Emissions-Aware Charging Scheduling for Electric Buses: Regional Electricity Mix Impacts in Great Britain

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Abstract

This dissertation tests whether regional variation in electricity grid carbon intensity impacts the emissions performance of optimised charging for battery-electric buses in Great Britain. A rolling horizon linear programming model is used to optimise charging schedules based on half hourly carbon intensity forecasts for the 14 regions managed by the National Energy System Operator. A consistent bus service schedule is applied across regions to isolate electricity mix effects.

Three questions are examined: whether emissions aware optimisation reduces charging emissions relative to a static overnight baseline; whether gains vary by region; and whether they vary by season. The model is evaluated over a full operating year. Statistical tests compare total emissions and the temporal distribution of charging activity.

Emissions fall on average by 33.5%, with regional savings ranging from 19-59%. Optimisation prompts charging behaviour to shift away from the early morning overnight schedule to a bimodal pattern centred on midday and late evening. Regional behaviour differs, with lower carbon intensity regions exhibiting more distributed charging and higher carbon intensity regions concentrating activity into narrower midday windows.

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List of Abbreviations

ANOVA analysis of variance

API application programming interface

BEB battery-electric bus

BODS Bus Open Data Service

CI carbon intensity

CO_2 carbon dioxide

DBE diesel-bus equivalent

EV electric vehicle

EVSP electric vehicle scheduling problem

GB Great Britain

GTFS General Transit Feed Specification

km kilometre

kW kilowatt

kWh kilowatt-hour

LB Lothian Buses

LP linear programming

MDVSP multi-depot vehicle scheduling problem

MILP mixed-integer linear programming

NESO National Energy System Operator

SDVSP single-depot vehicle scheduling problem

SoC state of charge

UK United Kingdom of Great Britain and Northern Ireland

VSP vehicle scheduling problem

Chapter 1

Introduction

The central aim of this dissertation is to evaluate how regional variation in electricity-grid carbon intensity (CI) affects the emissions performance of optimised battery-electric bus (BEB) fleet charging. This responds to evidence that aligning charging with lower-CI periods materially reduces lifecycle impacts and that average measures can mislead when marginal effects drive outcomes (Bruce et al., 2024). The study operationalises this premise using forecast-aware scheduling in Great Britain.

The problem is framed as a linear programming (LP) model in which the objective function minimises total charging-related emissions over a 24-hour horizon, calculated as the sum of half-hourly charging energy multiplied by the forecast CI for each interval. The decision variables are the quantities of energy charged in each half-hour slot. The optimisation is subject to constraints on meeting the total daily energy requirement derived from a fixed service timetable, per-interval charging capacity determined by depot occupancy and charger power, and non-negativity of charging quantities.

A rolling-horizon structure is used, re-optimising each day with 24-hour regional CI forecasts from the National Energy System Operator (NESO). The model is applied separately to each of the fourteen NESO grid regions over a full operating year, using the same operational constraints and depot configuration. This isolates the influence of regional electricity mix on emissions outcomes while holding service schedules and infrastructure constant. A static overnight charging schedule provides the baseline for comparison.

This topic is of critical relevance to the decarbonisation of public transport systems. Domestic transport remains the UK's highest-emitting sector, responsible for 29% of greenhouse-gas emissions in 2023 (Department for Energy and Net Zero, 2025). Globally, road transport accounts for nearly 70% of sector emissions (Jaramillo et al., 2023). Despite decades of policy action, UK transport emissions have fallen by just 3% since 1990. With the Climate Change Act 2008 (2050 Target Amendment) Order 2019 establishing a legally binding net-zero target, substantial reductions from urban mobility are required.

BEBs are central to this transition, offering zero tailpipe emissions, reduced noise, and improved air quality. Major UK cities are advancing large-scale rollouts. Greater Manchester aims to become fully electric by 2030 with a £2.5 billion investment in the Bee Network (Transport for Greater Manchester, 2025). London now operates over 2,000 zero-emission buses, up from 30 in 2016 (Transport for London, 2025). Coventry is nearing complete fleet electrification (Coventry City Council, 2024). However, the net environmental benefit of BEBs depends on the CI of the electricity used for charging.

Britain's bus network covers over 2 billion vehicle-kilometres annually: 1.64 billion in England, 275 million in Scotland, and 84 million in Wales (StatsWales, 2024). With BEBs typically consuming 1.0–1.3 kWh/km (Blades et al., 2022,)full electrification would require 2.0–2.6 TWh of electricity per year. Aligning this demand with low-CI supply is essential for maximising emissions savings. However, depot charging often follows fixed overnight schedules, with optimisation efforts focusing mainly on cost reduction rather than emissions (Zheng et al., 2023). While smart charging for private EVs is widely studied, applications to public depot-based fleets remain limited.

The contribution of this dissertation is threefold. First, it applies a rolling-horizon LP framework that integrates regional carbon-intensity forecasts with operationally realistic depot constraints for a BEB fleet. Second, it conducts a comparative analysis across all fourteen NESO regions to evaluate how regional electricity mix shapes emissions outcomes. Third, it examines seasonal and spatial patterns to assess the consistency of emissions-aware scheduling benefits across GB's grid contexts.

The dissertation proceeds as follows. Chapter 2 reviews literature on electricity carbon intensity, vehicle scheduling, and emissions-aware optimisation, identifying a gap at the intersection of subnational forecasts, depot-constrained operations, and temporal charging behaviour. Chapter 3 outlines the research design, data sources, and analytical methods used to compare optimised charging with a static overnight baseline. Chapter 4 presents results for all GB grid regions, including emissions savings and temporal charging shifts. Chapter 5 discusses these findings in relation to existing theory and practice, and Chapter 6 concludes with contributions, limitations, and future research directions.

Chapter 2

Literature Review

This chapter establishes the conceptual and empirical foundations for emissions-aware scheduling of battery-electric bus charging. It sets out why the timing and location of charging influence realised emissions, delineates the operational constraints that bound feasible decisions, and evaluates optimisation approaches that can act on time-varying electricity signals. The chapter frames the central question for the review: how regional variation in Great Britain's electricity mix conditions the emissions performance of fleet charging.

Section 2.1 summarises temporal and regional variation in carbon intensity and clarifies the signals that a scheduler can use, with emphasis on subnational, half-hourly forecasts. Section 2.2 defines the operational problem by outlining the vehicle scheduling paradigm, different depot and fleet configurations, and the range and flexibility of objective functions these methods can approach to solve. Section 2.3 reviews charging and scheduling models that respond to time-varying inputs, comparing Linear Programming, Mixed-Integer Linear Programming, and heuristic approaches, and highlights rolling-horizon designs suited to forecast-driven control. Section 2.4 synthesises these strands to identify the research gap, then restates the objectives that lead into the methodology.

2.1 National and Regional Electricity Mixes

Carbon intensity expresses the emissions per unit of electricity. It changes by hour and by region as the generation mix and system conditions evolve. For battery-electric buses this means the environmental impact of charging depends on when and where electricity is taken rather than being a fixed attribute of the vehicle. Evidence for Great Britain shows that aligning charging with lower-CI periods can reduce lifecycle impacts, and that reliance on averages can mislead when marginal effects drive outcomes

(Bruce et al., 2024).

Within Great Britain the supply side creates pronounced short-term variation. System studies identify recurring low-CI periods when renewable output exceeds demand, and show that as low-carbon capacity expands these low-net-demand conditions deepen and occur more often (Staffell and Pfenninger, 2018). Wind output follows seasonal and intraday rhythms and can ramp quickly, so the same day can include both very clean and relatively dirty supply intervals (Sinden, 2007; Cannon et al., 2015). These patterns define a temporal opportunity set for depot charging.

Evidence from other settings reinforces why timing and place matter. Where the grid has low renewable penetration, EV charging can carry high indirect emissions even with smart timing, while systems with large intraday swings reward careful scheduling (Twum-Duah et al., 2024). Urban studies reach the same conclusion from a services perspective and argue that the electricity mix behind each kWh should inform operations (Zubelzu and Álvarez, 2016).

International and regional comparisons illustrate the size of these effects. Szurke et al. (2025) analyse real electric-bus charging from Győr against hourly national intensities for Hungary, Poland, Germany and Sweden and find large reductions when charging shifts into cleaner hours.

Osaki et al. (2025) compare Denmark and Japan and show that with depot-only charging an optimal schedule in Denmark emits 81% less in summer and 71% less in winter than the same schedule in Japan. Distributing chargers across terminals secures winter feasibility and trims a further 4% by widening timing options.

City-scale work for Aachen links quarter-hourly CO_2 intensity to bus life-cycle results and shows strong time-of-day and seasonal effects, with lower renewable shares at night limiting gains (Rupp et al., 2019). Stockholm studies optimise charger siting and technology and show that emissions fall with certified renewable electricity, while battery sizing and fuel choices also shift outcomes (Xylia et al., 2017; Xylia, 2019).

UK evidence points to large subnational differences. McGrath et al. (2022) simulate identical double-deck operations in Aberdeen, Belfast, London and Cardiff, combine them with hourly seasonal average CI, and report up to a five-fold gap in average charging emissions, with the widest difference between Aberdeen and Belfast. Building on these insights, this dissertation compares subnational electricity mixes within Great Britain in a common BEB scheduling model at half-hour resolution to show how within-country regional differences translate into operational emissions under depot constraints.

Average measures can hide important dynamics. Using average carbon intensity can misstate the emissions from an incremental unit of demand. Marginal emissions reflect the generator that responds to a small change in load.

Siler-Evans et al. (2012) estimate regional marginal emissions factors for the United States and show that average factors can misestimate avoided emissions, with large regional differences in benefits. For the same intervention, the Midwest avoids about 70% more CO_2 per MWh than the West, along with much larger SO_2 and NO_x reductions.

Zivin et al. (2014) report strong spatial and intraday variation in marginal CO_2. Marginal rates are more than three times higher in the upper Midwest than in the western United States, and within a region some hours have more than double the marginal rate of others. Applying these rates to plug-in vehicles, they find that night-time charging that is cheap on price can be dirtier on emissions, and that PEVs beat efficient hybrids in some regions but not others because the marginal mix dominates outcomes.

Tamayao et al. (2015) show that EV life-cycle results can shift by up to 50% when using marginal rather than average factors, and by up to 120% when changing regional boundaries. They argue that consumption-based marginal factors are the right choice for added load, and they find that delayed midnight charging raises emissions in coal-marginal systems while the relative ranking of BEVs and efficient hybrids depends on time and place.

Operational studies show how to act on these signals. Mehlig et al. (2022) estimate that a typical 2019 BEV emitted about 41 gCO_2/km on an average-mix basis in Britain, with marginal CO_2 about 25% higher. Simple smart timing cut average CO_2 by roughly 10% but could raise marginal emissions if it targeted the wrong hours, which supports following short-term signals rather than static off-peak rules.

Casals et al. (2016) show that whether EVs deliver a greenhouse benefit depends on the power mix and efficiency thresholds. Low-CI systems such as France and Norway yield immediate gains, while transitional systems such as Germany and the UK deliver weaker near-term reductions unless charging aligns with cleaner supply. Tu et al. (2020) minimise greenhouse gases with a marginal-emissions model for Ontario and find that the optimised schedule emits about half of a simple “after 3 am” rule and far less than a petrol baseline, while revealing trade-offs in infrastructure needs. In Britain, Dixon et al. (2020) use half-hourly intensity data to coordinate charging and report around 28–40 gCO_2/km versus 35–56 gCO_2/km under dumb charging, and show scope to absorb otherwise curtailed wind energy.

Recent UK applications use the same regional intensity signals in other domains and show they are practical for optimisation. Domestic EV charging scheduled with multi-session model predictive control across fourteen GB regions cuts emissions by 40–46% versus uncontrolled charging and by 19–26% versus single-session timing when charging follows low-CI windows (Wieberneit et al., 2025).

Building-scale simulations that integrate photovoltaic/thermal, heat pumps, EV charging and phase-change storage achieve higher daily coefficient of performance and lower CO_2 when operations track cleaner periods (Kutlu et al., 2025). City-scale modelling for Nottingham, guided by NESO Future Energy Scenarios for 2035 and 2050, tests EV and renewable integration and vehicle-to-grid under constrained renewables and finds that up to 97% of EVs remain uncharged or partly charged on low-renewable days in the most constrained case, while ambitious scenarios create overgeneration and management challenges (Dik et al., 2025).

Taken together, the literature shows that regional and intraday variation in carbon intensity is material for bus charging and that average-based rules can be misleading when marginal supply is fossil-dominated. What has not been tested is a within-country comparison of BEB depot operations across Great Britain's regions under a single operational design at half-hour resolution, with service patterns and depot configuration held constant so that differences reflect the electricity mix rather than changes in operations. This study fills that gap by embedding regional half-hourly forecasts in a forecast-aware charging model for a depot-based fleet and by evaluating outcomes across all fourteen regions. The next section sets the operational structures that bound feasible charging and situates the model within the vehicle scheduling problem paradigm, covering duty construction, layover windows, charger capacity and depot presence.

2.2 Operational Structure and Constraints

Battery-electric deployment sets hard limits on what schedules are feasible. Range, charging logistics, charger locations and capacity, depot presence, and state-of-charge tracking together shape vehicle allocation and route planning. Recent work integrates these elements into multi-layered optimisation frameworks that couple depot design, charging and battery constraints. Examples include (Alamatsaz et al., 2022)and (Perumal et al., 2022). A related strand incorporates carbon-aware objectives under realistic depot conditions (Behnia et al., 2024).

The remainder of this section introduces the Vehicle Scheduling Problem (VSP) and the Electric Vehicle Scheduling Problem (EVSP) as the organising framework for the optimisation model. It then states the operational constraints that matter in bus operations, including duty construction and layover windows, depot layout and presence, charger capacity and siting, energy balance and state of charge, and fleet homogeneity versus heterogeneity. It also reviews common objective functions, including cost, emissions, reliability and multi-objective formulations. These choices bound the temporal flexibility available for low-carbon charging and connect back to the timing opportunities outlined in Section 2.1.

2.2.1 The Vehicle Scheduling Problem

The Vehicle Scheduling Problem has roots in mid-twentieth-century linear programming, first formalised by Dantzig and Fulkerson (1954) for optimising United States Naval supply chains, and only later adapted to public-transport operations. In the base public-transport context the objective is to assign vehicles to timetabled trips while satisfying three conditions: each trip is serviced exactly once, each vehicle follows a feasible conflict-free sequence of trips, and overall operating cost is minimised (Bunte and Kliewer, 2009). Early extensions incorporated additional operational constraints such as fleet size, crew scheduling and depot capacity (Ball et al., 1983). Further work generalised these ideas and confirmed the adaptability of the VSP to diverse operational priorities (Carraresi and Gallo, 1984).

The transition to battery-electric buses reshapes this structure. The Electric Vehicle Scheduling Problem introduces energy-aware constraints such as range limits, recharge duration, charger availability and explicit state-of-charge management. Reuer et al. (2015) define the EVSP as a constrained optimisation problem that satisfies trip coverage and depot return while maintaining energy feasibility along each vehicle's schedule. Recent surveys describe its evolution into a multi-objective framework that can incorporate emissions reduction, power-system coordination and infrastructure planning alongside cost (Pasha et al., 2024). Most EVSP applications that target environmental performance still rely on static or national-average carbon intensity, with few integrating regional and time-varying forecasts that can be exploited through schedule design.

This study does not introduce a new VSP or EVSP formulation. It uses the VSP as a flexible, established paradigm to structure a depot-based charging problem. The contribution lies in embedding a forecast-driven emissions objective within standard depot constraints.

2.2.2 Depot and Fleet Configuration

Depot layout and fleet-assignment rules are major determinants of scheduling complexity. In the single-depot vehicle scheduling problem (SDVSP) all vehicles begin and end duties at the same depot, forming continuous sequences of trips under timing and coverage constraints. When fleets are homogeneous and depot exclusivity is enforced, SDVSP formulations can often be expressed as assignment or flow problems that are solvable in polynomial time using linear-programming methods (Freling et al., 2001). Classic work on network and assignment structures supports the same conclusion for related classes of problems (Lenstra and Kan, 1981). These characteristics make SDVSP models tractable and transparent, and they are easier to integrate with detailed operational constraints such as state-of-charge limits. Their strict depot-return requirement also constrains opportunities to shift charging geographically to locations with lower carbon intensity, which is a limitation rarely addressed in the literature.

The multi-depot vehicle scheduling problem (MDVSP) introduces spatial flexibility by allowing vehicles to operate from more than one depot within the planning horizon. This can reduce deadhead mileage and improve utilisation of dispersed charging infrastructure, but it couples depot operations in ways that increase computational difficulty. MDVSP is NP-hard, and tractable solutions often rely on decomposition or hybrid optimisation methods (Desaulniers et al., 2002). Subsequent approaches include matheuristics and advanced column-generation frameworks (Pepin et al., 2009). Practical implementations span genetic-algorithm and column-generation hybrids (Wang et al., 2021,)bi-objective mixed-integer linear programming (Wu et al., 2022,)and adaptive large-neighbourhood search (Wen et al., 2016). While multi-depot models could enable carbon-aware strategies such as daytime opportunity charging at whichever depot a bus is nearest, most published examples focus on cost minimisation and ignore grid-carbon variability.

Fleet composition adds further complexity. Many real-world systems operate heterogeneous fleets with differences in battery capacity, charging interface and energy efficiency that must be reflected in scheduling constraints. Representative treatments include Zhang A. et al. (2022) and Sung et al. (2022). The multi-vehicle-type electric-bus scheduling problem generalises the formulation to capture such heterogeneity and aligns vehicle–route assignments with type-specific energy demands, charger compatibility and range requirements (Zhang M. et al., 2023). Duda et al. (2022) extend this further to a multi-depot mixed-fleet context and incorporate both electric and diesel buses in a multi-objective MILP that balances technical, economic and environmental goals. These models improve realism, yet they rarely integrate type-specific modelling with carbon-intensity-aware objective functions. In most cases, heterogeneity is leveraged to improve utilisation or reduce cost rather than to maximise alignment between charging demand and low-carbon supply.

2.2.3 Objective Functions

Objective functions in electric-bus scheduling have evolved from a near-exclusive focus on cost minimisation toward more complex multi-objective formulations. Early models targeted operating-cost reduction through fleet-size minimisation, vehicle-kilometre reduction and efficient trip chaining (Jiang et al., 2022). As BEBs gained traction, additional cost drivers such as electricity pricing, battery degradation and charging logistics entered the optimisation space, prompting strategies such as time-of-use scheduling (Alvo et al., 2021)and partial-charging regimes (Sistig and Sauer, 2023).

In multi-depot contexts, secondary goals such as reducing deadhead mileage and idle time have been prominent, with inter-depot movements affecting both energy efficiency and charger utilisation (Lu et al., 2021; Olsen et al., 2022). Other work embeds infrastructure-sensitive variables directly into the objective function and co-optimises charger allocation, transformer capacity and local power flows alongside trip assignment (Liu and Ceder, 2020; Wu et al., 2022).

Environmental objectives have emerged more recently and remain relatively uncommon. Some studies incorporate carbon emissions into the objective function, either as a cost component or as a binding constraint (Duda et al., 2022; Zhou et al., 2020,)while others schedule charging to coincide with forecast low carbon-intensity periods (Tookanlou et al., 2021; Kapsali and Fidas, 2025). Even in these cases, CI inputs are often highly aggregated, frequently at national level rather than reflecting the finer-grained regional variation available in some electricity systems. Few models combine such forecasts with rolling-horizon decision-making, and most still treat CI as a fixed parameter rather than a time-dependent variable influencing operational choices in real time.

Overall, the VSP/EVSP paradigm and linear programming are highly flexible. The same structure can optimise cost, utilisation, infrastructure coordination, reliability or environmental outcomes, and it can combine these in multi-objective settings. In this work we use that flexibility to treat emissions as a primary objective alongside operational feasibility, and we show how multiple objectives are balanced in later sections. Environmental objectives remain less common than cost-focused ones, so the contribution here is to apply a forecast-driven, regionally resolved emissions objective within a depot-constrained rolling-horizon schedule, without claiming novelty in the VSP itself. The next section reviews optimisation approaches that support these objectives and introduces the formulation we adopt.

2.3 Charging Strategies and Scheduling Models

Electric-bus scheduling spans several layers of optimisation, including charging logistics, depot constraints and temporal planning. Recent reviews document wide methodological diversity, with linear-programming and heuristic approaches used for cost, grid integration, emissions and infrastructure planning (Salam et al., 2024; Pasha et al., 2024). These approaches differ in formulation and in assumptions about fleet composition, service frequency, depot access and the balance between runtime and solution quality (Salam et al., 2024; Pasha et al., 2024).

This section has two aims. Section 2.3.1 targets the research gap by testing how a fixed decision regime and planning horizon shape charging behaviour under different regional electricity mixes. Section 2.3.2 justifies linear programming over other optimisation techniques because it is transparent, auditable and able to handle diverse constraints flexibly. We do not propose a new VSP or EVSP; rather, the contribution is contextual: a standard LP with an emissions-focused objective, evaluated across distinct regional carbon-intensity scenarios with identical operational constraints.

2.3.1 Temporal Horizons in Modelling and Charging Behaviour

In optimisation, the planning horizon is the finite sequence of future periods over which forecasts and constraints are considered when making decisions. The literature distinguishes forecast, solution and rolling horizons to compare decision regimes (Chand et al., 2002).

We use three policy labels. *Static* means one open-loop plan over a fixed solution window. *Myopic* means a one-step look-ahead that optimises only the current period with a zero terminal value and ignores the cost-to-go Puterman (1994). Approximate dynamic programming generalises this idea and shows when myopic logic fails without a value function or surrogate look-ahead Powell (2011). *Rolling-horizon* means repeated finite-horizon re-optimisation with only the first control implemented before the window advances. This aligns with model predictive control in control engineering (Rawlings et al., 2017).

Classic results show that horizon length and terminal conditions can matter as much as forecast accuracy. Short windows risk end effects unless terminal costs or constraints are set, while longer windows improve look-ahead at higher computational cost (Baker, 1977; McClain and Thomas, 1977). A dynamic-programming view also explains why rolling procedures are sensible when distant forecasting is costly and information arrives over time (Sethi and Sorger, 1991).

For clarity in this review, the planning horizon is treated as a modelling input, whereas temporal charging behaviour is treated as an empirical output. Outputs are summarised along three axes: 24-hour charging profiles, day-type differences across weekday, Saturday and Sunday services, and seasonal variation.

Evidence on dynamic transport and energy planning informs the design choices adopted here. Dynamic vehicle routing formalises the cadence of re-optimisation under information arrival and indicates that higher dynamism warrants shorter windows with more frequent updates (Pillac et al., 2013). Rolling-horizon work in energy systems demonstrates gains over myopic or one-shot plans and sets out the tractability–fidelity trade-off created by time aggregation. Excessive aggregation can obscure intraday carbon-intensity structure that matters for charging (Cuisinier et al., 2022). Robust linear programming with uncertain right-hand sides explains horizon-edge pathologies and motivates terminal constraints or valid inequalities to prevent exporting infeasibility to subsequent windows (Bredström et al., 2013). Within electric-bus scheduling, single-depot formulations make explicit the coupling among duty construction, depot presence, charger capacity and state of charge, and they justify staged solution approaches at scale (Davatgari et al., 2024).

These points motivate the design used here: a finite rolling window with within-day granularity, explicit terminal conditions and a fixed decision regime under depot constraints. We then examine how this design conditions observed charging behaviour across regions, which is the research gap identified in the section preface.

Observed scheduling practice tends to prioritise overnight depot charging. Model-based studies show why that convention persists and how structured timing improves outcomes under price signals. A single-station mixed-integer model that co-optimises daytime and overnight charging under peak–valley tariffs and time-varying charger power achieves 7–8% cost savings relative to first-come, first-served, but does not target emissions explicitly (Zheng et al., 2023). At network scale, opportunity fast-charging can be represented in discrete time or as discrete events. A discrete-event formulation improves tractability and outperforms common-sense heuristics while also moderating grid impacts (Abdelwahed et al., 2020). Rolling-horizon formulations appear widely outside public transport in cluster-based EV aggregation and receding-horizon routing, where they stabilise loads, reduce queuing and raise charger utilisation. These results rely on strong observability assumptions and are not evaluated against regional carbon-intensity signals (Song et al., 2023; Xiang et al., 2022). Public-transport demonstrations exist but are local and cost-focused. A campus-bus charging-station model uses a rolling horizon with PV inputs and reports large cost reductions, yet it does not analyse temporal emissions profiles (Zaneti et al., 2022). Battery-swapping studies further illustrate the operational gains from rolling optimisation and learning-based demand prediction, again with objectives framed around profit and throughput rather than emissions (Shalaby et al., 2022). Day-to-day rolling models for bus operations show how to decompose long- and short-horizon decisions under real constraints, but they optimise risk and cost rather than carbon outcomes (He, 2024).

In this review, horizon choice is treated as a modelling input and charging behaviour as an empirical output. The literature provides tools that make repeated re-optimisation practical, but it seldom links planning horizon to observed temporal charging profiles under regionally varying electricity mixes. That linkage motivates the comparative, horizon-aware assessment that follows.

2.3.2 Schedule Optimisation Approaches

Heuristic scheduling denotes rule-based or constructive algorithms that produce good feasible solutions quickly but without optimality guarantees (Ruiz, 2015). In electric-vehicle scheduling problems, heuristics are often adopted to maintain tractability under battery and depot constraints with many variables. Examples include k-greedy coordination of charging and dispatch in partially electrified fleets, and two-stage schemes that first generate energy-feasible duty blocks and then assign depot-constrained charging (Paul and Yamada, 2014; Reuer et al., 2015). The attraction lies in speed and scalability. The limitation lies in the absence of optimality certificates and the difficulty of enforcing cross-temporal feasibility conditions consistently. In emissions-aware settings, one-step or locally improving rules may ignore short-lived low-carbon intervals that require coordinated adjustments across vehicles and time blocks, or may create later infeasibilities in state of charge and depot eligibility (Sassi and Oulamara, 2017; Wen et al., 2016). Heuristics therefore provide useful baselines and hybrid components, but their rule sets can be brittle when objectives rely on precise temporal alignment with external signals.

By contrast, linear programming and mixed-integer linear programming allow operational and environmental requirements to be expressed as hard constraints and audited against an explicit objective (Franco et al., 2015; Bauer et al., 2025). LP, as formalised by Dantzig (1963), optimises a linear objective subject to linear equalities and inequalities. MILP extends this framework by constraining some variables to integer values, which enables discrete decisions such as charger activation, slot selection or block assignment to be integrated with continuous energy and state-of-charge variables (Bertsimas and Tsitsiklis, 1997).

Within the electric-vehicle domain, LP and MILP have been used for charging logistics, depot siting and service coordination. Early grid-aware charging models coordinated flexible loads subject to network limits but did not include fixed public-transport timetables or depot eligibility (Sundström and Binding, 2011; Jin et al., 2013). Subsequent studies embedded MILP within hybrid frameworks to address charger access, duty segmentation and state-of-charge feasibility. Examples include adaptive large-neighbourhood search, column generation and metaheuristics combined with MILP components (Wen et al., 2016; van Kooten Niekerk et al., 2017; Rigas et al., 2018). For battery-electric buses, MILP formulations frequently emphasise infrastructure coordination, charger scheduling and grid-side constraints (Franco et al., 2015; Li et al., 2020; Zhou et al., 2020; Bodenschatz et al., 2020; Duan et al., 2023; Bauer et al., 2025). Carbon mitigation in these works is often indirect, for example by smoothing demand or lowering total energy use, rather than by explicitly minimising emissions.

Studies that introduce real-time or forecast-based signals show how linear models can respond to dynamic inputs. Examples include price-aligned charging and location planning under capacity limits (Taheri et al., 2013; Elkholy et al., 2024). Where forecast carbon intensity has been incorporated, the focus has tended to be private mobility rather than depot-constrained public transport, and subnational resolution has been limited (Dixon et al., 2020; Romano et al., 2025). More recent work addresses uncertainty through stochastic or game-theoretic extensions, trading off interpretability and tractability against richer behavioural realism (Wang et al., 2025; Ma et al., 2024). Taken together, the literature indicates that LP and MILP provide an interpretable and auditable means to encode intertemporal feasibility and to align charging with time-varying external signals under depot constraints, while highlighting that explicit emissions objectives and region-specific forecast use remain relatively scarce. Linear formulations therefore provide a clear route to encode intertemporal feasibility and to align charging with time-varying regional signals, which is central to the gap identified above.

2.4 Research Gap and Objectives

The environmental performance of battery-electric buses depends not only on electrification but on aligning charging with the electricity system in time and space. Regional and intraday variation in carbon intensity is well documented and implies that otherwise identical operations can have different emissions by place and hour (Xylia, 2017; McGrath et al., 2022). Comparative studies show that identical depot routines can yield different life-cycle outcomes when the generation mix changes across systems (Rupp et al., 2019; Osaki et al., 2025). Work on average versus marginal intensity further warns that static averages can mislead when marginal supply is fossil-dominated, which supports the use of forecasts as a decision signal (Xylia, 2019; Szurke et al., 2025).

Section 2.2 sets the operational constraints that depots must respect, including charger limits, depot availability and vehicle state of charge. The design of the planning horizon then shapes realised behaviour once these constraints bind. Rolling-horizon studies and dynamic fleet operations show that window length and terminal conditions affect feasibility and the temporal profile of actions (Rawlings et al., 2017; Pillac et al., 2013). Subsequent work highlights that update cadence interacts with forecast refresh to steer timing decisions (Cuisinier et al., 2022; Davatgari et al., 2024). Classic production-control results reach similar conclusions about policy sensitivity to horizon choice and boundary conditions (Baker, 1977; McClain and Thomas, 1977). Theory on hierarchical and switching control explains stability and performance under rolling updates, which motivates explicit state carry-over in our model (Sethi and Sorger, 1991; Chand et al., 2002).

Evidence from current practice and cost-focused models explains the dominance of overnight charging in bus depots and shows that structured timing under tariffs improves utilisation and queuing (Zheng et al., 2023; Abdelwahed et al., 2020). Recent demonstrations report benefits from time-structured policies in fleet contexts, although they remain cost-led rather than emissions-led (Song et al., 2023; Xiang et al., 2022). Public-transport optimisation typically targets feasibility and operating cost, with carbon handled only indirectly through load smoothing (Zaneti et al., 2022; Shalaby et al., 2022). Few studies link horizon design to observed charging profiles under regionally varying electricity mixes, which leaves open the question of how a fixed decision regime translates into temporal behaviour across different grids (He, 2024).

Against this backdrop, three related gaps remain. First, the literature rarely traces how a fixed scheduling regime and planning horizon shape the timing of charging once state-of-charge and depot constraints bind. Second, regional day-ahead carbon-intensity forecasts are seldom integrated into a single, auditable schedule that also enforces charger limits, depot availability and per-bus feasibility at subnational resolution. Third, within-country comparisons that hold service patterns, depot layout and charging configuration constant are limited, so it is difficult to isolate how regional electricity mixes condition both charging behaviour and emissions.

In response, this study asks how Great Britain's regional electricity mix affects the emissions performance of electric-bus fleet charging. To answer this question, the evaluation proceeds in three steps. First, it tests whether a forecast-driven schedule reduces daily charging emissions relative to a static overnight baseline within each NESO region, reported in Section 4.2. Next, it quantifies how the schedule restructures temporal charging behaviour across time of day, day type and season, analysed in Sections 4.3 and 4.4. Finally, it estimates the main and interaction effects of region and season on emissions savings, presented in Section 4.5. The Discussion interprets these results against the literature, and the Conclusion confirms the research aim and objectives and states the contribution.

Chapter 3

Methodology

This study investigates how regional differences in electricity grid carbon intensity influence the environmental performance of electric bus charging strategies. The central research question is:

How does Great Britain's regional electricity mix affect the emissions performance of electric bus fleet charging?

The question addresses whether emissions outcomes are primarily a function of charging strategy or are strongly conditioned by regional grid composition. In particular, it asks whether geographically differentiated carbon-intensity profiles constrain or enhance the effectiveness of emissions-aware scheduling policies.

To isolate grid-side effects, a fixed operational schedule is applied uniformly across all fourteen National Energy System Operator (NESO) electricity regions in Great Britain. Northern Ireland is not included in this analysis because its electricity network is operated separately by EirGrid, the transmission system operator for the all-island Irish grid, and therefore falls outside NESO's remit. Fleet size, service pattern, charging infrastructure and depot access windows are held constant so that observed differences in emissions arise from regional carbon intensity rather than operational variation. Analysis was conducted in Python within JupyterLab. Linear programmes were formulated and solved in `gurobipy` with the Gurobi Optimizer, and statistical tests were performed using SciPy and `statsmodels` (Kluyver et al., 2016; Gurobi Optimization, 2024).

The study is located within quantitative operations research and energy-systems analytics. A model-based, deductive approach was adopted to test whether rolling-horizon linear programming can translate day-ahead, region-specific carbon-intensity forecasts into lower charging emissions under fixed depot constraints. Linear programming was preferred over heuristic rules because it provides an auditable objective, hard feasibility guarantees under intertemporal constraints and transparent sensitivity to regional signals.

Mixed-integer features were not required because charger activation and assignments were aggregated at depot level. This perspective is consistent with the aim to explain observed emissions differences by exogenous grid variation rather than by endogenous operational redesign.

3.1 Operational Scenario

A sample bus service from Edinburgh operated by Lothian Buses (LB) is used to model emissions-aware depot charging. LB has begun electrifying operations via high-capacity charging at the Annandale Street depot, which supports the city's first fully electrified services, Routes 8 and 9, operated with Volvo BZL double-deckers (Lothian Buses, 2025). The scenario treats these routes as a single-depot, homogeneous-fleet corridor consistent with current practice: Annandale Street is the only LB depot with installed BEB charging (Lothian Buses, 2024,)and the Volvo BZL is used exclusively on Routes 8 and 9.

Although public reports indicate up to fifty BEBs on the corridor, a twenty-five-vehicle fleet is modelled to maintain realistic depot congestion and increase optimisation challenge (see Section 3.2.2 for the depot-presence rationale). Wider LB services include mixed fleets and multiple depots; reconstructing those duties would require vehicle allocation and fuel tracking data that are not publicly available, and would introduce additional modelling assumptions with limited relevance to the research question. Focusing on the 8/9 corridor therefore provides a bounded, policy-aligned testbed with stable service patterns and exclusive charging infrastructure. As highlighted in the literature, relaxing homogeneity typically requires charger-compatibility matrices, battery-specific state-of-charge behaviour and route-differentiated energy profiles (Zhang et al., 2023; Mahyari et al., 2023); retaining homogeneity preserves tractability and alignment with operator practice on these services.

By fixing the vehicle schedule and infrastructure context and applying the same scenario across all NESO regions, the influence of regional carbon intensity on emissions-aware scheduling can be attributed without confounding from operational differences. The problem is scoped as a depot-level charging schedule rather than a full EVSP with trip-to-vehicle assignment. This follows the review's argument that depot availability, charger power and state-of-charge feasibility are the binding constraints for emissions-aware timing. Trip coverage and block sequencing are held fixed to isolate grid-side effects.

Vehicle parameters reflect the Volvo BZL double-decker used on Routes 8 and 9 (Volvo, 2023)and are used to parameterise state-of-charge calculations and depot charging limits: battery capacity 470 kWh, motor power 200 kW, estimated range about 300 km, consumption 1.5 kWh/km and maximum depot charging rate 150 kW.

3.2 Data Collection and Pre-processing

The sampling frame spans 1 March 2024 to 28 February 2025 and is applied uniformly across all National Energy System Operator (NESO) regions under a fixed operational scenario. Inclusion required complete day-ahead regional forecasts aligned to the service calendar. Five dates lacked complete regional coverage and were excluded from analysis: 11 June 2024, 12 June 2024, 31 December 2024, 12 January 2025 and 13 January 2025. No human participants were involved and a response rate is not applicable because the unit of analysis is the region–day. The realised dataset therefore comprises 360 calendar days and 5,040 region-days. The analysis covers all fourteen NESO regions over the study year. Days with incomplete forecasts are excluded with counts reported. The study uses secondary, non-identifiable data and complies with School guidance on ethics for secondary analysis.

3.2.1 Carbon-intensity Forecasts

Carbon-intensity data were obtained from the NESO application programming interface, which provides half-hourly forecasts for fourteen electricity regions in Great Britain; Northern Ireland lies outside NESO's remit. For the study window from spring 2024 to winter 2025, daily 24-hour day-ahead forecasts were collected and then quality-screened, yielding 360 days per region and 17,280 half-hourly intervals for each region. Each forecast provides numerical intensity values in gCO_2/kWh and categorical labels used later for the clean-charging proportion ("very low," "low," "moderate," "high," "very high").

NESO also publishes 48-hour forecasts. Within the study window these were identical to the 24-hour series. Equality was verified programmatically at the interval level across all regions by comparing the 24-hour vectors with the first 24 hours of the corresponding 48-hour vectors retrieved at the same publication timestamp. No discrepancies were detected. The analysis therefore relies on 24-hour forecasts, which most closely represent the emissions signal available at the point of day-ahead planning.

At subnational scale NESO publishes forecasts only. Real-time and historical actuals are provided at national level but not by region, so regional back-testing is not currently possible. NESO flags the regional-forecast service as beta and documents that only forecast values are released at this spatial resolution. Accordingly, the 24-hour regional forecasts serve both as model inputs and as the basis for evaluating emissions performance across NESO-defined regions.

3.2.2 Bus Timetables and Depot Presence

Timetable data for Routes 8 and 9 were manually transcribed from the operator's published PDF schedules to reflect the services advertised to passengers (Lothian Buses, 2025a; Lothian Buses, 2025b). This was necessary because the Bus Open Data Service GTFS feed under-reported peak-period services on these routes, omitting scheduled trips and understating duty intensity (Department for Transport, 2025). Evidence and the checking method are in Appendix C, with a compact visual in Section 4.1. To avoid bias toward an easier problem, the manual timetables were used for duty timing and depot-presence analysis, and GTFS was retained only for route structure and stop metadata.

Three master schedules (weekday, Saturday and Sunday) were compiled, yielding 512 trips with terminal departure and arrival times. Trips were timestamped on a fixed anchor date in 24-hour time. After-midnight services were recorded beyond 24:00 and normalised by adding one day to arrival. Two anomalies were corrected. Durations were validated to 5–90 minutes. Partial journeys were retained but excluded from duration statistics.

Depot presence was derived in two steps. First, for each day type, departure and return were mapped to 30-minute bins using a simple rule: a vehicle leaves in the bin before its first scheduled trip and returns in the bin after its final trip. The in-service count per bin was subtracted from the modelled fleet to obtain depot occupancy, yielding one presence vector per day type that was face-checked against departure frequencies. Second, these vectors were applied to the simulation calendar by classifying each date as weekday, Saturday or Sunday. The five dates with incomplete regional carbon-intensity forecasts were excluded. The result is a timestamp-aligned presence matrix that gives the number of vehicles at the depot in each 30-minute interval.

The modelled fleet size was set to twenty-five vehicles. Preliminary runs with fifty, which matches the reported corridor allocation, left daytime charging largely unconstrained and did not reflect the operator's emphasis on overnight charging. A twenty-five-vehicle fleet preserved timetable coverage while introducing realistic daytime contention for chargers. Per-vehicle daily charging targets are derived from distances and consumption in Section 3.2.3.

3.2.3 Trip Distances and Energy demand

Trip distances were derived from scheduled activity using a simplified speed–duration model anchored to observed route geometry. End-to-end inter-stop distances for Routes 8 and 9 were taken from an openly available community dataset derived from the Transport for Edinburgh Open Data API; route lengths were computed by summing consecutive inter-stop distances and were treated as fixed over the study window (Lellep, 2025a; Lellep, 2025b; Transport for Edinburgh, 2024). Scheduled runtimes were combined with these lengths to infer average speeds by route–direction pair. Per-trip distances were then estimated by multiplying each trip's duration by the relevant route–direction average speed.

Distances were converted to energy using a base consumption rate of 1.5 kWh/km consistent with the Volvo BZL specification. Seasonal variation was introduced using simulated data for UK cities (McGrath et al., 2022). Seasonal midpoints were scaled so that the annual mean matched 1.5 kWh/km. The scaled rates range from 1.414 kWh/km in summer to 1.617 kWh/km in winter.

Energy demand is calculated at the day level. For each service day, trip-level energy is summed and divided evenly across the twenty-five-bus fleet to yield a per-vehicle daily charging target. This preserves differences in demand between weekdays, Saturdays and Sundays and avoids duty-level assumptions that could not be reliably reconstructed from available data.

Battery and charging limits follow the vehicle specifications in Section 3.1. Each vehicle begins the day fully charged (470 kWh). Energy is depleted as trips are served and replenished via depot charging capped at 150 kW, which equates to 75 kWh per 30-minute interval. Charging is subject to depot presence and battery-capacity constraints. Feasibility is enforced by a state-of-charge check at the start of each scheduled trip. Infeasible trips are flagged and excluded from emissions calculations, with counts reported separately.

3.3 Model Design

An emissions-aware scheduling model was developed as a linear programme embedded in a day-ahead rolling-horizon simulation. The model reflects how a depot would plan charging using the 24-hour regional carbon-intensity forecasts available at scheduling time. Inputs are the depot-presence matrix (Section 3.2.2), the per-vehicle daily energy targets (Section 3.2.3), and the regional forecast series. Decisions are the charging energies per half-hour interval at the depot. The objective is to minimise forecast-weighted charging emissions over a 24-hour window, subject to per-interval depot capacity implied by vehicle presence and the per-bus charging cap. Only the current day's decisions are implemented, and battery states are simulated and passed forward to initialise the next day.

A fixed overnight charging strategy provides the baseline. All feasible charging is scheduled between 00:00 and 04:00, subject to the same depot-presence and per-bus power limits as the optimisation. If the window cannot deliver the day's full requirement, baseline charging is proportionally scaled to maintain feasibility. Performance is compared on total daily charging emissions in gCO_2.

3.3.1 Rolling-horizon Model

The linear programme is solved once per simulation day for each NESO region using only that day's regional forecast. It produces a 48-slot plan, and only the current day is executed. Resulting state-of-charge trajectories are simulated and carried forward as initial conditions for the next day, which enforces a one-day execution window and prevents any foresight beyond the 24-hour horizon. Forecasts are treated as accurate within their published window so the evaluation isolates scheduling effects rather than forecast error. Feasibility is verified by checking state of charge at each trip start; any infeasible trip is counted for reporting and excluded from emissions tallies.

End-of-horizon effects are mitigated by passing the end-of-day state of charge to the next day and by reporting any infeasibilities. In sensitivity analysis a minimum end-of-day buffer is required and headline effects are confirmed to persist.

3.3.2 Linear Programming Formulation

Let $t \in \{1, \ldots, 48\}$ index half-hour intervals. Let C_t be the energy charged at the depot in interval t (kWh), G_t the forecast carbon intensity (gCO_2/kWh), and n_t the number of buses present at the depot in interval t. With a per-bus charging cap of 150 kW and a 30-minute slot, the per-bus energy limit is 75 kWh. The depot capacity in interval t is

$$D_t = 75\, n_t \quad \text{(kWh).} \tag{3.1}$$

Let R denote the daily fleet energy requirement (kWh) from Section 3.2.3. The optimisation is

$$\begin{aligned}
\min_{\{C_t\}} \quad & \sum_{t=1}^{48} G_t\, C_t && (3.2)\\
\text{s.t.} \quad & \sum_{t=1}^{48} C_t = R, && (3.3)\\
& 0 \le C_t \le D_t \quad \text{for } t = 1, \ldots, 48. && (3.4)
\end{aligned}$$

The decision variable is aggregated depot energy C_t. To align with the review's emphasis on intertemporal feasibility, per-bus state of charge is simulated during execution and infeasible trips are flagged. This aggregation avoids duty-level reconstruction while still enforcing feasibility at the point of use. A robustness check adds a simple cumulative inventory cap that prevents the programme from scheduling more energy by time t than can be absorbed by buses present up to t; results are stable under this refinement.

The programme is solved independently for each simulation day and region. Only the current day's $\{C_t\}$ are implemented and state of charge is updated by simulation for the next day, realising the rolling-horizon structure in Section 3.3.1.

3.4 Evaluation and Analysis Plan

The evaluation operationalises the review by testing a regional, forecast-driven schedule under depot constraints, describing the temporal charging behaviour produced by a fixed rolling-horizon design, and assessing how optimisation effectiveness varies by region and by season. The comparison is between a baseline and a forecast-aware schedule. The baseline reflects current practice in which depot charging is concentrated between 00:00 and 04:00 irrespective of carbon intensity. Identical depot presence and per-bus caps are used in both arms so the comparison isolates timing. The linear programme reallocates the same daily energy across half-hour intervals to minimise forecast-weighted emissions subject to state of charge, charger capacity, depot availability and duty feasibility. Service patterns, depot configuration, fleet and the rolling-horizon decision regime are held constant across regions and seasons.

The primary outcome is total daily charging emissions in grams of CO_2, computed as the half-hour sum of scheduled energy multiplied by the corresponding regional day-ahead carbon-intensity forecast. Secondary outcomes characterise behaviour: the share of daily energy charged between 00:00 and 04:00, and slot-level time-of-day profiles by day type (weekday, Saturday and Sunday) and by season. Feasibility indicators, including end-of-day state of charge, charger contention and unmet energy, are reported for context.

For Objective (i), paired daily emissions are compared within each region using a one-tailed paired t-test (Field, 2024). If normality is rejected by the Shapiro–Wilk test, a Wilcoxon signed-rank test is used (Shapiro and Wilk, 1965; Wilcoxon, 1945). Results report the mean paired difference, a 95% confidence interval, a p-value and an effect size for paired data. Where many regional tests are run, a false-discovery adjustment is reported as a sensitivity.

For Objective (ii), the 00:00–04:00 energy share is compared within region using the same paired procedures (Field, 2024; Shapiro and Wilk, 1965; Wilcoxon, 1945). Slot-level profiles are presented descriptively to show how the rolling-horizon schedule reallocates charging across the day by day type and by season. This treats the planning horizon as a modelling input and the temporal profile as an empirical output.

For Objective (iii), percentage emissions savings are analysed using a two-way analysis of variance with region and season as categorical factors. Seasons are winter (December–February), spring (March–May), summer (June–August) and autumn (September–November). Main and interaction effects are interpreted following established guidance, with model assumptions checked and reported (Montgomery, 2017).

Schedule feasibility is summarised by region and by season. If any days are infeasible under state-of-charge or depot constraints, a sensitivity assigns baseline-level emissions to those days so that exclusions do not inflate estimated benefits. Additional sensitivities include shifting the baseline window, tightening end-of-window state-of-charge requirements and modest perturbation of forecast intensity to assess stability. This evaluation keeps the decision regime and horizon fixed and reads temporal behaviour as an outcome. It therefore provides a clean test of emissions gains from a forecast-driven schedule, how that schedule restructures charging across the day and the week, and how effectiveness depends on regional electricity mix and season.

3.5 Limitations and Boundaries

Several methodological and data-related limitations constrain the generalisability of the results beyond fixed-schedule, depot-based operations.

The analysis relies on manually transcribed timetables from operator PDFs rather than an official GTFS feed because the Bus Open Data Service GTFS under-reported peak trips on the study routes. The simulation is therefore limited to three representative day types (weekday, Saturday and Sunday). Bank holidays and seasonal timetable shifts are not modelled. This isolates grid-side effects but reduces operational realism across the year.

Detailed operational datasets such as duty blocks, vehicle identifiers and crew rosters were unavailable. Depot presence was inferred by subtracting in-service vehicles from the modelled fleet and assuming departure in the 30-minute bin before the first trip and return in the bin after the last. This abstraction avoids unavailable geospatial data but may over-simplify intra-day availability and does not capture layover-based top-ups.

Trip distances were estimated from scheduled durations combined with inter-stop route lengths derived from Transport for Edinburgh data (via a community dataset). The BODS GTFS feed lacked segment geometries and the Transport for Edinburgh API was closed to new users during the study window. Energy was computed using a base 1.5 kWh/km rate, with seasonal multipliers to reflect UK variation reported by McGrath et al. (2022). The model does not capture regenerative braking, HVAC, idling, gradient or passenger-load effects, which introduces noise in trip-level energy estimates.

The simulation models a 25-bus electric fleet. Although public reports suggest around fifty vehicles operate the corridor, preliminary tests with fifty left daytime charging largely unconstrained, so a 25-bus fleet was adopted to keep depot capacity binding while preserving timetable coverage.

Carbon-intensity inputs are NESO 24-hour regional forecasts, treated as accurate within the published horizon to isolate scheduling effects. The 48-hour regional series were verified to duplicate the first 24 hours of the 24-hour series over the study window (see Appendix B). Regional actuals are not published, so forecast accuracy cannot be back-tested at subnational scale.

The simulation spans 360 days (1 March 2024 to 28 February 2025), omitting five dates with missing regional forecasts (11–12 June 2024, 31 December 2024, 12–13 January 2025). Seasons are classified meteorologically. The service pattern is held constant across the year, while energy consumption varies seasonally via the multipliers noted above.

In this study the optimisation objective excludes monetary costs and targets emissions reduction under depot feasibility. Energy prices, demand-related network charges and staffing requirements are not modelled. The schedules therefore demonstrate technical feasibility and environmental benefit rather than financial viability. These boundaries are revisited in Chapters 5 and 6.

Finally, the linear programme is aggregate at the depot level. Individual bus state-of-charge trajectories are not optimised. A simplified feasibility check is applied at each trip start and infeasible trips are excluded from emissions tallies and reported separately. Workforce constraints such as driver breaks, shifts and staffing are not modelled. These would be required for operational deployment and are left to future work.

The next chapter reports the realised sample and data characteristics, documents validity checks and execution issues, and presents the comparative emissions results by region, time of day, day type and season under the pre-specified analysis plan.

Chapter 4

Findings and Analysis

This chapter reports the empirical results and addresses the three evaluation objectives set in Section 2.4. It applies the fixed operational scenario and rolling-horizon linear program from Chapter 3 to all fourteen NESO regions across the 360-day study window. Section 4.1 summarises data sources and preparation, including regional carbon-intensity profiles, timetable construction, depot presence, and energy totals. Section 4.2 quantifies emissions reductions relative to the overnight baseline and reports region-specific savings with confidence intervals and significance tests. Section 4.3 examines how the optimiser restructures charging across the day, and Section 4.4 compares temporal profiles across regions grouped by overnight low-carbon availability. Section 4.5 tests main and interaction effects of region and season on percentage savings via a two-way ANOVA.

Unless stated otherwise, emissions are computed as half-hourly scheduled energy multiplied by the corresponding regional day-ahead carbon-intensity forecast, with totals expressed in grams of CO_2. Paired comparisons are within region and use one-tailed tests as pre-specified. The chapter concludes by linking the patterns observed here to the mechanism discussed in Chapter 5.

4.1 Data Sources and Preparation

Emissions-aware charging was evaluated over 360 days (1 March 2024 to 24 February 2025) for a fixed fleet of twenty-five battery-electric buses operating two urban routes. Two schedules were assessed: a static overnight baseline that charges exclusively between 00:00 and 04:00, and a linear-programming schedule that responds to day-ahead carbon-intensity forecasts.

The analysis draws on three aligned inputs. First, half-hourly regional carbon-intensity forecasts from the National Energy System Operator were available for all fourteen regions on 360 of 365 calendar days, with five dates excluded due to missing forecasts. All timestamps are in local clock time with daylight-saving transitions handled. Second, fixed weekday, Saturday and Sunday service templates for Routes 8 and 9 were transcribed from operator timetables (source PDFs in Appendices A1–A2). Third, a calendar-aligned depot-presence matrix was derived by combining the service templates with in-service vehicle counts to indicate how many vehicles were available to charge in each 30-minute interval across the year. Detailed construction procedures are reported in Chapter 3; the present section summarises the resulting data characteristics used for analysis.

Daily fleet energy demand, derived from the compiled service, varied by day type and season, with lower totals on summer Sundays and higher totals on winter weekdays. These totals were translated into per-vehicle daily charging targets for use in the comparative schedule evaluation. Data checks included validation of timetable timestamps and durations, cross-checks of depot-presence vectors against departure frequencies, and verification that forecast coverage matched the simulation calendar.

4.1.1 Regional Carbon-intensity Profiles

Carbon-intensity forecasts from the National Energy System Operator provide half-hourly estimates of electricity-related emissions for all fourteen grid regions in Great Britain. Over the 360-day window this yields 17,280 records per region (360×48). Each record includes a timestamp, a continuous carbon-intensity value (gCO_2/kWh), an NESO categorical label ("very low" to "very high"), a region identifier and name, calendar date, derived day type (weekday, Saturday and Sunday), and a derived meteorological-season indicator. The continuous values are used for optimisation and evaluation; NESO labels are retained for descriptive summaries.

To aid interpretation, the figures are arranged in two panels (Figures 4.1 and 4.2) based on overnight low-carbon availability. For each region we compute the share of half-hours between 00:00 and 04:00 labelled "very low" or "low" across the study period, then group regions accordingly. The cleaner panel comprises North East England, North West England, South Scotland, North Wales, Merseyside and Cheshire, North Scotland, West Midlands and East England. The companion panel contains London, South East England, South Yorkshire, East Midlands, South England, South Wales and South West England. An all-regions Total panel is included for context only and is not part of the split.

Figure 4.1 represents the cleaner grid regions. North East England is the clearest case: from 00:00 to 03:30 every slot consists entirely of "very low" or "low" labels (for example, 00:00 records 347 "very low" and 13 "low"). There are no "very high" observations at any time of day, and "high" appears only as isolated single-day counts. South Scotland shows similarly clean nights with no "very high" in any slot and "high" limited to at

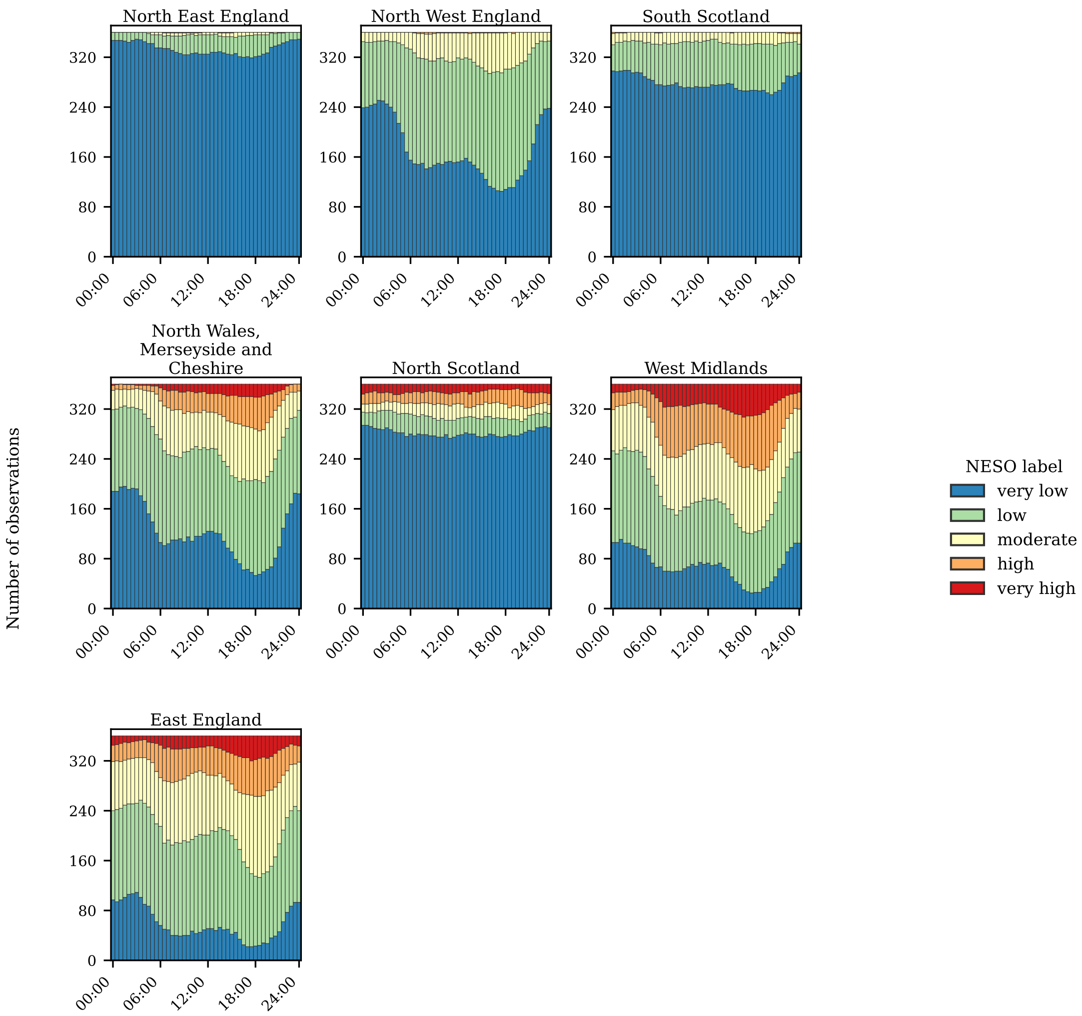

Figure 4.1: Low-Carbon Regions

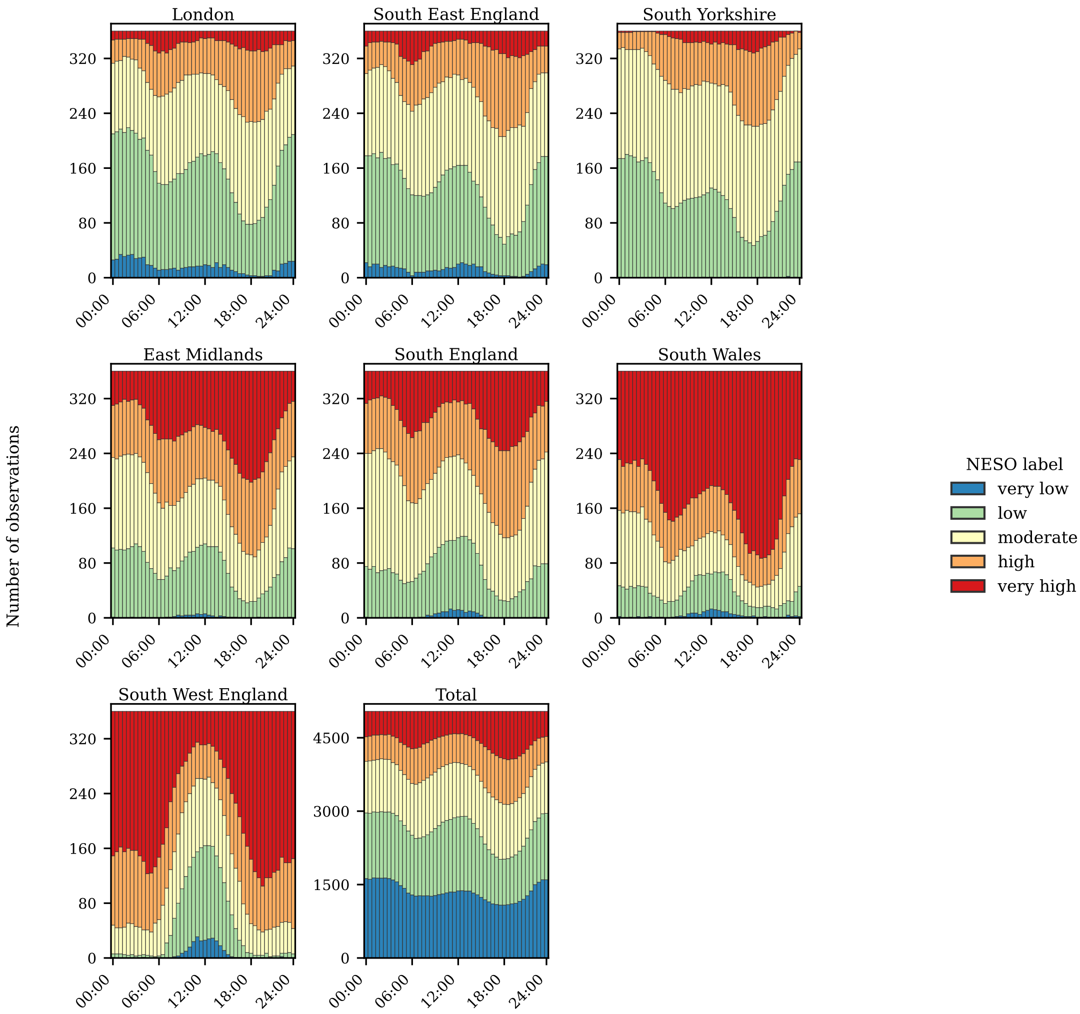

Figure 4.2: Carbon-Intensive Regions

most one or two late-evening days. At 00:00 the very-low+low total is 340 of 360. North West England also records no “very high” across the day and keeps “high” to single-digit counts. North Scotland retains a broad low-intensity overnight window but occasionally registers “high” and “very high” on a minority of nights. East England and West Midlands are low overnight then trend higher through the late afternoon and evening. East England reaches roughly forty “very high” around 17:30–18:00, and West Midlands reaches about 49–53 “very high” between 16:30 and 19:00. North Wales, Merseyside and Cheshire is clean overnight but intensifies through the late afternoon and early evening. For example, 17:30 shows 85 “high” and 20 “very high”.

Figure 4.2 presents the more carbon-intense regions. South West England is the most carbon-intense profile: “very high” exceeds 200 even before dawn (for example, 237 at 04:30) and climbs to 243–255 during the evening peak. South Wales is consistently carbon-intense from morning to night, with “very high” above 200 from around 06:00 and peaking near 18:30 at 273. East Midlands and South England show strong evening

Table 4.1: Trip dataset fields for Lothian Buses Routes 8 and 9 used to build the weekday, Saturday and Sunday service templates.

Feature	**Description**
day_type	Service day classification (Weekday, Saturday, Sunday).
direction	Direction of travel (Inbound or Outbound).
route_id	Route number (8 or 9).
start_stop	Scheduled departure stop name.
end_stop	Scheduled arrival stop name.
departure_time	Scheduled departure time in 24-hour local clock.
arrival_time	Scheduled arrival time; may exceed 24:00 for post-midnight trips.
partial_journey	Boolean flag for incomplete or truncated journeys.

intensification, with East Midlands reaching about 156–162 "very high" at 17:00–18:00 and South England around 110–116 at 18:00–18:30. London and South East England are less extreme but still exhibit pronounced high-intensity pockets, including early-morning and evening "very high" counts (London roughly 25–32; South East up to about 49 at 06:00 and around 39 in the early evening). The Total panel synthesises the national diurnal pattern: "very low/low" dominates overnight, while "high" and "very high" build through the day and crest around 18:30, where "very high" reaches roughly 989 before easing back overnight.

These regional label profiles establish the empirical context for the schedule comparison that follows. Regions such as North East England and South Scotland offer deep overnight low-intensity windows, whereas South West England and South Wales present extended high-intensity periods, including overnight, so potential LP gains depend on aligning charging with the former and selecting against the latter.

4.1.2 Bus Timetable and Depot Presence

Trip data were manually transcribed from PDF timetables published by Lothian Buses for Routes 8 and 9. For each direction (inbound and outbound), service schedules were collected separately for weekdays, Saturdays and Sundays, yielding six structured CSV files. This secondary data collection was necessary because the Bus Open Data Service (BODS) GTFS feed under-reports peak services. The curated dataset comprises 512 scheduled trips. Variable definitions are given in Table 4.1.

To support time-based modelling, `departure_time` and `arrival_time` were converted to timestamps using a fixed anchor date (2099-01-01). This removes ambiguity for post-midnight services and enables a consistent `duration_min` in minutes. Most durations fall within an expected range (interquartile range 46–59 minutes), though several valid

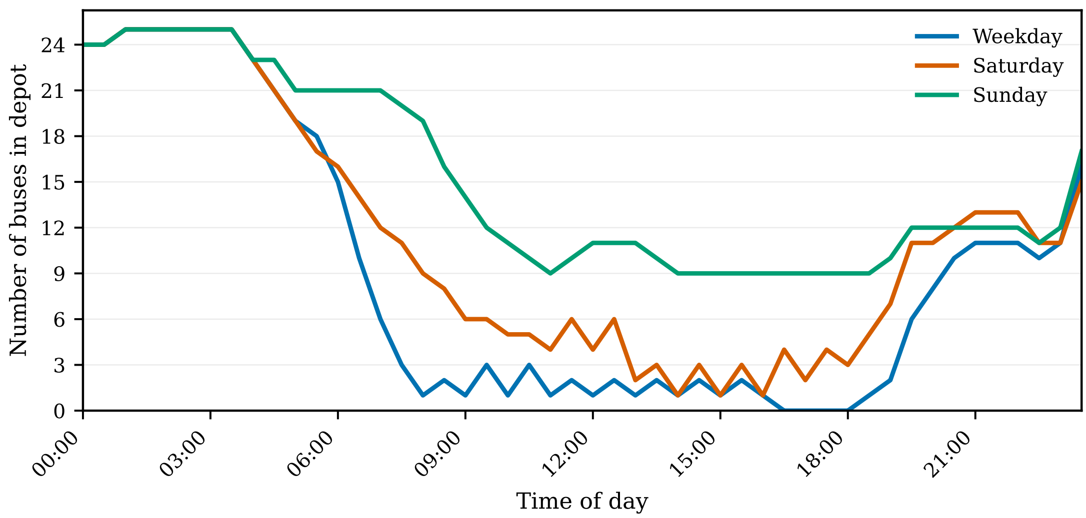

Figure 4.3: Depot Presence

long trips, including some exceeding 90 minutes, were retained.

The six files were combined into a single dataset, from which three master schedule templates were built based on weekday, Saturday and Sunday service levels and were applied across the 360-day simulation calendar. Each date was assigned a day type and populated with its corresponding template, preserving realistic variation in frequency and span across the week.

Depot presence was inferred from these canonical schedules and is depicted in Figure 4.3. For each day type, vehicles were assumed to leave the depot in the interval immediately before their first scheduled trip and to return in the interval immediately after their final arrival. The number of active vehicles was counted in each 30–minute interval and subtracted from the fixed fleet size of twenty-five buses to yield a time-resolved depot-presence vector.

These vectors show consistent intraday structure with pronounced overnight availability. On weekdays, depot presence holds at 24–25 buses from 01:00 through 03:30 (for example, 01:00–03:30 equals 25), tapers after 04:00 and reaches a daytime minimum of zero between 16:30 and 18:30 before rising again into the evening (for example, 23:30 equals 16). Saturdays follow the same pattern but retain at least one bus on site at all times. The minimum is one bus in the mid-afternoon around 14:00–16:00, with overnight levels again at 24–25. Sundays maintain higher daytime availability than the other day types. Depot presence never falls below nine buses from late morning through early evening, with 24–25 overnight and a late-evening rise to 17 at 23:30. In all three templates, availability peaks between 00:00 and 04:00 when most or all of the fleet is idle, drops after morning dispatch, stays low through the core service day and increases as vehicles return.

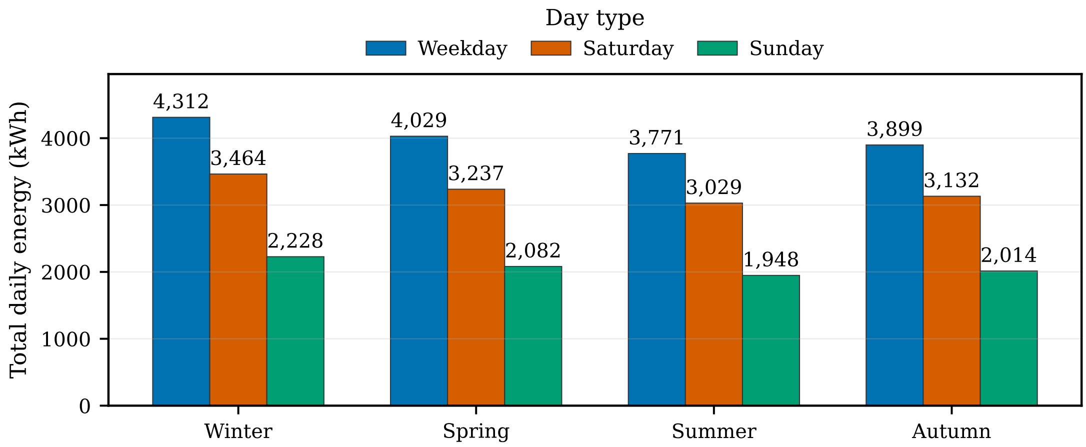

Figure 4.4: Daily Energy Demand by Day Type and Season

The three day-type vectors were extrapolated across the simulation calendar to create a full-year depot-presence matrix. This matrix served as a structural constraint in the optimisation model and dictates when charging could feasibly occur on the basis of physical bus availability.

4.1.3 Energy Cost

Trip-level energy demand was estimated from scheduled durations using route-specific average speeds: 14.10 km/h for Route 8 and 12.06 km/h for Route 9. Distances implied by these speeds were multiplied by a base traction rate of 1.50 kWh/km, then adjusted by seasonal multipliers from McGrath et al. (2022), giving effective rates from 1.414 kWh/km in summer to 1.617 kWh/km in winter.

Daily fleet totals were then aggregated by day type and season and are presented in Figure 4.4. Two patterns dominate. Energy demand is highest on weekdays, lower on Saturdays and lowest on Sundays. It peaks in winter and is smallest in summer. Across the year this spans roughly 1.95 MWh on summer Sundays to 4.31 MWh on winter weekdays, equivalent to about 78–172 kWh per bus.

These totals were divided evenly across the twenty-five-bus fleet to set per-vehicle state-of-charge targets for both the baseline and LP schedules. Charging was constrained by 150 kW per vehicle (75 kWh per 30 minutes) and a 470 kWh battery. The baseline fixes charging to 00:00–04:00 regardless of grid intensity, whereas the LP schedule allocates charging dynamically across the day, selecting cleaner intervals subject to depot presence and power limits. All days were feasible under these constraints, so the full set of 5,040 region–days (14×360) was retained for emissions analysis.

4.2 Emissions Reductions

This subsection addresses Objective (i). The baseline assumes all vehicles charge between 00:00 and 04:00 regardless of carbon intensity. The LP model schedules charging to minimise emissions subject to depot presence and daily energy targets. Paired daily emissions (gCO_2) were computed for the baseline and LP schedules in each NESO region. Normality of paired differences was tested with Shapiro–Wilk. All regions were non-normal ($p < 0.05$), so one-tailed Wilcoxon signed-rank tests were applied with the alternative baseline > LP. Effect sizes (rank-biserial r) and 95% confidence intervals for percentage saving were reported. p-values are one-tailed. In line with the pre-specified test, the null hypothesis of no median reduction (median baseline–LP ≤ 0) is rejected in every region (all $p < 0.001$).

Table 4.2: Emissions reduction by region (LP vs baseline). Alternative hypothesis: baseline > LP. p-values are one-tailed. Effect size: rank-biserial r for Wilcoxon.

Region	**Emissions saving (%)**	**95% CI (%)**	**p (one-tailed)**	**Test**	$n_{\mathbf{used}}$	**Effect size**
East England	37.11	[33.33, 40.87]	< 0.001	Wilcoxon	342	1.0
East Midlands	25.21	[22.82, 27.64]	< 0.001	Wilcoxon	345	1.0
London	26.35	[23.59, 28.96]	< 0.001	Wilcoxon	348	1.0
North East England	28.28	[25.24, 31.65]	< 0.001	Wilcoxon	335	1.0
North Scotland	58.65	[49.41, 68.51]	< 0.001	Wilcoxon	132	1.0
North Wales, Merseyside and Cheshire	38.93	[35.27, 42.84]	< 0.001	Wilcoxon	342	1.0
North West England	37.30	[33.63, 40.97]	< 0.001	Wilcoxon	338	1.0
South East England	27.17	[24.74, 29.75]	< 0.001	Wilcoxon	349	1.0
South England	23.11	[20.95, 25.13]	< 0.001	Wilcoxon	348	1.0
South Scotland	49.21	[44.47, 53.83]	< 0.001	Wilcoxon	300	1.0
South Wales	26.74	[24.18, 29.50]	< 0.001	Wilcoxon	346	1.0
South West England	38.50	[36.14, 40.87]	< 0.001	Wilcoxon	356	1.0
South Yorkshire	19.08	[17.12, 21.13]	< 0.001	Wilcoxon	340	1.0
West Midlands	33.59	[29.56, 37.51]	< 0.001	Wilcoxon	330	1.0
Total (mean)	**33.52**					

Table 4.2 reports mean emissions saving by region with 95% confidence intervals, test and significance. Across Great Britain the LP model reduced emissions by 33.52% on average. Every region shows a statistically significant improvement at $p < 0.001$. Savings range

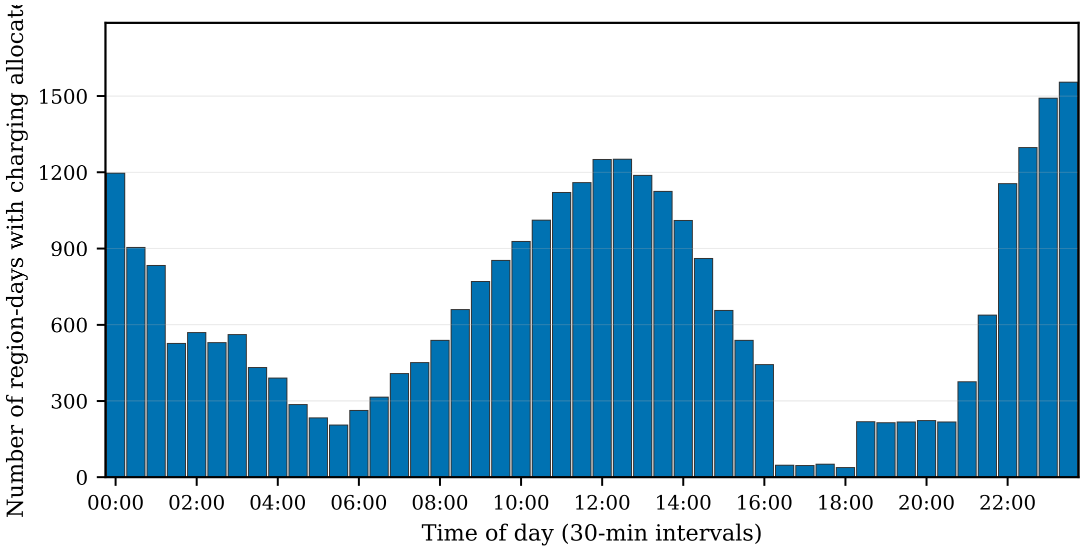

Figure 4.5: Charging Activity by Time of Day

from 19.08% in South Yorkshire to 58.65% in North Scotland, which is consistent with regional variation in grid carbon intensity. Seven of the fourteen regions exceed the GB mean of 33.52%: East England, North West England, North Wales, Merseyside and Cheshire, South West England, South Scotland, North Scotland and West Midlands. The East Midlands, London, North East England, South East England, South England and South Wales fall below the mean but remain materially positive. The interquartile range across regions is 26.74% to 38.93%, which indicates consistent but context-sensitive performance. Rank-biserial r rounds to 1.000 in all regions because, among the paired non-zero days used by Wilcoxon, the observed differences overwhelmingly favour the LP schedule. Lower n_{used} values in some areas, for example $n_{\text{used}} = 132$ in North Scotland, reflect many exact ties rather than weaker effects. Rare instances where LP emissions exceeded baseline were confined to a handful of days (0.28–0.83% of the year depending on region) and were observed only in East Midlands, London, North East England, North Wales, Merseyside and Cheshire, South East England and South Yorkshire.

4.3 Time-of-day Charging Behaviour

This subsection addresses Objective (ii) by showing how the LP schedule restructures charging away from the 00:00–04:00 window. Figure 4.5 presents the aggregate charging frequency across a 24-hour period across all days and regions, and Figure 4.6 displays the same information controlling for the service level for each day type.

Across all regions and days, charging is reallocated out of the small hours. Activity starts high at 00:00 (1,197 events) but falls to a minimum at 05:30 (205). A broad midday peak

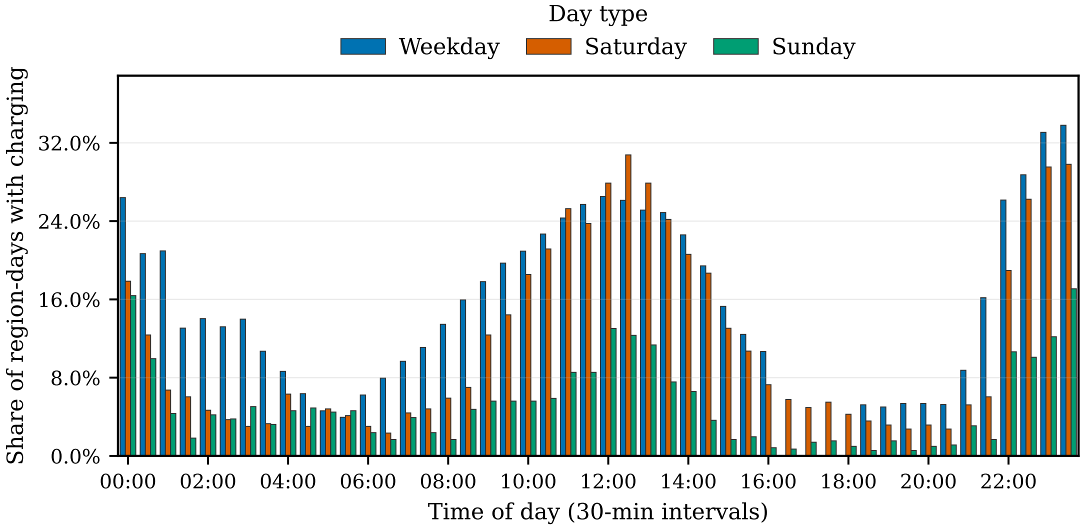

Figure 4.6: Charging Profiles by Day Type

follows, exceeding 900 events per slot from 10:00 to 14:00 and peaking at 12:30 (1,252), before dipping in late afternoon and rising to the daily maximum at 23:30 (1,555). The 00:00–04:00 window now accounts for 17.3% of LP events, down from 100% under the baseline.

The day-type profiles reinforce this pattern. Weekdays are clearly bimodal, with a sustained midday plateau from 10:30 to 13:30 (peak 0.265 region–days per interval at 12:00) and a higher late-evening maximum at 23:30 (0.338). Saturdays follow the same structure with a stronger midday emphasis (peak 0.308 at 12:30) and a near-matching late-evening rise (0.298 at 23:30). Sundays are flatter overall, consistent with lower demand, but still show a modest midday bump (0.130 at 12:00) and a smaller evening rise (0.171 at 23:30). Together, these profiles show systematic time-of-day restructuring: the optimiser concentrates charging into cleaner midday and late-evening intervals while substantially de-emphasising 00:00–04:00, consistent with day-ahead carbon signals and the depot and power constraints in Section 4.1.

4.4 Regional Charging Patterns

This subsection extends Objective (ii) by comparing day-type patterns and regional heterogeneity in temporal profiles. Regions are grouped by overnight low-carbon availability into the same low-carbon and carbon-intense panels defined in Section 4.1.1. Panels show, for each region, the share of region–days with any charging in each 30-minute slot, disaggregated by day type. Percentages are small by construction. A value of 0.03 corresponds to roughly three per cent of days.

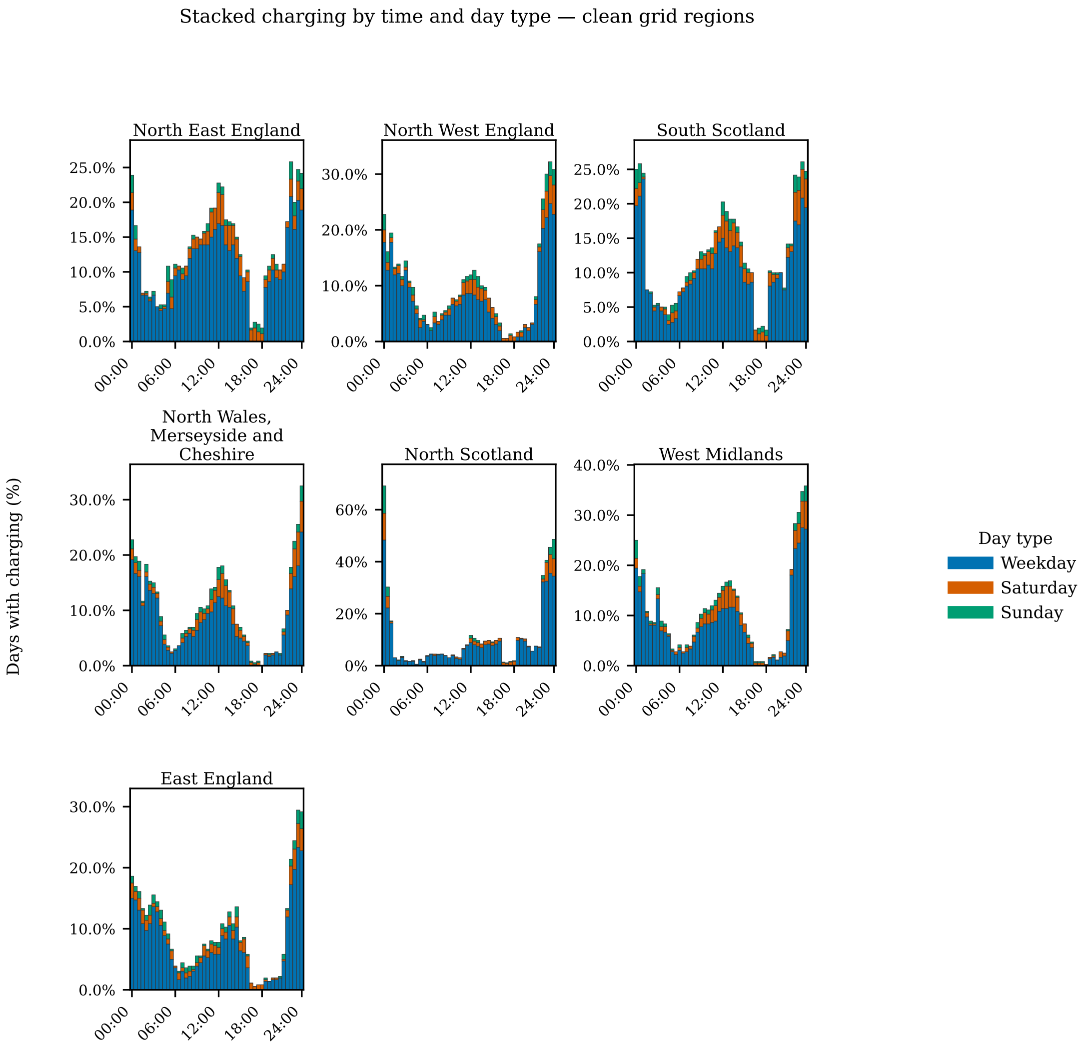

Figure 4.7: Charging by Time and Day Type — Low-Carbon Regions

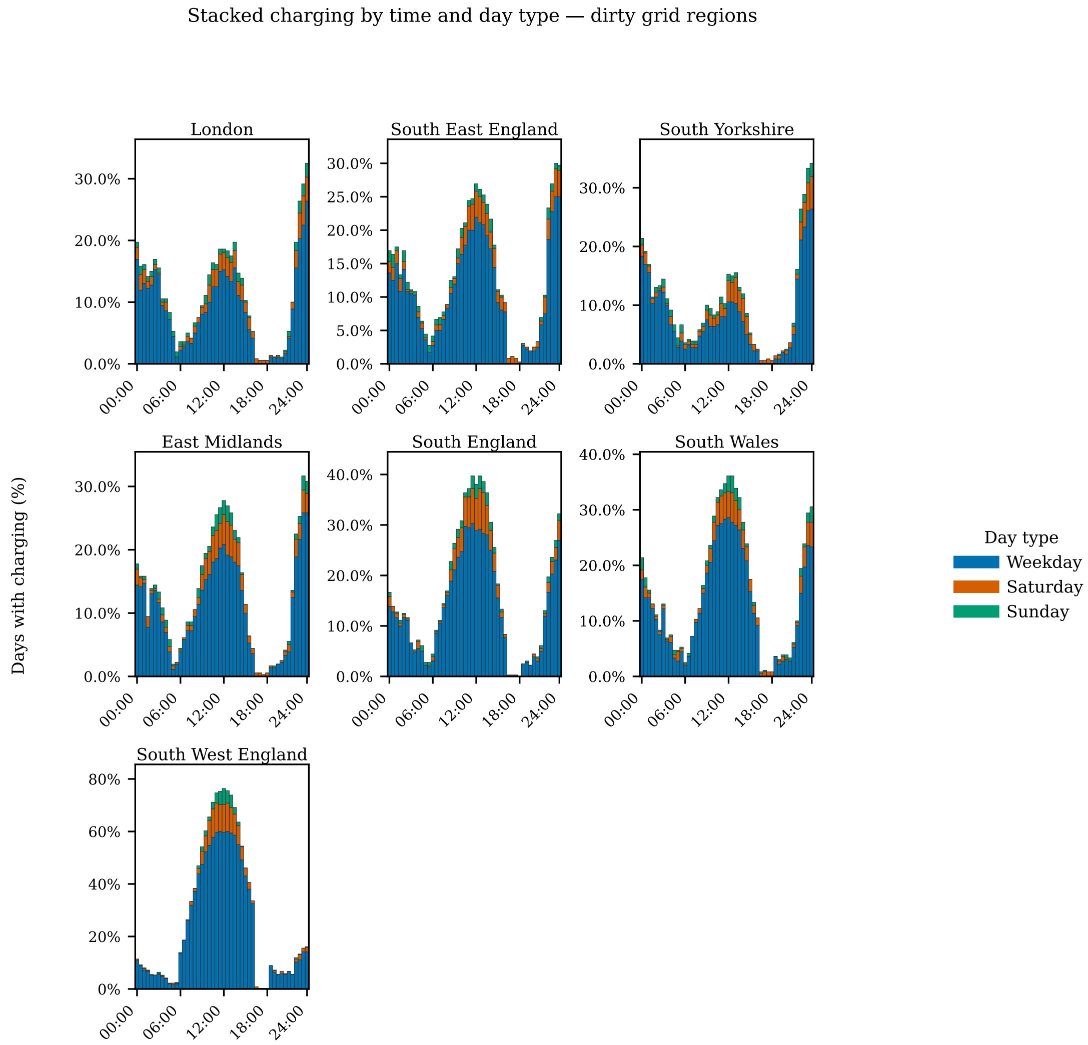

Figure 4.8: Charging by Time and Day Type — Carbon-Intensive Regions

Across the cleaner regions in Figure 4.7, late-evening charging is consistently preferred over the small hours. North East England, North West England and East England all peak around 22:30–23:30, with muted use before 04:00 and only modest midday activity. South Scotland shows the same evening emphasis. North Wales, Merseyside and Cheshire pushes the late-night top-up slightly higher, peaking near 0.027–0.028 by 23:30. North Scotland is the main outlier. Weekday activity spikes at midnight at roughly 0.048, then drops back and rises again late evening. Sundays also show a noticeable late-evening lift. West Midlands follows the general pattern of subdued morning, moderate midday and a clear late-evening top-up. Sunday profiles are flatter across the clean panel, which reflects lower demand, with most charging concentrated late evening.

In higher-carbon regions shown in Figure 4.8, charging clusters into narrow midday windows, with late-evening use present but less dominant. South West England is the clearest case. Weekday charging concentrates between about 10:30 and 13:00, peaking near 0.06, with much weaker late-evening presence near 0.014. South England also emphasises midday, especially on Saturdays with peaks around 0.04, while evenings rise only modestly. South Wales shows a broad weekday midday band from roughly 10:30 to 13:30 at around 0.027–0.029 and a smaller late-evening shoulder. East Midlands balances both windows, with midday near 0.023–0.026 and late evening up to about 0.026. South East England exhibits a pronounced midday arc on weekdays and Saturdays with a modest lift around 22:30. London is less extreme than South West England or South Wales, maintaining moderate midday activity and a clearer late-evening preference that tops out near 23:30. South Yorkshire presents narrow Saturday midday humps and a small late-evening peak with minimal early-morning use.

Leaner regions support more dispersed charging with a pronounced late-evening focus and only selective use of 00:00–04:00. Dirtier regions compress charging into short midday troughs in grid intensity, especially on weekdays, and use late-evening slots more cautiously. Sundays remain light everywhere. When charging occurs it tends to coalesce late evening in cleaner regions and in brief midday bursts in higher-carbon regions. These spatial patterns mirror the carbon-intensity structure in Section 4.1.1 and help explain the regional variation in emissions savings reported in Section 4.2.

4.5 Seasonal Variation

This subsection addresses Objective (iii) by testing main effects of region and season, and their interaction, on *Emissions saving (%)*—the percentage reduction in gCO_2 versus the baseline.

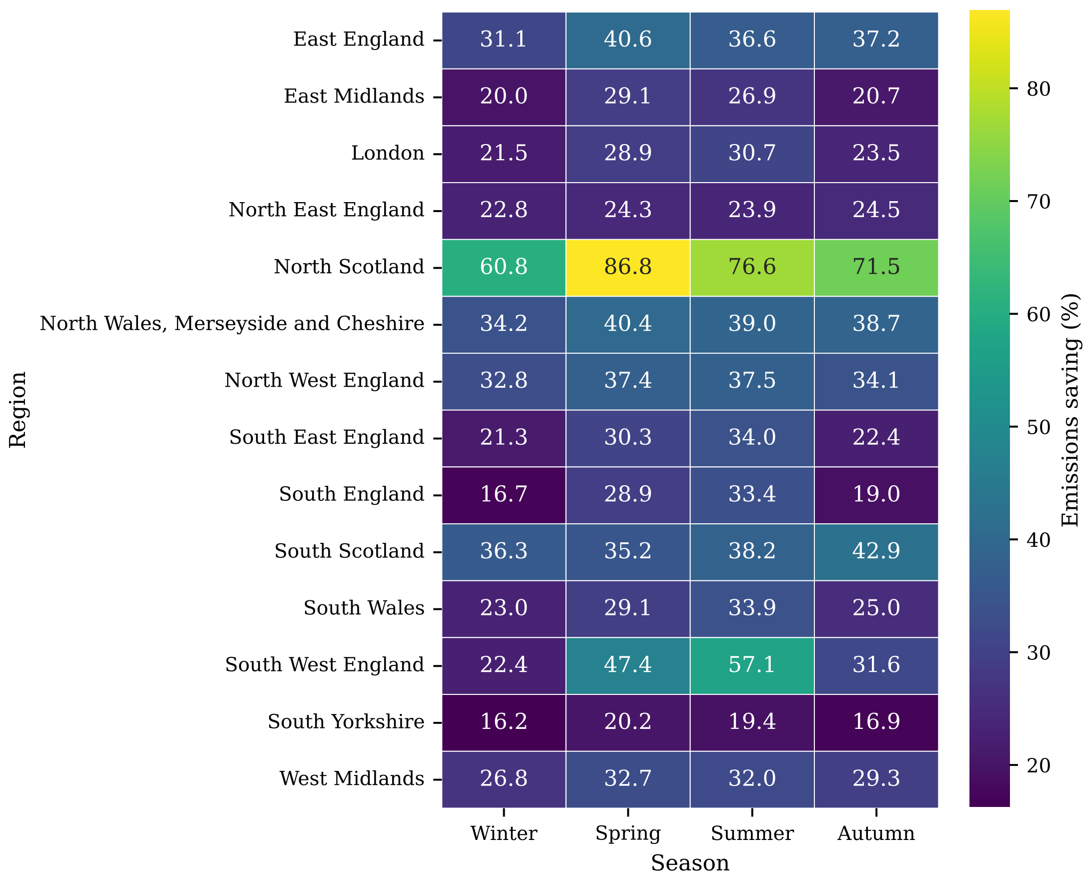

Figure 4.9: Emissions Savings Heatmap

Table 4.3: Two-way ANOVA on percentage emissions saving (LP vs baseline).

Term	**Sum Sq**	**df**	**F**	***p*-value**	η^2	**partial** η^2	**Sig.**
Region	449,879	13	63.63	< 0.001	0.14	0.15	***
Season	66,419	3	40.71	< 0.001	0.02	0.03	***
Region × Season	68,004	39	3.21	< 0.001	0.02	0.03	***
Residual	2,589,796	4762			0.82		

All three terms are highly significant. Region explains the largest share of variance ($\eta^2 = 0.14$), which indicates that geography is the dominant driver of differences in average savings. Season and the Region×Season interaction have smaller effect sizes ($\eta^2 = 0.02$ each) but remain statistically meaningful. Seasonal shifts in grid mix modify outcomes and these shifts vary by location. In practical terms, the benefit of emissions-aware optimisation depends both on where buses charge and when during the year that charging takes place.

The heatmap in Figure 4.9 reveals the underlying spatial–seasonal structure. North Scotland consistently leads (about 61–87%), peaking in spring and summer. Regions with strong midday clean-energy windows show pronounced summer lifts. South West England climbs from about 22% in winter to about 57% in summer, while South Scotland strengthens into autumn at about 43%. East England peaks in spring at about 41%, and North Wales, Merseyside and Cheshire holds a steady 34–40%. At the lower end, South Yorkshire remains modest at about 16–20%. South England and East Midlands improve in warmer months but remain below about 33% overall. London and South East England post moderate summer gains but weaker winters. North East England is unusually stable, with about 23–25% savings year-round.

Taken together, the ANOVA and heatmap confirm that emissions-aware scheduling outcomes are jointly shaped by geography and season. Regional differences dominate, but seasonal clean-energy availability can amplify or limit reductions. The significant Region×Season term underscores that aligning charging behaviour with both local grid conditions and seasonal generation patterns yields the greatest benefits.

Chapter 5

Discussion

This study asked how regional variation in electricity-grid carbon intensity shapes the emissions performance of an optimisation-based charging schedule for battery-electric buses. The objectives were to test whether optimisation reduces charging emissions relative to a static overnight baseline, to explain the temporal behaviour produced by a rolling optimisation model, and to assess how regional and seasonal differences influence outcomes. Across Great Britain the model cut emissions by about one third on average, with savings from roughly one fifth to well over one half by region, and significance achieved in every case. The optimiser rescheduled charging away from the small hours into two reliable windows and did so while protecting departures through late-evening top-ups. The early-morning share fell to about one sixth across weekday, Saturday and Sunday profiles from a baseline that was fully overnight. These outcomes confirm the premise in Chapter 2 that intraday and regional variation is operationally exploitable, and they implement the temporal-horizon logic set out in Section 2.3.1. A short rolling horizon with state carry-over turns half-hourly forecasts into actionable windows while respecting depot presence and state-of-charge limits (Rawlings, Mayne and Diehl, 2017). Classic results on policy sensitivity to horizon and boundary conditions reinforce this mechanism and explain why the behaviour is stable under our design (Baker, 1977; McClain and Thomas, 1977; Sethi and Sorger, 1991).

The results sit alongside a public-transport charging literature that has prioritised operating cost and feasibility, which tends to reproduce overnight concentration under flat or off-peak tariffs. Depot and corridor studies in this line minimise energy cost or charger investment while holding service constraints, and they confirm that structured timing improves utilisation even when the objective is not environmental (Zheng et al., 2023; Abdelwahed et al., 2020). Recent fleet demonstrations maintain this cost-led emphasis and show tangible benefits from tariff-driven schedules rather than carbon-aware ones (Song et al., 2023; Xiang et al., 2022). Bus optimisation papers that smooth load or enforce feasibility often treat emissions only indirectly through the chosen tariff or through peak-shaving rules (Zaneti et al., 2022; Shalaby et al., 2022). The present study complements that work by aligning the objective with time-varying carbon intensity and by enforcing depot-level feasibility within an auditable linear program. It also parallels a UK-focused approach that used half-hourly carbon data for EV charging experiments, and it extends that idea by testing all fourteen NESO regions under a common service plan (Dixon et al., 2020; He, 2024).

The temporal behaviour in Figures 4.7–4.8 shows the mechanism behind the headline effects. A day-ahead rolling horizon locks in only the immediate action and then re-optimises as new information arrives, which connects forecast refresh to decisions on the ground (Pillac et al., 2013). Window length and terminal conditions shape feasibility and the profile of actions, so a horizon that is long enough to see the next low-intensity trough and that passes state of charge forward will defer from the small hours into cleaner midday and late-evening periods (Rawlings, Mayne and Diehl, 2017; Bredström et al., 2013). Update cadence then interacts with the forecast cadence to stabilise the two-peak pattern observed in all three day types (Cuisinier et al., 2022; Davatgari et al., 2024). The consistency of this bimodal structure across weekday, Saturday and Sunday confirms that the outcome is a property of the decision regime rather than a quirk of any one timetable. Earlier control and production-planning results explain the same stability when policies embed horizon choice and boundary conditions explicitly (Baker, 1977; McClain and Thomas, 1977; Sethi and Sorger, 1991).

Regional and seasonal structure matters for both the size and the shape of the benefit. The two-way ANOVA in Section 4.5 finds main effects of region and season with a strong interaction, which indicates that differences across the map are not sampling noise. The North East England case illustrates the mechanism. Average intensity is already low and intraday variance is modest, so the optimiser removes a handful of dirtier half-hours and yields significant yet smaller absolute savings. In regions with deeper troughs the model shifts more load and achieves larger reductions. This pattern matches evidence that average intensity can mislead when the marginal generator is fossil-dominated and when intraday swings are large (Siler-Evans et al., 2012; Zivin et al., 2014). It also aligns with studies showing that identical operations can produce different emissions because the electricity mix varies in both level and profile within and across systems (Tamayao et al., 2015; Rupp et al., 2019). The comparative point carries through to recent regional analyses that document spatial heterogeneity in carbon intensity and show why forecast-aligned schedules outperform static rules (Szurke et al., 2025; Osaki et al., 2025; McGrath et al., 2022). Seasonal findings are consistent with UK supply rhythms where wind conditions and net-demand cycles create predictable low-intensity windows that flexible depot charging can absorb (Sinden, 2007; Staffell and Pfenninger,

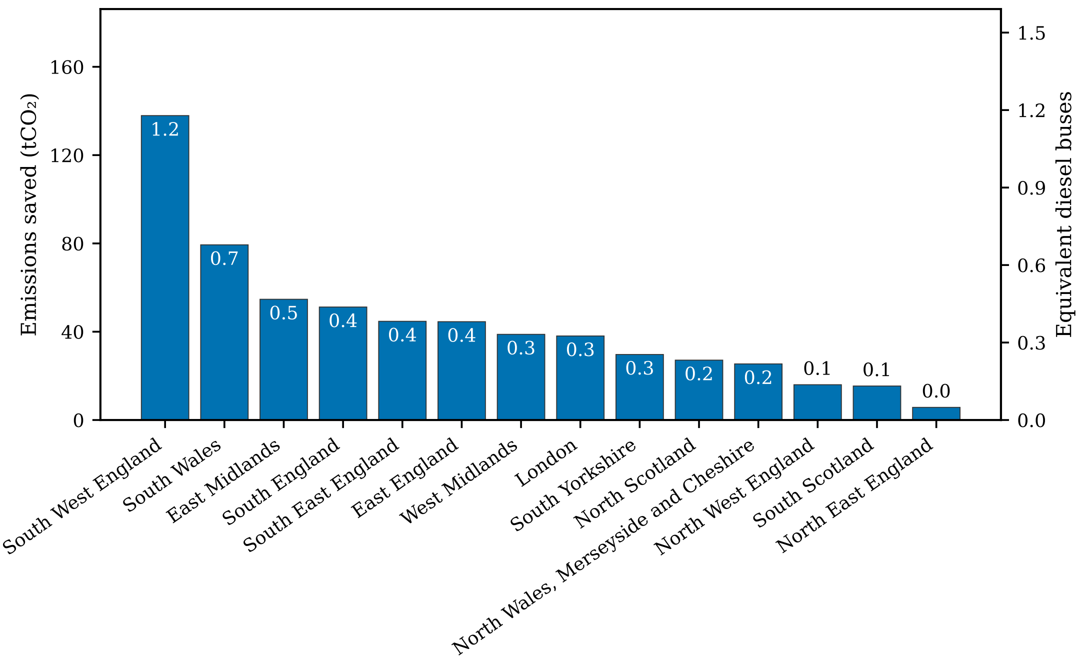

Figure 5.1: Emissions Saved and Diesel-Bus Equivalents

2018). Evidence on surplus events and curtailment risk supports the same conclusion for summer in several northern and western regions, which matches the patterns in Figure 4.7 (Cannon et al., 2015).

Figure 5.1 translates annual tonnes of CO_2 saved into Diesel Bus Equivalents to communicate scale for practitioners. Converting emissions to an indicative count of diesel buses taken off the road helps a non-specialist audience gauge materiality when briefing committees or boards. The underlying values match Section 4.2 and the conversion is documented in Appendix D. The figure should be read as an absolute scale indicator rather than a league table of optimisation performance. Absolute tonnes reflect both the size of the baseline and the success of timing. A region can post a high percentage saving yet sit mid-pack on absolute tonnes if its baseline was small, and a region with a large baseline can report substantial tonnes saved even when the percentage gain is modest. This distinction avoids over-interpreting rank order and keeps the focus on scale and planning relevance.

When considering fleet growth beyond the twenty-five-bus case, linear extrapolation is unlikely to hold. Operators tend to electrify the most promising routes first, so expanding to hillier lines or longer deadheads can lower the average saving per additional bus. Favourable charging windows are finite and, even when aggregate feasibility holds, midday and late-evening troughs can saturate at the charger-bay level. Headroom also varies across regions and seasons, which means depots in areas with short or shallow dips will meet binding limits earlier than those with deeper troughs. These limits are consistent with the regional variance noted in Section 2.1 and with the day-type availability patterns in Section 4.1.1 that determine when buses are actually present to charge. The figure therefore supports discussion of investment phasing, charger allocation and route selection rather than a simple multiply-up narrative.

Figure 5.2 positions regions by their performance relative to the Great Britain mean. Ordering bars by the difference from the national average helps identify where the same method applied to the same service clears above or below expectation. This is useful for targeting pilots, preparing funding cases and sequencing infrastructure upgrades. The plot should be constructed from the percentage savings in Table 4.2, with labels showing percentage-point differences to avoid confusion with percentage change. Because the comparison holds service and depot configuration constant, the deviation highlights the role of the regional electricity mix and the local feasibility limits described earlier rather than differences in operations. The graphic is therefore a tool for prioritisation, not a normative ranking of agencies.

Taken together, the two figures frame both the absolute and the relative implications of emissions-aware scheduling. They corroborate the central claim in the literature that tracking marginal supply lowers impact more reliably than relying on coarse averages, and they add evidence that this can be achieved with day-ahead regional forecasts under depot constraints at subnational scale. The rolling horizon is central to that result because it turns forecast information into operational windows while the fleet continues to run. This mechanism aligns with the control and production-planning arguments summarised in Section 2.3.1 and links the empirical behaviour documented in Chapter 4 to the theoretical expectations on horizon length, terminal conditions and update cadence.

A deployment decision must consider emissions and cost together. As noted in Section 3.5, the present formulation does not include tariffs, demand charges or labour costs, which means that a plan that is optimal for carbon may be financially unattractive where price signals diverge from carbon signals. Future research should adopt a multi-objective design that either traces a trade-off curve between carbon and cost or maximises emissions savings subject to a depot-level cost cap, using aligned day-ahead price forecasts and site-specific network terms. The regional prioritisation logic in Figure 5.2 remains informative under a joint objective, although the ordering may change where carbon and price differ.

The methodological contribution lies in combining regional day-ahead carbon-intensity forecasts with an auditable linear program that enforces charger limits, depot availability and per-bus feasibility. The design responds directly to the gaps identified in Section 2.4. First, it shows how a fixed decision regime and horizon shape timing once state-of-charge and presence constraints bind, which grounds dynamic-scheduling arguments in a public-

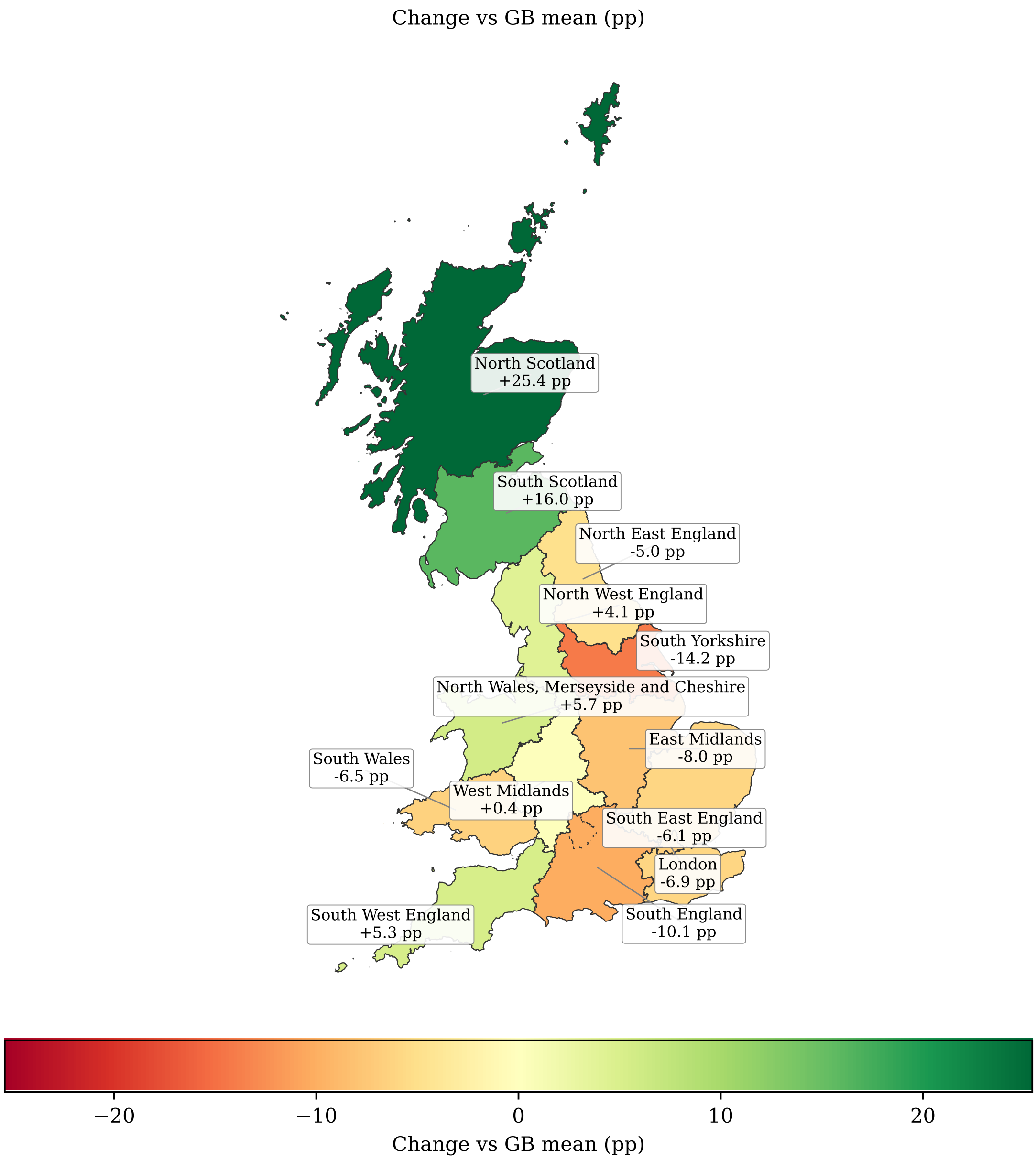

Figure 5.2: Regional Percentage Savings: Deviation from GB Mean

transport setting. Second, it integrates regional forecasts into a single schedule that is easy to audit and that produces material savings in every region. Third, it delivers a within-country comparison under a common service plan and depot configuration. That isolates grid-mix effects from operations and provides evidence that has been rare in studies of public fleets.

The study has limits that set expectations for adoption. It assumes published regional forecasts are accurate within the planning horizon. Regional actuals are not published, so subnational back-testing is not yet possible. The optimisation is depot-aggregate rather than bus-level, and workforce constraints are not modelled. Chapters 3 and 4 already note these boundaries. They do not change the sign of the main effects, yet they matter for implementation. They point to future work on per-bus assignment within the LP, on joint scheduling with duty construction and on the use of probabilistic forecasts when those become available at regional resolution.

This chapter has shown that an emissions-aware, depot-constrained schedule can convert regional and intraday carbon signals into real reductions while remaining operationally feasible. It explained the mechanism behind the gains, identified where regional and seasonal structure conditions performance and translated outcomes for practice with displays that speak to absolute scale and relative priority. The argument now shifts from interpretation to synthesis. Chapter 6 draws these threads together. It confirms whether the aim and objectives have been achieved, states a clear answer to the research question and explains the contribution for operators, local authorities and the academic community. It also sets fair limits on what can be claimed and outlines the next steps for implementation and research. Priorities include moving from depot-aggregate to bus-level scheduling, co-optimising duty construction with charging, testing probabilistic regional forecasts, coordinating with tariffs and transformer limits, and assessing battery wear effects. The conclusion uses the evidence here to show where the approach is most valuable and how it can be scaled responsibly.

Chapter 6

Conclusion

This chapter brings together the aim, objectives, methodological design and principal findings, and it sets out what the study adds for both practice and academic work. The core motivation from Chapter 1 was that electrification delivers the greatest benefit when charging aligns with low-carbon periods, and the literature gap in Chapter 2 noted the lack of forecast-aware testing across multiple subnational regions under depot constraints. The design in Chapter 3 responded to that gap with a depot-feasible rolling linear program driven by day-ahead regional forecasts. Chapter 4 quantified outcomes under a common service plan across all fourteen NESO regions, and Chapter 5 situated the results in the literature and explained their practical meaning.

The research question asked whether regional variation in Great Britain's electricity mix affects the emissions performance of an optimisation-based depot charging schedule. The evidence supports an affirmative answer. Under identical service and fleet assumptions in every region, the model reduced charging emissions by an average of 33.52%, with regional savings ranging from 19.08% to 58.65% and significance achieved in each case. The mechanism was consistent across day types. The baseline concentrated energy between 00:00 and 04:00, whereas the optimised schedule reduced that early-morning share to about 17.3% and shifted energy into two repeatable windows: a midday period that captured cleaner supply and a late-evening top-up that protected first departures the following day. These outcomes implement the temporal-horizon logic set out in Section 2.3.1 and make practical use of the regional intraday structure described in Section 2.1.

Spatial and seasonal context shaped both the size and the distribution of benefits. Regions with deeper or more frequent low-intensity periods tended to yield larger savings, and several areas showed stronger alignment in summer. The two-way analysis reported in Section 4.5 confirmed main effects of region and season and a significant interaction, which indicates that observed differences are structural rather than incidental. North

Scotland illustrated the potential where clean windows are both deep and regular. North East England provided a useful contrast: average intensity is already low and intraday variance is modest, so the optimiser removed the few dirtier half-hours and percentage savings were real, yet absolute tonnes saved remained modest. That distinction between percentage performance and absolute impact is central for policy and evaluation and is reflected in the way results should be presented.

The study's contribution is threefold. It demonstrates how a rolling-horizon design can translate subnational day-ahead carbon-intensity forecasts into an auditable and depot-feasible charging schedule whose behaviour in time is stable and interpretable. It provides a controlled GB-wide comparison that isolates grid effects more cleanly than cross-city studies with differing operations by fixing service and fleet assumptions across regions. It quantifies regional and seasonal heterogeneity and explains how structural headroom limits absolute tonnes even when percentage savings are meaningful, which clarifies where timing delivers the most practical value.

Implications for practice follow directly from the results and from the two figures introduced in the Discussion. Figure 5.1 translates annual tonnes of CO_2 saved into Diesel Bus Equivalents so that non-specialist audiences can gauge materiality when preparing briefings or investment cases. The display should be read as an absolute scale indicator rather than a league table. Absolute tonnes reflect both the baseline size and the success of timing, which means a high percentage can sit alongside modest tonnes if the baseline is small, and large baselines can deliver substantial tonnes even when percentage gains are moderate. Figure 5.2 complements this by ordering regions according to their deviation from the Great Britain mean percentage saving. Because service and depot configuration are held constant, these deviations highlight where the same method clears above or below expectation for reasons linked to regional electricity mix and local feasibility. Together, the two figures support planning decisions that require both a sense of scale and a rule for prioritisation.

Operational feasibility was maintained throughout under the depot capacity rules used in the study. The gains were achieved through smarter timing rather than through additional chargers, a larger fleet or route changes. At the same time, scaling beyond the twenty-five-bus scenario should not be assumed to deliver linear returns. Operators tend to electrify the most promising routes first, favourable charging windows at the depot are finite and can saturate at the bay level, and regional and seasonal headroom varies. Adoption should therefore proceed in phases, using the Diesel Bus Equivalent view to communicate scale and the deviation-from-mean view to target pilots and upgrades.

The claims in this dissertation sit within clear bounds that follow from the scope in Chapter 3. The abstraction is single-depot with aggregate charging decisions and a fixed service plan. The model does not track per-vehicle state of charge across the day or enforce bus-level charger assignment, and it does not capture workforce rules or queueing. Energy use is estimated from route characteristics and average factors, so gradients, temperature, onboard loads and passenger weight are abstracted. The optimisation relies on day-ahead regional forecasts and cannot be back-tested at subnational resolution because realised regional intensities are not published. The scope covers Great Britain as defined by NESO regions. These are boundaries rather than flaws and they mark where the conclusions are strongest, namely in the design of timing policy and in regional comparison under common operations.

Future work follows from these limits and from the priorities identified in the Discussion. A first priority is to address the omission noted in Section 3.5 by developing a multi-objective model that optimises jointly for cost and carbon, and, where relevant, for battery wear. Such a design would align half-hourly carbon forecasts with price forecasts, incorporate local tariff structures and demand-related charges, and report either a carbon–cost frontier or an emissions-first plan subject to an explicit cost cap. This extension would make the approach more appealing and justifiable for operators and local authorities and is necessary for business cases that must balance climate targets with budget constraints. A further set of steps includes modelling forecast error and testing sensitivity to misclassified hours of carbon intensity, adopting a daily planning horizon that solves each day as a stand-alone problem with start-of-day energy set to protect first departures, and incorporating per-vehicle state of charge and charger assignment. A tractable path for the latter is a two-stage design in which the first stage sets the aggregate timing plan and the second stage allocates charging to vehicles while respecting the aggregate plan and depot constraints. Validation against realised regional intensity when those data become available, together with sensitivity studies that vary charger count, bay layout and route mix, would quantify the non-linear scale effects noted above and support business-case development.

The argument established across Chapters 1 to 5 now supports a clear final position. Regional electricity mix and its intraday profile influence the emissions performance of optimised depot charging, and accounting for this variation delivers material reductions relative to a standard overnight policy. For operators and local authorities, emissions-aware timing can be adopted with existing assets where regional structure and depot headroom allow, using Figure 5.1 to communicate scale and Figure 5.2 to choose starting points. For researchers, the next steps include extending the method to bus-level scheduling and probabilistic forecasts and testing joint designs that incorporate duties, tariffs and transformer limits. The wider implication is that electrification policy should treat forecasts, horizons and regional context as core design inputs rather than background details, since those elements determine how far timing can extend the benefits of the transition.

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Appendix A   Source operator timetables

The operator timetables that were manually transcribed in Section 3.2.2 and referenced in Section 4.1 are reproduced for verification.

Appendix A1. Service 8 timetable: Muirhouse – Royal Infirmary

Source: Lothian Buses (2025a). [pages=-,fitpaper=true,pagecommand=]8-250406.pdf

Appendix A2. Service 9 timetable: Muirhouse – King's Buildings

Source: Lothian Buses (2025b). [pages=-,fitpaper=true,pagecommand=]9-250406.pdf

Appendix B NESO 24-hour vs 48-hour forecast equivalence

This appendix tests whether the first 24 hours of the 48-hour regional forecast add any foresight beyond the 24-hour feed used in the study. We drew a random sample of 16 dates within the study window. For each date and each of the 14 NESO distribution regions, we fetched both endpoints published at the same time and trimmed them to the first 24 hours in UTC. We then compared numeric forecast values at the exact half-hour timestamp and region.

All numeric values matched across the sample. In total we checked 10,752 region–timestamp pairs and found no numeric differences. Some rows showed different NESO "index" labels even when the numbers were the same. These labels are qualitative categories and are not used by the optimisation, so they do not affect results. The replication file is provided for audit. Regional actuals are not published, so subnational back-testing is not currently possible.

Table B.1: Summary of regional forecast equivalence check

Checked region–timestamp pairs	10,752
Numeric mismatches	0
Label-only mismatches	Present (do not affect optimisation)
Regions covered	14
Sampled dates	16

Appendix C Evidence of BODS GTFS under-reporting

This figure compares depot presence derived from the BODS GTFS feed with depot presence computed from the manually collected operator timetables for Routes 8 and 9. Trips were expanded from `stop_times` to start–end windows and counted in half-hour bins in Europe/London time. In-depot buses equal the study fleet size minus the count in service. A representative weekday, Saturday and Sunday within the study window were used. Solid lines show GTFS. Dotted lines show the manual timetable.

The GTFS curves sit above the manual curves through the morning and evening peaks. This means the feed shows more buses remaining in depot and therefore fewer buses out on the road than the operator timetables indicate. The effect is strongest between about 07:00–09:30 and 16:00–19:30, which is when the operator timetables show the tightest headways. The overlay supports the claim that the BODS GTFS feed under-reports peak services on these routes.

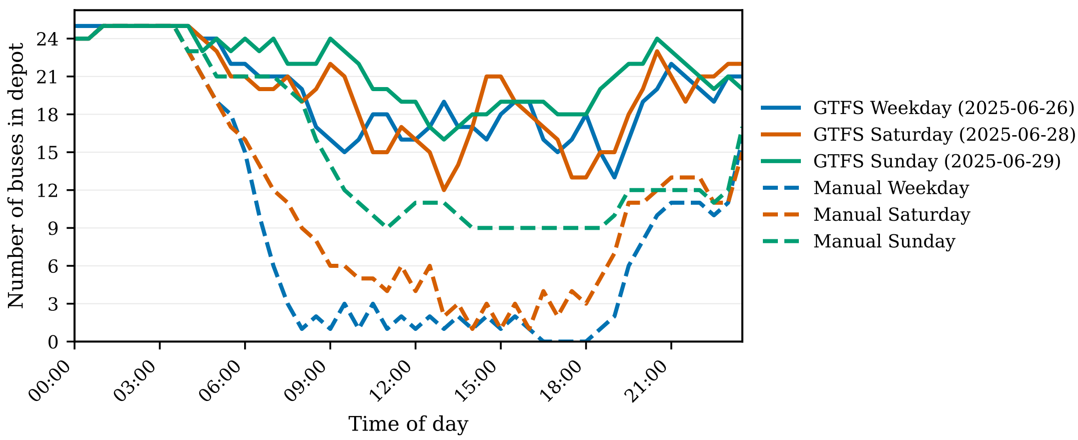

Figure C.1: Depot Presence — GTFS vs Operator Timetables

Appendix D Diesel-bus equivalent methodology

This appendix defines the diesel-bus equivalent (DBE) used to communicate avoided tailpipe CO_2 in intuitive terms. For each region r, take the annual avoided emissions A_r from Chapter 4 and express that quantity as the number of Euro VI diesel buses that would emit the same amount in one year. The annual emissions of a typical Euro VI diesel bus E_{bus} are taken as 117,000 kg CO_2 per bus-year. The DBE is

$$\text{DBE}_r = \frac{A_r}{E_{\text{bus}}}.$$

Results are rounded to one decimal place. The DBE is a communication metric. It reports tailpipe CO_2 only and does not include upstream fuel emissions or local air-quality species.

South West England saved A_r = 137,902 kg CO_2 (that is 137.90 t). With E_{bus} = 117,000 kg, the DBE is:

$$\frac{137{,}902}{117{,}000} \approx 1.18,$$

reported as 1.2 buses after rounding.