charging experiences over time (Guo et al., 2022). Jin et al. (2024) define this tendency as 'charging inertia', whereby drivers' charging behaviour remains unchanged under similar conditions.

Finally, bounded rationality among private EV drivers is reinforced by limited information about other users. Private drivers generally act independently, with minimal

communication and incomplete knowledge of other drivers' decisions, state-of-charge levels, or exact queueing times at charging stations (Yan and Tang, 2025). This lack of complete information further brings uncertainty and limits rational decision-making. This feature was discussed in more detail in Section 2.2.2.

2.3.2 Learning Ability and Adaptive Behaviours

The theoretical foundation of adaptive behaviour can be traced back to the constructivism theory, first articulated by Jean Piaget (Piaget and Cook, 1952). Constructivism stands in contrast to nativism, which conceptualises knowledge as entirely innate, and empiricism, which treats knowledge as the passive recording of information from the environment. Instead, constructivism posits that individuals actively construct knowledge through interaction with the environment, and subsequently act upon that environment using newly developed cognitive structures (Waite-Stupiansky, 2022).

Building on this foundation, Bandura's Social Cognitive Theory (1986, 1977) provides a comprehensive framework for understanding adaptive behaviour. As Bandura noted:

‘In the social learning view, man is neither driven by inner forces nor buffeted helplessly by environmental influences. Rather, psychological functioning is best understood in terms of a continuous reciprocal interaction between behaviour and its controlling conditions’ (Bandura and Walters, 1977)

Within this interactive system, individuals acquire new behavioural strategies through observational learning rather than trial and error, and use these observations as a template for new behaviours (Bandura and Walters, 1977). However, the learning process does not end with observation. As individuals implement these strategies, they engage in a cognitive process of ‘self-regulation’, adopting internal standards that guide and motivate behaviour and allow actions to be regulated anticipatorily through a dynamic interplay of self-generated and external influences (Bandura, 1991). This regulation is critically supported by ‘enactive learning’, in which individuals learn from the outcomes of their actions:

'The initial approximations of response patterns learned observationally are further refined through self-corrective adjustments based on informative feedback from performance' (Bandura, 1977b)

Over time, this learning process serves a predictive function. It enables individuals to anticipate future outcomes and regulate behaviour accordingly. As Bandura noted:

‘As a result of prior experiences, people come to expect that certain actions will gain them outcomes they value, others will have no appreciable effects, and still others will produce undesired results’ (Bandura and Walters, 1977)

In the context of EV driver behaviours, adaptive learning leads to reduced range anxiety and more efficient use of charging infrastructure. One of the earliest discussions of such behaviour adaptation emerged from analyses of the MINI E Trial. Based on findings from this trial, Turrentine et al. (2011) identify three phases in EV drivers’ learning processes: Discovery, Translation, and Application. During these phases, drivers first familiarise themselves with the unique characteristics of EVs, then interpret and form opinions about their experiences, integrate these insights into everyday driving habits, and finally consolidate new behavioural patterns. Helmbrecht et al. (2013) further argue that evidence from the MINI E Trial demonstrates that increased driving experiences allow EV drivers to become more accustomed to specific circumstances, including driving range limitations and the recharging process. They can incorporate both past experience and anticipated mobility demand into their decision-making, thereby improving driving efficiency (Adenaw and Lienkamp, 2021; Rainieri, Buizza and Ghilardi, 2023).

A widely discussed form of behavioural adaptation in empirical studies is the gradual reduction of range anxiety among EV drivers. Research shows that EV users gain confidence as they complete more journeys, and their concerns about limited driving range decline as experience accumulates (Azadfar, Sreeram and Harries, 2015). Over time, drivers get more satisfied with vehicle range and find advance planning less challenging than initially expected (Daramy-Williams, Anable and Grant-Muller, 2019). Some drivers even start to use EVs for longer journeys, with the interval between charging events steadily increasing (Bunce, Harris and Burgess, 2014; Daramy-Williams, Anable and Grant-Muller, 2019). Rauh et al. (2015) further note that although range anxiety may

initially intensify during early stages of EV adoption, a few weeks of real-world driving experience are typically sufficient to initiate adaptation and reduce range-related stress.

Besides range anxiety, EV drivers also adapt their behaviours to improve charging efficiency and avoid unpleasant charging experiences. Previous studies indicate that drivers place high weights on queueing conditions when making charging decisions (Wang, Yao and Pan, 2021). Drivers make charging decisions to minimise the risk that preferred charging stations will be occupied and to avoid waiting or balking experiences (Sweda, Dolinskaya and Klabjan, 2017). In addition, when taking alternative transport modes into consideration, adaptive behaviours may include switching to conventional vehicles or public transport when these options are available and perceived as more convenient.

2.3.3 Range Anxiety

The bounded rationality and adaptive learning abilities discussed in Sections 2.3.1 and 2.3.2 are not unique to EV drivers but apply to all individuals regardless of the vehicle type they operate. This section therefore moves beyond these general behavioural mechanisms to focus specifically on range anxiety, a phenomenon unique to EV drivers. Range anxiety is often considered a critical behavioural characteristic influencing EV adoption and is commonly incorporated into EV driver simulation models (Chaudhari et al., 2019; van der Kam et al., 2019; Ling et al., 2022; Li et al., 2024). This section will introduce the evolution of range anxiety from a psychological concern to a measurable determinant of driver behaviour, and explore how it shapes EV driving and charging decisions.

The concept of range anxiety originated from early user experiences with battery EVs. The term was initially coined by users of EV1, the first modern mass-produced pure battery EV. The users described range anxiety as their persistent concern, or even fear, of becoming stranded with a discharged battery at locations away from the electric infrastructure (Tate, Harpster and Savagian, 2008; Eberle and Von Helmolt, 2010). One of the earliest and most influential academic discussions was presented by Franke et al. (2012), who discussed how drivers perceive EV range and how they subsequently respond to these perceptions. Franke et al. (2012) integrated the concept of range anxiety with the ‘safety buffer’ proposed by Kurani et al. (1994), and introduced the term ‘comfortable range’. It refers to the subjective portion of battery capacity that a driver is comfortable

using before stress associated with limited range begins to affect behaviour. This perception arises from an imbalance between mobility needs (e.g. journey distance, route profile, trip purpose) and mobility resources (e.g. remaining range, individual coping skills) for a given journey (Franke et al., 2012). As noted by Rainieri et al. (2023), the greater the discrepancy becomes between available battery charge and drivers' preferred safety margin, the more likely discomfort and stress are to occur. Later studies have conceptualised 'comfortable range' in various ways, including the point at which range anxiety begins to significantly influence driving behaviour (Yuan et al., 2018), or the maximum distance between charging activities (Pevec et al., 2019). In simulation studies of EV drivers, this concept is often represented as a 'state-of-charge (SOC) threshold' (Marmaras, Xydas and Cipcigan, 2017; Wasesa and Sateriano, 2023), or a 'range buffer' (Liu, Tayarani and Gao, 2022).

Range anxiety is dynamic rather than static and evolves with driving experience and contextual factors. Franke et al. (2016) find that fewer encounters with critical range situations, greater practical experience, and increased trust in range estimation systems contribute to lower range-related stress. As discussed in Section 2.3.2, drivers show adaptive behaviours, and these factors collectively help drivers develop more accurate mental models of energy consumption and their trip planning (Rauh, Franke and Krems, 2015; Yuan et al., 2018; Rainieri, Buizza and Ghilardi, 2023), particularly when they wish to use EVs for longer journeys (Azadfar, Sreeram and Harries, 2015). In addition to adaptive behaviours of drivers, vehicle characteristics such as battery capacity and energy consumption efficiency also influence the level of range anxiety experienced (Musabini et al., 2020).

When range anxiety is triggered, it leads to distinct behavioural responses from EV drivers. One of the most common reactions is increased monitoring of the SOC display (Rauh, Franke and Krems, 2015), accompanied by a higher likelihood of seeking nearby charging opportunities (Fotouhi et al., 2019). Zhang et al. (2021) further suggest that EV drivers experiencing range anxiety tend to find fast chargers to alleviate stress more quickly. Although drivers value detour and waiting time (Tian et al., 2018; Visaria et al., 2022), these factors become less influential when recharging urgency increases (Thorhauge, Rich and Mabit, 2024). Range anxiety can also affect route choice. Ashkrof et al., (2020) find that drivers facing low battery levels would prefer routes with lower energy consumption, and they would favour local streets and arterial roads over motorways. However, such

reactive behaviours do not always occur, as many drivers show preventative charging strategies by recharging early or opportunistically, even when battery levels remain relatively high (Pevac et al., 2020; Thorhauge, Rich and Mabit, 2024).

However, the relevance of range anxiety as a long-term research focus has been challenged by recent technological developments. A common critique is that advances in battery technology, improved range prediction, and enhanced driver assistance systems may eventually make range-related concerns largely obsolete (Franke et al., 2012; Azadfar, Sreeram and Harries, 2015). Besides, EV drivers often mitigate stress by relying on alternative transport options, such as ICE vehicles or public transport, to avoid range anxiety (Langbroek, Franklin and Susilo, 2018; Daramy-Williams, Anable and Grant-Muller, 2019). As a result, attention has increasingly shifted toward related but distinct concerns. One emerging concept is ‘charging anxiety’. As discussed in Section 2.2.2, it reflects uncertainty about charger availability, queueing, and reliability upon arrival and may increasingly replace range anxiety as the dominant concern for EV drivers (Hanig et al., 2025). Another is ‘time-related range anxiety’, which refers not to the spatial fear of being stranded but to temporal stress arising from potential schedule disruption and uncertainty about reaching the destination on time (Wang et al., 2024).

2.4 Summary

The previous sections of this chapter have reviewed the complex behaviours of EV drivers and their interactions with the environment. They have established the foundations for the development of EV driver simulation models. Section 2.1 outlined the evolution of transport electrification and the growth of EV markets. It highlighted how the EV driver population has shifted from a small group of early adopters to a heterogeneous user base characterised by diverse socio-demographic attributes, usage patterns, and behavioural features. This chapter also emphasised the focus of this research on private EV drivers, whose travel and charging patterns differ substantially from those of commercial EV fleets.

Section 2.2 explored how EV driver behaviours are shaped by both the built environment and social interactions with other drivers. It discussed the roles of home and workplace charging and the characteristics of public charging infrastructure in shaping charging choices. It further explored EV drivers’ social interactions mediated through digital platforms, as well as their direct competition for chargers at charging stations.

Section 2.3 shifted the focus from contextual influences to the intrinsic behavioural characteristics of EV drivers. It introduced bounded rationality as a core determinant of decision-making, discussed learning ability and adaptive behaviours emerging from driving experiences, and explored range anxiety as a distinctive feature of EV use.

Building on this conceptual understanding of EV driver behaviour and its interaction with the environment, the following chapter reviews the methodological literature on how these behavioural and contextual factors can be modelled.

Chapter 3

Modelling Electric Vehicle Drivers

3.1 Introduction

Understanding and modelling EV driver behaviours is important for planning future charging infrastructure that meets driver needs while supporting broader decarbonisation goals. The previous chapter reviewed the theoretical frameworks and empirical findings that characterise EV driver behaviour. It clarified that EV driver behaviour is shaped by a complex interplay of the built environment, social interactions, and cognitive factors, including bounded rationality, adaptive learning, and range anxiety. As a result, an adequate methodological framework for representing this system must be capable of:

- Representing the heterogeneity of individual behavioural patterns in terms of preferences and choices.
- Capturing individuals' learning ability and adaptability that evolve through their experiences.
- Representing social interdependence between individuals, allowing decisions to influence and be influenced by the choices of other drivers.
- Capturing interactions between individuals and the environment, including feedback loops between charger availability and driver behaviours.

These requirements place EV driver modelling within the broader challenge of modelling complex systems. Although no single definition of a complex system is universally accepted, such systems are generally characterised by a large number of interacting elements, non-linear behavioural dynamics, hierarchical structures, non-decomposability, unpredictability, and self-organisation (Mesjasz, 2010). A defining feature of complexity is that local interactions among components generate emergent outcomes at the system level that cannot be inferred from the properties of individual elements alone (O'Sullivan, 2004; Batty, 2010). As succinctly stated by Nigel Goldenfeld ('No man is an island, 2009), complexity arises when causality breaks down.

Transport systems show these complex characteristics. They comprise many cognitive travellers whose interdependent decisions give rise to emergent phenomena, such as congestion, that are difficult to predict from individual behaviour in isolation. EV charging systems inherit this complexity while introducing additional dimensions. Helmus et al. (2019) provide one of the earliest comprehensive definitions of EV charging systems as complex systems, and highlight features such as self-organisation, feedback loops, non-linearity, emergence, and path-dependency. For example, individual charging decisions generate competition among EV drivers for charging infrastructure, leading to collective queueing patterns that, in turn, feedback into subsequent station selection decisions. Additionally, as noted by Batty (2010), individuals can show a level of complexity comparable to that of the aggregated system. As discussed in Chapter 2, EV drivers themselves are complex adaptive agents who learn from experience, adapt their behaviour, and modify their strategies over time. Modelling such systems therefore requires methodological approaches capable of capturing these multi-level and adaptive dynamics.

Building on this complexity perspective, this chapter will review existing approaches to modelling EV driver behaviour and justify the methodological framework adopted in this research. Section 3.2 reviews statistical and analytical approaches used to model EV driver behaviour. Section 3.3 reviews computational approaches, including discrete event simulation and ABMs. It will also introduce a critique of ABMs. Section 3.4 will review the machine learning models applied in and for ABMs, with a particular focus on the emerging integration of RL as a promising approach for capturing adaptive human behaviour in EV driver modelling. Finally, Section 3.5 summarises the chapter.

3.2 Statistical and Analytical Methods for Modelling EV Drivers

This section reviews statistical and analytical methods used to model EV drivers and identifies their key limitations. In particular, it focuses on two widely adopted approaches: regression models and discrete choice models. It should be noted that, due to the aggregate nature of these methods, most existing studies do not explicitly model individual EV driver behaviour. Instead, studies often use an aggregate concept, charging demand, to represent overall charger usage patterns.

Before the widespread adoption of regression and discrete choice models, early studies explored EV charging demand by ‘mapping’ its spatial distribution using available data sources. When empirical EV usage data were scarce, these mapping-based studies relied primarily on demographic and land-use information to estimate where charging demand was likely to occur, and the results were typically used to inform infrastructure deployment decisions. A representative example is Frade et al. (2011), who developed indicators of daytime charging demand distribution based on employment concentrations and nighttime demand from population distributions. As more empirical EV data become available, demand-mapping methods have evolved to incorporate increasingly diverse and granular data sources, including GPS data (Kang et al., 2022) and POI data (Wang et al., 2023). These data are applied based on methods such as kernel density estimation to infer charging demand distribution. However, mapping-based approaches remain limited in their predictive capacity and explanatory power. In particular, they cannot explain why drivers choose when and where to charge, nor can they predict how charging behaviour may change under different conditions.

Regression-based approaches provide an interpretable framework for analysing factors associated with EV charging behaviour. In the literature, regression models are primarily used either to identify key factors influencing charging demand, or to predict future charging demand distributions (Almaghrebi et al., 2020). The latter objective, demand prediction, overlaps with the broader domain of machine learning and will therefore be further discussed in Section 3.3.3. Most regression-based studies focus on identifying and quantifying determinants of charging demand distribution (Liu et al., 2024; Zhao et al., 2024; Dai et al., 2025; Hamim, Chen and Ukkusuri, 2026). For example, Borlaug et al. (2023) used regression models to quantify the relationship between charging speed, price, location type, temporal factors, and public charger usage rates. However, standard linear regression models typically assume spatially independent relationships in the regression error terms. To address this limitation, recent studies have adopted geographically weighted approaches to capture spatial heterogeneity. Hamim et al. (2026) applied geographically weighted random forest regression to explore how sociodemographic characteristics, the built environment, and station attributes are associated with charging station usage. Similarly, Liu et al. (2024) used geographically weighted regression to explore spatially varying relationships between urban infrastructure and charger usage. Despite their interpretability, regression-based approaches are usually formulated at an aggregate level. They use charging events or stations as the primary unit of analysis. This

can obscure heterogeneity in individual behaviours, preferences, and decision-making processes.

Discrete choice models (DCMs) offer an alternative analytical framework by explicitly modelling individual charging decisions. Grounded in random utility theory (McFadden, 1972), DCMs assume that EV drivers act as rational utility maximisers when selecting a charging option from a set of discrete alternatives (Train, 2009). Unlike standard regression models, DCMs explicitly define the choice set available to individuals. Most empirical DCM studies rely on stated preference data collected from charger users (Ge, 2019; Bhat, Tiwari and Verma, 2024; Sica et al., 2025). For example, Ge (2019) modelled charging decisions for both short- and long-distance trips of EV users. Sica et al. (2025) focused on routine activities and modelled user choices among private chargers and public chargers near home, work, and other activity locations. However, despite their ability to represent individual decision-making, DCMs assume that observations are independent across individuals (Le Pira et al., 2017). As a result, they cannot capture interactions among EV drivers, whose decisions may be interdependent and influenced by the behaviour of others at charging stations, as discussed in Section 2.2.2.

Overall, statistical and analytical approaches have made important contributions to understanding EV charging demand but face inherent limitations in representing individual behaviour. These methods have been effective in mapping spatial distribution of charging demand, identifying key influencing factors, and modelling individual charging choices. They remain an active and valuable area of research; however, their capacity to represent real-world decision-making at the individual level is limited (DeAngelis and Diaz, 2019). Demand mapping approaches operate primarily at an aggregate level and offer limited predictive and explanatory capability. Regression models provide interpretability in identifying factors associated with charging demand but cannot capture heterogeneous decision-making processes at the individual level. DCMs, while explicitly modelling individual choices, are constrained in their ability to represent social interactions among individuals. These limitations motivate the use of computational approaches, which are better suited to capturing heterogeneous behaviours across populations (DeAngelis and Diaz, 2019). Such computational approaches will be reviewed in the next section.

3.3 Computational Modelling of EV Drivers

‘If any analytical solution to a mathematical model is available and is computationally efficient, it is usually desirable to study the model in this way rather than via a simulation. However, many systems are highly complex, so that valid mathematical models of them are themselves complex, precluding any possibility of an analytical solution. In this case, the model must be studied by means of simulation’ (Law, Kelton and Kelton, 2007)

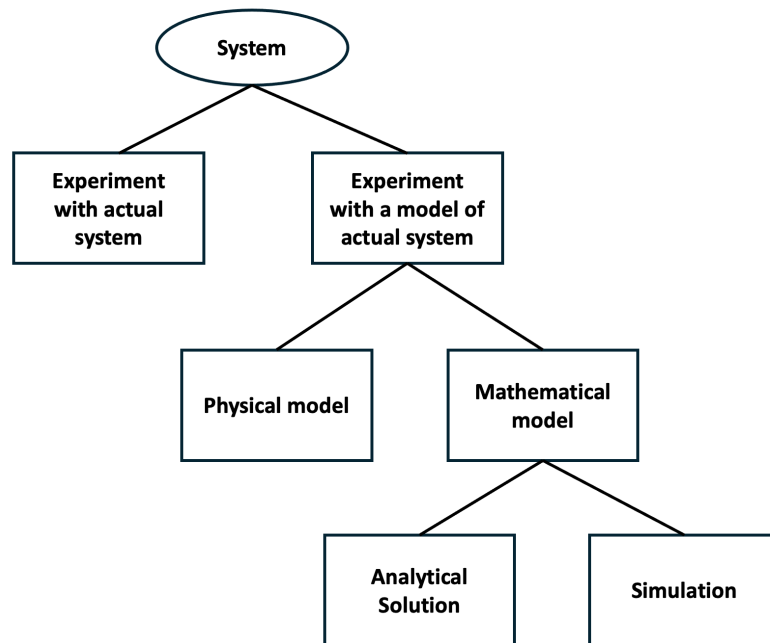


Figure 3.1 Ways to study a system (Law et al., 2007)

Law et al. (2007) summarise the main approaches for studying a system, as shown in Figure 3.1. As described in Sections 3.1 and 3.2, EV driving and charging systems are too complex to be effectively captured by analytical approaches alone. Additionally, in the context of EV driving and charging, direct experimentation with the real-world system is often impractical due to the rigid nature of charging infrastructure: once charging stations are deployed, it is costly to make any modifications. When experimenting with the real system is expensive or infeasible, modelling provides a practical alternative (Borshchev and Filippov, 2004).

Computational methods are therefore well suited to representing the complex behaviours of EV drivers described in Chapter 2. A wide range of computational modelling approaches has been applied in this context, including Monte Carlo simulation, discrete-event simulation, ABM, system dynamics, and ML methods. These approaches are not

mutually exclusive and are often combined to capture different aspects of complex systems. This section does not aim to review all computational approaches used to model EV driver behaviours. Instead, it focuses on two approaches, discrete-event simulation and ABM, which are widely used in EV driver behaviour simulation. Section 3.3.1 will review discrete event simulation, and Section 3.3.2 will review ABMs. ML models will be reviewed separately in Section 3.4.

3.3.1 Discrete Event Simulation

Discrete Event Simulation (DES) is one of the most widely used computational methods for modelling EV systems, alongside ABMs and ML approaches. DESs represent systems and their dynamics on an event-by-event basis at discrete points in time (Fishman, 2001). This section will not provide a comprehensive review of discrete event simulation techniques; instead, it will focus on the studies that apply DES specifically to EV driver simulation. Detailed methodological discussions of DES can be found in Fishman (2001) and Law et al. (2007).

In the context of EV charging systems, DES models provide a more detailed representation of EV charging systems than analytical approaches by explicitly modelling driving and charging events. Early applications originated in the operational research and logistics literature, where DES was used to optimise charging schedules when replacing conventional fleets with EVs (Ruzmetov et al., 2015; Ferro et al., 2019). Other studies have applied DES to charging infrastructure evaluation. These studies focus primarily on station-level events such as vehicle arrival, charging, and departure, without modelling driving behaviour or station selection processes outside charging locations. For example, Darabi & Ferdowsi (2014) developed a DES framework with events of queueing, arriving, balking, and charging to assess whether existing power systems could meet charging demand. Similarly, Pruckner et al. (2017) modelled charging events at stations to evaluate station load and expected waiting times under different network expansion scenarios. More recent DES studies have extended beyond station-level events to incorporate elements of EV drivers' trip diaries, such as departures from home and arrivals at destinations (Lopez, Allana and Biona, 2021; Wahyudi, Rahman and Hariyanto, 2024).

Despite its ability to represent detailed event sequences, DES has several limitations that restrict its suitability for the research objectives of this study. As mentioned earlier, DES is

a process-oriented, top-down modelling approach in which system logic and event flows are specified exogenously to individuals. As discussed by Siebers et al. (2010), it is particularly effective for modelling systems characterised by well-defined event sequences, such as queueing systems or networks of queues. In DES, individual entities are typically passive, with their behaviour governed by the system rather than by autonomous decision-making (Siebers et al., 2010; Maidstone, 2012). However, as discussed in Chapter 2, private EV drivers are proactive decision-makers who autonomously determine when, where, and how long to charge based on internal states, such as remaining battery level, range anxiety, and past experiences. These decisions are not predetermined event sequences but emergent outcomes of individual-level reasoning and adaptation. Consequently, a decentralised, individual-centric simulation approach is needed to represent populations of heterogeneous drivers with various proactive behaviours and interactions.

3.3.2 Agent-based Models

As indicated by Borshchev & Filippov (2004), ABM is suitable for those who seek to go beyond the limitations of DES, especially when the system being modelled contains active entities. Unlike DES, the ABM modeller defines behaviour at individual level. This section will provide a brief introduction to the ABM methodology, and Section 3.3.3 will review its application to EV driver simulations.

ABM falls into the broader category of individual-based models, which also includes Cellular Automata and Microsimulation. A detailed comparison of these modelling techniques can be found in Heppenstall et al. (2012). ABM can be defined as a computerised simulation of a number of autonomous agents with heterogeneous attributes and dynamic behaviours that interact according to prescribed rules (Farmer and Foley, 2009; Heckbert, Baynes and Reeson, 2010). In ABMs, agents interact with one another and with their environments, and these interactions give rise to emergent system-level outcomes, which in turn influence subsequent agent behaviour and interactions (An, 2012; An et al., 2021; Bonabeau, 2002a; Railsback & Grimm, 2019).

Agents, interactions, and environment

A typical ABM comprises three key components: agent, environment, and relationships and methods of interaction (Macal and North, 2010). There is no universal agreement on the precise definition of agents (Macal and North, 2009). Brown et al. (2005) describe agents as autonomous entities capable of acting and making decisions based on a set of rules or strategies. Macal & North (2009) further emphasise that agents are diverse, heterogeneous and dynamic in both their attributes and behavioural rules. Agent behaviour may be governed by deterministic ‘if-then’ rules which assign only one possible behaviour to an individual in a particular circumstance, or alternatively, a probabilistic rule with different likelihoods to a range of possible actions in response to stimuli (DeAngelis and Diaz, 2019). Alternatively, behaviours can be informed by concepts from cognitive science or artificial intelligence (Macal and North, 2009). Such behavioural rules are typically derived from existing literature, expert knowledge, data analysis, or numerical work and form the foundation of an agent’s behaviour (Crooks and Heppenstall, 2012). Through the behaviours, agents interact with each other. Interactions in ABM are the underlying topology of connectedness that defines how and with whom agents interact (Macal and North, 2010). These interactions may occur between agents or between agents and the environment. Agent interactions are heterogeneous and can generate network effects (Bonabeau, 2002).

The environment in ABM provides the contextual space in which agents operate and interact. Gilbert (2020) describes the environment as a virtual world in which the agents act. More specifically, it is the space in which agents operate and interact with the environment and other agents (Crooks and Heppenstall, 2012). In many ABMs, the environment is spatially represented, although the level of spatial detail and the level of detail of the agent-environment interactions vary considerably (Stanilov, 2012). Some models adopt implicit or non-geographic representations of space, and focus primarily on agent behaviours and social processes. Other models explicitly represent space but in an abstract manner, such as through grid cells or non-geographic coordinate systems (Manson et al., 2020). Another group of ABMs, closely aligned with geographic research, incorporates rich and explicit geographical information and seeks to establish direct links between environmental characteristics and agent behaviour (Macal and North, 2010; Stanilov, 2012).

Agent-based Models and Discrete Choice Models

Before reviewing the empirical application of ABMs, this section compares ABMs with DCMs, an important basis of activity-based travel demand models (Rasouli and Timmermans, 2014). As introduced in Section 3.2, DCMs are grounded in random utility theory (McFadden, 1972). Each decision-maker is assumed to select the option that maximises a utility function from a finite set of alternatives (Train, 2009). Model parameters are estimated from observed or stated preference data, and estimated coefficients are directly interpretable (Ben-Akiva and Lerman, 1985; Ge and MacKenzie, 2022). Empirical studies based on DCMs have explored the choice of chargers with different types (Sun, Yamamoto and Morikawa, 2016), locations (Ge, 2019), and prices (Sica et al., 2025).

Although both frameworks can represent decision-making, there are two main differences between ABMs and DCMs. The first difference concerns the representation of interaction. DCMs treat choices as independent across decision-makers (Le Pira et al., 2017), whereas in ABMs the decisions of individual agents are interdependent through direct interactions in a shared environment (Bonabeau, 2002). As discussed in Section 2.2.2, EV drivers' behaviours can affect and be affected by others through competition for a limited number of public chargers. The second difference between DCMs and ABMs concerns the representation of how decision-making changes over time. In a DCM, the utility function is estimated from observed choices and remains fixed (Train, 2009). There is therefore limited scope for representing how driving and charging strategies evolve with experience, a process that Chapter 2 identified as central to EV charging behaviour. ABMs, particularly when combined with reinforcement learning (RL) algorithms, which will be discussed in Section 3.4, can relax these assumptions and model evolving behaviours based on past experiences (Ale Ebrahim Dehkordi et al., 2023). Nevertheless, these differences should not be interpreted as one framework dominating the other. The two modelling frameworks are increasingly treated as complementary, and DCMs are often combined with ABMs in many empirical studies of EV adoption choices (Brown, 2012) and charging decisions (Wolbertus et al., 2021).

Application of ABMs

ABMs have become a widely used bottom-up tool for studying complexity in both theoretical and empirical research (An, 2012). They enable researchers to replicate or generate the emergence of empirically complex social phenomena (Crooks and

Heppenstall, 2012). Consequently, ABMs have been applied across a wide range of disciplines, including physical, biological, social and management sciences (Macal and North, 2010).

Within the transport domain, ABMs have been particularly influential due to their ability to capture the dynamic, stochastic, and heterogeneous nature of transport systems (Huang et al., 2022). Bastariantto et al. (2023a) provided a comprehensive review of transport-related ABM applications, including pedestrian and vehicle movements, travel behaviour, emerging transport modes, transport policy analysis, urban logistics, travel demand, and public transport systems. More recently, ABMs have been increasingly applied to the simulation of EV driver behaviour, covering both EV adoption decisions and post-adoption driving and charging behaviour. These applications are reviewed in detail in Section 3.3.3.

3.3.3 Agent-based Models of EV drivers

Early ABMs of EVs emerged during the initial stages of EV adoption, when the primary research focus was whether consumers would adopt EVs at all. Consequently, ABMs developed during this period largely concentrated on EV adoption and vehicle purchase decisions, rather than on post-adoption operational behaviours such as driving and charging. For example, Shafiei et al. (2012) developed an ABM to explore consumer vehicle purchase behaviour and the resulting evolution of EV market share. Their model incorporated various technical and economic factors influencing EV purchase decisions, including fuel prices, vehicle costs, driving range, recharging concerns, and vehicle taxation. Beyond technological and economic considerations, Brown (2012) developed an ABM of EV diffusion that models how individuals' willingness to adopt EVs evolves through social interactions and peer influence. Similarly, Eppstein et al. (2011) combined economic considerations with social and spatial interactions, modelling EV adoption as a process influenced by others' uptake within social networks, neighbourhoods, and the media environment. More recent adoption-focused ABMs have introduced greater psychological realism. For example, in the EV choice ABM proposed by Kangur et al. (2017), agents are not assumed to be strict utility maximisers; instead, depending on their levels of satisfaction and uncertainty, agents switch between different cognitive strategies including habitual behaviour, reliance on social advice, and deliberate comparison. Despite these advances, early ABMs primarily focused on adoption decisions and largely neglected post-purchase travel and charging behaviours. These behaviours are important to model, as

they differ substantially from those of conventional vehicle users due to range constraints and charging availability (Zhan et al., 2025).

As EV adoption increased, ABMs began to shift attention toward post-adoption behaviours and explore how EV drivers actually travel and charge. A representative study is from Adepetu et al. (2016), who developed an EV ecosystem ABM that jointly models EV adoption and usage. In this model, EV driver agents purchase vehicles for daily travel and follow predefined workday and non-workday schedules. The framework is designed for ‘what-if’ analysis to evaluate how policy interventions, such as purchase rebates and battery technology improvements, influence EV adoption and charging station usage. However, travel and charging behaviours in this model remain highly simplified. EV drivers consider only travel distance and charge at the nearest station once their SOC becomes insufficient to complete a trip. They also charge only the amount required to reach their destination. Important behavioural factors are omitted, including individual preferences, financial and temporal costs, and charging stations’ speed and availability. Another study that bridges EV adoption with driving and charging behaviours is Yang et al. (2018). Compared with Adepetu et al. (2016), Yang et al. (2018) extend behavioural rules by incorporating charging price and charging time into drivers' decision-making processes. The model also accounts for competition among EV drivers for limited low-cost energy resources. Nevertheless, both studies assume EV drivers behave as utility maximisers who evaluate trade-offs among financial cost, travel distance, and time cost. Heuristic decision-making processes and psychological features of real-world EV drivers are largely neglected. In addition, the representation of road networks in these models is either simplified or implicit, which limits their ability to capture spatially detailed driving and charging dynamics.

A major advance in modelling EV driver behaviour has arisen from the integration with open-source transport simulation frameworks. These frameworks are highly modular, and allow users to develop, modify, or replace individual components with custom implementations. Among existing transport simulation frameworks, Multi-Agent Transport Simulation framework (MATSim) (Axhausen and ETH Zürich, 2016) has become the most widely adopted (Bastarion et al., 2023), alongside a growing number of related platforms for EV simulation, which are reviewed in detail by Harris et al. (2024). Compared with earlier ABMs, MATSim enables the integration of high-resolution road networks within an explicit geographic context (Waraich et al., 2013). Waraich (2013) was among the first to

apply MATSim to EV contexts and simulate electricity demand by tracking battery depletion of EVs. Building on this foundation, Gopal et al. (2017) introduced the Behaviour, Energy, Mobility, and Autonomy (BEAM) framework as an extension of MATSim. BEAM supports more realistic and spatially explicit representations of EV charging infrastructure with charger types and numbers of ports. Following these developments, MATSim-based frameworks have been widely used to replicate real-world charger usage patterns (Yi et al., 2023) and to predict charging demand distributions (Zhuge and Shao, 2018). Despite these strengths, important limitations remain. Although simulation environments have progressed from hypothetical grid environments (Chaudhari et al., 2019) or simplified network topologies (Marmaras, Xydias and Cipcigan, 2017) toward geographically explicit real-world road networks, most existing studies remain confined to city-level settings. As a result, inter-city travel, where EV range constraints are often most critical, is rarely represented. Moreover, as noted by Adenaw and Lienkamp (2021), many MATSim-based EV models treat charging as a stand-alone activity. They assume that drivers continue driving until charging becomes unavoidable or disconnect immediately once charging is complete. Such assumptions constrain the realistic representation of cognitively bounded EV drivers, who may plan to charge anticipatorily and whose decisions are influenced by range anxiety and past experiences.

More recent ABMs of EV driver behaviour have moved beyond exogenous and deterministic rules by placing greater emphasis on psychological and cognitive factors. A notable contribution is provided by van der Kam et al. (2019), who, in contrast to earlier utility-maximising approaches, explicitly incorporate psychological and normative attributes into EV driver agents, including environmental self-identity and range anxiety. Subsequent studies have further refined representations of range anxiety. Chaudhari et al. (2019) introduce the concept of a ‘critical SOC’, defined as the lowest permissible SOC level for an EV driver. In their model, range anxiety is modelled as a function of driver experience, with more experienced drivers assigned lower anxiety levels and lower critical SOC thresholds. Willey and Salmon (2021) further distinguish between two types of charging behaviour: ‘necessary charging’, which is similar to the critical SOC concept, and ‘convenience charging’, which occurs opportunistically when drivers encounter charging infrastructure while parked at intermediate locations. More recently, Ling et al. (2022) incorporate heterogeneity in range anxiety by assigning different psychological anxiety levels to individual EV driver agents. However, across these studies, range anxiety is typically modelled as a static attribute that varies between individuals but

remains fixed for each agent over time. This assumption overlooks the dynamic nature of charging behaviour. As discussed in Chapter 2, charging decisions are fundamentally adaptive: EV drivers learn from past experiences, update expectations, and adjust both their decision-making strategies and their levels of range anxiety over time. A more detailed discussion of this limitation is provided in Section 3.3.4.

3.3.4 A Critique of Agent-based Modelling

One prominent critique of ABMs for simulating human behaviour concerns their limited capacity to represent adaptive behaviour. Here, ‘adaptive’ does not refer merely to agents’ ability to select different actions — a feature often cited as an advantage of ABMs over other modelling techniques — but rather to their capacity to develop new strategies (Rand, 2006). As discussed in Section 3.3.3, most ABMs simulating EV driver behaviour rely on static behavioural rules, such as initiating charging when SOC falls below a fixed threshold. Even when psychological factors such as range anxiety are incorporated, they are typically modelled as static attributes that vary across individuals but remain unchanged within individuals over time (van der Kam et al., 2019; Ling et al., 2022).

Adaptive and cognitive complexity of human behaviour is less represented in rule-based ABMs. The development of ABMs commonly follows an ‘if-then’ structure (DeAngelis and Diaz, 2019), in which deterministic rules assign a single behavioural response to a given situation (Grimm and Railsback, 2005). Conte & Paolucci (2014) indicate that, following a principle of minimality, ABMs are often rule-oriented rather than agent-oriented: what is achieved is a set of rules, rather than an agent view. In other words, modellers tend to describe behaviour as observed externally rather than modelling how behaviour is internally generated. With a few notable exceptions, such as the El Farol Bar Problem (Arthur, 1994), relatively few early rule-based ABMs incorporate explicit adaptive mechanisms (Rand, 2006). An (2012) describes adaptive mechanisms as processes through which humans learn, adapt, and revise their decision-making paradigms. Individuals respond to changing environments, and these responses, in turn, reshape the context for future decisions. Among all adaptive mechanisms, learning ability is particularly important for modelling human behaviour. Balke & Gilbert (2014) identify learning capability as a key dimension distinguishing agent architecture in ABMs. They define it in terms of whether agents can learn and, if so, at what level—such as updating

parameters within decision rules, learning successful decision strategies, or developing new decision rules.

Despite its importance, representing adaptive behaviour remains a fundamental challenge in ABMs, particularly when modelling human systems. Representing human behaviour adds further complexity due to social interactions in increasingly complex networks, anticipation of the behaviour of others, memory, learning, and emotions (An et al., 2021). Bonabeau (2002) refers to such subjective and non-rational human behaviours as ‘soft factors’, which are difficult to quantify. In addition, ABMs can face substantial computational challenges when the number and details of agents, interactions, decision rules, scheduling, and environment increase (Sun et al., 2016; Zhang, Li and Zhang, 2020). Large parameter spaces and multiple interlinked sub-models further complicate model verification (Sun et al., 2016). Incorporating heterogeneous adaptive and cognitive processes intensifies these challenges and must be addressed through appropriate methodological choices (Sun, 2009).

In response to these limitations, AI (Artificial Intelligence) algorithms have been introduced to extend ABMs beyond fixed rules and enable more sophisticated decision-making consistent with our understanding of reality. Such rules or strategies are often dynamic and subject to evolution (An, 2012). They can support the development of more intelligent agents and more accurately simulate emerging phenomena in a system (Sun, 2009). One established approach integrates ABM with genetic algorithms (Holland, 1992). Another increasingly common approach is embedding ML methods within ABMs, which allow agents to modify their actions and strategies based on what proves worthwhile (Rand, 2006).

Among these approaches, RL is particularly promising in modelling adaptive behaviour in human systems. RL allows agents to learn optimal strategies through trial-and-error interactions with their environment. The following section reviews RL methods and their application to modelling EV driver behaviour and charging systems.

3.4 Reinforcement Learning Models of EV Drivers

3.4.1 Machine Learning in and for ABMs

ML techniques provide a promising avenue for addressing the limited representation of adaptive and cognitive complexity in rule-based ABMs. As identified in the previous section, many ABMs rely on static, predefined behavioural rules that struggle to capture how human agents learn from experience and adjust decisions over time. Integrating ML into ABMs allows agents to acquire, refine, and adapt behavioural strategies dynamically. This section introduces the basic concepts of ML and outlines how ML methods are used in and for ABMs. The application of these approaches specifically to EV driver simulations is discussed in detail in Section 3.4.2.

ML is a subfield of AI that has evolved rapidly into a broad family of computational methods. It is commonly defined as a set of techniques that enable computers to learn patterns and improve performance without being explicitly programmed (Samuel, 1959). Based on the type of feedback used during learning, ML methods are often classified into supervised learning, unsupervised learning, semi-supervised learning, and RL (Ale Ebrahim Dehkordi et al., 2023; Zhang, Valencia and Chang, 2023). As a comprehensive review of all ML approaches is beyond the scope of this chapter, readers are referred to Russell & Norvig (2016) for a more detailed overview.

The integration of ML with ABMs can take various forms depending on the modelling objective and the stage of the modelling process. Although the first use of ML in ABMs is difficult to pinpoint, an early and notable contribution is Rand (2006)'s systematic framework for incorporating ML into ABMs, where ML models are used to inform agent decision-making for prediction purposes. Later studies have extended this framework beyond agent decision-making to encompass the broader modelling workflow. Zhang et al. (2023) categorise ML applications across data preprocessing, agent behaviour specification during simulation, and model output analysis. Ale Ebrahim Dehkordi et al. (2023) further classify ML-ABM integration based on three dimensions: the ML technique employed, the ABM challenge addressed, and the modelling purpose. More detailed classifications are provided in Ale Ebrahim Dehkordi et al. (2023).

This study focuses specifically on ML's contribution to addressing the behavioural modelling challenge of ABMs – namely, the development of more realistic and adaptive representations of agent behaviour. Agents governed by predefined rules are inherently

limited in their ability to learn and remember previous decisions (Brearcliffe and Crooks, 2021). This can limit the explanatory power of simulations (Macal, 2016). As ABMs increase in scale to increase explanatory capacity, model complexity can become increasingly difficult to manage (Dahlke et al., 2020). It is therefore important to improve the intelligence and adaptability of agents through dynamic, experience-based rules (Macal and North, 2010), thereby improving the credibility and explanatory power of simulations. In this regard, ML techniques provide great potential to bring higher levels of agent intelligence into ABMs (Ale Ebrahim Dehkordi et al., 2023). They can support sequential decision-making by learning agents' behavioural patterns, and extend hard-coded behavioural rules into adaptive models (Zhang, Valencia and Chang, 2023). However, ML approaches, such as supervised, unsupervised, and semi-supervised learning, depend heavily on the availability of training data. In practice, studies can face insufficient or incomplete data when identifying appropriate model structures and parameters (An et al., 2023), a challenge also shared by ABMs more generally (Heppenstall et al., 2012).

Among the various ML techniques, RL is particularly well suited to address data constraints in behavioural modelling. RL is guided by rewards and penalties and enables agents to learn through interactions with other agents and the environment (Sutton and Barto, 1998; Russell and Norvig, 2016). It does not require predefined 'correct' decisions and can operate under conditions of limited prior knowledge (Mohri, Rostamizadeh and Talwalkar, 2018). Through repeated exposure to the environment and interactions with other agents, RL agents navigate spaces as if they were human, and gradually learn behavioural strategies that maximise cumulative reward (An et al., 2021, 2023; Malleson et al., 2022). This iterative process is repeated, with experiences defined by state–action–reward tuples continuously used to update the agent's policy. As such, RL can realistically model adaptive human decision-making behaviour (Ale Ebrahim Dehkordi et al., 2023). More details of the RL formulations will be discussed in Chapter 6.

Despite the advantages, integrating ML into ABMs introduces important trade-offs that must be carefully considered. Several studies have questioned whether it is worth the effort to add ML to ABMs (Dahlke et al., 2020; Brearcliffe and Crooks, 2021). While ML can substantially improve behavioural realism, it may also reduce model transparency and result in intelligent yet 'black-box' ABMs that are difficult to interpret (Dahlke et al., 2020). Additionally, optimisation-oriented RL agents may conflict with the notion of agents following simple rules of thumb and again get trapped in the neoclassical

assumption of rational optimising agents (Dahlke et al., 2020). Brearcliffe & Crooks (2021) highlight that ML algorithms are computationally demanding and often require extensive hyperparameter tuning, raising concerns regarding scalability and cost-effectiveness relative to performance gains.

It should also be noted that the behavioural adaptation of RL is different from the utility-based scheme of MATSim discussed in Section 3.3.3. In MATSim, agent learning is organised through a co-evolutionary algorithm (Axhausen and ETH Zürich, 2016). Each agent maintains a set of alternative plans over a fixed time period, typically a full day, covering choice dimensions such as routes, departure times, and transport modes (Flötteröd, Chen and Nagel, 2012). In each iteration, the selected plans of all agents are executed simultaneously, with each executed plan being scored by a utility function that translates the experienced conditions of that iteration into a single score (Axhausen and ETH Zürich, 2016). Agents then adapt on the basis of these scores: they normally prefer plans that have performed well, occasionally re-evaluate inferior plans, and sometimes obtain new plans by modifying copies of existing ones (Flötteröd, Chen and Nagel, 2012). Two differences from the RL approach follow from this plan-based design. The first concerns the representation of behaviour itself. A MATSim plan constitutes a complete sequence of decisions committed before the simulated day begins and executed regardless of the conditions the agent subsequently encounters, with adaptation occurring only between iterations through plan scoring and selection. An RL agent, by contrast, specifies no plan in advance. It instead holds a mapping from observed states to actions (Sutton and Barto, 1998), so that each decision is conditioned on the currently experienced state, such as the remaining SOC and the observed availability of chargers. The second difference concerns the feedback mechanism. In MATSim, replanning operates only on the total plan score, and the learning mechanism therefore has no means of attributing a plan's performance to the individual decisions within it. By contrast, the RL agents make sequential decisions conditioned on the currently observed state, and the value of each state-action pair is updated step by step according to the difference between expected and experienced outcomes (Watkins and Dayan, 1992; Sutton and Barto, 1998).

3.4.2 Agent-based Reinforcement Learning models of EV Drivers

The application of RL to EV driver behaviour contexts has expanded rapidly in recent years and can be broadly classified into two groups: system-level optimisation and

individual-level behavioural optimisation. These two groups differ fundamentally in how agents are defined and in the objectives they are designed to achieve.

Early and most prevalent applications of RL in EV contexts have primarily emerged from power systems and smart grid research, where the focus is on system-level optimisation. In these studies, the primary objective is to optimise charging schedules to reduce system-level grid impacts or operational costs. Agent representation varies depending on model design. In single-agent formulations, the RL agent typically represents a centralised decision-maker, such as a charging station operator or fleet manager. This agent schedules charging for multiple vehicles while treating individual EVs as part of the environment. For example, Sultanuddin et al. (2023) developed a smart deep RL framework in which a single agent generates charging schedules for an entire EV fleet to minimise grid load variance while ensuring that all vehicles are sufficiently charged before departure. Wang et al. (2021) proposed an RL framework to jointly optimise charging schedules and pricing strategies in order to maximise charging station profit. Meanwhile, other studies use decentralised multi-agent formulations, where each EV is modelled as an independent agent learning its own charging policy (Guo and Xu, 2022), or where each charging port is treated as an agent controlling connected vehicles (Jin et al., 2022). Compared with classical optimisation approaches such as linear programming, these optimisation-oriented RL models are better suited to handling the nonlinearity and stochasticity inherent in EV charging activities (Michailidis, Michailidis and Kosmatopoulos, 2025). Nevertheless, within these formulations, individual drivers are primarily treated as controllable resources or sources of uncertainty to be managed, rather than as private EV drivers with autonomous decision-making.

A smaller body of research has shifted RL applications from system-level optimal objectives towards optimising charging strategies for individual private EV drivers. In contrast to system-level optimisation, agents in these models act independently and do not coordinate or share experiences with one another in a timely manner. The objective of each agent is to identify an optimal sequence of charging and routing choices that minimises travel time (K.-B. Lee et al., 2020), reduces energy consumption (Aljohani and Mohammed, 2022), lowers charging costs (Wang et al., 2020), or alleviates driver anxiety (Yan et al., 2021). Such models are particularly relevant for the development of online decision-support tools that recommend charging and routing strategies to EV drivers. For example, Dorokhova et al. (2021) developed an RL framework to generate energy feasible

paths for EV drivers between origins and destinations. However, despite shifting the decision-making role from system operators to drivers, these studies remain optimisation-oriented, with drivers learning strategies that maximise utility rather than reproducing how drivers with learning ability and bounded rationality actually behave in everyday contexts.

More broadly, agent-based RL has predominantly been used to prescribe what drivers should do rather than to describe what drivers actually do. Although RL is well suited to representing adaptive learning under uncertainty, its application to modelling realistic charging behaviour of private EV drivers remains limited. In the wider transportation literature, RL has been used to simulate traveller learning processes in which agents adapt decisions based on experienced outcomes rather than solving for globally optimal strategies. For example, Wei et al. (2014) demonstrated that RL provides an effective framework for modelling day-to-day route choice under bounded rationality and limited memory. More recently, Zhao & Liang (2023) proposed an RL framework that captures the nonlinear and stochastic preferences of human drivers in route choice. Choi et al. (2021) applied RL to learn from observed trajectory data and generate realistic vehicle movements. Despite these advances in modelling adaptive routing behaviour, the application of agent-based RL to simulate EV charging decisions under bounded rationality and real-world uncertainty remains underexplored. This gap highlights the need for agent-based RL frameworks that explicitly represent how EV drivers learn, adapt, and make charging decisions under uncertainty and bounded rationality.

3.5 Summary

EV driver behaviour is shaped by a complex interplay of the built environment, social interactions, and cognitive factors. An appropriate methodological framework for modelling EV driving and charging systems must therefore be capable of representing heterogeneous preferences and choices, capturing adaptive behaviour and bounded rationality, and accounting for complex interactions with the environment and other drivers. These requirements place EV driver modelling within the broader challenge of modelling complex systems.

This chapter has reviewed existing methodologies for modelling EV driver behaviour and identified their key limitations. Section 3.2 reviewed statistical and analytical methods for modelling EV drivers and highlighted their limited ability to represent individual decision-

making processes and interactions. Section 3.3 then reviewed computational modelling approaches that seek to address these limitations. While discrete event simulation provides a detailed representation of driving and charging events, it adopts a process-oriented, top-down perspective in which individual entities remain largely passive. Rule-based ABMs offer a more suitable framework for simulating private EV drivers as autonomous and proactive decision-makers whose interactions generate emergent system-level outcomes. However, a key limitation of rule-based agents lies in their limited capacity to represent the adaptive and cognitive complexity of human behaviour.

ML approaches, particularly RL, provide a promising pathway to address this behavioural modelling challenge. As reviewed in Section 3.4, ML techniques can be integrated with ABMs to improve agent adaptability. The review further highlighted that the application of agent-based RL to simulate EV charging decisions under bounded rationality and real-world uncertainty remains underexplored. Consequently, there is a need for agent-based RL frameworks that explicitly represent how EV drivers learn, adapt, and make charging decisions under real-world uncertainty and bounded rationality. The research gaps discussed in this chapter provide a foundation for the models in Chapters 5 and 6.

Chapter 4

Exploring the Factors Associated with Public Charger Usage in Great Britain¹

Preface

Understanding the usage patterns of public chargers can provide an important context for modelling how EV drivers interact with charging infrastructure. Chapter 2 reviewed the literature on EV driver behaviour and discussed the critical role of public charging infrastructure in shaping these behaviours. To establish an empirical foundation for the subsequent modelling work, this chapter analyses charging session data from public EV chargers across three key urban areas in Great Britain (GB).

Specifically, this chapter explores the usage patterns of existing public chargers and the factors associated with them. Section 4.1 introduces the background and the research objective of this chapter. Section 4.2 reviews previous literature on public charger usage patterns and their associated factors. Section 4.3 introduces the three case study regions – Greater London, Greater Manchester, and the Central Belt of Scotland – and presents an exploratory analysis of the charging session dataset. Section 4.4 outlines the spatial regression methodology used to analyse the relationships between charger usage and contextual factors. Section 4.5 presents the regression results, showing how charger type, motorway proximity, day types, and residential property characteristics are associated with usage patterns. Section 4.6 discusses the contributions of this chapter and the implications for region-specific infrastructure planning. Section 4.7 concludes by summarising the key findings and policy implications.

¹ This chapter is based on paper Feng, Z., Zhao, Q., & Heppenstall, A. (2026). Exploring the influencing factors of public electric vehicle charger usage in Great Britain. *Journal of Transport Geography*, 134, 104667.

4.1 Introduction

The electrification of global road transport is expected to significantly reduce emissions in the coming decades (International Energy Agency, 2024). Effective infrastructure planning and the provision of cost-effective charging systems are key to promoting EV adoption. While home chargers offer a convenient daily charging solution for EV drivers, not everyone lives in a property suitable for installing one. Currently, the UK has one of the highest reported shares of home charging access, with 93% of EV owners able to charge at home, though this high percentage is largely attributed to the fact that early EV adopters tend to be homeowners who can install chargers on their own properties (International Energy Agency, 2024). To address this challenge and ensure sufficient provision of charging infrastructures, the UK government has launched a £381 million Local Electric Vehicle Infrastructure Fund to support local authorities in accelerating the rollout of EV charge points (Department for Transport, 2024d). Nevertheless, to effectively invest in future charging infrastructure, it is important to gain a deeper understanding of the usage patterns of existing public charging stations.

Based on charging profiles of individual drivers, most previous studies have focused on how the characteristics of vehicles and socio-demographic features of drivers influence preferences for public chargers and affect charger choices (Helmus, Lees and Van Den Hoed, 2020; J. H. Lee et al., 2020; Siddique et al., 2022; Li et al., 2023). However, charging session data from individual vehicles may not cover all geographical areas, times of day, or user types, potentially introducing spatial, temporal, and user-representativeness biases when analysing public charger usage patterns. With the improved availability of charging session data of public chargers, more recent studies have started to explore how different factors shape the usage rates of public chargers in various contexts, including the United States (J. H. Lee et al., 2020; Siddique et al., 2022; Borlaug et al., 2023), Canada (Jonas, Daniels and Macht, 2023), Netherlands (Helmus, Lees and Van Den Hoed, 2020), Germany (Mortimer et al., 2022), and China (Li et al., 2023). However, there are few studies studying public charger use in the UK. One notable recent study found focusing on the public charger usage patterns in the UK is that by Bayram et al. (2023). Their study looked at a sample size of 270 charger points. However, as of 1 April, 2024, there were 59,670 public electric vehicle charging devices available in the UK (Department for

Transport, 2024a). Given this vast expansion, further research is needed to provide updated findings of the current UK public charging network landscape.

Additionally, a notable research gap remains: there is a lack of comparative studies across different cities and regions. Research has shown that charging station utilisation is not generalisable, as charging behaviour varies significantly across different urban contexts (Jonas and Macht, 2024). Previous studies have primarily explored influencing factors within a single geographical context, either a region or a city (Helmus, Lees and Van Den Hoed, 2020; Bayram et al., 2023). A comparative analysis is therefore needed to provide insights for developing targeted charging infrastructure strategies suited to different urban environments

The overarching goal of this chapter is to provide insights into the public charger usage patterns and key factors influencing them in major regions in GB. In this study, charger usage refers to the usage rate of public EV charging stations, defined as the proportion of time each charger is occupied by a user during defined timeslots: daytime (06:00–20:00) and nighttime (20:00–06:00). We conducted a comparative analysis of three case study areas: Greater London, Greater Manchester, and the Central Belt of Scotland, which spans from Glasgow to Stirling and Edinburgh and contains around 2.61 million people (National Records of Scotland, 2023). Using charging session data from the public charging stations, we applied spatial regression models to explore the relationships among charging station usage rates, charger characteristics (i.e. charger type), and contextual driving factors across space and time. The final research outcomes aim to provide a deeper understanding of public EV charger usage in GB before modelling EV driver behaviours.

4.2 Background

4.2.1 Empirical studies on public charger usage

Many studies have explored how the characteristics of vehicles and socio-demographic features of drivers influence public charger usage patterns based on charging profiles of individual drivers. Key factors considered include drivers' age, gender, household income, education level, risk-averse attitude, vehicle battery size, and vehicle type (Helmus, Lees and Van Den Hoed, 2020; J. H. Lee et al., 2020; Li et al., 2023). However, one limitation of using charging profiles from a group of individual vehicles is that the travel diaries of

these groups may not cover all geographical areas or times of day. This can introduce spatial and temporal biases when analysing public charger usage patterns in specific regions. Additionally, the representativeness of charging session data from certain EV fleets is questionable. The data used in existing research may not accurately reflect the behaviours of all public charger users, including drivers of private vehicles, ride-hailing vehicles, company vans, and commercial trucks.

With improved availability of charging session data of public chargers, more recent studies have started to explore how different factors shape the usage rates of public chargers in various contexts, including the United States (J. H. Lee et al., 2020; Siddique et al., 2022; Borlaug et al., 2023), Canada (Jonas, Daniels and Macht, 2023), Netherlands (Helmus, Lees and Van Den Hoed, 2020), Germany (Mortimer et al., 2022), and China (Li et al., 2023). One group of studies applied cluster analysis to explore different types of charging sessions based on factors such as their usage durations and usage time (Bayram et al., 2023; Helmus and Wolbertus, 2023). Another group of studies uses linear or logistic regression models to explore different determinants of public charger usage (Siddique et al., 2022; Borlaug et al., 2023; Zhao et al., 2024). While these studies identify important determinants, they do not account for the spatial structure of public charger networks in their modelling frameworks. The studies by Hamim et al. (2026) and Liu et al. (2024) took a step further by applying geographically weighted regression models to capture spatially varying relationships between different determinants and public charger usage. However, geographically weighted regression focuses on spatial heterogeneity in model coefficients rather than the spatial interaction between chargers themselves. The models cannot account for the spatial dependence that may exist among geographically proximate chargers. In practice, the usage of a public charger is likely influenced by nearby chargers. For example, when a charger is occupied, drivers may divert to an alternative charger nearby, redistributing the demand across neighbouring chargers. As a result, spatial econometric models that explicitly account for the dependence between neighbouring chargers are needed to provide a more complete understanding of how different factors shape public charger usage.

4.2.2 Determinants of public charger usage

The determinants of public charger usage can be categorised into three main groups: charger characteristics, temporal factors, and environmental factors. For charger

characteristics, studies have found that there is a preference for semi-fast (22-43kW) or fast (50 kW or above) chargers compared with the slow ones due to drivers' concern with charging efficiency and risk-averse attitude (Xu et al., 2017; Anderson, Lehne and Hardinghaus, 2018). Charging costs also play an important role in determining charging demand, with lower-cost chargers generally attract more drivers (ten Have, Gkiotsalitis and Geurs, 2020). Additionally, pricing schemes—including home electricity rates and workplace charging fees—can influence charger selection at different locations (Chakraborty et al., 2019; Visaria et al., 2022). The convenience of charging stations is another critical factor. Stations with a higher likelihood of charger availability and additional facilities, such as restrooms, restaurants, and Wi-Fi, tend to attract more users (Ge and MacKenzie, 2022; Visaria et al., 2022). Additionally, payment methods can influence station usage. Card-based payment systems are more user-friendly than web-based methods, making them more accessible to a wider range of users of all ages and potentially increasing station usage (Gutjar and Kowald, 2023). For temporal factors, public charger usage varies by time of day and weekdays and weekends/holidays. As noted by Song and Potoglou (2025), these variations are influenced by drivers' schedules. Regular public charger users tend to charge more on weekdays, particularly during peak working hours (Kim et al., 2017; Gellrich, Block and Leikert-Böhm, 2022). Regarding environmental factors, the location of a charger can influence its usage. Proximity to motorways, major transit routes, or their exits can attract more usage from drivers on long-distance trips (Anderson, Lehne and Hardinghaus, 2018; Ge and MacKenzie, 2022; Gellrich, Block and Leikert-Böhm, 2022). The surrounding location types also impact the usage of charging stations. For example, a slow charger located next to shopping areas has a higher usage rate compared to those in other areas (ten Have, Gkiotsalitis and Geurs, 2020). Additionally, Sheldon et al. (2019) quantified the willingness to pay for access to specific charging stations, finding that workplace chargers have a higher willingness to pay compared to those near motorways, homes, and grocery stores.

Despite the extensive consideration of the factors discussed above, one of the least explored factors is the residential property type around public chargers. Residents of high-rise apartment buildings do not have the same level of access to home charging as those living in houses. Therefore, they tend to rely more on public charging stations (Chakraborty et al., 2019; Visaria et al., 2022; Xu et al., 2017). While the property type has been acknowledged as a key factor affecting the charging choices of EV drivers, the specific impact of surrounding property types on the usage of public chargers remains

underexplored. It is important to determine whether the usage of the charger is driven by the daily needs of nearby residents or by enroute drivers. This distinction can inform pricing strategies and improve demand estimation for future public charging infrastructure.

4.3 Study area and data

In this analysis, Greater London, Greater Manchester, and the Central Belt of Scotland were selected as case study areas. These regions represent diverse urban contexts in the UK, each with different levels of charging infrastructure development. Greater London is a major metropolitan area with 8.95 million population (Mayor of London, 2023) and has an extensive public charger network. Greater Manchester is located in the north of England and is highly urbanised, with a population of 2.87 million (Greater Manchester Combined Authority, 2023). It has the most densely distributed public charging network outside London in our dataset. Due to the limited number of public charger data available in Glasgow and Edinburgh, the Central Belt area spanning from Glasgow to Stirling and Edinburgh – was selected to represent the public charger usage patterns in Scotland. This region has the majority of the Scottish population, with 2.61 million people in the area (National Records of Scotland, 2023). It is a well-connected economic corridor with substantial commuter traffic between Glasgow, Edinburgh, Stirling, and the surrounding areas. This makes it a suitable case for analysing regional charging infrastructure and usage dynamics.

4.3.1 Charging session data of public EV chargers

The charging session data were scraped from the ChargePoint website (ChargePoint, 2023) every 15 minutes (at 0, 15, 30, and 45 minutes past each hour) from December 6, 2023, to March 31, 2024. ChargePoint is an EV charging infrastructure platform that aggregates public charger information from multiple public charger providers across North America and Europe. It should be noted that many other EV charging network providers are not included in the dataset, especially for those EV charging networks operated by local councils. The chargers in the dataset represent 23.56% of the total public chargers in Greater London, 40.85% in Greater Manchester, and 15.62% in the Central Belt of Scotland. A completeness and representation analysis of the scraped data is provided in Appendix A. A full list of EV charging station network providers in ChargePoint is

presented in Table A1. Although the scraped charger datasets cannot represent all the EV chargers in the three regions and may introduce some potential bias in the analysis, this is by far the best data we can obtain for this type of analysis across the UK.

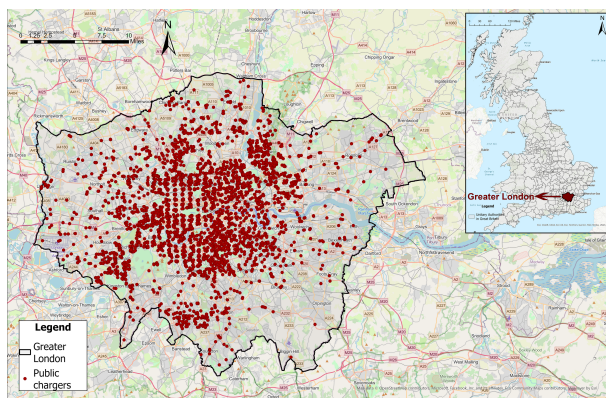
The dataset includes 17,114 chargers with a total of 25,923 ports in GB. On average, each charger has 1.51 charging ports. A summary of the public charger information is shown in Table 4.1. While using web scraping to gather the availability status and other details of public chargers, we ensured that our activities were restricted to publicly accessible information and conducted solely for non-commercial academic research purposes. Our scraping process strictly adhered to the web scraping policy by the Office for National Statistics (Office for National Statistics, 2020) and complied with UK copyright law, which permits lawful access to material for non-commercial academic research (Intellectual Property Office, 2021).

The spatial distribution of the public chargers across the three case study regions are shown in Figure 4.1. Among the three regions, London has the highest density of public charging stations in our dataset. The Central Belt of Scotland features a relatively dense distribution of chargers within Glasgow and Edinburgh, while chargers in other areas are more sparsely distributed.

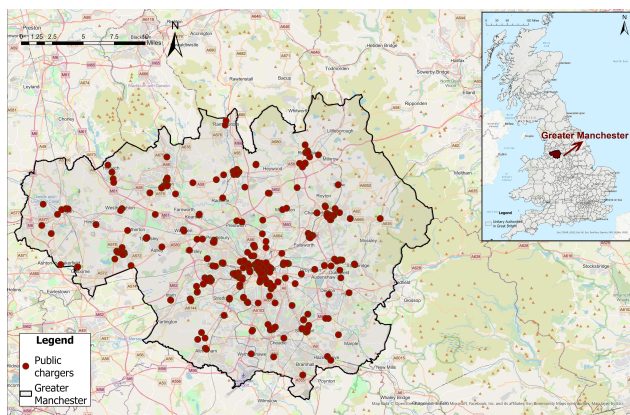
Table 4.1 Public charger attributes.

Name	Definition	Value range
Charger ID	Unique identifier for each charger.	-
Port number	The number of charging ports at each charger.	1.0-12.0
Location	The geographic coordinates (latitude and longitude) of the charger.	-
Price (£/KWh)	The cost of electricity per kilowatt-hour for charging.	0.3-1.1
Speed (KW)	The charging speed of the charger in kilowatts.	6.4-300.2
Initial parking fee (£)	The parking fee for the first hour during charging.	0.0-0.6
Additional parking fee (£/h)	The parking fee for each additional hour during the charging session.	1.2-24.0
Availability	The status of the charger, including 'In Use', 'Available', and 'Closed'.	-

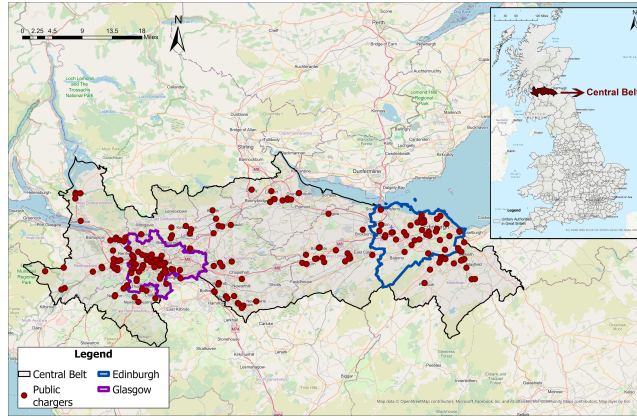
Figure 4.2 shows the changes in public charger usage ratios in the Greater London, Greater Manchester, and Central Belt of Scotland during a sampled week in December 2023. The usage ratio is calculated as the percentage of occupied chargers relative to the total number of chargers in each region. Additional sample weeks are provided in Appendix B. Greater Manchester and the Central Belt of Scotland have peak public charger usage during the daytime hours, particularly between 11:00 and 13:00, while usage rates remain relatively low at night, from 20:00 to 6:00. In contrast, Greater London has a unique pattern, with higher charger usage rates at night and lower rates during the day.



(a) Distribution of public chargers in Greater London (3996 chargers).

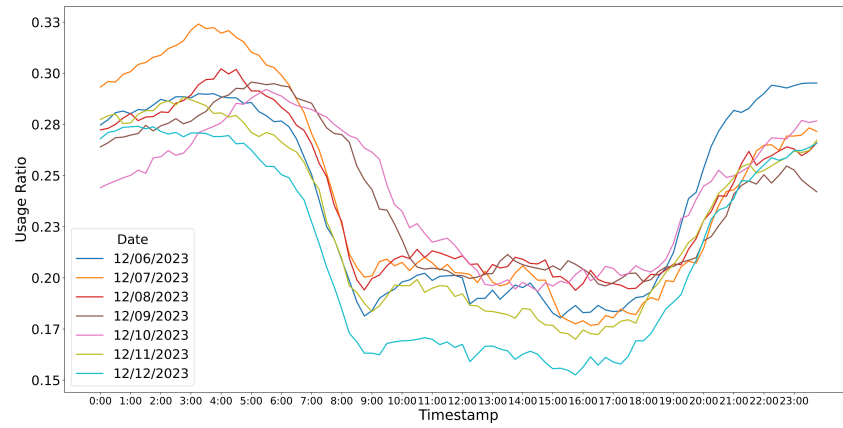


(b) Distribution of public chargers in Greater Manchester (317 chargers).

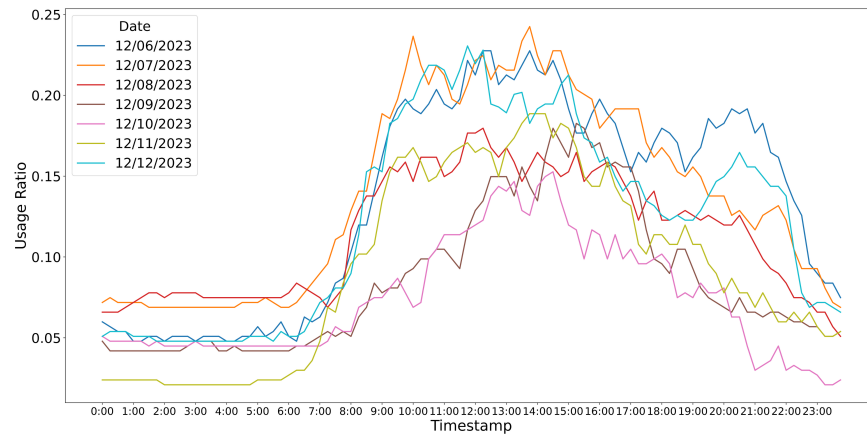


(c) Distribution of public chargers in the Central Belt of Scotland (253 chargers).

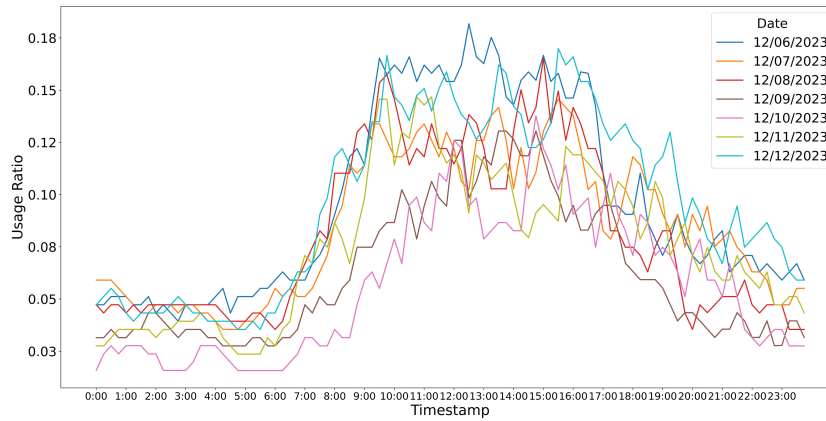
Figure 4.1 Public charger distributions in the case study areas.



(a) Usage rate of public chargers in Greater London.



(b) Usage rate of public chargers in Greater Manchester.



(c) Usage rate of public chargers in Central Belt of Scotland.

Figure 4.2 Usage ratio of public chargers for three regions from 6th Dec to 12th Dec 2023.

4.3.2 Data for influencing factors of public charger usage rate

Based on the literature review in Section 4.2, seven factors representing the characteristics of charging stations and their contextual situations are selected as independent variables in the regression models. Table 4.2 details each variable along with its data source and the corresponding literature.

Table 4.2 Explanatory variables.

Variable Name	Data Source	Description	References
Charger type	ChargePoint (2023)	Dummy variable of charger type: 1 for DC (Direct Current) Fast, 0 for AC (Alternating Current) Slow.	(Xu et al., 2017; Anderson, Lehne and Hardinghaus, 2018; ten Have, Gkiotsalitis and Geurs, 2020)
Day type		Dummy variables for different types of day: weekdays (reference), weekends, and public holidays.	(Kim et al., 2017; Xu et al., 2017)
Timeslot		Dummy variable for two timeslots over a day: 1 for 20:00-06:00, 0 for 06:00-20:00	(Gellrich, Block and Leikert-Böhm, 2022; Ma, Yi and Fan, 2022)
Area of flats	UK building classes (The	Areas of residential flats within a 500-meter buffer zone around each charging station.	(Chakraborty et al., 2019; Visaria et al., 2022; Xu et al., 2017)

Area of terraces	GeoInformation Group, 2020)	Areas of residential terraces within a 500-meter buffer zone around each charging station.	
Area of detached and semi-detached houses		Areas of residential semi-detached and detached houses within a 500-meter buffer zone around each charging station.	
Proximity to motorway	OS Open Roads (Ordnance Survey, 2023b)	Dummy variable indicating if the charger is within the 250-meter buffer zone of motorways based on Euclidean distance.	(Anderson, Lehne and Hardinghaus, 2018; Ge and MacKenzie, 2022)

In our model, the dependent variable is the usage rate of public charging stations, which reflects the proportion of time each charger is actively in use by a user. To capture daily variation, we divide each day into two timeslots: daytime (06:00–20:00) and nighttime (20:00–06:00). For each charger and each timeslot, we calculate the usage rate as the total time the charger is marked as ‘In use’ divided by the total operation duration of the timeslot, excluding periods when the charger is ‘Closed’. These usage rates are then grouped by day type (weekday, weekend, or holiday) and timeslot, and averaged across the entire four-month observation period. This results in a representative average usage rate for each charger under each combination of day type and time period. A natural log transformation was applied to address the right-skewed distribution of the original usage rates.

For the independent variables, we first consider variables of day type and time of day to explore the impact of temporal factors on charger usage. The dataset spans from early December 2023 to the late March 2024 and includes major holidays (Christmas and New Year) in the country. We assume that charger usage patterns during longer holidays may differ from those on regular weekends. Based on this, the day type variable is categorised into weekdays, weekends, and public holidays. Each day is further divided into daytime (06:00–20:00) and nighttime (20:00–06:00) periods to represent the onset of morning traffic at 6 am and the conclusion of most evening return trips at 8 pm. These temporal

boundaries also align well with the observed transitions in charging demand as shown in Figure 4.2.

The charger type is selected as a key feature of chargers that may influence charger usage rate. While charging speed and price are also expected to affect charger usage rates, they are removed from our model due to their high Variance Inflation Factor (VIF) values when included in the regression model. Details supporting this are included in Appendix C. The initial-hour parking fee and the additional parking fee are also not considered given the high proportion of missing values in the dataset.

To explore how different residential property types influence public charger usage, we consider the areas of residential flats, semi-detached and detached houses (houses), and terraces within a 500-meter buffer zone around each charger. The choice of a 500-meter buffer zone is consistent with previous studies on public charger usage, where it is commonly used as a boundary to represent the built environment surrounding public chargers (Guo et al., 2022; Wolbertus, 2024; Zhao et al., 2024; Zheng et al., 2024). We use the UK building classes dataset (The GeoInformation Group, 2020) to classify the residential property types. While this dataset is relatively dated compared to the study period (2023-2024), it remains the most detailed available source that specifies residential property types. We therefore assume minimal changes in the distribution of the residential property types within our case study areas. The specific reclassification methods are detailed in Appendix C. In the UK, residents of flats or apartments typically lack access to private parking spaces for installing home chargers and may rely on on-street parking. In contrast, residents of houses generally have access to garages or other off-street parking, making home charger installation more feasible (Senior, Webster and Blank, 2006; RAC Foundation, 2012). The situation for terrace houses is more varied. Some residential terraces have driveways or garages, while others rely on on-street parking similar to flat residents.

Proximity to the motorway is also considered a key factor influencing public charger usage. We assume that chargers near motorways may experience different usage patterns compared to other locations, as they are more likely to be used by drivers on long-distance trips. To capture this effect, we created 250-meter buffer zones around motorways based on Euclidean distance. The chargers are then categorised as either within or outside these buffer zones. The 250-meter threshold was chosen to align with previous studies that use

this distance to define public chargers located near motorways (Anderson, Lehne and Hardinghaus, 2018).

Table 4.3 shows summary statistics for the dependent variables and numerical independent variables. As shown in the table, London has the highest average public charger usage rate and greatest variability compared to the other two regions. Across all regions, there are periods of both zero and full charger usage. Additionally, London has the highest average area of flats, houses, and terraces within the 500-meter buffer zones of chargers, which indicates a denser distribution of residential properties around chargers in London. Due to the right-skewed distributions of these area variables, we apply natural log transformations to normalise their distributions in our regression model.

Figure 4.3 shows the summary distribution of the motorway proximity and charger type variables. Most of the chargers are located outside of the 250-meter motorway buffers. Compared with London and Manchester, the Central Belt of Scotland has the highest percentage of chargers located near motorways. In Greater London and Greater Manchester, the number of AC slow chargers is higher than that of DC fast chargers. In contrast, in the Central Belt of Scotland, the number of DC fast chargers slightly exceeds the number of AC slow chargers.

Table 4.3 Summary statistics of dependent variable and numerical independent variables (before log-transformation).

	Mean			Range			Std		
	London	Manchester	Central Belt	London	Manchester	Central Belt	London	Manchester	Central Belt
Public charger usage rate	0.17	0.08	0.06	0.0-1.0	0.0-1.0	0.0-1.0	0.21	0.11	0.11
Building area of houses (km ²)	0.036	0.019	0.014	0.0-0.15	0.0-0.08	0.0-0.07	0.03	0.02	0.02
Building area of flats (km ²)	0.019	0.003	0.006	0.0-0.10	0.0-0.02	0.0-0.06	0.02	0.01	0.01
Building area of	0.059	0.005	0.003	0.0-0.30	0.0-0.05	0.0-0.03	0.05	0.01	0.01

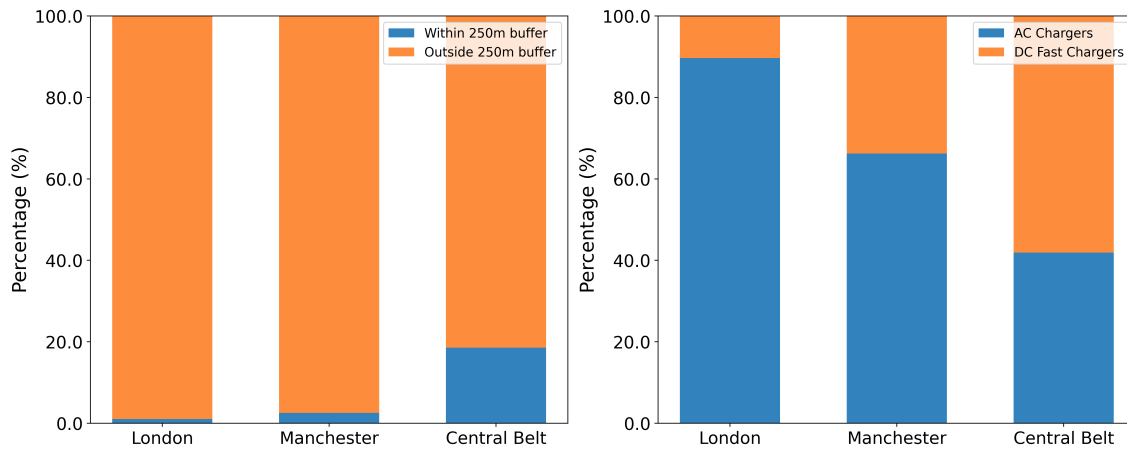


Figure 4.3 Distribution of motorway proximity and charger type variables.

4.4 Methods

In this research, we use spatial econometric models to explore the relationships between public charger usage rates and the influencing factors. Dependent variable (public charger usage rate) and three numerical independent variables (building areas of houses, of flats, and terraces) were log-transformed, with a small constant (0.0001) added to handle zero values during the log transformation. As the zero-value observations are determined by the choice of constant rather than a true empirical measurement, the model parameters and statistical inference can be affected (Ekwaru and Veugelers, 2018).

We first estimate a standard linear regression model. As shown in Equation (4-1), in a linear regression model, Y is the dependent variable, which in our case, is the public charger usage rate. X represents the independent variables. ϵ is the vector of random errors. The error terms and independent variables in a linear regression model is assumed independent of each other (Montgomery, Peck and Vining, 2021).

$$Y = \beta X + \epsilon \quad (4-1)$$

However, public charger usage rates are likely to show spatial dependence. The usage rate of a particular charger may be influenced by both the characteristics and usage rates of surrounding chargers. Through public charger websites and apps, EV drivers can access

real-time information about the availability and attributes of nearby chargers. Studies have shown that although station users are assumed to be queueing-averse, they prefer waiting at a nearby charging station to traveling a longer distance to avoid charging queues (Huang and Kockelman, 2020). As a result, they can choose among neighbouring options and reroute to an alternative charger in cases of congestion. Therefore, the observations and error terms in the linear regression model are less likely to be independent. Given this, we construct spatial weight matrix W using a fixed distance criterion, and use the Global Moran's I to examine spatial autocorrelation of the residuals and if spatial models are needed (Getis, 1995):

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} z_i z_j}{S_0 \sum_{i=1}^n z_i^2} \quad (4-2)$$

The specific methods of developing and selecting the fixed distance of W is detailed in Appendix D. w_{ij} is the elements of the W . S_0 is the sum of all the weights, and z_i is the deviation of an attribute for feature i from its mean.

We follow the model selection procedure outlined by Elhorst (2010). We first applied Lagrange Multiplier (LM) tests to determine the specific type of spatial autocorrelation (Anselin, 1988; LeSage and Pace, 2009). The results can indicate whether to include a spatially autocorrelated error term or a spatially lagged dependent variable. If both LM lag and error tests are significant, robust LM tests are further applied to determine the type of spatial models to be used. If both robust LM tests are also significant, this suggests a complex spatial dependence structure that cannot be fully captured by either a spatial lag or spatial error model alone. In this case, the Spatial Durbin Model (SDM) should be estimated. Likelihood Ratio (LR) tests are then conducted to formally test whether the SDM can be simplified to a spatial error model (SEM) or a spatial lag model (SLM).

Based on the test results, we distinguish the specific spatial term(s) to include and select the most suitable model among spatial error model (SEM) (Equation (4-3) and (4-4)), the spatial autoregressive model (SAR) (Equation (4-5)), or Spatial Durbin Model (SDM) (Equation (4-6)). A SEM accounts for spatial dependence in the error terms. It assumes that the error terms across different spatial units are correlated. A SAR, also known as

spatial lag model (SLM), assumes autocorrelation is present in the dependent variable, and that the value of the dependent variable in one location is influenced by the values of the same variable in neighbouring locations. A SDM combines the characteristics of SLM and SEM and assumes autocorrelation may be present in both independent and the dependent variables.

Accordingly, in the equations, y is the dependent variable and X is the independent variables. W is the selected spatial weight matrix reflecting the spatial interactions. $W\mu$ is the spatially lagged error term. Wy is the spatial lag of the dependent variable. WX is the spatial lags of independent variables.

$$y = X\beta + \mu \quad (4-3)$$

$$\mu = \lambda W\mu + \varepsilon \quad (4-4)$$

$$y = \rho Wy + X\beta + \varepsilon \quad (4-5)$$

$$y = \rho Wy + X\beta + WX\theta + \varepsilon \quad (4-6)$$

4.5 Results

We first use the global Moran's I test to identify potential spatial autocorrelation in the residuals of the linear regression model. The results of linear regression model are included in Appendix C. As shown in Table 4.4, the statistically significant and above 0.3 global Moran's I values for Greater London, Greater Manchester, and the Central Belt of Scotland indicate spatial autocorrelation in these regions. Spatial regression models are therefore necessary to account for these spatial dependencies.

Table 4.4 Global Moran's I test.

	Greater London	Greater Manchester	Central Belt
Moran's I	0.38***	0.24***	0.59***

P-value: Level of statistical significance, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.5 Diagnostics for Spatial Dependence.

	Greater London	Greater Manchester	Central Belt of Scotland
Lagrange Multiplier (lag)	782.43***	221.16***	549.18***
Robust LM (lag)	5.41**	4.82**	5.29**
Lagrange Multiplier (error)	963.49***	317.12***	587.12***
Robust LM (error)	186.47***	100.78***	43.24***
LR value	577.51***	131.61***	481.65***

P-value: Level of statistical significance, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

After identifying statistically significant spatial autocorrelation, we apply LM tests to determine whether the spatial dependence in the data is better captured by including a spatial lag term or a spatial error term. Since both LM tests have significant results, we then use robust LM tests to further decide between the two terms. As shown in Table 4.5, all LM and robust LM tests show significant results, while Robust LM error test has higher significance levels and values than the Robust LM lag test. To further determine whether a SDM provides a better fit than a SEM, we conduct likelihood ratio (LR) tests as the final step of model selection (LeSage and Pace, 2009). The LR test results, presented in Table 4.5, show significant p-values (< 0.01) for all three regions, indicating that the SDM best fits the data and cannot be simplified. As a result, SDMs are developed separately for the three case study regions. The regression results are shown in Table 4.6.

Table 4.6 SDM Regression Results.

	Greater London	Greater Manchester	Central Belt of Scotland
Constant	0.087***	0.120***	0.066***
Charger type (reference: AC Slow)	0.059***	-0.008	0.010**
Binary motorway proximity: 1 if within buffer	-0.064***	0.020	0.017**
Time_20:00-06:00 (reference: 06:00-20:00)	-0.053***	-0.035***	-0.058***
Log(Area of terraces)		-0.002***	-0.003***
Log(Area of flats)	0.003***	0.003***	0.002***
Log(Area of houses)	0.001*	-0.001**	0.003***
Day Type: holidays (reference: weekdays)	-0.015***	-0.035***	-0.032***
Day type: weekends (reference: weekdays)	0.004*	-0.013**	-0.023***
Time_20:00-06:00* Log(Area of flats)	0.008***	-0.000	0.001

Charger type: DC Fast* Motorway	0.075***	0.027	0.024***
proximity			

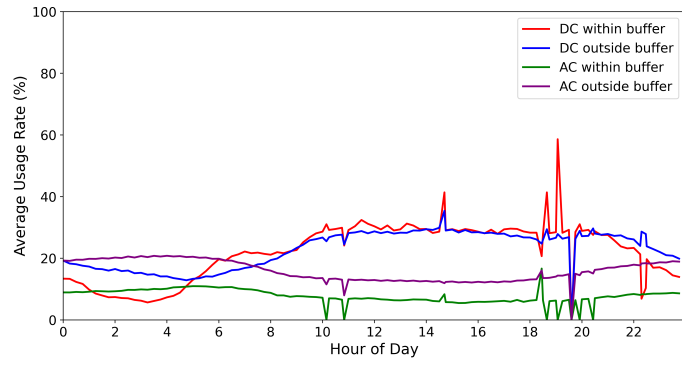
* P-value: Level of statistical significance, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

* The constant and spatial autoregressive parameter ρ are reported as model parameters, and total impacts are reported for all other variables. The full decomposition of direct, indirect, and total impacts alongside raw coefficients is provided in Appendix C.

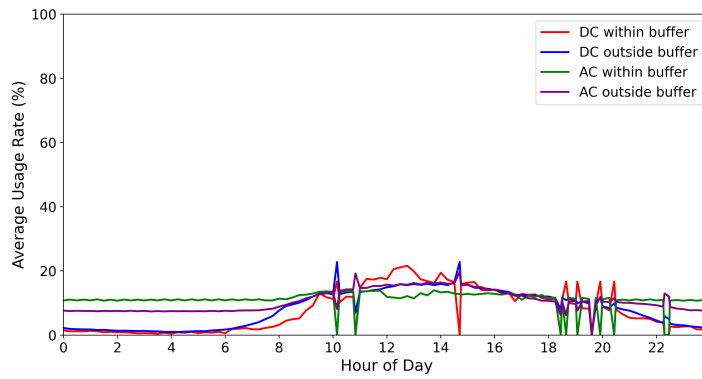
It should be noted that although terrace housing is an important component of UK's residential landscape, the 'area of terraces' variable is excluded from the London model due to its high collinearity brought to the model ($VIF = 28.38$). This exclusion from the London model does not compromise our analysis since we do not directly compare coefficient magnitudes across the three regional models.

Charger type and proximity to motorways

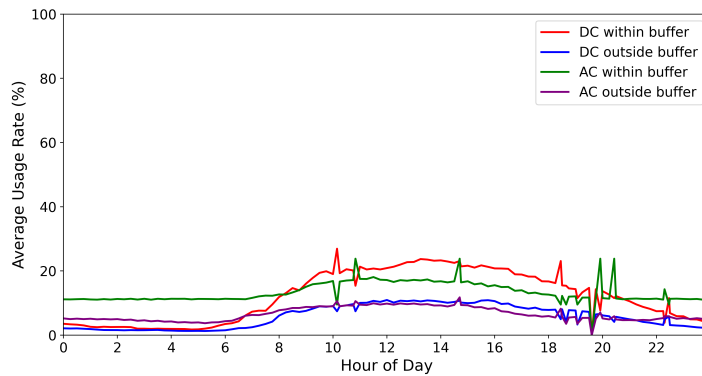
In Greater London, DC fast chargers show about 6.1% (calculated as $e^{0.059} - 1$) higher usage rates than AC slow chargers when located outside of motorway buffer zones, while being within motorway buffer zones adds an extra 7.8% (calculated as $e^{0.075} - 1$) increase in usage rates. To better illustrate the usage patterns, we plot the average usage rate (%) of chargers grouped into four categories based on charger type (DC or AC) and their proximity to motorways (within or outside the motorway buffer zones) (Figure 4.4). The usage rate for each group at each timestamp is calculated as the number of chargers in use divided by the total number of chargers. The averages are then calculated across all timestamps over the four-month period. As shown in Figure 4.4 (a), drivers in Greater London primarily use DC chargers during active travel hours from 8:00 to 22:00, regardless of their proximity to motorways. The usage of AC slow chargers outside of buffer zones only exceed DC ones during nighttime hours. This pattern is likely driven by higher parking fees and more intensive travel schedules caused by congestion in Greater London, making fast chargers a more time-efficient and cost-effective option for drivers in the region.



(a) Greater London (3996 chargers).



(b) Greater Manchester (317 chargers).



(c) Central Belt of Scotland (253 chargers).

Figure 4.4 Distribution of charger usage rates by charger type and motorway proximity.

For Greater Manchester, the regression shows no significant differences in usage rates between charger types or motorway proximity. This is mostly consistent with the pattern shown in Figure 4.4 (b), where all four categories show similar charger usage rates between 10 am and 8 pm. However, the figure also shows that, during nighttime hours, AC chargers have higher usage rates than DC chargers. This pattern likely reflects local residents using AC chargers for overnight charging.

A different charger usage pattern can be found in the Central Belt of Scotland. Based on the regression results, DC chargers show 1% higher usage rates than AC chargers when located outside of motorway buffer zones. DC chargers within the motorway buffer zones can bring an additional 2.4% increase in usage rates. Figure 4.4 (c) provides additional information on the differences between AC and DC chargers within the motorway buffer zone. DC chargers within the motorway buffer zone show higher usage rates than other groups of chargers, particularly during daytime hours from 9 am to 6pm. Meanwhile, AC chargers within the buffer zone maintain consistently higher usage rates than those outside the buffer zone throughout the day. Nevertheless, regardless of charger type, chargers near motorways are more frequently used by drivers in this region, especially the fast chargers. This may be attributed to the high volume of long-distance daily commutes between major cities such as Glasgow and Edinburgh, with most trips concentrated along the motorways in this area.

Day types

To explore how temporal factors influence public charger usage rate across the three regions, we included day type dummy variables (weekday, weekend, and public holiday). The results show that, compared to weekdays, public charger usage decreases on holidays in all three regions. However, the impact of weekends on charger usage varies across regions. Compared to weekdays, London shows 0.4% increased charger usage rate on weekends, while Greater Manchester and the Central Belt of Scotland have 1.3% and 2.3% lower weekend usage rates, respectively. This may be attributed to two factors. A decreased weekend usage can be explained by the decreased usage of public chargers by fleet and company vehicles that primarily charge during weekday working hours (Skippon and Chappell, 2019). Meanwhile, the overall trip volume change on weekends also means a different number of EVs on the road and using public chargers. For example, as reported by Transport for London (2023), London has more private vehicle trips on weekends than weekdays, with a corresponding decrease in public transport use.

Since our dataset does not include user-specific information from EV drivers, we are unable to explore these differences further. However, the results still provide valuable insights into charging demand change across different day types and highlight the distinct charger usage pattern in London over weekends.

Timeslots and residential property types

As mentioned in Section 4.2, in this study, we pay particular attention to how residential property types and time of day influence public charger usage. Given that previous literature has extensively discussed that residents of flats often rely on public chargers for routine overnight charging (Chakraborty et al., 2019; Visaria et al., 2022; Xu et al., 2017), we included an interaction term between the nighttime hours 20:00-06:00 (reference: daytime hours 06:00-20:00) and flat areas to capture this relationship.

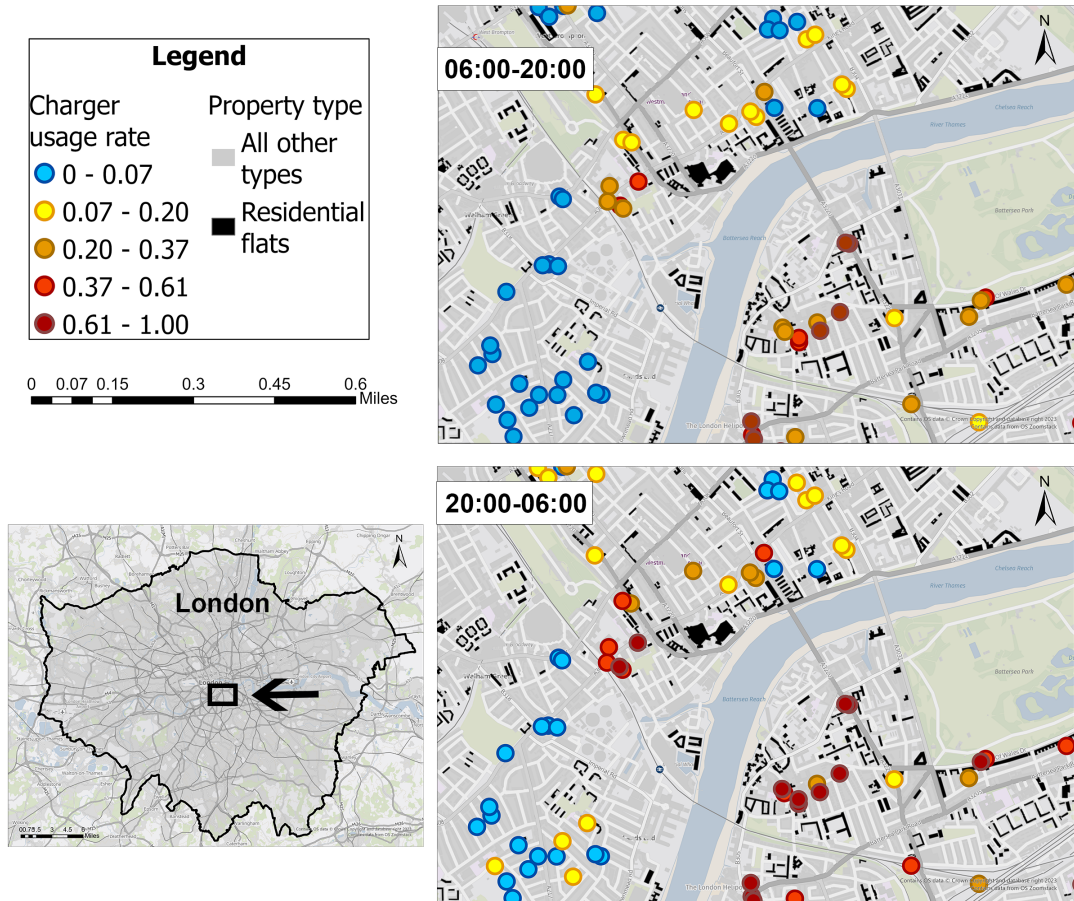


Figure 4.5 Distribution of flats around public chargers in London.

In Greater London, a 1% increase of house areas can lead to a minimal 0.001% increase of charger usage rates. Compared with the house areas, the results highlight a more important role of flat areas, although the impact is still minimal. During the daytime (06:00-20:00), a 1% increase of flats can induce 0.003% increase of charger usage rate. During the nighttime, there is an additional 0.008% increase of usage rate, bringing the total nighttime effect to 0.011%. While these effects are still minimal, they are notably higher than those observed for house areas. This enhanced effect can be attributed to the limited access to private parking space and private chargers for flat residents, which increases their reliance on on-street public chargers for charging, particularly overnight charging (Nazari, Mohammadian and

Stephens, 2019; Hsu and Fingerman, 2021). To further illustrate this pattern, we chose a sampled area in London and present its usage rate during active travel daytime and nighttime in Figure 4.5. It shows that chargers in areas densely surrounded by flats have higher usage rates at night compared to the daytime. This pattern may reflect both the limited daytime parking availability in London and the cost advantages of nighttime charging under dynamic pricing schemes.

In Greater Manchester, a 1% increase in the area of flats is associated with a 0.003% rise in usage rates. Similar to London, this suggests that residents of flats may rely more on nearby public chargers, though the effect remains minimal. Additionally, the influence of flat areas in Manchester shows no significant variation between daytime and nighttime usage. Houses and terraces in Greater Manchester show a smaller but opposite effect. A 1% increase in areas of terraces can lead to a 0.002% decrease in charger usage rates, while a 1% increase in areas of house can lead to a 0.001% decrease in usage rates. This negative relationship is likely because these property types are more feasible for home charger installation. Houses often include private parking spaces, which makes it easier to install home chargers. Although the availability of private driveways and garages varies across different types of terraces, the lower usage rates of public chargers suggest that Manchester's EV users in terraces are more likely to have access to private driveways or garages. This enables them to install home chargers and reduces their reliance on public charging infrastructure.

In the Central Belt of Scotland, a 1% increase in the area of flats is associated with a 0.003% rise in charger usage rates, and this relationship remains consistent across daytime and nighttime. An increase in the area of terraces is linked to a decrease in charger usage rates, suggesting that current EV adopters living in terraces may have better access to private home chargers. A notable factor to discuss in Central Belt of Scotland is the area of houses. Unlike in Manchester, both London and the Central Belt of Scotland show an increase in charger usage rates as the area of houses increases. This finding goes against the common expectation that residents in houses have a higher chance to install home charger and a lower reliance on public chargers. This might be because, while home chargers are generally feasible, their adoption remains low in the two areas, leading to continued reliance on nearby public chargers. As the area of houses increases, the number of residents and EVs also grows, resulting in higher public charger usage.

4.6 Discussion

Using charging session data and the spatial regression analysis, this paper explores the relationship between public charger usage and various influencing factors across three regions: Greater London, Greater Manchester, and Central Belt of Scotland. The findings reveal distinct public charger usage patterns in each area. The results emphasise that, beyond the total number of public chargers, it is important to implement region-specific strategies to develop a more sustainable charging network.

In Greater London, the regression results reveal that the effect of flat density on public charger usage is significantly stronger during nighttime hours than during the daytime. This daytime-nighttime difference in London likely reflects two reasons. First, the prevalence of flats and apartments in London limits the feasibility of home charger installations, leading many EV drivers to rely on nearby public chargers for routine overnight charging. Second, London's dynamic parking pricing may result in lower overnight parking fees, making nighttime charging more cost-effective and further concentrating demand during these hours. Additionally, EV drivers in London show a strong preference for fast chargers over slow ones, regardless of their proximity to motorways. This preference is likely influenced by the higher parking fees and the more intensive travel schedules caused by London's traffic congestion. Although fast chargers typically have higher charging fees, their quick turnaround time makes them a more time- and cost-efficient option for drivers in the city. In recent years, initiatives such as the On-street Residential Charge Point Scheme and the Go Ultra Low City Scheme have supported London boroughs in expanding on-street residential charging infrastructure (Office for Zero Emission Vehicles, 2024). Our analysis provides additional insights for these planning policies: while supporting the focus on residential charging, our results highlight the need for more public chargers near flats and apartment buildings compared to other residential areas. Additionally, we suggest that fast chargers should be strategically placed near high-traffic areas and along major routes to complement the planned slow chargers.

In Greater Manchester, drivers rely more on public chargers located in areas densely populated with flats, whereas areas with higher densities of houses or terraces show lower reliance on public chargers. As of 2024, the Manchester Electric Vehicle Charging Strategy highlights the importance of installing chargers in residential areas (Manchester City Council, 2024). Our findings extend this strategy by identifying specific residential patterns: in Greater Manchester, particular attention should be given to deploying chargers near flats. In

areas with more terraces, semi-detached and detached houses, charger deployment should be balanced with the existing availability of home charging options.

In the Central Belt of Scotland, there is notably high demand for chargers near motorways, likely driven by long-distance daily commutes along major motorways. According to Transport Scotland (2024), the majority of public EV charging infrastructure is concentrated in Scotland's urban areas, across the Central, and along the trunk road network. However, while chargers have been installed along motorways, our results suggest a need for additional charging points near motorways. There is particular higher demand for fast chargers to ensure quick turnaround time, reduce potential queueing times, and improve charging efficiency. Additionally, the updated Scotland EV Charging Network Implementation Plan (Transport Scotland, 2024) emphasises that the demand for public charging is directly influenced by the availability of other types of EV charging such as home charging. Our findings provide further insights into the extent and variability of this influence across different property types. In the Central Belt of Scotland, public charging demand is not limited to areas with flats; areas with houses, although typically suitable for home charger installation, also show significant demand for public charging. A similar pattern is observed in Greater London, where higher house density is also associated with greater public charger usage.

More importantly, these findings suggest that public charger deployment strategies should be tailored to distinct regional types characterised by urban form, housing composition, and commuting patterns. While this study focuses on three regions in Great Britain, the three case regions represent urban archetypes found internationally: a high-density megacity dominated by flats, a polycentric conurbation with mixed housing, and an inter-city commuting corridor. The key relationships identified are likely applicable to cities with similar urban forms. In large and dense metropolitan cities with a high prevalence of flats and persistent traffic congestion constraints, strategies should prioritise residential on-street charging and combine slow overnight chargers with strategically located fast chargers. In polycentric conurbations with mixed housing types and a higher proportion of houses, targeted deployment of public chargers near flatted neighbourhoods may be more cost-effective than blanket coverage. Finally, in regional corridors with substantial inter-city commuting, greater emphasis should be placed on motorway and trunk-road charging hubs, with fast chargers deployed to serve transit-based rather than purely destination-based charging demand. Nevertheless, the transferability of these findings is conditional on other

contextual factors such as electricity pricing and home charging adoption rates. Future research should explore these relationships across different national contexts to evaluate the generalisability of the observed patterns.

Despite the planning strategies discussed above, it is important to acknowledge the practical constraints that may hinder the implementation of such plans. One of the most discussed obstacles is the dependence of public chargers on the power grid. Connecting a new charger to the existing electricity network can cause disruption to the local grid and increase regional power demand (Hardman et al., 2018; Nurulin et al., 2023; Yousuf et al., 2024). Additionally, the installation of new charging stations often requires approval from various authorities, and is subject to environmental regulations. The permitting process can lead to increased costs and, in some cases, prevent the installation of a charging point. Another challenge is the availability of space for long-term EV parking. New public chargers must be well-integrated with existing infrastructure, such as parking spaces and current gas stations (Hardman et al., 2018).

This paper also has limitations in the following aspects. First, the scraped charging session dataset includes only charger providers covered by ChargePoint and does not capture all public chargers in the three study areas. The dataset covers only 23.56% of public chargers in London, 40.85% in Manchester and 15.62% in Central Scotland. Chargers operated by companies not included in ChargePoint may differ in terms of usage patterns, locations, or user demographics, which could introduce sample bias into the analysis. The lack of effective validation data can also limit our ability to present a complete picture of the UK's public EV charging system when using the scraped data for analysis. Additionally, many new chargers have been installed after the data scraping period. This can further increase the potential bias in our dataset. Despite these limitations, the ChargePoint dataset remains by far the most comprehensive source of charger usage data currently available. Once a more complete, nationwide dataset on public charger usage becomes available, or when aggregated statistics about charger usage rates are available, future research can apply more robust adjustments to mitigate potential sampling bias or perform external validation. This would allow for a more detailed and reliable exploration of charger usage patterns and their driving factors. Second, parking fees can significantly influence charger selection and usage rates. However, due to a high percentage of missing values in both initial and additional parking fees, we did not include them in our models. Further studies should incorporate parking fees as a key variable to better explain variations in usage rates.

Another notable limitation is the lack of information on user types. The scraped data only shows whether a specific charger is occupied at a given timestamp, without any details about the type of user, such as private vehicles, commercial fleets, or ride-hailing vehicles. Third, privacy concerns further restrict the availability of user-related attributes. However, different user types can show varied charging behaviours. Their charging times can depend on their daily activities. Future research with more comprehensive datasets should consider user type as a critical factor to provide deeper insights into charging behaviours and infrastructure needs across different user groups. Fourth, the relationship between residential property types and charger usage could be influenced by unobserved confounding variables, such as income and other socio-demographic factors. To quantify the possible impact of unmeasured confounding, we conducted a sensitivity analysis in Appendix E. Fifth, it should also be noted that temporal autocorrelation, the dependence of a charger's usage rate across successive time periods, is not accounted for in the modelling framework in this chapter, and future work could explore panel spatial models to address this. Lastly, future research could examine inequalities in EV adoption and public charger accessibility among drivers from different demographic and socioeconomic backgrounds, explore the charging demand of underrepresented communities, and develop strategies to promote broader EV adoption.

4.7 Conclusion

In this chapter, we identified distinct relationships between public charger usage and influencing factors across Greater London, Greater Manchester, and the Central Belt of Scotland using charging session data and spatial regression models. This study is one of the few comprehensive analyses of public charger usage across multiple UK regions. Unlike previous studies that relied on sampled EV drivers, we used charging session data from public chargers, which enables us to capture behaviour patterns of a diverse range of users.

We highlight region-specific charger planning strategies to help build a more sustainable charging network. These region-specific findings can also be generalised into broader planning strategies for urban EV charging infrastructure. In high-density, high-traffic urban areas dominated by flat housing, public charging demand is driven by limited access to home charging and time-sensitive mobility needs. In such contexts, fast chargers are necessary to provide quick turnaround times, while residential-area chargers are needed to accommodate

users without access to private parking. In regions with significant inter-city mobility, public chargers near motorways or other major transport corridors become critical to meet long-distance travel demand. Public charger deployment in residential areas should account for property type differences, along with the feasibility and actual adoption of home charging solutions.

This chapter provides an empirical foundation on the public charger usage patterns in GB and identifies contextual factors associated with public charger usage demand. However, as discussed in Section 3.2 in Chapter 3, the regression models are limited in representing heterogenous decision-making and interactions at individual level. The following chapter will apply computational approaches and develop an ABM on the driving and charging behaviours of EV drivers in this public charger network

Chapter 5

Using Agent-based Models to Simulate the Electric Vehicle Driver Behaviours in Great Britain²

Preface

Chapter 4 applied spatial regression models to understand the public charger usage patterns in three case study areas in GB and identified contextual factors associated with charger usage. However, as discussed in Chapter 3, regression-based approaches have notable limitations despite their interpretability. They are formulated at an aggregate level, use charging stations as the primary unit of analysis, and are limited in representing heterogeneous decision-making and interactions at the individual level. ABM, also discussed in Chapter 3, is well suited to representing the complex behaviours of EV drivers. It can simulate a number of autonomous agents with heterogeneous attributes and dynamic behaviours that interact according to prescribed rules (Farmer and Foley, 2009; Heckbert, Baynes and Reeson, 2010).

To better represent the EV drivers' decision-making processes at the individual level and estimate their charging demand distribution, this chapter develops an ABM to simulate the charging and driving behaviours of EV drivers. Section 5.1 introduces the background of EV uptake and the research trajectories in EV driver behaviours, as well as the objective of this chapter. Section 5.2 reviews previous studies on EV driver charging and driving behaviours. Section 5.3 details the input data used for the ABM and the study area. Section 5.4 details the behavioural rules of the ABM. Section 5.5 presents the simulation results of

² This chapter is based on a published paper: Feng, Z., Zhao, Q. and Heppenstall, A. (2026) 'Using agent-based models to simulate the electric vehicle driving behaviours in Great Britain', *Cities*, 106864. doi: 10.1016/j.cities.2026.106864

public charger usage durations and EV trajectories. Section 5.6 discusses the implications and limitations of the results. Section 5.7 concludes the chapter.

5.1 Introduction

Promoting EV adoption has become a key strategy for many countries aiming to create a net-zero carbon emission transportation system. The transition from conventional vehicles to EVs can significantly reduce global greenhouse gas emissions and air pollution (Metais et al., 2022; Unterluggauer et al., 2022). The UK government has set out a path for all new cars to be zero emission by 2035 (Department for Transport, 2024c). The new target accelerates the transition toward alternative fuel vehicles, particularly EVs. As indicated by the Department for Transport (2022), the public discourse on zero emission vehicles has now shifted from whether it will happen, to when it will happen.

However, increasing EV adoption also introduces considerable uncertainty for public charging infrastructure planning. The differences between EVs and conventional vehicles, particularly in driving range and charging duration (Miri, Fotouhi and Ewin, 2021; Wang, Yao and Pan, 2021), make it harder to predict future travel behaviours, such as daily travel distances (Wu et al., 2024), park locations and durations (Sun et al., 2022), and trip frequencies (Langbroek, Franklin and Susilo, 2018). Key questions remain regarding how many chargers will be required, where they should be located, which types of chargers are most suitable for different contexts, and how charging demand is spatially distributed. Addressing these questions requires a deeper understanding of the complex behaviours of EV drivers which can help reveal the spatial distribution of charging demand and enable planners and policymakers to design a more accessible, equitable, and sustainable charging network that supports long-term EV adoption.

Researchers have adopted different methods to explore charging demand of EV drivers. One set of studies uses statistical and analytical methods to estimate the charging demand distribution of EV drivers. The studies use statistics such as origin-destination (OD) matrices (Cruz-Zambrano et al., 2013), population density, as well as high-granular trajectory data of conventional vehicles (Kontou et al., 2019) or EV fleets like taxis (Tu et al., 2016). These datasets are typically processed to extract trip start points, destinations, and intermediate waypoints, after which statistical analyses are applied to estimate the spatial distribution of EV charging demand. However, the travel survey or trajectory data of private EV drivers remain scarce in most regions due to the privacy concerns and the relatively early stage of EV adoption. As a result, these studies often rely on proxy data

from conventional vehicles or commercial fleets, assuming that private EV drivers would travel in the same way. However, EV drivers behave differently compared with the conventional vehicle drivers regarding travel distance, refuelling choices, as well as the tendency to charge promptly (Yang et al., 2016; Philipsen et al., 2018; Wolbertus et al., 2021). The extent to which such proxies accurately represent private EV usage is questionable, and this substitution may introduce sampling bias and systematic errors in the resulting estimates.

Another set of studies uses simulation-based methods to predict charging demand of EV drivers, such as DES (Pruckner, German and Eckhoff, 2017; Lopez, Allana and Biona, 2021; Wahyudi, Rahman and Hariyanto, 2024) and agent-based modelling (Chaudhari et al., 2019; van der Kam et al., 2019; Willey and Salmon, 2021). Compared to analytical approaches, DES can have a detailed representation of EV charging systems by explicitly modelling driving and charging events. For example, Wahyudi et al. (2024) developed a DES model to simulate sequential events of EV drivers' departure from home, arrival and leaving charging station, and arrival at destinations. However, despite the ability to represent detailed travel and charging process, DES is a process-oriented, top-down modelling approach, where individual entities are typically passive, with their behaviour governed by the system rather than by autonomous decision-making (Siebers et al., 2010; Maidstone, 2012). This makes it an unsuitable approach for modelling private EV drivers, who are proactive decision-makers who autonomously determine where to drive and charge.

ABM offers a tool to plan, design, and experiment with autonomous micro-agents in an artificial computational environment (Olmez et al., 2022). Compared to DES, it is a decentralised, bottom-up modelling approach and can represent a richer and more detailed set of individual agents (Davis and Morris, 2009) and enable interactions both between and within agent types (Heppenstall et al., 2021). Many previous studies have applied ABM to simulate the behaviours of EV drivers (Chaudhari et al., 2019; van der Kam et al., 2019; Willey and Salmon, 2021; Yi et al., 2023) by pre-defining the driving and charging behavioural rules of EV drivers and simulating their public charger choices. However, research gaps still remain because they either incorporated a limited set of behavioural rules of EV drivers in a city-level context (Yi et al., 2023), or were implemented in hypothetical grid environment (Chaudhari et al., 2019) rather than large-scale real-world road networks with both inter-city and inner-city trips. Additionally, there is often a lack of

validation against real-world charging station usage, which makes it difficult to assess the accuracy of simulation results, potentially leading to misguided infrastructure planning.

The overarching goal of this chapter is to provide a deeper understanding of the driving and charging behaviours of EV drivers through (i) developing an ABM with comprehensive behavioural rules of private EV drivers, (ii) implementing the model in a real-world road network in GB based on the 2022 UK NTS dataset, and (iii) validating the model with real-world charging session data to evaluate the accuracy and reliability of the simulation results. This model can enhance our understanding of EV driver behaviours and their charging demand distribution, guiding the future development of transportation infrastructure as we transition to greener transport systems.

5.2 Background

Research on estimating the charging demand of EV drivers can be broadly classified into those using statistical and analytical approaches, and those using simulation-based approaches.

5.2.1 Statistical and Analytical Approaches

Before the emergence of highly granular trajectory data of EV drivers, most studies mapped the spatial distribution of charging demand based on statistics such as population density, employment rate, travel flow volume, travel distance, and POIs (Frade et al., 2011; Dong et al., 2019; Wang et al., 2019). One of the key data sources is the travel survey data, on which the majority of EV travel research draws. From this data, origin-destination (OD) information is derived to measure the spatio-temporal distribution of travel activities and charging demand (Cruz-Zambrano et al., 2013; Dong, Liu and Lin, 2014; Li and Jenn, 2022; Yi, Liu and Wei, 2022). However, the mapping-based approaches based on these datasets are limited in their ability to show the detailed travel patterns of individuals and their decision-making processes when choosing charging stations.

More recently, the improved availability of real-time location data has made it possible for researchers to integrate high-granular spatial and temporal information of driving behaviour into the demand estimation process (Daina, Sivakumar and Polak, 2017b). The most commonly used real-time location dataset is connected vehicle data, which describes

the trajectory information of vehicles. The data is presented to determine the OD information, the distribution of actual driving paths, and the time periods during which an EV is charging (Li et al., 2015; Tu et al., 2016; Jochem, Szimba and Reuter-Oppermann, 2019; Roni, Yi and Smart, 2019; Xing et al., 2019; Yi, Liu and Wei, 2022). However, due to the privacy concerns and relatively early stage of EV adoption for private drivers, such datasets are usually from the trajectories of conventional vehicles or commercial EV fleets such as freight or taxis. The connected vehicle data is currently only available for limited areas, which makes it difficult to generalise the research design to other geographical areas. More importantly, their representativeness of private EV driver trajectories can be questionable, potentially introducing a sampling bias problem and leading to systematic errors when determining travel patterns and charging demand of private EV drivers. For example, the behaviours of EV drivers of commercial fleets or taxis differ substantially from private EV drivers because their charging demand can either be predefined by their job requirements or influenced by the random customer requests they receive. The travel patterns of conventional vehicles also differ from those of EVs because conventional vehicle drivers can endure longer travel distances before refuelling. As a result, the direct use of these datasets to build indicators and estimate charging demand distribution cannot fully capture the various features of private EV drivers, such as their sensitivities to charging costs and psychological preferences. Sensitivities to charging costs can affect a driver's behaviours in various ways, such as sensitivity to the payment for charging (Ge, MacKenzie and Keith, 2018), travel distance (Wolbertus et al., 2021), time spent waiting (Davidov, 2020), parking costs (Yi et al., 2020), and charging duration (Yang et al., 2016). The psychological factors include the tendency to charge promptly (Philipsen et al., 2018), a driver's comfort level with reaching a low SOC before seeking to recharge (Yi et al., 2020), and a risk-averse attitude (Zhang et al., 2022).

Another group of analytical studies uses DCMs to explicitly model individual charging decisions. Based on the stated preference data collected from EV drivers, studies based on DCMs define the choice set available to individuals and model their charging decisions (Ge, 2019; Bhat, Tiwari and Verma, 2024; Sica et al., 2025). For example, Sica et al. (2025) developed a DCM to model EV drivers' choices among private chargers and public chargers near home, work, and other activity locations. However, although DCMs can incorporate various choices for EV drivers and better represent their decision-making process than mapping-based approaches, they assume that observations are independent across individuals (Le Pira et al., 2017) and cannot capture interactions among EV drivers.

For example, private EV drivers may interact with each other through changing public charger status visible to other drivers when taking up a charger, and queueing behind each other when waiting for chargers.

5.2.2 Simulation-based approaches

Simulation-based approaches provide an opportunity to explore travel patterns while reflecting the unique features of EV drivers, and can address the limitations of statistical and analytical approaches as identified in the previous section. Common simulation-based approaches to estimating EV drivers' charging demand include DES and ABM. Many empirical studies have developed DES that simulate queueing, arriving, balking, and charging events for EV drivers (Darabi and Ferdowsi, 2014; Lopez, Allana and Biona, 2021; Wahyudi, Rahman and Hariyanto, 2024). However, in DES, the system and its interactions are modelled first, and then the behaviour of the elements within the model is observed (Lebeau et al., 2013). This approach focuses on system-level processes but is less suited to capturing individual-level heterogeneity and behavioural change.

In contrast to DES, agent-based modelling (ABM) is a decentralised modelling approach where global behaviour of the system emerges from the interactions of many individual agents (An, 2012; An et al., 2021; Bonabeau, 2002a; Railsback & Grimm, 2019). ABM allows for the integration of quantitative measures and qualitative theories, and can facilitate the connection of observations and hypotheses within a single, interactive framework (Crooks et al., 2019). It can address the limitations of statistical and analytical methods and the DES models by modelling each EV driver as an autonomous decision-maker with heterogeneous attributes, explicit behavioural rules, and the ability to interact with both other agents and the environment.

Previous studies have developed ABMs with various agent attributes and behavioural rules to simulate the trajectories and charging demands of EV drivers. In these studies, an EV agent typically combines the driver and the vehicle into one identity. Agents are initialised with travel diaries, which include trip purposes, origins, stopovers, destinations, and operate based on the EV driver's decisions and strategies while being constrained by the vehicle's built-in features, including battery capacity, energy consumption rate, maximum driving range, and fuel level (Novosel et al., 2015; Mallig et al., 2016; Marmaras, Xydias and Cipcigan, 2017; Chaudhari et al., 2019; Fischer et al., 2019; Pagani et al., 2019;

Venegas, Petit and Perez, 2019; Adenaw and Lienkamp, 2021). Various behavioural rules of EV drivers are developed to depict driving and charging behaviours of EV drivers. Some studies are based on EV behaviour rules in open-source simulation frameworks such as MATSim (Novosel et al., 2015; Yi et al., 2023). However, these frameworks are based on relatively simplified behavioural rules and are thus limited in their ability to represent complex decision-making of EV drivers and precisely simulate charging demand. To better capture the unique features of EV drivers, other studies have developed custom behavioural rules based on EV drivers' costs and benefits, habits, psychological preferences, and trip features (van der Kam et al., 2019; Willey and Salmon, 2021). Among all the features, the cost-benefit trade-off is the most commonly modelled one. In previous ABMs, a driver seeks to balance the desire to minimise the financial and time costs with the need to use charge infrastructure (Marmaras, Xydas and Cipcigan, 2017; Pagani et al., 2019; Willey and Salmon, 2021). For example, in the models developed by Lin et al. (2019) and Yi et al. (2023), a driver may opt not to charge if the parking time is too short. Similarly, in the ABM by Adenaw and Lienkamp (2021), a driver agent aims to save time and integrates charging into their daily activities and only charges during parking for those activities. However, many models are critiqued for their over-emphasis on cost-benefit evaluations and for overlooking the cognitively bounded rationality of EV drivers. Therefore, psychological features such as range anxiety are also considered in many ABMs (van der Kam et al., 2019). Range anxiety refers to the subjective portion of battery capacity that a driver is comfortable using before stress associated with limited range begins to affect behaviour (Franke et al., 2012). In previous ABMs of EV drivers, this concept is also represented as a 'state-of-charge (SOC) threshold' (Marmaras, Xydas and Cipcigan, 2017; Wasesa and Sateriano, 2023), or a 'range buffer' (Liu, Tayarani and Gao, 2022).

Nevertheless, despite the wide range of behavioural rules considered by previous ABMs, a key limitation in previous ABMs is that most models typically assume that all drivers share the same preferences when making choices and are assigned the same EV make and model, and the heterogeneity of drivers' preferences and behavioural patterns has been less considered. As discussed in Chapter 2, the EV driver population has shifted from a small group of early adopters to a heterogeneous user base characterised by diverse socio-demographic attributes, usage patterns, and behavioural features. An ABM that accounts for this diversity is therefore needed to reflect the evolving composition of the EV driver population and produce more robust estimates of charging demand distribution.

Besides the agent attributes and behavioural rules, the simulation environment also constitutes an important part of ABMs. Previous studies have applied the ABMs of EV drivers in various environments and geographical scales. Some studies use simplified network topologies (Marmaras, Xydias and Cipcigan, 2017) or artificial grids (Chaudhari et al., 2019) to represent road networks. Other studies use real-world road networks as simulation environment to generate high-resolution driving profiles for EV drivers (Willey and Salmon, 2021; Yi et al., 2023). However, the EV drivers' charging demand during long-distance inter-city trips is overlooked when using such city-level road networks or artificial grids as simulation environments. Empirical surveys have shown that public chargers are more important for long-distance journeys compared to shorter ones, as they provide crucial backup and ensure sufficient battery charge for long-distance drivers (Hardman et al., 2018). More importantly, the details of real-world charging stations, such as locations, prices, and charging speeds, have been less considered in the modelling environments of previous ABMs. An ABM that situates EV drivers within a realistic inter-city road network and incorporates detailed charging station information is therefore necessary to model realistic charging behaviour and more accurately predict real-world public charger usage patterns.

Overall, understanding the behavioural patterns and charging demand of EV drivers is a fast-developing research area with many studies using either statistical and analytical or simulation-based approaches. With the limited availability of the trajectory data of private EV drivers, ABMs provide opportunities to represent heterogeneous and autonomous individual EV drivers and simulate their charging and driving behaviours in real-world road and public charger networks. Many previous studies have adopted ABMs to simulate the behaviours of EV drivers yet usually assume homogeneous characteristics and behavioural rules across all driver agents. Additionally, inter-city commuting at the regional or national scales, along with real-world charging station information, has not been fully considered in all the previous simulation environments. Therefore, to fill the research gaps, this research aims to develop an ABM that incorporates heterogeneous EV drivers with unique preferences when making choices on a national-scale road network with real-world charging station information.

5.3 Data and Study Area

In this study, we focus on simulating the EV drivers of England travelling across Great Britain (GB). GB comprises England, Scotland, and Wales, and features an extensive road network along with a growing amount of public charging infrastructure. As the most populous part of GB, England has a significant number of drivers commuting daily both within the country and across GB. This makes it an ideal setting for simulating the driving and charging patterns of EV drivers.

The 2022 NTS data (UK Data Service, 2022) and UK postcode points data (Ordnance Survey, 2023a) are used to determine the trip schedules of the EV driver agents. The EV make and model information is obtained from the EV Database website (EV database, 2024) and is used to formulate the attributes of the EVs in the simulation. The public charger data and the road network data are used together as the simulation environment. The public charger data is scraped from ChargePoint website (ChargePoint, 2023). The road network data for GB is obtained from OS Open Roads dataset (Ordnance Survey, 2023b).

5.3.1 National Travel Survey Data

The 2022 UK NTS data is used to determine the trip schedules of EV driver agents in the ABM. Details of the schedules include the origins, destinations, trip distances, and trip start times of EV drivers. The NTS is a continuous longitudinal survey of personal travel at the household level. It provides regular information about personal travel and monitors trends in travel behaviour over time (Department For Transport, 2023). In 2022, the survey was conducted on a random sample of households in England, with every person in the household interviewed. Besides trips within England, the trip information is still collected when a resident of England makes trips that start or end in Scotland or Wales. We first conducted a cluster analysis based on the ‘trip distance’ and the ‘trip start time’ of all ‘vehicle drivers’ in the dataset. The results of the cluster analysis are shown in Appendix F. Based on the cluster analysis results, we used a stratified sampling process to select a total of 1,000 drivers from the dataset as agents of the model and assume they have adopted EVs and conducted their trips using EVs.

The variables ‘origin unitary authority’, ‘destination unitary authority’, ‘trip start time’, and ‘trip distance excluding short walks’ from the dataset are used to formulate the trip schedule of the driver agents. Specifically, we assume that the vehicle drivers in the NTS

data have adopted EVs while their trip origins and destinations remain unchanged. As the OD information at the unitary authority level is not spatially precise enough to initialise agent locations in the ABM, postcode point data (Ordnance Survey, 2023a) are combined with the NTS data to determine the start and end coordinates for each trip. Specific methods are detailed in Appendix G.

Trip start times are taken directly from the dataset. The variable ‘trip distance excluding short walks’ is used only to categorise trips by relative length rather than to represent exact travel distances. This is because we assume that, after adopting an EV, a driver chooses different routes and incorporates charging stops, resulting in different travel times and distances compared to using a conventional vehicle. Following the NTS classification, trips longer than 50 miles are defined as long-distance (Department For Transport, 2023). Based on the cluster analysis results presented in Appendix F, trips between 25 and 50 miles are classified as medium-distance, while trips below 25 miles are considered short-distance.

5.3.2 ChargePoint charging session data

The public charging station data in GB were scraped from ChargePoint's charging station map website (ChargePoint, 2023). More details of the dataset attributes and collection methods are described in Section 4.3.1 in Chapter 4.

The distribution and size of these public chargers across GB are shown in Figure 5.1. Figure 5.2 shows the total charger usage duration dynamics in GB in a sample week. The usage durations from the dataset will be used to validate the simulation results. On average, the peak hours of usage occur from 12:00 to 14:00. Thursdays and Fridays (02-08-2024, and 02-09-2024) show a higher volume of usage compared to other weekdays. More samples of weekly charger usage duration changes are included in Appendix B. Due to data availability limitation, there are temporal discrepancies between our NTS data and the charging session data. At the start of this research, the 2022 NTS dataset was the most up-to-date version available. Using the web scraping method, we were unable to access historical charging session data prior to December 5, 2023. We acknowledge that EV adoption and charging behaviours may evolve over time. In our modelling process, we assumed minimal changes in public charger usage patterns from 2022 to late 2023 and early 2024. This assumption is supported by the fact that the adoption rate of electric cars in GB has seen a moderate increase from 2022 to 2024. According to statistics from the

Department for Transport and Driver and Vehicle Licensing Agency (2024), EV registration rose by 0.9% from Q4 2022 to Q4 2023 and by 0.5% from Q4 2023 to Q2 2024. Also, EV adoption in the UK is still in its early stages. Early adopters of EVs are more likely to be homeowners with access to private chargers (Lavieri and De Oliveira, 2023; Stajić et al., 2023), which can further limit the variability in public charger usage over this period.

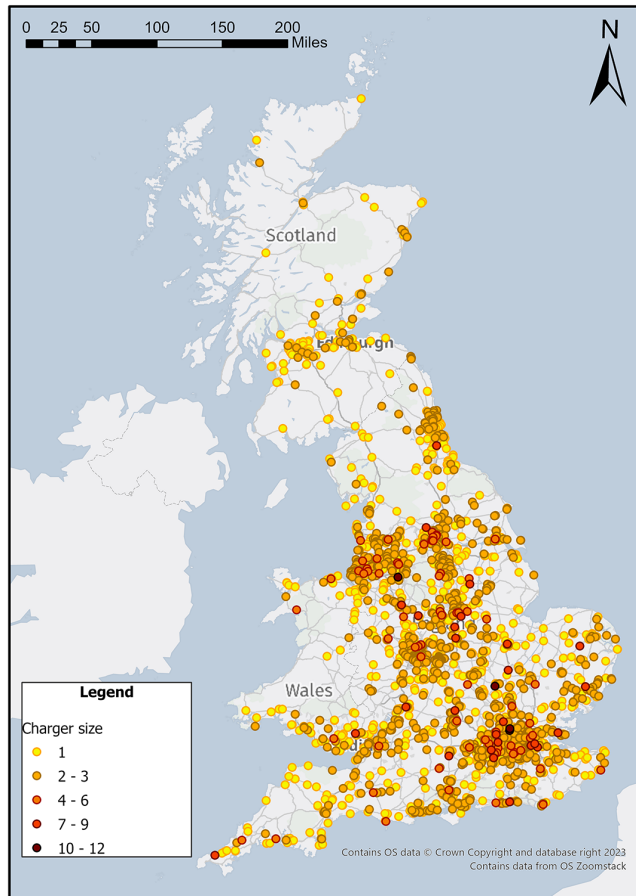


Figure 5.1 Public charger distribution in GB.

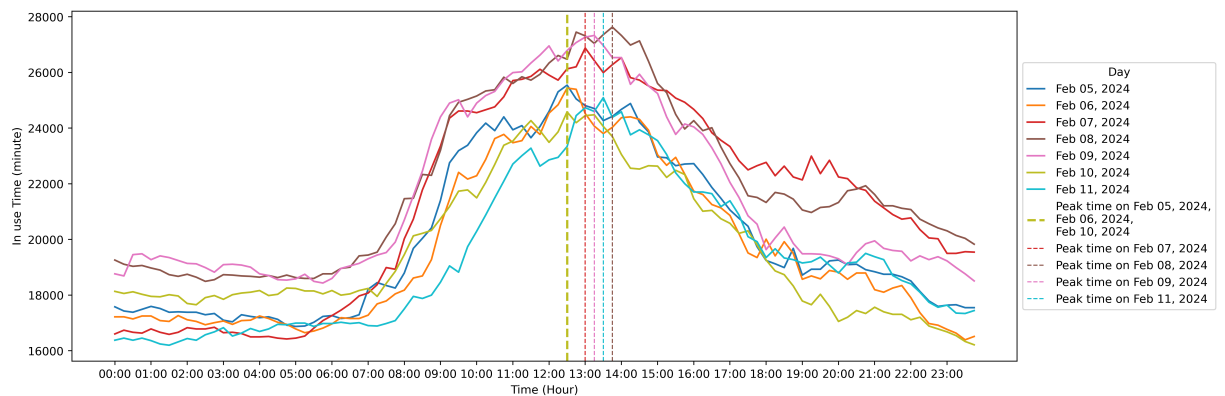


Figure 5.2 Total usage duration of all public chargers in GB in a sample week (Feb 5-11, 2024).

5.3.3 EV datasets

The EV attribute data is sourced from the EV database (2024). The website provides detailed information on the make, model, battery range, and consumption rates of EVs currently available on the UK market. As of February 18, 2024, the dataset includes 231 distinct EV types in the UK. To ensure the model accurately reflects the diversity of EVs, all EV types, each with a unique battery size and consumption rate, have been sourced from the dataset. The summary statistics for all the applied EV types are shown in Table 5.1. In the ABM, each EV driver is randomly assigned one of the 231 vehicle types, with the corresponding battery size and consumption rate upon initialisation. The attributes of battery size and consumption rate used in the model represent those of new vehicles. Since this chapter focuses on the behavioural patterns of EV drivers rather than the technical aspects, the diminished battery ranges and altered consumption rates resulting from vehicle usage are not considered.

Table 5.1 Summary statistics of battery size and consumption rates of the 231 EV types.

	Mean	Median	Range	Std.
Battery size (KWh)	72.8	74.0	21.3-118.0	20.4
Consumption Rate				
(Wh/mi)	307.0	300.0	221.0-474.0	43.1

5.4 Methods

5.4.1 Simulation environment

The road network of GB from the OS Open Roads dataset is transformed into a graph structure and used to formulate the modelling environment. The public charger network from ChargePoint (2023) is also included as part of the simulation environment. It is assumed that EV drivers can access up-to-date information through websites or mobile phone applications about the price, parking fee, speed, location, and availability of public chargers. In the simulation environment, each charger can have one or more ports for multiple vehicles to charge at the same time. The ports from the same charger have the same geographical location but each maintains its own availability status.

5.4.2 Agents

An agent in the model combines the driver and the vehicle into one identity. Each EV driver has one or more trips in their travel schedules. All agents are initialised at the location of the origin of their first trip. The attributes of an agent are listed in Table 5.2.

Table 5.2 Attributes of EV driver agents.

Attribute name	Description
Individual ID	Unique identifier of EV drivers.
Trip Schedule	The start time, origin, and destination of each trip during the day.
Sensitivities to financial cost (α)	Level of importance the driver places on the financial payment for charging and parking.
Sensitivities to time cost (β)	Level of importance the driver places on the time spent on driving and charging.
SOC threshold	Level of SOC where the driver was incentivised to charge due to range anxiety.
Vehicle make and model	Brand and version of the EV.
Full battery size	Total energy capacity of an EV's battery.
Start SOC	The SOC level when the driver starts the trip over a day.
Battery consumption rate	Energy (kWh) consumed per kilometre.

Each EV driver agent is assigned a trip schedule based on the NTS dataset as described in Section 5.3.1. A trip schedule can consist of one or more trips during a day. Each driver also has psychological attributes of sensitivities to financial cost (α), sensitivities to time cost (β), and SOC threshold. Specifically, α is introduced to quantify the EV driver's unique preference for financial costs associated with charging. Each driver is initialised with a value of α randomly drawn from a truncated normal distribution bounded within the interval (0,1). β is the driver's sensitivity towards time cost and $\beta = 1 - \alpha$. For an EV driver, the total perceived cost of charging, C , can be expressed as a weighted sum of the financial payment, F , and the time spent charging, T , as shown in equation (5-1).

$$C = \alpha * F + \beta * T \quad (5-1)$$

Besides, a driver's decision is also subject to the SOC threshold, which is the minimum acceptable level of SOC at which the driver feels compelled to charge. When the SOC falls below this threshold, the driver recognises that the battery has depleted to a level where recharging is necessary. To account for individual differences in risk tolerance, each driver is randomly assigned a SOC threshold based on a truncated normal distribution bounded within the interval (0,1).

Besides psychological factors, each driver agent is initialised with a specific vehicle make and model with fixed battery capacity and energy consumption rate. The variability of battery consumption rate due to external factors like weather conditions, is not considered in the model.

The initial SOC level of each driver agent represents the battery level at the start of the first trip. The usage of home chargers is not considered in this research because we do not have access to the home charger data. However, the availability of a home charger can have a significant impact on the daily charging patterns of EV drivers. A driver who owns a home charger can have higher SOC levels when leaving home than those without home chargers. To mitigate the impact of the absence of home charger data, and to reflect the variation in initial SOC levels arising from differences in home charger ownership, we initialise each EV with a random SOC level using a truncated normal distribution with a mean of 0.5 and a standard deviation of 0.167, bounded within the interval (0, 1).

In this study, the driving speed for each driver is treated as a constant and is assigned a random value within specified ranges. For short- to medium-distance trips, the speed is assigned using a truncated normal distribution within the range of 20 to 40 miles per hour. For long-distance trips over 50 miles, the speed is assigned using the same method but within the range of 50 to 70 miles per hour. In reality, an EV's driving speed can impact its battery consumption rate and consequently, its power range. This impact can vary widely across different EVs due to various factors such as the vehicle's make and model. Delving into these complexities falls outside the primary focus of our model, which is to explore the EV drivers' charging choices. Therefore, the speed variations and their impact on battery consumption are not considered in this model.

As the parameters of financial sensitivity, SOC threshold, and initial SOC, are important for shaping EV driver behaviour in the model, we conducted a model calibration with sensitivity analysis to test the robustness of the results. Details of this analysis are included in Appendix H.

5.4.3 Behavioural rules

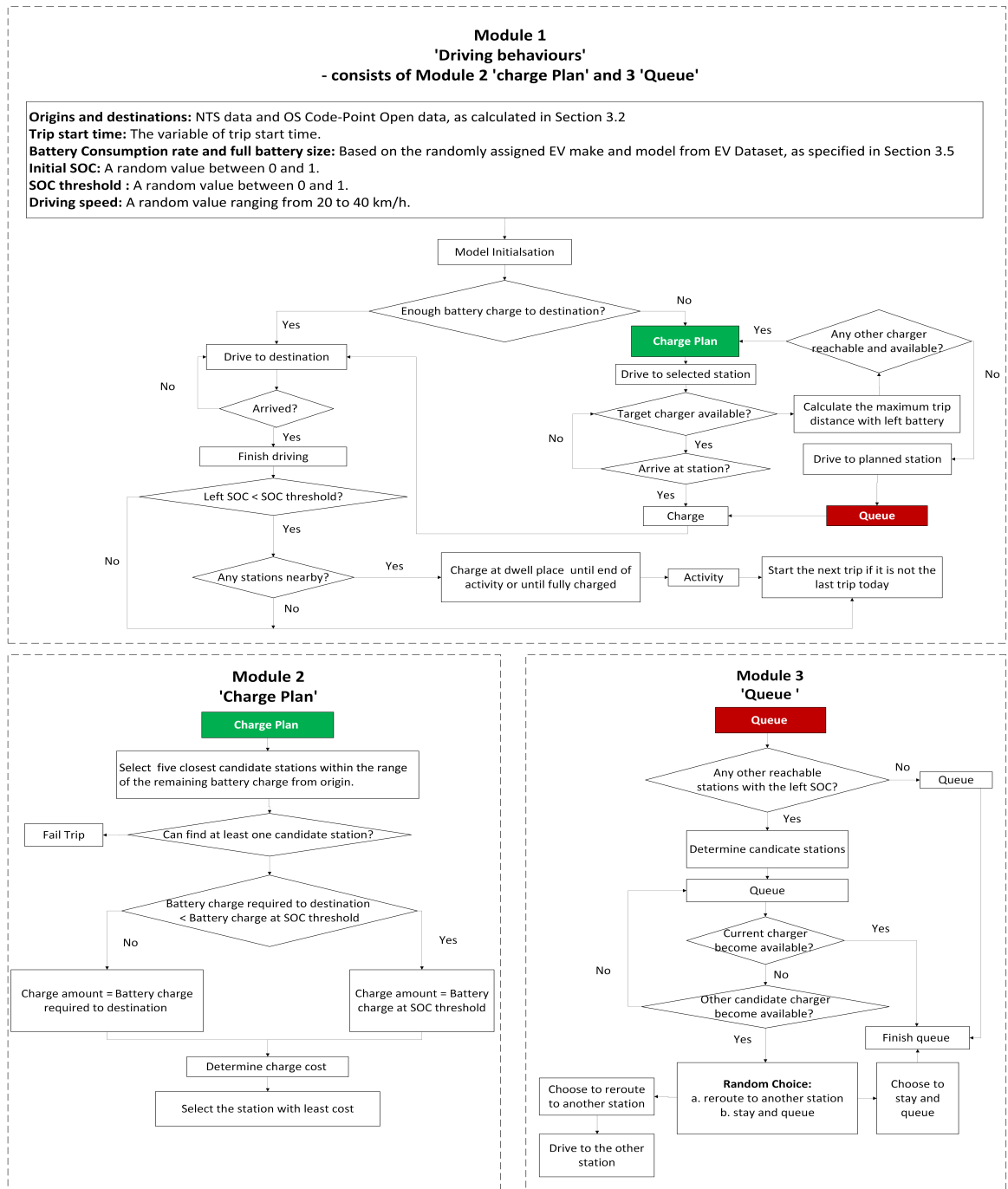


Figure 5.3 Behavioural rules of the models.

Figure 5.3 shows the behavioural rules of EV driver agents in the ABM. All agents are initialised simultaneously at the origin of their first scheduled trip and depart according to their assigned start times. For each journey, agents follow the Dijkstra shortest path between origin and destination.

Destination charging when SOC is sufficient

At the beginning of every trip, the driver evaluates whether the remaining SOC is sufficient to reach the destination. If the available charge is adequate, the driver travels directly to the destination. Upon arrival, charging decisions depend on the remaining SOC. If the SOC exceeds the SOC threshold, the driver does not charge. Otherwise, the driver searches for charging stations within a 500 m radius. This distance is assumed to be the maximum acceptable walking distance from the charging point to the destination. If one or more stations is available, the driver selects the station with the lowest total cost.

The station cost C_i at station i is shown in equation (5-2) - (5-3).

$$C_i = \alpha * \left(Q_i * P_i + C_{\text{initial},i} + C_{\text{additional},i} \cdot \max\left(0, \left\lfloor \frac{Q_i}{R_i} - 1 \right\rfloor \right) \right) + \beta * \left(\frac{Q_i}{R_i} + \frac{D_i}{S} \right) \quad (5-2)$$

$$Q_i = \min(T_{\text{available}} \cdot R_i, Q_{\text{battery}} - Q_{\text{current}}) \quad (5-3)$$

The station cost C_i consists of financial cost and time cost. The financial cost includes the electricity expense and parking fees, while the time cost consists of both the driving time to the charger and the charging duration. Parameters α and β represent sensitivities to financial and time costs respectively, with $\alpha + \beta = 1$. Here, P_i denotes the electricity price at charger i , R_i the charging speed, $C_{\text{initial},i}$ the initial parking fee, $C_{\text{additional},i}$ the additional hourly parking fee, D_i the travel distance to station i , and S the driving speed. The charging amount Q_i is limited by either the available parking time $T_{\text{available}}$ or the remaining battery capacity. If no subsequent trip is scheduled, $T_{\text{available}}$ is assumed to be infinite, and the vehicle charges to full capacity Q_{battery} .

Enroute charging when SOC is insufficient

If the initial SOC is insufficient to reach the destination, the driver plans a charging stop before departure. In this situation, charging is prioritised to ensure trip feasibility. The set of reachable candidate stations is defined as:

$$I = \left\{ i \in \text{Stations} \mid d(\text{current}, i) < \frac{Q_{\text{current}}}{k} \right\} \quad (5-4)$$

where k represents the battery consumption rate and $d(\text{current}, i)$ is the network distance from the current location to station i .

The driver evaluates up to the five nearest reachable stations and selects the one with the lowest cost. If no station is reachable, the trip is abandoned and recorded as a failed trip for that time step. The planned charging amount is determined by:

$$Q_i = \max(|\text{SOC}_{\text{threshold}} \cdot Q_{\text{battery}} - Q_{\text{current}}|, Q_{\text{destination},i}) \quad (5-5)$$

$$Q_{\text{destination},i} = (d(\text{current}, i) + d(i, \text{dest})) * R_i \quad (5-6)$$

where $Q_{\text{destination},i}$ is the energy required to travel from the current location to the charger and subsequently to the destination. If the required battery charge to reach the destination $Q_{\text{destination},i}$ is greater than the $\text{SOC}_{\text{threshold}}$, $Q_{\text{destination},i}$ is set as the planned charge amount. Conversely, the driver charges until reaching the $\text{SOC}_{\text{threshold}}$. All distances are calculated based on the Dijkstra shortest-distance algorithm.

Dynamic availability, rerouting, and queueing

After selecting a charging station, the driver travels towards it while receiving real-time updates on charger availability. Availability is checked at each network node along the route. If the chosen charger remains available, the driver continues as planned. If the charger becomes occupied, the driver searches for alternative stations that are both reachable and available, again considering up to five candidates while re-evaluating costs. If no alternative is found, the driver proceeds to the originally selected station.

Upon arrival at the charging station, the driver begins charging immediately if a charger is available. Otherwise, the driver joins the queue and waits. During the waiting period, the driver continues to monitor nearby stations and may randomly decide either to remain in

the queue or reroute to a newly available station with a lower cost. After charging is completed, the driver resumes travel to the destination and continues the daily schedule.

5.5 Results

5.5.1 EV trajectories

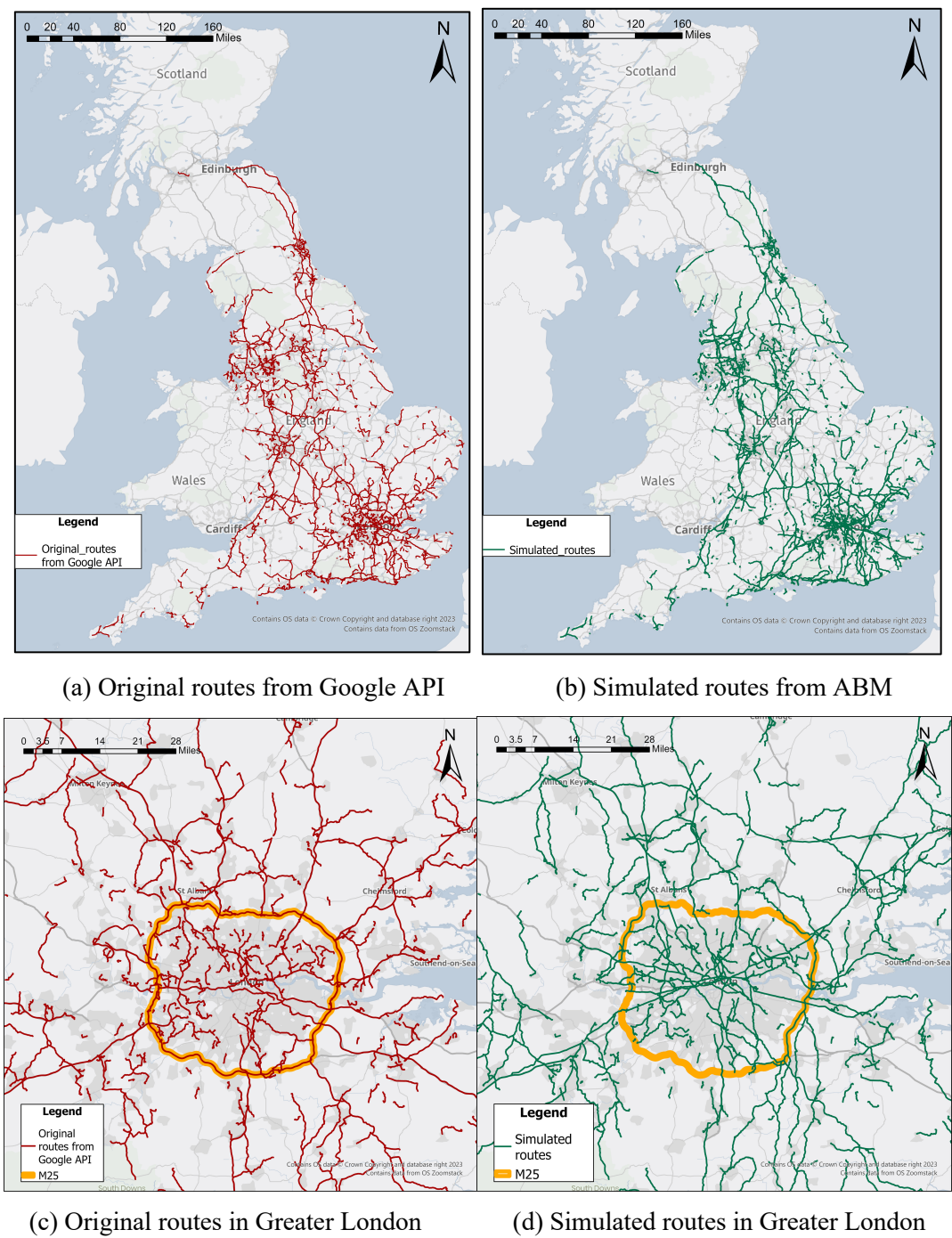


Figure 5.4 Original and simulated routes from Google API and simulated routes from ABM.

Due to limited computational capacity, a random sample of 1,000 drivers were selected to construct the daily schedule of the corresponding EV agent, resulting in a total of 2,946 trips. To reduce the influence of initial conditions and stochastic variability, the simulation was run for five consecutive time steps, each representing a 24-hour day. Agents carried over their end-of-day SOC to the next day, enabling the model to capture cumulative battery depletion and its effects on charging behaviour across multiple days.

Among the 1,000 agents, four began with an SOC below 1% and were unable to start their trips because they could not reach any stations or destinations. Long-distance travel generated substantially higher charging demand. Approximately 54.1% of the long-distance drivers charged enroute. In contrast, only 8.5% of other drivers required enroute charging. In addition, 57 drivers charged while parked at their destinations. This typically occurred when drivers had sufficient charge to reach the first destination but either lacked enough energy for the subsequent trip or fell below their SOC threshold and triggered range anxiety. Despite these charging events, the majority of drivers completed all trips without using public chargers. Specifically, 39.3% of long-distance drivers and 86.1% of other drivers required no charging over the five simulated days. These findings suggest that, despite the frequently discussed concerns about the range limitations of EVs relative to conventional vehicles, current EV battery capacities are generally sufficient for most short- and medium-distance travel. However, long-distance journeys (LDJ) remain a key source of charging demand and bring challenges for EV charging decisions.

Figure 5.4 (a) and (b) compare original trajectories generated using the Google routing API with simulated EV routes. The simulated routes appear more direct than the Google API-generated routes. This difference arises because the Google API optimises for travel time using real-time traffic conditions, road closures, and speed limits, whereas the simulation applies Dijkstra's shortest-distance routing. Consequently, simulated drivers may select geometrically shorter paths that would be slower under real traffic conditions. For example, as shown in Figure 5.4 (c) and (d), many Google-based routes between central London and surrounding areas preferentially use the M25 motorway, which offers faster travel despite longer distances. In contrast, simulated drivers often choose more direct but potentially congested inner-city routes.

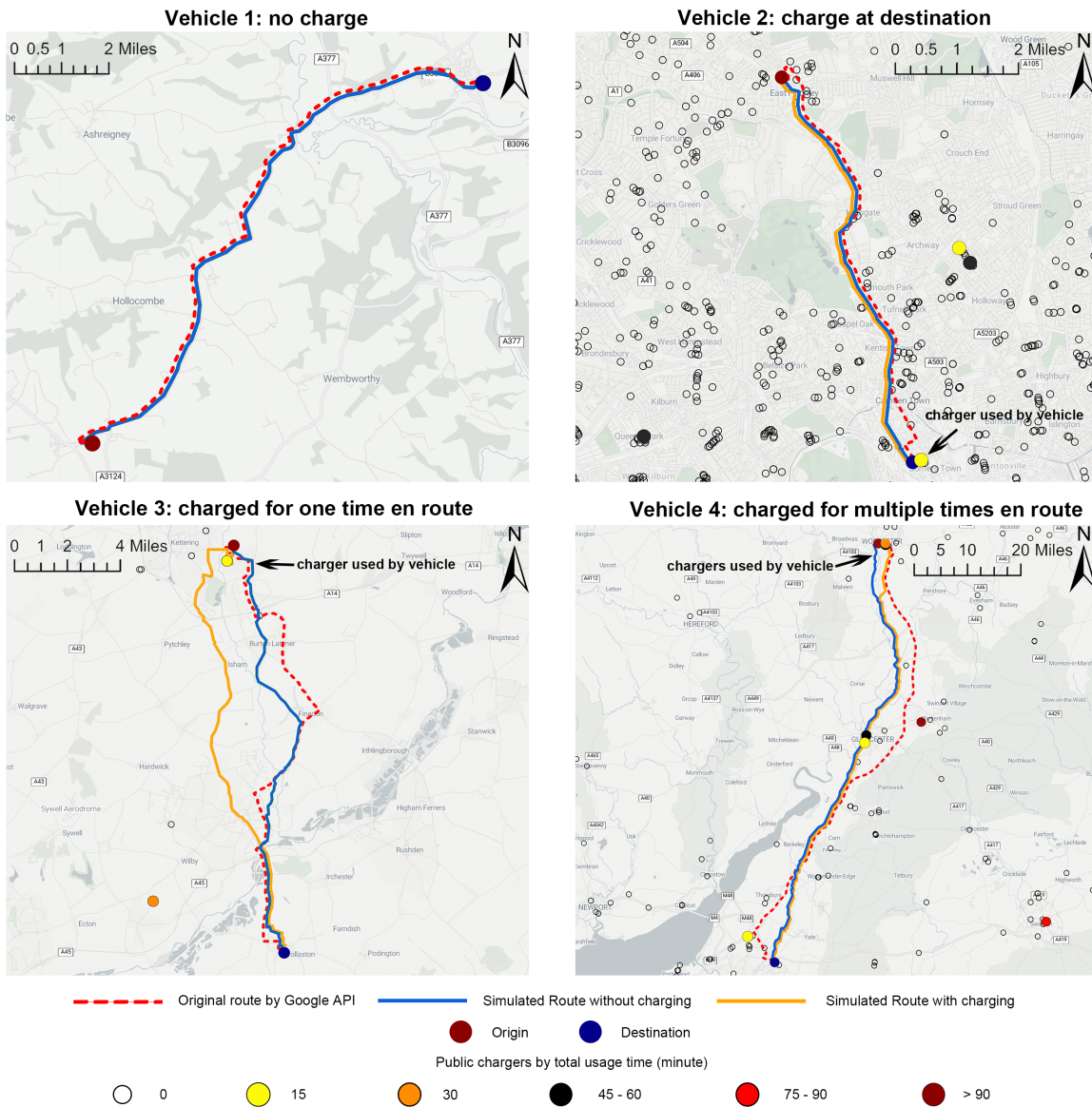
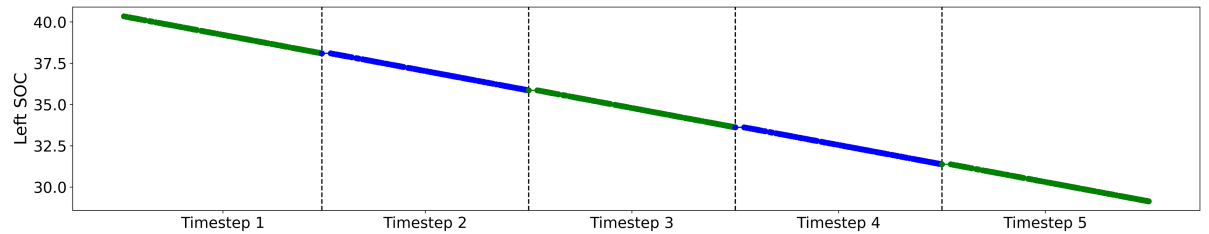


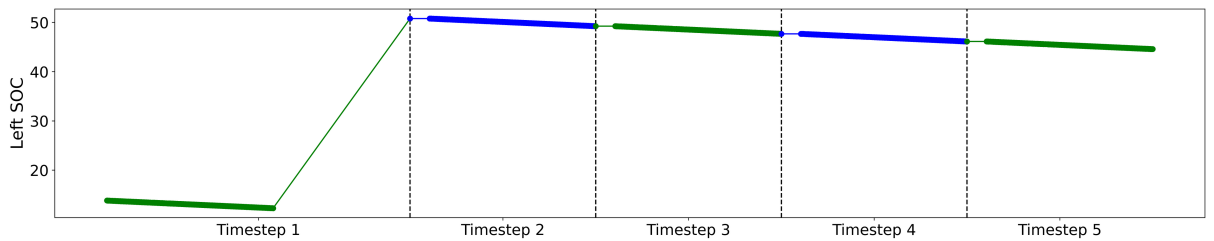
Figure 5.5 Samples of EV drivers.

Although the simulated routing does not fully capture real-world traffic complexity, it still effectively captures EV drivers' charging choices and highlights clear deviations related to charging activities. Figure 5.5 and Figure 5.6 show trajectories and SOC profiles for four representative drivers, respectively. Vehicle 1 represents the most common type of EV driver in the model. This driver has low charging demand associated with short-distance travel, and completed all trips without charging and maintained sufficient battery capacity throughout the five days. Vehicle 2 reached its destination without charging but chose to charge while parked. This behaviour occurred either because the remaining SOC fell below the driver's threshold or because the charge was insufficient for the next scheduled trip. After charging during the first time step, Vehicle 2 did not charge during the subsequent time steps. Vehicles 3 and 4 represent cases where enroute charging was necessary during

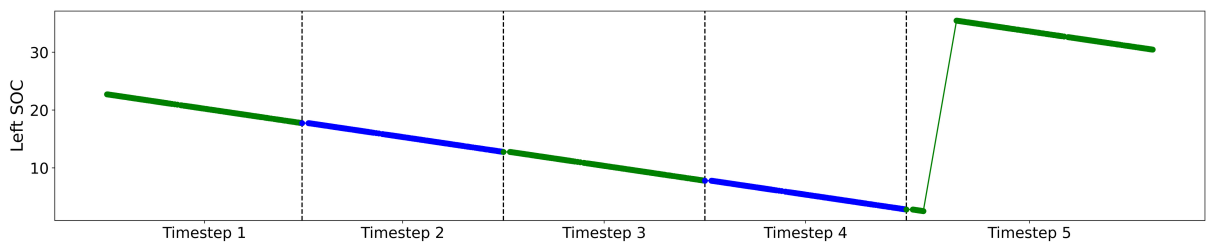
travel. Both drivers encountered insufficient SOC to reach their destinations and therefore planned enroute charging stops. These charging activities lead to deviations from the original shortest paths. Vehicle 3 charged once over the five time steps, whereas Vehicle 4 required charging in four time steps, demonstrating higher energy demand and greater route disruption.



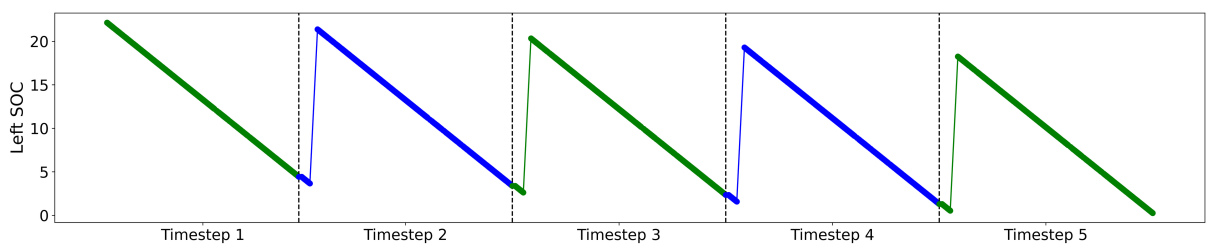
(a) SOC change of Vehicle 1



(b) SOC change of Vehicle 2



(c) SOC change of Vehicle 3



(d) SOC change of Vehicle 4

Figure 5.6 Samples of battery charge patterns.

5.5.2 Charging station usage duration

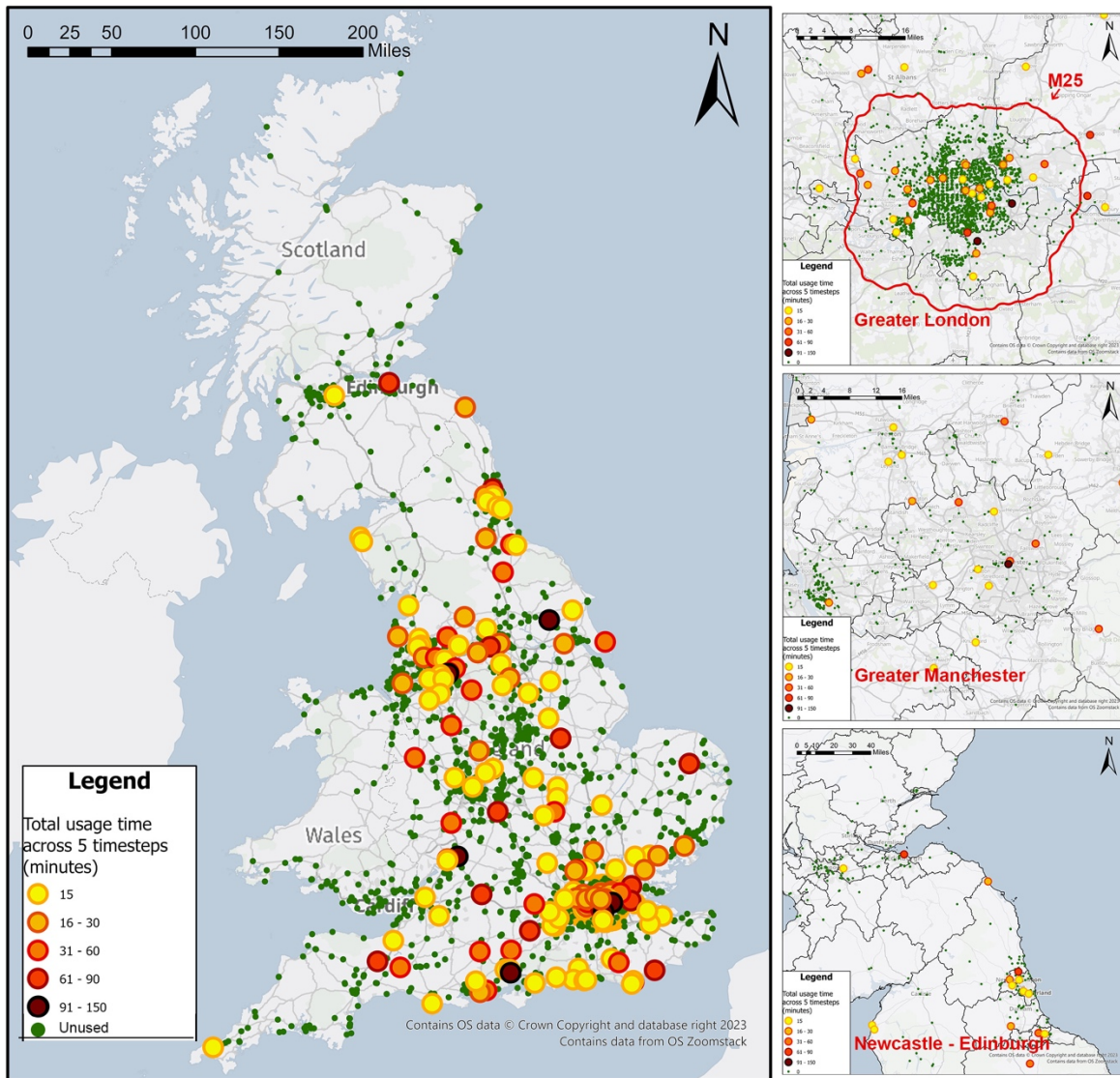


Figure 5.7 Total usage duration of public chargers in the simulation process.

Besides individual driver behaviours, the model also reveals the spatial distribution of public charger usage across GB. Figure 5.7 presents the locations of chargers that were used during the simulation, together with zoomed-in views of Greater London, Greater Manchester, and the Newcastle–Edinburgh corridor. Usage intensity varies considerably across space. Some chargers record long usage durations, which reflect either frequent turnover by multiple vehicles or extended charging sessions by a single vehicle. In contrast, many chargers remain unused. This pattern occurs because the model simulates only a small population of EV drivers relative to the full charging network. Consequently, demand concentrates on a limited subset of stations while a large share of infrastructure remains idle.

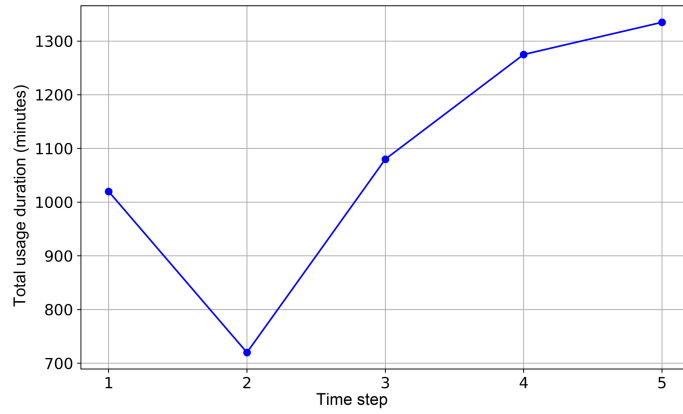


Figure 5.8 Total charger usage duration for all stations over five time steps.

Figure 5.8 shows the total charger usage duration across the five time steps. The total duration declines from time step 1 to time step 2 and then increases steadily from time step 2 to time step 5. The initial decrease can be explained by the charging activities that occurred during Time step 1. Many drivers start with low or insufficient SOC and therefore charge either enroute or at their destinations. After these initial charges, vehicles begin the second time step with higher SOC levels. This makes it less likely for them to encounter insufficient battery charge in time step 2. Charging usage duration increases after time step 2 because daily trips continuously consume battery energy, which gradually regenerates the need for charging in later time steps. This pattern indicates that charging demand depends not only on daily travel but also on the carry-over effects of battery levels from previous days.

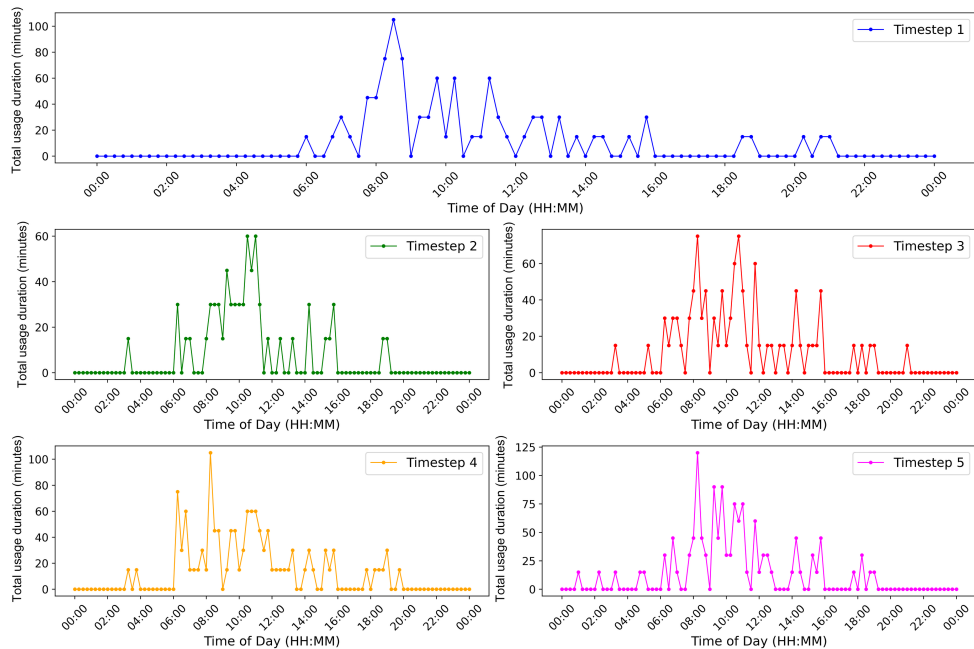


Figure 5.9 Total charger usage duration of all chargers from 0:00 to 24:00.

Figure 5.9 shows the total charger usage duration of all chargers within each time step. Charging activity concentrates primarily during daytime hours across all time steps. However, the timing of peak demand varies between days. Time steps 1, 4, and 5 show relatively early peak hours at around 8:00 - 8:30, while time steps 2 and 3 show postponed peak hours at around 11:00.

5.5.3 Model Validation

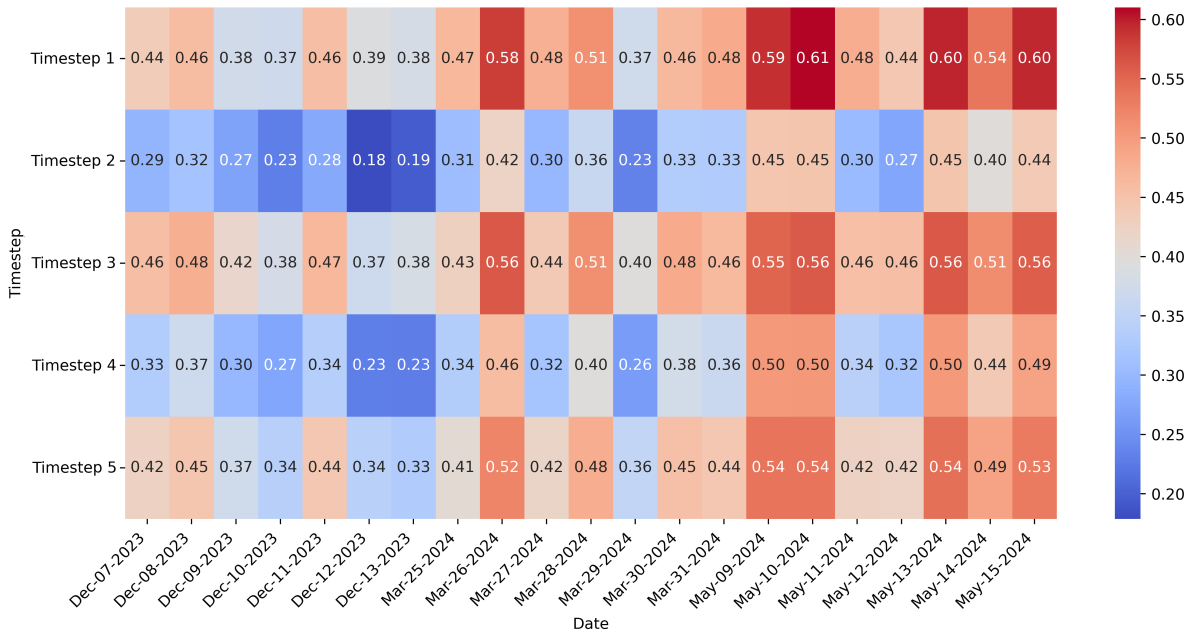


Figure 5.10 Cross-correlation of charger usage between each time step and 21 real world days.

The model is validated by comparing simulated temporal charging patterns with real-world charging session data from ChargePoint (2023). Figure 5.2 shows the total charger usage duration across the sampled week derived from the scraped dataset. Its peak usage falls between 11:00 and 14:00. This aligns with the charger usage patterns observed in time steps 2 and 3, whereas time steps 1, 4, and 5 show earlier peak hours. To further assess consistency between the simulated and observed patterns, a cross-correlation analysis was conducted between each simulated time step and 21 real-world days. Based on the availability of our scraped data, we randomly selected one week each from December 2023, March 2024, and May 2024 to represent public charger usage patterns across different seasons.

As shown in Figure 5.10, although all 105 correlation values are statistically significant, December 7-13 and March 29 show a moderate positive correlation (less than 0.51)

between the simulated results and the real data. One possible reason for the discrepancies is that March 29 was a national holiday in the UK, and the sampled December week occurred immediately before the Christmas and New Year period. Travel and commuting behaviour during holidays can differ from typical weeks. The discrepancies therefore suggest that the simulation better reflects regular daily behaviour rather than atypical seasonal or holiday travel.

It is worth noting why meaningful agreement between simulated and observed patterns can be expected despite the partial representation of both the EV driver population and the charger network. The validation compares normalised temporal patterns using cross-correlation, which measures the similarity of pattern shape rather than absolute usage volumes. The aggregated temporal change of charging demand emerges from population-level travel routines captured in the NTS data, rather than from the size of the simulated population. A representative sample of 1,000 agents can therefore be expected to reproduce the temporal shape of aggregate charging demand, even though absolute volumes are not comparable. The validation should thus be interpreted as evidence that the model captures the behavioural dynamics generating charging patterns, rather than as confirmation of absolute demand levels.

5.5.4 Sensitivity analysis of long-distance journey weight

As identified in Section 5.5.1, current EV battery capacities are generally sufficient for most short- and medium-distance travel, and LDJs remain a key source of charging demand and bring challenges for EV charging decisions. To further explore the impact of the weight of long-distance-journey samples on the simulation results, we conducted a sensitivity analysis by varying the percentage of long-distance-journey samples and evaluated the resulting total charging demand and its spatial distribution. The results are shown in Figure 5.11 and Figure 5.12.

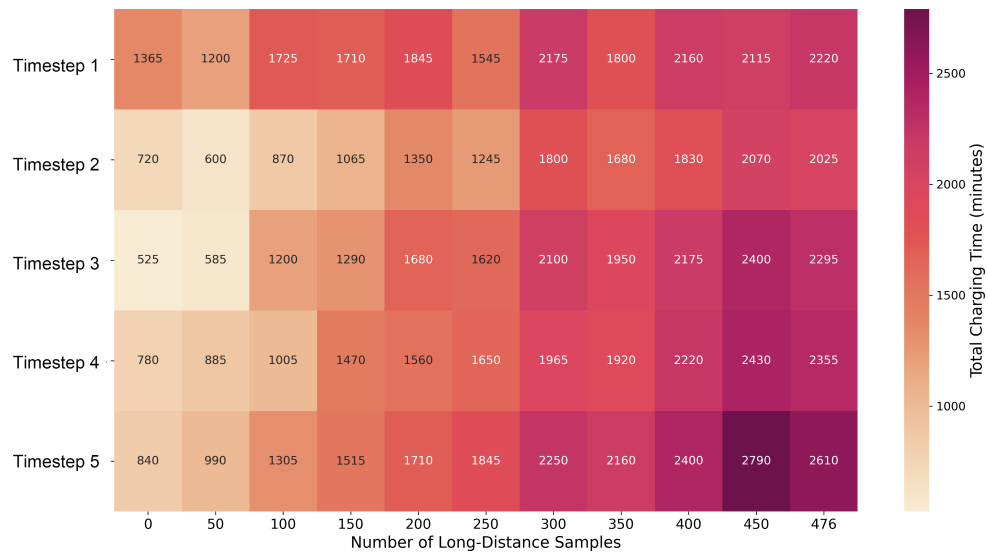


Figure 5.11 Sensitivity analysis of weight of LDJ sample and total charging demand.

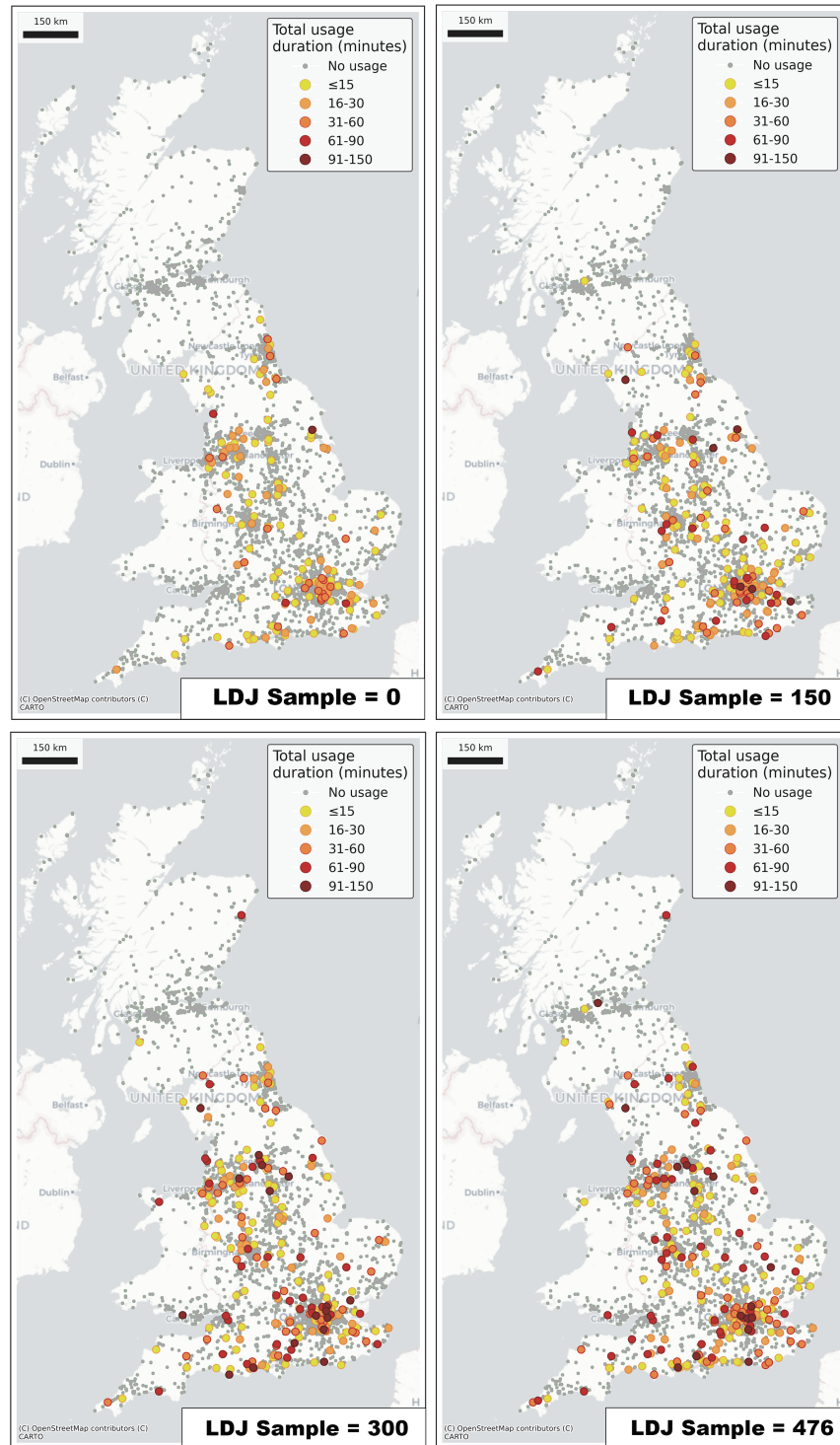


Figure 5.12 Total usage duration of public chargers.

In Figure 5.11, the x-axis shows the total number of LDJ samples included in the model, ranging from 0 to the maximum number of long-distance-journey samples available in the NTS (476), in increments of 50. The y-axis shows the five time steps in the simulation. The value of each cell shows the total charger usage duration of all chargers. The results indicate that the percentage of LDJ samples has a substantial impact on total charging demand. As the number of LDJ samples increases, total charger usage duration shows an

overall increasing trend. This further supports the conclusion that LDJ drivers are important users of public charging station. Figure 5.12 shows the total charger usage duration under four scenarios: when no LDJ samples are included ($LDJ = 0$), when 150 and 300 samples are included ($LDJ = 150$ and 300), and when all available LDJ samples are included ($LDJ = 476$). The results demonstrate that increasing the weight of LDJ from the minimum to the maximum leads to a substantial increase in the charger usage across the network.

5.6 Discussion

This chapter developed an ABM to simulate the driving and charging patterns of EV drivers in GB. The model reproduces individual travel trajectories, charging decisions, and the resulting spatial and temporal patterns of public charger usage. The results indicate that, despite persistent concerns regarding limited driving range, current EV battery capacities are sufficient to support most short- and medium-distance trips without frequent public charging. Additionally, since many of these trips occur within urban areas where chargers are relatively dense and home or workplace charging may also be available, reliance on public infrastructure for daily travel can be relatively limited. In contrast, long-distance journeys generate substantially higher charging demand for public chargers to sustain the journey and reach the destination, as well as to reduce range anxiety when the battery charge is lower than the SOC threshold.

These findings also provide implications for future public charger planning. To support inter-city travel and reduce uncertainty for drivers, future deployment should prioritise fast, enroute chargers along major motorways and regional corridors to enable rapid charging and quick turnarounds. While urban areas generally have denser charging networks and more public chargers than rural or inter-city routes, strategies are needed to optimise charger placement to improve network accessibility at destinations.

Beyond the empirical findings, the proposed ABM also provides several methodological contributions. Compared to statistical and analytical approaches, the ABM explicitly simulates individual routes, SOC dynamics, and public charger usage, which enables the analysis of behavioural mechanisms that cannot be captured through aggregate demand estimation. This ABM also improves previous ABMs of EV drivers by providing a more detailed description of the behavioural patterns of heterogeneous EV drivers. It also

reflects the diversity of EV types in the market by allocating each agent with a unique EV make and model. Additionally, the model includes the national-scale road network and public charger network as an important part of the simulation environment. Compared with previous research focusing on city-level environment or artificial grids, the simulated large-scale geographical area provides important insights into the charging demand from long-distance travel. More importantly, it provides a platform to experiment with diverse EV driver agents in a computational environment. The architecture of the model demonstrates broad applicability and adaptability, with the capacity to integrate diverse data sources. It can effectively be applied to other travel datasets beyond the one used in this study or in different geographical contexts.

Nevertheless, the research also has several limitations. First, the study uses trips and individuals from the 2022 NTS data to model agents. Although the trips span across GB, the NTS dataset surveys only residents of England, and those from Scotland and Wales are not available in the dataset. As a result, a greater concentration of trips is observed in England, with Scotland and Wales having fewer samples, especially in terms of short-distance trips. Consequently, the charger usage patterns and travel behaviours in Scotland and Wales may not be fully represented in the simulation results in this chapter. Additionally, there are temporal discrepancies between our NTS data and the charging session data. Future studies will aim to update the simulation using newer, temporally aligned data when available. Another limitation is that the model does not consider the home charger ownership due to limited data availability. Instead, a truncated normal distribution is used to generate the starting battery charge of vehicles. Further studies should consider home charger ownership as an important variable affecting the decisions of EV drivers. Additionally, there are more factors that need to be considered in future research, such as the impact of weather on EV performance, and the dynamic charging efficiency at different battery levels.

Lastly, two sources of bias should be acknowledged when interpreting the validation results. First, the real-world public charging network comprises more chargers than those covered by the ChargePoint dataset, and the observed patterns may therefore not fully represent network-wide usage. Second, the observed usage data include charging sessions from both commercial fleets and private drivers, whereas the model simulates only private EV drivers. Both factors can contribute to discrepancies between simulated and observed patterns, and the simulated charging demand should therefore be interpreted within these

constraints rather than as an exact representation of network-wide charging demand. Future research should explore alternative datasets with more comprehensive coverage of diverse user types and public chargers.

5.7 Conclusions

This chapter developed an ABM to simulate the driving and charging behaviours of EV drivers in GB. The simulation results were validated against real-world public charger usage data. It was found that, despite long-standing concerns about the limited driving range of EVs compared to conventional vehicles, the charging demand for drivers undertaking short- to medium-distance trips remains relatively low. Charging is typically required only after several days of driving, when the remaining battery charge becomes insufficient for subsequent trips. In contrast, EV drivers undertaking long-distance journeys show higher demand for public charging. Moreover, compared to previous ABMs of EV drivers, the ABM proposed in this chapter provides a more detailed description of the behavioural patterns and a more explicit representation of heterogeneous EV drivers with diverse preferences and different vehicle types. More importantly, it provides a platform to experiment with diverse EV driver agents in a computational environment. The architecture of the model can also be applied to other travel datasets beyond the one used in this study or in different geographical contexts.

Nevertheless, as discussed in Chapter 3, one critique of ABMs lies in their limited capacity to capture adaptive behaviour. As noted by An (2012), adaptive mechanisms are processes through which humans learn, adapt, and revise their decision-making paradigms. The ABM in this chapter employs rule-based agents that rely on static behavioural rules, and the adaptive and cognitive complexity of behaviours is less represented in this model. EV drivers, as identified in Chapter 2, have learning ability and can change their behavioural patterns over time based on past driving and charging past experiences. Incorporating such adaptive mechanisms can improve the predictive accuracy of charging demand. To address this limitation, the next chapter introduces a RL-trained ABM that enables agents to learn and adapt their charging strategies dynamically.

Chapter 6

Replicating the Behaviour of Electric Vehicle Drivers Using an Agent-based Reinforcement Learning Model³

Preface

Chapter 5 developed an ABM with rule-based agents to simulate the driving and charging behaviours of private EV drivers. However, as discussed in Chapter 5, one critique of rule-based ABMs lies in their limited capacity to capture adaptive behaviour. When simulating human behaviours, ABMs should integrate the adaptability and learning capabilities of agents to improve the explanatory power of simulations. For example, as drivers gain experience, they may reduce their range anxiety and charge less frequently (Rauh, Franke and Krems, 2015). They may also learn from experience which charging stations tend to be congested and have longer waiting times, adjusting their charging choices accordingly. However, representing such adaptive behaviour in rule-based ABMs is challenging because the dynamic, subjective choices of humans are difficult to quantify.

To better represent the adaptive behaviours of private EV drivers, this chapter develops an agent-based RL model to simulate their charging and driving behaviours of EV drivers. The model captures the adaptive learning processes of private EV drivers who operate independently, have limited communication with one another, and show bounded rationality and learning ability. Section 6.1 introduces the background of diverse EV adopters and the research trajectories in EV driver behaviours, as well as the objective of this chapter. Section 6.2 reviews previous statistical and analytical studies, as well as simulation-based approaches to modelling EV driver charging and driving behaviours, and identifies research gaps in the representation of adaptive behaviours. Section 6.3 describes

³ This chapter is based on a published paper Feng, Z., Zhao, Q., & Heppenstall, A. (2026). Replicating the behaviour of electric vehicle drivers using an agent-based reinforcement learning model. *Environment and Planning B: Urban Analytics and City Science*, 23998083261455937.

the data used for the agent-based RL model. Section 6.4 details the methodological framework and the algorithms of the RL model. Section 6.5 presents the results of model validation and the charging demand distribution across GB. Section 6.6 discusses the contributions and limitations of the research, and Section 6.7 concludes the chapter.

6.1 Introduction

With global net-zero carbon transition targets, rapid technological advancements, and declining battery costs, many countries have witnessed a significant rise in EV adoption (Mahmud, Medha and Hasanuzzaman, 2023). In the early stages of this transition, EV adopters were predominantly households with garages or off-street parking suitable for installing home chargers (LaMonaca and Ryan, 2022). However, as EV ownership expands from early adopters to the mass market (Intellectual Property Office, 2021), an increasing percentage of EV drivers lack access to home chargers, particularly those living in flats or without dedicated parking spaces. This shift has driven substantial demand for public charging infrastructure.

Despite growing investment in public charging networks, concerns have emerged about whether current deployment strategies are effectively meeting user needs. Recent research has questioned whether the emission reduction benefits of EVs can be sustained given variability in consumer charging behaviour (Nunes, Woodley and Rossetti, 2022), while others have raised concerns that charging network expansion may be misallocating resources and failing to adapt to diverse user needs (Metais et al., 2022). Survey evidence suggests that existing EV drivers seek to integrate charging into their trip schedules and daily routines, while potential adopters prioritise proximity, reliability, and dependability of chargers as key factors in their decision to switch (Department for Transport, 2022). Understanding the complex behaviours of diverse EV drivers and accurately estimating charging demand are therefore important for developing a more effective charging network.

Previous studies have explored EV driver behaviours and estimated their charging demand using either statistical and analytical or simulation-based approaches. However, despite their contributions, both approaches have limitations. Statistical and analytical methods often face limited access to EV-specific datasets due to privacy concerns (Park and Joe, 2024). As a result, researchers often rely on alternative datasets, such as socio-demographic data (Crozier, Morstyn and McCulloch, 2021), GPS data from conventional vehicles (Kontou et al., 2019) or commercial EV fleets (Hu et al., 2022). While these datasets offer high granularity or rich attributes, they may lead to biased representations of private EV drivers. Meanwhile, simulation-based approaches, such as DESs (Pruckner,

German and Eckhoff, 2017; Lopez, Allana and Biona, 2021; Wahyudi, Rahman and Hariyanto, 2024) and ABMs (van der Kam et al., 2019; Yi et al., 2023), have been proven effective in modelling charging and driving behaviours of EV drivers. However, DES is a process-oriented, top-down modelling approach and its individual behaviours are governed by the system rather than by autonomous decision-making (Siebers et al., 2010; Maidstone, 2012). This makes it an unsuitable approach for modelling proactive and autonomous private EV drivers. In contrast, ABM is a bottom-up modelling approach which can effectively model autonomous individuals. However, previous ABMs of EV drivers are often based on rule-based agents, which follow pre-determined rules set by modellers and fail to reflect the adaptive nature of human drivers in response to changing conditions. For example, as drivers gain experience, they may reduce their range anxiety and tend to charge less frequently and become more comfortable operating with lower battery levels (Rauh, Franke and Krems, 2015). They may also learn from experience which charging stations tend to be congested and have longer waiting times, adjusting their charging choices accordingly. Capturing such adaptive behaviours using ABMs with static behavioural rules is challenging, as doing so would require highly complex models with large parameter spaces, and create significant difficulties for model verification.

The objective of this chapter is to develop an agent-based RL model using a Deep Q-Network (DQN) to simulate the adaptive driving and charging behaviours of heterogeneous EV drivers in GB. Specifically, the model aims to (1) capture the adaptive learning processes through which EV drivers adjust their charging decisions over time, and (2) estimate the spatial distribution of public charging demand and identify locations with high risks of battery depletion. To achieve these objectives, this chapter proposes a novel multi-episode training-simulation framework. First, EV drivers are categorised based on key characteristics, including travel distance, battery status, trip purpose, and environmental factors. Representative agents from each cluster then learn charging behaviours through RL across multiple training episodes. These learned behaviours are subsequently applied to simulate the broader population of drivers within their respective groups, generating an updated charging environment that feeds back into the next training episode. This iterative process captures both the adaptive charging behaviours of individual EV drivers and the evolving interactions among drivers at charging stations. This framework simulates heterogeneous adaptive behaviours of different EV drivers and contributes to more accurate estimation of charging demand among private EV drivers and

can inform future charging infrastructure planning by identifying locations that may require additional public chargers.

6.2 Background

Extensive research has explored EV driver behaviour and estimated charging demand using statistical and analytical approaches or simulation-based approaches. Many studies based on statistical and analytical approaches develop indicators to estimate the spatial distribution of charging demand based on aggregate data sources, such as population density, average travel distance, and travel flow volumes, to estimate charging demand distribution (Dong et al., 2019; Hardinghaus, Seidel and Anderson, 2019). However, these aggregate datasets often lack the granularity needed to capture individual-level travel patterns and charging decisions. With improved data availability, more recent research studies use highly granular vehicle trajectories to infer EV charging demand, including trajectories of conventional vehicles (Kontou et al., 2019) and commercial EV fleets such as taxis (Hu et al., 2022). While these datasets offer spatial and temporal resolution, they may not accurately represent the travel and charging patterns of private EV drivers, whose behaviour differs from that of commercial fleets or conventional vehicle users. As a result, relying on such proxy data can introduce systematic biases when estimating charging demand for the private EV population.

Meanwhile, trajectory data for private EV drivers remains scarce due to the early stage of EV adoption and privacy concerns about connected vehicle data. One notable exception is the use of surveys to collect data on private EV drivers (Hasan and Simsekoglu, 2020). While such surveys provide valuable insights into driver behaviours, their high costs often restrict sample sizes and geographical coverage, and limit their generalisability to broader spatial contexts.

Given the limitations of statistical and analytical approaches, simulation-based approaches, such as DESs and ABMs, have been developed to simulate the charging and driving behaviours of EV drivers and estimate their charging demand. DES is one of the most commonly used simulation approaches (Pruckner, German and Eckhoff, 2017; Lopez, Allana and Biona, 2021; Wahyudi, Rahman and Hariyanto, 2024). However, DES is a process-oriented, top-down modelling approach in which individual behaviours are governed by the system rather than by autonomous decision-making (Siebers et al., 2010;

Maidstone, 2012). While DES is suitable for modelling EV fleets with pre-determined tasks and charging schedules, it is less appropriate for modelling private EV drivers who have proactive decision-making processes.

In contrast, as discussed in Chapter 5, bottom-up ABMs can capture the behaviours of autonomous EV drivers with heterogeneous psychological features, financial preferences, and vehicle attributes (Adenaw and Lienkamp, 2021; Liu, Tayarani and Gao, 2022). However, despite their detailed representation of individual behaviours and interactions, questions remain about the ability of rule-based ABMs to represent EV drivers' adaptability and learning capacity. A key critique of rule-based ABMs is their limited capacity to represent adaptive behaviour, which refers to agents' ability to develop new strategies and modify their actions over time (Rand, 2006). An (2012) described adaptive mechanisms as processes through which humans learn, adapt, and revise their decision-making paradigms. They make decisions in response to changing environments, which will in turn change their context for future decisions. Macal (2016) similarly argued that ABMs should integrate adaptability and learning capabilities of the agents to improve the explanatory power and credibility in simulations. However, representing such adaptive behaviour in ABMs is challenging because the dynamic, subjective choices of humans are difficult to quantify. Additionally, incorporating adaptive mechanisms can result in highly complex models with large parameter spaces and multiple interlinked sub-processes, thus posing significant challenges for model verification (Sun et al., 2016).

Compared to rule-based agents, RL-trained agents have demonstrated advantages in capturing adaptive human behaviours, where positive behaviours are learned through repeated exposure to an environment (Malleson et al., 2022). RL is a goal-directed learning framework commonly used for studying sequential and dynamic decision-making problems. RL-trained agents learn by receiving rewards and penalties based on their actions (Sutton and Barto, 1998; Russell and Norvig, 2016). They do not require predefined 'correct' decisions and can operate under conditions of limited prior knowledge (Mohri, Rostamizadeh and Talwalkar, 2018). Unlike other ML methods, RL is particularly valuable when no dataset of correct answers exists (Dahlke et al., 2020). As such, RL can realistically model adaptive human decision-making processes (Ale Ebrahim Dehkordi et al., 2023). It is well-suited for studying private EV drivers whose trajectory data remains limited.

In transportation research, RL has been widely applied to optimise vehicle routing and charging decisions (Koh et al., 2020; Jebessa et al., 2022). One notable feature of these studies is their emphasis on optimisation (Lee, Lee and Kim, 2020; Yan et al., 2021). One group of studies assumes agents share information in a timely manner and uses RL to optimise coordinated decision-making among EV fleets (Lin, Ghaddar and Nathwani, 2022; Sultanuddin et al., 2023). Another group of studies focuses on individual driver optimisation, where RL is used to identify optimal routing and charging strategies that minimise travel time, energy consumption, or charging cost (Jin and Xu, 2022; Yu et al., 2023; Dastpak et al., 2024). However, the assumptions of complete information exchange and perfect rationality underlying these studies do not apply to private EV drivers, who operate under bounded rationality, have limited communication with one another and act independently. Recent research on cognitive decision-making has increasingly emphasised the importance of incorporating bounded rationality into behavioural models (Manley and Cheng, 2018; Pappalardo et al., 2023). Despite RL's capacity for adaptive learning, there remain gaps in going beyond maximal utility assumptions and integrating bounded rationality into RL frameworks, which is important for modelling the adaptive behaviours of private EV drivers. More broadly, agent-based RL has predominantly been used to prescribe what drivers should do rather than to describe what drivers actually do. Although RL is well suited to representing adaptive learning under uncertainty, its application to modelling realistic charging behaviour among private EV drivers remains limited.

Another limitation of previous studies using RL to train and simulate EV drivers is the challenge of scalability. Exploring EV driver behaviours across large geographical scales is critical, as long-distance journeys present unique challenges for EV drivers in terms of route planning and charging decisions. While some ABM studies have simulated EV drivers at regional or national scales (Anjos, Gendron and Joyce-Moniz, 2020; Liao et al., 2023), incorporating RL into such large geographical scales introduces additional computational challenges due to the larger road networks and expanded charging networks. Although progress has been made in cooperative multi-agent RL, simulating thousands of independent RL-trained agents with limited inter-agent communication across geographically large-scale scenarios remains an area requiring further exploration.

In summary, despite significant progress in estimating charging demand and analysing EV driver behaviour through both data-driven and simulation-based approaches, several critical gaps remain. Data-driven methods face challenges related to biased representations

and limited data availability for private EV drivers. Simulation-based models often rely on static behavioural rules and fail to capture the adaptive and heterogeneous nature of human decision-making. While RL offers clear advantages for incorporating adaptive learning processes, previous studies have primarily applied RL to EV fleet optimisation under assumptions of full rationality. The use of RL to simulate private EV drivers operating under bounded rationality and with limited inter-agent communication remains underexplored, particularly in large-scale geographical contexts with high computational demands.

6.3 Data and study area

This study takes GB as its study area, which comprises England, Scotland, and Wales. We focus on the trips made by England residents travelling across GB. Over the past decade, GB has seen consistent growth in its public charging network. As of April 2024, there are 59,125 publicly available chargers in the region (Department for Transport, 2024a). Additionally, England has a high volume of trips taken by private vehicles, with its residents travelling an average of 5,373 miles in 2022 (Department for Transport, 2023b).

In our model, agents represent a combination of EV drivers and their vehicles. Travel schedules of EV drivers are established using attributes derived from National Travel Survey data (UK Data Service, 2022), combined with Ordnance Survey (OS) Code-Point data (Ordnance Survey, 2023a). EV attributes are sourced from the EV Database (EV database, 2024). The simulation environment integrates road networks from OS Open Roads dataset (Ordnance Survey, 2023b) and public chargers from ChargePoint dataset (ChargePoint, 2023). The availability status of chargers is scraped from the ChargePoint website and are used for model validation (ChargePoint, 2023).

6.3.1 Data for simulation environment

We use the road network data from the OS Open Roads dataset (Ordnance Survey, 2023b), and public charger data from the ChargePoint dataset (ChargePoint, 2023) to establish the modelling environment. The attributes of the chargers are listed in Table 4.1, and the distribution of all chargers is shown in Figure 5.1. More details of the dataset attributes and collection methods are described in Section 4.3.1 in Chapter 4.

6.3.2 Data for EV driver agents

Pareschi et al. (2020) found that travel diaries drawn from travel survey data, together with appropriate settings of EV-related attributes, can provide a reliable and accurate foundation for simulating EV driver behaviour and charging loads. Based on this foundation, we formulate synthetic EV driver populations based on trip schedules from NTS dataset, and EV-specific attributes generated based on recognised range and distributions from previous studies and EV type datasets. Data sources of different variables are summarised in Table 6.1 and explained in detail in this section.

Trip Schedule

Since EV-specific travel data is rarely available due to privacy concerns and limited market penetration, we follow the common approach in EV simulation studies of using general travel survey data to represent EV driver travel diaries (Pareschi et al., 2020; Yan et al., 2020). It should be noted that NTS dataset does not identify EV owners; rather, we use the travel patterns from the survey and assume that drivers maintain their existing travel plans upon switching to EVs (Yan et al., 2020). Trip schedule information derived from NTS dataset includes trip purposes, origin and destination unitary authorities, trip distance, and trip start time.

Table 6.1 Data sources for formulating the EV population.

Variable Name	Description	Processing details
Trip schedule from NTS dataset		
Trip purpose	The purposes of the trip	Specific reclassification methods are included in the Data Pre-processing section.
Origin unitary authority	The unitary authority the trip origin belongs to	These three variables (origin, destination, and trip distance) are combined with the OS Code-Point data to determine the specific origin and destination coordinates of the trip, as well as the shortest path without charging detours. Details are
Destination unitary authority	The unitary authority the trip destination belongs to	
Trip distance	Total trip distance by vehicles excluding short distance walks (miles)	

included in the Data Pre-processing section.

Trip start time	Time in minutes past midnight when the trip starts	Directly derived from the dataset.
EV-specific attributes		
Initial SOC	The SOC level when driver start the trip over a day.	Generated based on truncated normal distribution bounded within the interval (0,1) (Pareschi et al., 2020; Yang et al., 2025).
Battery size and Battery consumption rate	Extracted from the EV Database website (EV database, 2024)	Each EV driver is randomly assigned a vehicle type available on UK's market when initialising the model.
Environmental attributes		
Charger density surrounding each driver	Number of public chargers within 500m buffer of shortest path, normalised by trip length.	Calculated from charger locations and route geometry.
Trip co-occurrence density surrounding each driver	Number of concurrent trips intersecting the route's 500m buffer, normalised by trip length.	Calculated from trip schedules and route geometry.

Initial SOC

Drivers may start the day with different initial SOC levels. These differences can be influenced by factors such as home charger availability (Liao et al., 2023) and access to workplace charger (Andrenacci and Valentini, 2023). Drivers with access to either a home or workplace charger are more likely to start their trips with a higher SOC than those without access. However, home and workplace charging is not considered in this research due to the lack of data on home and workplace charger accessibility in the UK. Obtaining such data is challenging due to privacy concerns and the fragmented nature of data across multiple charger providers.

Given these data constraints and following established practice in EV simulation literature (Pareschi et al., 2020; Yang et al., 2025), we initialise each EV with a random initial SOC level based on a truncated normal distribution bounded within the interval (0,1). This

approach captures population-level heterogeneity in initial SOC while avoiding assumptions about the relationship between individual socio-demographic features and charging behaviour, which is difficult to validate with available data.

Battery size and battery consumption rate

The EV attribute data is extracted from the EV Database website (EV database, 2024), which provides information on vehicle make and model, battery range, and consumption rates of EVs available in the UK market. As of February 18, 2024, there are 231 EV types included in the dataset. Each EV driver is randomly assigned a vehicle type when initialising the model. Since the primary objective of this study is to analyse driver behaviour rather than technical aspects of vehicle performance, we do not account for the effects of battery aging or varying consumption over time. Instead, the specifications used in the simulation reflect those of newly manufactured EVs. Examples of EV models are shown in Table 6.2.

Table 6.2 Examples of EV models in the UK.

EV Name	Battery Size (kWh)	Consumption Rate (Wh/mi)
Tesla Model Y	57.5	267.0
Tesla Model 3	57.5	221.0
Kia Niro EV	64.8	270.0
Volkswagen ID.3	59.0	268.0
Nissan Leaf	39.0	269.0

Environmental factors

Besides individual preferences and trip-specific features, a driver's behaviour can also be influenced by the surrounding environmental factors. These include the distribution of the public chargers nearby and the presence of other EVs traveling within overlapping time windows. Therefore, after identifying the OD coordinates and calculating the shortest paths between them (as detailed in Appendix G), we introduce two environmental indicators to quantify charging infrastructure availability and potential competition for public chargers among drivers.

Charger density (CD) is defined as the number of public chargers within a 500-meter buffer along the shortest path, normalised by the total path length. This metric represents the relative availability of charging infrastructure along a driver's route. As shown in

Equation (6-1), d_i is the distance of from charger i to the shortest path. L_{trip} is the length of the shortest path. N_c is the total number of public chargers considered, and the indicator function $1(d_i \leq 500)$ equals 1 if charger i lies within 500 meters of the shortest path, and 0 otherwise.

$$CD = \frac{\sum_{i=1}^{N_c} 1(d_i \leq 500)}{L_{\text{trip}}} \quad (6-1)$$

Trip co-occurrence density (TCD) is defined as the number of concurrent trips intersecting the route's 500-meter buffer zone during the travel time window, normalised by trip distance. It quantifies the potential charging competition along the trip. As denoted in Equation (6-2), N_t is the total number of concurrent trips within the travel time window. R_j is the route of the concurrent trip from other drivers. B is the 500-meter buffer zone around the shortest path.

$$TCD = \frac{\sum_{j=1}^{N_t} 1(R_j \cap B \neq \emptyset)}{L_{\text{trip}}} \quad (6-2)$$

6.3.3 Data for model validation

The charging session data from ChargePoint is used to validate the model. Besides the attributes, the availability status of chargers is also scraped, which includes statuses of ‘In-use’, ‘Available’, and ‘Closed’. The status data is collected at 15-minute intervals from December 5, 2023, to May 15, 2024. Figure 6.1 shows the total charger usage time change in GB for a sample week in February. On average, peak usage hours occur between 12:00 and 14:00.

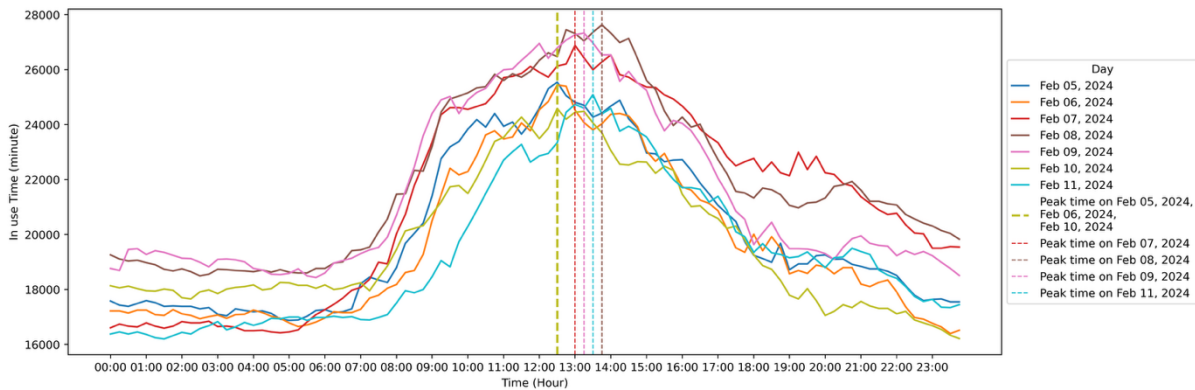


Figure 6.1 Total usage time of all public charger in GB in a sample week (Feb 5-11, 2024).

6.4 Methods

6.4.1 Multi-stage Training-Simulation Framework

To address the challenges identified in Section 6.2, this chapter proposes a scalable multi-episode training-simulation framework that combines agent clustering with iterative RL training and population-level simulation. In this framework, EV drivers are first grouped into clusters based on key characteristics. At each training episode, a representative agent from each cluster is trained using a DQN. The learned policies are then applied to simulate the behaviour of all agents within the respective clusters, generating updated charging patterns across the network. This updated environment feeds back into the next training episode, allowing agents to adapt to evolving conditions. Through continuous validation against real-world charging session data at each episode, the framework identifies the training episode whose simulated charger usage patterns most closely reflect observed behaviour, rather than selecting the episode with optimal performance. This approach provides a practical solution for modelling large-scale systems. It allows for the inclusion of larger agent populations and application across diverse scenarios while maintaining computational efficiency.

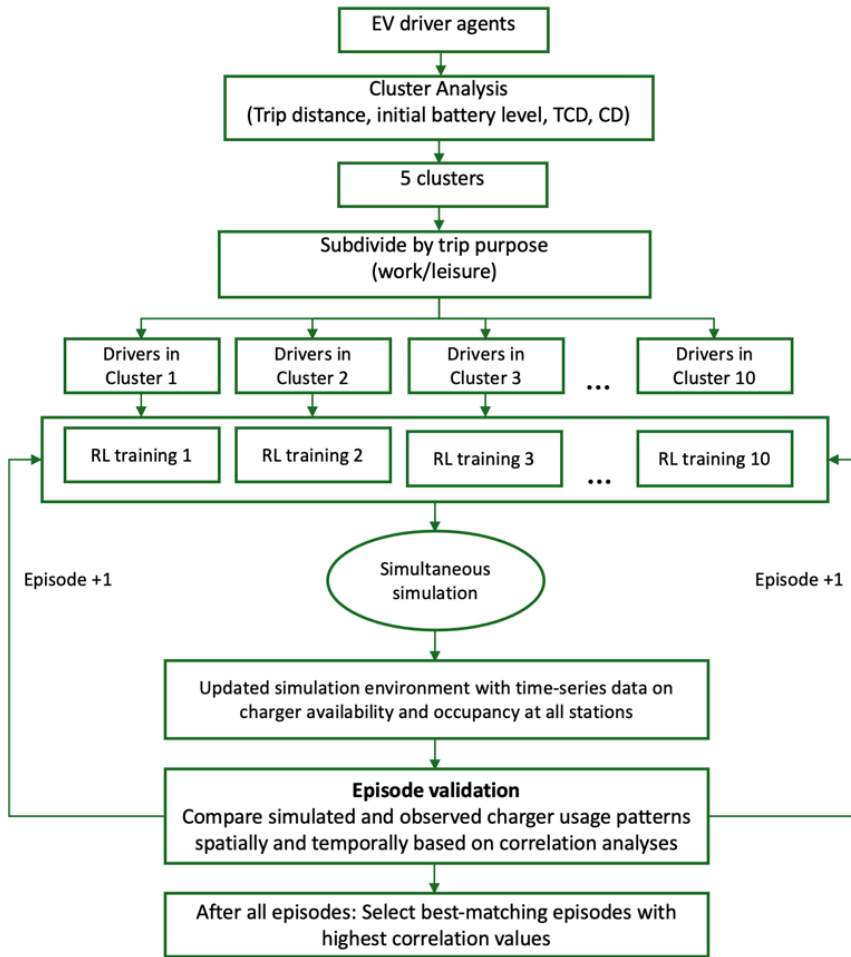


Figure 6.2 Methodological framework.

The details of the methodological framework are shown in Figure 6.2. EV drivers from the NTS dataset are first clustered based on four key characteristics using k-means clustering: trip distance, initial battery level, TCD, and CD. Trip purpose (work, leisure) is not directly included in the cluster analysis process due to the limited sample size of leisure trips and the categorical nature of this variable, which could introduce bias into the clustering results. Instead, following the clustering analysis, each cluster is further subdivided based on the trip purpose to account for the different behavioural patterns associated with work and leisure trips.

Following clustering analysis, representative agents are selected for RL training. For each cluster, the two agents closest to the cluster centroid are identified, as these agents best represent the typical characteristics of their respective clusters. These two agents are then assigned to two separate training sets, ensuring that each training set contains one representative agent per cluster. Meanwhile, simulation agents are randomly sampled from the full agent population. Ten simulation agent sets are generated, each containing a

different random sample of agents. To ensure model robustness and minimise overfitting, the model is run for all combinations of the two training sets and the ten simulation sets, resulting in twenty model runs. This number balances statistical robustness with computational resource constraints.

The details of the RL model are specified in Section 6.4.2. After each training episode, the learned policies are applied in the simulation phase to guide the behaviour of all agents within their respective clusters. During simulation, all agents operate within a shared environment where individual charging decisions affect charger availability for others. Agents interact with each other through two mechanisms: (1) All EV drivers are assumed to have access to the real-time charger status updates via mobile apps or websites. When a driver occupies a charger, its status changes from ‘available’ to ‘in use’, and this update is visible to all other drivers; (2) When a charger is occupied, this does not necessarily prevent other drivers from travelling to the same charger. Due to limited charger availability in certain areas, drivers may still choose to travel to an occupied charger and queue behind other vehicles. Since charging apps and websites do not display queue lengths, drivers must make decisions on queueing and balking based on their personal experiences.

After each episode, the simulated charger usage patterns, including the usage time windows for each charger, are incorporated into the state space for the next training episode. This iterative feedback loop enables agents to learn from system-wide charging patterns and adapt their behaviours based on past experiences. The model is executed on Amazon Web Service, using 64 vCPUs and 128 GB of RAM. Key hyperparameters, including the learning rate, discount factor, and exploration rate, are calibrated to improve the model's performance. The model calibration results are shown in Appendix I.

At the end of each episode, the model is validated by comparing simulated charger usage patterns, including the spatial distribution and temporal profiles of charging sessions, against real-world charging session data from the ChargePoint dataset. This comparison uses spatial and temporal correlation analysis detailed in Section 6.5. After all episodes are complete, the episodes with the highest correlation scores are selected as the stage where simulated behaviour most closely aligns with observed real-world patterns.

It is important to note that the best-matching episodes do not correspond to the episodes in which agents have fully converged toward optimal behaviour. Instead, the episode with the highest correlation to real-world data typically falls between the early exploratory stage and the final convergence stage. This intermediate stage captures a realistic mix of driver experience levels within the population: some drivers may still be learning and exploring, while others have developed more stable charging routines. The best-matching episode therefore represents a population-level blend of varying experience stages, rather than a uniformly optimal outcome.

6.4.2 RL model

Many different RL frameworks have been applied to train and simulate EV drivers, spanning both on-policy and off-policy models. These include Policy Gradient (Acquarone, Borneo and Misul, 2022), State-Action-Reward-State-Action (SARSA) (Aljohani and Mohammed, 2022), Q-learning (Jiang et al., 2018; Lee and Brown, 2021), and Soft Actor-Critic (Chu et al., 2022). While these methods have been effective for optimisation tasks, not all are suitable for modelling the adaptive behaviour of decentralised private EV drivers.

On-policy models such as SARSA require the agent to learn by following the policy it is updating, meaning the learned behaviours must align with the current policy. In contrast, off-policy models such as Q-learning enable agents to learn from behaviours generated by ‘older’ policies (Precup, Sutton and Dasgupta, 2001; Van Seijen et al., 2009). This chapter uses off-policy RL, Q-learning, to enable agents representing human drivers to learn from diverse past experiences beyond their current policy. While value-based Q-learning performs well in scenarios with discrete states and actions, its reliance on a tabular approach limits scalability. Training becomes inefficient when dealing with large state and action spaces, such as those in our study. To address this challenge, we employ the Deep Q-Network (DQN) framework introduced by Mnih et al. (2015). By leveraging deep neural networks to approximate the Q-value function to enhance performance, DQN is a more practical choice for this research.

The agent’s objective throughout this process is to complete all planned trips while avoiding battery depletion. The charging decision-making process of EV drivers is formulated as an RL problem, where agents observe a state, take an action, receive a

reward, and undergo a transition based on their chosen action. Each agent is initialised with a SOC and a daily trip schedule comprising one or more destinations. The agent navigates the road networks using Dijkstra's shortest path algorithm, moving from its current node at time t (P_t) to the next node at time $t+1$ (P_{t+1}) while continuously evaluating charging decisions. At any time step t , the agent's state S_t is represented as a tuple of five variables:

$$S_t = (\text{SOC}_t, \text{Dist}_t, \text{Time}_t, \text{Stations}_t, \text{Trip}_t) \quad (6-3)$$

Where SOC_t represents the SOC at time t , indicating the vehicle's battery status. Dist_t is the shortest distance from the current position to the destination. Time_t indicates the time in minutes past midnight on the given day at time step t . Trip_t is the number of remaining trips in the driver's daily trip plan. Stations_t is the percentage of available stations relative to all reachable stations within the vehicle's remaining driving range, based on its SOC_t and energy consumption rate at location P_t at time t . At each subsequent time step ($t+1$), the agent re-evaluates the reachable stations, and recalculates Stations_{t+1} based on its updated location (P_{t+1}) and updated remaining SOC (SOC_{t+1}).

At each time step t , the agent selects an action $a_{t,i}$ from the action space A_t using a greedy strategy. The action space A_t is defined as follows

$$A_t = \{a_{t,0}\} \cap \{a_{t,n,k} | n \in \{10, 20, 30 \dots 100\}, k \in K\} \quad (6-4)$$

Where:

- $a_{t,0}$ indicates moving from the current node P_t to P_{t+1} without charging.
- $a_{t,n,k}$ includes rerouting to one of the reachable and available charging stations k ($k \in K$) and charging the battery by $n\%$

We implement the learning process using a DQN, which maps state-action pairs to Q-values through hidden layers. The DQN takes the state variables S_t as input and outputs Q-values for each possible action $a_{t,i}$. The Q-value, $Q(s, a)$, represents the agent's expected cumulative reward from taking action a in state S :

$$Q(s, a) = r + \gamma \max_{a'} Q(s', a') \quad (6-5)$$

r is the immediate reward for the action. γ is the discount factor $\max_{a'} Q(s', a')$ represents the maximum estimated reward achievable from the next state s' . The action selection follows an ϵ -greedy strategy to balance exploration and exploitation. With a probability of ϵ , the agent explores by randomly selecting an action from the available action space. Otherwise, the agent exploits by selecting the action with the highest Q-value. The exploration rate ϵ is initialised at 0.99 to encourage exploration during the early stages of training. As training progresses, ϵ gradually decays over time to reach a minimum value of 0.01 by the end of training (2000 episodes). This decay ensures that agents transition from predominantly exploratory behaviour to predominantly exploitative behaviour. It ensures the agent learns from diverse experiences while refining its decision-making over time.

After performing the selected action $a_{t,i}$, the agent receives a reward R_t , and transitions to a new state S_{t+1} . These transitions are stored as experiences in an experience replay buffer (Equations (6-6)-(6-7)). During training, random minibatches of experiences are sampled from the replay buffer D_t during the training. This approach helps break temporal correlations and improves learning efficiency by allowing the agent to revisit rare transitions multiple times, thereby enhancing stability in the learning process (Mnih et al., 2015; Schaul et al., 2015).

$$e_t = \{S_t, a_{t,i}, R_t, S_{t+1}\} \quad (6-6)$$

$$D_t = \{e_1, e_2, \dots, e_t\} \quad (6-7)$$

For each mini-batch, the network computes the predicted Q-values and the target Q-values using the Bellman Equation. The network parameters are then updated by minimising the loss function $L(\theta)$, which is the mean squared error of the target Q-value and predicted Q-value:

$$L(\theta) = \mathbb{E}_{s,a,s',a'} \left[\left(r + \gamma \max_{a'} Q(s', a'; \theta') - Q(s, a; \theta) \right)^2 \right] \quad (6-8)$$

Another important term to define the agent's experience is the reward R_t . It is the immediate reward received for taking an action $a_{t,i}$. The reward considers financial costs,

charging urgency, trip status, and SOC threshold of drivers (Equations (6-9) -(6-13)). More details of the justification of reward function design are provided in Appendix K.

$$D_{\text{SOC}} = \text{SOC}_t - \text{SOC}_{\text{threshold}} \quad (6-9)$$

$$D_{\text{charge}} = \mathbb{I}_{\text{charge},t} \cdot \varepsilon \cdot \ln(\text{timing}_{\text{charge}} \cdot \text{chance}_{\text{charge}} \cdot \text{status}_{\text{battery}} + 1) \quad (6-10)$$

$$\mathbb{I}_{\text{charge},t} = \begin{cases} 1, & \text{if charge at } t \\ 0, & \text{if not charge at } t \end{cases} \quad (6-11)$$

$$D_{\text{cost}} = (\alpha \cdot \log(1 + \text{Payment} \cdot \mathbb{I}_{\text{charge},t}) + \beta \cdot \log(1 + T_{\text{travel}} + T_{\text{charge}} \cdot \mathbb{I}_{\text{charge},t}) + 1)^{\frac{n}{m}} \quad (6-12)$$

$$R_t = \frac{\gamma \cdot D_{\text{SOC}}}{D_{\text{charge}} \cdot D_{\text{cost}}} + \rho \cdot \text{Status} \quad (6-13)$$

Where:

- D_{SOC} is the SOC threshold impact. It is the difference between the current SOC level at t and the drivers' SOC threshold $\text{SOC}_{\text{threshold}}$. It measures how well the driver is maintaining a sufficient battery level relative to their psychological threshold.
- D_{charge} is the charging urgency factor. It evaluates the urgency of a charging decision. This variable is only considered if a charge behaviour happens.
- $\text{timing}_{\text{charge}}$ is the lengths of time between the trips starts and the charging activity starts, indicating whether charging occurs early or late in the trip.
- $\text{chance}_{\text{charge}}$ is the charging opportunity ratio. It is defined as the ratio of CD to TCD, as described in the Data and Study Area section in the Supplementary Materials.
- $\text{status}_{\text{battery}}$ is the start battery level of a driver.
- D_{cost} is the cost impact. It consists of the financial payment for charging, the time spent for rerouting to charging station, and the actual charging duration.
- n is the number of times the agent charges. It introduces an exponential penalty when the total charge time increases.

- m is a categorical variable of the trip distance class. Compared with longer-distance trips, shorter-distance trips will incur a greater penalty for repetitive charging.
- Status is a categorical variable with values 0, 1, or -1. It represents the driver's trip completion status. A value of -1 results a penalty and indicates that the driver fails to complete the trip. A value of 0 means the driver continues the trip without additional rewards or penalties. A value of 1 means the driver earns an additional reward by successfully reaching a destination.
- ρ is the weight coefficient for the trip completion status. It determines the magnitude of the reward associated with trip completion outcomes.

6.4.3 Model validation

The model is validated using 21 days of real-world charging session data. Correlation analysis was performed between the simulated results of each episode and the daily charging session data, both spatially and temporally.

Spatial validation was conducted by comparing the geographical distribution of charging activity between simulated and real-world data. For each charger i , the usage rate $u_i \in [0,1]$ is defined as the proportion of time during which the charger was recorded as in use over a given day. A Kernel Density Estimation (KDE) surface weighted by u_i was then generated for both simulated and real-world data across GB. The estimated charging intensity at location x is defined in Equation (6-14). The normalisation constants typically found in KDE are omitted here, as their inclusion would not alter the Pearson correlation coefficients used to compare the simulated and real-world surfaces.

$$\hat{f}(x) = \sum_{i=1}^N u_i \cdot K\left(\frac{x - x_i}{h}\right) \quad (6-14)$$

where N is the total number of chargers, x_i is the location of charger i , $K(\cdot)$ is the Gaussian kernel function, and h is the bandwidth. The value of each grid cell is therefore jointly determined by the usage rates and proximity of chargers. The KDE surfaces were then flattened into one-dimensional arrays to enable Pearson correlation between corresponding grid cells. The Pearson correlation between the simulated surface S_e at episode e and the real surface R_d for day d was computed as:

$$r_{e,d}^{spatial} = \frac{\sum_{k=1}^M (S_{e,k} - \bar{S}_e)(R_{d,k} - \bar{R}_d)}{\sqrt{\sum_{k=1}^M (S_{e,k} - \bar{S}_e)^2 \sum_{k=1}^M (R_{d,k} - \bar{R}_d)^2}} \quad (6-15)$$

where $k = 1, \dots, M$ indexes each grid cell in the flattened surface, M is the total number of grid cells, $S_{e,k}$ and $R_{d,k}$ are the values at grid cell k of the flattened simulated and real surfaces respectively, and $\bar{S}_e$ and $\bar{R}_d$ are their respective means. This approach validates whether the simulation reproduces the broad geographical patterns of charging demand across GB, rather than comparing usage at individual charger level, which would be an overly strict criterion at national scale.

Temporal validation was conducted by comparing the time-of-day distribution of charging activity between simulated and real-world data. For each episode, the total charger usage duration U_t at each 15-minute interval t during each day was computed by aggregating the in-use duration across all chargers:

$$U_t = \sum_{i=1}^N m_{i,t} \quad (6-16)$$

where $m_{i,t}$ is the total minutes charger i was in use during 15-minute interval t , and N is the total number of chargers. This aggregation was performed for both simulated and real-world data. The Pearson correlation between the simulated time-of-day profile P_e at episode e and the real profile Q_d for day d was computed as:

$$r_{e,d}^{temporal} = \frac{\sum_{t=1}^T (P_{e,t} - \bar{P}_e)(Q_{d,t} - \bar{Q}_d)}{\sqrt{\sum_{t=1}^T (P_{e,t} - \bar{P}_e)^2 \sum_{t=1}^T (Q_{d,t} - \bar{Q}_d)^2}} \quad (6-17)$$

where $t = 1, \dots, T$ indexes each 15-minute interval over 24 hours ($T = 96$), $P_{e,t}$ and $Q_{d,t}$ are the total charger usage durations at interval t for the simulated and real profiles respectively, where $\bar{P}_e$ and $\bar{Q}_d$ are their respective means. This validates whether the simulation accurately reproduces the temporal patterns of charging demand across GB.

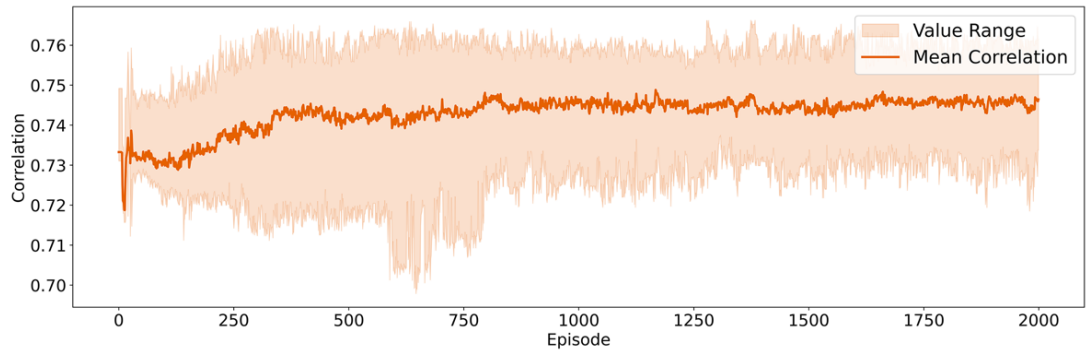
6.5 Results

The cluster analysis was conducted using k-means clustering based on four continuous features: total trip distance, initial battery level, trip co-occurrence density, and public charger density. Five clusters were identified based on these features. The optimal cluster selection process and the centroid of the resulting clusters is provided in Appendix J. The cumulative reward change for each type of training agent across all episodes can be found in Figure K.1 in Appendix K.

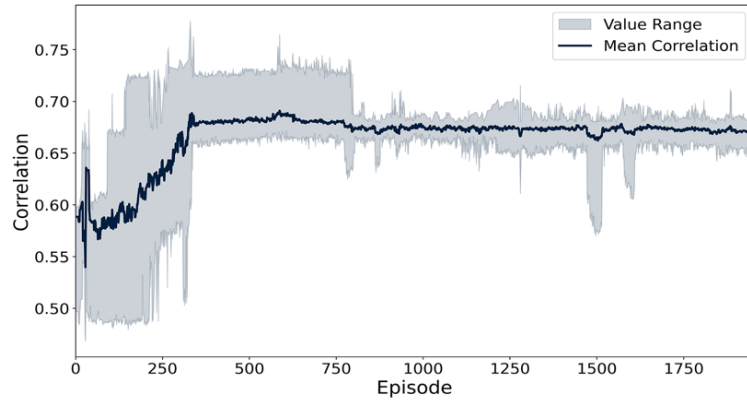
6.5.1 Validation results

The correlation results are shown in Figure 6.3. In the figure, the shaded area represents the range of correlation values observed across different model runs with different combinations of training and simulation agents, while the solid line indicates the mean correlation. This variation arises from the use of different agent combinations across model runs to ensure the robustness of the results. The spatial correlation values stabilise after around the 350th episode, with mean values ranging between 0.74 and 0.75 in later episodes. Temporal validation shows a more dynamic pattern compared to the spatial validation results. It shows an upward trend during the early episodes, followed by a stable phase between the 350th and 750th episodes, and a gradual decline thereafter. Episodes between the 350th and 750th episodes mark the peak phase of temporal correlation, with values falling between 0.65 and 0.70. This indicates strong model performance when replicating the observed ChargePoint usage patterns. Compared to ABM with static behaviour rules in Chapter 5, which worked on similar modelling objectives for private EV driver behaviours, the higher correlation values obtained here highlight the better accuracy of RL-based ABM in replicating observed charging patterns.

As discussed in Section 5.5.3, meaningful agreement can be expected despite the partial representation of the EV driver population and the charger network, as the correlation-based validation compares spatial and temporal pattern shapes rather than absolute usage volumes. The validation results should therefore be interpreted as evidence that the RL-trained agents capture the behavioural dynamics generating spatial and temporal charging patterns at ChargePoint chargers, rather than as confirmation of absolute demand levels across the full network.



(a) Correlations of spatial distribution



(b) Correlations of temporal distribution

Figure 6.3 Correlation results.

6.5.2 Action selection Patterns of Agents

The validity of the model is further supported by the emergent behaviours of trained agents, which align with common-sense expectations about how different types of EV drivers would behave under varying conditions. This section evaluates the dominant action selection patterns across different driver clusters. Two distinct groups of agents are used for training. Figure 6.4 shows the actions most frequently selected by one group of agents over 2,000 episodes, while the action selection patterns for the other group of training agents are included Figure L.1 in Appendix L.

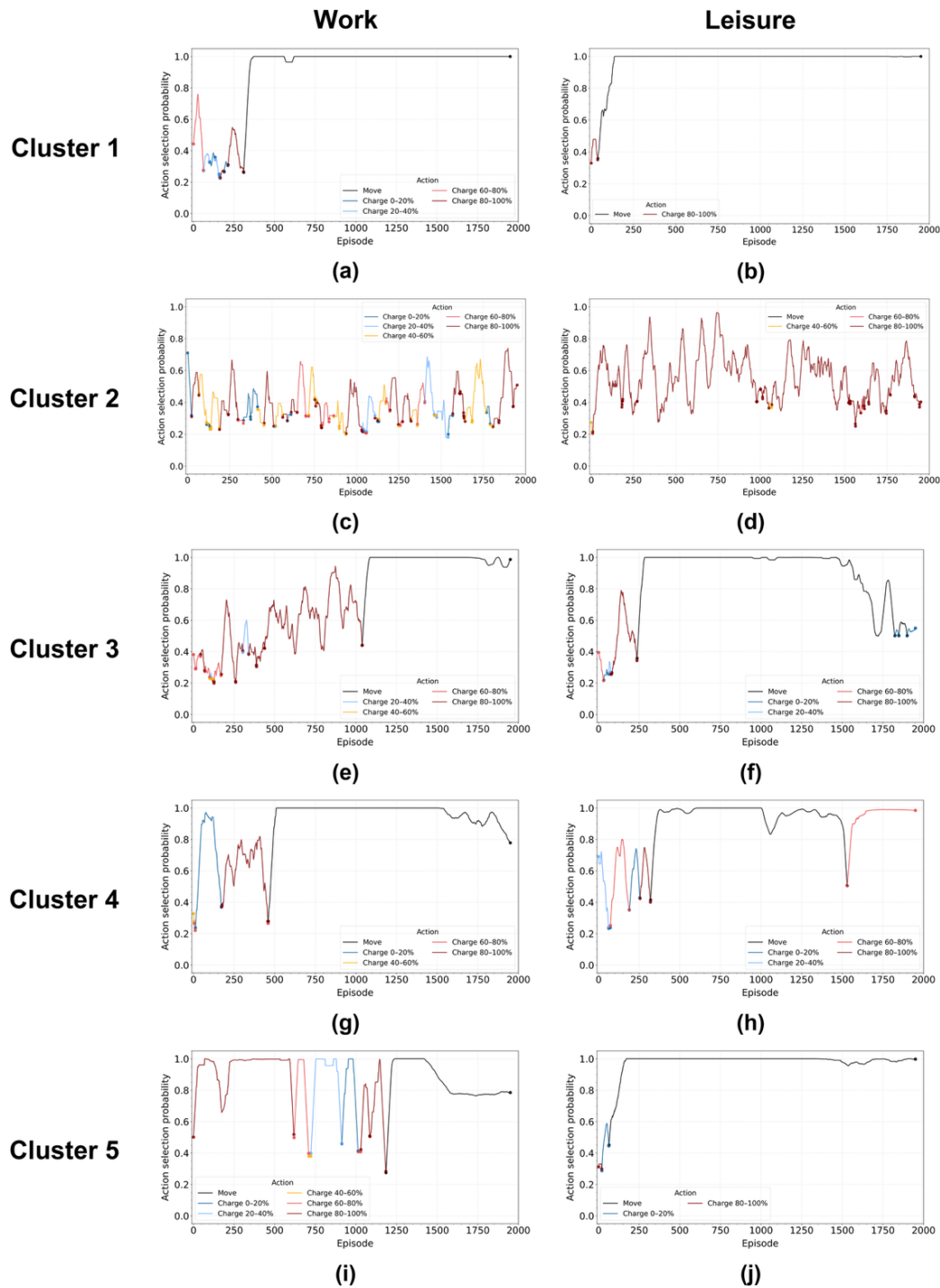


Figure 6.4 Dominant action selection for Group 1 drivers in Cluster 1 - 5.

Figure 6.4 (a) and (b) shows the training agents from Cluster 1. These EV drivers start with a medium battery level and undertake medium-distance trips. They face low competition levels due to low TCD and limited charger availability in their surroundings. Regardless of trip purpose, their action choices stabilise after approximately 250-300 episodes, at which point they tend to avoid charging.

The action choices for drivers in Cluster 2 are shown in Figure 6.4 (c) and (d). These drivers start with low battery levels, undertake long-distance trips, and experience low competition but face limited charging opportunities. Over the course of training, work drivers progressively adjust their charging behaviours, ultimately selecting high charge amounts (70%–100%). In contrast, leisure drivers show more consistent behaviours throughout training and converge on slightly higher charge levels (90%–100%), reflecting their greater schedule flexibility and capacity to accommodate longer charging durations.

The action choices of drivers in Cluster 3 are shown in Figure 6.4 (e) and (f). These drivers start with medium battery levels, undertake medium-distance trips, and encounter significant competition but have sufficient access to charging infrastructure. Such agents are likely located in major urban areas, where chargers are densely distributed and a large number of EV drivers compete for access. In later training episodes, work commuters tend to avoid charging due to potentially long wait times at stations. In contrast, leisure drivers either proceed directly to their destinations or charge moderately, as their flexible schedules allow them to manage range anxiety more effectively.

The action choices of agents in Cluster 4 are shown in Figure 6.4 (g) and (h). These drivers start with high battery levels, encounter fewer surrounding EVs, and have limited charging opportunities. A notable difference is observed between work commuters and leisure travellers. Work commuters travel directly to their destinations without stopping to charge, whereas leisure drivers make charging stops, even when their battery levels are sufficient to complete their trips. These results suggest that drivers with adequate battery to complete their trips but facing tight schedules, such as work commuters, prioritise reaching their destinations without delay. In contrast, leisure drivers, who have more flexible schedules, tend to stop for charging, potentially as a way to reduce range anxiety, even when it is not strictly necessary.

The action choices of agents in Cluster 5 are shown in Figure 6.4 (i) and (j). These drivers also start with high battery levels but undertake short-distance trips. Unlike Cluster 3, they face higher congestion levels and have the most extensive access to charging infrastructure. These drivers are likely located in city centres. Despite the abundance of charging options, all drivers tend to travel directly to their destinations without stopping to charge in later training episodes. This behaviour suggests that charger availability does not

substantially influence drivers' decisions when their battery levels are already sufficient for short trips.

6.5.3 Charging demand distribution

After model validation, we analysed the SOC distribution along road networks using data from the 703rd episode, one of the episodes with highest spatial and temporal correlation with real-world data. The model generated SOC values for each network node based on all passing EV drivers, and the mean SOC at each node is calculated to represent the average battery status at that location.

Given the dense distribution of network nodes, the H3 hexagonal spatial indexing system is used to better visualise SOC variations. H3 is an open-source geospatial grid system that divides the Earth's surface into hexagonal cells at varying resolutions. It provides a consistent and scalable method for spatial aggregation (H3, 2024). Lower resolution levels correspond to larger hexagons and broader spatial aggregation, while higher levels offer finer spatial detail. Mean SOC levels are calculated for each hexagonal cell and the results are visualised at resolutions 7 and 6 (Figure 6.5 (a) and (b)). Resolution 7 cells have an average area of approximately 5.2 km², while resolution 6 cells average around 36.1 km².

To identify areas where EV drivers face a higher risk of battery depletion, the resolution 6 SOC map is classified into five categories using natural breaks. The analysis focuses on locations where SOC falls into the lowest category (0 - 0.22) (Figure 6.5 (c)). However, these patterns alone do not definitively indicate charging risk, as they may simply reflect drivers' willingness to operate at lower battery levels rather than highlighting areas where charging infrastructure is insufficient. To accurately identify true risk areas, it is essential to consider both SOC patterns and the availability of public chargers together.

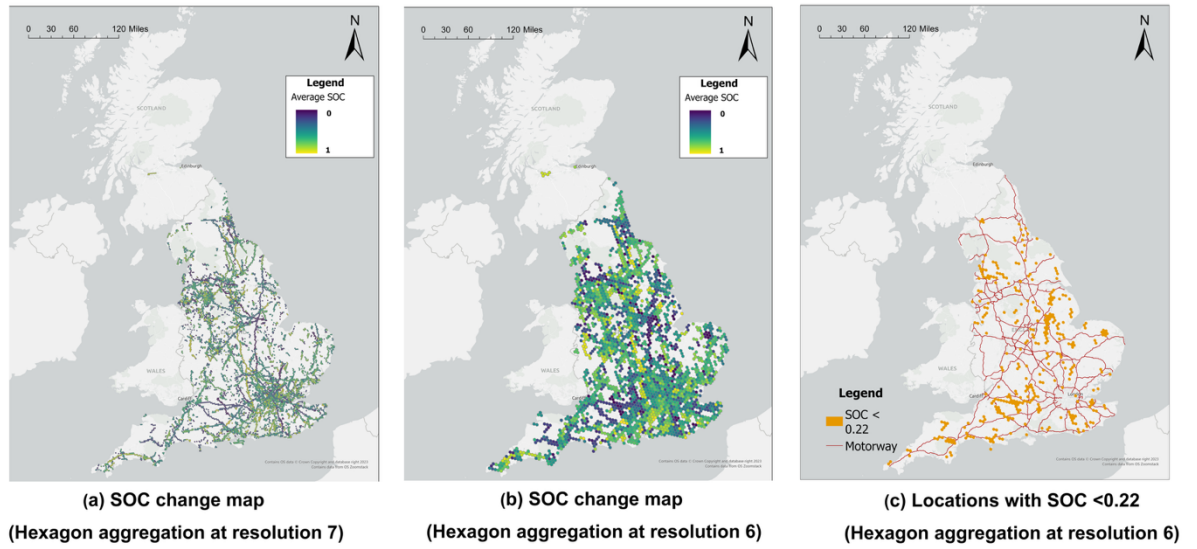


Figure 6.5 Consecutive SOC change distribution along road networks at the 703rd episode.

A combined analysis is therefore conducted by creating buffer zones of 500m, 1000m, and 1500m around each node and calculating the number of chargers within each buffer. Using k-means clustering with charger counts and mean SOC values, we identified three distinct clusters for each buffer distance (Figure 6.6 (a), (b), and (c)). The process for selecting the optimal number of clusters is included in Appendix M. Across all buffer distances, Cluster 0 consistently represents locations with both low average SOC values and limited nearby charging infrastructure, which can indicate higher risks of battery depletion for EV drivers. The spatial distribution of these high-risk locations varies with buffer size and are shown in Figure 6.6 (d), (e), and (f).

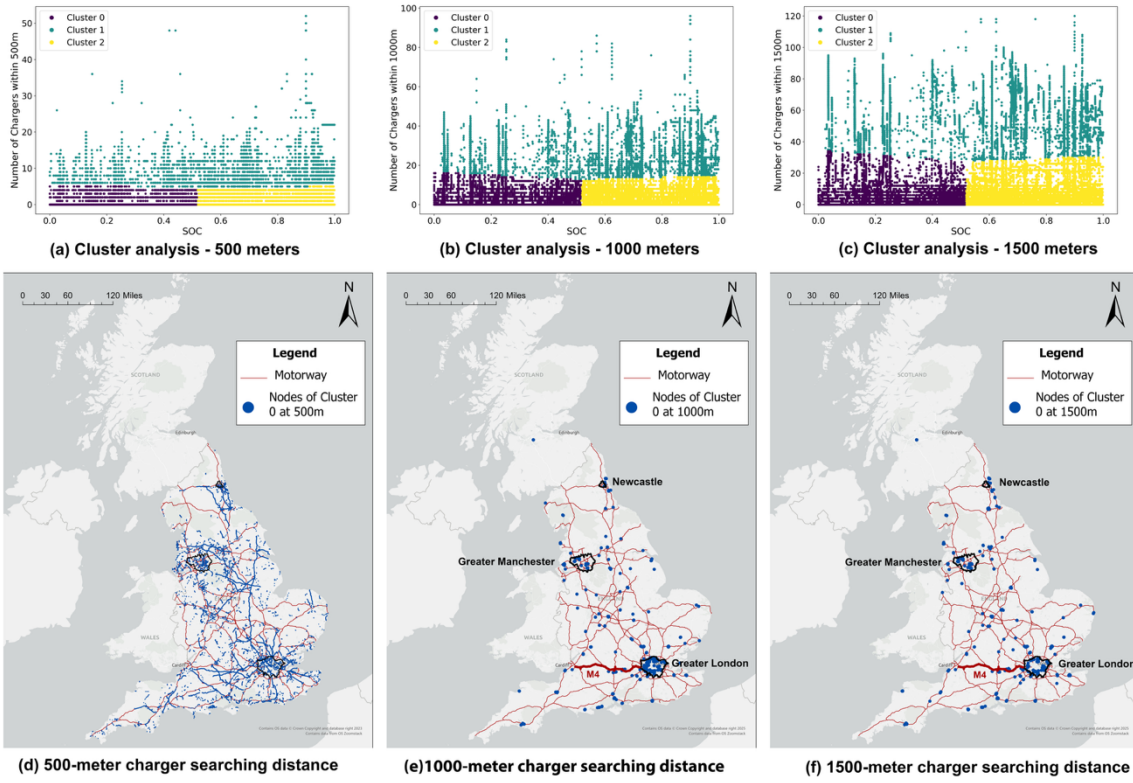


Figure 6.6 Areas with high-risk of battery depletion.

The 500-meter buffer analysis identified widely distributed high-risk areas. However, this distance likely overestimates infrastructure needs, as drivers would typically be willing to make detours of more than 500 meters to access charging. In contrast, the 1000-m and 1500-m analyses revealed more realistic risk patterns. They both highlight areas such as Outer London, the eastern M4 corridor, Greater Manchester, and south Newcastle. The main difference between these two buffer distances is observed in Greater London. The 1500m analysis primarily highlighted high-risk areas along London’s boundaries, whereas the 1000m analysis identified more high-risk areas toward Inner London. Notably, compared to the SOC-only analysis shown in Figure 6.5 (c), fewer areas along the M4 and M1 corridors are classified as high-risk. This suggests that, despite frequent low SOC observations, these corridors have relatively sufficient public charging infrastructure, which reduces the actual risk of battery depletion.

6.6 Discussion

This chapter presents a large-scale, multi-episode agent-based RL model to train and simulate EV drivers’ charging and driving behaviours in GB. Unlike previous studies that

apply RL to optimise EV fleet operation strategies, the proposed approach uses RL to capture the adaptive learning process of private EV drivers, who operate independently and have limited communication with one another. By validating each training episode against real-world charging data, the simulation stage that best reflects reality is identified, which represents a balance between adaptive behaviour and bounded rationality. The validity of the model is further supported by the emergent behaviours of different types of trained agents, which align with established understandings of EV driver behaviour. For example, leisure drivers show more flexible charging behaviours than commuters, while long-distance inter-city trips generate higher demand for enroute charging. These patterns demonstrate that the framework effectively captures realistic decision-making processes. Additionally, areas with higher risks of battery depletion are identified based on available EV charging station data and the simulation results.

The model generates a high-resolution aggregated SOC distribution along road networks. It allows for the identification of locations with higher risks of battery depletion from both charging demand and infrastructure supply perspectives. Many areas with low average SOC are situated along inter-city motorways, likely due to the prevalence of long-distance travel in these corridors. By exploring charging risks across multiple search distances, key 'charging deserts' in GB are identified. These locations face both low SOC levels and limited charger provision. Key examples include the boundaries of Outer London, Greater Manchester, the area south of Newcastle, and the eastern section of the M4 corridor. Charging failures in these areas could pose greater risks for long-distance travellers. While initial charger deployment focused on destination and residential charging (Department for Transport, 2022), these findings support recent policy shifts toward developing rapid charging hubs along motorway corridors and urban peripheries (Department for Transport et al., 2022; Sirel and Brandt, 2023; Mohammed et al., 2024).

This chapter also introduces a novel modelling framework that extends RL applications beyond fleet optimisation to understand how individual private EV drivers adapt their charging and driving behaviours. By simulating diverse charging patterns across a national-scale road network, the model goes beyond intra-city scenarios and captures the charging demand from long-distance, inter-city trips. Additionally, by validating the model with real-world charging session data, the framework effectively captures the learning process under bounded rationality and limited inter-communication between private EV drivers.

There are several limitations in this study that warrant further research. First, although the RL framework represents an avenue for modelling adaptive agent behaviours, questions remain regarding model interpretability. While it is possible to observe EV drivers' final decisions in each episode, the exact reasoning behind their choices cannot be explicitly specified. Second, due to computational resource limitations, this study simulates only 1000 agents simultaneously. Future research could explore opportunities to apply the trained model to larger-scale applications using high performance computing infrastructure and simulate a greater number of EV drivers. Third, the NTS data includes only England residents and lacks trips by Scotland and Wales residents. Future work could incorporate additional data sources to address this regional bias. Fourth, the initial SOC levels in this study are generated using a truncated normal distribution, which does not explicitly account for access to home and workplace charging. Access to home and workplace chargers are likely to be the most direct determinants of initial SOC. Future research could improve this by integrating data on home and workplace charger availability, once such data becomes available, to generate more realistic initial SOC distributions. Fifth, while the current framework captures heterogeneity in learning progress across agent types, future research could more explicitly model the mix of experienced and novice drivers within the EV driver population. This could be achieved by introducing rule-based agents with simple decision heuristics to represent novice drivers and combining them with RL-trained agents representing experienced drivers. Such an approach would create a more explicitly heterogeneous agent population and allow for investigation of how the proportion of novice versus experienced drivers affects aggregate charging patterns. Sixth, public chargers serve various user groups, including private EV drivers, EV fleets, and hired vehicles. Since this study accounts only for charging demand from private EV drivers, future work could incorporate a broader range of user groups to provide a more comprehensive representation of public charger usage. Seventh, the model assumes that drivers follow the shortest path to their destinations as determined by Dijkstra's algorithm. While this ensures computational efficiency, real-world drivers may deviate from optimal routes due to personal preferences, habitual behaviour, or incomplete information. Future research could incorporate bounded rationality in route choices through approaches such as stochastic shortest path formulations. This can enable a more realistic reflection of driving and route choice behaviour of EV drivers. Finally, the charger location data used in this study has limited coverage and may not include all public chargers across GB. This limitation may affect the accuracy of identifying "charging deserts" and the overall

representation of charging accessibility. Once a more complete, nationwide dataset on public charger data becomes available, a more detailed and reliable exploration of charging deserts will be possible.

6.7 Conclusion

This chapter develops an agent-based RL model using DQN to capture the behaviours of heterogeneous EV drivers in GB. Unlike previous RL applications that optimise EV fleet charging strategies under assumptions of full rationality and complete information exchange, this model captures the adaptive learning processes of private EV drivers who operate independently, have limited communication with one another, and show bounded rationality and learning ability. Rather than selecting the training episode with optimal performance, the model is validated against real-world charging session data to identify episodes that most closely reflect observed charger usage. The validity of the model is further supported by the emergent behaviours of trained agents, which align with common-sense expectations.

By simulating diverse charging patterns across a national-scale road network, the model extends beyond intra-city scenarios to capture charging demand from long-distance travel. The results provide a detailed estimates of the spatial distribution of charging demand and identify areas at high risk of battery depletion. These findings support recent policy shifts toward establishing rapid charging hubs along motorway corridors and urban peripheries.

The charging demand estimates generated in this chapter can also serve as inputs for public charger location optimisation models, contributing to more robust infrastructure planning decisions. As noted by Kchaou-Boujelben (2021), one of the major challenges in applying public charger location models lies in accurately estimating the spatial and temporal distribution of charging demand. Recent studies have begun to address this limitation. For example, Yi et al. (2023) used rule-based ABMs to generate high-resolution driving profiles of EV drivers and predict where charging requests are likely to arise before optimising charger placement. The agent-based RL model proposed in this chapter can extend this line of research by integrating the highly granular charging demand generated by adaptive RL-trained agents, thereby providing more accurate and granular representation of charging demand distribution. The next chapter will develop an

integrated simulation-optimisation framework that optimises future public charger locations based on the charging demand distribution identified in this chapter.

Chapter 7

An Integrated Simulation-Optimisation Framework for Future Public Electric Vehicle Charger Deployment⁴

Preface

Chapter 6 developed an agent-based RL model to simulate the adaptive charging and driving behaviours of EV drivers and identified locations with high risk of battery depletion. As discussed in Chapter 6, one of the major challenges in applying public charger location optimisation models lies in accurately estimating the spatial and temporal distribution of charging demand. The validated, granular charging demand estimates generated by the agent-based RL model can serve as inputs for public charger location optimisation models, contributing to more robust infrastructure planning decisions.

Based on the agent-based RL model developed in Chapter 6, this chapter designs a spatial optimisation model to allocate new public chargers. The RL model is then re-implemented to evaluate how EV drivers adjust their behaviours in response to changes in infrastructure provision. Section 7.1 introduces the background of public charger provision and the research objective of this chapter. Section 7.2 reviews the literature on the charging demand estimation and charger location optimisation. Section 7.3 describes the data used for the agent-based RL model and the optimisation model. Section 7.4 describes the methodological framework and proposes a location optimisation model for public chargers. Section 7.5 presents the results of the simulation and optimisation models. Section 7.6 discusses the policy implications of the results, the contributions of the methodological framework, and the limitations of the research, and Section 7.7 concludes the chapter.

⁴ This chapter is based on a paper currently under review: Feng, Z., Zhao, Q. and Heppenstall, A. (under review) 'An Integrated Simulation-Optimisation Framework for Future Public Electric Vehicle Charger Deployment', *Computers, Environment, and Urban Systems*.

7.1 Introduction

The public EV charging infrastructure has moved beyond its initial deployment stage yet remains less mature than conventional refuelling systems. Globally, public charging infrastructure has expanded rapidly in response to the rapid growth in EV sales. According to the Global EV Outlook (International Energy Agency, 2025), China and the European Union have maintained a relatively steady pace of public charger deployment. However, in the U.S. and the UK, where access to home charging is more prevalent, the expansion of public charging infrastructure has failed to keep pace with EV adoption. As of 2025, there are over 75,107 public charging stations in the U.S. (Diaz, 2025). In the UK, over 86,000 public chargers have been installed as of October 2025 (Department for Transport, 2025b). However, despite this rapid growth, many EV drivers continue to experience difficulties in finding available public chargers at convenient locations and times. For example, as discussed in Chapter 4, in GB, public chargers are occupied for approximately 15% of the day on average, yet substantial heterogeneity exists across locations: some charging sites have frequent congestion and long queueing times, while others are underused and have consistently low usage rates. This imbalance suggests a mismatch between charger deployment and actual charging demand and highlights the need for a more demand-responsive approach to public charging network planning.

Although extensive research has explored where to locate public chargers within the transportation facility location domain, most optimisation approaches oversimplify charging demand by inadequately representing the spatial and temporal distribution of charging demand (Kchaou-Boujelben., 2021). The availability of EV trajectory data remains limited due to the relatively early stage of EV adoption and concerns over data privacy. As a result, many optimisation models, such as node-based and flow-based models, simplify the complex decision-making processes of EV drivers by assuming that a driver will recharge whenever a charging station is available along their route. In practice, however, EV drivers do not charge whenever or wherever a charger is available. Such assumptions overlook the complex behavioural, psychological, and contextual factors that trigger recharging decisions. Moreover, the behavioural heterogeneity across EV drivers has been less considered and incorporated in current optimisation models.

To address these limitations, recent studies have integrated agent-based models (ABMs) with location optimisation frameworks to represent the complex behaviours of individuals. Such integrated ABM-location optimisation models can simulate complex and heterogeneous behaviours of EV drivers and their interactions, and provide bottom-up insights into how aggregate charger usage patterns emerge from drivers' decision-making processes (Yi et al., 2023). However, ABMs that rely on static, rule-based behaviours may struggle to capture the adaptive and evolving nature of EV drivers' behaviours under changing conditions. For example, a driver who experiences long queues at a charging station may avoid going to that same charger in the future. As noted by Macal (2016), improving the adaptability and learning ability of agents remains a central challenge in ABM development, as these features are critical for improving the explanatory power and credibility of such models. In this regard, RL provides a promising extension to rule-based ABMs. Compared with rule-based agents, RL-trained agents can learn from repeated interactions with their environment and better represent human-like adaptive behaviours (Malleon et al., 2022). However, despite this potential, few studies have explored how RL-trained agents can be integrated into public charger location optimisation frameworks to capture the adaptive and heterogeneous charging behaviours of EV drivers in dynamic environments.

Additionally, previous location optimisation models are unidirectional: they use current traffic flows and infrastructure status to estimate charging demand and subsequently locate public chargers, but fail to account for how drivers respond to infrastructure changes after new deployment. In reality, the relationship between infrastructure and driver behaviour is bidirectional. While demand dictates where chargers should be located, the introduction of new chargers can, in turn, reshape the behaviours of EV drivers (Wolbertus and Van Den Hoed, 2020). However, previous optimisation studies have paid limited attention to validating how drivers adapt to an optimised charger network, creating the risk that proposed solutions may become less effective as driver behaviours evolve within the new environment. This limitation highlights the need for a robust post-optimisation validation process to quantify how effective the new infrastructure is in practice and how it reshapes the charging demand it is built to serve.

The overarching goal of this chapter is to develop an integrated, bi-directional simulation-optimisation framework that optimises future public charger locations while explicitly evaluating the subsequent adaptive responses of EV drivers. To achieve this, this study

first develops and validates an agent-based RL model that simulates the adaptive driving and charging behaviours of EV drivers, together with the evolution of their SOC along the road network. Building on this simulation, a spatial optimisation model is formulated to determine optimal public charger locations by maximising coverage of both EV trajectories weighted by trip distance, and key road junctions characterised by low SOC levels and high traffic flow volumes. Finally, the RL model is re-implemented under different charger deployment scenarios to analyse how drivers adapt to the updated infrastructure and to evaluate the effectiveness of the optimised charging network. This newly developed methodological framework can help transport planners, policy makers, and the EV industry achieve a more thorough and effective decision-making process when planning future EV charging infrastructure.

7.2 Background

7.2.1 Charging demand estimation and charger location optimisation

Optimising the locations of public EV chargers falls within the domain of transport facility location problems. The modelling approaches have evolved from node-based to arc-based, and subsequently to flow-based models. Early studies predominantly adopted node-based formulations, which represent demand at fixed spatial points or nodes of a road network. Classic examples include the location set covering problem (Toregas et al., 1971), the maximal covering location problem (Church and ReVelle, 1974), and the p-median model (ReVelle and Swain, 1970). In these frameworks, charging demand is typically assumed to originate from routine activity locations such as homes, workplaces, or shopping centres (Kchaou-Boujelben, 2021). Accordingly, demand is often proxied using static indicators, including traffic volumes (Yongxi Zhang et al., 2024), points of interest (POI) locations (Li and Jenn, 2022), population coverage (Wang and Wang, 2010), electricity system characteristics and energy loss (Pal, Bhattacharya and Chakraborty, 2021; Cui, Hu and Duan, 2023), or historical charging patterns at existing chargers (Gopalakrishnan et al., 2016).

A fundamental limitation of node-based approaches is their inability to capture the path-dependent nature of EV travel and charging demand (Hodgson, 1990). In reality, charging demand does not always manifest at nodes but emerges along travel routes as vehicles

move through the network. Additionally, for range-limited EVs, a single charging station along a route may be insufficient for completing a long-distance trip (Kuby and Lim, 2005). To address this limitation, flow-based models were developed to capture demand generated by vehicle movement between origins and destinations, rather than at isolated points.

Flow-based models explicitly represent charging demand as vehicle flows through the network and can be further classified into arc-based and path-based formulations. Early arc-based models, such as those proposed by Bapna et al. (2002) and Goodchild and Noronha (1987), capture demand along individual road segments. However, these formulations show notable limitations. The model by Goodchild and Noronha (1987) has been criticised for its tendency to double-count flows traversing multiple links, while the model by Bapna et al. (2002) may force drivers onto inefficient roundabout paths without ensuring that the full origin-destination (OD) journey is feasible (Kuby and Lim, 2005). Path-based models were subsequently introduced to address these limitations by representing demand as complete OD trip flows that can be refuelled given a vehicle's driving range. These models identify optimal combinations of refuelling stations that collectively maximise the total flow volume that can be successfully refuelled. Key examples include the Flow Capturing Location Model (Hodgson, 1990), the Flow Intercepting Location Model (Berman, Larson and Fouska, 1992), and the Flow Refuelling Location Model (FRLM) (Kuby and Lim, 2005). Building on these foundations, further extensions have incorporated additional realism by considering the limited charger capacity (Upchurch, Kuby and Lim, 2009), drivers' willingness to deviate from shortest paths to access charging stations (Kim and Kuby, 2012), and the integration of regional flow capture with local site accessibility constraints (Zhao et al., 2019).

Despite their ability to locate refuelling stations within real-world road networks, path-based optimisation models still oversimplify the behavioural processes underlying EV drivers' charging decisions. In practice, a driver's decision to select and deviate toward a public charger involves complex behavioural considerations that extend beyond the algorithmic route alternatives. As noted by Kchaou-Boujelben (2021), one of the major challenges in applying public charger location models lies in accurately estimating the spatial and temporal distribution of charging demand. The charging decisions of EV drivers are shaped by a wide range of factors, including socio-demographic characteristics (He, Sun and Luo, 2022), range anxiety (Yi et al., 2020), sensitivity to charging payments

(Ge, MacKenzie and Keith, 2018), and sensitivity to time costs (Davidov, 2020).

Additionally, each driver has a unique trip schedule (Sun, Yamamoto and Morikawa, 2016) and possesses different vehicle types (Zhan et al., 2025), both of which can further affect charging behaviours. These factors also vary substantially across individuals. For example, new EV adopters tend to be more risk-averse and prefer to recharge promptly, whereas experienced EV drivers may tolerate lower SOC levels before seeking to charge (Rainieri, Buizza and Ghilardi, 2023). Collectively, these factors influence when and where the recharging requests arise, as well as the target SOC level drivers aim to achieve.

Capturing such heterogeneous behaviours, particularly among private EV drivers, remains a major challenge for existing location optimisation approaches. Such complexity cannot be adequately captured by static proxies such as POIs, traffic volumes, population density, or trip flows. Meanwhile, the availability of EV trajectory data remains limited due to the relatively early stage of EV adoption and concerns over data privacy. Some data-driven optimisation studies have therefore relied on the trajectory data of conventional vehicles (Andrenacci, Ragona and Valenti, 2016) or EV fleets, such as taxis (Tu et al., 2016), to estimate charging demand. While these datasets can help estimate charging demand at finer spatial resolutions, their representativeness of private EV drivers is questionable. Using such data as proxies can introduce sampling bias and lead to systematic errors in demand estimation and charger placement. Although high-resolution EV trial data have been used to capture detailed EV charging behaviours (Crozier et al., 2021), such data are rare and particularly difficult to obtain at large geographical scales where long-distance travel is common. As a result, there is a need for demand estimation frameworks that explicitly account for the heterogeneous behaviours of EV drivers to accurately model charging demand and support effective public charger deployment.

To better represent the complex behaviours of EV drivers, some studies have integrated ABMs with charging location optimisation models. In these studies, ABMs are used to simulate EV drivers' driving and charging behaviours and to estimate charging demand prior to optimising public charger locations. For example, Yi et al. (2023) used ABMs to generate high-resolution driving profiles of EV drivers and predict where charging requests are likely to arise before determining optimal charger placements. Similarly, Liu and Bie (2019) simulated charger usage and queueing times to inform the placement of fast and slow chargers. Jahn et al. (2020) modelled potential charging opportunities at activity-stop locations to support charging infrastructure planning. Despite these research

advancements, a key limitation remains: these integrated simulation-optimisation studies represent charging demand as discrete points at charger sites or activity locations. Such representations overlook the continuous evolution of EV energy consumption along trips, which can critically affect when and where charging demand emerges.

Moreover, previous simulation-optimisation frameworks rely on rule-based ABMs, which limits their ability to capture EV drivers' learning and adaptive behaviour over time. In rule-based ABMs, charging decisions are triggered by static, predefined rules such as SOC thresholds (Liu and Bie, 2019; Jahn et al., 2020; Yi et al., 2023). However, EV drivers are cognitive agents who can learn from past experiences and adapt their decision-making in response to changing environments. For rule-based ABMs, capturing such adaptive behaviour can substantially increase the parameter space and pose challenges for model verification. Compared to rule-based agents, RL-trained agents offer a more realistic representation of adaptive behaviour by learning decision strategies through repeated interactions with an environment (Sutton and Barto, 1998; Malleson et al., 2022). Given the limited availability of trajectory data for private EV drivers, RL provides a particularly suitable modelling approach, as it does not rely on pre-existing behavioural datasets for training (Dahlke et al., 2020). Despite this potential, the integration of RL-trained agents into public charger location optimisation frameworks remains underexplored, particularly with respect to capturing adaptive and heterogeneous charging behaviours under bounded rationality in dynamic charging environments.

7.2.2 Validation of optimised charger placements

A further limitation of existing public charger location studies lies in the insufficient validation of the effectiveness of optimised charger placements, particularly regarding how drivers would respond to new placements. The rigid nature of the charging infrastructure makes it costly to modify once installed, making inappropriate placement decisions especially problematic. Conducting realistic experiments to validate optimisation outcomes is therefore challenging. As a result, validating the effectiveness of optimised charger locations within the modelling process is crucial for assessing their practical value.

A small number of studies have attempted to address this issue through various validation approaches. For example, Kuby et al. (2018) and Lopez Jaramillo et al. (2021) adopted participatory planning methods that allow stakeholders to interactively modify and assess

station planning results based on expert knowledge, and identified high-priority locations and rollout strategies for future expansion. While informative, these approaches are often resource-intensive and costly, particularly when applied at large geographical scales. Consequently, there remains a need for a robust and efficient post-optimisation validation process that can evaluate the effectiveness of optimised infrastructure in practice, and assess the level of infrastructure expansion required to achieve sufficient network coverage.

In summary, despite substantial progress in public charger location optimisation, important methodological gaps remain. Existing studies, whether data-driven or simulation-based, continue to face challenges in modelling the adaptive behaviours of EV drivers, accurately capturing the spatio-temporal dynamics of charging demand, and validating how individual drivers would respond to new charger placements. As a result, there is a need for an integrated simulation-optimisation framework capable of modelling the adaptive and heterogeneous behaviours of EV drivers, generating granular demand estimates, and explicitly evaluating behavioural responses to infrastructure expansion.

7.3 Data

7.3.1 Data for agent-based RL model

This study implements the proposed modelling framework using GB as the case study area. In the agent-based RL model, each agent represents a combined entity of an EV driver and their vehicle. Agent attributes are derived from the 2022 UK National Travel Survey (NTS) data (UK Data Service, 2022) and the UK EV Database (EV Database, 2024). The UK EV Database includes all EV types available on the UK market. The simulation environment comprises the national road network of GB (Ordnance Survey, 2023b) and the existing public charging infrastructure obtained from the ChargePoint public charger dataset (ChargePoint, 2023). Charging session records covering December 2023 to February 2024 in the ChargePoint dataset are used to validate the RL model. Further details of the ChargePoint dataset can be found in Chapter 5 and 6.

EV driver agents

Table 7.1 Attributes of EV driver agents.

Attribute	Description
ID	Unique identifier of each agent.
Trip purpose	The purpose of the trip is categorised as either work or leisure.
Total trip distance	Total distance travelled by the driver without charging.
Trip start time	Time in minutes past midnight when the trip starts (e.g., 480 = 8:00 AM).
Sensitivity to financial cost (α)	The degree to which the driver is affected by the monetary cost of charging.
Sensitivity to time cost (β)	The degree to which the driver is affected by the time cost associated with detouring, queueing, and charging; $\beta = 1 - \alpha$ to represent the trade-off between monetary cost and time cost.
SOC threshold	Minimum SOC that the driver can tolerate before seeking to recharge.
Initial battery level	SOC at the beginning of the first trip, generated from a normalised distribution between 0 and 1 to reflect variations in home-charging availability.
Battery consumption rate	Energy consumption per mile (Wh/mile).
Full battery size	Total battery capacity of the vehicle (kWh).
Charger density (CD)	Total number of public chargers within a 500-meter buffer zone along the shortest path, normalised by the total path length. This metric represents the relative availability of charging infrastructure along a driver's route.
Trip co-occurrence density (TCD)	The number of concurrent trips by other EV drivers whose trajectories intersect with the 500-meter buffer zone around the agent's route during the same travel time window, normalised by trip distance. It quantifies the potential charging competition along the trip.

Trip schedule information for private drivers from the NTS data is used to define the trip attributes of the agents, including origins, destinations, trip start times, and trip purposes. It is assumed that when transitioning from conventional vehicles to EVs, drivers retain these

trip features to meet their daily travel needs. Each driver is randomly assigned a vehicle make and model from the EV Database, along with the associated attributes of full battery range and energy consumption rate.

To capture the heterogeneity of EV driver agents, agents are assigned unique individual preferences and contextual measures. Specifically, EV driver agents are assigned unique preferences for financial costs and time costs. In addition, two environmental factors are introduced to characterise external influences on driving and charging behaviour: (1) Charger Density (CD) measures the availability of charging infrastructure throughout the trips; (2) Trip Co-occurrence Density (TCD) quantifies the potential competition a driver may face from other EV drivers along the route. The attributes of each agent are listed in Table 7.1.

Training and simulation environment

The modelling environment is formulated with the road network from OS Open Roads (Ordnance Survey, 2023b) and the existing public charger network from the ChargePoint dataset (ChargePoint, 2023). The distribution and size of these public chargers across GB are shown in Figure 5.1. More details of the dataset attributes and collection methods are described in Section 4.3.1 in Chapter 4.

7.3.2 Data for location optimisation

The charger location optimisation model incorporates multiple demand- and risk-related factors that influence placement decisions. Three key inputs are considered: (1) EV flow demand, represented by vehicle trajectories to ensure trip completion; (2) battery depletion risk, identified through road junctions with lower average SOC values; and (3) locations with high traffic volumes, where a greater number of EV drivers are likely to pass. Data for the first two components —EV trajectories and SOC distributions— are generated by the agent-based RL model (detailed in Section 7.4). Traffic volume is represented using annual average traffic flow data at road junctions from the 2022 GB Road Traffic Counts (Department for Transport, 2025a). This dataset provides the annual average number of vehicles passing each observation point in the road network (Department for Transport, 2022c). Specifically, this study uses the annual average car volume, defined as the number of passenger vehicles with nine or fewer seats, three-wheeled cars, and four-wheel-drive

‘sports utility vehicles’ (Department for Transport, 2025c). Details of how the traffic volume data are integrated into the modelling environment are provided in Appendix N.

7.4 Methods

This study develops an integrated simulation-optimisation framework that jointly simulates private EV drivers’ behaviour, estimates charging demand distribution, optimises the locations of future public chargers, and evaluates how EV drivers respond to new charger placements. An overview of the methodological framework is shown in Figure 7.1.

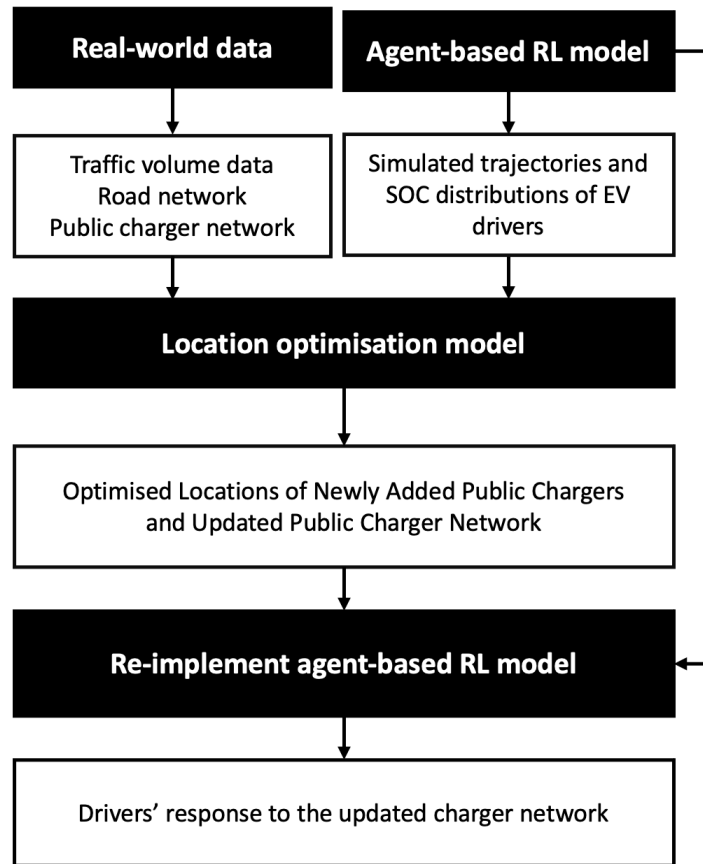


Figure 7.1 Methodology framework.

The agent-based RL model is detailed in Chapter 6, with its structure shown in Figure 7.2. EV driver agents are first clustered based on their trip distance, trip purpose, initial battery level, and two environmental exposure factors — CD and TCD. Details of the clustering analysis are described in Chapter 6. During each episode, the learned policies are fed into the simulation model to guide the driving and charging behaviour of agents within their respective groups. Agents interact with one another by observing charger availability status affected by other drivers, as well as by queueing behind one another at occupied chargers.

Through repeated exposure to the charging environment, agents learn from past experiences of driving, charging, and queueing, thereby improving their behaviours over time. Throughout the training-simulation process, the charger usage patterns, defined as the availability status of each public charger at every timestamp, are continuously recorded and updated across episodes. Details of the multi-agent RL algorithm are provided in Section 7.4.1.

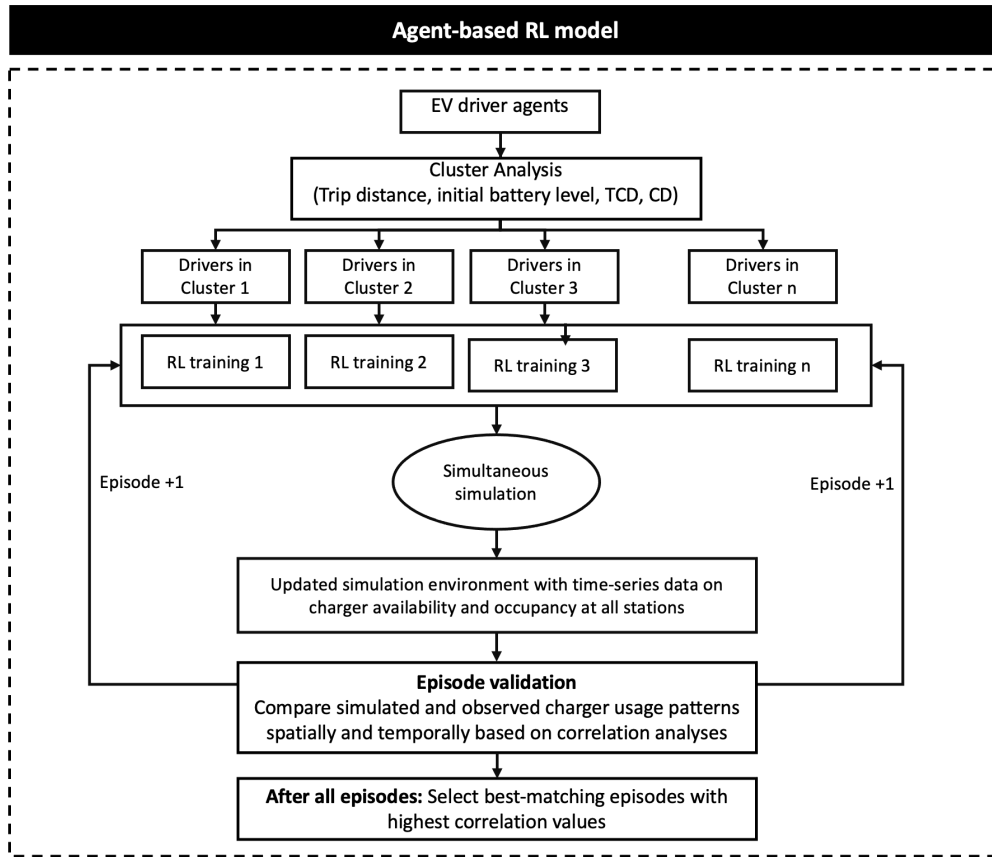


Figure 7.2 Framework of Agent-based RL Model.

Model validation is conducted by comparing simulated charger usage patterns from each episode against observed real-world charging session data from the ChargePoint dataset (ChargePoint, 2023). The episodes that most closely reproduce real-world patterns are identified. From these validated episodes, the simulated SOC distributions along the road network and the EV driver trajectories are extracted. These outputs collectively represent the estimated charging demand and are used as inputs for the optimisation model.

The objective of the optimisation model is to maximise a weighted sum of two components: (1) the coverage of EV trajectories, weighted by trip distance, and (2) the coverage of critical road junctions with lower average SOC and higher traffic volume.

Specifically, the optimisation aims to enable the completion of as many trips as possible, particularly those covering longer distances. It is assumed that such journeys can pose greater range challenges for EV drivers and generate higher enroute charging demand than trips over shorter distances. This assumption is supported by previous behavioural analyses of EV drivers using both rule-based ABM in Chapter 5 and RL-trained ABM in Chapter 6. Moreover, simulated SOC levels at road junctions are used to reflect the risk of EV battery depletion: junctions with lower average SOC values indicate a higher likelihood of charging demand. In addition, traffic volume at road junctions is incorporated into the objective function based on the assumption that higher traffic volumes are related to greater EV flows and thus higher charging demand. Full details of the optimisation model are provided in Section 7.4.2. The optimisation model is implemented under multiple scenarios with different numbers of added chargers.

Finally, the optimised charger deployments are reintroduced into the existing charger network within the simulation environment. The RL-based training and simulation process is then re-implemented to evaluate how EV drivers respond to the updated public charging network and how SOC distributions change following the optimisation.

7.4.1 Agent-based RL model

This section presents the formulation of the agent-based RL model used to simulate EV drivers' driving and charging behaviours. Additional details on the model design rationale and implementation are provided in the previous work Chapter 6. In the model, each driver acts as an autonomous agent that interacts with both the environment and other agents through sequential decision-making. The driving and charging process is formulated as an RL problem, where at each time step t , an agent observes the current state S_t , selects an action a_t , receives an immediate reward R_t , and transitions to a new state S_{t+1} as a result of that action.

The overarching objective of each agent is to complete all planned trips without running out of charge. Each agent begins the simulation day with an initial SOC and a pre-defined trip schedule that includes one or more destinations. Agents follow the Dijkstra's shortest-path algorithm for route selection. Agents move between consecutive nodes (from current node P_t at time t to the next node P_{t+1} at time $t + 1$) on the road network. While travelling, agents continuously evaluate whether and where to recharge.

At time t , the state S_t is defined as a vector of the following five variables.

$$S_t = (\text{SOC}_t, \text{Dist}_t, \text{Time}_t, \text{Stn}_t, \text{Trip}_t) \quad (7-1)$$

Where:

- SOC_t is the current battery state of charge.
- Dist_t is the shortest-path distance from the current position to the destination.
- Time_t is the time in minutes past midnight.
- Stn_t is the percentage of available charging stations among all stations reachable with the remaining battery charge. At each new location, agents re-evaluate reachable stations and recalculate Stn_t based on their updated location and remaining SOC.
- Trip_t is the number of remaining trips in the driver's daily plan.

At each decision point, the agent selects an action $a_{t,i}$ from the action space A_t :

$$A_t = \{a_{t,0}\} \cup \{a_{t,k,\delta} \mid \delta \in \{10, 20, 30, \dots, 100\}, k \in K\} \quad (7-2)$$

Where:

- $a_{t,0}$ indicates continuing driving to the next node ($P_t \rightarrow P_{t+1}$) without recharging.
- $a_{t,k,\delta}$ indicates rerouting to a reachable and available charger k ($k \in K$) and recharge by δ % of the battery capacity.

The agent's decision-making process is learned using a DQN, which maps state-action pairs to the agent's expected cumulative reward (Q-values) through neural network layers. The framework was introduced by Mnih et al. (2015), and is particularly suitable for large-scale simulations. The Q-value, $Q(s, a)$, is defined in Equation (7-3).

$$Q(s, a) = r + \gamma \max_{a'} Q(s', a') \quad (7-3)$$

Where r is the immediate reward for an action. γ is the discount factor, and $\max_{a'} Q(s', a')$ is the maximum estimated reward achievable from the next state. Action selection follows an

ϵ -greedy strategy. The exploration rate ϵ is initialised at 0.99 to encourage exploration during the early stages of training. As training progresses, ϵ gradually decayed over time and reach a minimum value of 0.01 by the end of training. This allows agents to explore diverse experiences early on before converging toward more stable and exploitative behaviours.

After executing an action $a_{t,i}$, the agent receives the reward R_t , and the transition experience $e_t = \{S_t, a_{t,i}, R_t, S_{t+1}\}$ is stored in a replay buffer $D_t = \{e_1, e_2, \dots, e_t\}$. Random minibatches of experiences are sampled from D_t to train the DQN. For each minibatch, the network parameters θ are updated by minimising the mean squared Bellman error:

$$L(\theta) = \mathbb{E}_{s,a,s',a'} \left[\left(r + \gamma \max_{a'} Q(s', a'; \theta') - Q(s, a; \theta) \right)^2 \right] \quad (7-4)$$

After taking an action $a_{t,i}$, the agent receives a reward R_t that quantifies the desirability of its decision. The reward is designed to balance the agent's financial costs, charging urgency, trip completion status, and SOC threshold:

$$R_t = \frac{\gamma \cdot D_{SOC}}{D_{charge} \cdot D_{cost}} + \rho \cdot \text{Status} \quad (7-5)$$

$$D_{SOC} = SOC_t - SOC_{threshold} \quad (7-6)$$

$$D_{charge} = \mathbb{I}_{charge,t} \cdot \epsilon \cdot \ln(\tau_{charge} \cdot \chi_{charge} \cdot b_{init} + 1) \quad (7-7)$$

$$\mathbb{I}_{charge,t} = \begin{cases} 1, & \text{if charge at } t \\ 0, & \text{if not charge at } t \end{cases} \quad (7-8)$$

$$D_{cost} = (\alpha \cdot \log(1 + \text{Pay} \cdot \mathbb{I}_{charge,t}) + \beta \cdot \log(1 + T_{travel} + T_{charge} \cdot \mathbb{I}_{charge,t}) + 1)^{\frac{v}{\mu}} \quad (7-9)$$

$$\text{Status} \in \{-1, 0, 1\} \quad (7-10)$$

Where:

- D_{SOC} is the difference between the current SOC, SOC_t , and the minimum SOC level the agent can endure, $\text{SOC}_{\text{threshold}}$.
- D_{charge} is the urgency of recharging. It is only activated when the agent chooses to charge ($\mathbb{I}_{\text{charge},t} = 1$).
- τ_{charge} is the elapsed time between the start of the first trip to the start of the charging event. Larger values indicate later charging events.
- χ_{charge} is the charging opportunity ratio. It is defined as CD/TCD . It reflects the relative charger availability along the route when considering both charger availability and competition for chargers.
- b_{init} is the driver's initial battery level at the start of the day.
- D_{cost} is the cost impact. It consists of the financial, travel-time, and charging-duration costs. v is the number of charging events. It introduces an exponential penalty for frequent charging. μ is the trip distance class. Shorter-distance trips incur a greater penalty for repetitive charging compared with longer-distance trips.
- Status represents the driver's trip completion outcome. -1 indicates a penalty for failed trips. 0 indicates an ongoing trip without additional rewards or penalties. 1 indicates the driver earns an additional reward by successfully completing a trip and reaching the destination. ρ is the weight coefficient for trip completion status.

7.4.2 Location optimisation model

This section proposes a flow-based location optimisation model for effectively locating public EV charging stations. The model builds upon the basic assumptions of the FRLM (Kuby and Lim, 2005) and the threshold extension FRLM (Hong and Kuby, 2016), while incorporating spatial information on SOC, EV trajectory distributions, and traffic volumes. The key assumptions include: (1) EV drivers follow Dijkstra's shortest path between each OD pair; (2) battery energy consumption is assumed to vary linearly with travel distance; (3) vehicles share an average driving range, calculated as the mean range of all vehicle types used in the upstream RL simulation; and (4) a trip is considered refuellable if a driver can complete a round trip between the origin and destination without running out of charge with the support of charging infrastructure.

Candidate facility locations are defined as road junctions with both valid traffic volume observations and average SOC data from the RL simulation. This selection ensures that

each candidate site has valid inputs for the node coverage component of the objective function, which requires the simultaneous presence of traffic flow data and SOC values to identify locations with known charging demand potential (Equation 7-11). Moreover, the locations of existing charging stations are not excluded from this candidate site set; the model allows for both ‘greenfield’ (new site) and ‘brownfield’ (site expansion) solutions. This design choice is adopted for two reasons. First, the influence of the existing charger network is already embedded in the SOC profiles and trajectory distributions that are shaped by drivers’ interactions with the environment in the upstream RL simulation. Second, EV charging infrastructure is inherently modular and expandable. Unlike conventional refuelling, which is characterised by rapid turnover, EV charging involves prolonged dwell times. This makes the number of available charging ports an important factor for serving charging demand. Consequently, if the optimisation model selects a location where a charging station already exists, this signals a capacity bottleneck where demand exceeds current supply. This indicates the need for charger or port expansion to address unserved demand and reduce queueing, rather than simply placing a new station elsewhere or nearby.

The objective function of the model maximises a weighted sum of flow coverage and node coverage (Equation (7-13)). It should be noted that the optimisation model operates within a simulation-based planning framework, where simulated EV trajectories and SOC distributions, as well as normalised traffic volumes are used to represent relative spatial patterns of charging demand and depletion risk, rather than absolute or real-world demand levels.

The flow coverage component ($\sum_{m \in M} d_m y_m$) aims to maximise the total number of trips that can be completed within the vehicle’s driving range. Each trip (m) is weighted by its distance (d_m) to prioritise journeys with longer distances, which are more vulnerable to battery depletion. The node coverage term ($\sum_{k \in K} n_k x_k$) prioritises candidate sites with higher priority scores n_k (Equation (7-11)), which represent locations with greater charging demand potential. This score is defined as the normalised product of traffic volume (V_k) and battery depletion risk (Ω_k). As shown in Equation (7-12), the battery depletion risk at node k is defined as one minus the average SOC of all EVs passing through that node.

$$n_k = \frac{V_k \cdot \Omega_k}{\text{Max}_{h \in K} \{V_h \cdot \Omega_h\}} \quad (7-11)$$

$$\Omega_k = 1 - \frac{\sum_{m \in M_k} SOC_{mk}}{|M_k|} \quad (7-12)$$

The weight parameter $W \in [0,1]$ controls the trade-off between node and flow coverage. Lower W values place greater emphasis on serving critical nodes with low SOC and high traffic flows, whereas higher W values prioritise maximising the total number of refuellable EV trips.

$$\text{Max } Z = W \sum_{m \in M} d_m y_m + (1 - W) \sum_{k \in K} n_k x_k \quad (7-13)$$

Subject to:

$$\sum_{k \in K_{ij}^m} x_k \geq y_m \quad \forall m \in M, \forall l_{ij} \in L_m \quad (7-14)$$

$$\sum_{k \in K} x_k = p \quad (7-15)$$

$$x_k \in \{0,1\} \quad \forall k \in K \quad (7-16)$$

$$y_m \in [0,1] \quad \forall m \in M \quad (7-17)$$

Where:

M : Set of all OD pair trips

m : Index of a specific OD pair trip ($m \in M$)

K : Set of candidate facility locations

k, h : Indices for candidate facility locations ($k, h \in K$)

p : Total number of stations to be built

x_k : 1 if a facility is built at k , 0 otherwise

y_m : 1 if the route is refuelled, 0 otherwise

n_k : Normalised node priority score for location k

Ω_k : Battery depletion risk at node k

d_m : Normalised trip distance for trip m

W : Weight parameter controlling the trade-off between trip coverage and node priority

K_{ij}^m : Set of nodes that can refuel arc l_{ij} on path m (within range)

l_{ij} : Individual arc from node i to j

L_m : Set of all directional arcs on round trip m

M_k : Set of trips that pass through node k

SOC_{mk} : SOC value of trip m at node k

V_k : Traffic Volume at node k

The constraints of the model are defined in Equations (7-14) and (7-15). Equation (7-14) adopts the Arc-cover Path-cover (AC-PC) formulation proposed by Capar et al. (2013). It ensures that a round trip is considered covered only if every directional arc $l_{ij} \in L_m$ on the trip has at least one open charger within its corresponding cover set K_{ij}^m ; that is, a station that enables the vehicle to traverse the arc without exceeding its driving range.

Equation (7-15) constrains the total number of installed chargers to exactly p . Equations (7-16) and (7-17) define the decision variables in the optimisation formulation. The binary variable x_k indicates whether a charger is installed at node k . y_m indicates whether trip m is successfully refuelled. Following Kuby and Lim (2005), the binary constraints on y_m are relaxed to continuous variables between 0 and 1. Due to the structure of the maximisation objective and the covering constraints, these variables naturally converge to binary solutions without requiring explicit binary restrictions. This can help to improve computational efficiency.

7.5 Results

The agent-based RL model was trained and simulated for 2,000 episodes to capture EV drivers' driving and charging behaviours. The model was deployed on an AWS EC2 instance with 64 vCPUs and 128 GB of memory. Model calibration was conducted through sensitivity analyses of key RL parameters, including the learning rate, discount factor, and exploration rate. Further details of the calibration process are provided in Chapter 6. To ensure accurate replication of real-world patterns, the model was validated after each episode by comparing simulated charger usage patterns with real-world charging session data (ChargePoint, 2023). The validation results demonstrate that the model effectively

captures real-world charging patterns both spatially and temporally. Correlations between simulated and observed patterns converge after approximately 350 episodes, with spatial correlations stabilising at 0.74–0.75 and temporal correlations at 0.65–0.70. Full validation results are reported in Section 6.5.1 in Chapter 6. As in Chapter 6, the same interpretive constraints apply to this Chapter. The simulation outputs represent relative spatial and temporal patterns of charging demand rather than absolute network-wide volumes, and resulting charging demand distribution therefore indicates where demand is likely to concentrate relative to other locations, rather than the actual charging volumes at specific chargers.

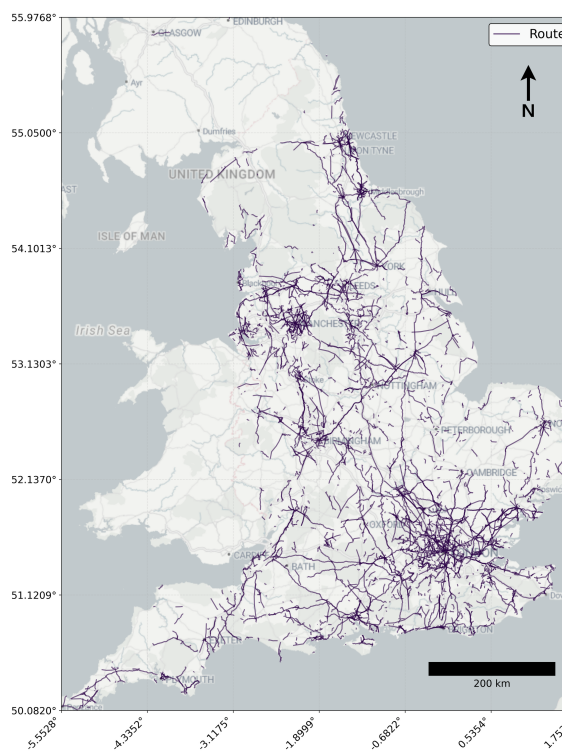


Figure 7.3 Simulated EV driver trajectories.

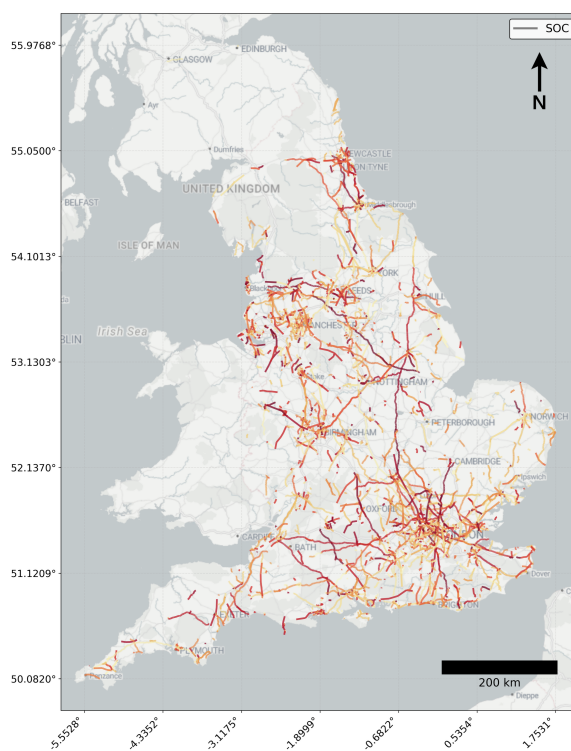


Figure 7.4 Simulated SOC distributions.

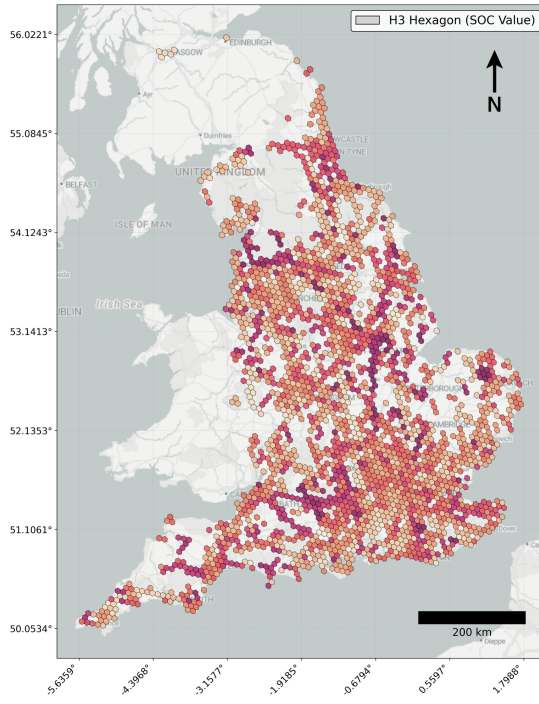


Figure 7.5 Simulated SOC Distributions by H3 hexagons.

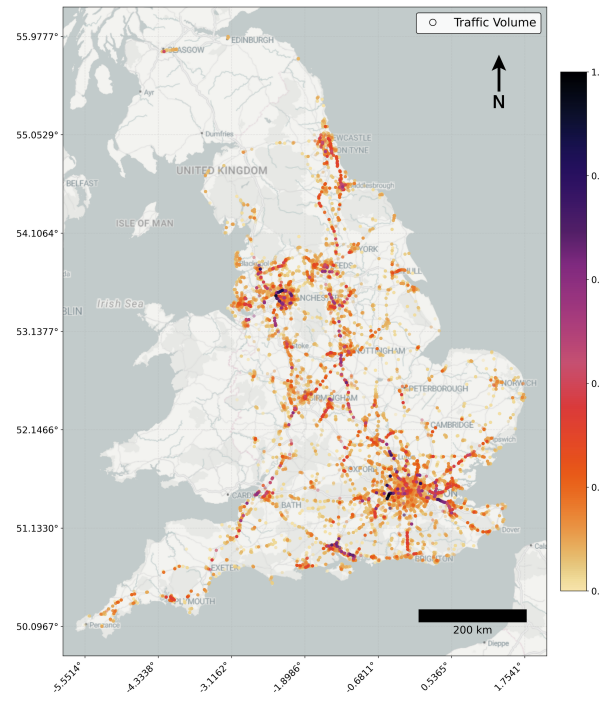


Figure 7.6 Traffic volume distribution (normalise).

Based on the validation results, representative simulation outputs are extracted from episodes that best replicate observed charging patterns. Across multiple runs, simulated outcomes most closely align with real-world data between approximately 350 and 750 episodes. One episode is randomly selected from this range, and the EV driver trajectories from this episode are extracted and presented in Figure 7.3. Figure 7.4 shows the corresponding SOC distributions along the national road network. The SOC value at each road junction represents the average SOC of all EVs passing through it, reflecting the overall energy state of EVs at that location. To improve the visual interpretability of spatial disparities in SOC levels, junction-level SOC values are aggregated using H3 hexagonal cells at resolution 6 (Figure 7.5). H3 is a hierarchical spatial indexing system that divides the Earth's surface into hexagonal cells at multiple resolutions (H3, 2024). The aggregated results reveal clear spatial disparities in battery depletion levels. In addition to simulated EV trajectories and SOC distributions, traffic volume is also incorporated as a factor in the optimisation objective function. Figure 7.6 shows the normalised annual traffic volume at road junctions, scaled to the range $[0, 1]$ using min-max normalisation.

The EV trajectories, SOC distributions, and traffic volumes are subsequently used as inputs to the charger location optimisation model. The optimisation problem is solved for 21 scenarios with different numbers of new public charging stations ($p = 100, 250, 500, 750,$

1000, 1,250, and 1,500) and different weight values ($W = 0.2, 0.5$, and 0.8) to control the trade-off between node and flow coverage objectives. All optimisation configurations are solved to optimality using the Gurobi optimiser. The average vehicle range is set to 193 kilometres, which is the mean range of all vehicle types used in the agent-based RL model.

Figure 7.7 shows the optimised locations of new public chargers for $W = 0.5$ when $p = 100, 500, 1000$, and $1,500$. The optimisation results for $p = 250, 750$ and $1,250$ when $W = 0.5$ are shown in Figure O.1 in Appendix O. The optimisation results for $W = 0.2$ and $W = 0.8$ are shown in Figure O.2 and O.3 in Appendix O. Figure 7.8 summarises the resulting coverage percentages of routes and nodes. The results indicate that newly deployed public chargers are predominantly located along major motorway corridors and within densely populated urban areas. As the number of facilities increases, flow coverage rises across all scenarios as expected. Higher weights on flow coverage yield higher overall coverage levels. The maximum flow coverage of 71.3% is achieved when $p = 1,500$ and $W = 0.8$. In contrast, node coverage (shown on the right y-axis) depends solely on the number of added chargers relative to the total number of candidate sites and is therefore insensitive to the choice of W . Node coverage increases steadily from approximately 1.5% ($p = 100$) to around 14% ($p = 1,500$).

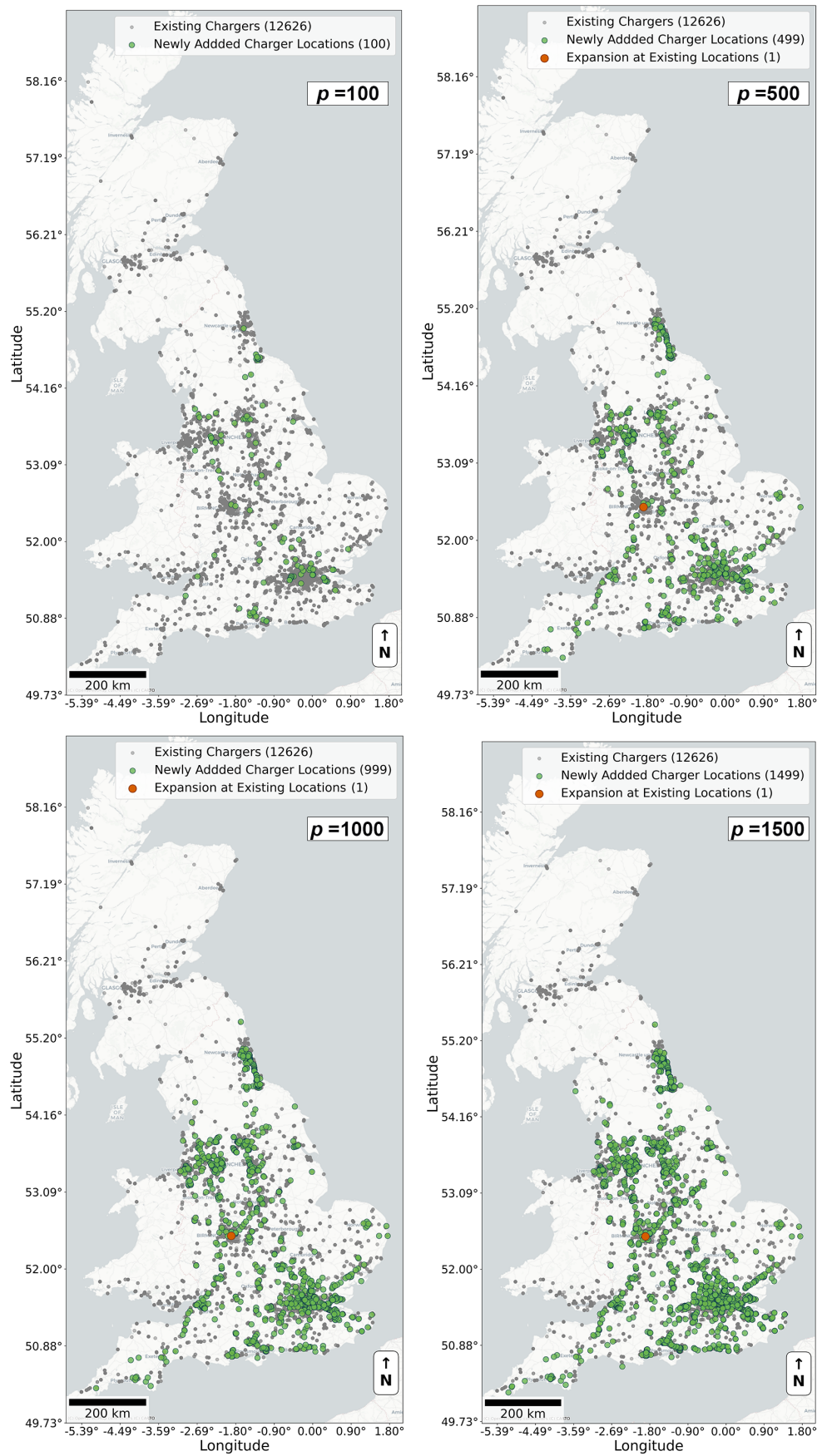


Figure 7.7 Optimised public chargers (Weight = 0.5).

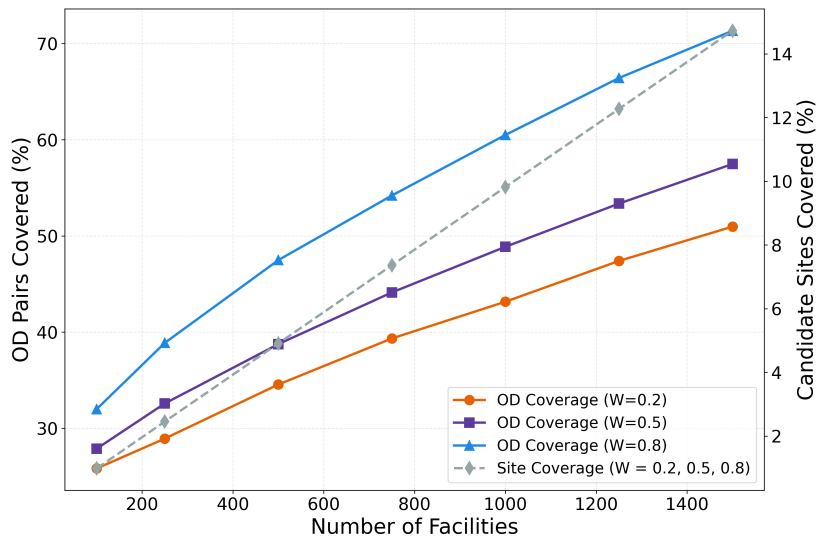


Figure 7.8 Flow coverage and site coverage percentage across scenarios.

To evaluate the behavioural impacts of optimised charger deployment, the newly selected chargers are integrated into the existing public charging network to re-implement the RL simulation. Since the optimisation model does not differentiate between charger types, each newly added charger is assumed to include two charging points: one at 50 kW and one at 12.7 kW. These values are based on the mode values of fast and slow chargers observed in the existing charging network.

Reintroducing the updated charging network into the agent-based RL model reveals non-linear behavioural responses in EV drivers' charging strategies. Figure 7.9 shows the average SOC across all road junctions under varying numbers of newly added chargers and different weighting parameters. The results indicate that average network-wide SOC initially increases when up to 500 chargers are added ($W = 0.2$) or when up to 250 chargers are added (for $W = 0.5$ and 0.8). Beyond these thresholds, however, average SOC begins to decline despite continued infrastructure expansion. This pattern indicates the emergence of a perceived 'safer charging environment' observed by EV driver agents, in which drivers develop greater confidence in charger availability and consequently tolerate lower SOC levels before recharging.

Additionally, the timing of this behavioural shift is strongly influenced by the optimisation objective weighting (W). As the weight assigned to route coverage increases from $W = 0.2$ to $W = 0.5$ or 0.8 , the decline in average SOC occurs earlier in the expansion process. This suggests that a larger share of trips becomes refuellable at earlier stages of network expansion, allowing EV drivers to experience improved accessibility sooner. As a result,

EV drivers gain confidence in the charging network more rapidly than under scenarios with lower weight values ($W = 0.2$).

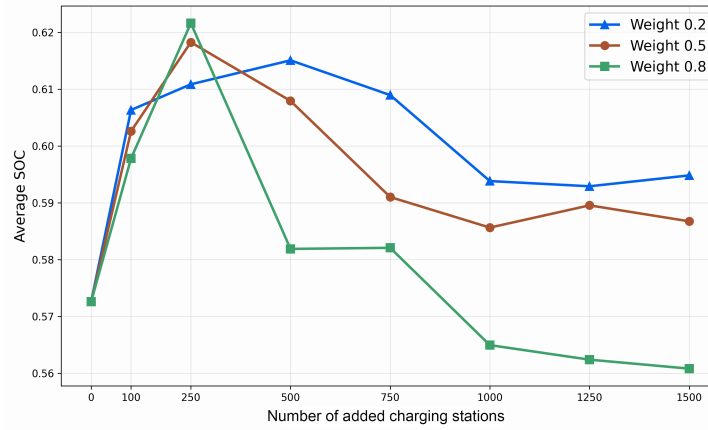


Figure 7.9 Average SOC under different numbers of added charging stations and weights.

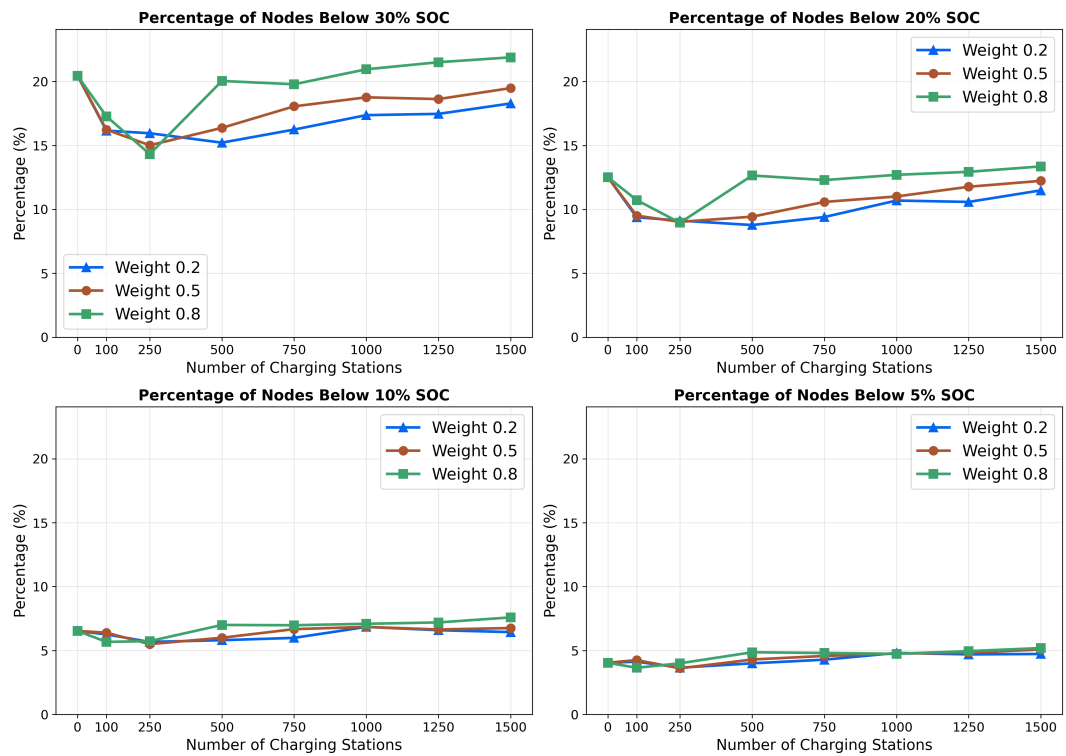


Figure 7.10 Percentage of low-SOC nodes across different scenarios.

Figure 7.10 shows the percentage of road junctions where the average SOC falls below selected thresholds as charging infrastructure expands. The results indicate that SOC levels in the range of 20–30% represent a critical behavioural zone in which EV drivers are most responsive to changes in charging infrastructure. When the threshold is set at 20%–30%, the share of low-SOC junctions initially declines as up to 250 chargers ($W = 0.5$ and 0.8), or 500 chargers ($W = 0.2$) are added. However, as additional chargers are added, the

proportion of junctions with SOC below 20% and 30% begins to rise again. This pattern reflects two competing behavioural responses: in the early stages of network expansion, increased charger availability allows drivers to recharge more frequently and maintain higher SOC levels. As the network expands further, however, drivers develop greater confidence in charger availability and delay charging, allowing SOC to drift into the 20–30% range without fear of battery depletion. Consequently, areas that previously maintained higher SOC levels converge toward this 20%–30% band, making this SOC level more prevalent across the network. In contrast, the share of junctions with critically low SOC (below 5% or 10%) remains consistently small across all scenarios. This indicates that drivers consistently avoid extreme battery depletion regardless of infrastructure density.

Figure 7.11 summarises the percentage of H3 hexagons without any public chargers under different numbers of newly added chargers (0–1500), SOC thresholds (5%, 10%, and 20%) and weighting configurations ($W = 0.2, 0.5$, and 0.8). Each panel in the figure corresponds to a specific combination of SOC threshold and weighting, with line plots showing how the percentage of charger-free hexagons evolves as the network expands. The values reported at the centre of each panel represent the average percentages across all charger network expansion levels.

When the SOC threshold is set to 5%, the percentage of no-charger hexagons remains between 1.0% and 1.2% across all scenarios. Network expansion does not substantially affect the share of these areas. At the 10% SOC threshold, there is an initial increase in the percentage of no-charger hexagons, followed by gradual decline as more chargers are added. This pattern reflects a relatively uneven charger allocation during the early stages of public charger deployment, which becomes more spatially balanced as the network grows. Additionally, the earlier decline observed for $W = 0.5$ and 0.8 , compared to $W = 0.2$, further suggests that prioritising node coverage leads to a more uneven spatial distribution of chargers at earlier stages of deployment. When the SOC threshold is set to 20%, the percentage of no-charger hexagons fluctuates more substantially across scenarios. As discussed above, this SOC range corresponds to the zone in which drivers show the strongest behavioural adaptation to infrastructure expansion. Consequently, the observed variability likely results from the combined effects of shifting SOC values within each hexagon and the evolving spatial distribution of newly added chargers.

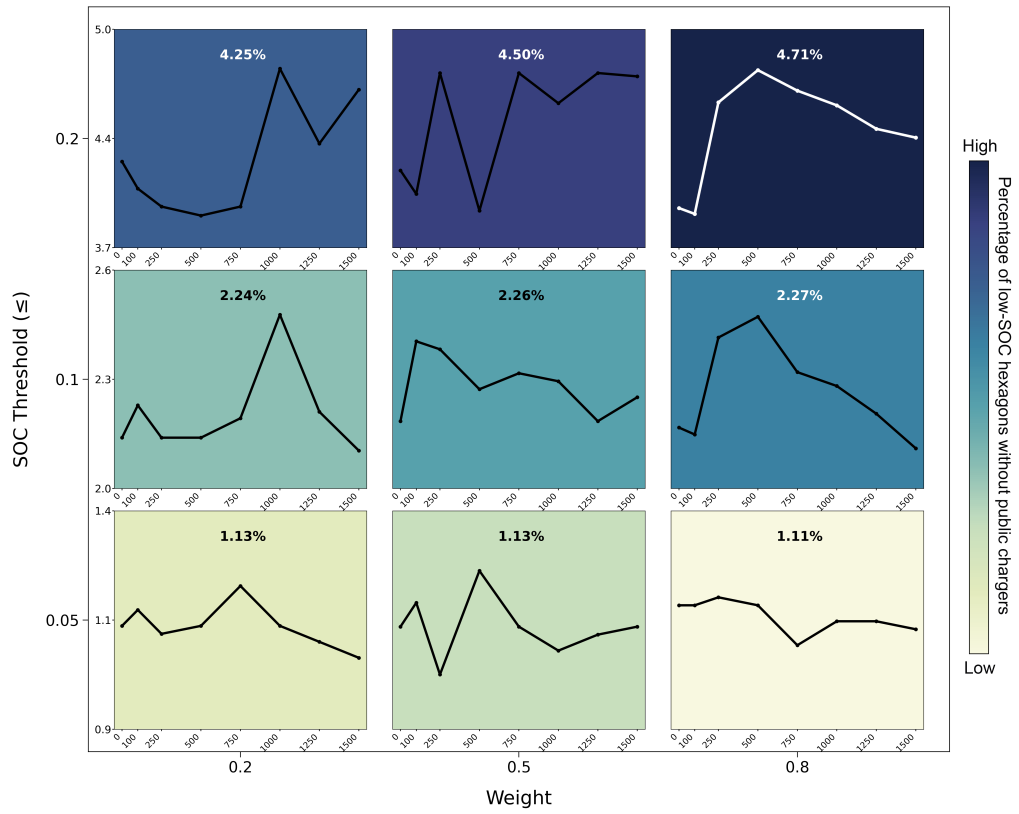


Figure 7.11 Percentage of low-SOC hexagons without public chargers after network updates.

7.6 Discussion

This chapter develops an integrated agent-based RL and spatial optimisation framework to simulate EV driver behaviours, inform the optimal placement of future public charging infrastructure, and reveal how drivers would respond to the optimised charger network. Beyond the specific findings from the GB case study, the proposed framework offers a transferable analytical approach that can be readily adapted to other geographical contexts or updated charging infrastructure datasets. It provides a flexible tool to support the planning of future phases of public charging network expansion.

One contribution of this chapter lies in the use of RL-trained agents to capture the adaptive decision-making processes of EV drivers. Compared with rule-based ABMs, RL-trained agents more effectively represent how human drivers learn from experience and adjust their driving and charging strategies in response to evolving conditions such as charger availability and queueing time. By simulating detailed EV trajectories and granular SOC distributions, the model generates high-resolution estimates of charging demand that emerge from individual behaviour. This approach is particularly valuable in contexts where empirical EV trajectory or battery data remain scarce or currently unavailable.

The spatial optimisation model extends the FRLM by integrating flow coverage and node coverage into a unified objective function. Rather than relying on a single dimension of demand representation, the optimisation balances trip coverage and node priority to provide a more comprehensive basis for charger placement. The flow coverage component ensures that trips, particularly long-distance ones, can be completed without battery depletion. The node coverage component prioritises junctions characterised by high traffic volumes and high battery depletion risk. By jointly considering these objectives, the optimisation model ensures that new chargers both support travel feasibility for EVs and provide targeted 'safety nets' at locations with high charging demand in the network.

More importantly, the framework explicitly evaluates post-deployment behavioural responses to newly optimised charging infrastructure. By integrating the optimised charger locations into the RL-based simulation, the chapter explores how EV drivers adapt their charging behaviour in response to the updated infrastructure and how SOC distributions change under different deployment scenarios. This post-optimisation assessment addresses a critical gap in existing public charger location studies, which typically optimise infrastructure placement without evaluating how drivers respond after implementation. The framework provides new insights into the feedback mechanisms between infrastructure provision and EV driver behaviour.

The results indicate that newly deployed public chargers are predominantly located along major motorway corridors and within densely populated urban areas (see Figure 7.7). These locations are characterised by high travel demand and heavy traffic flows. This pattern closely aligns with the objectives set out in the UK Government's EV Infrastructure Strategy, which identifies two primary roles for public charging infrastructure: supporting long-distance journeys and serving households without access to off-street parking (HM Government, 2022). On-street public chargers are particularly important in large urban areas where densely populated residential areas with flats or apartments often lack access to private parking and are therefore more reliant on public charging facilities.

The results also reveal non-linear behavioural responses of EV drivers to network expansion. As new chargers are added, average SOC across the network initially increases. However, as the network continues to expand, average SOC declines. This pattern may indicate the emergence of a perceived 'safe charging environment' in which EV drivers develop greater confidence in charger availability and delay charging as infrastructure

reaches a certain scale and begins to resemble a conventional refuelling system. Part of the potential safety gains from infrastructure expansion is thus absorbed by behavioural adaptation rather than appearing as continuously higher SOC levels. Within this context, SOC levels between 20% and 30% emerge as a critical range in which EV drivers most actively adjust their charging decisions in response to a denser charging network. Additionally, it is important to note that road junctions with low SOC values should not automatically be interpreted as ‘charging deserts’. Particularly at later stages of network expansion, such locations may instead reflect areas where drivers feel sufficiently confident in charger accessibility to delay recharging and continue travelling at lower SOC levels before recharging elsewhere. However, this behavioural adaptation result should nevertheless be interpreted with caution. With 1000 simulated agents, competition for chargers and queuing effects are underrepresented compared to real-world situation, and the observed SOC decline reflects adaptation under conditions of relatively abundant charger availability per agent.

One important limitation of this research is the simplified representation of the EV driver population and traffic conditions. With more abundant data and realistic parameters, the empirical results discussed above could change in several ways. For example, with a full synthetic population data or realistic EV adoption levels, competition for chargers would intensify and queuing effects would emerge, likely making drivers less confident in charger availability. The perceived 'safer charging environment' would therefore be expected to emerge at higher levels of infrastructure provision. Incorporating more realistic congestion dynamics would increase travel times and energy consumption, generating additional en-route charging demand or changing drivers' charger choices. Additionally, if financial and time cost sensitivities were differentiated by sociodemographic characteristics rather than randomly assigned, behavioural responses to infrastructure expansion would vary across population groups, and the aggregate SOC thresholds identified can change. Future research should incorporate these elements once more comprehensive data on individual preferences and synthetic populations of EV drivers become available, alongside more detailed representation of road conditions and congestion.

Additionally, this chapter has mainly discussed how to effectively deploy future public chargers, and future studies could also tweak the modelling framework to consider the equitable distribution of public chargers and ensure more geographically balanced network

expansion. Public charging infrastructure in the UK remains unevenly distributed across regions and socio-economic groups. In particular, rural areas are often underserved due to limited public and private infrastructure investment (Wallace, Darwish and Lai, 2024). Future work should therefore place greater emphasis on equity-oriented charger deployment strategies to ensure that the transition to electric mobility benefits all regions and population groups.

7.7 Conclusion

This chapter developed an integrated agent-based RL and spatial optimisation framework to model EV drivers' driving and charging behaviours, estimate the spatial distribution of charging demand, and optimise the locations of future public chargers. By re-integrating the optimised charger locations into the simulation environment, the framework further evaluates how EV drivers adapt their charging decisions and how SOC distributions evolve under different charging infrastructure deployment scenarios. The proposed modelling framework provides a new perspective for integrating adaptive individual behaviours with spatial optimisation. Compared with conventional optimisation approaches based on static demand assumptions, the framework captures how charging demand emerges from individual behaviour and how these behaviours respond to changing infrastructure provision.

The results indicate that, as the charging network expands, average network-wide SOC initially increases with improved accessibility and charging opportunities. However, further expansion leads to a gradual decline in average SOC, indicating the emergence of a perceived 'safe charging environment' in which drivers become more confident in charger availability and are willing to operate at lower SOC levels before recharging. As a result, part of the potential safety gains from infrastructure expansion is absorbed by behavioural adaptation rather than manifesting as continuously higher SOC levels. In particular, SOC levels between 20% and 30% emerge as a critical behavioural range within which EV drivers most actively adjust their charging decisions in response to a denser charging network.

This chapter provides an analytical foundation for more effective and behaviour-aware planning of public EV charging infrastructure. The proposed framework is transferable and can be applied to other geographical contexts, as well as extended to support future

research and policy analysis, such as incorporating equity-oriented deployment objectives. Further details on future research directions are discussed in Chapter 8.

Chapter 8

Conclusion

8.1 Introduction

This thesis proposes a novel modelling framework to simulate the driving and charging behaviours of private EV drivers, optimise the locations of future public chargers, and evaluate how drivers respond to the newly proposed chargers. The framework is applied to a case study area of GB. The research first empirically explores the usage patterns of existing public chargers and the factors shaping these patterns. It then develops a rule-based ABM to simulate the driving and charging behaviours of private EV drivers, followed by an agent-based RL model to account for their adaptive behaviours. Based on the charging demand distribution generated by the simulation models, the research formulates an integrated simulation-optimisation framework to optimise the locations of future public chargers and evaluate how EV drivers adjust their behaviours in response to changes in infrastructure provision.

The contributions of this research are both methodological and empirical. The bidirectional simulation-optimisation model represents the methodological contribution, providing a framework to evaluate the relationships between public infrastructure provision and adaptive behaviours of EV drivers. It is transferable and can be applied in other geographical areas or infrastructure contexts. The thesis also contributes empirically with the findings generated by the model, including the comparative charger usage patterns in different regions, the simulated charging demand distribution across GB, and non-linear behavioural responses to public charger provision scenarios.

Section 8.2 summarises the main research findings and reflects on how the research objectives outlined in Chapter 1 have been addressed. Section 8.3 discusses the limitations of the research. Section 8.4 identifies directions for future work. The chapter closes with concluding remarks in Section 8.5.

8.2 Summary of the Research Findings

As stated in Chapter 1, the aim of this research is to explore the driving and charging behaviours of EV drivers, estimate the spatial distribution of charging demand, identify optimal locations for future charging infrastructure, and explore drivers' response to the new placements. To accomplish this aim, several research objectives were formulated. This section revisits these objectives and discusses the extent to which they have been addressed.

1: Review and discuss the literature on EV driver behaviour and existing modelling techniques to identify the key factors shaping the driving and charging behaviours of private EV drivers, evaluate how these behaviours have been represented in existing models, and identify methodological research gaps.

This objective was accomplished through Chapters 2 and 3. Chapter 2 reviewed how EV drivers' behaviours are shaped by their interactions with both the built environment and other EV drivers, as well as by their bounded rationality, learning ability, and range anxiety. Chapter 3 reviewed existing approaches to modelling EV driver behaviours.

Chapter 2 demonstrated that, as EV adoption has expanded, the profile of EV adopters has diversified beyond the homogeneous early adopter groups to include a wider range of users with varied socio-demographic characteristics and behavioural features. EV drivers' charging decisions are collectively shaped by their access to home, workplace, and public chargers. In particular, public charging decisions are shaped by charging speed, price, parking fees, and route-based accessibility. The social interactions among EV drivers can also shape their behaviours. EV drivers interact with each other through digital platforms where they access real-time information about public charger availability. They also interact through direct competition at charging stations, such as queueing, reneging, and balking. Together, these findings highlight the factors to be considered when modelling the charging and driving behaviours of private EV drivers.

Chapter 3 conducted a detailed review of existing approaches to modelling EV driver behaviours. The chapter first reviewed three commonly used statistical and analytical methods to estimate the charging demand of EV drivers: indicator-based mapping, regression models, and DCMs. The indicator-based mapping approach was effective in visualising the spatial distribution of charging demand but offers limited predictive and explanatory capability. Regression models provide interpretability in identifying factors

associated with charging demand, but cannot capture heterogeneous decision-making processes at the individual level. DCMs, while explicitly modelling individual choices, are constrained in their ability to represent social interactions among individuals.

As EV driver behaviours and interactions cannot be effectively captured by statistical and analytical approaches alone, and the rigid nature of charging infrastructure makes experimenting with the real system infeasible, computational modelling provides a practical approach to explore the complex behaviours of EV drivers. Chapter 3 first reviewed two important simulation approaches: DES and ABM. Although DES can represent detailed driving and charging events, its process-oriented, top-down modelling approach means that individuals are passively governed by the system. It is therefore inappropriate to represent proactive drivers who autonomously determine when, where, and how long to charge. In contrast, ABM, a bottom-up computational approach that models autonomous and heterogeneous agents and their interactions with one another and the environment, was identified as an effective approach to model the driving and charging behaviours of private EV drivers. Chapter 3 further reviewed the evolution of EV driver models from those assuming purely rational drivers to those incorporating psychological and cognitive factors.

However, rule-based ABMs were also critiqued for their limited capacity to represent adaptive behaviours in accurately modelling human behaviour. The subjective nature of human behaviour makes it difficult to quantify, and ABMs can face substantial computational challenges when increased behavioural detail leads to a large parameter space and brings model verification challenges. In response to these limitations, RL algorithms were identified as a promising approach for modelling adaptive behaviour in human systems, particularly when the availability of EV trajectory data is limited and no ‘correct answer’ exists. Chapter 3 then reviewed previous studies using RL-based ABMs to simulate the behaviours of EV drivers and identified that these studies mainly apply RL to optimise EV charging strategies and prescribe what drivers should do rather than describe what drivers actually do. Using agent-based RL to simulate EV charging decisions under bounded rationality and real-world uncertainty remains underexplored.

2: Analyse the usage patterns of existing public charger network and quantify their relationships with contextual factors using spatial regression models.

This research objective was accomplished in Chapter 4, which provides an empirical foundation on the public charger usage patterns in GB and identifies contextual factors associated with public charger usage. The analysis reveals that public charger usage patterns vary across regions and that region-specific strategies are needed to develop a more effective charging network. Based on the charging session data, an exploratory data analysis shows that Greater Manchester and the Central Belt of Scotland have peak public charger usage during daytime hours, while usage rates remain relatively low at night. In contrast, Greater London shows a distinct pattern, with higher charger usage rates at night and lower rates during the day. The chapter also developed a spatial regression model to quantify the relationships between charger usage rates and multiple influencing factors. It is the first comparative analysis of public charger usage across multiple regions. The results indicate that, in large and dense metropolitan cities with a high prevalence of flats and persistent traffic congestion such as Greater London, strategies should prioritise residential on-street charging and combine slow overnight chargers with strategically located fast chargers. In polycentric conurbations with mixed housing types and a higher proportion of houses such as Greater Manchester, targeted deployment of public chargers near flatted neighbourhoods may be more cost-effective than blanket coverage. Finally, in regional corridors with substantial inter-city commuting such as the Central Belt of Scotland, greater emphasis should be placed on motorway and trunk-road charging hubs, with fast chargers deployed to serve transit-based rather than purely destination-based charging demand.

3: Design and implement a rule-based ABM and an RL-trained ABM to simulate the charging and driving behaviours of EV drivers and estimate the spatial distribution of charging demand.

Chapters 5 and 6 achieve this objective by developing a rule-based and an RL-trained ABM to simulate the driving and charging behaviours of EV drivers and the resulting charging demand distribution.

The rule-based ABM in Chapter 5 provides an explicit representation of heterogeneous EV drivers who interact with one another and with the charger network and road network environment. Specifically, the EV driver agents are formulated with trip schedules, vehicle types, sensitivities to time and financial cost, as well as psychological features such as range anxiety. The simulation is conducted at a large geographical scale across GB, with a

realistic road network and public charger network. The simulation results show that, despite long-standing concerns about the limited driving range of EVs compared to conventional vehicles, the charging demand for drivers undertaking short- to medium-distance trips remains relatively low. Charging is typically required only after several days of driving when the remaining battery charge becomes insufficient for subsequent trips. In contrast, EV drivers undertaking long-distance journeys show higher demand for public charging.

However, despite the explicit representation of individual EV drivers, the adaptive learning processes identified in Chapter 2 are not fully represented in the rule-based ABM. To address this limitation, Chapter 6 develops an agent-based RL model using DQN to capture the adaptive driving and charging behaviours of heterogeneous EV drivers. Unlike previous RL applications that typically optimise EV fleet charging strategies under assumptions of full rationality and complete information exchange, the model captures the adaptive learning processes of private EV drivers who operate independently, have limited communication with one another, and show bounded rationality and learning ability. The model also introduces an efficient training-simulation framework capable of scaling to large geographical areas with large agent populations. Moreover, based on the SOC records at road junctions generated by the EV driver agents, the results provide high-granularity estimates of the spatial distribution of charging demand and identify areas at high risk of battery depletion, which are mainly located along motorway corridors and urban peripheries, supporting recent policy shifts towards these areas.

4: Develop an integrated simulation-optimisation framework that identifies optimal locations for future public chargers and evaluates how EV drivers adapt their charging behaviours in response to infrastructure expansion.

Building upon the agent-based RL model, Chapter 7 achieves this objective by developing an integrated, bi-directional simulation–optimisation framework to optimise future public charger locations and evaluate drivers’ behavioural responses to newly deployed chargers. A spatial optimisation model is designed to allocate new public chargers based on traffic volumes, EV trajectories, and SOC distributions generated by the agent-based RL model. The RL model is then re-implemented to evaluate how EV drivers adjust their behaviours in response to infrastructure provision changes. Applied to the case study area of GB, the results show that network-wide SOC increases in the early stages of network expansion but

declines as the network continues to expand. The decline reflects a perceived ‘safer charging environment’, where drivers become more confident in tolerating lower SOC levels before recharging. Consequently, part of the charging gains from infrastructure expansion is absorbed by behavioural adaptation rather than translating into higher SOC levels.

The proposed modelling framework also provides a new perspective for integrating adaptive individual behaviours with spatial optimisation. Compared with conventional optimisation approaches based on static demand assumptions, the framework captures how charging demand emerges from individual behaviour. More importantly, the post-optimisation assessment addresses a critical gap in existing public charger location studies, provides new insights into the feedback mechanisms between infrastructure provision and EV driver behaviour, and supports behaviour-aware planning of public EV charging infrastructure.

5: Critically reflect on the research findings and assess the effectiveness and limitations of the proposed models in capturing EV driver behaviours and informing public charger placement decisions.

The modelling framework developed in this thesis has demonstrated its effectiveness in understanding EV driver behaviours. The progression from rule-based ABM to RL-trained ABM has shown improvements in accuracy when replicating real-world charging patterns. The two ABMs were validated against real-world charging session data. Compared to the rule-based ABM, the RL-trained ABM showed higher accuracy in replicating real-world situations by accounting for the adaptive behaviours of EV drivers. The simulation-optimisation framework further demonstrated that integrating behavioural simulation with spatial optimisation can reveal important feedback effects between infrastructure provision and driver behaviour that are not captured by conventional models. Nevertheless, the proposed models rely on several simplifying assumptions and face data constraints that can affect their accuracy and generalisability. A detailed discussion of these limitations is provided in Section 8.3, followed by directions for future research in Section 8.4.

8.3 A Critique of the Research

8.3.1 Data Limitations

NTS data

Although the case study area in this research covers GB, the NTS data used to generate trip schedules include only trips made by residents of England travelling across GB. Since 2013, the NTS sample has been restricted to England, with trips made by residents of Scotland and Wales no longer included (Department for Transport, 2023c). Census data were initially considered as a means of achieving broader geographic coverage; however, the release of the 2022 Scottish census data was delayed and not available until late 2024. As a result, the NTS remained the most up-to-date source with sufficiently detailed trip-related attributes for generating trip schedules at the time of this research.

Another limitation is the number of agents used in the simulation. The models in Chapters 5 to 7 simulate 1,000 EV driver agents relative to the actual EV population in GB. This means that charger occupancy and competition for public chargers are underrepresented. This can reduce the likelihood of queuing effects emerging in the simulation. As a result, findings such as the reduction in agents' SOC with increased charging infrastructure should be interpreted as an indication of directional trends rather than precise quantitative estimates. Once more computational resources become available, future research can use a full synthetic population to simulate more realistic charging demand dynamics, enabling more precise quantitative estimates of future infrastructure impacts.

Public charger network

One important data limitation is that ChargePoint charging session data cover only a subset of the public charger network and do not include sessions from many other public charger operators. This can therefore make the charging patterns in Chapter 4 partly reflect the characteristics of the sampled charger network rather than the full public charging network. Chargers from operators not covered by ChargePoint may serve different locations or user groups with different temporal usage profiles. As a result, the regional patterns identified in Chapter 4 should be interpreted with appropriate caution. Additionally, the partial network coverage means that validation in Chapters 5 to 7 is performed against a subset of the public charging network. Agreement between simulated and observed usage patterns therefore indicates only that the model reproduces the behaviour of ChargePoint-covered

chargers well, but does not necessarily confirm its accuracy in representing the broader public charging network.

Moreover, the charging session data capture usage from all types of EV users, including EV fleets and ride-hailing vehicles. Since the simulation model focuses on the charging behaviour of private EV drivers, using aggregate public charger usage data for validation in Chapters 5 to 7 may introduce discrepancies. Future research could address this limitation when more detailed charging session data with user type information become available.

Parking fees, particularly time-varying pricing schemes, were not included in the Chapter 4 regression models due to a high proportion of missing values in the dataset (see Table C.3. in Appendix C). This is a notable limitation given that parking costs are an important driver of charger selection and usage timing. For example, the higher nighttime usage rates observed in London may partly reflect lower overnight parking costs compared to daytime under dynamic pricing schemes, but this hypothesis cannot be directly tested with the available data. Future research should prioritise incorporating time-varying parking fee data to better explain temporal variations in public charger usage.

Home and workplace charging

The ownership of home chargers and access to workplace chargers are important factors influencing the public charger usage patterns of EV drivers but the location information of these two datasets is missing. Obtaining home charger ownership data and workplace charger data is challenging due to privacy concerns and the fragmented nature of records held across various charger providers. One potential approach to inferring home charger availability is through household property type and other socio-demographic factors; however, this could introduce additional assumptions that cannot be validated without relevant empirical data.

The absence of home and workplace charger data has two direct implications for the research findings. First, in Chapter 4, home and workplace charging availability can be important confounding variables in the relationship between public charger usage and various independent variables. This may therefore affect the interpretation of these associations. Second, in reality, home and workplace charging availability shapes when

and how frequently drivers use public chargers in Chapters 5 to 7. The lack of such data leads to additional assumptions in EV drivers' SOC value changes and can affect the validity of the simulation results. Future research could improve upon the model once more comprehensive data on home and workplace charger data become accessible.

8.3.2 Driving behaviours of EV drivers

Throughout Chapters 5 to 7, there are multiple assumptions in terms of EV driver behavioural design.

First, EV driver agents are assumed to follow Dijkstra's shortest paths when driving between each pair of origins and destinations. However, the assumption that drivers always follow the shortest network path does not fully reflect realistic route choice behaviour. As discussed in Chapter 5, a comparison between the simulated EV trajectories and those obtained from the Google Directions API showed that the simulated routes tend to select geometrically shorter paths that do not account for real-time traffic conditions. This simplification was adopted primarily to reduce the computational cost associated with API usage. Future work could incorporate more realistic route choice models, such as routes from commercial routing APIs or stochastic route choice models, to better simulate driving behaviour.

Second, vehicle types and multiple behavioural parameters of EV driver agents, including financial sensitivity, time sensitivity, and SOC threshold, are randomly assigned using truncated normal distributions, without explicit linkage to sociodemographic characteristics such as income and property type. In reality, these parameters can be systematically shaped by sociodemographic characteristics. For example, higher-income drivers may be less price-sensitive and more likely to own longer-range vehicles. Drivers without home charging access may have higher public charging frequency than those owning home chargers. The assumptions in the ABMs in this research can therefore limit the model's ability to represent realistic charging behaviour, particularly in applied or policy contexts. Specifically, the models cannot capture the differences in charging and mobility behaviour across sociodemographic groups, meaning that simulation results reflect an averaged population response rather than the distinct behavioural patterns of different income levels and household types. Future research could improve upon this by calibrating behavioural parameters of different population groups with empirical

sociodemographic data, such as NTS household characteristics or census income estimates, to produce more policy-relevant simulation outputs.

8.3.3 Amenities

The availability of surrounding amenities at charging stations is an important factor affecting drivers' charging station choices but was not incorporated in this research. This is a simplification of the behaviour modelling, as EV charging requires longer dwell times than traditional petrol refuelling, and drivers often seek to combine charging with other activities. Amenities can therefore compensate for the waiting time, particularly during long-distance trips when drivers may combine charging with other activities such as eating or drinking (Guo et al., 2022; Visaria et al., 2022). Studies have shown that restrooms, restaurants, shopping centres, retail stores, and Wi-Fi are important contributors to charging station choice (ten Have, Gkiotsalitis and Geurs, 2020; Ge and MacKenzie, 2022). Visaria et al. (2022b) further found that EV drivers are willing to accept additional detours to access charging stations that offer desirable amenities, compared to stations lacking such facilities. Omitting these factors may underestimate the attractiveness of well-serviced charging locations and overestimate usage at stations that lack such facilities. Future models should incorporate amenity-related attributes when simulating charging behaviours to improve the accuracy of behavioural modelling.

8.3.4 Battery energy consumption

A further limitation concerns the modelling of battery energy depletion. The simulation models in this research assume that battery energy is consumed linearly in proportion to the distance travelled. However, real-world EV energy consumption is nonlinear and is influenced by many factors, including driving speed and acceleration patterns (Kozłowski et al., 2024), road gradient (Janpoom et al., 2023), and ambient temperature (Taggart, 2017). Incorporating a more realistic, nonlinear energy consumption model that accounts for these factors would improve the accuracy of the simulated spatial distribution of charging demand and battery depletion risk areas.

8.4 Directions for Future Work

There are many directions for future work arising from the limitations identified in Section 8.3 and the discussions in Chapters 4 to 7. Rather than revisiting these, this section focuses on one particularly important avenue: equitable public charger planning.

Public charging infrastructure remains unevenly distributed across regions and socio-economic groups. In the UK, targeted public charging investment along major roads and urban areas has created emerging ‘market failures’ in blackspot areas (The Energyst, 2020). Infrastructure providers tend to prioritise new investments in profitable urban markets (Bonsu, 2019), whereas towns, villages, and rural areas are often underserved due to limited public and private infrastructure investment (Pemberton, Nobajas and Waller, 2021; Wallace, Darwish and Lai, 2024). Such failures could undermine efforts to build a nationwide ‘just transition’ to electric mobility (Pemberton, Nobajas and Waller, 2021). Studies from other contexts, such as the U.S. (Bwire et al., 2026) and Central Europe (Formánek and Lacko, 2025), have also found substantial disparities in charging infrastructure accessibility between urban and rural areas, with rural residents having longer average travel distances to the nearest charging station.

Research on social equity in EV charging infrastructure is relatively nascent compared to studies on efficient charger deployment. Zhang et al. (2024) defined charging equity along two dimensions: horizontal equity, which relates to the spatial distribution of chargers, and vertical equity, which relates to access disparities for vulnerable groups, such as low-income and elderly populations. Hopkins et al. (2023) systematically discussed social equity in EV charging infrastructure provision. They pointed out that studies formulating EV charging infrastructure planning as an optimisation problem typically aim to maximise profit or the volume of electrified vehicle miles yet may magnify existing inequities and exclude underserved populations. Current optimisation models may reinforce existing spatial inequities by directing new infrastructure toward areas where demand is already visible, while overlooking underserved areas where unmet demand remains hidden.

This research has focused primarily on simulating current charging demand and deploying public chargers to maximise demand coverage. However, such a framework can mask underlying social inequities. Future work should place greater emphasis on equity-oriented charger deployment strategies to ensure that the transition to electric mobility benefits all rural and urban regions as well as broader population groups, contributing to the availability, reliability, and accessibility of the public charging network.

8.5 Concluding Remarks

This thesis has developed a rule-based ABM and an RL-trained ABM to simulate the heterogeneous driving and charging behaviours of private EV drivers. Based on the simulated charging demand, the thesis further develops an integrated, bi-directional simulation-optimisation framework to optimise the locations of future public chargers and explore how EV drivers respond to the newly proposed infrastructure. It has effectively captured adaptive learning, bounded rationality, and the dynamic feedback between driver behaviour and infrastructure provision. Although the framework has some limitations, it represents a significant step toward bridging the gap between behavioural simulation and infrastructure planning, two domains that have traditionally been addressed in isolation. It is hoped that, with further refinement of the model, better data availability, and the incorporation of equity-oriented objectives, the framework could support policymakers and infrastructure planners in making more behaviourally informed, socially equitable decisions on future public charger network development.

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Appendix A

The completeness analysis of the scraped data

This Appendix evaluates the completeness and representativeness of the ChargePoint dataset. The ChargePoint website does not include all public chargers in the UK; instead, it includes chargers from selected network operators only. The networks are listed in Table A.1.

To assess the completeness of the chargers in this dataset, the number of chargers in the dataset was compared against official public charger statistics provided by Department for Transport (2023c). According to the statistics, the total number of publicly available EV charging devices in Greater London, Greater Manchester, and the Central Belt of Scotland is 16,963, 776, and 1,620, respectively. Consequently, the chargers in the dataset account for 23.56%, 40.85%, and 15.62% of the total public chargers in these three regions.

Table A.1. List of charging networks in ChargePoint dataset.

ID	Charging Network
1	ChargePlace Scotland
2	Charge Your Car
3	POD Point
4	Osprey Charging Network Ltd
5	Ecotricity (Electric Highway)
6	Monta ApS
7	RAW Charging
8	Chargemaster (POLAR)
9	ChargePoint Network
10	The New Motion
11	Everon Roaming Hub
12	GreenFlux Netherlands
13	Last Mile Solutions CPO Network
14	Engenie
15	Fastned
16	The GeniePoint Network

17	IONITY GmbH
18	Franklin Energy LiFe
19	Liikennevirta Oy (CPO)
20	E.ON Drive Infrastructure GmbH
21	Alfa Power Charging
22	York City Council
23	Bosch Charging Solutions GmbH
24	GMEV
25	Charge Your Car, Merseytravel
26	Ubitricity
27	Allego B.V
28	Cheshire East Council
29	Plug-N-Go
30	Swarco E.Connect
31	Char.gy
32	EV Driver
33	Essex County Council
34	Cotswold District Council
35	Source West
36	SSE, The GeniePoint Network
37	Source London
38	Kent County Council
39	SSE
40	First Group
41	London Borough of Hackney
42	C3EV
43	Heathrow Airport Limited
44	EO Charging
45	Freshmile CPO

Figure A.1 shows the absolute difference in the normalised total number of chargers between the two datasets by local authority, while Figure A.2 shows the absolute difference in the normalised proportion of DC fast chargers. Values close to zero indicate minimal discrepancy, while values closer to one suggest greater divergence. For the total number of chargers, five local authorities in eastern Greater London and one in the Central Belt of Scotland show notable discrepancies, while most other local authorities show

relatively small differences. For the proportion of DC fast chargers, the Central Belt of Scotland shows relatively small differences between the datasets, whereas three local authorities in both Greater London and Greater Manchester show greater divergence, which indicates higher risks of data bias in these areas.

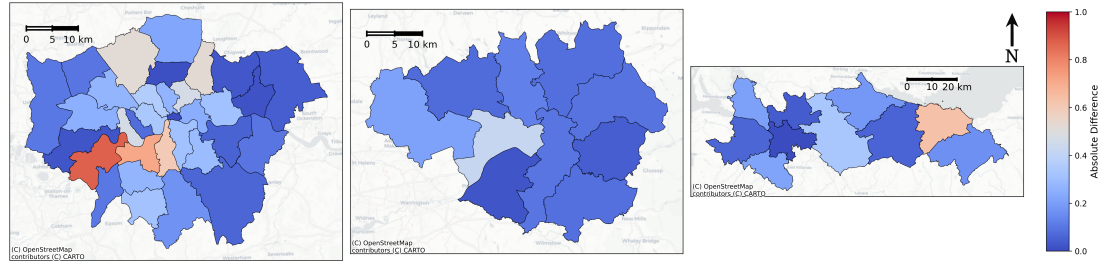


Figure A.1. Difference of total number of chargers by local authority between scraped data and the EV public statistics

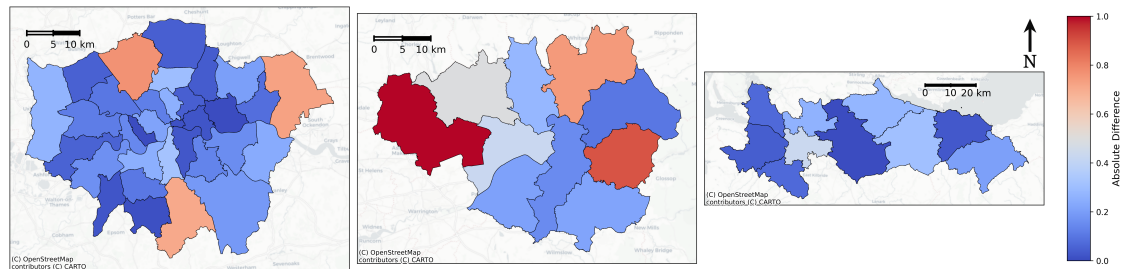
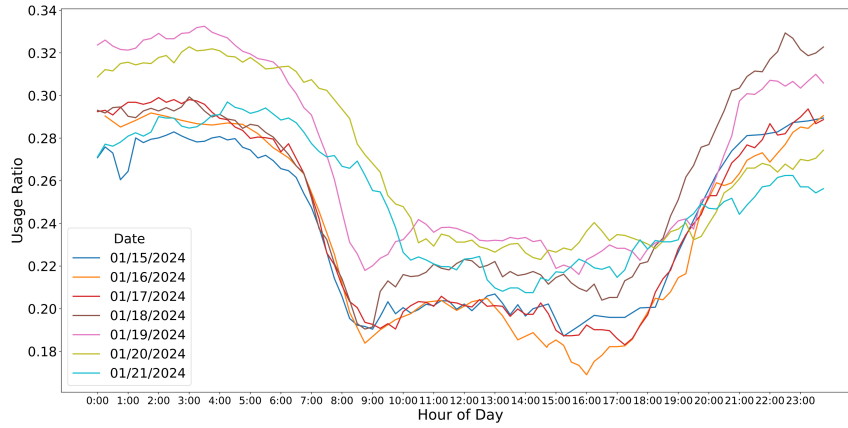


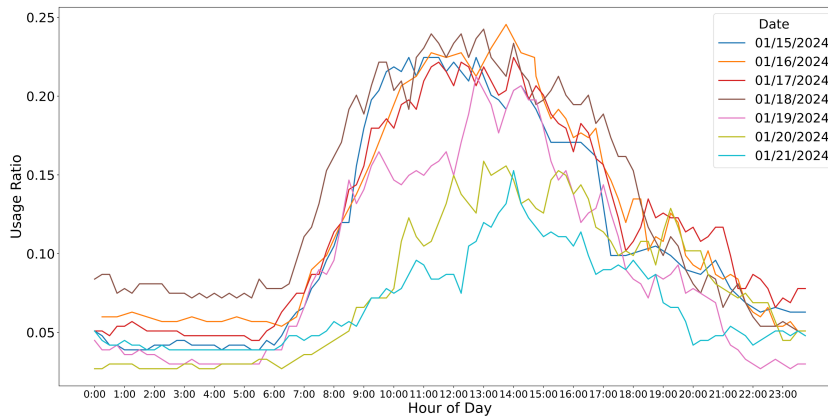
Figure A.2. Difference of DC charger percentages by local authority between scraped data and the EV public statistics

Appendix B

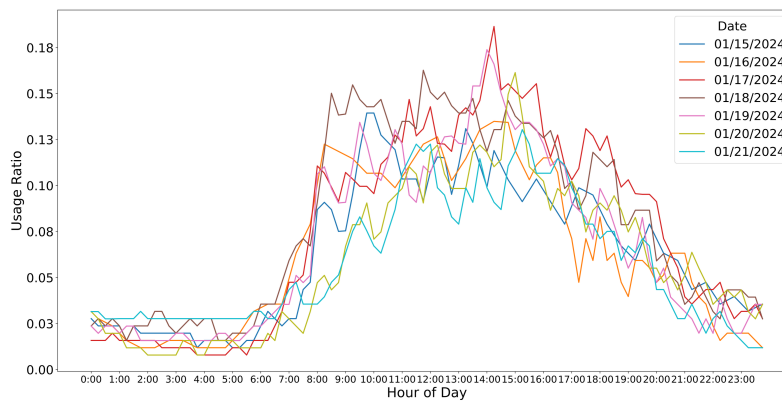
Additional Sample Weeks



(a) Greater London.



(b) Greater Manchester.



(c) Central Belt of Scotland.

Figure B.1. Usage ratio of public chargers for three regions from 15th Jan to 21st Jan 2024.

Appendix C

Variable Selection, Ordinary Least Square Results, and Spatial Regression Results

Building Type Classification

The building type variable is derived from the buildings class dataset (The GeoInformation Group, 2020). It should be noted that this data were generated in 2014 and is therefore relatively outdated compared to the study period of 2023-24; however, it remains the most comprehensive and detailed dataset available for this analysis. The original property classes were reclassified into three broader categories, as shown in Table C-1.

Table C.1. Reclassification of Building Classes.

Original classes	Reclassified classes
Very Tall Flats (point blocks)	Flats
Tall flats 6-15 storeys (slabs)	
Medium height flats 5-6 storeys	
Lower 3-4 storey and smaller flats, detached and linked	
Standard size semis	Detached and semi-detached houses
Semi type house in multiples of 4,6,8 etc.	
Large property semis	
Smaller detached houses	
Large, detached houses	
Very large, detached houses, sometimes converted to flats	Terraces
Tall terraces	
Low terraces	

Exclusion of Charge Price, Charge Speed, and Parking Fee Variables

The charge price and charge speed attributes were excluded from the regression model due to high multicollinearity. Table C.2 shows the Variance Inflation Factor (VIF) values for

these two variables. Moreover, as shown in Figures C.1 and C.2, the distributions of both log-transformed price and log-transformed speed show clear separation between AC and DC chargers, with minimal overlap. This suggests that these variables largely capture information already represented by the charger type variable. The only exception is the distribution of log price in Greater London, where some overlap exists between AC and DC fast chargers. Nevertheless, both variables were excluded across all regions to maintain model consistency and avoid multicollinearity.

Table C.2. VIF values for charge price and charge speed variables.

Region	VIF value	
	charge price	charge speed
Greater London	42.61	18.54
Greater Manchester	29.50	33.11
Central Belt of Scotland	14.95	18.00

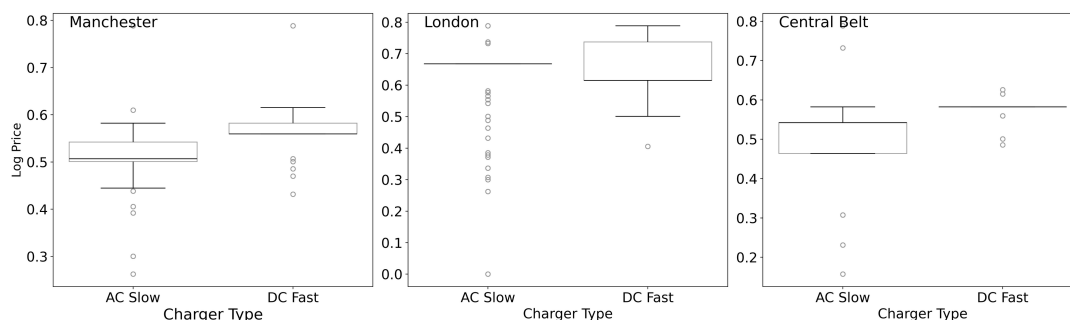


Figure C.1. Distribution of log charging price by charger type.

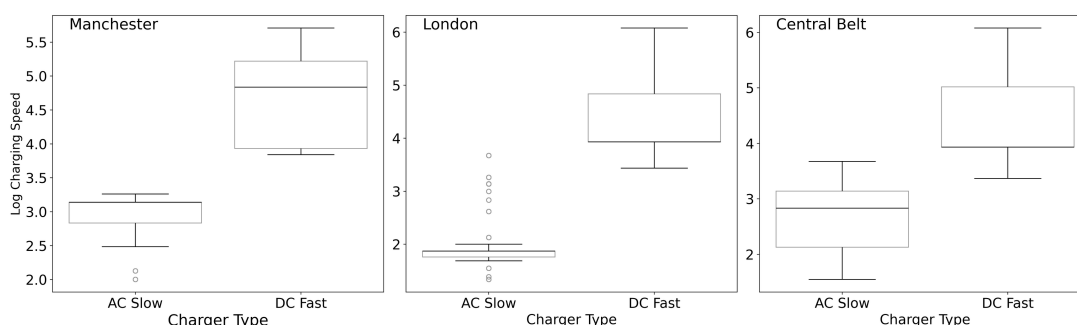


Figure C.2. Distribution of log charging speed by charger type.

Additionally, parking fee variables are also excluded from the models due to the high percentage of missing values. The dataset includes two parking fees: The initial parking fee

and the additional parking fee. The initial parking fee at a charging station is the cost applied for the first hour of parking, while the additional parking fee refers to the rate charged for each subsequent hour. As shown in Table C.3, 98.74% of observations in Greater Manchester and 94.12% in Greater London lack parking fee data, and no observations are available for the Central Belt of Scotland. Including these variables directly in the regression models could lead to a significantly reduced sample size.

Table C.3. Missing rate of the parking fee variables.

Region	Variable Name	Missing Rate (%)
Greater London	Initial parking fee	94.12
	Additional parking fee	94.12
Greater Manchester	Initial parking fee	98.74
	Additional parking fee	98.74
Central Belt of Scotland	Initial parking fee	0
	Additional parking fee	0

Linear Regression Results

Table C.4. Linear regression results.

	London	Manchester	Central Belt of Scotland
Constant	0.086***	0.118***	0.066***
Charger type: DC Fast (reference: AC Slow)	0.059***	-0.004	0.004
Binary motorway proximity: 1 if within buffer	-0.064***	0.074***	0.041***
Day Type: holidays (reference: weekdays)	-0.015***	-0.035***	-0.026***
Day type: weekends (reference: weekdays)	0.004*	-0.014***	-0.015***
Time_20:00-06:00 (reference: 06:00-20:00)	-0.053***	-0.038***	-0.035***
Log(Area of terraces)	-	-0.002***	-0.005***
Log(Area of flats)	0.003***	0.003***	0.004***
Log(Area of houses)	0.001**	-0.002***	0.002***
Time_20:00-06:00* Log(Area of flats)	0.008***	-0.000	-0.001
Charger type: DC Fast * Motorway proximity	0.075***	-0.083***	-0.003

P-value: Level of statistical significance, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Before fitting the spatial regression models presented in Chapter 4, linear regression models were estimated as a baseline. Table C.4 shows the Ordinary Least Square (OLS) regression results for the three study regions.

Spatial Regression Results

Table C.5. Full SDM impact decomposition and raw coefficients.

Variable	Raw Coefficient	Direct	Indirect	Total
Greater London				
Constant	0.088***	—	—	—
ρ	-0.006	—	—	—
Charger type: DC Fast	0.059***	0.060***	-0.000	0.059***
Binary motorway proximity	-0.064***	-0.064***	0.000	-0.064***
DC Fast $\times$ Motorway proximity	0.075***	0.075***	-0.000	0.075***
Time_20:00–06:00	-0.053***	-0.053***	0.000	-0.053***
Log (Area of flats)	0.003***	0.003***	-0.000	0.003***
Log (Area of houses)	0.001**	0.001**	-0.000	0.001**
Log (Area of terraces)	—	—	—	—
Day type: weekends	0.004*	0.004*	-0.000	0.004*
Day type: holidays	-0.015***	-0.015***	0.000	-0.015***
Time_20:00–06:00 $\times$ Log (Area of flats)	0.008***	0.008***	-0.000	0.008***
Greater Manchester				
Variable	Raw Coefficient	Direct	Indirect	Total
Constant	0.120***	—	—	—
ρ	0.001	—	—	—
Charger type: DC Fast	-0.008	-0.008	-0.000	-0.008
Binary motorway proximity	0.020	0.020	0.000	0.020
DC Fast $\times$ Motorway proximity	0.024	0.024	0.000	0.024
Time_20:00–06:00	-0.035***	-0.035***	-0.000	-0.035***
Log (Area of flats)	0.004***	0.004***	0.000	0.004***
Log (Area of houses)	-0.002**	-0.002**	-0.000	-0.002**
Log (Area of terraces)	-0.002***	-0.002***	-0.000	-0.002***
Day type: weekends	-0.013**	-0.013**	-0.000	-0.013**
Day type: holidays	-0.035***	-0.035***	-0.000	-0.035***
Time_20:00–06:00 $\times$ Log (Area of flats)	-0.000	-0.000	-0.000	-0.000
Central Belt of Scotland				

Variable	Raw Coefficient	Direct	Indirect	Total
Constant	0.066***	—	—	—
ρ	0.488***	—	—	—
Charger type: DC Fast	0.010**	0.010**	0.010**	0.020**
Binary motorway proximity	0.017**	0.017**	0.016**	0.033**
DC Fast $\times$ Motorway proximity	0.024***	0.024***	0.023***	0.047***
Time_20:00–06:00	-0.058***	-0.058***	-0.055***	-0.114***
Log (Area of flats)	0.002***	0.002***	0.002***	0.004***
Log (Area of houses)	0.003***	0.003***	0.003***	0.006***
Log (Area of terraces)	-0.003***	-0.004***	-0.003***	-0.007***
Day type: weekends	-0.023***	-0.023***	-0.022***	-0.044***
Day type: holidays	-0.032***	-0.032***	-0.030***	-0.062***
Time_20:00–06:00 $\times$ Log (Area of flats)	0.001	0.001	0.001	0.002

P-value: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix D

Spatial Weight Matrix Selection

A spatial weight matrix is a necessary element for quantifying the relative strength of relationships between pairs of locations (Griffith, 2017). A general expression of a $n \times n$ spatial weight matrix W is:

$$W = \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{pmatrix} \quad (D1)$$

In this study, we use fixed distance matrices constructed based on a specific distance threshold. Within W , each element w_{ij} indicates the strength of the potential interaction between the i -th and j -th public charger observations. w_{ij} are ones for all sites within distance d of location i , and are zeros elsewhere (including the diagonal) (Páez and Scott, 2004).

Each charger contributes six observations from different temporal categories to the dataset. To accommodate this structure, the base $N \times N$ charger-level matrix W is extended into a block-diagonal panel weights matrix of dimension $(N \times T) \times (N \times T)$, where $T = 6$, as follows:

$$W^* = \begin{pmatrix} W & 0 & \cdots & 0 \\ 0 & W & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & W \end{pmatrix} \quad (D2)$$

where each diagonal block is the $N \times N$ charger level matrix W , and all off-diagonal blocks are $N \times N$ zero matrices. This ensures that spatial lags are computed only within the same temporal period, preventing cross-period spatial spillovers.

In spatial econometric model, the selection of spatial weight matrix W is important because miss-specified matrices can lead to biased estimates. We use Bayesian Information Criterion (BIC) to determine the optimal distance threshold d for W . BIC is one of the

most widely used tools in statistical model selection. It is a penalised log-likelihood function, where the penalty term multiplies the number of parameters by the logarithm of the sample size (Claeskens and Hjort, 2008). As shown in Equation C3, n is the sample size and k is the number of parameters for the model studied. $\hat{\theta}$ is the maximised value of the likelihood function of the model.

$$BIC = -2 \ln(\hat{\theta}) + k \ln(n) \quad (D3)$$

Specifically, we test W_i with different fixed distances ranging from 100 to 1000 meters and compute the BIC for each configuration. The optimal threshold is selected based on the model with the lowest BIC value. The BIC values of models with different distance thresholds across three case study areas are shown in Figure D.1. As a result, a fixed distance of 1000m, 1000m, 100m are selected for Greater London, Greater Manchester, and Central Belt of Scotland, respectively.

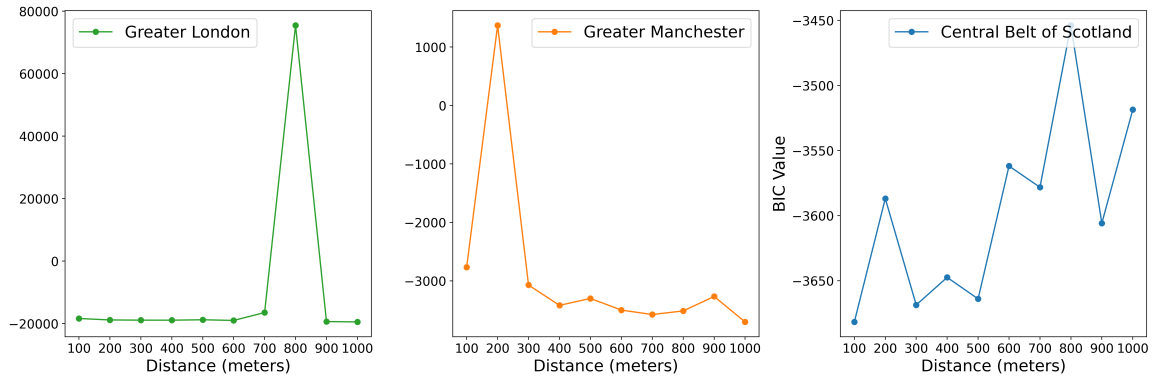


Figure D.1. BIC values of models with different distance thresholds.

Appendix E

Unobserved confounding variables

The regression models explore the relationship between areas of different types of residential properties and the public charger usage rate. However, this relationship could be influenced by unobserved confounding variables. One widely discussed mechanism relates to accessibility to off-street parking availability: residents of flats or apartments are less likely to have access to private driveways or home chargers compared to those living in detached, semi-detached, or terraced houses (Senior, Webster and Blank, 2006; RAC Foundation, 2012). Additionally, different residential property types are associated with different population densities, and higher density is associated with an increased number of trips originating and terminating in an area (Zhang et al., 2019; McDonald et al., 2023), which can in turn affect the demand for public charging infrastructure. Moreover, there are variations in sociodemographic characteristics across residential types—such as income, age, employment status, and the presence of children. These factors may also influence car ownership, vehicle type, and travel behaviour, and consequently affect charger usage rates.

Despite the importance of these variables, detailed socio-demographic data are not always publicly available at the fine spatial resolution required for charger-level analysis (e.g. 500-meter buffers). Using data from larger spatial units can obscure local variation and may introduce bias into the results.

Nevertheless, to address concerns about unobserved confounders, a sensitivity analysis was conducted using the Impact Threshold for a Confounding Variable (ITCV) (Frank, 2000; Pan and Frank, 2004). The ITCV is a diagnostic tool that quantifies how strong the correlation between an unmeasured confounder and both the independent and dependent variables would need to be, in order to invalidate a statistically significant inference. In other words, it represents a threshold at which the impact of a confounder would be sufficient to alter the inference (Bendig and Hoke, 2024). The specific formulae for calculating ITCV can be found in Frank (2000). As ITCV is designed for linear regression, the values were computed using OLS models before incorporating spatial terms. ITCV values were calculated for three key variables: area of flats, area of houses, and area of terraces. The results are shown in Table E.1.

Table E.1. ITCV and strongest absolute impact value.

	Greater London		Greater Manchester		Central Belt of Scotland	
	ITCV	Strongest absolute impact value	ITCV	Strongest absolute impact value	ITCV	Strongest absolute impact value
Area of flats	0.012	0.0583	0.044	0.0991	0.062	0.0378
Area of houses	0.002	0.0016	0.023	0.0632	0.042	0.0557
Area of terraces	-	-	0.046	0.0598	0.085	0.0243

* The 'area of terraces' variable is excluded from the London model due to its high collinearity introduced to the model

The robustness of each estimate was assessed by comparing its ITCV with the strongest absolute impact value among the included control variables, defined as the product of the partial correlation between the control variable and the dependent variable, and the partial correlation between the control variable and the independent variable of interest (Frank, 2000). If the ITCV exceeds the maximum impact value of the control variables, then a stronger unmeasured confounder would be required to overturn the result, and the estimate is thus considered robust.

As shown in Table E.1, the ITCV results indicate varying levels of vulnerability to unobserved confounders across the three models. In the Central Belt of Scotland, the ITCV values for flats (0.062) and terraces (0.085) exceed the strongest observed confounding influence among control variables (0.0378 and 0.0243), which indicates robust inferences and little concern regarding omitted variable bias. In Greater Manchester, the ITCV values for flats (0.044) and houses (0.023) are much lower than the maximum observed control variable impact (0.0991 and 0.0632), indicating greater vulnerability to potential unmeasured confounding. Similarly, in Greater London, the low ITCV for flats (0.012) compared to the strongest control variable impact suggests a higher risk that an unobserved variable could bias the results. In contrast, the inference for the houses variable (0.002) is more robust, as its ITCV exceeds the benchmark impact (0.0016), suggesting an unmeasured confounder would be less likely to invalidate this result.

In summary, the ITCV sensitivity analysis provides a diagnostic assessment of the robustness of the regression estimates and highlights which variables and models are more

sensitive to potential omitted variable bias. While some residential property variables show robust associations with charger usage rates, others appear more vulnerable to unobserved confounding. This suggests that unmeasured factors, such as population density, income, or other demographic characteristics, may still influence these relationships. Therefore, results for these more vulnerable variables should be interpreted with caution. A key limitation of this research is the lack of granular socio-demographic data, which restricts the ability to fully control for relevant confounders. Future research would benefit from incorporating more detailed, disaggregated data at the individual, household, or neighbourhood level to build richer models that more accurately capture the determinants of public charger usage.

Appendix F

Cluster Analysis of Trips

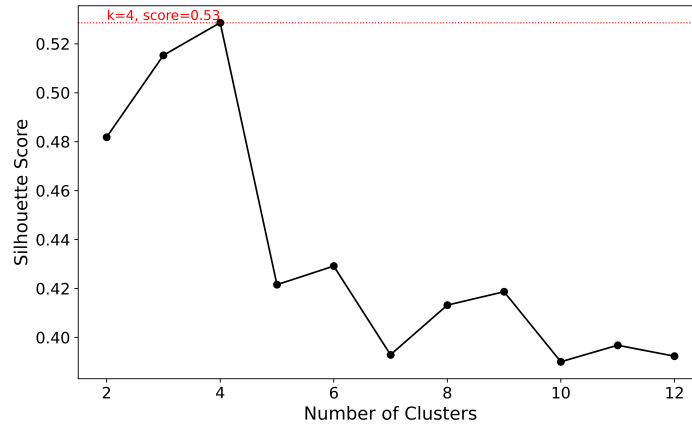


Figure F.1. Silhouette score for different number of clusters (2 - 12).

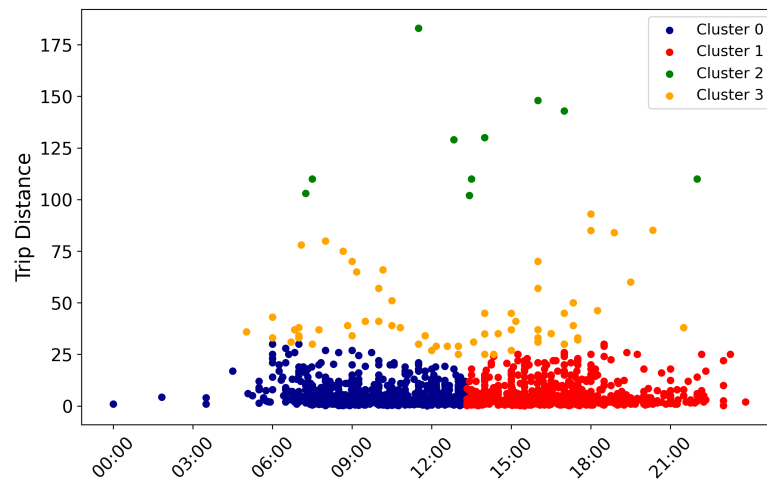


Figure F.2. Clusters of trips by start time and distance (cluster =4).

To determine the optimal number of clusters for classifying trip types, silhouette scores were calculated for cluster numbers ranging from 2 to 12 to evaluate the separation distance between the resulting clusters. As shown in Figure F.1, the 4-cluster solution shows the highest average silhouette score (0.53) and is therefore chosen as the optimal number of clusters. Figure F.2 shows the resulting clusters by trip start time and distance, using a stratified sample of 3% of the data points for visual clarity.

Appendix G

Trip Origin and Destination Assignment

It is assumed that the drivers in the NTS data have adopted EVs while their trip origins and destinations (OD) remain unchanged. The variables of trip origin unitary authority and trip destination unitary authority from the dataset are therefore selected to define the OD information for the simulated EV driver trips. As OD information at the unitary authority levels is not sufficiently precise to serve as OD points when initialising the model, OS Code-Point data (Ordnance Survey, 2023a), which provides over 1.7 million postcode units across GB, is combined with the NTS data to determine the start and end coordinates for each trip in the model. This process is designed to ensure that the OD distances in the model closely match the trip distance values in the NTS dataset, while also reducing the computational burden associated with calculating large OD matrices.

The selection of origins and destinations for each trip was carried out based on the UK postcode system, which follows a hierarchical structure as shown in Table G.1. A full postcode consists of two parts: the outward code and the inward code. The postcode area is the initial letter(s) to represent a major town or city. The postcode district adds one or two numbers or letters to the area, typically covering part of a town or urban area. The postcode sector includes the district plus the first digit of the inward code, usually representing a few thousand addresses. The postcode unit is the full postcode, identifying approximately 15–20 addresses on average.

Table G.1. UK postcode structure.

Postcode			
Outward code		Inward code	
Area	District	Sector	Unit
Example (SW1A 2AA)			
SW	SW1A	SW1A 2	SW1A 2AA

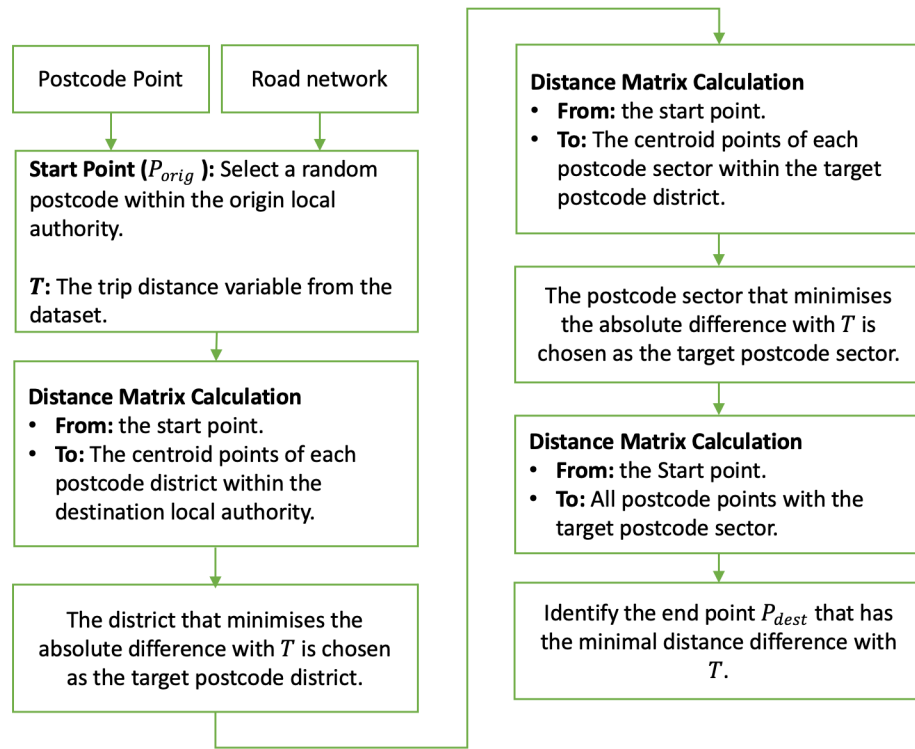


Figure G.1. Flowchart of selecting origin and destination for each trip.

The process for selecting each trip's origin and destination is shown in Figure G.1. The starting point of each trip P_{orig} is randomly selected from the postcodes within the trip origin unitary authority. Using Dijkstra's shortest path algorithm, the distances from P_{orig} to the centroid of each postcode district are calculated. The district that minimises the absolute difference with the trip distance T from the dataset is selected as the target postcode district. Following the same approach, the destination postcode sector is then determined within the selected district. Finally, among all postcode points within the target postcode sector, the destination P_{dest} is selected as the postcode point whose network distance from P_{orig} has the smallest absolute difference with T .

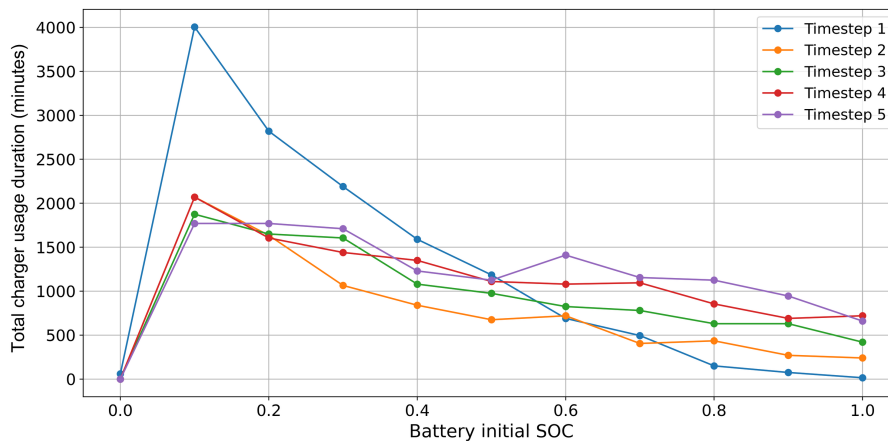
Appendix H

Model Calibration: ABM

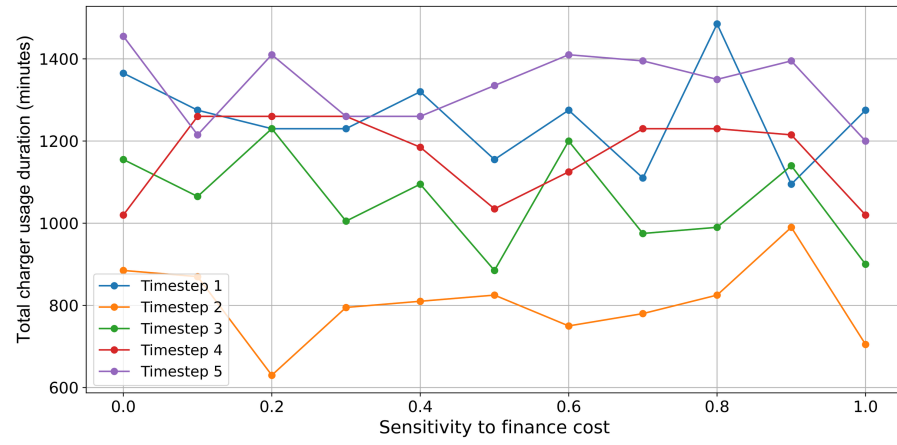
Table H.1. Parameters selected for model calibration.

Parameter Name	Description
Initial SOC	The SOC of the vehicle at the start of the first trip.
SOC threshold	The minimum battery charge level that drivers strive to maintain throughout their journeys. This parameter reflects the sensitivity of an EV driver to low battery status.
Sensitivities to finance cost	The driver's sensitivity to paying for charging during travel.

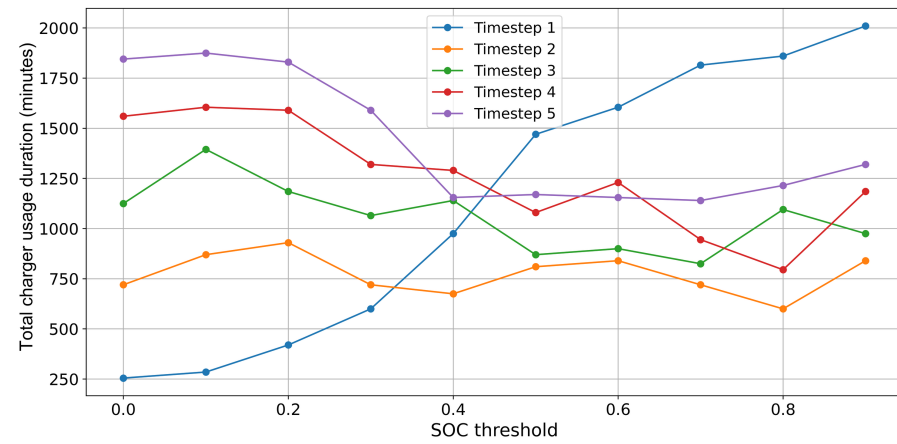
When modelling the EV driver agents, the parameters of initial SOC, financial sensitivity, and SOC threshold were set using truncated normal distributions bounded between 0 and 1, with a mean (μ) of 0.5 and a standard deviation (σ) of approximately 0.167. Both the One Factor at a Time (OFAT) method and Sobol' method-based sensitivity analyses were performed to assess the robustness of the results. The Sobol' sensitivity indices were calculated using the sampling scheme proposed by Saltelli (2002), and the confidence intervals were calculated at the 95% confidence level. The output variable used for model calibration was the total charger usage duration across all charging stations. The three parameters selected for calibration are listed in Table H.1. The results of the OFAT analysis and Sobol' analysis are shown in Figure H.1 and H.2, respectively.



(a) Battery initial SOC



(b) Sensitivity to finance cost



(c) SOC threshold

Figure H.1. OFAT results.

Initial SOC

The range adopted for initial SOC is empirically supported by the studies of Hipolito et al. (2022) and Fotouhi et al. (2019), which found that the distribution of the SOC across a population of EVs on a given day tends to fall within a similar range and follow an approximately normal distribution. Zhan et al. (2025) further demonstrate that EV drivers tend not to let SOC drop below 0.2 or charge beyond 0.8, with most charging occurring within this mid-range, which aligns with the chosen truncated normal distribution where the majority of values fall within these bounds. Higher SOC values than 0.8 and lower SOC values than 0.2 are still permitted to reflect extreme scenarios in the simulation.

The result of the OFAT analysis is shown in Figure H.1(a). Across all time steps, there is a marked increase in charger usage duration as the initial SOC rises from 0 to 0.1. Following this peak, the total usage duration decreases with higher initial SOC levels. When the initial SOC is at 0, vehicles start without any battery charge, making them unable to reach nearby public chargers or drive to their destination, except for those starting directly at a charging station. This results in few charging sessions during the simulation process. As vehicles begin with a very low SOC, chargers are used more intensively due to the need for longer charging sessions to reach an acceptable SOC. Further increases in initial SOC provide drivers with sufficient battery charge, thereby reducing their propensity to use public chargers.

Sensitivity to finance cost

This parameter is a dimensionless scaling factor that determines the relative influence of monetary cost compared to psychological preference in a driver's charger choice. Since these factors are measured in different units (currency versus qualitative preference), they are normalised to a (0, 1) range to prevent any single factor from dominating the decision-making process due to scale differences.

The result of the OFAT analysis is shown in Figure H.1 (b). The plot shows no clear monotonic trend; the charger usage duration fluctuates across different values of this parameter. This indicates the effect of financial sensitivity on charger usage duration is either non-linear or influenced by complex interactions not captured in the OFAT analysis. One possible explanation is that financial payment relative to time cost influences drivers' choice of which station to use but does not determine whether they need to charge in the first place.

SOC threshold

As defined in Table H.1, this parameter is related to range anxiety and reflects variation among drivers. As found by Thorhauge et al. (2024), some drivers run their batteries closer to depletion before charging, while others charge at an earlier stage. The SOC threshold is a heterogeneous quantity that varies considerably between user groups and can also be influenced by familiarity with EV technology, generally decreasing as users gain

experience (Rainieri, Buizza and Ghilardi, 2023). The chosen value distribution is therefore intended to capture this variability across the driver population.

The result of the OFAT analysis is shown in Figure H.1(c). The relationships between total charger usage duration and SOC threshold differs between time step 1 and subsequent time steps. During time step 1, total charger usage duration increases with the SOC threshold, implying a higher SOC threshold leads drivers to charge more frequently or for longer durations, resulting in greater charger occupancy. However, from time steps 2 to 5, the total usage duration decreases as the SOC threshold rises. This can be attributed to the fact that a higher SOC threshold increases the amount of energy added during each charging session. As a result, drivers who charged during time step 1 carry a sufficient charge into subsequent time steps, reducing charging station usage thereafter.

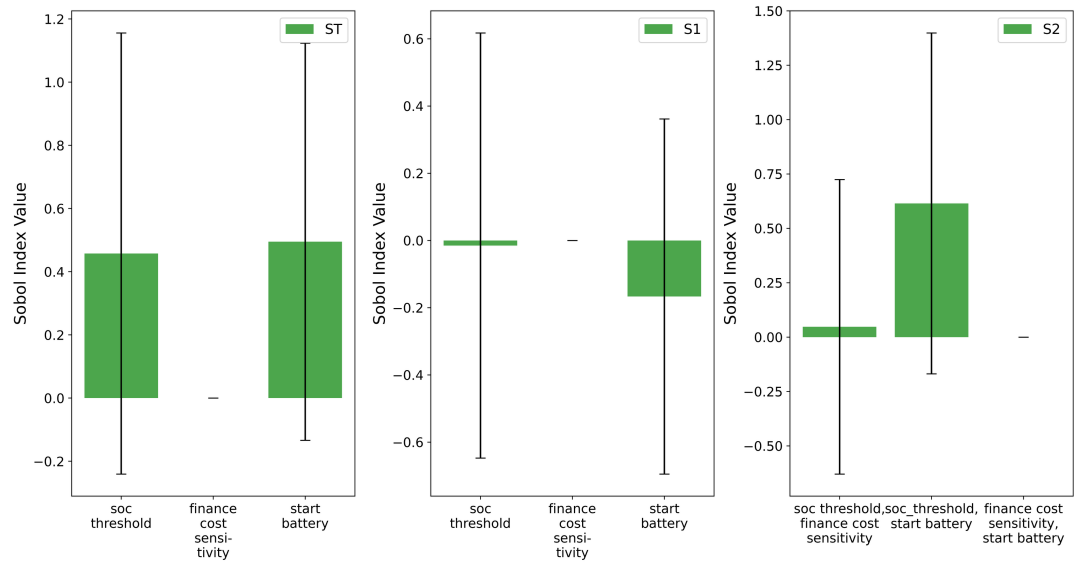


Figure H.2. Sobol' analysis results.

The Sobol' analysis results are presented in Figure H.2. The total-order sensitivity (ST) index represents the total contribution of each input variable to the output variance. The first-order sensitivity Index (S1) represents the direct contribution of each input variable to the output variance, excluding the interactions with other variables. The second-order sensitivity index (S2) measures the interaction effects between pairs of input variables. The results indicate that the initial SOC has the most substantial impact on the variance of total charging duration. The SOC threshold also shows a notable effect on the variance of total charging duration. The sensitivity to finance cost over time has relatively low contribution to the variance of total charging duration.

Appendix I

Model Calibration: RL

Three key parameters were calibrated: the learning rate, discount factor, and exploration rate. Each parameter was calibrated independently, with the tested values presented in Table I.1. The impact of these parameters on reward changes across all vehicle types is shown in Figures I.1-I.3, respectively.

Table I.1. Parameter values tested during calibration.

Parameter	Values
Learning rate	[0.001, 0.00075, 0.0005, 0.00025, 0.0001]
Discount factor	[0.9, 0.95, 0.99]
Exploration rate	[0.99→0.01, 0.98→0.01, 0.97→0.01, 0.96→0.01,
range	0.95→0.01]

The learning rate significantly affects the model's learning stability and convergence speed. As shown in Figure I.1, a learning rate of 0.0001 produced greater stability, with fewer fluctuations in reward values and a smoother learning trajectory.

The discount factor determines the importance agents place on future rewards. A higher discount factor encourages agents to prioritise long-term outcomes. Among the tested values, 0.95 was selected as it enabled agents to effectively balance immediate cost savings and future charging needs.

The exploration rate was calibrated with different starting values ($\epsilon_{\max} = 0.99, 0.98, 0.97, 0.96$, and 0.95). Following an ϵ -greedy strategy, a high initial exploration rate was chosen to allow agents to explore the environment more thoroughly by selecting random actions. Across all configurations, ϵ decays over the 2,000 training episodes from its starting value to 0.01 by the end of training, ensuring that agents progressively shift from exploration to exploitation of their learned policies.

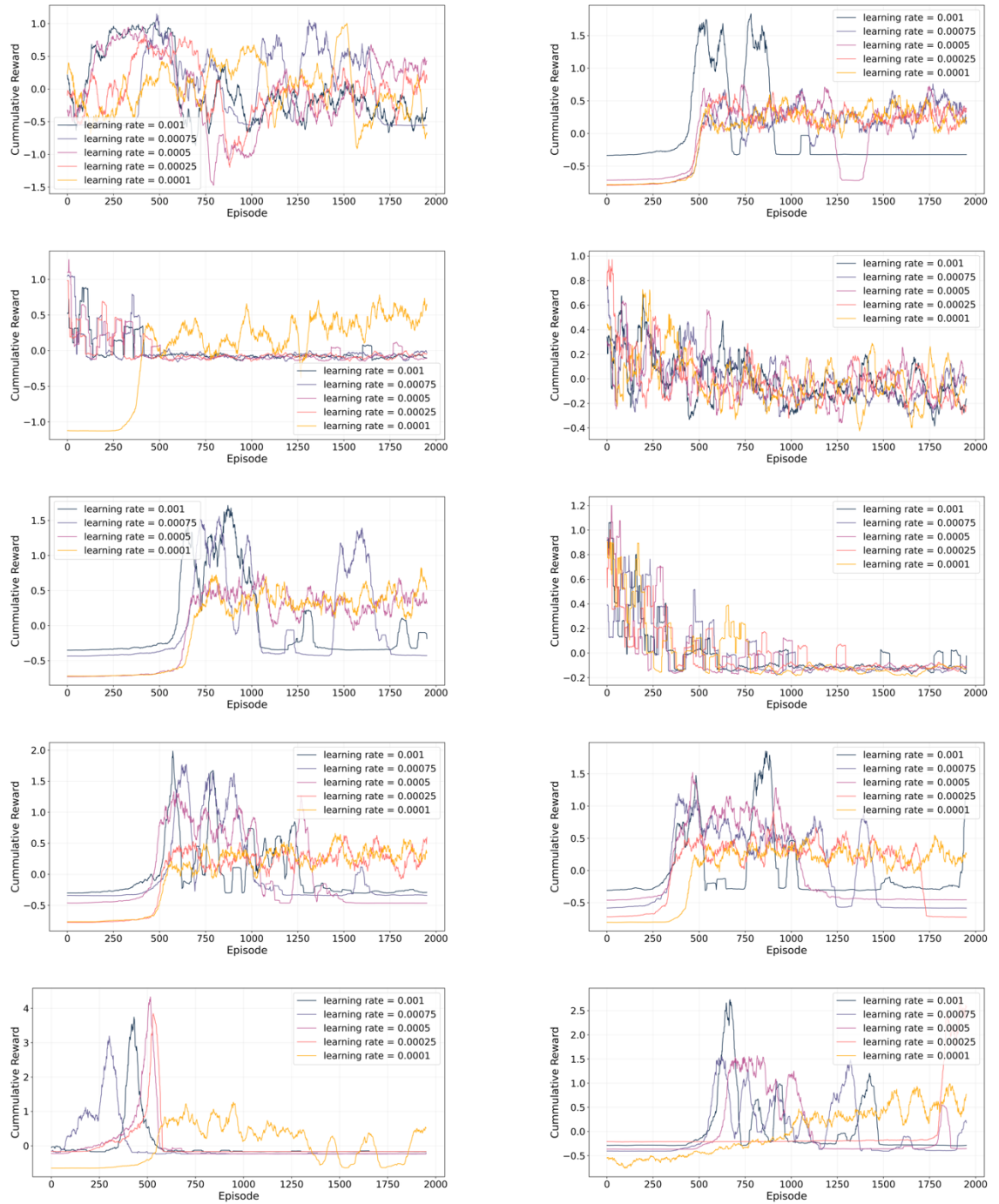


Figure I.1 Parameter calibration of learning rate.

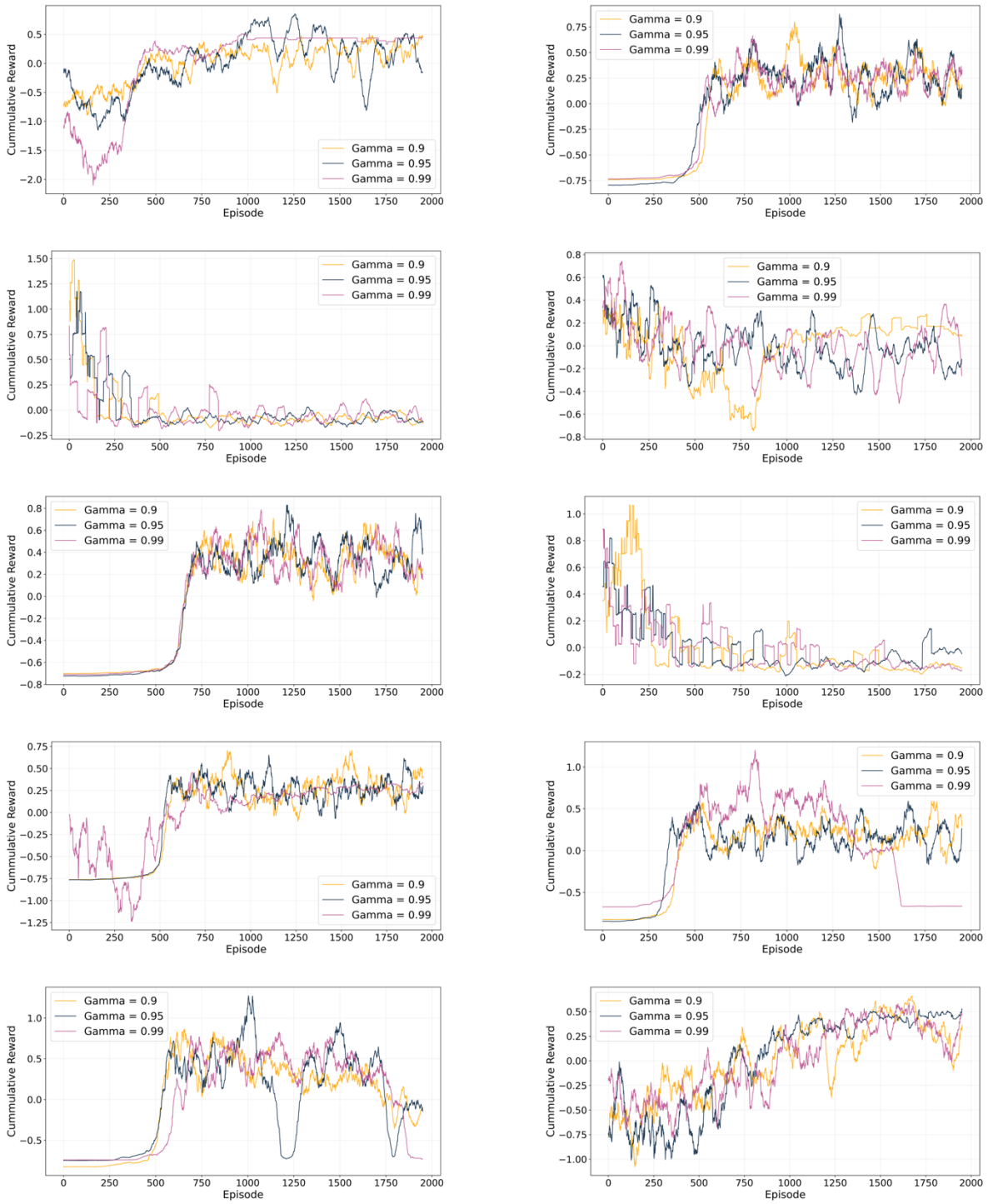


Figure I.2 Parameter calibration of discount factor.

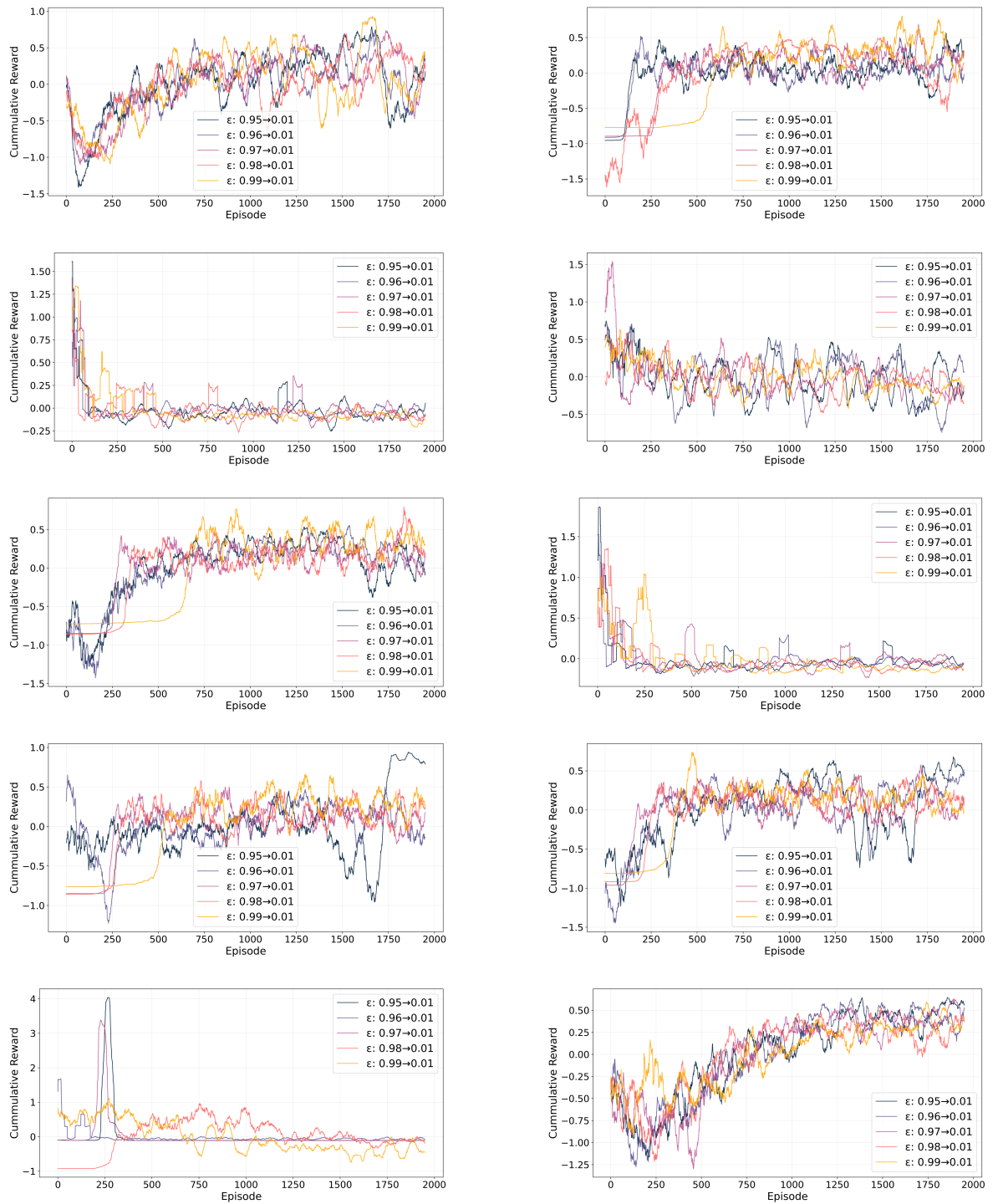


Figure I.3 Parameter calibration of exploration rate.

Appendix J

Trip purpose reclassification and Driver Clustering

Trip Purpose Reclassification

The trip purpose variable in the NTS dataset was reclassified into two broader categories: work and leisure. The reclassification scheme is shown in Table J.1.

Table J.1 Reclassification of trip purposes.

Original trip purposes	Reclassified trip purposes
Commuting	Work
Personal business	
Business	
Education/escort education	Leisure
Other escort	
Shopping	
Leisure	

Driver Clustering

The cluster analysis was conducted based on four continuous features: total trip distance, initial battery level, trip co-occurrence density, and public charger density. The optimal number of clusters was determined using the elbow method. We calculated the inertia, the sum of squared distances between data points and their cluster centroids, for cluster number ranging from 2 to 14. As shown in Figure J.1, the inertia curve shows a reduction in the rate of decline at $k=5$, after which each additional cluster contributes to smaller reductions in inertia. Five clusters were therefore used in the analysis.

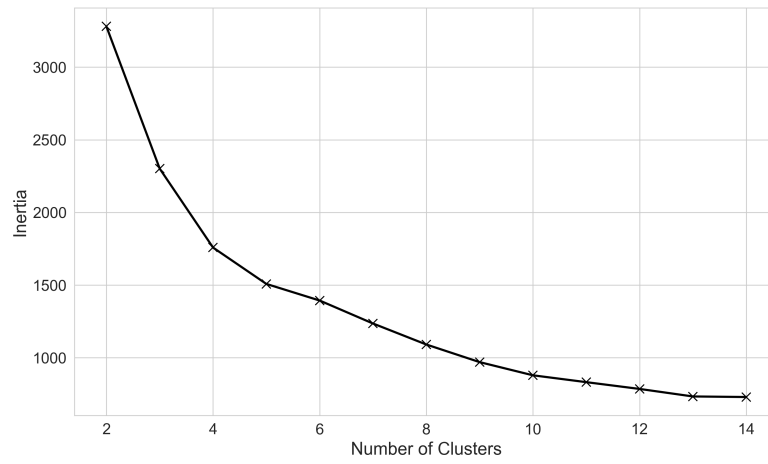


Figure J.1 Inertia plot for k-means EV driver clustering

Table J.2 Classifications and centroids of clustering analysis.

Cluster	Trip purpose	Public charger density	Trip co-occurrence density	Total trip distance	Initial battery level	Cluster feature
1	work	0.03	0.03	19.59	0.49	Mid-distance
	leisure					inter-city drivers
2	work	0.03	0.04	30.07	0.25	Long-distance
	leisure					Low-battery inter-city drivers
3	work	0.26	0.31	20.42	0.52	Mid-distance
	leisure					drivers in high-density areas
4	work	0.03	0.04	30.62	0.76	Long-distance
	leisure					inter-city drivers
5	work	1.00	0.49	10.61	0.70	Short-distance
	leisure					drivers in high-density areas

To capture behavioural differences associated with trip purpose, each cluster was subsequently subdivided by work and leisure trip types. Rather than incorporating categorical variables directly into the initial clustering process, this approach ensures more accurate distance-based cluster assignment while still capturing the behavioural

distinctions between work and leisure trips. The centroid of the resulting clusters is presented in Table J.2.

Appendix K

Justification of Reward Function Design and Reward Change

The reward function was designed to capture the key trade-offs faced by private EV drivers when making charging decisions. It comprises four components: SOC threshold impact (D_{SOC}), charging urgency factor (D_{charge}), cost impact (D_{cost}), and trips completion status (Status). The design is grounded in established understanding of EV driver decision-making from the literature and practical considerations for realistic behaviour simulation. The rationale for each component is discussed below.

Trips completion status (Status)

The primary objective of an EV driver is to complete their planned trips. The Status variable ensures that this fundamental goal is explicitly presented in the reward function. Successful trip completion yields an additional reward, while running out of charge before reaching the destination incurs a penalty. Without this component, agents might learn strategies that minimise charging costs at the expense of failing to complete trips.

This formulation reflects real-world behaviour, where drivers avoid strategies that risk being stranded due to battery depletion. Studies show that EV drivers show forward-looking behaviour and planning ability when scheduling charging and driving (Thorhauge, Rich and Mabit, 2024). Additionally, compared to other considerations, EV drivers perceive completing the planned trips the primary factor influencing their charging decisions (Ge and MacKenzie, 2022).

SOC Threshold Impact (D_{SOC})

Range anxiety has been identified as a critical determinant of EV drivers' charging behaviour (Chaudhari et al., 2019; van der Kam et al., 2019; Ling et al., 2022; Li, 2025). Building on the concept of 'safety buffer' (Kurani, Turrentine and Sperling, 1994), Franke et al. (2012) introduced the concept of 'comfortable range', which is defined as the subjective portion of battery capacity that a driver is willing to use without experiencing

stress. Rainieri et al. (2023) further showed that the greater the discrepancy between the available battery charge and a driver's preferred safety battery level, the more likely the driver is to experience discomfort and stress.

To capture this behavioural pattern, D_{SOC} is defined as the difference between the current SOC and the driver's psychological threshold ($SOC_{threshold}$). A larger positive difference indicates greater perceived comfort and results in a higher reward, whereas a negative difference reflects increased anxiety and reduces the reward accordingly.

Cost Impact (D_{cost})

EV drivers typically consider both monetary and time costs when making charging decisions (Wang et al., 2024; Yang et al., 2020), although the relative importance of these costs varies by drivers' preferences and travel contexts (Daina, Sivakumar and Polak, 2017a). To reflect this heterogeneity, each agent is assigned individual sensitivities to financial (α) and time costs (β). The exponent n/m is introduced to account for the interaction between charging frequency, trip length, and perceived disruption. Specifically, frequent charging imposes a greater perceived burden during short trips than during long-distance journeys, where charging stops are more expected and tolerated. This design enables the reward function to differentiate cost impacts across different travel contexts.

Charging Urgency Factor (D_{charge})

Charging urgency reflects drivers' perceptions of risk and opportunity associated with charging timing and infrastructure availability. Tate et al. (2008) indicated that EV drivers have pervasive concerns about becoming stranded with a depleted battery, particularly when operating away from charging infrastructure. Additionally, unlike refuelling conventional vehicles, EV charging requires extended dwell times at charging stations. As Helmus and Wolbertus (2023) noted, one user's occupation of a charging station reduces availability for others. In stochastic environments where private EV drivers have limited information about others' intentions, drivers may encounter congestion and queueing at popular chargers. To capture this effect, the reward function incorporates $chance_{charge}$, defined as the ratio of charger density (CD) to trip co-occurrence density (TCD). This ratio represents the perceived likelihood of accessing an available charger relative to potential

competition. Higher values indicate a greater perceived chance of charging without queueing.

The timing dimension of charging urgency depends on both the battery level at trip start ($\text{status}_{\text{battery}}$) and when charging occurs relative to the trip start ($\text{timing}_{\text{charge}}$). Lower initial battery levels increase perceived urgency, as drivers face a higher risk of depletion and reduced flexibility in charging choices. In contrast, lower values of $\text{timing}_{\text{charge}}$ correspond to early charging, which reduces perceived urgency as drivers secure charging opportunities proactively. This behaviour aligns with findings by Thorhauge et al. (2024) that, with forward-looking planning tendencies, many EV drivers charge during the early stages of trips even when sufficient battery charge remains.

Cumulative Reward Changes

The cumulative reward changes for each type of training agent across all episodes is shown in Figure K.1. The shaded area in the figure represents the variation in reward outcomes across different combinations of training and simulation agents. For agents in Cluster 1 (work and leisure), Cluster 3 (work), Cluster 4 (work and leisure), and Cluster 5 (leisure), an upward trend in cumulative rewards suggests that these agents progressively learned more effective charging strategies over the course of training. However, for agents in Cluster 2 (work and leisure) and Cluster 3 (leisure), a decrease in cumulative rewards upon convergence indicates that competition for chargers forced these agents to adopt less favourable strategies, reflecting the competitive dynamics inherent in shared charging infrastructure.

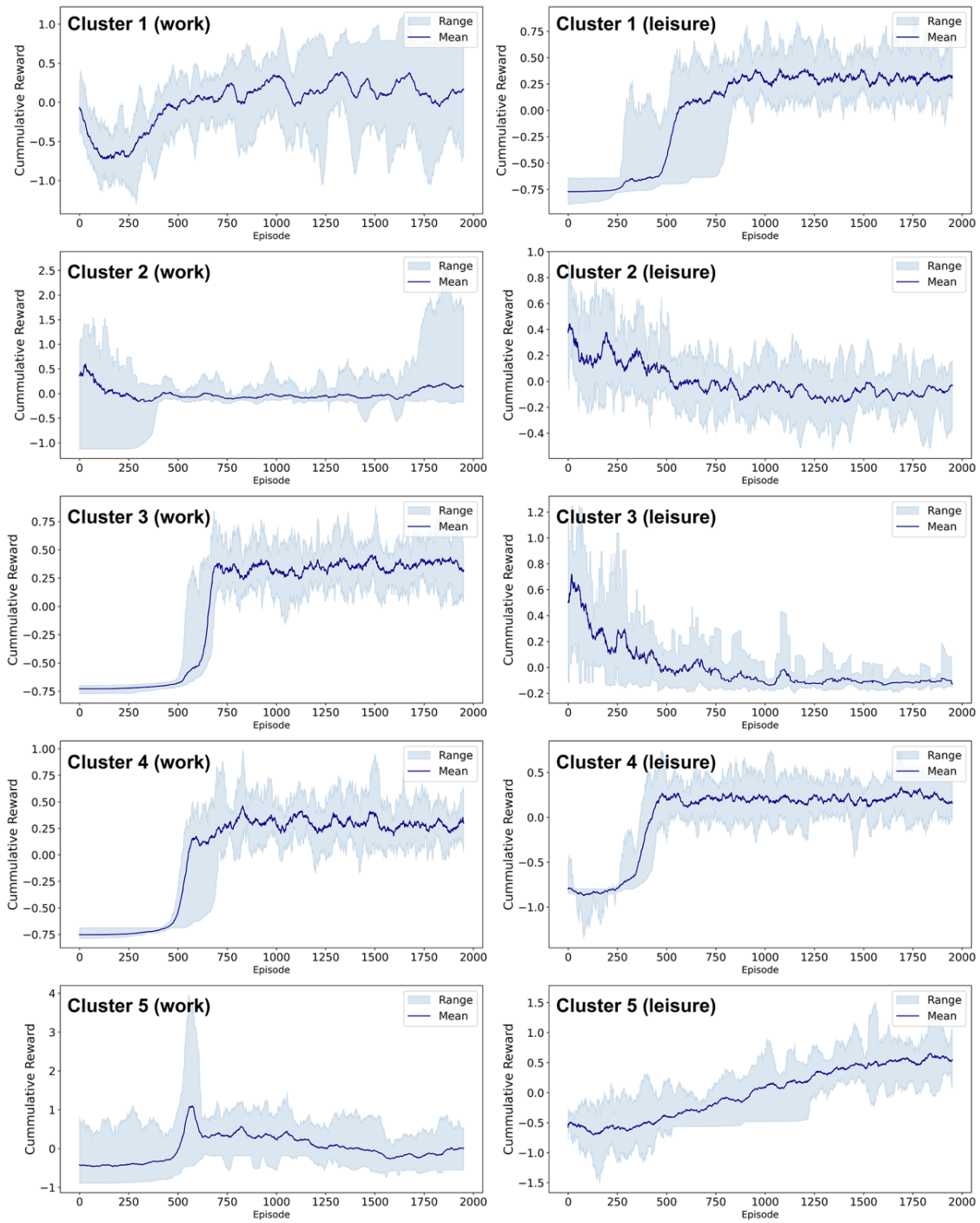


Figure K.1. Reward changes for the training agents.

Appendix L

Action Selection for Group 2 drivers

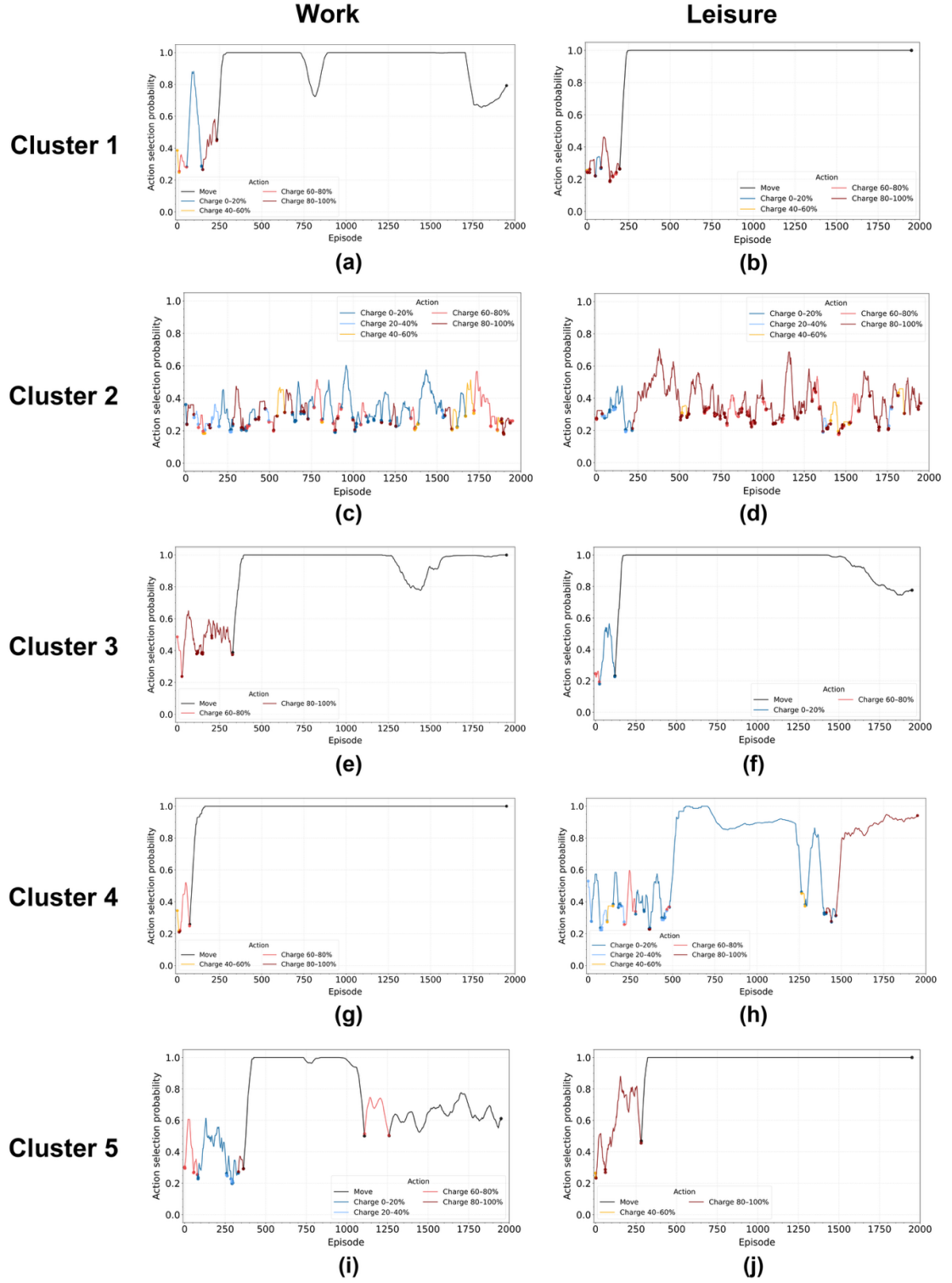


Figure L.1. Dominant action selection for Group 2 drivers in Cluster 1 - 5.

Appendix M

Optimal Cluster Selection

The optimal number of clusters was determined using the elbow method. The inertia value was calculated for each cluster number, defined as the sum of squared distances between data points and their respective cluster centroids. As shown in Figures M.1 to M.3, all three scenarios have an elbow point at a cluster number of three. Accordingly, three clusters were selected for the cluster analysis across all scenarios.

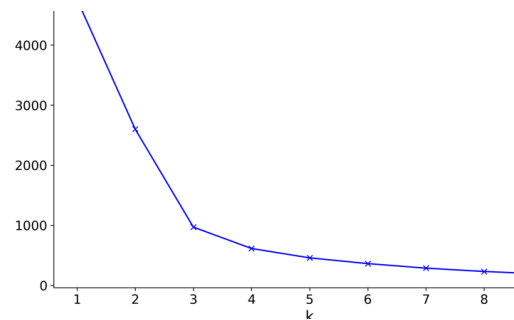


Figure M.1 Inertia plot for buffer distance of 500m.

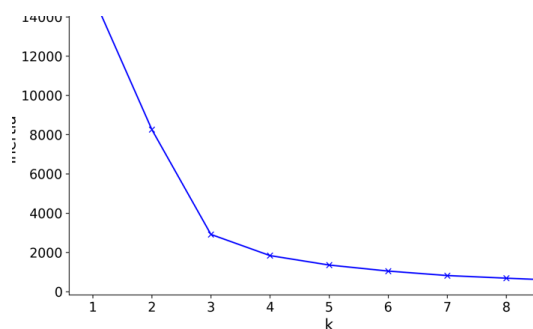


Figure M.2 Inertia plot for buffer distance of 1000m.

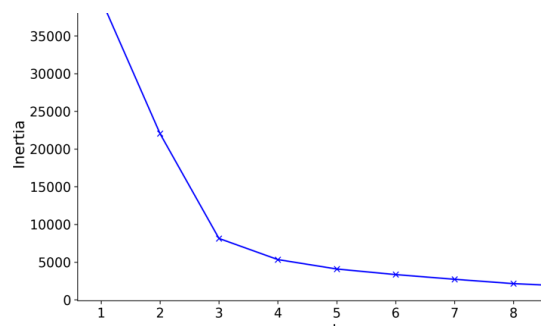


Figure M.3 Inertia plot for buffer distance of 1500m.

Appendix N

Linking traffic volume observation points to road network junctions

Traffic volume data are available for each junction on motorways and A roads, as well as for a sample of junctions on the minor road network, including B, C, and unclassified roads. The EV trips simulated in this study consist of continuous node-to-node movements along the road network. As a result, many simulated trajectories do not directly intersect with existing traffic observation points.

To associate each trip with representative traffic volumes, every node along the route was spatially joined to its nearest traffic observation point within a defined search radius. A radius that is too large may link nodes to traffic conditions that are not representative of their actual location, whereas a radius that is too small may leave many trips unmatched with any traffic observations. To determine a suitable threshold, a sensitivity analysis was conducted to explore how the percentage of trips with valid traffic observations changes under different search distances, ranging from 100 m to 1,000 m in 100 m increments. The results are shown in Figure N.1.

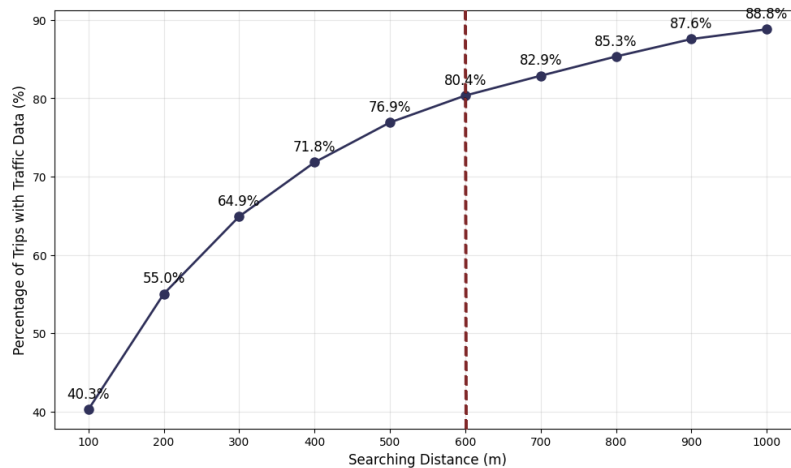


Figure N.1. Percentage of trips matched with valid traffic observation points under different search distances.

The results show that the percentage of trips with valid traffic data increases rapidly at first and then gradually levels off beyond 600 m. A threshold of 600 m was selected as it provides a reasonable balance between representativeness and data coverage, with 80.4% of trips successfully matched to traffic observation points. Trips without any observation points within 600 m were excluded from the analysis.

Appendix O

Public Charger Optimisation Results

Figure O.1 presents the optimisation results for the $W = 0.5$ scenario at selected added charger numbers ($p = 250, 750, 1250$). The results for the remaining weight settings ($W = 0.2$ and $W = 0.8$) across the full range of added chargers ($p = 100$ to 1500), are displayed in Figure O.2 and O.3.

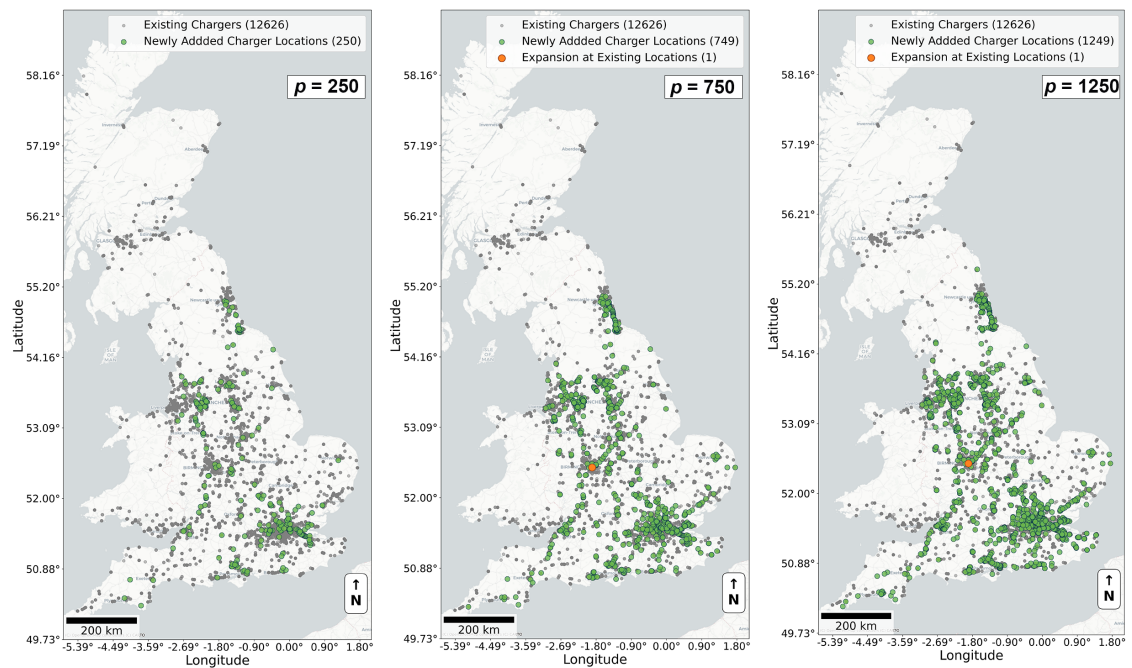


Figure O.1. Optimised public chargers (Weight = 0.5).

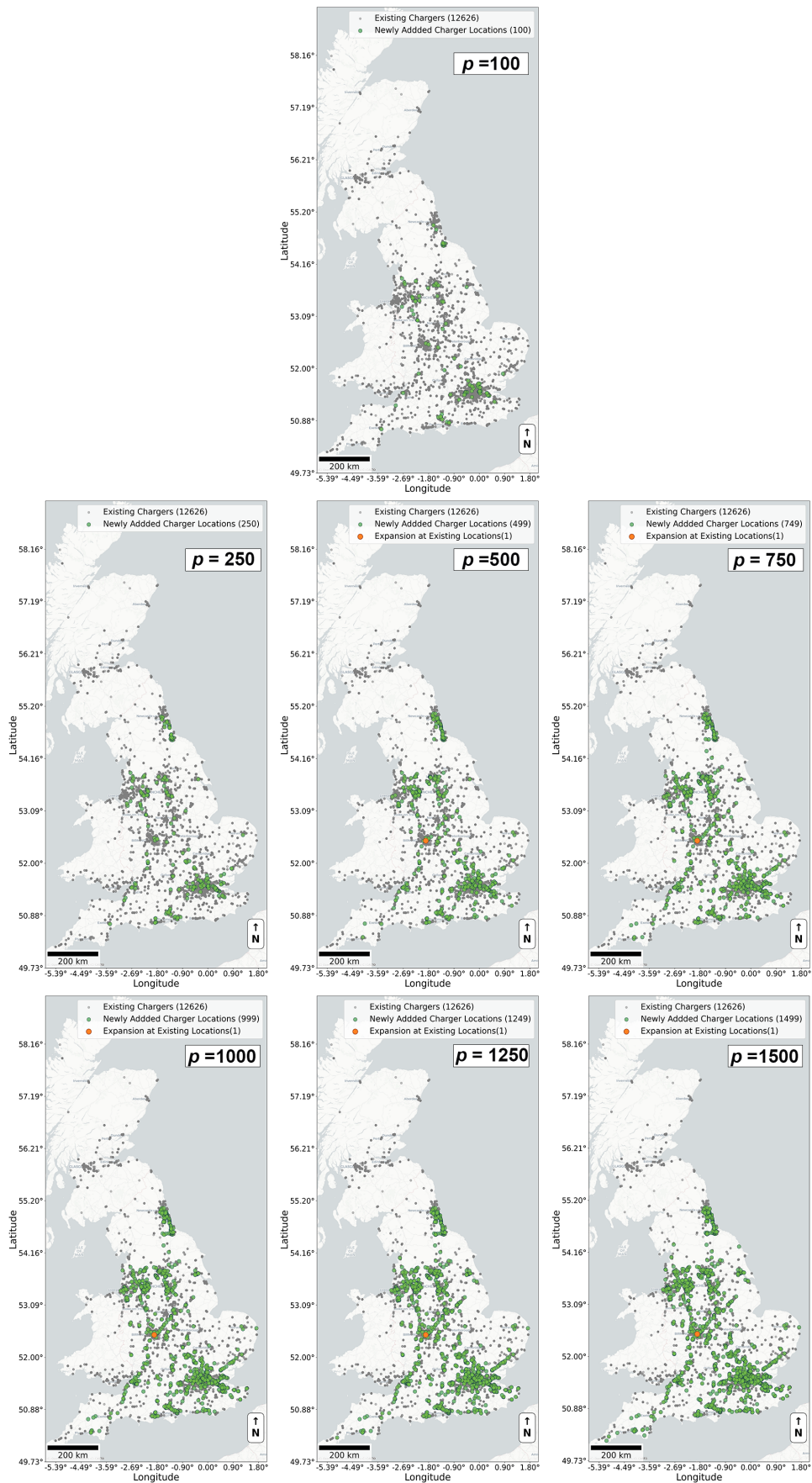


Figure O.2. Optimised public chargers (Weight = 0.2).

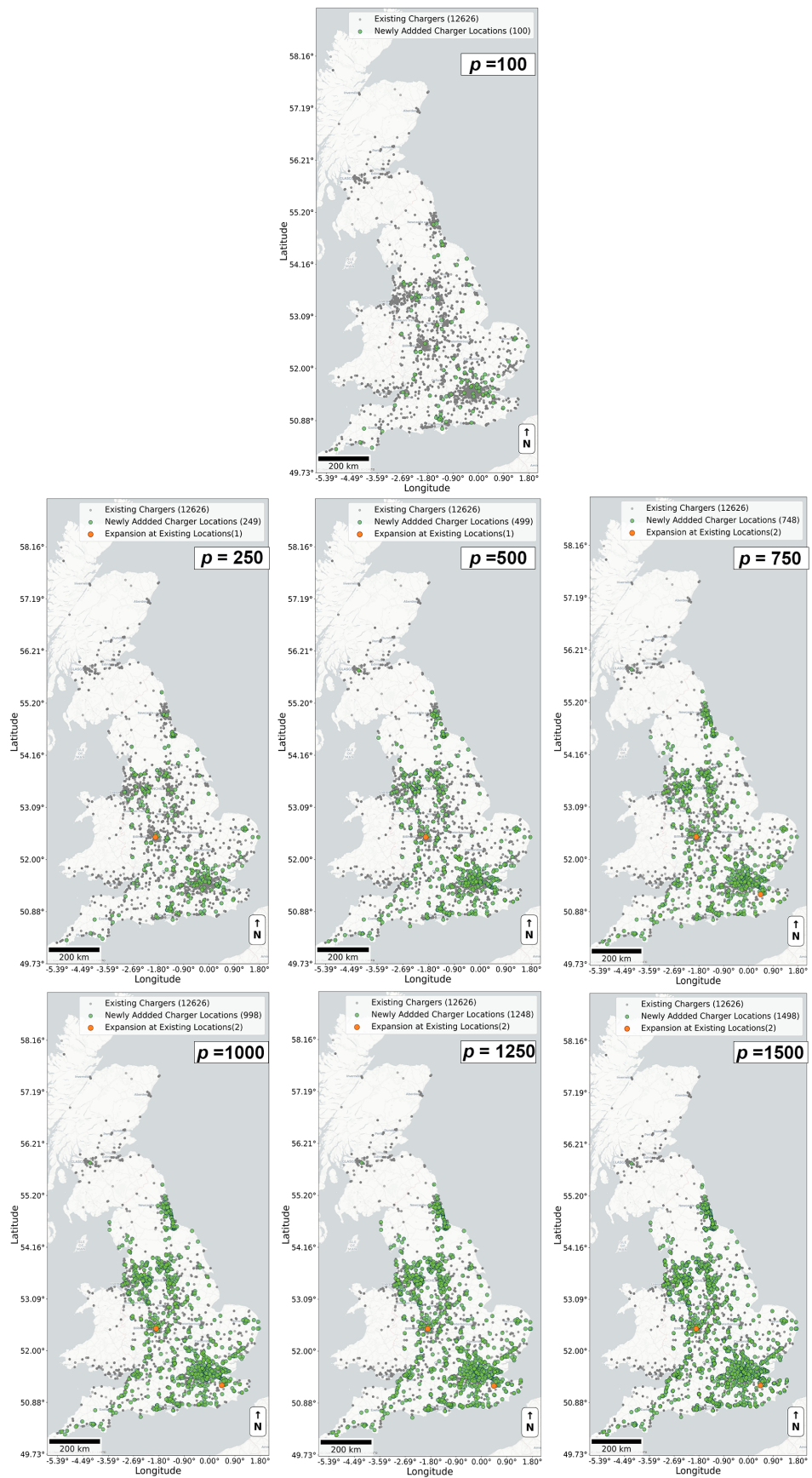


Figure O.3. Optimised public chargers (Weight = 0.8).