DATA-DRIVEN PLANNING OF EV CHARGING INFRASTRUCTURE IN COUPLED DISTRIBUTION AND TRANSPORTATION NETWORKS

A thesis submitted in fulfilment of the requirements for the degree of
Doctor of Philosophy

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Declaration

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This thesis represents the outcome of a sustained and rigorous research effort at the intersection of power systems, transportation electrification, and data-driven optimisation. Its development has been shaped not only by technical inquiry but also by the guidance, collaboration, and support of exceptional individuals.

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More broadly, this thesis has been driven by a commitment to advancing data-driven, system-level approaches for the planning and operation of EV charging infrastructure, with a focus on bridging power distribution networks and transportation systems. The intention has been to contribute not only to methodological development but also to decision-support tools that can inform industry, policy, and future research directions in the evolving energy landscape.

On a personal level, I would like to express my deepest appreciation to my family, especially my parents, whose unwavering support, sacrifices, and belief in my path have been the foundation of everything I have achieved. Their guidance has instilled in me the resilience, discipline, and long-term vision necessary to pursue and complete this journey.

Finally, I extend my sincere thanks to all those who have contributed to this work, directly or indirectly. Their support, whether academic, professional, or personal, has played an essential role in bringing this research to completion.

Statement of Impact

This thesis addresses a practical infrastructure-planning challenge posed by transport electrification: how to deploy electric vehicle charging infrastructure when charging demand, distribution-network constraints, mobility behaviour, and flexibility resources interact. Rather than treating electric vehicle charging stations as static electrical loads or isolated transport assets, the research develops a data-driven decision-support framework that links power-distribution-network feasibility, transportation-driven charging demand, battery energy storage support, and vehicle-to-grid flexibility.

The potential impact of the thesis lies in shifting EV charging infrastructure planning from demand-agnostic siting toward coordinated, system-aware decision-making. Using real-world Melbourne and Victorian demand, rooftop photovoltaic, traffic, and road-network data, the thesis demonstrates how deployment options can be assessed under conditions that better reflect practical planning environments. The framework supports technically credible deployment by embedding feeder constraints, voltage performance, power loss, and storage support into planning decisions. It also strengthens user-centred infrastructure assessment by linking charging demand to accessibility, travel costs, queueing behaviour, and service-quality outcomes.

The research is relevant to distribution network service providers, charging infrastructure developers, transport and urban planners, aggregators, market institutions, and policymakers involved in electrified transport planning. Its practical value is not a fixed deployment prescription, but a transferable planning logic for comparing infrastructure portfolios, identifying grid and service-quality trade-offs, and assessing flexibility readiness under realistic participation conditions. By distinguishing nominal bidirectional capability from practically realisable flexibility, the thesis provides a more credible basis for planning EV charging infrastructure that is reliable, accessible, adaptable, investment-efficient, and aligned with Australia's transition toward integrated low-carbon energy and mobility systems.

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List of Abbreviations

Abbrev.	Definition
AC	Alternating Current
BESS	Battery Energy Storage System
BLO	Bi-Level Optimisation
CAPEX	Capital Expenditure
CBA	Cost–Benefit Analysis
CO_2	Carbon Dioxide
DDPG	Deep Deterministic Policy Gradient
DER	Distributed Energy Resources
DG	Distributed Generation
DN	Distribution Network
DNSP	Distribution Network Service Provider
DR	Demand Response
DRL	Deep Reinforcement Learning
DSO	Distribution System Operator
DTA	Dynamic Traffic Assignment
ESS	Energy Storage System
EV	Electric Vehicle
EVCS	Electric Vehicle Charging Station
FCS	Fast Charging Station
FTO	Forecast-Then-Optimise
GA	Genetic Algorithm
GA-DDPG	Hybrid Genetic Algorithm and Deep Deterministic Policy Gradient
G2V	Grid-to-Vehicle
GIS	Geographic Information System
KPI	Key Performance Indicator
LTO	Learn-to-Optimise
MCS	Monte Carlo Simulation
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Nonlinear Programming
MOO	Multi-Objective Optimisation
MOEA	Multi-Objective Evolutionary Algorithm
NPV	Net Present Value
NSGA-II	Non-dominated Sorting Genetic Algorithm II
OD	Origin–Destination
OPF	Optimal Power Flow
OPEX	Operational Expenditure
PDN	Power Distribution Network
PDN–TN	Coupled Power Distribution and Transportation Network
POL	Plan-Operate-Learn
PV	Photovoltaic
PV-DG	Photovoltaic-based Distributed Generation
RE	Renewable Energy
RES	Renewable Energy Sources
RL	Reinforcement Learning
RQ	Research Question

RQ1	Research Question 1
RQ2	Research Question 2
RQ3	Research Question 3
SAC	Soft Actor–Critic
SBO	Simulation-Based Optimisation
SOC	State of Charge
TN	Transportation Network
TOU	Time-of-Use
TT	Travel Time
TC	Travel Cost
QT	Queue Time
UE	User Equilibrium
V2G	Vehicle-to-Grid
VD	Voltage Deviation
VSI	Voltage Stability Index
kV	Kilovolt
kW	Kilowatt
kWh	Kilowatt-hour

Abstract

The rapid electrification of road transportation is transforming electric vehicle charging infrastructure from a local electrical load into a coupled energy–mobility planning problem. Large-scale deployment of electric vehicle charging stations (EVCSs) can increase peak loading, network losses, voltage deviations, and stress on distribution assets. At the same time, charging demand is shaped by mobility behaviour, traffic congestion, accessibility, queueing conditions, and user response. Planning approaches that treat EV charging demand as static, exogenous, or independent of transportation behaviour risk producing infrastructure decisions that are electrically infeasible, poorly located, underutilised, or unnecessarily costly.

Despite growing research on EVCS planning, many frameworks still treat power distribution networks (PDNs), transportation networks (TNs), user behaviour, battery energy storage systems (BESSs), vehicle-to-grid (V2G) capability, and market-enabled flexibility as separate layers. This separation limits assessment of how mobility-driven charging demand is formed, mapped onto feeder-level constraints, and supported by operational flexibility. A key gap remains in the development of planning frameworks that integrate grid feasibility, transportation behaviour, flexibility resources, and operational control within a coherent decision-support structure.

This thesis develops a unified, data-driven framework for planning and operating EV charging infrastructure in coupled PDN–TN systems. The framework progresses through three stages. First, it establishes a grid-aware EVCS–BESS planning and operation model that links siting and sizing to BESS control under time-varying demand. Second, it extends the model to coupled PDN–TN planning by deriving charging demand from traffic flow, travel cost, accessibility, and queueing behaviour. Third, it incorporates V2G participation and market-driven flexibility by modelling EVs as conditional flexibility resources whose value depends on availability, state of charge, behavioural participation, and activation conditions.

A hybrid optimisation methodology combining genetic algorithms and deep deterministic policy gradient (DDPG) coordinates BESS and EVCS planning decisions. Time-indexed operational mechanisms, including local BESS control and V2G-enabled flexibility assessment, test whether planned infrastructure configurations remain technically credible under realised demand and grid constraints. The frameworks are evaluated using real-world datasets from Melbourne and Victoria, including residential smart-meter demand, rooftop photovoltaic generation, traffic measurements, road-network information, and charging-demand representations. Modified IEEE 33-bus and IEEE 123-bus systems are used to assess feeder-level impacts.

The results show that coordinated EVCS–BESS planning improves voltage performance and reduces distribution-network stress. Traffic-informed planning changes the spatial allocation of EVCSs by reducing travel burden and queueing delay while preserving feeder-level feasibility. V2G-enabled planning further expands the feasible deployment space, but only when participation uncertainty, market activation, and operational constraints are explicitly represented. These findings show that the value of flexibility is determined not by installed capacity alone, but by whether flexibility is behaviourally available, electrically usable, and operationally controllable.

Overall, this thesis advances EVCS planning from static, single-domain optimisation toward an integrated, data-driven, and deployment-oriented decision-support framework. By linking PDN constraints, mobility-driven demand, BESS coordination, and conditional V2G flexibility, it provides practical guidance for utilities, charging infrastructure operators, transport planners, aggregators, and policy stakeholders involved in future energy–mobility infrastructure planning.

Keywords: Electric vehicle charging infrastructure, battery energy storage systems, coupled power–transportation networks, vehicle-to-grid, multi-objective optimisation, traffic-informed charging demand, data-driven infrastructure planning, decision-support framework.

Chapter 1

Introduction

The planning of electric vehicle charging stations (EVCSs) has evolved from a narrow siting problem into a broader infrastructure design challenge involving power distribution constraints, transportation accessibility, operational flexibility, and deployment economics. As electric vehicle (EV) adoption increases, charging infrastructure can no longer be planned effectively using grid-only or transport-only logic. Instead, it must be designed as part of an integrated energy–mobility system in which charging demand, network feasibility, service accessibility, and flexibility resources are considered jointly.

This thesis addresses this challenge by developing a data-driven and deployment-relevant planning framework for EV charging infrastructure in coupled power distribution and transportation environments. The research is motivated by the need to move beyond static charging-demand assumptions and toward planning approaches that better reflect real-world demand variability, feeder-level constraints, mobility behaviour, and the emerging role of flexible resources such as battery energy storage systems (BESSs) and vehicle-to-grid (V2G) participation.

Accordingly, this opening chapter introduces the motivation for the research, defines the scope of the problem, explains the overall direction of the thesis, outlines the work's industry relevance, and provides a guide to the remainder of the document. The detailed research questions, knowledge gaps, and scientific contributions are derived after the critical literature review in Chapter 2, ensuring that the thesis objectives emerge from a clear assessment of what remains unresolved in existing EVCS planning research.

1.1 Motivation and Australian Context

The decarbonisation of transport and electricity systems has emerged as a critical engineering challenge in contemporary energy transitions. During this transition, the rapid adoption of EVs is widely recognised as a necessary pathway to reduce transport-sector emissions, improve energy efficiency, and support long-term sustainability [1]. However, the electrification of mobility does not simply replace liquid-fuel consumption with electricity demand. Instead, it introduces a new class of spatially concentrated and temporally variable electrical loads whose timing, location, and magnitude are shaped by travel behaviour, charging accessibility, service availability, state-of-charge dynamics, user preferences, and the technical capability of local electricity networks [2, 3, 4]. Consequently, EV charging infrastructure planning must be understood as a coupled energy–mobility infrastructure problem rather than as a conventional facility-location or load-connection task.

From the power-system perspective, widespread and unmanaged EV charging can increase peak demand, increase feeder congestion, aggravate voltage deviation (VD), and raise network losses, particularly in low- and medium-voltage distribution systems that were not originally designed to accommodate concentrated and synchronised charging demand [5, 6, 7, 8]. From the transportation perspective, EV users require a charging infrastructure that is accessible, time-efficient, reliable, and aligned with actual mobility demand. Poorly located charging stations may therefore create a dual failure: they can overload electrically weak feeder locations while simultaneously increasing travel detours, reducing user convenience, and worsening queueing conditions [9, 10, 11]. These coupled risks demonstrate that EVCS deployment cannot be evaluated through grid-side or transport-side criteria alone. It requires a planning framework that jointly considers electrical feasibility, mobility-driven demand formation, service accessibility, and operational flexibility.

This challenge is particularly important in Australia, where EV adoption, rooftop photovoltaic (PV) penetration, distributed energy resources, and urban mobility patterns are evolving simultaneously. At the national level, the Australian Government's National Electric Vehicle Strategy frames EV uptake around three mutually dependent pillars: increasing the supply of affordable and accessible EVs, establishing the resources, systems, and infrastructure required for rapid EV uptake, and encouraging stronger EV demand [12]. As shown in Fig. 1.1, the strategy explicitly positions systems and infrastructure as a central pillar of Australia's EV transition, with charging accessibility identified as one of the core national outcomes. The Strategy also emphasises national standards, data sharing, accessibility, regional and remote charging infrastructure, fleet procurement, and coordination with the electricity system. These priorities are directly aligned with the technical problem addressed in this thesis: rapid EV adoption cannot be supported by vehicle supply alone; it also requires charging networks that are spatially accessible, electrically feasible, data-informed, interoperable, and compatible with local distribution network capabilities.

This infrastructure challenge is also embedded within the broader operational transformation of the National Electricity Market (NEM). AEMO characterises the NEM as a large interconnected system supplying approximately 11 million customers through around 40,000 km of transmission infrastructure, with substantial rooftop PV and distributed energy resources connected across the system [13, 14]. For EVCS planning, this context is important because new charging infrastructure will be connected to distribution networks that are already being reshaped by changing net-demand profiles, behind-the-meter resources, and increasing requirements for visibility, forecasting, and flexible demand management.

The policy importance of charging infrastructure has become even clearer in the National Electric Vehicle Strategy Annual Update 2024–25. The update reports that, by June 2025, Australia had approximately 1,324 public fast and ultra-fast charging sites and 4,138 fast and ultra-fast charging plugs, increasing from 1,172 sites in December 2024 and 812 sites in December 2023 [15]. As illustrated in Fig. 1.2, this expansion is geographically distributed across Australian states and territories, but it is also uneven, reflecting differences in population density, travel corridors, state-level investment, private-sector activity, and local infrastructure needs. This growth indicates that public charging infrastructure is expanding rapidly; however, it also indicates that charging deployment is becoming a more complex planning problem. As the number of EVs, chargers, plug types, use cases, and charging locations increases, infrastructure planning must move beyond simple rollout targets and toward coordinated decision-making that accounts for where charging demand emerges, how it affects distribution feeders, and how supporting resources such as BESSs and V2G-enabled EVs can reduce local network stress.

Industry evidence reinforces the same conclusion. The Electric Vehicle Council's State of EVs 2025 report indicates that high-power public charging locations in Australia reached around 1,272 sites by mid-2025, while high-power public charging plugs increased from 3,436 to 4,192 over the previous year, corresponding to a 22% increase [16]. Figure 1.3 shows that this expansion has occurred through both site growth and connector growth, indicating that Australia's public charging market is moving from basic coverage expansion toward higher-capacity and denser charging provision. Importantly, the report notes that the market is shifting from simply filling geographic coverage gaps toward densifying locations, with more chargers, connectors, and bays installed per site. This distinction is critical for infrastructure planning. Early-stage charging rollout primarily focuses on coverage: ensuring drivers can find a charger within a reasonable distance. As the market matures, however, planning increasingly focuses on capacity, utilisation, queueing, reliability, and local grid hosting capability. In other words, the problem evolves from "where should chargers be installed?" to "where can additional charging capacity be deployed while maintaining network security, user accessibility, and infrastructure efficiency?"

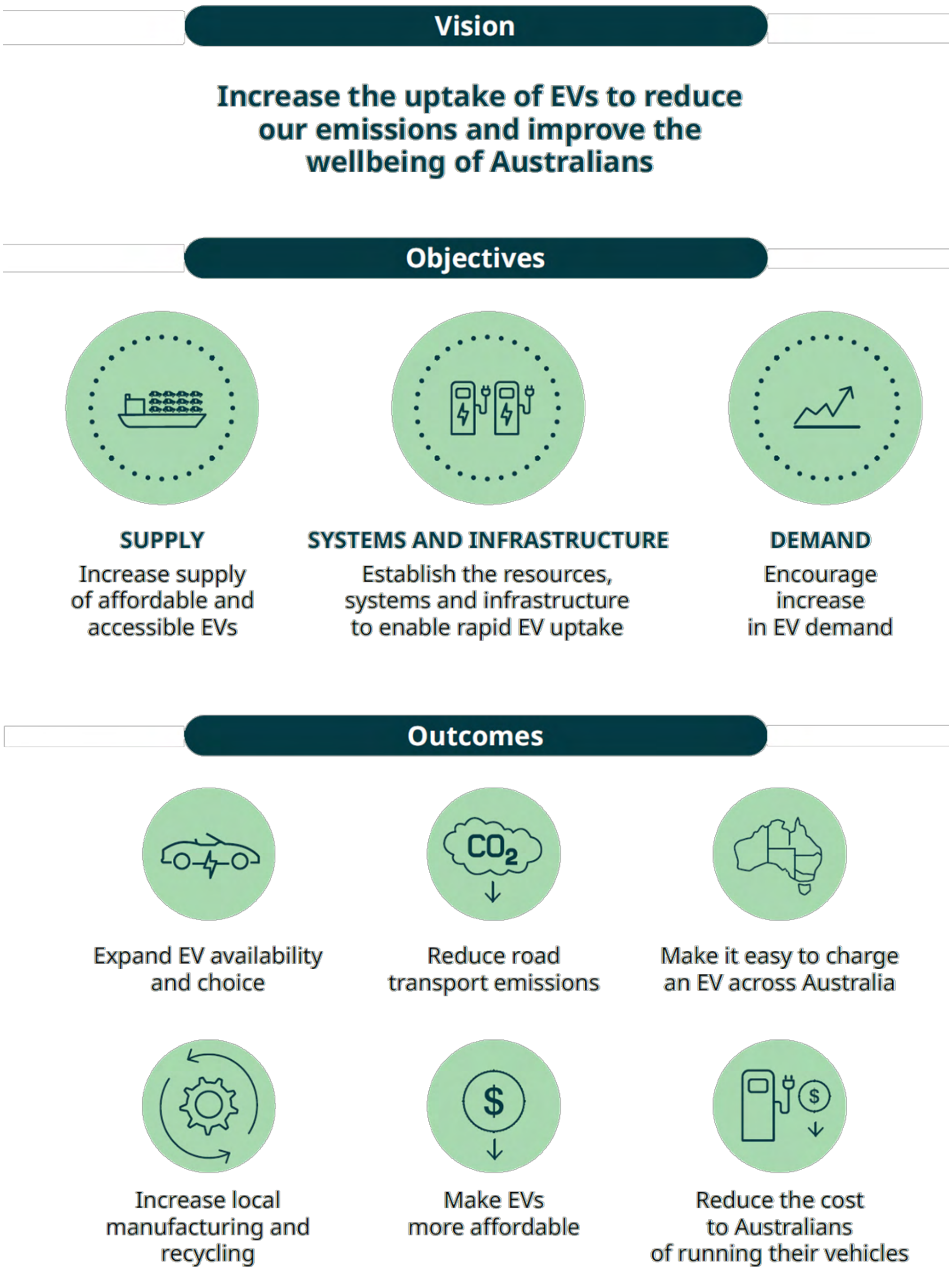


Figure 1.1: Australian National Electric Vehicle Strategy framework, showing the three policy pillars of supply, systems and infrastructure, and demand. Adapted from DCCEEW, National Electric Vehicle Strategy Annual Update 2024–25 [15].

Australia's charging infrastructure challenge is also a data challenge. The Electric Vehicle Council highlights that data integrity for EV supply equipment installations remains difficult because no single source of truth currently represents all public EV charging infrastructure in Australia [16]. This limitation has practical consequences. Without consistent and trustworthy data on charging locations, plugs, power levels, availability, usage, and connection points, infrastructure planners cannot reliably assess where investment is needed, where network constraints may emerge, or where charging-service gaps remain. The National EV Strategy similarly iden-

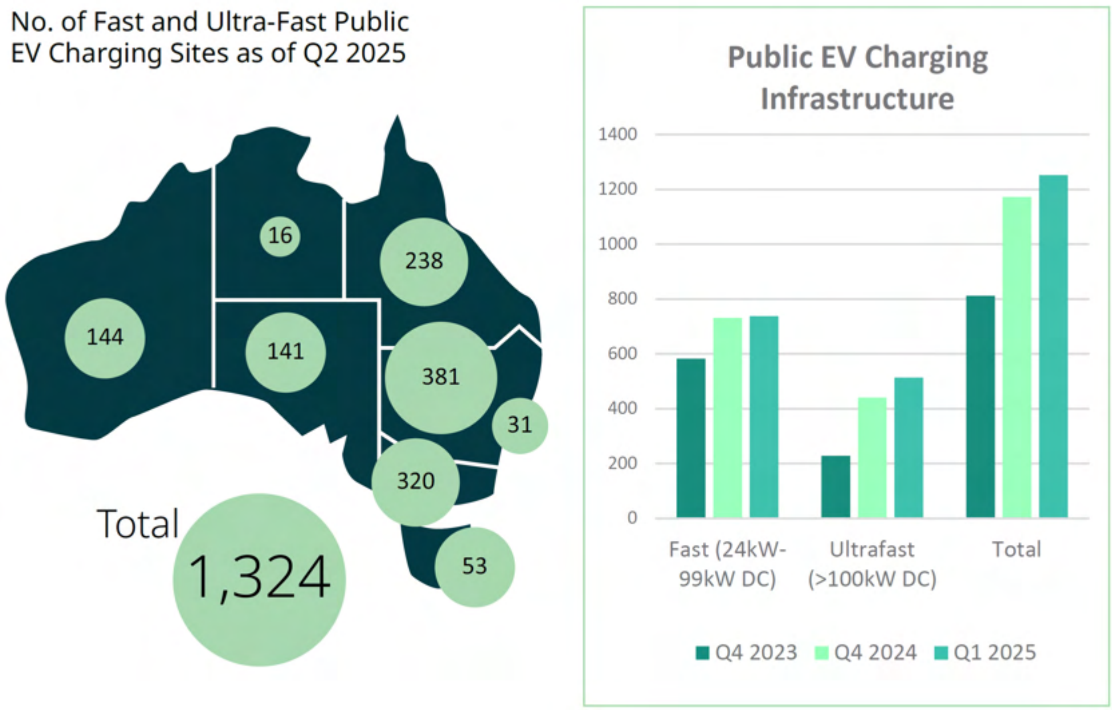
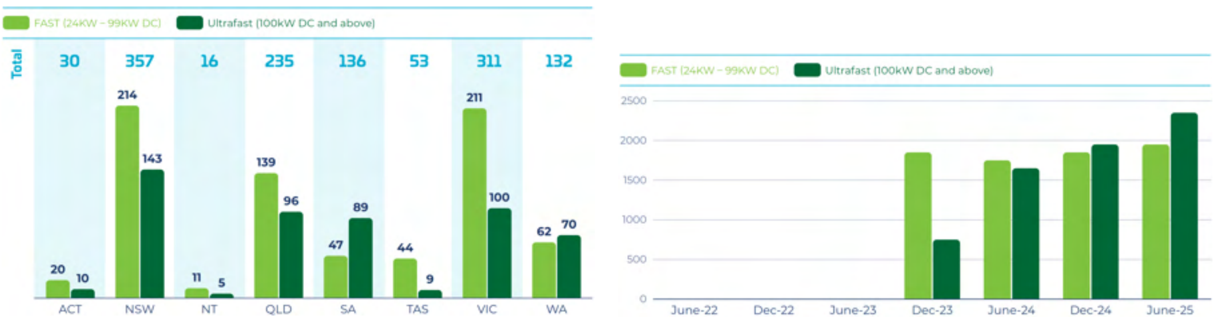


Figure 1.2: Public fast and ultra-fast EV charging infrastructure in Australia by state and territory, with reported growth from Q4 2023 to Q2 2025. Adapted from DCCEEW, National Electric Vehicle Strategy Annual Update 2024–25 [15].



(a) Charging locations.

(b) Charging connectors.

Figure 1.3: Growth of fast and ultra-fast public EV charging locations and connectors in Australia from June 2022 to June 2025. Adapted from Electric Vehicle Council, State of EVs 2025 [16].

tifies data sharing and national mapping as necessary elements of the transition, noting that infrastructure-related data are required to understand where EVs are charging and being driven, and to inform the best locations for charging infrastructure [12]. The development of the National EV Charging Infrastructure Mapping Tool directly reflects this need, as it aims to identify existing fast EV charging infrastructure and optimal zones for future development, thereby helping to guide investment decisions by governments and industry over the next five to ten years [15]. The data-driven orientation of this thesis is therefore not only a methodological preference; it responds to a recognised national planning requirement.

A further Australian-specific challenge concerns the diversity of charging contexts. The national annual update notes that around 80% of reported EV charging in Australia occurs at home, but also emphasises that demand for public, on-street, destination, and multi-residential

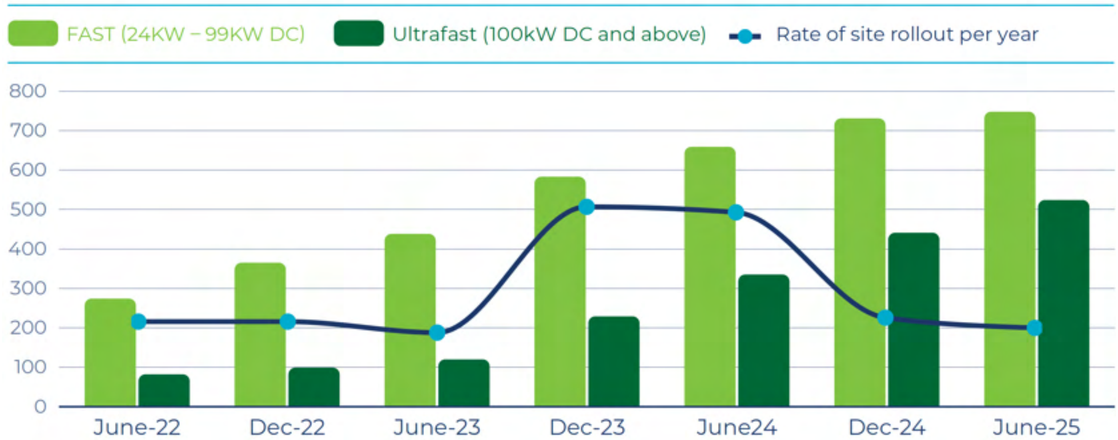


Figure 1.4: High-power public EV charging locations by Australian state and territory as of mid-2025. Adapted from Electric Vehicle Council, State of EVs 2025 [16].

charging will increase as EV adoption broadens [15]. This matters because not all future EV users will have access to private off-street charging. Residents of apartments and strata-title buildings, renters, fleet operators, regional travellers, and users relying on public or workplace charging may experience very different charging constraints. The National EV Strategy recognises this issue through guidance and policy work related to multi-residential buildings, regional charging, accessibility, and national charging standards [12]. These developments demonstrate that charging infrastructure planning must account for heterogeneity in user access, mobility behaviour, charging location type, and network connection conditions. A planning framework that assumes homogeneous charging behaviour or static demand profiles is unlikely to provide reliable guidance under such diverse deployment conditions.

These national issues are especially relevant to Victoria and metropolitan Melbourne, which provide the empirical setting for this thesis. Victoria combines dense urban travel patterns, diverse residential electricity demand, high rooftop PV penetration, and growing interest in distributed flexibility resources. As shown in Fig. 1.4, Victoria is one of Australia's major high-power public charging regions, with 311 fast and ultra-fast public charging locations reported by mid-2025 [16]. This reinforces the relevance of using Melbourne and Victoria as the empirical basis for the thesis. In such an environment, conventional maximum-demand planning logic can lead to conservative and costly network-reinforcement decisions. At the same time, transport-only EVCS siting may overlook feeder-hosting constraints and local voltage stress. Conversely, grid-only planning may identify technically favourable locations that are poorly aligned with travel demand, accessibility, or the convenience of charging services. This creates a clear planning gap: EVCS deployment must be evaluated within a coupled framework that considers traffic-informed demand, feeder-level constraints, charging service quality, and local flexibility resources simultaneously.

The role of distributed flexibility is particularly important in the Australian context. High rooftop PV penetration can create periods of local generation surplus, while evening charging demand can increase stress on distribution feeders. Coordinated EVCS and BESS planning can help shift energy across time, reduce local voltage issues, and improve utilisation of distributed renewable generation. In addition, the emergence of bidirectional charging and V2G capability creates the possibility that EVs may act as distributed flexibility resources rather than only as passive electrical loads. The National EV Strategy Annual Update notes recent progress on vehicle-to-home and V2G charging, including the revised Australian Standard that enables bidirectional charging in Australian homes and removes a barrier to many distribution network service providers accepting V2G chargers on their networks [15]. However, technical capability alone does not guarantee useful flexibility. This issue is consistent with AEMO's broader framing of consumer energy resources, where rooftop PV, behind-the-meter batteries, EVs, VPPs, and flexible demand are increasingly relevant to system operation but are also associated with lower visibility, predictability, and controllability than conventional scheduled resources [13]. For EVCS planning, this reinforces the need to distinguish between nominal V2G capability and practically realisable flexibility. The value of V2G, therefore, depends not only on bidirectional charging technology but also on user participation, temporal availability, state of charge, incentives, communication infrastructure, interoperability, and market activation.

The practical motivation for the thesis is therefore clear. Australia is no longer in a stage where EV infrastructure planning can be treated as a simple question of installing more chargers. The national policy framework, industry data, and charging infrastructure trends all point to a more complex planning problem involving spatial demand, grid capacity, data quality, accessibility, reliability, and readiness for flexibility. The challenge is not only to accelerate EVCS rollout, but to ensure that rollout is technically credible, economically efficient, user-accessible, and coordinated with distribution-network constraints. This requires planning methods that can connect real traffic patterns with charging-demand formation, map charging demand onto distribution feeders, evaluate voltage and loss impacts, incorporate BESS support, and assess how V2G participation changes the value and feasibility of infrastructure deployment.

This thesis is motivated by that practical need. It develops an integrated EVCS planning framework using real-world data from Melbourne and Victoria, Australia, including residential smart-meter demand, rooftop PV generation, traffic measurements, road-network information, and charging-demand representations. Across the thesis, EVCSs, BESSs, and V2G participation are treated not as isolated technical additions but as interacting infrastructure components whose value depends on how well their deployment aligns with both power distribution network (PDN) constraints and transportation network (TN) dynamics. The central motivation is therefore not only to improve methodological sophistication, but also to develop planning logic that is realistic, operationally meaningful, and useful for infrastructure decision-making under Australian urban conditions.

The research is positioned at the intersection of national policy needs, industry deployment challenges, and technical planning gaps. Australia's EV transition requires more than rapid vehicle uptake and charger installation; it requires decision-support frameworks that can determine where charging infrastructure should be deployed, how local flexibility resources should support it, and how its value changes when mobility demand, grid constraints, and V2G-enabled flexibility are considered together. By progressing from grid-aware EVCS–BESS coordination, to traffic-informed coupled PDN–TN planning, and finally to flexibility-aware infrastructure planning under heterogeneous V2G participation and market-driven activation, this thesis responds directly to the infrastructure-planning challenges emerging in Australia's electrified transport transition.

1.2 Scope of Work

The core problem addressed in this thesis is the coordinated planning and operational support of EV charging infrastructure in environments where PDNs and TNs are structurally coupled. In such settings, infrastructure decisions must account for both mobility-driven demand formation and feeder-level technical feasibility within a unified planning framework. EV charging demand cannot be adequately represented as a static or purely exogenous electrical load; rather, it emerges from the interaction among traffic flow, charging accessibility, state-of-charge dynamics, route choice, service availability, and user behaviour. Once charging demand materialises, it is mapped onto specific feeder locations, where it influences voltage performance, power loss, hosting capacity, and the operational value of local flexibility resources. Consequently, EVCS planning must be formulated as a coordinated infrastructure problem in which transportation-driven demand and grid feasibility are assessed jointly rather than sequentially or in isolation [2, 17, 18].

Within this broader problem, the thesis considers the joint siting and sizing of EVCS and BESS infrastructure and, at a more advanced stage, the incorporation of bidirectional charging, heterogeneous V2G participation, and market-driven activation of flexibility. The planning problem is inherently multi-objective because it involves multiple stakeholders with partially aligned and partially competing interests. Distribution Network Service Providers (DNSPs) and grid operators seek to preserve voltage quality, reduce technical losses, and avoid unnecessary augmentation. EVCS owners and investors seek economically efficient deployment decisions. EV users seek an accessible and reliable charging service with acceptable travel and waiting times. In coupled PDN–TN settings, transportation planners and local authorities are also concerned with how infrastructure placement affects service accessibility, traffic distribution, and the practical usability of electrified mobility [19, 20, 9].

The scope of the thesis is deliberately defined to maintain a balance among realism, analytical tractability, and deployment relevance. First, the thesis focuses on distribution-level infrastructure planning rather than bulk transmission expansion. Second, it focuses on planning and operational support for public or shared charging infrastructure rather than on detailed, individual-level scheduling for private home charging. Third, the analysis adopts a representative 24-hour weekday horizon discretised into 48 half-hour time steps so that time-varying load, PV generation, traffic patterns, and charging demand can be evaluated consistently across the proposed frameworks. Fourth, the experimental studies are grounded in real Melbourne and Victoria datasets while using modified IEEE distribution feeders as interpretable electrical backbones.

At the same time, the thesis does not attempt to model every layer of the broader electrification problem. It does not provide a full long-horizon EV adoption forecast, a microscopic city-scale transport simulator, or a complete wholesale-market settlement model. Instead, it focuses on a more specific but highly consequential planning question: how to design and support EV charging infrastructure so that it remains electrically feasible, mobility-aware, flexible, and decision-relevant under realistic urban operating conditions. This focus is appropriate because many practical deployment risks arise precisely at the interface between feeder-level electrical limits and spatial charging-service demand.

1.3 Research Aim and Thesis Direction

Building on the motivation and scope defined above, the overarching aim of this thesis is to develop a data-driven, deployment-relevant planning framework for EV charging infrastructure that accounts for interactions among distribution-network constraints, transportation-system dynamics, and flexibility resources. Rather than treating EVCS deployment as a static siting problem, the thesis investigates how infrastructure planning can be improved by incorporating operational feasibility, mobility-driven demand formation, and V2G-enabled flexibility into the decision-making process.

The thesis is organised around a progressive modelling direction. It begins with EVCS and BESS planning within distribution networks, where the central concern is whether charging infrastructure can be deployed without violating network constraints or creating excessive technical stress. It then extends the planning boundary to coupled PDN–TN environments, where charging demand is shaped by traffic flow, accessibility, travel cost, and queueing behaviour. Finally, it examines the role of bidirectional charging and V2G participation, in which EVs are no longer treated solely as passive loads but as conditional flexibility resources whose contribution depends on user participation and market activation.

At this stage of the thesis, the aim is intentionally stated at a high level. The detailed research questions and scientific contributions are not introduced here as standalone assumptions; instead, they are derived from the literature gaps synthesised in Chapter 2. This structure ensures that the research questions emerge logically from the limitations of existing EVCS planning frameworks and that the thesis's novelty is situated in relation to the state of the literature rather than asserted prematurely.

1.4 Industry Outcomes and Decision Support

A central premise of this thesis is that EVCS planning frameworks should function as decision-support tools rather than purely analytical models. Accordingly, the proposed framework is intended to translate complex interactions among grid constraints, transportation dynamics, and flexibility resources into actionable planning insights for infrastructure stakeholders, including distribution network operators, charging infrastructure providers, urban planners, and energy system investors.

From the perspective of PDNs, the thesis provides a basis for identifying where charging infrastructure can be deployed with acceptable technical risk and how local flexibility resources can expand effective hosting capacity. Rather than relying only on conservative maximum-demand assumptions, the framework evaluates time-varying demand, feeder-level voltage constraints, and the interaction between EV charging and distributed generation. This supports more informed decisions regarding the siting and sizing of EVCS and BESS assets, particularly in Australian urban environments characterised by heterogeneous feeder conditions and high rooftop PV penetration. In practical terms, this planning perspective supports deferring unnecessary network augmentation by identifying where targeted deployment of flexibility can achieve comparable technical outcomes at lower cost.

From a mobility and service delivery perspective, the thesis emphasises that electrical feasibility alone is insufficient for infrastructure planning. Charging infrastructure that is technically attractive from a grid standpoint may fail to deliver practical value if it is poorly aligned with travel demand, accessibility requirements, or user behaviour. By incorporating traffic flow, travel cost, and queueing dynamics into the planning framework, EVCS locations are evaluated not only as electrical nodes but also as service points within a transportation system. This integrated perspective supports the identification of locations that balance grid constraints with user accessibility and service quality.

From an investment and flexibility perspective, the thesis treats BESS and V2G resources as infrastructure components that can reshape the planning space rather than as purely operational add-ons. Strategically located BESS units can buffer concentrated charging demand, reduce local network stress, and increase the feasible penetration of EVCS infrastructure. Similarly, modelling V2G participation under realistic behavioural and market conditions helps distinguish between technical V2G capability and practically realisable flexibility. This distinction is important for stakeholders evaluating flexibility-enabled deployment strategies under uncertainty, particularly where future EV uptake, user participation, and market arrangements remain uncertain.

The use of real-world datasets from Melbourne and Victoria further strengthens the thesis's practical orientation. By grounding the analysis in observed traffic patterns, residential demand profiles, and PV generation data, the framework captures the spatial and temporal characteristics of urban electrification more faithfully than approaches based solely on synthetic assumptions. As a result, the findings of the thesis are intended to provide context-specific insights that can inform infrastructure planning in Australian cities and comparable urban energy–mobility systems.

Importantly, the thesis does not prescribe a single universal infrastructure configuration. Instead, it provides a structured basis for reasoning about infrastructure decisions under coupled technical, spatial, and behavioural complexity. It clarifies which factors must be considered jointly, how trade-offs between grid performance and service accessibility emerge, and how the value of flexibility depends on both physical infrastructure and operational participation. In this sense, the industry value of the thesis lies in its ability to convert methodological developments into decision-support intelligence for more robust, efficient, and context-aware deployment of EV charging infrastructure.

1.5 Thesis Structure

The thesis is structured to reflect the progressive development of the proposed planning paradigm, while ensuring that the detailed research questions and contributions are introduced only after the literature has been critically reviewed. Each chapter contributes to the gradual enrichment of the EVCS planning framework, moving from foundational concepts toward an integrated, data-driven, and flexibility-aware decision-support perspective.

Chapter 2 establishes the intellectual foundation of the thesis through a critical review of EV charging infrastructure planning literature. It traces the evolution of the field from grid-centric formulations toward coupled PDN–TN planning, data-driven demand modelling, V2G participation, and flexibility-aware infrastructure design. After synthesising the remaining knowledge gaps, the chapter derives the research questions, design requirements, and contribution structure that guide the thesis's methodological development.

Chapter 3 defines the empirical and experimental context within which the proposed frameworks are developed and evaluated. It introduces the Melbourne and Victoria case-study environment, including real-world traffic data, residential demand, and PV generation profiles. The chapter also presents the modified IEEE distribution feeders, the transportation-network representation, the construction of traffic-informed charging demand, and the performance metrics used for evaluation. Together, these elements establish a consistent and reproducible foundation for the subsequent analyses.

Chapter 4 initiates the methodological development by addressing the coordinated planning and operation of EVCS and BESS infrastructure within the PDN. It formulates a multi-objective optimisation problem that integrates infrastructure siting, operational scheduling, and adaptive support from BESS resources. This chapter establishes the first modelling layer of the thesis by examining how distribution-network constraints and local flexibility resources affect EVCS deployment decisions.

Chapter 5 extends the planning framework to a coupled PDN–TN setting, in which charging demand is explicitly linked to transportation-system dynamics. By incorporating traffic-informed demand modelling, accessibility considerations, and service-level metrics such as travel cost and queueing time, the chapter reformulates EVCS planning as a multi-stakeholder infrastructure problem. This stage demonstrates how mobility behaviour reshapes both the location and the value of charging infrastructure.

Chapter 6 further enriches the framework by incorporating V2G participation, behavioural heterogeneity, and market-driven flexibility activation. Building on the coupled PDN–TN formulation, this chapter introduces a more realistic representation of EVs as conditional flexibility resources. It examines how bidirectional charging capability, when modelled under realistic participation constraints, alters operational outcomes and infrastructure planning decisions.

Chapter 7 situates the thesis's contributions within the broader research landscape by developing a structured synthesis and comparative framework. It introduces a decision-centric taxonomy that distinguishes between planning-layer and operation-layer formulations and uses this perspective to interpret existing studies and the thesis contributions. This chapter strengthens the conceptual clarity of the thesis and provides a basis for systematic comparison across methodologies.

Chapter 8 concludes the thesis by consolidating the main findings, translating the methodological contributions into industry-relevant decision-support guidance, discussing planning and policy implications, identifying limitations and translation boundaries, and outlining future research directions. This final chapter integrates the thesis's scientific conclusions with practical deployment considerations, linking the proposed planning frameworks to real-world infrastructure decision-making in Australian urban contexts.

For readers primarily interested in methodological development, Chapters 4–6 may be read as a coherent sequence of model enrichment, progressing from grid-aware planning to transport-aware integration and finally to flexibility-enabled infrastructure design. For readers focused on planning logic and deployment relevance, Chapters 3–8 together show how real-world data, infrastructure decisions, mobility dynamics, flexibility behaviour, and industry translation interact to produce increasingly realistic EVCS planning outcomes. Read as a whole, the thesis advances a cumulative argument: EV charging infrastructure planning becomes materially more robust, credible, and industry-relevant when it evolves from static, grid-only formulations toward coordinated, data-driven, and system-level decision frameworks.

Chapter 2

Foundations and Research Gaps in EV Charging Infrastructure Planning

The planning of EVCSs has evolved from a narrowly defined location–allocation problem into a multi-layered infrastructure design challenge spanning power systems, transportation systems, user behaviour, and energy market coordination. As electric mobility expands, EV charging demand cannot be treated as a static electrical load on existing distribution feeders. Instead, it represents a spatially and temporally dynamic service demand shaped by travel behaviour, charging accessibility, power network constraints, and the operational flexibility of distributed energy resources. Consequently, the EVCS planning literature has progressively shifted from purely grid-centric formulations toward integrated infrastructure planning frameworks that jointly consider PDNs, TNs, BESSs, data-driven demand estimation, and emerging flexibility mechanisms such as V2G participation and market-enabled energy services.

This chapter establishes the conceptual and methodological foundation for the thesis by critically reviewing the principal strands of research on EV charging infrastructure planning and identifying the technical, methodological, and deployment-oriented gaps that motivate the proposed framework. Rather than treating the literature as a collection of isolated methods, the review is organised around the broadening of EVCS planning from grid-centric formulations toward coupled, data-driven, and flexibility-aware infrastructure design. In doing so, the chapter provides the analytical basis for the progressively enriched planning framework developed in the subsequent chapters.

The remainder of this chapter is organised as follows. Section 2.1 establishes the problem context for EV charging infrastructure planning by reviewing the system-level drivers, stakeholder objectives, and technical and economic cost factors that shape infrastructure deployment. Section 2.2 reviews EVCS planning approaches within PDNs, followed by Section 2.3, which examines coordinated planning of charging infrastructure and local energy resources. Section 2.4 discusses the influence of transportation-system dynamics on charging demand and infrastructure accessibility. Section 2.5 reviews integrated PDN–TN planning frameworks that jointly model power and mobility systems. Section 2.6 examines data-driven approaches to EVCS allocation, while Sections 2.7 and 2.8 examine how bidirectional charging, V2G participation, and market-enabled flexibility reposition EV charging infrastructure from a passive demand asset toward an active flexibility resource. Section 2.9 reviews methodological advances in optimisation, learning, and hybrid planning strategies. Finally, Section 2.10 synthesises the remaining research gaps and translates them into a set of design requirements that guide the integrated EVCS planning frameworks developed throughout this thesis.

2.1 EV Charging Infrastructure Planning: System Perspective and Cost Drivers

The large-scale adoption of EVs is increasingly recognised as a central component of transport decarbonisation and the transition toward low-carbon energy systems [1]. However, electric mobility also introduces a new infrastructure planning problem because charging demand affects both the provision of charging services and the operational performance of power networks.

From a power-system perspective, widespread and unmanaged EV charging can increase feeder loading, aggravate VD, and raise network losses, particularly in distribution systems that were not originally designed for concentrated and temporally variable charging demand [5, 6]. From a mobility perspective, EV users require a charging infrastructure that is spatially accessible and aligned with travel demand; otherwise, poorly located EVCSs may increase detours, reduce service convenience, and produce uneven infrastructure utilisation. EVCS planning, therefore, cannot be treated as a single-domain siting problem. It must be framed as a system-level infrastructure planning problem that jointly considers electrical feasibility, service accessibility, and long-term deployment efficiency.

Traditional distribution-network planning has often separated long-term planning from short-term operation. In this paradigm, planning focuses on demand growth forecasts and network reinforcement, whereas operation focuses on maintaining reliability and power quality using existing assets [21]. However, under rapid EV adoption and increasing DER penetration, design-for-maximum-demand approaches can lead to conservative infrastructure decisions and substantial reinforcement costs. This has motivated a shift toward more flexible and data-informed planning paradigms in which charging demand, distributed flexibility resources, and operational constraints are coordinated more explicitly.

Within this broader planning paradigm, EVCS deployment involves multiple stakeholders and competing performance criteria. From the PDN perspective, infrastructure planning aims to reduce power loss, minimise VD, improve the VSI, and defer unnecessary network reinforcement. From the transportation-system perspective, planning objectives include improving accessibility, reducing travel and waiting times, and aligning station locations with spatial traffic demand. From the EVCS investor and operator perspective, deployment decisions must also account for construction costs, maintenance costs, profitability, utilisation, and service reliability. These partially aligned objectives make EVCS planning inherently multi-objective rather than reducible to a single technical or economic criterion.

The cost structure of EVCS planning reflects this multi-stakeholder setting. Investment and operational cost drivers include charger procurement, transformer capacity upgrades, land acquisition or leasing, civil infrastructure works, maintenance, and electricity procurement. In addition, advanced planning models increasingly include user-related costs, such as travel time, waiting time, and congestion penalties, to represent the service quality experienced by EV drivers. On the technical side, the feasibility of EVCS deployment is shaped by network losses, voltage regulation limits, hosting capacity constraints, and localised peak-demand growth within distribution feeders.

Accordingly, the literature has progressively moved from simplified EVCS location–allocation models toward more integrated planning frameworks. Early studies often relied on static charging-demand assumptions, grid-only feasibility constraints, or simplified demand-coverage models. More recent work has incorporated time-varying charging demand, coordination with distributed energy resources, transportation-system dynamics, and flexibility mechanisms such as V2G and market-enabled energy services. This progression indicates that EVCS planning is increasingly being treated as a hierarchical, multi-layer decision problem in which mobility-driven demand, electrical feasibility, operational control, and market participation must be distinguished and coordinated.

This distinction is important for the thesis because planning variables, operational controls, and flexibility mechanisms do not operate at the same decision layer. Siting and sizing decisions are long-term infrastructure choices, whereas storage dispatch, charging control, and V2G activation are operational or market-mediated actions. Blending these layers without a clear structure can obscure the source of planning benefits and weaken the interpretability of infrastructure outcomes. Therefore, a structured review of the literature is required to clarify how existing studies approach EVCS planning and to identify the remaining gaps.

This thesis follows this progression by first addressing EVCS planning within distribution networks, then extending the planning problem to coupled power–transportation systems, and finally incorporating flexibility mechanisms such as V2G participation and market-driven coordination. The following sections, therefore, review the literature along this same progression, beginning with PDN-oriented EVCS planning and moving toward increasingly integrated, data-driven, and flexibility-aware infrastructure planning frameworks.

2.2 Distribution Network Planning for EV Charging Integration

The increasing penetration of EVs has introduced new operational and planning challenges for PDNs. Unlike conventional loads, EV charging demand is characterised by high simultaneity, stochastic user behaviour, and strong spatial concentration around charging locations. When large numbers of EVs are connected to the same feeder, transformer, or electrically weak area, the resulting demand can cause voltage violations, feeder congestion, increased power losses, and accelerated asset degradation. Accordingly, distribution networks require planning approaches that can accommodate EV charging infrastructure while preserving reliability, voltage quality, and asset utilisation [5, 6].

Early EVCS planning studies, therefore, focused primarily on the electrical feasibility of integrating charging stations into distribution networks. In these formulations, EVCSs were commonly modelled as additional electrical loads, and the planning problem was formulated as selecting optimal locations and capacities subject to network operating constraints. Typical objectives included minimising power losses, reducing VDs, improving voltage stability indices, and limiting reinforcement requirements associated with feeder and transformer upgrades. Power-flow-constrained optimisation models were widely adopted to ensure that candidate EVCS deployments remained within nodal voltage and thermal limits, as well as feeder capacity constraints.

Within this grid-centric literature, EVCS siting decisions were mainly driven by electrical network characteristics rather than by mobility behaviour. Planning variables typically included station location and capacity, while the constraint set represented feeder loading, voltage bounds, and power-flow feasibility. A broad range of optimisation methods, including mixed-integer programming, nonlinear optimisation, and metaheuristic algorithms, has been applied to solve these discrete and nonlinear planning problems. These studies provided an important foundation by demonstrating how EVCS deployment can be made compatible with distribution-network operating limits.

As EV penetration increased and DERs became more prominent, the literature began to move beyond EVCS-only planning toward coordinated planning of charging infrastructure and local energy resources. In particular, BESSs have been investigated as complementary assets that can mitigate the adverse grid impacts of concentrated EV charging. By providing local energy buffering, peak shaving, and voltage support, BESSs can reduce feeder loading, improve voltage profiles, and increase the effective hosting capacity of PDNs for EVCS deployment. Consequently, several studies have formulated joint EVCS–BESS planning problems to improve both technical performance and investment efficiency.

Despite these advances, a fundamental limitation remains in many PDN-oriented EVCS planning models: charging demand is usually treated as an exogenous or spatially simplified input. In many cases, EV demand is represented through static load profiles, aggregated penetration assumptions, fixed arrival patterns, or simplified spatial demand distributions. Such representations are useful for electrical feasibility studies, but they do not capture the spatiotemporal mechanisms through which charging demand is generated in real transportation systems. In practice, EV charging demand depends on travel behaviour, route choice, charging accessibility, state-of-charge dynamics, service availability, and queuing conditions.

This limitation creates a structural mismatch between technically feasible planning outcomes and behaviourally realisable use of infrastructure. A solution may satisfy distribution-network constraints yet be poorly aligned with where and when EV drivers actually require charging services. Conversely, locations with strong mobility demand may be neglected if planning is driven solely by feeder-level electrical indicators. Therefore, PDN-oriented planning models, although essential for ensuring grid feasibility, cannot by themselves guarantee that optimal EVCS deployment will deliver accessible and effectively utilised charging services.

The key gap is therefore not simply the absence of additional constraints, but the decoupling of infrastructure siting from demand formation. Treating EV charging demand as externally imposed separates the planning decision from the behavioural and spatial processes that create charging needs. This weakens the realism of infrastructure outcomes and limits their transferability to practical deployment contexts. Addressing this issue requires EVCS planning models to integrate mobility-driven demand formation with distribution-network feasibility within a unified planning structure.

Accordingly, the literature has progressively shifted toward approaches that incorporate transportation-system factors, including traffic flow, accessibility, congestion, travel cost, and queueing dynamics. These factors determine not only the attractiveness and utilisation of charging locations, but also the spatial distribution of electrical demand imposed on the PDN. The following sections, therefore, examine how transportation-system dynamics and coupled PDN–TN formulations extend grid-centric EVCS planning toward more realistic and deployment-relevant infrastructure design.

2.3 Coordinated Planning of Charging Infrastructure and Local Energy Resources

As EVCS deployment studies have matured, it has become increasingly evident that charging infrastructure should not be planned independently from local energy resources. Concentrated EV charging can intensify voltage fluctuations, increase peak loading, and raise network losses, particularly under high EV penetration and time-varying charging behaviour. Although optimal EVCS siting can reduce some of these impacts, siting alone is often insufficient when charging demand emerges in electrically constrained areas. This has motivated a substantial body of research on the coordinated planning of EVCSs with local energy resources, including BESSs, PV units, wind generators (WGs), and voltage-support devices.

Renewable distributed generators, such as solar PV systems, WGs, and distribution static VAr compensators (DSTATCOMs), have been widely considered supporting technologies to reduce the grid impact of EVCS integration [22, 23]. However, a high reliance on non-dispatchable renewable generation can introduce operational uncertainty, as renewable output is intermittent and only partially aligned with charging demand [24]. This has led to increasing emphasis on dispatchable flexibility resources, particularly BESSs, which can buffer renewable variability while supporting EV charging demand and network voltage performance [25].

BESSs are widely recognised as effective assets for enhancing the operational value of distributed generation and improving distribution-network performance [26, 27, 28, 29, 30, 31]. They can provide local peak shaving, energy shifting, ride-through capability, voltage support, and energy arbitrage, while also mitigating the intermittency of RESs [32]. In EVCS planning contexts, this makes BESSs particularly valuable because they can reduce the mismatch between temporally concentrated charging demand and feeder-level network constraints. As a result, EVCS infrastructure is increasingly treated not only as an additional demand source but also as part of a coordinated local energy system whose performance depends on the interaction among charging facilities, storage assets, renewable generation, and operational control.

A significant portion of the literature, therefore, formulates joint planning problems in which EVCSs and supporting energy resources are optimised simultaneously. These frameworks commonly consider technical and economic objectives such as minimising power loss, reducing VD, improving voltage stability, and limiting installation and operational costs. Single-objective and multi-objective optimisation approaches have been used to determine the optimal locations and capacities of EVCSs, BESSs, PV units, and other supporting assets within distribution networks [7, 25, 26, 27, 28, 29, 30, 31]. Because these problems combine nonlinear power-flow equations, discrete investment decisions, and time-dependent operating constraints, they are typically NP-hard combinatorial optimisation problems. Consequently, metaheuristic algorithms, RL-based methods, and hybrid optimisation frameworks have been widely adopted to improve tractability and search performance.

Several representative studies demonstrate the benefits of coordinated EVCS–BESS and EVCS–DER planning. Adetunji et al. [7] proposed a multi-objective framework for the optimal placement of distributed generation and BESS using a hybrid combination of the Genetic Algorithm (GA), Whale Optimisation Algorithm (WOA), and RL. Deb et al. [33] introduced a hybrid optimisation method that combines Chicken Swarm Optimisation (CSO) and Teaching-Learning-Based Optimisation (TLBO) to improve grid stability and allocate charging stations in the IEEE 33-bus distribution network. Other studies have incorporated time-varying load profiles, renewable coordination, investment-cost modelling, and uncertainty treatment in joint EVCS–BESS planning frameworks [34, 35, 36, 37]. Collectively, these works show that coordinated planning can improve hosting capacity, reduce technical stress, and limit the need for conservative network reinforcement compared with EVCS-only deployment.

However, important limitations remain. Many studies size and locate BESS units using maximum or worst-case EVCS demand assumptions. Although this can ensure conservative network operation, it may lead to oversized storage assets and inflated investment requirements because peak charging demand typically occurs only during limited periods of the day [38]. Similarly, several frameworks either simplify existing DER behaviour or neglect interactions among EVCS demand, household net demand, and behind-the-meter PV generation. These simplifications reduce planning models' ability to reflect realistic distribution-network operating conditions.

To improve realism, more recent studies have incorporated data-driven demand modelling, smart-meter measurements, household net-demand profiles, and expected daily EVCS demand patterns. These inputs enable more representative 24-hour planning studies and allow planners to evaluate how excess daytime renewable generation may be shifted through BESS operation to support evening or nighttime EV charging. Some studies have also introduced real-time distributed BESS control strategies that adjust charging or discharging actions in response to deviations from planned demand profiles. This represents an important transition from static asset-planning models toward joint planning-and-operation frameworks.

Nevertheless, even these enhanced EVCS–DER coordination models often retain a fundamental dependency on externally imposed charging demand. Time-varying profiles improve temporal realism, but they do not necessarily explain why charging demand appears at particular locations or how it changes with travel behaviour, accessibility, congestion, or queueing conditions. Therefore, coordinated EVCS–DER planning remains conditionally optimal: its outcomes are valid under assumed demand scenarios, but not necessarily under behaviourally consistent mobility-driven demand formation.

This limitation defines the boundary of PDN-centred EVCS planning. Coordinating EVCSs with BESSs and other DERs improves electrical feasibility and operational flexibility, but it does not fully resolve the spatial origin of charging demand. For deployment-oriented infrastructure planning, the next modelling step is to connect charging demand to the transportation system that generates it. To consolidate this first layer of the literature, Table 2.1 summarises representative studies on EVCS planning in distribution networks and coordinated EVCS–BESS/DER deployment. Rather than listing studies descriptively, the table highlights their methodological contributions and the limitations most relevant to integrated EVCS infrastructure planning.

This observation motivates the next stage of the literature review. Beyond coordinated planning within the electrical domain, realistic EVCS deployment also depends on transportation-system conditions that influence station attractiveness, service accessibility, and demand distribution across space and time. The following section, therefore, examines how transportation-system factors shape charging infrastructure planning and why their integration is essential for moving from grid-centric design toward coupled power–transportation planning frameworks.

Table 2.1: Representative studies on PDN-oriented EVCS planning and local energy-resource coordination (S: sizing; L: location).

Ref.	Method	S,L	Units	Objective Functions	Pros and Cons
[7]	GA, Whale Algorithm, State Action Reward State Action	S, L	EVCS, BESS, PV	• minimising power loss, VD, and VSI, • minimising installation & operational costs • maximising environmental benefit	+ Considering environmental, technical, and economic benefits – Limiting validation – Ignoring dynamic EV charging behaviours
[25]	Multi-Objective Student Psychology-Based	S, L	EVCS, BESS, PV, WG	• minimising power loss & installation costs	+ Considering the time horizon load – computational complexity
[26]	Second-order conic programming	S, L	EVCS, BESS, PV	• minimising power loss	+ Considering time-varying profiles – Ignoring power grid operational constraints – Assuming perfect forecasting of demand
[27]	Harris Hawks Optimisation, Grey Wolf Optimisation	S, L	EVCS, BESS, PV	• minimising energy loss, VD • minimising investment & operation costs	+ Considering real-world uncertainties – Ignoring dynamic re-routing behaviour of EVs while considering static traffic congestion – Ignoring convergence and scalability
[28]	Robust Optimisation	S, L	EVCS, BESS, PV, WG	• minimising investment & operational costs	+ Considering stability with Integrating EVCS – Ignoring dynamic traffic patterns
[29]	Slime Mould Algorithm	S, L	EVCS, BESS, PV, WG	• minimising power loss	+ Increasing convergence efficiency – Assuming constant EVCS loads, ignoring real-time variations in charging demand
[30]	Honey Badger Algorithm	S, L	EVCS, BESS, WG	• minimising energy loss	+ Reducing active and reactive energy losses – Ignoring the impact of EVCS – Ignoring real-time energy market participation
[31]	GA	L	EVCS, BESS, PV	• minimising active energy loss	+ Ensuring voltage stability improvement – Assuming perfect forecasting of load demand – Ignoring dynamic network conditions for BESS charging/discharging
[36]	Crow Search Algorithm - Particle Swarm Optimisation	S	EVCS, BESS, PV, WG, Mini-hydro	• minimising installation & operational costs	– Ignoring real-time market pricing fluctuations – Ignoring static grid constraints – Uses simplified power loss Modelling
[37]	Grey Wolf Optimisation	S, L	EVCS, BESS, PV	• minimising power loss & VD	– Ignoring real-time grid congestion effects – Relying on idealized renewable generation and storage assumptions
[35]	Gorilla Troop Optimisation	S, L	EVCS, BESS, PV, WG	• minimising power loss, VD, and line loading	+ Considering daily charging profiles – Assuming fixed renewable energy locations – Using idealized forecasting for PV and wind
[34]	Chaotic Student Psychology-Based Optimisation	S, L	EVCS, BESS	• minimising power loss, VD, energy loss cost, and operational cost	+ Proposing a time-sequenced optimisation + Considering multiple load types – Relying on simulated data

2.4 Transport-System Influences on Charging Infrastructure Deployment

While early studies on EV charging infrastructure planning primarily focused on electrical feasibility within distribution networks, the demand for EV charging services is fundamentally driven by mobility patterns within transportation systems. In practice, EV users require charging facilities that are spatially accessible along their travel routes and temporally aligned with travel demand. Consequently, EVCS deployment must account not only for electrical constraints but also for transportation-related factors that affect how frequently and efficiently charging infrastructure is used.

One of the most influential transportation factors affecting EVCS planning is spatial accessibility. Charging stations that appear optimal from a purely electrical perspective may still perform poorly if they are not conveniently accessible to EV users within the TN. Accessibility is therefore commonly evaluated in terms of travel distance, travel time, or Generalised travel cost required for EV drivers to reach charging facilities. Studies have shown that inadequate spatial distribution of EVCSs can lead to increased travel detours, inefficient routing behaviour, and uneven utilisation of charging infrastructure across urban regions. As a result, modern planning frameworks increasingly incorporate accessibility metrics to ensure that charging stations are deployed in locations that minimise user inconvenience while maintaining electrical feasibility.

Traffic dynamics represent another key determinant of charging demand patterns. Traffic congestion, road capacity constraints, and route choice behaviour shape vehicle movement across TNs and, in turn, influence the spatial distribution of potential charging demand. High-traffic corridors, urban centres, and major intersections frequently experience concentrated EV charging demand because of the high density of passing vehicles. Ignoring such traffic dynamics may lead to infrastructure deployment strategies that underestimate or misallocate charging demand across candidate locations. Consequently, several studies have incorporated traffic flow models and origin–destination (OD) travel data to more realistically estimate spatially distributed EV charging demand.

Queueing behaviour at charging stations also plays an important role in transportation-aware EVCS planning. As EV adoption increases, charging stations in high-demand areas may experience congestion and longer wait times, particularly during peak travel periods. Long queues at charging facilities can reduce service quality, discourage EV adoption, and increase the effective travel cost experienced by EV drivers. To address this issue, queueing models have been incorporated into EVCS planning frameworks to capture interactions among charging demand, service capacity, and waiting time. These models enable planners to evaluate not only where to locate charging stations but also how many chargers to install to maintain acceptable service levels.

Beyond these individual factors, transportation systems introduce significant temporal variability into EV charging demand. Travel behaviour fluctuates throughout the day according to commuting patterns, commercial activity, and broader urban mobility dynamics. Consequently, EV charging demand often exhibits pronounced temporal peaks that interact with traffic congestion patterns and road network usage. Planning models that incorporate time-varying traffic demand can therefore provide a more accurate representation of charging infrastructure utilisation compared with models based on static demand assumptions.

Despite these advances, many EVCS planning studies still represent transportation factors in simplified ways. In numerous models, traffic demand is approximated using aggregated EV penetration levels or simplified spatial demand distributions rather than detailed TN representations. Such simplifications may fail to capture the complex interactions among travel behaviour, charging accessibility, and infrastructure utilisation. As EV adoption continues to grow, these limitations highlight the need for more comprehensive planning approaches that explicitly integrate both electrical and transportation systems.

Recognising this challenge, recent research has increasingly explored integrated planning frameworks that combine TNs with power distribution systems in EVCS planning models. By jointly considering traffic flow patterns, accessibility constraints, and electrical network limitations, these frameworks aim to more accurately represent the operational environment in which EV charging infrastructure operates. The next section, therefore, reviews the emerging literature on coupled power–transportation planning approaches and discusses how integrated infrastructure models can improve the effectiveness and realism of EVCS deployment strategies.

2.5 Coupled Power–Transportation Planning

The rapid electrification of urban mobility is fundamentally reshaping the interaction between TNs and PDNs. Unlike conventional electrical loads, EV charging demand exhibits strong spatial and temporal variability driven by route choices, charging accessibility, and heterogeneous travel behaviours. As EV adoption increases, charging activities translate transportation dynamics into geographically concentrated and time-varying electrical stress on distribution feeders. At the same time, congestion and routing responses within transportation systems can redistribute charging demand across space and time. Consequently, EV charging infrastructure planning can no longer be treated within a single-network paradigm; rather, it must be formulated as a coupled power–transportation system problem in which transportation equilibrium and electrical feasibility are jointly considered [2, 3, 4].

Coupled PDN–TN planning enables a more realistic assessment of EVCS deployment by explicitly linking traffic flows with spatially resolved grid constraints. Such coordination mitigates the risks that arise when mobility attractiveness and electrical viability are assessed in isolation, including congestion-induced demand shifts, localised grid overload, and inefficient infrastructure investment [2, 17]. From a planning perspective, charging infrastructure introduces a strong interdependency between transportation systems and PDNs. Charging demand is determined by traffic flow patterns, driver behaviour, and urban mobility dynamics, both spatially and temporally, whereas the capacity to serve that demand depends on feeder limits, voltage constraints, and the availability of supporting flexible resources.

Accordingly, recent research has increasingly adopted integrated frameworks that simultaneously consider both transportation and electrical perspectives. In these coordinated planning approaches, traffic flows are used to estimate spatial charging demand, which is then evaluated against the PDN's operational limits. For example, Gan et al. [19] applied Mixed-Integer Quadratically Constrained Programming (MIQCP) to determine optimal EVCS locations based on traffic flow while minimising power loss. Similarly, Saadati et al. [39] integrated uncertainty in renewable energy and traffic deviation paths into a Mixed-Integer Linear Programming (MILP) framework to determine the optimal deployment of charging infrastructure. Campana and Inga [40] addressed the strategic deployment of fast-charging stations by integrating traffic conditions into PDN sizing, while Hou et al. [20] applied a heuristic method to optimise EVCS placement while balancing PDN loading.

Such integrated PDN–TN frameworks aim to align the objectives of multiple stakeholders, including EV drivers, charging infrastructure operators, and power network managers. From the PDN perspective, planning models typically focus on minimising power loss, VD, and investment cost while ensuring secure grid operation. From the TN perspective, the objective is to distribute charging demand efficiently across the TN, reduce congestion, and improve accessibility. Consequently, multi-objective optimisation approaches have become widely adopted in the literature to capture these competing objectives within a unified framework [9].

Despite these advances, the relationship between infrastructure planning and operational decision-making remains structurally uneven across much of the literature. Many studies do not explicitly distinguish between planning-layer decisions and operation-layer decisions within coordinated PDN–TN frameworks. Planning-layer decisions are long-horizon, largely irreversible choices, such as EVCS siting, capacity sizing, and phased expansion. In contrast, operation-layer decisions involve short-horizon, adaptive actions, including charging control, V2G scheduling, storage dispatch, pricing, and routing. Without a clear decision hierarchy, cross-study comparisons become structurally inconsistent: some works assume fixed infrastructure and optimise only operations, while others address siting under simplified or exogenous operational assumptions. This ambiguity obscures how transportation-driven demand is translated into grid-feasible infrastructure decisions and limits the practical interpretability of the literature for deployment-oriented planning.

More importantly, the absence of an explicit hierarchy prevents the formulation of consistent objective functions across planning and operation layers, leading to implicit assumptions about user response, charging behaviour, and system controllability. This ambiguity directly affects the interpretability and transferability of planning results.

Several additional limitations remain. Many frameworks focus primarily on the objectives of EV drivers or EVCS investors while giving limited attention to the operational requirements of distribution network operators. For example, some studies consider travel distance and charging costs without explicitly addressing VD or power loss constraints [10, 41, 42]. Conversely, grid-focused approaches may incorporate detailed power system constraints while representing transportation demand through simplified traffic assumptions. As a result, relatively few studies fully capture the interactions among EV drivers, infrastructure operators, and power system operators within a unified planning framework.

Another important limitation concerns the treatment of dynamic charging demand and travel behaviour. Several studies still rely on simplified assumptions regarding EV penetration levels, static demand distributions, or randomly generated charging patterns, which can lead to unrealistic infrastructure planning outcomes. In practice, EV charging demand is strongly influenced by traffic congestion, route-choice behaviour, travel schedules, and drivers' charging preferences. Ignoring these behavioural dynamics may lead to inaccurate demand estimates and suboptimal EVCS placement.

To make these differences more explicit, Table 2.2 summarises representative studies on coordinated PDN–TN EVCS planning. The table highlights not only the diversity of methods and objectives reported in the literature, but also the recurring gap between transportation-aware service modelling and PDN-aware technical feasibility.

Overall, coupled PDN–TN planning represents a decisive advance beyond single-domain EVCS planning. However, the literature still requires stronger integration of realistic traffic dynamics, clearer separation between planning and operational decision layers, greater use of real-world data, and more explicit consideration of flexibility-aware infrastructure design. These unresolved issues motivate the next sections, which examine the role of data-driven planning, V2G participation, and market-enabled flexibility in advancing EVCS allocation frameworks beyond conventional coupled formulations.

Table 2.2: Representative studies on coupled PDN–TN EVCS planning and integrated deployment strategies (S: sizing; L: location).

Ref.	Method	S,L	Objective Functions	Pros and Cons
[43]	Bilevel Optimisation	S, L	1- minimising annualized net cost 2- Satisfying PDN operational constraints	+ Reformulated as MILP for efficiency – Complex Modelling with high data
[44]	Stochastic Programming	S, L	1- Incorporate V2G technology 2- Consider human behaviour	+ Enables detailed stochastic Modelling – Requires extensive Behavioural data
[9]	MILP	L	1- minimising investment cost 2- minimising travel cost	+ Considering sensitivity analyses – Ignoring the benefit of the EVCS owner
[10]	RL (PPO-Attention)	L	1- maximising demand coverage 2- maximising fairness of EVCS distribution 3- minimising travel time	+ Considering charging demand – Ignoring power loss and voltage
[45]	Soft Actor-Critic (RL)	L	1- maximising charging service profit 2- minimising construction and maintenance cost 3- minimising distance cost	+ Considering the distance cost – Ignoring voltage and power loss – focus on long-term impacts
[11]	Voronoi diagram	L	1- minimising investment and operational costs 2- minimising travel cost	+ Considering queuing time – Ignoring the complexities of local traffic
[19]	MIQCP	L	1- minimising traffic congestion 2- Reducing investment Cost 3- minimising power loss	+ Considering traffic congestion + Considering validation different networks – Ignoring RES and economic analysis
[39]	MILP CDFRLM	S, L	1- minimising investment and installation cost 2- minimising energy loss 3- minimising unsatisfied charging demands	+ Considering the uncertainties in EV arrival SoC and renewable energy – Ignoring the benefit of the EVCS owner
[40]	Hungarian Algorithm	S, L	1- maximising load balance 2- maximising accessibility and efficiency	+ Considering heterogeneity in vehicle flow – Assuming ideal EV penetration patterns
[20]	Heuristic Algorithm	L	1- maximising economic benefits 2- maximising load balance	+ Considering SOC of BESS – Ignoring managing the traffic flow
[41]	Hungarian Algorithm	S, L	1- maximising charging demand effectively 2- maximising accessibility and efficiency	+ Considering the charging demand – Ignoring PDN objectives and constraints
[42]	Multi-Layer Perceptron	S, L	1- minimising installation cost 2- maximising demand coverage	+ Considering charging demand – Ignoring PDN objectives and constraints
[46]	Bi-layer Optimisation	S, L	1- minimising operation costs 2- maximising EVCS profits & EV user satisfaction	+ Considering incentive-based pricing – High complexity from bi-layer market model

2.6 Data-Driven Approaches for EV Charging Infrastructure Allocation

Accurate representation of EV charging demand is a fundamental prerequisite for effective EVCS planning. Early research in this area often relied on simplifying assumptions, such as uniform EV penetration levels, aggregated charging profiles, or randomly generated charging events, to represent EV demand. Although these assumptions simplify modelling and reduce computational complexity, they fail to capture the highly dynamic and spatially heterogeneous nature of EV charging behaviour. In reality, charging demand emerges from complex interactions among travel behaviour, traffic conditions, electricity consumption patterns, and user charging preferences. Consequently, planning frameworks that rely solely on simplified demand assumptions may lead to infrastructure deployment strategies that do not accurately reflect real-world charging requirements.

To address these limitations, recent studies have increasingly adopted data-driven approaches for EVCS planning. Data-driven methodologies leverage real-world datasets to estimate EV charging demand more accurately and to better represent the operational environment in which charging infrastructure is deployed. These datasets may include traffic flow measurements, origin–destination (OD) travel data, charging station utilisation records, smart meter electricity consumption data, and renewable generation profiles. By incorporating such datasets into planning models, researchers can capture the spatial and temporal variability of EV charging demand and significantly improve the realism of EVCS deployment strategies.

Transportation-related datasets play a particularly important role in data-driven EVCS planning frameworks. Traffic flow information and OD travel patterns provide valuable insights into vehicle mobility across TNs and enable planners to estimate where EV charging demand is most likely to occur. Similarly, queueing-aware and accessibility-aware demand representations improve the spatial accuracy of charging demand estimation compared with simplified demand assumptions. These approaches demonstrate that mobility data can substantially enhance the realism of EVCS planning, particularly in metropolitan areas where traffic concentration and urban accessibility strongly shape charging demand patterns.

Another important data source for EVCS planning is smart meter data obtained from electricity consumers. Smart meters provide high-resolution measurements of electricity consumption over time and can therefore be used to estimate the net demand profiles of households and buildings connected to distribution networks. Incorporating smart meter data into EVCS planning models allows researchers to evaluate how EV charging demand interacts with existing electricity consumption patterns in the grid. In particular, such information can help identify periods when surplus renewable generation may be available to support EV charging demand, thereby enabling more efficient use of distributed energy resources.

Data-driven approaches also enable a more accurate representation of temporal charging dynamics. EV charging demand typically exhibits strong daily and seasonal variations driven by commuting patterns, workplace mobility, and residential charging behaviour. By constructing time-dependent charging demand profiles from real-world observations, data-driven models can capture temporal fluctuations and evaluate how demand evolves throughout the day. This capability is particularly important for integrated energy and mobility systems, where charging demand must be coordinated with grid operational constraints and the availability of renewable generation.

At a broader methodological level, these approaches differ not only in algorithmic structure but in how they treat uncertainty, feedback, and decision coupling. Forecast-then-Optimise (FTO) frameworks remain sensitive to prediction errors due to their sequential nature, while Learn-to-Optimise (LTO) approaches improve adaptivity at the cost of reduced interpretability.

More critically, most paradigms still lack endogenous feedback between mobility behaviour and infrastructure decisions. Even in advanced frameworks such as POL and BLO, behavioural responses are often approximated rather than structurally embedded, limiting their ability to model real-world system adaptation.

Despite the advantages of data-driven planning frameworks, several challenges remain in their practical implementation. Data availability and accessibility can vary significantly across regions, and privacy considerations may restrict the use of detailed mobility or electricity consumption datasets. Furthermore, integrating heterogeneous datasets, such as transportation flows, electricity demand profiles, and renewable generation data, requires sophisticated modelling techniques and substantial computational resources. These challenges highlight the need for robust data processing and integration frameworks that can combine multiple data sources into unified EVCS planning models.

Nevertheless, the rapid expansion of urban mobility datasets, smart grid measurements, and charging infrastructure records has significantly accelerated the development of data-driven EVCS planning methodologies. By enabling infrastructure planning models better to represent real-world interactions between transportation systems and PDNs, these approaches have emerged as a critical research direction for designing reliable, data-informed, and deployment-relevant EV charging ecosystems.

Building on these developments, recent research has begun to explore advanced planning frameworks that integrate data-driven demand estimation with emerging technologies, such as bidirectional charging and V2G participation [47, 48, 49, 50, 51, 52]. These approaches aim to transform EV charging infrastructure from passive electricity-consumption facilities into active components of future integrated energy–mobility systems that provide operational flexibility and support grid stability. The following section, therefore, examines how V2G-enabled charging infrastructure can enhance system flexibility and unlock additional operational value within coupled power-TNs.

2.7 Impact of Bidirectional Charging on EV Charging Infrastructure Planning

V2G technology has emerged as a transformative concept in the evolution of electric mobility and smart energy systems. Unlike conventional unidirectional charging, where EVs act solely as electricity consumers, V2G enables bidirectional power exchange between EV batteries and the power grid. With a bidirectional charging infrastructure, EVs can store electricity during periods of low demand or high renewable generation and discharge energy back to the grid when additional support is needed. This capability enables EV fleets to serve as distributed energy storage resources, enhancing grid flexibility and supporting power system stability.

From a power system perspective, V2G participation provides several operational benefits. Bidirectional charging enables EV batteries to contribute to peak shaving, voltage support, frequency regulation, and energy balancing within distribution networks. By allowing EVs to discharge energy during peak-demand periods, V2G strategies can reduce network congestion and mitigate VDs resulting from concentrated charging demand. Furthermore, coordinated V2G operation can increase the hosting capacity of distribution networks by smoothing demand fluctuations and improving the utilisation of distributed renewable energy resources [47, 48, 49].

Another important advantage of V2G technology is its potential to facilitate the integration of renewable energy. The variability and intermittency of renewable generation, particularly from solar PV and wind, pose operational challenges for power systems. EV batteries participating in V2G programs can absorb excess renewable generation during periods of high output and release stored energy when renewable production declines. This capability helps reduce renewable curtailment and improves the overall efficiency of energy utilisation in smart grids [50, 51].

Beyond these technical benefits, V2G participation also creates new economic opportunities for EV owners and grid operators. Bidirectional charging allows EVs to participate in electricity markets by providing ancillary services, demand response, and energy trading. Through coordinated aggregation strategies, fleets of EVs can offer flexibility services to grid operators, thereby generating additional revenue streams while supporting system reliability. Several studies have therefore investigated optimal V2G scheduling strategies that maximise economic benefits while respecting battery degradation constraints and user mobility requirements [52].

In the context of EVCS planning, incorporating V2G capabilities fundamentally changes the role of charging infrastructure within energy systems. Conventional EVCS planning models typically treat charging stations as passive load centres that increase electricity demand within PDNs. When V2G participation is considered, however, charging stations become active energy hubs capable of both consuming and supplying electricity. This transformation introduces additional operational flexibility into infrastructure planning and enables more advanced strategies for managing EV charging demand.

Recent research has therefore explored integrated planning frameworks that incorporate V2G participation into EVCS allocation models. These frameworks aim to jointly determine the optimal placement of charging infrastructure and the operational strategies for bidirectional charging while accounting for transportation demand, power network constraints, and user behaviour. Within such models, EV batteries are treated as distributed storage resources, with their charging and discharging decisions coordinated to improve overall system performance.

Despite the promising potential of V2G technology, several challenges remain in its large-scale deployment. Battery degradation concerns, charging infrastructure costs, communication requirements, and uncertainties in user participation may limit the practical adoption of bidirectional charging systems. In addition, effective V2G operation requires advanced coordination mechanisms that balance the interests of EV drivers, charging infrastructure operators, and power system operators.

An additional limitation in the literature is that technical V2G capability is often assumed rather than modelled behaviourally and spatially. In practice, not all EV users are equally willing to participate in V2G programs, not all locations offer the same opportunities for bidirectional energy exchange, and not all V2G-capable charging stations provide the same level of practical flexibility. Consequently, V2G-enabled infrastructure should not be evaluated solely based on hardware availability. It must also be assessed in relation to the likelihood of participation, site characteristics, temporal availability, and operational coordination mechanisms.

For this reason, more recent studies have moved beyond static V2G assumptions and begun to examine user willingness, access radius, heterogeneity in participation, and integrated G2V/V2G planning [44, 50, 49, 48]. These developments are particularly relevant to this thesis, as they highlight a richer interpretation of EVCS planning in which bidirectional charging is not merely an operational add-on but a structural determinant of siting value, hosting capacity, and long-term system flexibility.

To summarise the V2G-related branch of the literature within the broader coupled-planning context, Table 2.3 lists representative studies that explicitly consider V2G, behaviour, or bidirectional charging in EVCS planning.

Table 2.3: Representative EVCS planning studies incorporating V2G, user behaviour, or bidirectional charging (S: sizing; L: location).

Ref.	Method	S,L	Objective Functions	Pros and Cons
[47]	Grey Wolf Optimiser	L	1- minimising EV transportation energy loss 2- minimising power loss	Illustrates the potential value of V2G integration, but without detailed traffic Modelling, VD, or VSI treatment.
[48]	Mixed-Integer Nonlinear Programming	S, L	1- minimising investment and operational costs 2- minimising travel cost under user equilibrium	Strong integration of V2G and traffic assignment, but PDN objective richness and operational hierarchy remain limited.
[49]	Gaussian Weighted Opposition Particle Swarm	L	1- minimising installation and operation costs 2- maximising net profit	Captures V2G and capacitor support, but omits several core PDN metrics such as VD and VSI.
[51]	GA and Self-Adaptive Multi-Population	S, L	1- minimising DG, EVCS investment/operation costs 2- Incorporating uncertainty and demand response	Useful scenario-based uncertainty and V2G inclusion, but traffic and user-behaviour realism remain weak.
[52]	Parallel search real-coded GA	S, L	1- minimising technical and operational costs 2- Integrating time-of-use (TOU) electricity pricing	Shows the importance of user response to TOU and V2G, but with limited PDN-feasibility representation.
[43]	Bilevel Optimisation	S, L	1- minimising annualized net cost 2- Satisfying PDN operational constraints	Methodologically rigorous and efficient after reformulation, but data requirements and Modelling complexity are high.
[44]	Stochastic Programming	S, L	1- Incorporating V2G technology 2- Considering human behaviour	A valuable step toward behaviour-aware V2G planning, though it requires extensive Behavioural data.

Overall, the V2G literature clearly demonstrates that bidirectional charging can substantially increase the technical and economic value of EVCS infrastructure. However, this value can only be fully realised when participation behaviour, spatial deployment characteristics, and coordinated operational strategies are considered together. These observations naturally raise the next question: how should the flexibility provided by V2G-enabled EV fleets be activated, coordinated, and valued within market-oriented energy systems?

2.8 EV Charging Infrastructure as a Market-Enabled Flexibility Resource

The rapid electrification of transportation systems has introduced a new class of flexible energy resources into modern power systems. EVs equipped with bidirectional charging capabilities can provide a wide range of flexibility services that support the operation of power networks. When aggregated across large fleets, EV batteries can serve as distributed energy storage resources that adjust charging and discharging behaviour in response to system conditions. This capability allows EV charging infrastructure to contribute not only to transportation electrification but also to providing flexibility services that enhance the efficiency and stability of future smart energy systems.

Flexibility provision refers to the ability of energy resources to adjust their power consumption or generation in response to system needs. In power systems with high penetration of renewable energy, flexibility has become increasingly critical for maintaining the balance between electricity supply and demand. Variability in renewable generation from solar PV and wind resources introduces operational fluctuations that must be compensated through flexible resources. EV batteries participating in coordinated charging programs can absorb surplus generation during periods of high renewable output and reduce charging demand during peak system conditions, thereby contributing to demand-side flexibility and grid balancing.

From an infrastructure perspective, EV charging stations represent strategic nodes through which aggregated EV fleets can provide grid services. Charging infrastructure operators can coordinate the charging behaviour of connected EVs to deliver services such as peak shaving, load shifting, and voltage support within distribution networks. By modulating charging demand in response to grid conditions, EVCS operators can reduce congestion in distribution feeders and improve the overall operational reliability of local power systems. Several studies have demonstrated that coordinated EV charging and discharging strategies can significantly improve distribution network performance while maintaining acceptable levels of user convenience [47, 48, 49].

Beyond technical grid support, EV fleet flexibility services can also participate in electricity markets. Market-enabled energy services allow aggregated EV resources to provide ancillary services, such as frequency regulation, contingency reserve, and demand response. Through appropriate aggregation mechanisms, EV fleets can respond to market price signals and deliver energy services that support system balancing while generating economic value for EV owners and infrastructure operators. These market-based mechanisms transform EV charging infrastructure from passive electricity consumers into active participants in electricity markets.

The integration of EV flexibility into electricity markets requires sophisticated coordination frameworks capable of managing large numbers of distributed resources. Aggregators play a central role in this process by coordinating the charging behaviour of multiple EVs and interacting with electricity markets on behalf of EV owners. Through aggregation platforms, EV fleets can provide flexible energy services while respecting operational constraints, including battery degradation limits, mobility requirements, and user charging preferences [48, 50, 51].

From a planning perspective, the introduction of market and pricing mechanisms moves EVCS design beyond purely static engineering formulations. Time-of-use tariffs, locational pricing, ancillary-service participation, and incentive-based charging strategies can all reshape where flexibility becomes valuable and which charging locations are economically attractive. However, market participation is not equivalent to technical capability. A charging station may be technically V2G-ready yet provide limited practical flexibility due to low user participation, poor temporal alignment, insufficient aggregation, or inadequate communication and control infrastructure. This distinction is particularly important for infrastructure planning, where the objective is not simply to quantify nominal flexibility but to identify deployable, economically realisable flexibility.

Recent research has therefore explored integrated planning frameworks that simultaneously consider EVCS deployment, power network constraints, transportation demand, and market participation mechanisms. These frameworks aim to determine how charging infrastructure should be located and operated to maximise both system reliability and economic value. Within such models, EV batteries are treated as distributed flexibility assets, with their charging and discharging decisions optimised across both energy and transportation systems.

Despite the promising potential of market-enabled flexibility services, several challenges remain in their practical implementation. Effective participation in electricity markets requires reliable communication infrastructure, advanced control strategies, and regulatory frameworks that allow distributed energy resources to provide market services. In addition, uncertainty in EV availability, user mobility behaviour, and charging preferences adds complexity to flexibility provision models. These uncertainties highlight the need for robust optimisation and coordination strategies to manage large EV fleets under uncertain operating conditions.

Nevertheless, the increasing penetration of EVs and the growing need for flexibility in renewable-dominated power systems have significantly intensified interest in EV-based flexibility services. As energy systems transition toward decentralised and digitally coordinated architectures, EV charging infrastructure is expected to play an increasingly important role in supporting both grid stability and electricity market operation. The remaining question is, therefore, methodological: which planning approaches can integrate transportation dynamics, power network constraints, data-driven demand estimation, and flexibility-oriented market participation into practical, deployable EVCS infrastructure decisions?

2.9 Methodological Approaches for Infrastructure Planning

Planning EV charging infrastructure within modern energy–mobility ecosystems has evolved into a complex multidisciplinary optimisation problem. Effective EVCS deployment requires simultaneous consideration of electrical constraints in PDNs, mobility dynamics in TNs, user behaviour, and economic objectives. As a result, planning frameworks increasingly rely on advanced computational methodologies to solve large-scale, nonlinear, and multi-objective decision problems.

Early studies in EVCS infrastructure planning primarily relied on deterministic mathematical optimisation approaches. In these formulations, EVCS siting and sizing are typically expressed using MILP, Mixed-Integer Quadratically Constrained Programming (MIQCP), or related convex optimisation frameworks. For example, Gan et al. [19] applied MIQCP to determine optimal charging-station locations while accounting for traffic-flow constraints. Similarly, Saadati et al. [39] addressed the joint optimisation of fast-charging station deployment and renewable energy integration using a capacitated deviation-flow refuelling-location model combined with MILP formulations. Such analytical approaches provide strong mathematical guarantees and clear interpretability; however, they often struggle to scale when nonlinear grid dynamics, stochastic demand patterns, and high-dimensional decision spaces are incorporated.

To address the computational complexity of EVCS planning, researchers have increasingly adopted metaheuristic optimisation techniques. These algorithms are particularly well-suited to solving large-scale NP-hard combinatorial problems, such as the optimal siting and sizing of EVCS and BESS assets. Metaheuristic approaches, including GAs, Particle Swarm Optimisation (PSO), Grey Wolf Optimisation (GWO), and other swarm intelligence methods, have therefore been widely applied in the literature. For instance, GWO has been used to simultaneously minimise EV transportation energy loss and power loss in distribution networks [47]. Yuvaraj et al. [29] employed a Slime Mould Algorithm to reduce network power losses in systems with EVCS integration. Other studies have proposed hybrid swarm intelligence approaches to improve convergence efficiency and mitigate premature convergence issues. Deb et al. [33], for example, introduced a hybrid algorithm combining Chicken Swarm Optimisation (CSO) and Teaching-Learning-Based Optimisation (TLBO) within a multi-objective framework to enhance grid stability while allocating charging stations in the IEEE 33-bus network.

Despite their flexibility, metaheuristic approaches typically rely on predefined models of charging demand and user behaviour. Because EV charging demand is highly stochastic and strongly influenced by traffic dynamics, recent research has increasingly explored learning-based methodologies that capture complex behavioural patterns and system interactions. RL algorithms, in particular, have emerged as powerful tools for EV charging planning and operational control. Ding et al. [53] proposed a Deep Deterministic Policy Gradient (DDPG) framework in which two-layer agents coordinate EV charging scheduling and voltage regulation in distribution networks. Similarly, Zhao et al. [54] introduced a multi-agent deep RL framework based on MADDPG to recommend optimal charging stations in multi-regional urban environments. Learning-based methods enable infrastructure planning frameworks to adapt dynamically to traffic conditions, charging demand variability, and grid states, which is particularly valuable in coupled PDN–TN environments.

Recognising the complementary strengths of optimisation and learning approaches, recent studies have increasingly explored hybrid methodologies. Hybrid frameworks aim to combine the strong search capabilities and constraint-handling of optimisation algorithms with the adaptive learning capabilities of data-driven models. For example, Adetunji et al. [7] proposed a hybrid framework that combines GA, the Whale Optimisation Algorithm (WOA), and RL to determine the optimal placement of distributed generation units and BESS assets in distribution networks. Other integrated frameworks combine evolutionary optimisation with deep RL to jointly address infrastructure planning and operational decision-making.

At a broader methodological level, the recent review literature indicates that EVCS planning approaches can be organised into several distinct planning paradigms, including FTO, LTO, Graph-based Candidate Screening (GCS), Plan–Operate–Learn (POL), Bi-Level Optimisation (BLO), and Simulation-Based Optimisation (SBO). These paradigms differ not only in the algorithms employed but also in how they structure the interaction between prediction, optimisation, simulation, and operational feedback. FTO separates forecasting and optimisation into sequential stages and remains attractive for its transparency and tractability, though it is vulnerable to the propagation of forecast errors. LTO replaces repeated optimisation with learned policies that enable rapid online inference but introduce challenges related to interpretability and dependence on training data. GCS improves scalability by filtering large candidate sets before detailed optimisation, although it risks excluding globally optimal locations if screening criteria are overly restrictive. POL establishes a closed loop between planning, operation, and learning, improving adaptivity but requiring advanced sensing and control infrastructure. BLO captures hierarchical interactions between long-term planning decisions and short-term operational responses, though it often leads to computationally demanding formulations. Finally, SBO provides high modelling flexibility by coupling detailed simulators with optimisation algorithms, albeit at high computational cost.

Because EVCS infrastructure planning involves multiple competing objectives, multi-objective optimisation has become a central paradigm in the literature. Power system operators typically aim to minimise power losses, VDs, and operational costs, while transportation planners seek to minimise travel time, charging detours, and waiting times. Infrastructure investors, meanwhile, prioritise profitability and service reliability. To address these conflicting objectives, modern planning frameworks frequently employ Pareto-based optimisation techniques. Multi-objective evolutionary algorithms such as NSGA-II and NSGA-III are widely used to approximate Pareto-optimal solution sets, enabling planners to evaluate trade-offs among economic, technical, and service-oriented objectives.

More recently, integrated planning frameworks have combined multi-objective optimisation with data-driven modelling and traffic-aware demand estimation. These approaches incorporate real-world datasets, such as smart meter measurements, renewable generation profiles, traffic flows, and EV charging demand observations, to enhance the realism and practical relevance of EVCS planning models. Overall, the methodological evolution of EVCS planning reflects a transition from deterministic optimisation to hybrid, data-driven, and learning-enabled planning architectures that capture the complex interactions among power systems, TNs, EV user behaviour, and electricity markets.

Building on these methodological advancements, this thesis presents an integrated planning and operational framework that combines multi-objective optimisation, RL, and real-world data integration. This hybrid methodology enables coordinated decision-making across coupled PDN and TN environments, supporting efficient EVCS deployment while simultaneously addressing grid stability, transportation efficiency, and emerging market-based flexibility mechanisms.

2.10 Knowledge Gaps and Design Requirements for Integrated EVCS Planning

The preceding sections reviewed the major strands of EVCS planning research, including PDN-oriented siting, coordination with local energy resources, transportation-aware deployment, coupled PDN–TN modelling, data-driven demand estimation, bidirectional charging, market-enabled flexibility, and methodological advances in optimisation, learning, and hybrid planning strategies. Collectively, this literature shows that EV charging infrastructure has evolved from a conventional location–allocation problem into a coupled energy–mobility infrastructure planning problem. EVCS deployment must therefore support transport electrification while maintaining distribution-network reliability, ensuring user accessibility, and enabling flexible energy services under increasingly complex operational conditions.

The reviewed literature also reveals a clear methodological progression. Early EVCS planning studies primarily emphasised transport-side service coverage and facility allocation, while later grid-aware formulations incorporated feeder constraints, voltage regulation, and power-loss considerations. More recent coupled PDN–TN models have sought to link mobility-driven demand formation to distribution-network feasibility, and emerging studies further extend this coupling through data-driven demand modelling, BESS coordination, V2G participation, and market-enabled flexibility. This progression confirms that the central challenge is no longer the isolated placement of charging stations, but the design of a coordinated planning architecture that links infrastructure decisions, mobility behaviour, grid constraints, and operational flexibility.

Despite substantial progress, the review also shows that several structural limitations continue to restrict the relevance of existing EVCS planning frameworks for deployment.

First, many studies remain primarily grid-centric. EV charging demand is often represented using aggregated load profiles, assumed penetration levels, or fixed charging scenarios without explicitly linking demand to real mobility behaviour. Such approaches are useful for assessing electrical feasibility, but they do not explain where, when, and why charging demand emerges in transportation systems. Since EV charging demand is shaped by traffic flow, route choice, accessibility, state of charge, service availability, and queueing conditions, treating it as an exogenous electrical input can produce infrastructure decisions that are technically feasible but behaviourally misaligned.

Second, although recent studies increasingly recognise the need to couple PDNs and TNs, the degree of coupling often remains partial. Transportation information is often captured using simplified indicators such as static traffic density, distance-based demand coverage, or aggregated demand proxies. These abstractions may overlook the spatiotemporal interaction between traffic flows, station accessibility, queueing, and the electrical stress imposed on specific feeder locations. As a result, many coupled models still struggle to represent how mobility-side dynamics reshape power-network impacts and how grid constraints, in turn, influence charging-service accessibility.

Third, the use of real-world data remains uneven across the literature. Many EVCS planning studies rely on synthetic charging profiles, stylised traffic scenarios, or simplified electricity-demand assumptions. While such models are analytically useful, they can limit the transferability of planning outcomes to practical deployment environments. Integrated infrastructure planning requires empirical grounding through realistic representations of load, PV, traffic, and charging demand so that the spatial and temporal variability of real urban systems can be captured more credibly.

Fourth, most planning models still treat EVs primarily as passive and unidirectional electrical loads. V2G technology challenges this assumption by enabling EVs to serve as distributed flexibility resources that support peak-load management, voltage regulation, renewable integration, and energy-market services. However, the planning value of V2G depends on user willingness, EV availability, battery state of charge, spatial location, incentives, and market activation. Therefore, assuming uniform or fully available V2G participation can substantially overestimate the flexibility that is practically realisable.

Fifth, market-oriented flexibility remains insufficiently embedded in EVCS infrastructure planning. Aggregated EV fleets, BESS units, and bidirectional charging stations can potentially participate in demand response, energy trading, and ancillary-service markets. Nevertheless, most planning frameworks focus primarily on technical feasibility and network performance, while the interaction between infrastructure placement, flexibility availability, and market-based activation is treated only superficially or excluded altogether. This limits planning models' ability to evaluate the practical economic value of flexibility-enabled charging infrastructure.

Sixth, a persistent separation remains between long-term infrastructure planning and short-term operational coordination. EVCS siting and capacity decisions are often optimised independently from operational strategies such as charging control, BESS dispatch, voltage regulation, or V2G scheduling. Conversely, operational studies usually assume fixed infrastructure configurations. This separation weakens the practical value of planning outcomes because real charging behaviour and network conditions frequently deviate from nominal planning assumptions.

Finally, the literature still lacks a sufficiently clear decision structure for distinguishing planning-layer variables from operational and market-mediated actions. Siting and sizing decisions are long-term and largely irreversible, whereas BESS dispatch, charging control, routing, pricing, and V2G activation are short-term adaptive decisions. When these layers are blended without an explicit hierarchy, it becomes difficult to determine whether the observed benefits stem from improved infrastructure placement, operational control, demand redistribution, or market participation. This reduces the interpretability of planning results and limits their usefulness for deployment-oriented decision-making.

Taken together, these gaps indicate that next-generation EVCS planning frameworks must satisfy several design requirements. They must:

- represents EV charging demand as a mobility-driven and time-varying phenomenon rather than as a static exogenous load;
- jointly evaluate electrical feasibility and transportation-side service performance;

- coordinate EVCS deployment with local flexibility resources such as BESSs and renewable generation;
- use realistic data inputs to improve the credibility and transferability of planning outcomes;
- distinguish between nominal V2G capability and behaviourally realisable V2G participation;
- account for market-enabled flexibility mechanisms where EVs and storage resources contribute to system operation;
- connect long-term infrastructure decisions with operational control layers to ensure that planned deployments remain feasible under real-time variability; and
- maintain a clear decision hierarchy between planning variables, operational controls, and market-mediated flexibility actions.

These requirements motivate the central research direction of this thesis. The thesis develops a progressively integrated, data-driven EVCS planning framework that moves from grid-aware infrastructure planning to coupled power–transportation planning and finally to flexibility-aware planning with V2G participation and market-driven activation. This progression is not merely chronological; it reflects a sequence of modelling refinements that address the structural limitations identified in the literature.

Based on the gaps and design requirements synthesised above, the thesis addresses the following research questions:

RQ1: How can EVCS and BESS infrastructure be jointly planned and operationally coordinated in PDNs to mitigate voltage instability, reduce technical stress, and improve grid support under time-varying charging demand?

RQ2: How should EV charging infrastructure be optimally planned in coupled power distribution and transportation networks when charging demand is shaped jointly by electrical constraints, traffic flow dynamics, accessibility, travel cost, and queueing behaviour?

RQ3: How do V2G participation behaviour, heterogeneous user profiles, and market-driven flexibility mechanisms affect the planning and operational value of EVCS and BESS infrastructure in coupled PDN–TN environments?

These research questions are deliberately sequential rather than independent. RQ1 establishes the planning–operation foundation within the electrical domain by coordinating EVCS and BESS deployment under distribution-network constraints. RQ2 addresses the limitation of grid-only planning by introducing mobility-driven charging demand and transportation-side service quality into the planning framework. RQ3 then extends the coupled PDN–TN formulation by modelling EVs not only as charging loads, but as conditional flexibility resources whose contribution depends on behavioural participation and market activation.

This progression defines the thesis's scientific contribution. At the first level, the thesis contributes a coordinated EVCS–BESS planning and operation framework that links infrastructure placement with adaptive BESS support. This addresses the limitation of planning models that assume demand profiles are realised exactly during operation. By allowing BESS units to respond to voltage deviations and demand variability, the framework connects long-term planning with short-term operational support.

At the second level, the thesis contributes a coupled PDN–TN planning framework in which charging demand is derived from transportation-system dynamics rather than imposed as a fixed electrical input. By incorporating traffic-informed demand, travel cost, accessibility, and queueing performance, the framework aligns grid feasibility with mobility-side service requirements. It provides a more realistic basis for EVCS siting and sizing.

At the third level, the thesis contributes a flexibility-aware EVCS planning framework that explicitly models heterogeneous V2G participation and market-driven activation. This distinguishes between nominal V2G capacity and practically realisable flexibility, thereby reducing the risk of overestimating EV contributions to grid support. It also clarifies how behavioural and economic conditions influence the planning value of bidirectional charging infrastructure.

Across all three levels, the thesis is grounded in real-world Melbourne and Victoria datasets, including traffic measurements, residential demand, PV generation, and charging-demand representations. This empirical grounding strengthens the relevance of the proposed framework for deployment and supports its interpretation as a decision-support approach for future urban energy–mobility systems.

The research narrative that follows from these contributions is one of progressive enrichment. The thesis begins by addressing the electrical-domain problem of EVCS and BESS coordination, then extends the planning boundary to include transportation-driven demand formation, and finally introduces V2G-enabled flexibility and market participation. Each stage resolves a limitation of the previous one: RQ1 links planning and operation, RQ2 links charging demand to mobility behaviour, and RQ3 links infrastructure planning to the provision of conditional flexibility. As a result, the thesis advances EVCS planning from static, grid-centred allocation toward a coordinated, data-driven, and flexibility-aware infrastructure design paradigm.

The subsequent chapters implement this progression. Chapter 4 develops the coordinated EVCS–BESS planning and operation framework for PDNs. Chapter 5 extends the formulation to coupled PDN–TN planning using traffic-informed charging demand and real Melbourne mobility data. Chapter 6 incorporates heterogeneous V2G participation, market-enabled flexibility, and operational coordination. Through this structure, the thesis bridges the gap between theoretical EVCS planning models and the practical requirements of deployable infrastructure planning in integrated future energy–mobility systems.

Chapter 3

Real-World Data and Experimental Design

This chapter establishes the unified data, modelling, and experimental foundation used throughout the thesis. While Chapter 2 identified the literature gaps and design requirements for integrated EVCS planning, this chapter defines the empirical and computational environment in which the proposed frameworks are developed, evaluated, and compared. Its role is therefore not to introduce a new optimisation method, but to provide the common experimental backbone that supports the progressively enriched planning studies in Chapters 4–6.

The chapter is constructed using real-world datasets from Melbourne and the broader Victoria region, including residential smart-meter demand, rooftop PV generation, traffic measurements, road infrastructure attributes, and public transport statistics [55, 56, 57, 58]. These datasets represent both the electrical and mobility dimensions of EVCS planning. On the electrical side, the data support time-varying load and PV modelling within modified IEEE distribution feeders. On the mobility side, traffic and road network information are used to construct transportation-driven representations of charging demand. This combination ensures that EV charging demand is not treated merely as an externally imposed electrical profile, but as a demand process linked to urban movement, accessibility, and service conditions.

A central purpose of this chapter is to ensure consistency across the thesis case studies. The three main research stages differ in modelling scope: Chapter 4 focuses on grid-oriented EVCS–BESS planning and operation, Chapter 5 extends the problem to coupled PDN–TN planning, and Chapter 6 incorporates V2G participation and market-driven flexibility. Despite these differences, all three stages rely on a common experimental logic based on a 24-hour horizon, 48 half-hour time intervals, real Victorian demand and PV data, traffic-informed construction of charging demand, and common performance indicators. This consistency is essential because it allows the thesis to evaluate the effect of increasing model realism without treating each research chapter as a disconnected case study.

The modelling environment is designed to preserve the key structural dependencies between mobility-driven demand formation and feeder-level electrical response. Transportation conditions influence where and when charging demand emerges, while power distribution constraints determine whether the resulting infrastructure deployment is technically feasible. Similarly, BESS and V2G-related mechanisms are evaluated not as isolated add-ons, but as flexibility resources whose value depends on their interaction with charging demand, local network stress, and operational conditions. The resulting coupled modelling environment is summarised in Fig. 3.1, which illustrates how transportation-driven demand formation is connected to feeder-level technical evaluation within the thesis case-study structure.

In addition to defining the data environment, this chapter establishes the scenario structure, key performance indicators (KPIs), benchmark models, parameter settings, computational implementation, and validity boundaries for subsequent chapters. The scenario design enables cumulative comparison throughout the thesis by progressing from grid-oriented planning to traffic-informed infrastructure deployment, and finally to flexibility-aware planning under heterogeneous V2G participation. The KPI structure ensures that each scenario is evaluated across grid performance, transportation service quality, and infrastructure economics rather than through a single isolated metric.

The remainder of the chapter is organised as follows. Section 3.1 defines the Melbourne/Victoria case-study context, planning assumptions, and spatial–temporal scope. Sec-

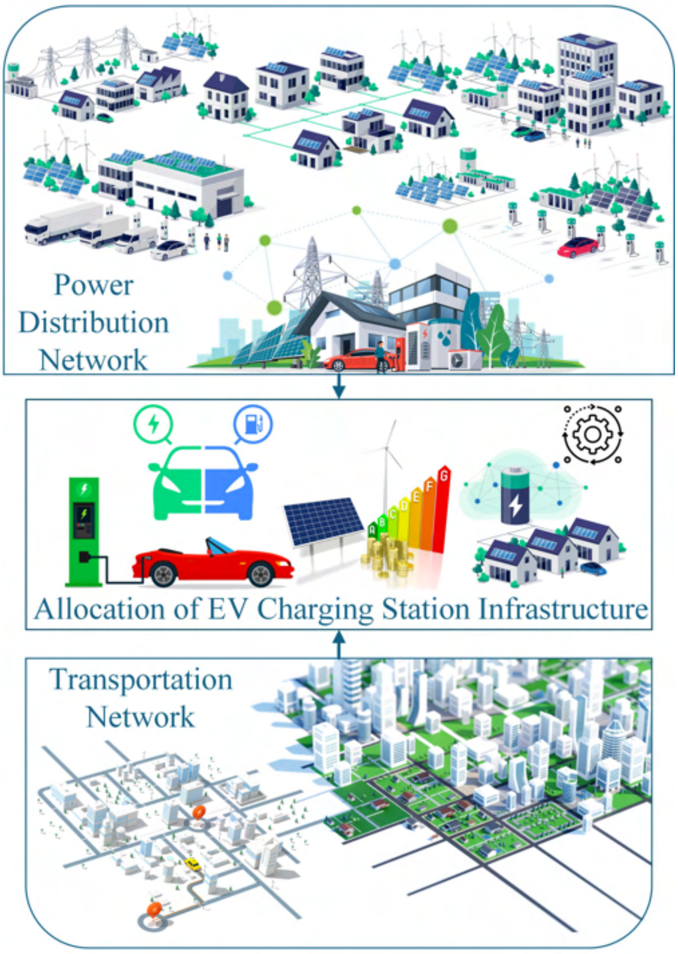


Figure 3.1: Conceptual representation of the coupled PDN–TN modelling environment used for data-driven EV charging infrastructure planning.

tion 3.2 presents the electrical distribution-network representation and datasets. Section 3.3 describes the transportation-network model and mobility data processing. Section 3.4 develops the traffic-informed charging-demand formulation. Section 3.5 defines the scenario structure, evaluation metrics, benchmark models, and parameter calibration strategy. Finally, Section 3.6 discusses the computational implementation, reproducibility, and validity boundaries of the experimental framework.

3.1 Study Context and Assumptions

This section defines the common study context, spatial and temporal scope, and planning assumptions that support all subsequent analyses in the thesis. Its purpose is to establish a single, coherent experimental backbone so that the later chapters can focus on methodological development and comparative interpretation without reintroducing case-specific assumptions.

The modelling environment is constructed to preserve the key structural dependencies between mobility-driven demand formation and feeder-level electrical response. This ensures that charging demand is not imposed as an external input, but emerges from traffic dynamics and is evaluated under explicit network feasibility constraints. Consequently, infrastructure decisions derived within this environment remain consistent with both behavioural demand formation and physical grid limitations. The resulting coupled modelling environment is summarised in Fig. 3.1, which illustrates how transportation-driven demand formation is linked to feeder-level technical evaluation within the thesis case study structure.

3.1.1 Melbourne/Victoria Case Study

The case study adopted in this thesis is centred on Melbourne, Victoria, Australia. Melbourne provides a particularly suitable environment for evaluating integrated EV infrastructure planning because it combines dense urban mobility corridors, heterogeneous residential electricity demand patterns, high rooftop PV penetration, and increasing EV adoption. These characteristics create strong interactions between transportation activity and distribution network operations, making the region a relevant testbed for coordinated planning of EVCS and BESS.

In such urban environments, poorly located charging infrastructure can simultaneously intensify feeder loading, increase VD, exacerbate network losses, and reduce user accessibility by increasing travel distance and queuing delays [9, 11]. This context introduces a constrained planning environment in which infrastructure decisions must satisfy simultaneous feasibility conditions across both network layers, rather than being optimised independently within each domain.

Within this case-study environment, the modelling framework must preserve voltage security, capture traffic flow and accessibility patterns, and remain compatible with the flexibility extensions introduced later in the thesis, including heterogeneous V2G participation and market-based activation mechanisms.

To construct this environment, the thesis integrates multiple real-world datasets on electrical and transportation systems from Melbourne and Victoria. On the transportation side, traffic measurements are obtained from VicRoads datasets and associated public resources, covering 60 major intersections and 95 roads that represent important urban travel corridors [55]. On the electrical side, residential load and PV generation data are derived from smart-meter and PV monitoring datasets collected across Victoria [58]. Additional geographic and infrastructure datasets describing road attributes, lane numbers, traffic signals, weather conditions, proximity to public transport, and regional EV statistics are obtained from public government data portals [56, 57].

This multi-source dataset integration allows the thesis to move beyond abstract planning assumptions and evaluate EV charging infrastructure deployment under realistic Australian urban conditions. Moreover, because the framework is calibrated using local traffic, electricity demand, and mobility conditions, the resulting analyses provide insights directly relevant to practical planning questions faced by utilities, charging network operators, and transport planners concerned with EV infrastructure deployment in Australian cities.

3.1.2 Spatial and Temporal Scope

The spatial scope of this thesis is defined through the coordinated representation of a PDN and, where applicable, a TN. On the electrical side, the study employs modified IEEE distribution feeders populated using real-world Victorian energy datasets. For grid-oriented planning investigations, the IEEE 33-bus and IEEE 123-bus systems are used to evaluate the behaviour of the proposed framework across benchmark feeders with varying sizes and structural characteristics.

In the coupled PDN–TN studies, the modified IEEE 33-bus feeder is integrated with a Melbourne-based TN. The TN is represented as a graph in which nodes correspond to major intersections and links represent impedance-weighted road connections. In the Melbourne case study, the network comprises 60 intersections and 95 roads derived from real traffic and road infrastructure datasets [55]. Traffic measurements are spatially mapped to the network using geographic proximity and road connectivity so that observed mobility patterns correspond to specific nodes and links in the transportation graph.

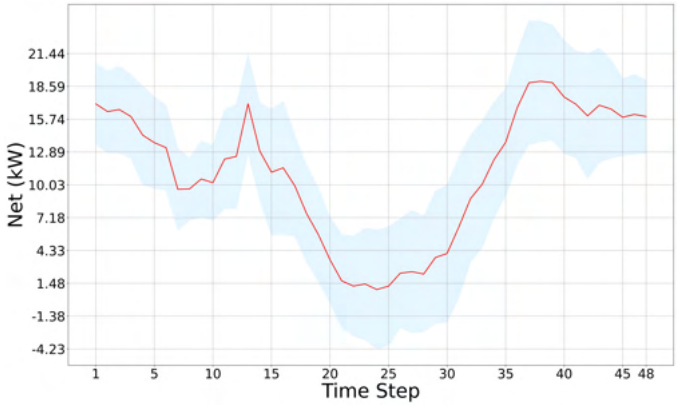


Figure 3.2: Average residential smart-meter net-demand profile used for the IEEE 33-bus case-study network.

The temporal scope of the thesis is defined as a representative 24-hour weekday operating cycle, discretised into 48 half-hour intervals. This temporal resolution is adopted consistently across the electrical, transportation, and charging-demand models. The 30-minute resolution is selected because it is sufficiently fine to capture the principal daily transitions relevant to EV infrastructure planning, including morning commuting peaks, midday PV generation, afternoon traffic build-up, and evening charging concentration, while remaining computationally tractable for time-indexed simulation and optimisation.

To maintain representativeness, the datasets used in the analysis correspond to typical weekdays under moderate weather conditions, with ambient temperatures generally between 20°C and 30°C. This filtering avoids anomalous operating days and ensures that the derived electrical and mobility patterns reflect normal urban conditions. Figure 3.2 shows the aggregated smart-meter net-demand profile, which exhibits the expected residential daily pattern with reduced daytime demand due to PV generation and increased evening demand associated with household activity and EV charging. Based on the same 48-interval horizon, Fig. 3.3 presents the temporal distribution of EV charging demand, highlighting the expected concentration of mobility-driven charging requirements across the day. The spatial counterpart of this variation is shown in Fig. 3.4, where peak charging demand is unevenly distributed across the TN and concentrated at intersections with higher traffic intensity and stronger accessibility.

The adopted spatial and temporal configuration provides a consistent evaluation backbone that preserves both temporal variability and spatial heterogeneity while maintaining computational tractability. This balance is essential because it allows the planning frameworks in subsequent chapters to capture realistic system interactions without incurring prohibitive computational complexity.

3.1.3 Planning Horizon and Core Assumptions

The planning assumptions adopted throughout this thesis are formulated as a coherent representation of demand formation, network feasibility, and service-level constraints, rather than as independent modelling simplifications.

EV charging demand is modelled as a spatiotemporal outcome of mobility behaviour, battery state-of-charge dynamics, and charging preferences. This ensures that demand is not imposed as an exogenous electrical load but instead emerges consistently from TN conditions.

From the power system perspective, distribution network operation is constrained to standard voltage limits (0.95–1.05 pu), while BESSs operate within defined state-of-charge bounds. These constraints ensure that all planning solutions remain physically feasible and compatible with distribution network operation.

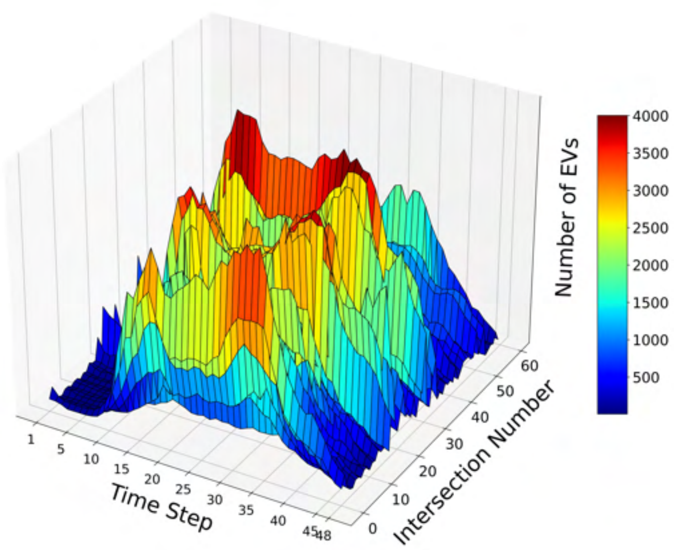


Figure 3.3: Temporal distribution of EV charging demand across TN intersections over the 24-hour planning horizon.

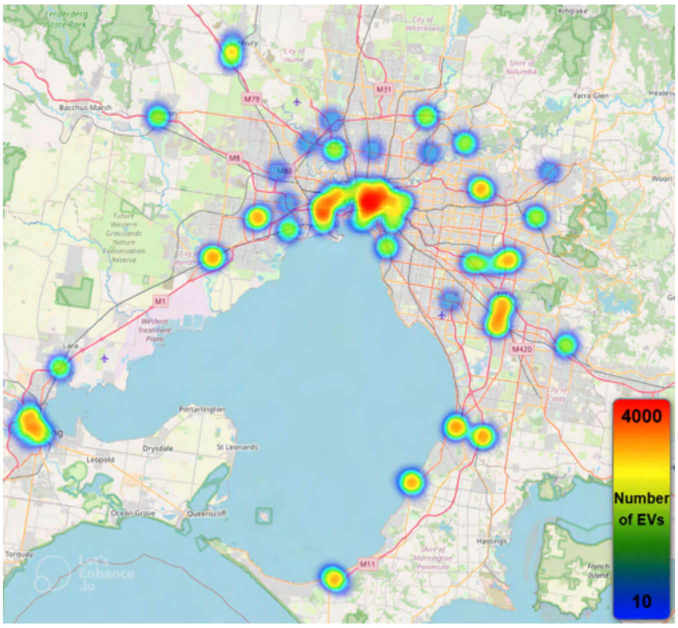


Figure 3.4: Spatial distribution of peak EV charging demand across TN intersections.

At the infrastructure level, EVCS deployment is subject to service-oriented constraints, including a bounded waiting time, a maximum allowable travel distance, and a minimum inter-station spacing. These conditions ensure that optimised solutions remain meaningful from the perspectives of user accessibility and service quality.

The underlying demand environment incorporates heterogeneous residential energy profiles, including varying levels of PV and BESS penetration across households. In advanced scenarios, V2G participation is modelled as conditional and behaviour-dependent rather than deterministic, reflecting realistic uncertainty in participation.

All datasets represent representative weekday conditions under moderate temperature ranges, ensuring that the resulting system behaviour reflects typical urban operation rather than extreme or atypical scenarios.

Collectively, these assumptions define a behaviourally consistent and physically constrained planning environment, enabling meaningful evaluation of EVCS and BESS deployment strategies across the subsequent chapters.

3.2 Power Distribution Network Data and Representation

This section establishes the electrical-network foundation used throughout the thesis to evaluate the coordinated planning and operation of EVCSs and BESSs. Because the proposed framework is ultimately assessed through its impact on distribution-grid performance, the PDN representation must preserve the key structural and operational characteristics that govern voltage behaviour, feeder losses, network stability, and local hosting capacity.

To achieve this objective, the thesis adopts modified benchmark distribution feeders populated with real-world Victorian residential load and PV generation data. This approach combines the analytical transparency of standard IEEE test systems with the practical realism of measured operating conditions, allowing feeder-level electrical behaviour to be evaluated under realistic net-demand dynamics rather than stylised benchmark assumptions alone. As a result, the electrical environment used in the thesis reflects realistic net-demand dynamics and the penetration of distributed energy resources rather than purely synthetic load assumptions.

The PDN representation plays two complementary roles across the thesis. First, it provides a physically meaningful environment for assessing the grid-side consequences of EVCS deployment, including impacts on power loss, VD, and voltage stability. Second, it enables evaluation of how BESS integration, traffic-driven charging demand, and, in advanced scenarios, V2G-enabled flexibility influence feeder operation under realistic, time-varying conditions. Consequently, the adopted network models are not treated merely as abstract benchmark systems but as structured electrical backbones into which measured household demand, distributed PV generation, and EV-related charging profiles are embedded. This PDN representation therefore forms the common electrical layer linking the grid-oriented analysis of Chapter 4, the coupled PDN–TN planning framework of Chapter 5, and the flexibility-aware extensions developed in Chapter 6.

3.2.1 Topology, Electrical Limits, and Test Feeders

The electrical case studies in this thesis are constructed using modified IEEE distribution test feeders to ensure methodological transparency and comparability with the existing literature. Two benchmark networks are employed: the IEEE 33-bus radial distribution feeder and the IEEE 123-bus feeder. The IEEE 33-bus system serves as the primary benchmark because it offers a clear radial topology widely used to analyse the voltage-sensitive impacts of EV charging integration. The IEEE 123-bus feeder is also used to examine the behaviour of the proposed framework on a larger, more detailed benchmark distribution network configuration.

The IEEE 33-bus feeder operates at a nominal voltage of 12.66 kV with a base apparent power of 100 MVA, consistent with the configuration adopted in the journal studies underlying this thesis. In the coupled PDN–TN case studies, this feeder serves as the electrical backbone of Melbourne, TN, enabling direct analysis of how traffic-driven EV charging demand maps onto feeder-level electrical constraints.

The feeders are not used in their original benchmark form. Instead, they are enhanced to accommodate distributed residential demand, rooftop PV generation, BESS integration, and EVCS installations. Each bus is treated as an aggregated service node that supplies residential consumers with heterogeneous distributed energy resources. This modelling interpretation enables the feeder structure to represent practical urban electricity environments rather than purely theoretical benchmark systems.

To ensure operational feasibility, feeder operation is constrained by standard distribution-network voltage limits:

$$V_{\min} \leq V_m \leq V_{\max}, \quad m = 1, 2, \ldots, M \tag{3.1}$$

where the minimum and maximum voltage limits are set to 0.95 pu and 1.05 pu, respectively. These bounds are applied consistently across all case studies and constitute a primary feasibility constraint for EVCS and BESS planning.

In addition, BESS operation is governed by state-of-charge dynamics:

$$\varphi_i(u+1) = \varphi_i(u) + T \times P_i(u) \tag{3.2}$$

where $P_i(u)$ denotes the BESS charging or discharging power at bus i during time interval u, and $T = 0.5$ represents the 30-minute time-step resolution used throughout the thesis. The SOC is constrained within operational limits:

$$\varphi_{\min} \leq \varphi_i(u) \leq \varphi_{\max} \tag{3.3}$$

with $\varphi_{\min} = 0.2$ and $\varphi_{\max} = 0.9$ of the BESS capacity. These limits ensure realistic battery operation and prevent excessive cycling or over-discharge conditions.

Therefore, the combined use of the IEEE 33-bus and IEEE 123-bus feeders provides a balanced experimental environment. The smaller feeder offers a transparent platform for analysing mobility–grid interactions. In comparison, the larger feeder provides an additional benchmark for assessing the consistency of the planning methodology across a more extensive distribution network configuration.

3.2.2 Load, PV, and BESS Data Construction

The electrical demand environment used in this thesis is derived from real-world residential datasets collected in Victoria, Australia. Smart-meter electricity consumption records and rooftop PV generation profiles are aggregated to construct feeder-level net-demand conditions over a representative weekday horizon.

For the modified IEEE 33-bus system, each bus represents an aggregation of 20 residential households. For the larger IEEE 123-bus system, each bus represents 80 households to emulate a denser residential environment. Within this aggregated representation, heterogeneous adoption of distributed energy resources is considered. Specifically:

- 10% of households possess both rooftop PV and behind-the-meter BESS,
- 30% possess rooftop PV only,
- 60% possess neither PV nor BESS.

This composition reflects realistic variability in distributed energy resource ownership and avoids unrealistic assumptions of uniform technology adoption across the feeder.

The smart-meter and PV datasets are sampled over a 24-hour weekday period and discretised into 48 half-hour intervals. The selected datasets correspond to typical weekdays with moderate weather conditions, generally within a temperature range of 20°C to 30°C. As illustrated in Fig. 3.2, the aggregated net-demand profile exhibits the expected residential daily pattern: daytime net demand decreases due to PV generation, while evening demand rises as household consumption and EV charging increase.

A key modelling feature of this thesis is the use of net demand rather than gross load. This representation implicitly captures the combined influence of household consumption and PV export behaviour. Embedding these dynamics within the feeder model is particularly important for BESS planning, as it allows storage units to respond not only to EVCS demand but also to underlying variations in residential load and PV generation.

PV penetration is explicitly incorporated into the feeder models. In the principal case studies, PV installations are assigned to 40% of buses in the IEEE 33-bus feeder and 30% in the IEEE 123-bus feeder. This level of penetration reflects realistic distributed PV adoption without saturating the feeder.

In addition to behind-the-meter storage assumptions, the planning framework also allows the installation of utility-visible BESS units. The proposed framework optimally locates these BESS resources to mitigate EVCS-induced VDs, reduce network losses, and support feeder stability. In the grid-oriented case studies, the BESS units operate within charge/discharge limits of ±50 kW with a nominal capacity of 500 kW and an initial SOC of 0.2.

Taken together, the load, PV, and BESS datasets define the electrical demand environment within which the planning framework evaluates hosting capacity, voltage stability, and the marginal value of spatially distributed flexibility resources.

3.2.3 Power-flow Modelling

A physically meaningful power-flow model is required to evaluate the effects of EVCS deployment and BESS dispatch on distribution-network operation. The thesis, therefore, adopts an AC power-flow representation consistent with the formulations used in the journal studies.

This modelling choice is particularly important for medium-voltage distribution systems, where line resistance is non-negligible, and voltage magnitude deviation is a primary planning constraint. Simplified DC approximations are insufficient in such environments because they neglect the nonlinear coupling between active power, reactive power, branch impedance, and bus voltage magnitudes.

Distribution-network performance is evaluated using several electrical performance indicators. The active power loss at time interval u is computed as

$$\begin{aligned} P_u^{LOSS} &= \sum_{m=1}^{M}\sum_{n=1}^{N} \alpha_{mn}(P_m^u P_n^u + Q_m^u Q_n^u) \\ &\quad + \beta_{mn}(Q_m^u P_n^u - P_m^u Q_n^u) \end{aligned} \tag{3.4}$$

where

$$\alpha_{mn} = \frac{r_{mn}}{V_m V_n}\cos(\delta_m - \delta_n), \qquad \beta_{mn} = \frac{r_{mn}}{V_m V_n}\sin(\delta_m - \delta_n) \tag{3.5}$$

VD is defined as

$$VD_u = \sum_{m=2}^{M} |V_m^u - V_{ref}| \tag{3.6}$$

In addition, voltage stability is assessed using the VSI:

$$\begin{aligned} VSI_{n,u+1} &= (|V_{m,u}|^2 - 2P_{m,u}R_{m,u} - 2Q_{m,u}X_{m,u})^2 \\ &\quad - 4(P_{m,u}^2 + Q_{m,u}^2)(R_{m,u}^2 + X_{m,u}^2) \end{aligned} \tag{3.7}$$

$$VSI_{m,u} = \frac{1}{\min(vsi_{n,u+1})} \tag{3.8}$$

The combined use of P^{LOSS}, VD, and VSI provides a comprehensive representation of grid-side performance. While power loss captures technical efficiency, VD reflects voltage-regulation quality, and VSI indicates the feeder's proximity to voltage instability.

Finally, the power-flow model is linked to nodal power-balance constraints that incorporate household demand, PV generation, BESS dispatch, and EVCS charging demand. In V2G-extended scenarios, the EVCS is further split into charging and discharging components, enabling bidirectional energy exchange between EV fleets and the grid.

Through this modelling framework, the thesis preserves the essential electrical mechanisms governing distribution-network operation while maintaining computational tractability for multi-time-step planning optimisation.

3.3 Transportation Network and Mobility Data

This section establishes the transportation network (TN) foundation used throughout the thesis to construct realistic, traffic-informed EV charging demand and evaluate the accessibility implications of EVCS deployment in urban environments. Because the proposed planning framework jointly considers the interests of PDN operators, EVCS owners, traffic authorities, and EV users, the TN cannot be represented adequately by a simple distance matrix or a static demand-allocation model. Instead, it must capture the spatial structure of the road system, the temporal evolution of mobility demand, and the practical factors that influence user access to charging infrastructure.

To this end, the thesis adopts a Melbourne-based TN representation derived from measured traffic records and publicly available urban infrastructure datasets. The TN is modelled as a graph in which nodes represent major intersections and links represent impedance-weighted road connections. This representation enables the framework to move beyond abstract charging-demand assumptions toward a mobility-aware planning environment in which traffic flow, accessibility, queueing exposure, and spatial EV charging demand can be evaluated explicitly. The resulting TN model is consistently used in the coupled PDN–TN studies in Chapters 5 and 6 and serves as the mobility layer on which the traffic-informed charging-demand model is built.

3.3.1 Traffic Data

The transportation case study is based on real-world traffic data collected in Melbourne, Victoria, Australia. In the coupled PDN–TN analyses, the TN comprises 60 major intersections and 95 road segments selected to represent key urban mobility corridors within the study region [55]. The primary dataset is obtained from VicRoads traffic measurements. It is complemented with publicly available geographic and transport infrastructure information, including road attributes, transport stops, and regional spatial datasets [55, 56, 57]. Together, these sources enable the construction of a realistic representation of urban mobility for EV charging demand modelling.

Before being incorporated into the modelling framework, the raw traffic records undergo systematic preprocessing. During this process, incomplete, inconsistent, or implausible measurements are identified and either corrected or removed. Temporal continuity across consecutive observations is verified, and nonnegative traffic counts are enforced to ensure numerical consistency in traffic-flow estimation. This cleaning stage is essential because the traffic dataset subsequently drives the construction of EV charging demand, accessibility evaluation, and optimisation procedures used throughout the thesis.

Following preprocessing, the traffic observations are aggregated into 48 half-hour intervals over a representative 24-hour weekday horizon. This temporal aggregation aligns the transportation dataset with the electrical and charging-demand models, which are evaluated using the same 30-minute time resolution. The selected interval length preserves the principal intra-day mobility dynamics relevant to EV infrastructure planning, including morning commuting peaks, midday urban activity, and evening travel concentration, while maintaining computational tractability.

To ensure representative operating conditions, the analysis focuses on typical weekday traffic patterns under moderate weather conditions. Under these circumstances, the processed traffic data reproduce the expected daily mobility structure, with the highest traffic intensity occurring during the main commuting period between approximately 7:30 AM and 5:30 PM. These mobility dynamics directly influence both the temporal and spatial distribution of EV charging demand derived in the subsequent modelling stages, as illustrated in Fig. 3.3 and Fig. 3.4.

The resulting transportation dataset, therefore, functions as a time-indexed mobility layer rather than merely as background traffic information. It provides the basis for estimating EV charging demand, evaluating accessibility to charging infrastructure, modelling queueing behaviour at charging stations, and supporting EVCS placement optimisation within the coupled PDN–TN planning framework developed in this thesis.

3.3.2 Road Impedance and Spatial Mapping

Observed traffic counts alone are insufficient to characterise realistic urban mobility patterns. In practice, the attractiveness and accessibility of a route depend not only on traffic volume but also on the physical and operational characteristics of the road network, including congestion, road type, traffic control devices, public transport interactions, and weather-sensitive driving conditions. For this reason, the thesis adopts an impedance-based TN representation in which road links are assigned Generalised travel resistance rather than simple geometric distance.

The TN is represented as a time-indexed graph defined as

$$\begin{cases} TN = \{I, W, T\} \\ I = \{i_j \mid j = 1, 2, \dots, n\} \\ W = \{w_{i,j}^t \mid i, j = 1, 2, \dots, n\} \\ T = \{t \mid t = 1, 2, \dots, 48\} \end{cases} \tag{3.9}$$

where I denotes the set of intersections, W represents the time-varying road impedance between intersections, and T corresponds to the 48 half-hour time intervals used in the study.

To estimate traffic interaction between connected locations, the thesis adopts a gravity-based mobility formulation. The traffic flow between intersections i and j at time step t is expressed as

$$V_{i,j}^t = C \frac{N_i^\alpha N_j^\gamma}{W_{i,j}^t} \tag{3.10}$$

where $V_{i,j}^t$ denotes the traffic flow between intersections i and j, C is a proportionality constant, N_i and N_j represent population or activity proxies associated with the corresponding regions, and $W_{i,j}^t$ denotes the Generalised travel impedance between them [59]. This formulation captures the expected relationship whereby traffic interaction increases with regional activity and decreases with higher effective travel resistance.

The Generalised road impedance incorporates both static infrastructure characteristics and time-dependent congestion effects. It is defined as

$$W_{i,j}^t = b_0 z_t^c + \sum_{k=1}^{K} b_k y_k \tag{3.11}$$

where z_t denotes the road saturation level at time step t, and y_k represents explanatory attributes such as the number of traffic lights, bus stops, train stations, tram stops, traffic lanes, road width, surface conditions, and weather-related factors. The coefficients b_k and exponent c are calibrated parameters that reflect the relative influence of these factors on effective travel resistance.

To ensure comparability across heterogeneous variables, all impedance-related attributes are normalised before aggregation. This normalisation preserves the expected monotonic relationship between travel burden and route impedance, such that higher congestion levels or more restrictive road conditions produce larger effective resistance values.

Spatial mapping is then performed by assigning each cleaned and aggregated traffic record to its corresponding TN node or link based on geographic proximity and road connectivity. This step establishes a direct correspondence between real-world traffic observations and the graph-based mobility representation used in the optimisation framework. The mapped TN subsequently serves as the mobility layer for generating charging-demand patterns and accessibility indicators. The resulting EV charging demand exhibits both temporal variability and spatial heterogeneity. The temporal charging-demand pattern shown in Fig. 3.3 reflects the typical weekday concentration of mobility-driven charging activity across the daily operating horizon. Correspondingly, the spatial distribution illustrated in Fig. 3.4 shows that peak charging demand is concentrated along high-activity urban corridors and major intersections. Together, these temporal and spatial patterns confirm that the constructed TN captures realistic Melbourne mobility behaviour and provides a credible basis for EVCS planning within the coupled PDN–TN framework.

3.3.3 Candidate EVCS Locations in Coupled Power–Transport Networks

The final step in the mobility representation is to translate the TN into a candidate charging-infrastructure layer that can be coupled explicitly with the PDN. This is a critical element of the thesis because EVCS demand is not treated as an exogenous electrical load arbitrarily attached to feeder buses. Instead, candidate EVCS locations emerge from the transportation system. They are then mapped into the electrical system so that infrastructure decisions can be evaluated simultaneously for accessibility and grid feasibility.

Candidate EVCS locations are defined with respect to the TN node structure, in which major intersections serve as demand concentration points and road accessibility determines service value. The optimisation framework considers the siting and, where relevant, the sizing of EVCS units subject to both user-side and network-side constraints. On the transportation side, practical deployment must meet service-oriented requirements such as bounded waiting times, acceptable travel distances, and adequate spacing between stations. These conditions are represented through constraints such as

$$w(t) \leq w_{\max} \tag{3.12}$$

for queueing time,

$$\min(l_{ik}) \leq l_{\max} \tag{3.13}$$

for EVCS accessibility from traffic intersections, and

$$d_{ik} \geq d_{\min} \tag{3.14}$$

for minimum spacing between EVCSs. In the coupled planning studies, the maximum queueing time is set to 20 minutes, the maximum driving distance is limited to a practical service range, and the minimum spacing between charging stations is fixed at 5 km in accordance with the planning assumptions adopted in this thesis.

The EVCS candidates derived from the TN are then coupled to the PDN through bus-level integration points. Conceptually, traffic-driven charging demand estimated at specific intersections is mapped to electrically feasible candidate buses, enabling evaluation of the impact of EVCS deployment on VD, power loss, and BESS support requirements. This TN–PDN coupling enables the thesis to move beyond conventional transport-only or power-only planning studies. It creates a unified decision-making environment in which improved user accessibility can be weighed directly against feeder-hosting limits and network operating constraints.

In the second study (Chapter 5), this coupling is used to optimise EVCS and BESS placement in a PDN jointly–TN framework. In the third study, the same coupling structure is extended to account for bidirectional charging behaviour, V2G-capable station types, and profile-dependent participation. Under the advanced formulation, EVCS locations are no longer treated as homogeneous service points; some candidate sites may support only G2V charging, whereas others may be V2G-enabled depending on planning outcomes and operational assumptions. This distinction becomes particularly important because the distance from users to the nearest V2G-capable station may differ from the distance to the nearest conventional EVCS.

The coupling process also enables the construction of charging-demand assignment and accessibility metrics. The shortest-path or generalised-impedance path from each traffic intersection to the nearest feasible EVCS determines the travel effort experienced by users, while the mapped PDN location determines the corresponding electrical burden or support potential. As a result, the siting problem is solved in a way that simultaneously reflects transport realism and grid realism. A station that is attractive from a mobility perspective may be electrically infeasible if it induces excessive voltage drop, while an electrically strong bus may be suboptimal from a user perspective if it is poorly accessible from major traffic nodes. The TN–PDN mapping developed in this thesis is designed precisely to expose and manage this trade-off.

Overall, the candidate-location and coupling framework provides the essential bridge between the mobility layer developed in this section and the charging-demand, queueing, and cost formulations introduced next. By formalising how real traffic intersections are transformed into candidate charging-service locations and then connected to distribution-network buses, the thesis establishes a coherent infrastructure-planning environment in which EVCS deployment can be optimised jointly across both network layers.

3.4 Traffic-informed Charging Demand Modelling

The charging-demand model developed in this thesis serves as the central coupling mechanism between the transportation and power system layers. Its role is not only to quantify charging demand, but to ensure that demand formation remains consistent with mobility behaviour, accessibility constraints, and service conditions. To achieve this, charging demand is constructed as a function of traffic flow, battery state-of-charge dynamics, and station accessibility, and is evaluated under queueing and service-capacity constraints. This formulation enables demand to respond endogenously to both spatial infrastructure placement and temporal system conditions, thereby preserving the feedback between user behaviour and network operation.

The traffic-informed charging-demand model developed in this thesis is designed to capture both the magnitude and the service implications of EV charging demand. On the one hand, it estimates how many EVs are likely to require charging at different locations and time intervals based on traffic flow and SOC-dependent charging behaviour. On the other hand, it evaluates how the spatial distribution of EVCSs affects user travel effort, time cost, and waiting time. This integrated treatment is important because an electrically feasible but poorly accessible charging station is unlikely to provide effective urban service. In contrast, an attractive charging station from a mobility perspective may create undesirable feeder stress if the resulting demand is concentrated at electrically weak locations.

Accordingly, the charging-demand model is built around three interrelated principles. First, charging needs vary over time because vehicle movement and battery depletion do. Second, charging convenience depends not only on the existence of a station but also on the generalised cost of reaching and using it. Third, demand must be evaluated under practical service assumptions, including charger type, queueing conditions, and user behaviour. These elements are discussed in the following subsections.

3.4.1 Accessibility and Generalised Travel Cost

The accessibility of EVCSs is a primary determinant of realistic charging demand. Even if a charging station exists within the broader planning region, it does not provide equivalent service value to all EV users. Its effectiveness depends on the station's proximity to active traffic nodes, the travel impedance to reach it, and the temporal congestion along the corresponding route. For this reason, the proposed framework does not assess EVCS attractiveness solely based on Euclidean distance. Instead, it evaluates accessibility with respect to actual intersection-based demand, the road network structure, and generalised travel effort across the TN.

Building on the graph-based TN representation introduced earlier, the number of EVs that require charging at a given intersection is estimated using traffic flow, EV penetration, and charging probability. In the coupled PDN–TN formulation, the expected number of EVs requiring charging at intersection i and time step t is expressed as

$$N_i^t = V_i^t \times \alpha \times P_{\text{charg}} \tag{3.15}$$

where α denotes the EV penetration level on the road network, V_i^t is the real-time traffic flow associated with intersection i, and P_{charg} is the probability that an EV initiates charging. In the later V2G-aware formulation, the same concept is refined to distinguish between charging and discharging demand streams. The expected number of EVs requiring grid-to-vehicle (G2V) charging is then given by

$$N_i^{\text{G2V},u} = V_i^u \, \alpha \, P_{\text{charg}} \tag{3.16}$$

where u indexes the half-hour time interval. This time-varying intersection-level demand becomes the core mobility-side input for EVCS planning.

Once charging-demand intensity has been estimated, the framework evaluates the generalised travel cost of serving this demand through candidate EVCS locations. The travel-related cost is formulated as the sum of an energy-related component and a time-related component. In the original coupled formulation, the annual travel cost associated with EVCS k is expressed as

$$C_k^2 = C_{kp} + C_{km} \tag{3.17}$$

where C_{kp} denotes the energy cost incurred while travelling to the station and C_{km} denotes the time-related cost of travel and waiting.

The energy-related component is defined as

$$C_{kp} = \sum_{t=1}^{T} \sum_{i=1}^{I} \frac{d_{i,k} \, N_i^t}{l_0} \times P_c \tag{3.18}$$

where $d_{i,k}$ is the driving distance from intersection i to EVCS k, N_i^t is the number of EVs at intersection i requiring charging, l_0 is the mileage per unit of electrical energy (km/kWh), and P_c is the electricity price (\$/kWh). This term reflects that the EVCS location directly affects the additional travel energy users consume before accessing the charging service.

The time-related component is expressed as

$$C_{km} = \left[\sum_{t=1}^{T} \sum_{i=1}^{I} \frac{d_{i,k} \, N_i^t}{V_{i,k}^t} + \sum_{t} W_k^t \right] \times c_{time} \tag{3.19}$$

where $V_{i,k}^t$ denotes the effective driving speed from intersection i to station k, W_k^t is the expected waiting time at EVCS k, and c_{time} is the monetary value assigned to user time. This formulation provides a generalised measure of accessibility because it reflects not only the physical separation between users and stations but also the temporal effort required to reach and use the service.

In the V2G-extended formulation, the generalised travel cost is further refined to distinguish between charging-oriented and discharging-oriented trips. The total annual travel cost is written as

$$C_k^T = C_{kp} + C_{km} \tag{3.20}$$

with the energy component

$$C_{kp} = \sum_{u=1}^{U} \sum_{i=1}^{N} \frac{d_{i,k_{G2V}}\, N_i^{G2V,u} + d_{i,k_{V2G}}\, N_i^{V2G,u}}{l_0} \times P_c \tag{3.21}$$

and the corresponding time-cost component

$$C_{km} = \left(\sum_{u=1}^{U} \sum_{i=1}^{N} \frac{d_{i,k_{G2V}}\, N_i^{G2V,u} + d_{i,k_{V2G}}\, N_i^{V2G,u}}{V_{i,k}^u} + \sum_{u} W_k^u \right) \times c_{time} \tag{3.22}$$

where $d_{i,k_{G2V}}$ and $d_{i,k_{V2G}}$ denote the travel distance from intersection i to the nearest G2V-capable and V2G-capable EVCS, respectively. This distinction is important in advanced scenarios because not all charging stations support bidirectional charging; therefore, the effective accessibility of charging and discharging services may differ.

Overall, the generalised travel-cost formulation is one of the most industry-relevant components of the thesis. It ensures that EVCS planning is not optimised solely from the viewpoint of electrical feasibility or construction cost, but also from the perspective of actual service quality experienced by users. As a result, the framework can expose trade-offs among grid-friendly placement, user convenience, and infrastructure expenditure, which is especially important in dense urban systems such as Melbourne.

3.4.2 Service Capacity, Waiting Time, and Behavioural Assumptions

Accessibility alone is insufficient to characterise realistic EV charging demand. A charging station may be geographically close and electrically feasible, yet still provide poor service if its charging capacity is inadequate or if wait times become excessive during busy periods. For this reason, the proposed framework extends the traffic-informed demand model by incorporating service-capacity constraints, queueing behaviour, and charging-choice assumptions. This allows the planning problem to account not only for where demand arises, but also for how effectively that demand can be served.

The thesis assumes that EVCSs may include both fast and slow charging options, thereby reflecting the heterogeneity of urban charging services. In the coupled PDN–TN case studies, charging stations are represented by two service classes: fast-charging piles and slow-charging piles. In the second journal study, the corresponding service rates are given by

$$\mu_{f,t} = 60 \text{ kW}, \qquad \mu_{s,t} = 15 \text{ kW} \tag{3.23}$$

whereas the broader system configuration used later in the thesis incorporates practical charger categories such as AC slow charging and DC fast charging with realistic service durations. In the V2G-aware scenarios, each EVCS unit aggregates five stations equipped with up to eight chargers, with representative charger types including 7.7 kW AC and 120 kW DC units. These assumptions are intended to emulate realistic urban charging service conditions rather than idealised unlimited access.

To account for congestion at charging stations, the thesis models waiting time using a dynamic M/M/C queueing framework, which is suitable for stochastic arrivals and multi-server charging environments [60, 61]. The total expected waiting time at the charging station k during the time period t is defined as

$$W_k^t = W_{k,f}^t + W_{k,s}^t \tag{3.24}$$

where $W_{k,f}^t$ and $W_{k,s}^t$ denote the queueing times associated with fast and slow charging, respectively.

For fast charging, the waiting time is expressed as

$$W_{k,f}^t = \frac{P_{0,f}}{(N_{k,f}-1)!}\left(\frac{\lambda_{f,t}}{\mu_{f,t}}\right)^{N_{k,f}} \frac{\mu_{f,t}}{N_{k,f}\mu_{f,t}-\lambda_{f,t}} \tag{3.25}$$

with the normalisation term

$$P_{0,f} = \left[\sum_{n=0}^{N_{k,f}-1} \frac{1}{n!}\left(\frac{\lambda_{f,t}}{\mu_{f,t}}\right)^n + \frac{1}{N_{k,f}!}\left(\frac{\lambda_{f,t}}{\mu_{f,t}}\right)^{N_{k,f}} \left(\frac{N_{k,f}\mu_{f,t}}{N_{k,f}\mu_{f,t}-\lambda_{f,t}}\right)\right]^{-1} \tag{3.26}$$

Similarly, for slow charging,

$$W_{k,s}^t = \frac{P_{0,s}}{(N_{k,s}-1)!}\left(\frac{\lambda_{s,t}}{\mu_{s,t}}\right)^{N_{k,s}} \frac{\mu_{s,t}}{N_{k,s}\mu_{s,t}-\lambda_{s,t}} \tag{3.27}$$

with

$$P_{0,s} = \left[\sum_{n=0}^{N_{k,s}-1} \frac{1}{n!}\left(\frac{\lambda_{s,t}}{\mu_{s,t}}\right)^n + \frac{1}{N_{k,s}!}\left(\frac{\lambda_{s,t}}{\mu_{s,t}}\right)^{N_{k,s}} \left(\frac{N_{k,s}\mu_{s,t}}{N_{k,s}\mu_{s,t}-\lambda_{s,t}}\right)\right]^{-1} \tag{3.28}$$

The corresponding arrival rates are defined as

$$\lambda_{f,t} = N_k^t \alpha \tag{3.29}$$

$$\lambda_{s,t} = N_k^t (1-\alpha) \tag{3.30}$$

where α in this context represents the probability that an EV user selects fast charging instead of slow charging during the given time interval.

To reflect realistic behavioural variation over the day, the probability of choosing fast charging is allowed to vary over time. In the journal formulation, during the daytime period from 8 AM to 8 PM,

$$\alpha = 0.5 \tag{3.31}$$

so that fast and slow charging are selected with equal probability. During the overnight period from 8 PM to 8 AM,

$$\alpha = 0.2 \tag{3.32}$$

so that slow charging becomes more likely than fast charging. This assumption reflects a practical service logic: daytime users generally value faster turnaround, whereas nighttime users can tolerate longer charging duration.

The thesis also imposes explicit service-quality constraints to ensure that EVCS deployment remains practically meaningful. In particular, the waiting time of EV users at charging stations must satisfy

$$w(t) \le w_{\max} \tag{3.33}$$

where the maximum acceptable queueing time is fixed at 20 minutes in the main coupled planning studies. Similarly, the maximum driving distance to an EVCS is constrained by

$$\min(l_{ik}) \le l_{\max} \tag{3.34}$$

with a practical service radius set according to the scenario formulation. These constraints are important because they prevent the optimisation from selecting electrically attractive but operationally poor charging solutions.

Behavioural assumptions are also embedded in the estimation of charging initiation. Following the journal formulations, EV driving distance over the day is modelled probabilistically using a mixed Gaussian distribution, while the likelihood of charging is linked to SOC depletion via a Weibull-based charging probability function. Although the detailed mileage and SOC formulations are introduced in the methodology chapters, the key point in the present chapter is that charging demand is treated as a probabilistic behavioural outcome rather than a deterministic fixed load. This substantially improves modelling realism by allowing demand intensity to respond jointly to traffic presence and charging need.

In V2G-aware scenarios, the behavioural layer is further extended to account for heterogeneity in participation. Under these conditions, EVs are no longer assumed to behave uniformly as passive charging loads; instead, some vehicles may participate in V2G depending on incentive, accessibility, schedule flexibility, and time-of-day effects. While the detailed utility-based V2G participation model is presented in Chapter 6, its relevance here is that the charging-service environment of this thesis is fundamentally behaviour-aware. It is designed to capture not only whether a user can access a station, but also the type of service the user is likely to seek and the operational conditions under which that service can be delivered.

Taken together, the service-capacity and behavioural assumptions presented above transform the charging-demand model from a simple traffic-weighted quantity into a realistic service-demand representation. This is one of the reasons the framework is suitable for industry-oriented EVCS planning: infrastructure performance depends not only on the level of charging demand but also on whether that demand can be served within acceptable time, distance, and operational quality limits. The resulting charging-demand construction therefore provides the essential input for the scenario design, performance metrics, and benchmarking procedures developed in the next section.

3.5 Scenario Design

This section defines the experimental comparison architecture adopted throughout the thesis, including the scenario structure, key performance indicators (KPIs), and benchmarking protocol used to evaluate the proposed planning and control frameworks. Since the thesis progresses from grid-oriented EVCS–BESS planning to coupled PDN–TN planning and, finally, to V2G- and market-aware infrastructure planning, all numerical results must be interpreted within a unified evaluation framework. The purpose of this section is therefore not merely to enumerate the metrics used in the journal studies, but to formalise how the scenarios, metrics, and benchmarks are organised, compared, and interpreted at the thesis level.

The scenario design is structured to support three complementary objectives. First, it enables the assessment of the effect of increasing model realism to be assessed systematically, beginning with PDN-focused planning and extending to traffic-informed and V2G-enabled formulations. Second, it provides a consistent basis for comparing grid-side, user-side, and infrastructure-side outcomes under different planning assumptions. Third, it supports transparent benchmarking against simpler or alternative planning paradigms, thereby demonstrating the value of the proposed framework through structured comparison rather than a qualitative claim.

The scenarios considered in this thesis are organised according to the progressive development of the proposed planning framework. Rather than treating each methodological chapter as an isolated numerical study, the scenario structure is designed to reflect a controlled increase in system realism, decision complexity, and practical relevance. In this way, the thesis evaluates how optimal infrastructure decisions change when additional real-world dimensions, including traffic dynamics, charging-service behaviour, V2G participation, and market-based flexibility, are introduced into the planning problem.

The first scenario group addresses grid-oriented EVCS–BESS planning within the PDN. In this group, the primary objective is to assess how the coordinated placement of BESS and EVCS affects feeder performance under realistic, time-varying residential demand and distributed PV conditions. The case studies are conducted on modified IEEE 33-bus and IEEE 123-bus feeders populated with Victorian smart-meter and PV data. The framework determines the locations and charge/discharge schedules of BESS units, as well as the locations of EVCSs. To test robustness against uncertainty in charging intensity, multiple EVCS demand patterns are considered, including a fixed planning profile, the real EVCS demand profile, and scaled upper- and lower-bound demand levels. These scenario variants are used to evaluate whether the planned BESS–EVCS configuration can maintain acceptable technical performance under nominal, stressed, and relaxed operating conditions.

The second scenario group extends the problem to a coupled PDN–TN setting. Here, charging demand is no longer represented as an exogenous feeder-side profile, but is derived from traffic flow, accessibility conditions, and queueing behaviour. This group is designed to expose the trade-off among feeder support, user convenience, and infrastructure costs as the number and distribution of BESS units and EVCSs vary. In the second journal study, two principal scenario groups are considered. In Scenario 1, four BESS units are installed, and the number of EVCSs varies from 5 to 13. In Scenario 2, five BESS units are installed, and the number of EVCSs varies from 9 to 17. Across these scenario groups, EVCS size decreases as station count increases, thereby reflecting the practical trade-off between broader service coverage and smaller per-station capacity. This formulation is important because it reveals how increasing EVCS spatial coverage can reduce travel and queueing costs while simultaneously affecting feeder performance and total infrastructure expenditure.

The third scenario group incorporates heterogeneity in V2G participation, market-driven flexibility, and real-time voltage control. In this group, EVCSs are no longer treated as homogeneous charging assets. Instead, some stations may remain G2V-only, while others may be V2G-enabled, depending on participation profiles, operational assumptions, and market activation conditions. In the third journal study, four representative scenarios are defined for this purpose. Scenario 1 represents full V2G support with 100% effective participation. Scenario 2 considers partial V2G deployment with full participation. Scenario 3 considers partial V2G deployment with only 50% effective participation. Scenario 4 serves as the baseline without V2G support. These scenarios are intentionally structured to show that the value of V2G depends not only on the existence of bidirectional charging hardware, but also on the spatial distribution of V2G-enabled stations and the extent to which the committed flexibility can actually be delivered in operation.

Taken together, these scenario groups define a coherent thesis-level evaluation pathway. The first group establishes the grid value of coordinated EVCS–BESS planning under realistic feeder conditions. The second demonstrates that traffic-informed charging demand and user accessibility materially alter optimal deployment outcomes. The third evaluates how planning outcomes change when EVs are treated not only as electrical loads but also as flexible distributed resources whose value depends on behavioural and market participation. This progression transforms the scenario design from a set of disconnected numerical cases into a structured evaluation protocol for infrastructure planning, operation-aware deployment, and flexibility-aware decision-making.

3.5.1 KPIs and Decision Metrics

To comprehensively evaluate the proposed framework, the thesis adopts a multidimensional set of KPIs spanning grid performance, transportation service quality, and infrastructure economics. This choice is deliberate. A charging-infrastructure configuration that performs well electrically but imposes excessive travel burden is not practically attractive, just as a highly accessible mobility solution is not useful if it produces unacceptable voltage stress or excessive system cost. Accordingly, all major scenarios are assessed through a common decision-metric structure that makes the trade-offs among these dimensions explicit.

On the PDN side, the principal technical KPIs are active power loss, VD, and voltage stability. Active power loss is measured using the feeder-level formulation introduced earlier in (3.4) and (3.5). This metric is important because spatially concentrated EV charging demand can intensify branch loading and increase resistive losses, whereas appropriately located BESS and V2G support can alleviate these effects. VD is evaluated using

$$VD_u = \sum_{m=2}^{M} |V_m^u - V_{ref}| \tag{3.35}$$

which captures the aggregate departure of bus voltages from nominal conditions. Voltage stability is quantified through the VSI formulation previously defined in (3.7) and (3.8). Together, these three indices form the core electrical-performance layer of the thesis and are applied consistently across the RQ1–RQ3 experiments.

In the first journal study, these technical metrics serve as the primary basis for evaluating the benefits of coordinated BESS and EVCS integration under realistic load and PV conditions. In later coupled studies, they remain essential because transportation-side improvements cannot be accepted unless the PDN continues to meet voltage security and power quality requirements. This is an important strength of the evaluation framework: user-side improvements are never assessed independently of electrical feasibility.

On the transportation side, the main KPIs are travel cost, travel-plus-queueing cost, and service accessibility. These metrics quantify the extent to which the EVCS network provides practical charging service to urban users. The generalised travel-cost structure introduced earlier in (3.17)–(3.22) is used to measure the costs imposed on EV users due to detour energy consumption, travel time, and queueing exposure. This perspective is especially important in the second and third journal studies, where one of the central contributions is the explicit inclusion of user-centric performance rather than optimising solely for grid-side technical outcomes or infrastructure-owner cost.

Accessibility is further constrained through service-quality conditions such as

$$\min(l_{ik}) \leq l_{\max} \tag{3.36}$$

and

$$w(t) \leq w_{\max}. \tag{3.37}$$

These are not merely feasibility constraints; they also define interpretable service-quality boundaries for judging whether a given station deployment is meaningful from a user perspective. In practical terms, a deployment that reduces feeder losses but forces long detours or unacceptable waiting times would not be considered successful under the evaluation framework adopted in this thesis.

The economic and infrastructure-side metrics are also treated explicitly. These include construction, operating, and maintenance costs, as well as loss-related costs. In the coupled planning formulations, the annual investment cost comprises EVCS construction, maintenance, and technical-loss components, while BESS-related costs are incorporated into the grid-oriented planning framework as part of the overall design trade-off. These economic metrics are important because they reveal the nontrivial balance between station quantity, station size, service quality, and total expenditure. For example, increasing the number of EVCSs generally improves accessibility and reduces user travel burden, but also increases construction and maintenance costs.

Conversely, concentrating charging capacity into fewer stations may reduce capital expenditure while worsening user-side metrics and increasing localised electrical stress.

In the V2G-aware scenario family, the same core metrics remain relevant, but their interpretation becomes richer. For example, an improvement in VD under V2G-enabled planning reflects not only improved siting, but also the contribution of bidirectional energy exchange to local grid support. Likewise, reductions in travel and queueing costs in V2G scenarios do not simply indicate better accessibility; they may also indicate that stronger electrical support has expanded the feasible EVCS deployment envelope, thereby improving the transportation system's service landscape. In this sense, the KPI structure remains consistent throughout the thesis, but its explanatory power increases with the planning model's realism.

Overall, the KPI framework is intentionally multi-layered. It is designed to support thesis-level conclusions that are both academically rigorous and industrially meaningful. By maintaining consistent technical, transportation, and economic metrics across all scenario families, the thesis ensures that the effects of increasing model richness can be evaluated transparently and cumulatively.

3.5.2 Benchmark Models and Parameter Calibration

A robust planning framework should not be assessed in isolation. It must be compared with alternative formulations, simpler baselines, or reduced-objective models to determine whether the added methodological complexity produces meaningful gains. For this reason, the thesis adopts an explicit benchmarking protocol that compares the proposed framework against baseline planning paradigms and calibrates the key model components using real-world data and validated parameter sources.

The benchmarking logic differs across the three RQs, reflecting the increasing complexity of the planning framework. In the first journal study, benchmarking is conducted primarily through scenario-based stress testing. The planned BESS–EVCS configuration is evaluated under a fixed EVCS planning profile, the real EVCS demand profile, and scaled upper- and lower-bound demand cases. This benchmark structure tests whether the proposed hierarchical planning-and-control framework remains effective when actual charging demand deviates materially from the nominal profile used in planning. In this sense, the benchmark is not another optimisation algorithm, but a robustness comparison between nominal planning assumptions and stressed operational conditions.

In the second journal study, the benchmarking protocol becomes more explicit. The proposed multi-objective optimisation framework is compared against two alternative paradigms for the common 13-EVCS configuration: a PDN-oriented single-objective formulation (SO-PDN) and a Pareto-based multi-objective baseline using NSGA-II. The SO-PDN formulation yields marginal improvement in grid-centric metrics but performs poorly on user-oriented outcomes, particularly travel and queueing costs. NSGA-II provides a more balanced compromise but still underperforms the proposed GA–DDPG framework in terms of transportation service quality. This comparison demonstrates that the performance advantage of the proposed framework does not arise solely from multi-objective formulation, but from explicitly modelling time-indexed interactions between mobility-driven demand and grid constraints, and from learning sequential decision structures under dynamic system conditions.

The advanced V2G-aware planning framework in the third journal study is benchmarked primarily through structured scenario comparison rather than algorithmic substitution. The baseline without V2G serves as the reference case, while the partial- and full-participation V2G scenarios reveal the extent to which bidirectional support and market-based flexibility improve planning outcomes. This benchmark structure is appropriate for RQ3 because the scientific question is not simply whether V2G can be included in the planning process, but how varying participation levels and operational profiles influence the practical value of the infrastructure.

Table 3.1: Key parameters and system-model configurations used across the thesis case studies.

Parameters	Value
BESS installation cost	1.161 \$/kWh
BESS operational cost	0.625 \$/kWh
Project duration	10 years
Lifetime of each charging station	20 years
Interest rate	3.6%
Inflation rate	3.2%
Discount rate r_0	0.15
Carbon emission factor	0.554 kg/kWh
Cost of power from the substation	5 \$/kWh
Electricity prices (slow/fast/grid)	0.50 / 0.75 / 0.13 \$/kWh
Fast charging rate $\mu_{f,t}$	60 kW
Slow charging rate $\mu_{s,t}$	15 kW
DC charging pile capacity	120 kW
Cost of travel time c_{time}	20 \$/h
Maximum queue time for each EV w_{max}	20 min
Maximum driving distance l_{max}	30 km
Minimum station distance d_{min}	5 km
Mileage per unit electrical energy l_0	4.1 km/kWh
EV penetration level α	0.5
Loss rates (G2V / V2G)	0.05 / 0.10
V2G pile cost rate (slow/fast)	1.2
Maximum V2G travel distance $\mathcal{D}_{\max}^{\mathrm{V2G}}$	30 km
Minimum V2G station distance $D_{\mathrm{V2G}}^{\min}$	2 km
Rated feeder voltage	12.66 kV
Voltage limits (minimum/threshold/maximum)	216 / 230 / 253 V
Open-circuit voltage	35 V
Short-circuit current	8 A
Voltage temperature coefficient	0.1 °C
Current temperature coefficient	0.05 °C
Real power from the substation	105 kW
GA parameters (population, generations, crossover, mutation)	(20, 50, 0.9, 0.1)
DDPG actor/critic layer size	[400, 300]
DDPG (batch size, learning rate)	(64, 0.001)

Calibration is equally important to the credibility of the framework. The thesis does not rely on arbitrary parameter tuning. Instead, the main data-driven and behavioural components are calibrated using real-world measurements or parameter values adopted from empirically validated literature. On the transportation side, the impedance model employs normalised and calibrated coefficients for road and congestion attributes, including traffic lights, lane counts, road width, surface type, proximity to public transport, speed-related conditions, and weather effects [55, 56, 57]. This calibration preserves the expected monotonic relationship between traffic burden and route impedance and ensures that the resulting traffic-flow patterns remain realistic for Melbourne urban conditions.

The charging-demand model is likewise calibrated using validated probabilistic representations. In the second journal study, the Gaussian-mixture parameters used to represent temporal driving mileage are adopted from empirically supported sources:

- first component: $\pi_1 = 0.078$, $\mu_1 = 14.86$, $\sigma_1 = 5.31$,
- second component: $\pi_2 = 0.051$, $\mu_2 = 8.75$, $\sigma_2 = 3.11$.

Similarly, the Weibull distribution used to model SOC-based charging behaviour is parameterised as

$$a = 6.31, \qquad b = 1.67 \tag{3.38}$$

following empirically grounded studies [11]. These calibrated parameters ensure that the charging-demand model reflects realistic mobility and charging behaviour rather than arbitrary assumptions.

The optimisation settings summarised in Table 3.1 are selected to achieve stable and computationally efficient performance. In the grid-oriented study, the GA is initialised with a population size of 50 and 100 iterations, while the DDPG module is trained with 50 episodes and 20 actions per episode. In the coupled PDN–TN and V2G-aware studies, the adopted settings include GA parameters of population size 20, maximum generations 50, crossover rate 0.9, and mutation rate 0.1, together with DDPG actor/critic layers of size $(400, 300)$, batch size 64, and learning rate 0.001. These values reflect a practical balance between convergence stability, runtime efficiency, and solution quality established during the development and refinement of the journal studies.

The computational environment used for benchmarking and calibration is also selected deliberately. In the coupled planning studies, all simulations are executed on an AWS EC2 `r7i.16xlarge` instance with 64 vCPUs and 512 GB RAM. This configuration ensures that time-indexed optimisation and learning procedures can be executed reproducibly and without hardware-induced instability. Under this setup, complete 48-time-step coupled simulations converge within a few minutes, which is appropriate for engineering-level planning studies and supports the framework's practical applicability.

Taken together, the benchmark models and calibration strategy provide the thesis with methodological credibility. The proposed framework is compared not only against different operating scenarios but also, where appropriate, against reduced-objective and alternative multi-objective baselines. At the same time, the key components of the traffic, charging, and optimisation models are calibrated using measured data or empirically grounded parameter values. This combination of structured benchmarking and data-informed calibration strengthens the validity of the conclusions drawn in the subsequent chapters.

3.6 Computational Settings

This section consolidates the implementation conditions, reproducibility assets, and validity boundaries of the experimental framework adopted throughout the thesis. Since the proposed methodology combines time-indexed optimisation, traffic-informed construction of charging demand, and, in advanced scenarios, V2G-aware planning and real-time control, it is necessary to demonstrate not only methodological soundness but also computational tractability, reproducibility, and interpretive reliability. The purpose of this section is therefore to clarify how the framework was implemented, what supports its practical reproducibility, and under what conditions its conclusions should be interpreted and transferred.

This section is important because the value of a planning framework depends not only on the sophistication of its mathematical formulation, but also on whether the framework can be executed consistently, whether its data-processing and modelling steps are transparent, and whether its results remain meaningful when interpreted within their intended scope. These issues are particularly important in industry-oriented infrastructure research, where practical relevance requires not only strong numerical performance but also credible implementation and clearly stated limits of applicability.

3.6.1 Implementation and Computational Setup

The proposed framework is implemented as a modular computational pipeline comprising data preprocessing, time-indexed network evaluation, and optimisation-based or learning-based decision stages. Across the thesis, the implementation follows the same overall structure. First, the PDN and TN datasets are prepared and aligned temporally. Second, time-varying charging-demand inputs are constructed from traffic flow, accessibility, and behavioural assumptions. Third, BESS and EVCS planning decisions are obtained using the designated optimisation modules. Finally, where relevant, real-time control logic and V2G-related operational mechanisms are applied. This modular implementation improves transparency, simplifies debugging, and enables the modelling framework to be progressively extended from RQ1 to RQ3 without redesigning the entire computational workflow.

In the grid-oriented studies, the implementation focuses on the coordinated evaluation of BESS and EVCS decisions over 48 half-hour time intervals using real smart-meter and PV data. In the coupled PDN–TN studies, this structure is extended to include traffic-flow estimation, road-impedance computation, charging-demand construction, queueing evaluation, and EVCS accessibility assessment at each time interval. In the V2G-aware scenarios, the same environment is further enriched by participation-profile assignment, market-flexibility activation logic, and local BESS-gain optimisation under real-time voltage conditions. The resulting computational structure reflects the thesis's layered progression and ensures that each successive RQ builds on a consistent implementation base rather than introducing disconnected, standalone simulations.

The coupled simulations reported in the later journal studies were executed on an AWS EC2 `r7i.16xlarge` instance running Windows Server, equipped with 64 vCPUs, 512 GB RAM, and a 512 GB EBS SSD. This environment was selected to provide sufficient memory headroom and stable runtime performance for multi-time-step optimisation and reinforcement-learning procedures. Under this setup, the complete 48-time-step simulation of the coupled PDN–TN framework on the modified IEEE 33-bus system converged within a few minutes. In the second journal study, the overall runtime was approximately 5–8 minutes, corresponding to roughly 6–10 seconds per time step. This level of computational performance is suitable for engineering-oriented planning studies within the selected benchmark and data-driven case-study environment.

From a computational perspective, the framework benefits from structural decomposition. The BESS planning task is handled by a GA-based module that is suitable for global search under mixed discrete–continuous feasibility constraints, while the EVCS planning task is handled by a DDPG-based module that learns sequential deployment decisions under evolving traffic and charging conditions. This separation avoids repeatedly solving a single monolithic mixed-decision problem over the full coupled PDN–TN state space. As a result, the computational burden remains manageable for the case studies considered in this thesis, even when the model includes spatiotemporal traffic variation, queueing effects, multiple performance objectives, and, in advanced scenarios, V2G participation and market activation logic.

The memory footprint of the framework is also modest relative to the available computational resources. In the journal studies, the replay buffer storage associated with the DDPG module remained small relative to total system memory, and the overall peak RAM usage during complete 48-step runs was estimated at only a few gigabytes, dominated mainly by the reinforcement-learning components rather than the GA module. This indicates that computational tractability is achieved not by removing the key modelling interactions, but by decomposing the decision process into manageable layers. The overall implementation, therefore, provides a practical balance among runtime, memory usage, and solution quality within the evaluated case-study settings.

The computational assessment is intentionally interpreted within the boundaries of the selected test systems and datasets. In the first journal study, the methodology was evaluated on both the modified IEEE 33-bus and IEEE 123-bus systems, showing that the grid-oriented planning logic can be applied to benchmark feeders of different sizes. In the later coupled studies, the modified IEEE 33-bus feeder served as the electrical backbone of the integrated Melbourne TN case study. At the same time, the transportation side included 60 intersections, 95 roads, and 48 time intervals. These experiments demonstrate that the implementation is sufficiently tractable for the thesis case studies and can be adapted to alternative networks and datasets. However, broader application to utility-scale feeders or more detailed city-wide transportation models would require additional validation, including larger network models, expanded traffic representations, and more systematic runtime analysis.

3.6.2 Reproducibility

The thesis's reproducibility is supported by three main asset categories: benchmark network models, real-world input datasets, and explicitly documented model configuration parameters. The use of modified IEEE distribution feeders provides a standard and recognisable electrical foundation, while the Melbourne/Victoria datasets ground the experiments in realistic operating conditions. This combination is important because it allows the results to remain both interpretable to the research community and relevant to practical infrastructure planning.

On the electrical side, the principal reproducibility assets include the modified IEEE 33-bus and IEEE 123-bus network models together with the smart-meter and PV data-processing rules used to construct bus-level residential net-demand profiles. The household composition assumptions, PV/BESS adoption ratios, feeder operating limits, BESS power bounds, SOC limits, and time-step structure are explicitly specified in the thesis and consistently inherited from the journal studies. This means the electrical test environment can be systematically reconstructed once the underlying datasets and parameter settings are available.

On the transportation side, reproducibility is supported by the explicit use of real traffic and infrastructure datasets, including VicRoads traffic measurements, public transport and road-attribute information, and publicly available demographic or government datasets used to estimate regional EV presence and travel conditions [55, 56, 57]. The thesis also documents the preprocessing logic applied to these data, including cleaning, aggregation into 48 half-hour intervals, spatial assignment to TN nodes and links, normalisation of impedance-related attributes, and calibration of route-impedance coefficients. These steps are essential reproducibility assets because they define how raw transport records are transformed into the graph-based mobility representation used by the optimisation framework.

The charging-demand model is also reproducible because its principal probabilistic parameters are stated explicitly. The Gaussian-mixture parameters used for mileage-related mobility variation and the Weibull parameters used for SOC-based charging probability are reported directly in the thesis, following empirically validated studies [11]. Likewise, the main charger-rate assumptions, maximum queueing time, maximum service distance, EV penetration level, and scenario-dependent V2G participation settings are documented in the system-parameter tables and accompanying case-study descriptions. These details make the charging-demand construction transparent and reproducible, even when exact numerical demand values depend on the specific traffic realisation and calibration inputs.

The optimisation and control configurations are similarly documented. The thesis reports the principal GA and DDPG hyperparameters, including population size, number of generations, crossover and mutation rates, actor–critic architecture, batch size, learning rate, number of episodes, and number of actions per episode. These values are part of the framework's reproducibility envelope because they materially affect convergence behaviour, runtime, and solution quality. Their explicit documentation allows later researchers to reproduce the reported case studies or to use them as a baseline for future extensions.

At the thesis level, reproducibility should be interpreted in a practical engineering sense rather than in the narrow sense of reproducing every exact intermediate state of a stochastic learning process. Because the framework includes stochastic optimisation and RL, some run-to-run variation may occur unless all random seeds, initialisation states, and software environments are fixed identically. Nevertheless, the modelling structure, parameterisation, and data-processing pipeline are specified at a level sufficient for independent reconstruction of the experiments and validation of the main findings. This level of reproducibility is appropriate for infrastructure-planning research that combines benchmark systems, real-world datasets, and learning-based decision modules.

3.6.3 Validity Boundaries and Adaptation Considerations

The findings of this thesis should be interpreted within the scope of its modelling assumptions, data boundaries, and planning objectives. The framework is designed to support realistic, data-informed infrastructure planning under typical urban operating conditions, but, like any integrated planning methodology, it is subject to several validity constraints. Stating these boundaries explicitly strengthens the thesis by clarifying what the framework can reliably do and what lies outside its current scope.

A first validity consideration concerns temporal representativeness. The case studies are based on typical weekday operation over a 24-hour horizon with 48 half-hour intervals, using filtered days under moderate weather conditions. This choice is appropriate for planning-oriented analysis because it captures the most relevant daily interactions among traffic flow, residential demand, PV generation, and EV charging. However, it also means that rare extreme events, such as major traffic disruptions, widespread outages, unusually severe weather, or emergency charging surges, are not modelled explicitly. The thesis, therefore, supports robust planning for normal daily variability rather than dedicated resilience analysis for exceptional conditions.

A second validity consideration concerns behavioural abstraction. Although the thesis incorporates a richer behavioural representation than many conventional EVCS planning studies, including SoC-dependent charging probability, fast/slow charging choice, queueing effects, V2G participation logic, and market-activation conditions, user behaviour is still represented probabilistically rather than through individual-level, survey-calibrated micro-simulation. This is a defensible choice for infrastructure-planning-scale studies, but it implies that the results should be interpreted as system-level planning insights rather than exact predictions of individual users' decisions.

A third validity consideration relates to network abstraction and geographic granularity. On the electrical side, the thesis uses modified IEEE test feeders populated with real Victorian data rather than proprietary utility feeder models. This is methodologically sound and common in the literature because it balances benchmark transparency with practical realism. However, it also means that the feeder topology is representative rather than a one-to-one digital twin of a specific service area. Similarly, the TN is constructed from real Melbourne traffic and road data but remains an abstracted graph-based representation rather than a complete city-scale microscopic transport simulation. These choices are appropriate for strategic infrastructure planning, but they define the scale at which the conclusions should be interpreted.

A fourth validity consideration concerns uncertainty in future EV uptake, charging technology, and participation behaviour. The thesis addresses part of this uncertainty explicitly through scenario design, stress testing, participation-level comparison, and V2G profile variation. Nevertheless, longer-term changes in EV adoption rates, charger standards, electricity pricing rules, and market participation behaviour may alter the precise quantitative outcomes of future planning studies. For this reason, the thesis should be interpreted as providing a structured planning framework that can be adapted to comparable contexts, rather than a fixed forecast of future infrastructure configurations.

Despite these limitations, the proposed framework contains transferable elements when applied within comparable data, modelling, and planning conditions. The modelling architecture is modular, and its main components, PDN representation, TN graph construction, traffic-informed charging-demand estimation, queueing-based service logic, multi-objective planning, and local control, can be adapted to other urban regions provided that similar datasets are available. In particular, the framework may be adapted to other Australian metropolitan settings where comparable EV uptake, distributed PV penetration, and urban mobility patterns generate similar planning challenges. The use of explicit feeder constraints, graph-based transport modelling, and documented parameter settings supports this adaptation, as the framework relies on interpretable engineering quantities rather than location-specific black-box assumptions.

The framework can also be conceptually extended across planning horizons. Although the thesis focuses on representative daily operation for infrastructure evaluation, the same methodology can be embedded into longer-term planning studies by updating demand, traffic, and technology parameters. Likewise, the V2G and market-flexibility layer can be extended to richer aggregator models, dynamic pricing mechanisms, or resilience-oriented operating conditions if the corresponding datasets become available. This adaptability is one of the reasons the framework has value beyond the specific case studies reported in the thesis.

Overall, the proposed experimental framework is computationally tractable, reproducible in a practical engineering sense, and valid for the planning-oriented objectives it is intended to address. Its conclusions should therefore be interpreted as robust infrastructure-planning insights under realistic daily urban conditions, rather than as exact predictions under all possible contingencies. Within that intended scope, the framework provides a credible basis for coordinated EVCS and BESS planning in coupled power and transportation systems, as well as a structured foundation for adaptation to comparable planning contexts.

Chapter 4

Integrated EVCS–BESS Planning and Operation in Distribution Networks

This chapter presents the first methodological stage of the thesis by addressing RQ1: coordinated EVCS–BESS planning and operation within distribution networks. The purpose of this stage is to establish the grid-oriented foundation of the overall planning framework before transportation-network coupling and V2G participation are introduced in Chapters 5 and 6. At this stage, EV charging demand is considered in terms of its impact on the PDN, and the central problem is how to coordinate EVCS deployment with BESS placement, scheduling, and local voltage-based control to improve feeder performance under time-varying demand conditions.

A key distinction in this chapter is the separation between the planning and operational layers. The planning layer concerns infrastructure decisions made before real-time operation, including the locations of EVCSs and BESS units, as well as the sizing or scheduling structure required to support expected EV charging demand. These decisions determine the physical allocation of charging and storage resources within the distribution network and are evaluated against technical, economic, and environmental objectives. In contrast, the operational layer concerns time-dependent actions that respond to the realised operating condition of the network. In this chapter, these actions include BESS charge/discharge scheduling and the local voltage-based control mechanism used to mitigate deviations between planned and realised demand.

This distinction is important because EVCS planning cannot be judged only by whether a nominal infrastructure configuration satisfies steady-state constraints. In practice, realised EV charging demand can deviate from the profile assumed during planning, and these deviations can affect voltage quality, power loss, and voltage stability. Therefore, the framework developed in this chapter links planning and operation without collapsing them into a single indistinguishable decision block. The planning layer identifies suitable EVCS and BESS deployment decisions, while the operational layer evaluates whether those decisions remain technically credible when time-varying demand and local voltage conditions are considered.

The proposed decision structure consists of three connected components. First, the EVCS–BESS planning problem is formulated as a multi-objective optimisation problem that captures power loss, voltage stability, voltage deviation, economic cost, and environmental impact. Second, a hybrid decision framework is introduced in which GA is used for BESS-related planning decisions, DDPG for EVCS allocation decisions, and an adaptive BESS control module to support voltage regulation during operation. Third, the framework is evaluated using modified IEEE 33-bus and IEEE 123-bus distribution networks populated with real Victorian demand, rooftop PV, and EVCS profiles. This structure allows RQ1 to test not only whether coordinated EVCS–BESS planning improves nominal feeder performance, but also whether the resulting infrastructure configuration remains operationally effective under stressed and variable demand conditions.

The chapter is organised as follows. Section 4.1 formulates the EVCS–BESS planning problem by defining the decision variables, objective functions, and operating constraints. Section 4.2 presents the proposed decision framework and clarifies how the planning and operational layers interact through GA, DDPG, and the voltage-based BESS control module. Section 4.3 presents the simulation setup and numerical results for the modified IEEE 33-bus and IEEE 123-bus feeders. Section 4.4 then translates the findings into practitioner-oriented design insights and explains how the results provide the grid-side foundation for the coupled PDN–TN planning framework developed in Chapter 5.

4.1 Problem Formulation

This chapter addresses RQ1 by formulating the coordinated integration of BESSs and EVCSs in a distribution network as a multi-objective optimisation problem. The formulation jointly determines the siting, sizing, and operation of BESSs and EVCSs while satisfying network technical limits and accounting for economic and environmental considerations. Consistent with the thesis-wide progression introduced in Chapter 1, the focus here is on establishing a grid-oriented planning-and-operation framework that moves beyond conventional maximum-demand assumptions and toward a more realistic representation of EV charging integration in distribution systems.

4.1.1 Decision Variables

The optimisation problem is defined in terms of three principal decision variables: x_i, c_i, and y_j. Variable x_i is a binary siting variable indicating whether a BESS is installed at bus i, c_i denotes the corresponding BESS charge/discharge rate, and y_j is a binary variable indicating whether an EVCS is installed at candidate location j. Together, these variables represent both long-term infrastructure decisions and time-indexed operational flexibility, allowing the framework to coordinate BESS placement, BESS operation, and EVCS deployment within the distribution network.

4.1.2 Objective Functions

The optimisation problem is constructed around five objective dimensions: power loss, voltage stability, VD, economic cost, and carbon emissions. Together, these objectives capture the central technical, economic, and environmental trade-offs associated with EVCS–BESS integration in distribution networks.

Power Loss

Power loss through DNs is calculated as:

$$P_t^{LOSS} = \sum_{m=1}^{M} \sum_{n=1}^{N} \alpha_{mn} \left(P_m^t P_n^t + Q_m^t Q_n^t \right) + \beta_{mn} \left(Q_m^t P_n^t - P_m^t Q_n^t \right) \tag{4.1}$$

where

$$\alpha_{mn} = \frac{r_{mn}}{V_m V_n} \cos(\delta_m - \delta_n) \tag{4.2}$$

and

$$\beta_{mn} = \frac{r_{mn}}{V_m V_n} \sin(\delta_m - \delta_n). \tag{4.3}$$

In these equations, the sending- and receiving-end busbars are denoted by m and n, respectively, and t denotes time. Additionally, the branch impedance from bus m to bus n is $Z_{mn} = r_{mn} + jx_{mn}$, where r_{mn} and x_{mn} indicate the resistance and reactance of the line connecting bus m to bus n, respectively. P and Q indicate the real and reactive power of each bus, respectively. V_m and V_n are the voltages of bus m and bus n, respectively, and the voltage angles are indicated by δ_m and δ_n. Here, α_{mn} and β_{mn} capture the contribution of real and reactive power flows, together with voltage-angle differences and line resistance, to feeder-level power loss [7].

Voltage Stability Index

Because an increasing and spatially concentrated load can push the feeder toward voltage instability, a VSI is used to quantify proximity to voltage collapse and is therefore maximised. It is calculated as:

$$VSI_{n,t+1} = \left(|V_{m,t}|^2 - 2P_{m,t}R_{m,t} - 2Q_{m,t}X_{m,t}\right)^2 - 4\left(P_{m,t}^2 + Q_{m,t}^2\right)\left(R_{m,t}^2 + X_{m,t}^2\right) \tag{4.4}$$

$$VSI_{m,t} = \frac{1}{\min(vsi_{n,t+1})} \tag{4.5}$$

Here, $R_{m,t}$ and $X_{m,t}$ indicate the resistance and reactance of branch m at time t [7].

Voltage Deviation

When integrating BESSs and EVCSs in DNs, voltage regulation is essential. VD is calculated as:

$$VD_t = \sum_{m=2}^{M} \left|V_m^t - V_{ref}\right| \tag{4.6}$$

Here, V_m denotes the voltage at bus m, and V_{ref} is the nominal voltage value of each busbar [7].

Economic Objective

From an economic perspective, the formulation considers the installation and operational costs. The installation cost is defined as:

$$C_{inst} = \sum_{b=1}^{B} n_b^B c^B. \tag{4.7}$$

Here, n^B and c^B denote the number of BESSs and the unit cost of the BESS, respectively. B indicates the candidate locations for installing BESSs, and b denotes each candidate location [7].

The operational cost includes maintenance and grid power. The overall operational cost over Y years is defined as:

$$C_{op} = \sum_{y=1}^{Y}\sum_{t=1}^{48}\sum_{s=1}^{N_s} p_s\left(C_{t,s}^{SS} \times P_{t,s}^{SS}\right)\left(\frac{1+inf}{1+int}\right)^{y-1} \tag{4.8}$$

where Y and N_s are the number of years and scenarios, respectively. y, t, and s are indices for the year, time, and scenario. p_s is the probability of scenario s. The cost and amount of power consumed by the substation are denoted by $C_{t,s}^{SS}$ and $P_{t,s}^{SS}$, respectively, and inf and int indicate inflation and interest rates for a specific year [7].

The EVCS installation cost is excluded from this formulation because EVCS deployment is assumed to rely on external funding and is therefore treated as exogenous to the grid-focused optimisation problem. Under this assumption, the economic objective prioritises the placement and operation of BESS resources required to mitigate the network impact of EVCS integration.

Environmental Objective

The environmental objective estimates the emissions associated with real-power import from the substation:

$$C_E = \sum_{y=1}^{Y} P_s^{SS} \times E_f \tag{4.9}$$

where P_s^{SS} is the real power imported from the substation, and E_f is the carbon emission factor in kg/kWh [7].

To manage these five objective functions within a single optimisation framework, the method assigns time-dependent weights and aggregates the resulting objective values across the operating horizon. From morning to noon, VD is given a higher weight. On the other hand, voltage stability carries greater weight from noon to midnight, while the weights for power loss, economic cost, and environmental cost remain equal across all time steps to ensure a balanced optimisation approach.

The above objectives reflect the fundamental trade-off in RQ1. Minimising technical stress on the network generally requires more supportive resources and operational flexibility, whereas reducing economic cost favours fewer investments and lower operational interventions. Similarly, reducing substation power import improves environmental performance, but this may conflict with the most economical or operationally simple solution. Therefore, the proposed formulation seeks an integrated planning outcome that balances grid performance, cost, and environmental impact.

4.1.3 Electrical Constraints

The formulation is subject to three principal groups of constraints: power-balance constraints, voltage limits, and BESS operational limits.

Power Balance Constraint

Power-flow equilibrium is enforced at the network level by requiring that the total real-power supply balance the total real-power demand, charging demand, and feeder losses. At each time step, PV generation and BESS discharge must collectively support household demand, BESS charging, EVCS demand, and network loss. This requirement is expressed as:

$$\sum_{m=1}^{M}\left(P_m^{LOSS}+P_m^{LOAD}+P_m^{CH}\right)+\sum_{m=1}^{M}\sum_{p\in P}P_{p,m}^{EV}=\sum_{m=1}^{M}P_m^{DG}+\sum_{m=1}^{M}P_m^{Dis} \tag{4.10}$$

where P_m^{LOSS}, P_m^{LOAD}, and P_m^{CH} denote the power loss, load, and BESS charging power at bus m, respectively. In addition, P_m^{DG} and P_m^{Dis} are the real power generated by PV and the real power discharged from BESS at bus m.

Voltage Constraint

To preserve power quality, the voltage magnitude at each bus must remain within the permissible operating range:

$$V_{min} \le V_m \le V_{max}, \qquad m = 1, 2, 3, \ldots, M. \tag{4.11}$$

This study considers the lower and upper voltage bounds at 0.95 pu and 1.05 pu, respectively.

BESS Operational Constraint

The proposed method calculates the state of charge (SoC) as follows:

$$SOC_i(t+1) = SOC_i(t) + T \times P_i(t) \tag{4.12}$$

where $P_i(t)$ and $SOC_i(t)$ denote the rate of charge/discharge and SoC of the BESS at bus i and time t, respectively. Since SOC is expressed in kWh and the dataset's time step is 30 minutes, T is set to 0.5.

Furthermore, the proposed method protects the BESS from overcharging or deep discharging:

$$SOC_{min} \leq SOC_i(t) \leq SOC_{max}. \tag{4.13}$$

Accordingly, the feasible charging and discharging trajectory of each BESS is constrained by the corresponding SOC_{min} and SOC_{max} bounds. Here, SOC_{max} and SOC_{min} are set as 0.9 and 0.2 of the BESS capacity, respectively.

Together, these constraints ensure that the obtained planning solution is not only optimal with respect to the selected objectives but also physically feasible, grid-compliant, and operationally implementable.

4.2 Decision Framework for EVCS–BESS Integration

This section defines the solution architecture for operationalising the RQ1 problem formulation. The framework jointly addresses infrastructure planning and operational adaptation to determine suitable EVCS and BESS decisions while preserving network feasibility under time-varying demand. Building on the formulation in Section 4.1, the chapter adopts a hybrid strategy that combines evolutionary optimisation and RL.

The proposed method first finds the optimal size and location of BESS and EVCS based on a typical EVCS consumption profile. Then, it designs an optimal controller for BESS charging to compensate for the deviations of EVCS charging from the typical value. The optimisation framework uses the objective functions in Eqs. 4.1, 4.5, 4.6, 4.7, 4.8, and 4.9, together with the constraints in Eqs. 4.10, 4.11, and 4.13, to determine BESS locations, BESS operating schedules, EVCS locations, and voltage-control gains.

The combined use of GA and DDPG reflects the different decision structures of the two planning tasks. GA is used for BESS planning because it is well-suited to static, discrete, multi-objective search over siting and scheduling decisions. DDPG is used for EVCS planning because it can learn sequential placement decisions in dynamic, high-dimensional system conditions. This hybrid decomposition improves computational tractability while preserving adaptability under uncertain EVCS demand.

In the following subsections, the proposed framework is described in two layers: a planning layer responsible for optimal infrastructure placement, and an operational layer responsible for real-time control.

4.2.1 Infrastructure Planning Layer

As shown in Fig. 4.1, the planning layer consists of two complementary modules: a BESS integration module and an EVCS integration module. Together, these modules determine the spatial allocation of BESS and EVCS assets and, where relevant, the corresponding BESS operating schedules.

BESS Planning and Integration Module

This module uses GA to solve the multi-objective BESS planning problem under mixed discrete and time-indexed decision constraints. Within the RQ1 framework, GA is responsible for identifying suitable BESS locations and corresponding charge/discharge schedules across the operating horizon. By locating BESS units at electrically influential buses and coordinating their operation over time, the module improves voltage stability, reduces feeder losses, and increases the network's ability to accommodate EVCS demand [62, 38].

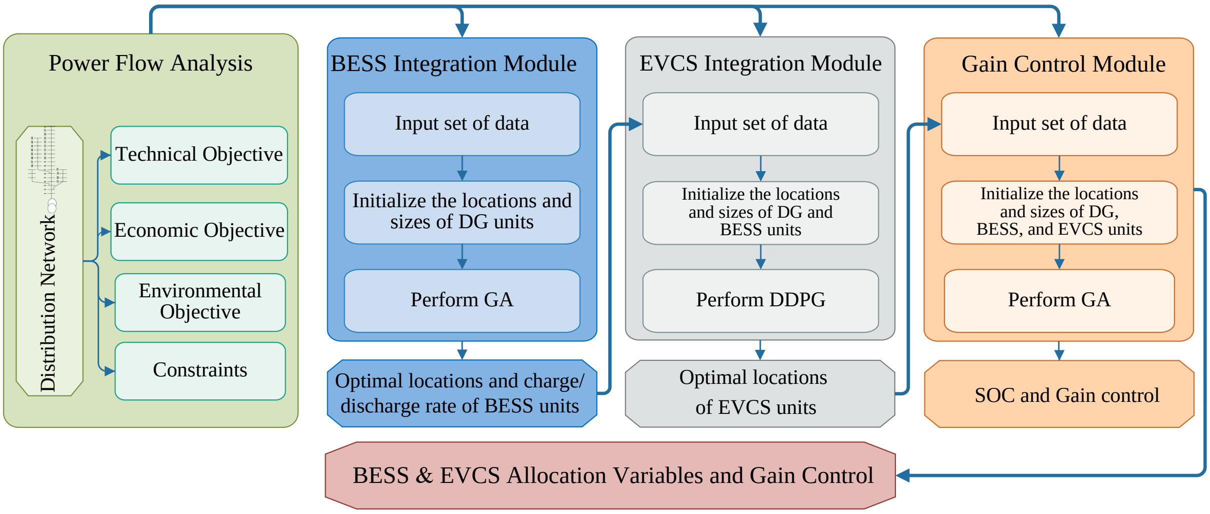


Figure 4.1: Proposed framework for coordinated EVCS–BESS planning and operation in distribution networks.

EV Charging Infrastructure Planning Module

This module formulates EVCS placement as a multi-objective Markov decision process and solves it using DDPG. The actor–critic structure is used to learn sequential EVCS placement decisions under evolving network conditions, in which the actor proposes actions, and the critic evaluates them based on the resulting reward. In the present context, the state at time step t represents the configuration of the DN, including PVs, loads, BESSs, and EVCSs; the action corresponds to the updated EVCS placement decision; and the reward reflects the aggregated objective value associated with that decision [63, 64]. To further stabilise the learning process, both the actor and critic elements must possess corresponding target networks, denoted as θ_A^t and θ_C^t, to change Q-values through:

$$\theta_A^t \leftarrow \Gamma\theta_A + (1-\Gamma)\theta_A^t \tag{4.14}$$

$$\theta_C^t \leftarrow \Gamma\theta_C + (1-\Gamma)\theta_C^t \tag{4.15}$$

Each action a_t taken in state s_t generates a tuple S_t, A_t, R_t, S_{t+1} stored in a replay buffer D, from which mini-batches are randomly sampled to update the actor and critic networks.

$$\iota = \frac{1}{T}\sum_{t\in T}\left(y_t - C(S_t|\theta_C)\right)^2 \tag{4.16}$$

$$y_t = R_t + \gamma \max_{a_{t+1}\in\mathcal{A}} Q(S_{t+1}, a_{t+1}|\theta_A) \tag{4.17}$$

In this context, when determining the optimal placement of EVCSs, the state of the DN at each time step t is treated as the current state S_t. It includes the places and sizes of PVs, loads, BESSs, and EVCSs. The action A_t, on the other hand, is the newly found places of EVCSs that transfer the current state S_t to S_{t+1}. The aggregated objective value associated with action A_t is used as the reward signal R_t.

4.2.2 Real-Time Operational Control Layer

The operational layer manages deviations between the EVCS demand profile assumed during planning and the actual charging behaviour observed in operation. To address this, a distributed BESS control mechanism is introduced to regulate BESS charging and discharging dynamically.

Adaptive BESS Voltage Control Mechanism

To mitigate the impact of real-time deviations from the EVCS demand profile used for BESS siting and sizing, a real-time controller has been integrated into the BESS system. It controls the charging rate of the BESS based on the locally measured voltage as

$$P_i(t) = K_i(t)[V_i(t) - V_{th}] \tag{4.18}$$

Where $V_i(t)$ and $K_i(t)$ denote the voltage of bus i and the control gain, respectively, all at time step t. V_{th} is the nominal voltage of the bus. Based on 4.18, if the EVCS demand is higher than the typical value such that a voltage drop is sensed on the bus, the BESS starts to discharge to compensate for it.

The Control Gain module in Fig. 4.1 calculates the optimal value of the gain $K_i(t)$ for all time steps across the 24-hour operating horizon. The proposed method utilises GA to calculate the $K_i(t)$ while satisfying the constraint in Eq. (4.13) for already located BESS. This distributed control scheme eliminates the need for the extensive communication infrastructure required by centralised control strategies.

The two-stage structure of the framework ensures computational efficiency. The planning stage determines the optimal locations and sizes of BESS and EVCS units using GA and DDPG, while the operational stage dynamically adjusts BESS charging behaviour in response to real-time network conditions.

Overall, the proposed framework integrates long-term planning decisions with real-time operational control strategies, enabling distribution networks to accommodate increasing EV charging demand while maintaining voltage stability and reducing the need for costly network upgrades.

4.3 Evaluation of the Proposed Planning Framework

This section presents the simulation results and discussion for RQ1. The proposed framework is evaluated for its ability to identify suitable EVCS–BESS planning decisions and to maintain acceptable distribution-network performance under both nominal and stressed operating conditions. The results are organised according to the planning-and-operation logic developed earlier in the chapter.

4.3.1 Simulation Setup

The common data environment, feeder construction, and principal modelling assumptions have already been defined in Chapter 3. Accordingly, only the RQ1-specific elements of the simulation setup are summarised here.

The RQ1 framework is evaluated on the modified IEEE 33-bus and IEEE 123-bus distribution networks to assess both planning performance and scalability. The electrical demand environment is constructed from Victorian smart-meter and PV data over a representative 24-hour weekday horizon with 48 half-hour time steps. Figure 4.2 shows the resulting average smart-meter profile, while Fig. 4.3 illustrates the modified IEEE 33-bus network used for the principal RQ1 case study.

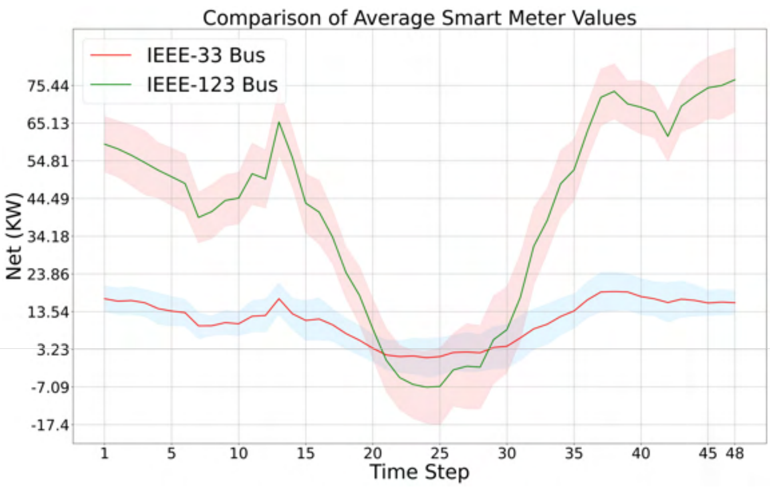


Figure 4.2: Average smart-meter demand profiles used in the IEEE 33-bus and IEEE 123-bus case-study networks.

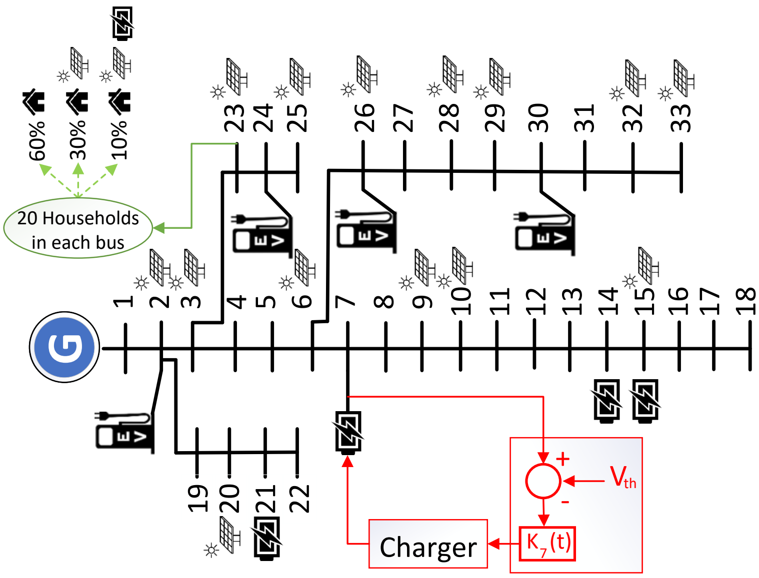


Figure 4.3: Modified IEEE 33-bus distribution feeder used for EVCS–BESS planning and operation analysis.

The feeder-level PV penetration, household composition, BESS operating assumptions, and optimisation settings follow the common configuration documented in Chapter 3. For the IEEE 33-bus case, the framework identifies four BESS and four EVCS locations; for the IEEE 123-bus case, the corresponding larger-scale configuration is reported in Table 4.1.

The principal RQ1 parameters are summarised in Table 4.2 for completeness; however, the

Table 4.1: Optimal BESS and EVCS locations in the modified IEEE 33-bus and IEEE 123-bus networks.

Network	BESS Location	EVCS Location
33-Bus	7, 14, 15, 21	2, 24, 26, 30
	2, 15, 19, 35, 58	13, 30, 33, 39, 40
123-Bus	62, 63, 78, 80, 86	44, 48, 58, 71, 84
	100, 103, 107, 113, 120	89, 95, 101, 109, 116

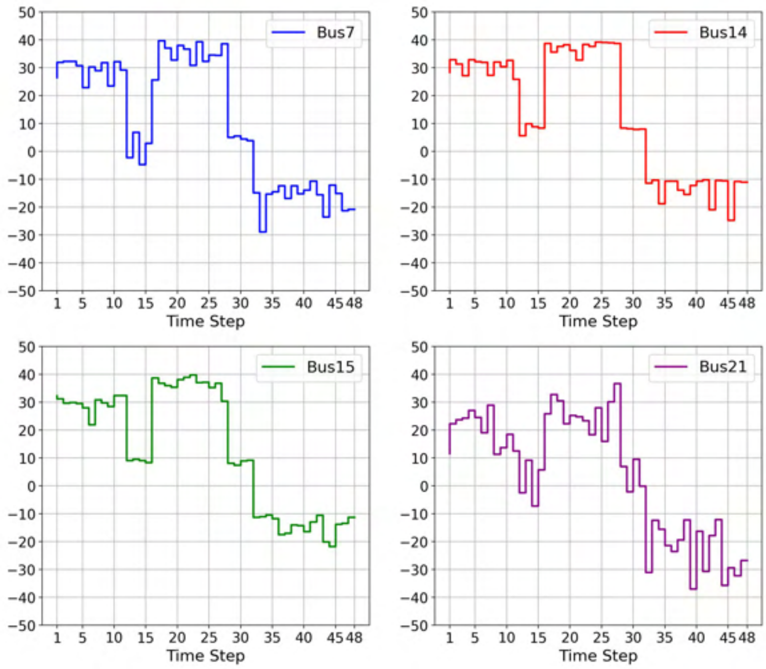


Figure 4.4: BESS charge/discharge profile over the 24-hour planning horizon for the IEEE 33-bus case study.

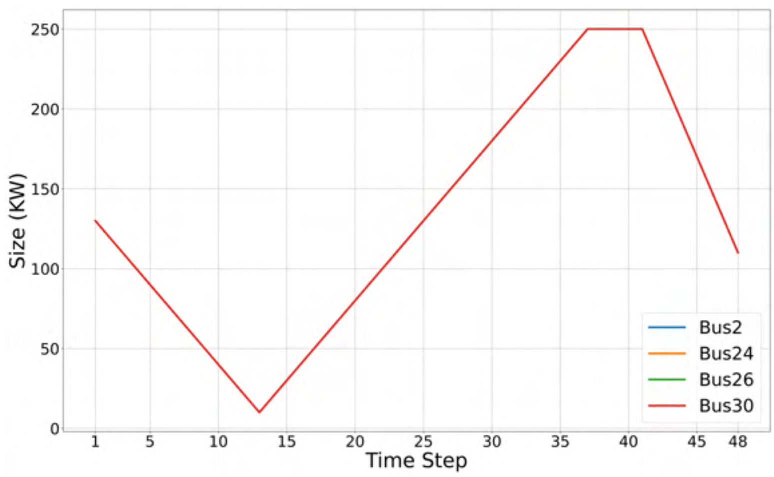


Figure 4.5: Time-varying EVCS demand profile used in the planning and control analysis.

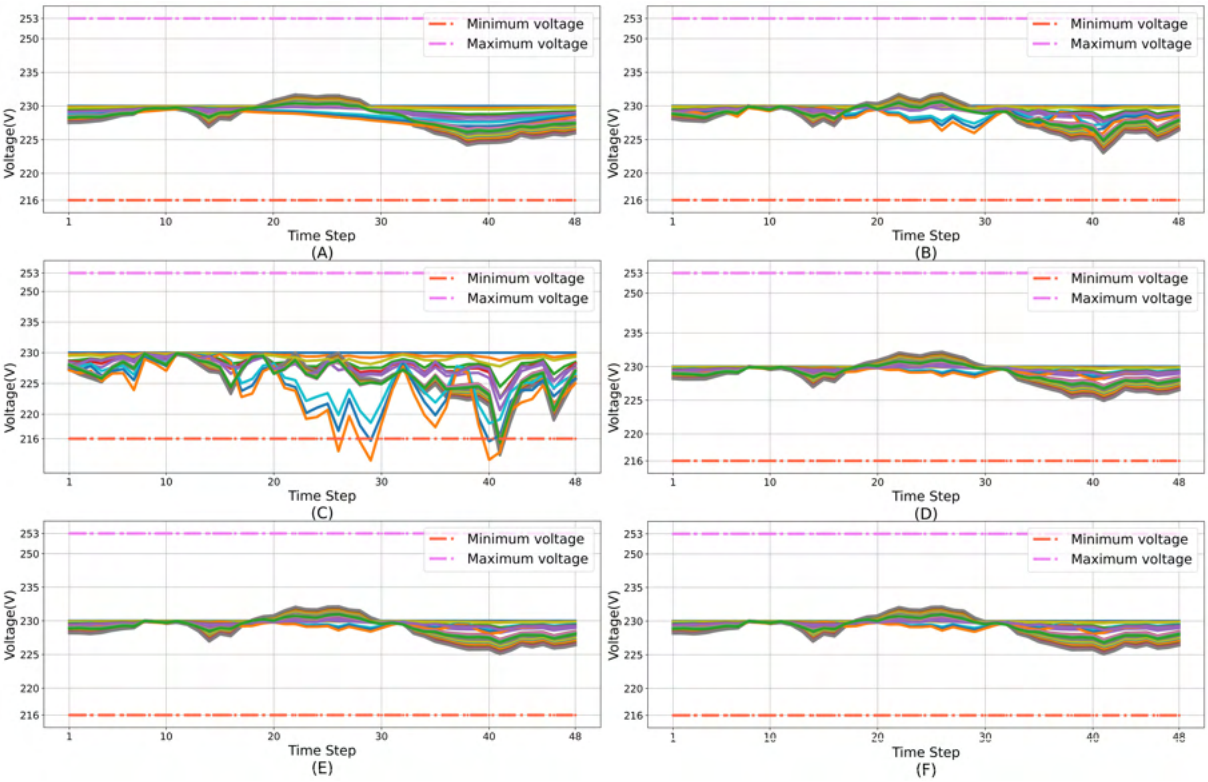


Figure 4.6: Voltage profiles of the IEEE 33-bus network under fixed, real, upper-bound, lower-bound, and controlled EVCS demand scenarios.

Table 4.2: Key parameters used for EVCS–BESS planning and operation in distribution networks.

Parameters	**Value**
BESS installation cost	1.161 \$/kWh
BESS operational cost	0.625 \$/kWh
Duration of project	10 years
Interest rate	3.6%
Inflation rate	3.2%
Carbon emissions	0.554 kg/kWh
Open-circuit voltage	35 V
Short-circuit current	8 A
Voltage temperature coefficient	0.1 °C
Current temperature coefficient	0.05 °C
Cost of power from the substation	5 \$/kWh
Real power from the substation	105 kW
Threshold voltage	230 V
Minimum of Voltage	216 V
Maximum of Voltage	253 V

common parameterisation and data-construction logic are defined in Chapter 3.

This simulation setup establishes the planning context for evaluating the proposed framework under both nominal and stressed EVCS demand conditions. It also enables consistent comparison of planning decisions and operational performance across two scales of the distribution network.

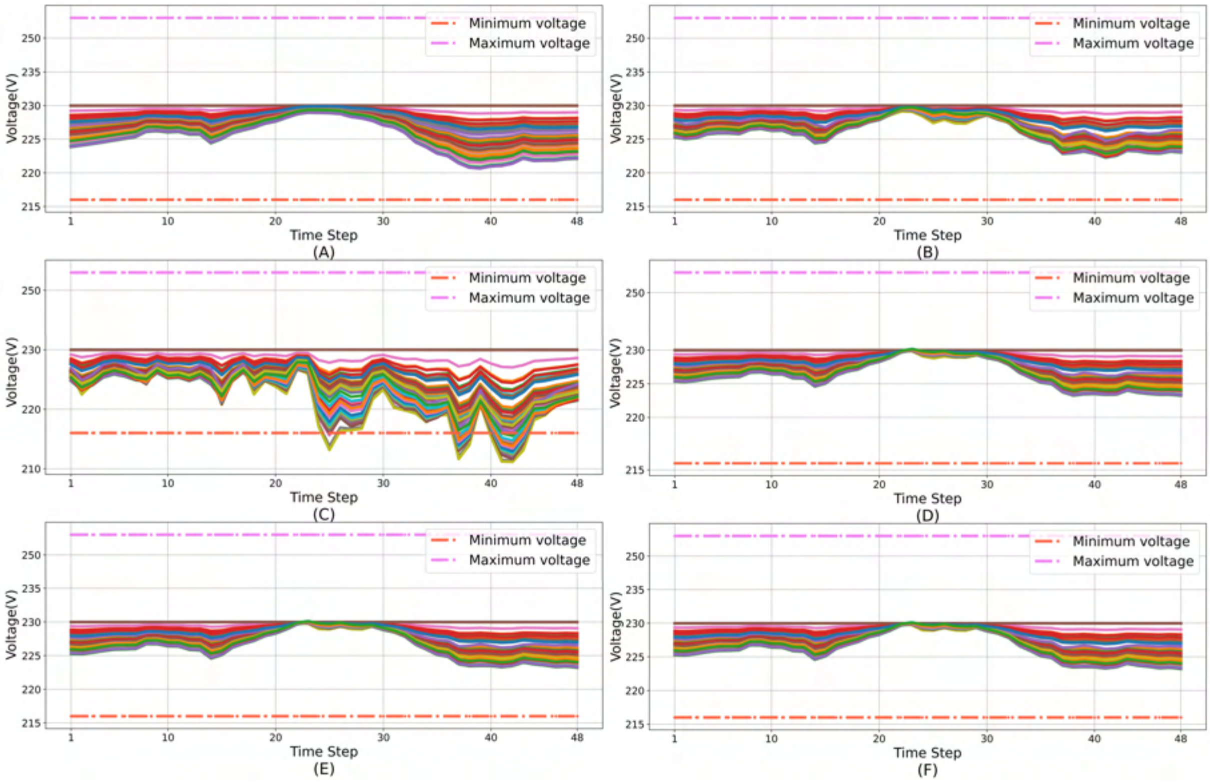


Figure 4.7: Voltage profiles of the IEEE 123-bus network under fixed, real, upper-bound, lower-bound, and controlled EVCS demand scenarios.

4.3.2 Planning Outcomes

After initialising the network with real data and ensuring that voltage levels remained within the acceptable range, the GA was first applied to determine the optimal locations and charge/discharge rates of the BESS, as shown in Fig. 4.4. The DDPG module was then employed to find the optimal locations for EVCS. The framework adopts a hierarchical implementation in which BESS locations and operating schedules are determined first, followed by EVCS placement based on the resulting feeder conditions. The EVCS sizing pattern shown in Fig. 4.5 is inspired by [65]. This method leverages real-world data from EVCSs in Victoria, Australia, using their 24-hour load profiles to determine the EVCS rate of change. To further assess the proposed method's robustness, simulations were performed using data scaled to 10 times the actual values (representing a peak-load scenario on a very busy day) and to 0.1 times the actual values (representing a very quiet day). The results for the IEEE 33-bus network are illustrated in Fig. 4.6, with similar outcomes shown for the IEEE 123-bus network in Fig. 4.7.

As shown in parts A, B, and D of Fig. 4.6 and Fig. 4.7, the voltage profiles of the buses exhibit stable behaviour across all time steps and remain within the acceptable range when using both the fixed pattern sizing and the actual data, as well as when using one-tenth of the real data. However, when the data is scaled up by a factor of 10, i.e., section C of Figs. 4.6 and 4.7, significant voltage drops occur at specific time steps, such as 7:00 p.m. This indicates that the network struggles to handle the high demand at charging stations during peak times, leading to potential instability and failures.

These findings underscore the importance of correctly sizing EVCSs to maintain voltage stability across the network. Using real-world data to set a fixed EVCS charging rate, combined with dynamic BESS control, is essential to prevent detrimental voltage fluctuations and ensure reliable power system operation. To mitigate voltage fluctuations, including unexpected

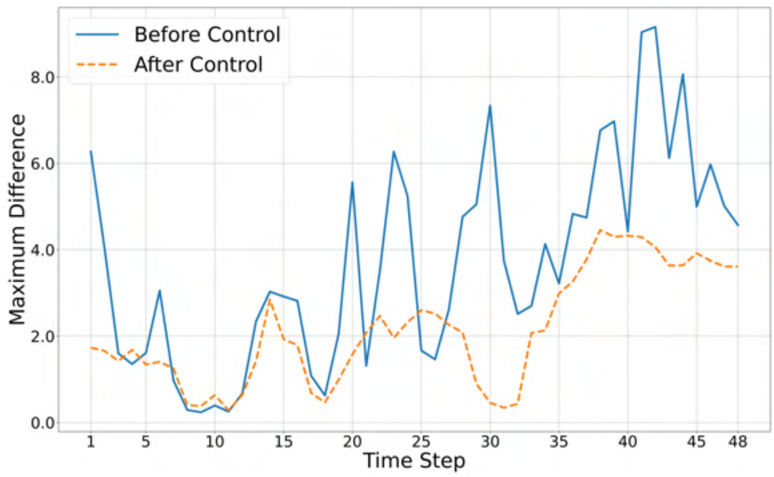


Figure 4.8: Voltage-error profile for the IEEE 33-bus feeder under different EVCS demand and control scenarios.

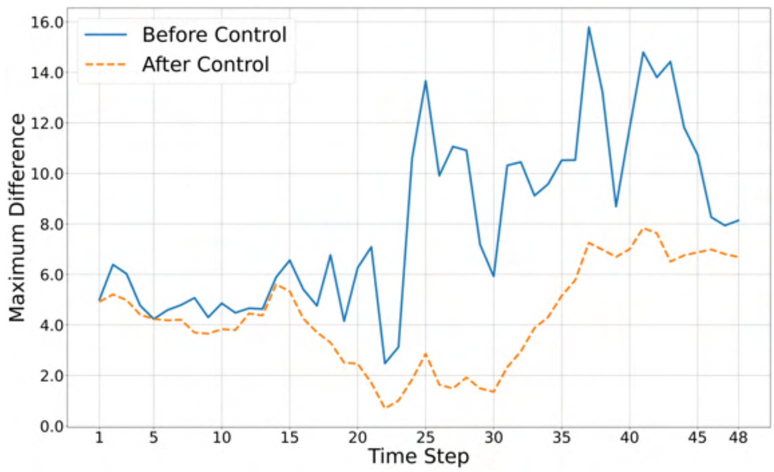


Figure 4.9: Voltage-error profile for the IEEE 123-bus feeder under different EVCS demand and control scenarios.

rises and drops, a Control module was implemented to adjust the BESS charge/discharge rates dynamically.

The above results demonstrate that the proposed planning framework can identify a feasible and effective EVCS–BESS configuration under realistic daily operating conditions. At the same time, they show that planning decisions alone are insufficient under extreme EVCS demand scenarios, thereby underscoring the importance of the operational control layer introduced in Section 4.2.

4.3.3 Benchmark Comparisons

To complement the network-level response analysis, this subsection presents two additional perspectives established in the preliminary stage of RQ1 that remain useful for interpreting the final planning logic. First, the required balance between EVCS and BESS units is examined. Second, the proposed method is compared with alternative benchmark methods to assess its relative planning performance.

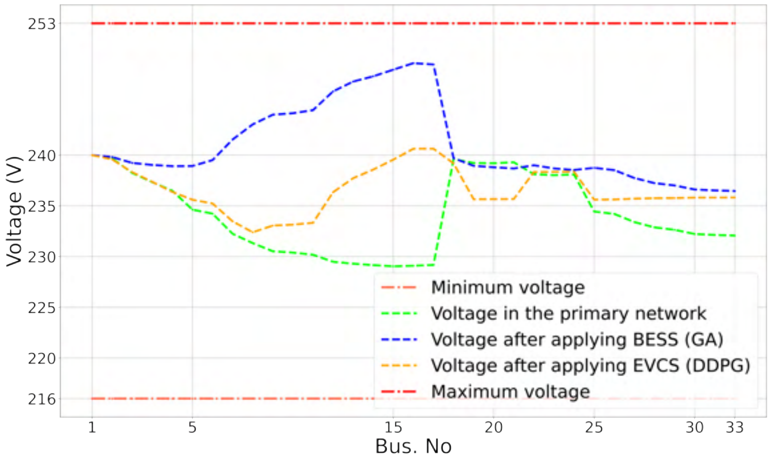


Figure 4.10: Voltage-profile evolution across the main planning and control stages of the proposed framework.

Balance Between EVCS and BESS Units

This subsection examines the balance between the number of BESS and EVCS units required to satisfy the optimisation problem. To demonstrate that the voltages of different busbars remain within the minimum and maximum values, we measure the voltages before the GA, after the GA, and after the DDPG. As shown in Fig. 4.10, voltages of all busbars are in the acceptable range when there is no EVCS or BESS added to the network. Then, we determine the locations and sizes of 4 BESS units using the GA method and add them to the network. Subsequently, using the DDPG algorithm, we determine the optimal locations and sizes of 4 EVCSs in the network. In the implementation, the maximum sizes of EVCS and BESS are set to 1000 kW and 300 kW, respectively.

In the next step, we study the correlation between the number of EVCSs and BESSs in a network. For example, we first add four EVCSs to busbars 5, 10, 12, and 20 of the network and three BESSs to busbars 12, 16, and 18. As shown in Fig. 4.11, with 3 BESS units, a significant voltage drop occurs across busbars 30-33. Therefore, the optimisation framework fails to converge when three BESSs are added to the network. In the case of four BESSs, the optimisation problem converges, and the BESS sizes and locations keep the voltage within the specified range. Fig. 4.11 also shows the acceptable result when six BESSs are connected to the network; however, from the economic perspective, having four BESSs in the network is preferred.

To conduct a comprehensive study, we established a framework to determine the minimum number of BESS units required to compensate for a given number of EVCSs. Fig. 4.12 shows that as the number of EVCS units increases, the required number of BESSs also increases. For example, when we have six EVCS on busbars 4, 6, 9, 17, 25, and 29, we need at least six BESS units to satisfy the optimisation framework's constraints.

These results make the planning trade-off of RQ1 more explicit. They show that EVCS deployment cannot be determined independently of supporting storage capacity, and that the proposed framework can identify the minimum BESS support level needed to maintain technical feasibility while avoiding unnecessarily conservative investment decisions.

Comparison with Benchmark Methods

This subsection compares the proposed method, GA–DDPG, with PSO–DDPG, WOA–DDPG, and WOAGA–RL techniques [7]. Table 4.3 shows the result of this comparison. The results show that the proposed technique can accommodate a higher EVCS capacity than has been reported in the literature. In particular, for the IEEE 33-bus network, the proposed technique

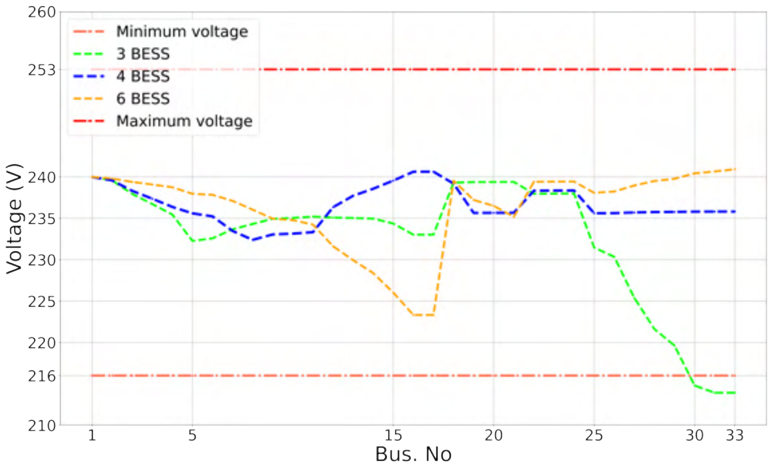


Figure 4.11: Voltage profiles under different BESS deployment levels for a four-EVCS network configuration.

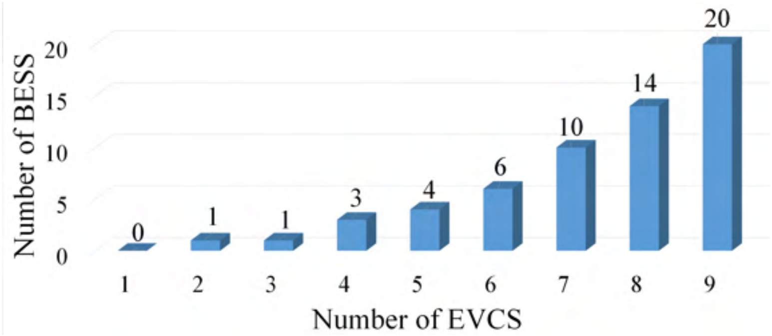


Figure 4.12: Relationship between EVCS deployment level and required BESS support in the distribution network.

can optimally locate four EVCS with a total power of 3,382 kW, compared to 2,740 kW for PSO–DDPG and 2,685 kW for WOA–DDPG. This has been done by adding almost the same amount of total BESS as shown in Table 4.3.

Table 4.3: Comparison of BESS and EVCS allocation decisions across the proposed and benchmark planning approaches.

Method	BESS		EVCS	
	Location	Size (kW)	Location	Size (kW)
PSO–DDPG	3, 15, 24, 28	283.6, 282, 295.3, 270	2, 15, 20, 30	552.4, 871.3, 778.2, 539.1
Proposed method	9, 14, 16, 17	278.4, 279.1, 290.6, 274.3	5, 10, 12, 20	838.3, 996.42, 595.1, 952.3
WOA–DDPG	11, 12, 16, 18	243.2, 232.3, 249.6, 242.5	2, 4, 8, 28	573.4, 759.8, 620.6, 733.6
WOAGA–RL [7]	9, 9, 10, 13, 18, 21	278.4, 246.7, 23.8, 135.3, 297.4, 80.7	4, 13, 22, 28	N/A

This benchmark comparison reinforces the planning interpretation of the RQ1 framework. It shows that the coordinated GA–DDPG strategy is not only technically feasible but also more effective at accommodating larger EVCS capacity while maintaining a similar level of BESS support. From a practical viewpoint, this suggests that the proposed framework offers a more resource-efficient pathway for EVCS deployment in constrained distribution networks.

4.3.4 Control Effectiveness Under Demand Variability

As outlined in Section 4.2, the Control Module leverages the GA to determine the optimal gain (K) values that prevent voltage fluctuations outside the predefined range. The gain control adjusts the BESS charge and discharge rates to ensure that, even with real EVCS data, the network voltage and SOC remain within the desired limits. Acting as a regulator for the battery network, the Control Module compensates for EVCS impacts on voltage levels, thereby mitigating potential voltage drops. Parts E and F in Fig. 4.6 show the voltage profile of the IEEE 33-bus network after implementing the Control Module, clearly showing that the voltage remains within the predefined range. Similarly, parts E and F of Fig. 4.7 show that the IEEE 123-bus network remains within the permissible voltage range after activating the control module under the stressed upper-bound and lower-bound EVCS demand scenarios.

To further demonstrate the control module's effectiveness in maintaining voltage within the predefined range, a new metric was introduced to quantify voltage error. This metric measures the maximum deviation from the nominal voltage of 230 V at each time step. As shown in Fig. 4.8 and Fig. 4.9, after running the control module, the voltage error is significantly reduced, indicating the module's efficacy.

This result confirms that the operational layer of the proposed framework provides the additional flexibility needed to maintain acceptable voltage performance when EVCS demand deviates from the typical planning profile. Hence, the integrated planning and control structure adopted in RQ1 is not only computationally effective but also operationally robust across both medium- and large-scale test networks.

Overall, the RQ1 results show that coordinated EVCS–BESS planning can maintain acceptable distribution-network performance under realistic daily operating conditions. At the same time, the adaptive control layer provides the additional flexibility required during stressed-demand scenarios. The results also confirm that the framework remains effective across both the IEEE 33-bus and IEEE 123-bus systems, indicating that the underlying planning logic is scalable and operationally robust. These findings complete the answer to RQ1 and motivate the practitioner-oriented design insights presented next.

4.4 Practitioner-Oriented Design Insights

The results of RQ1 provide several practical insights for distribution network planners, EV charging infrastructure developers, and industry stakeholders involved in EV integration. Overall, the findings show that reliable EVCS deployment in distribution networks cannot be achieved through isolated siting decisions alone; instead, it requires coordinated planning of charging infrastructure, supporting storage, and local operational control.

A first key insight is that BESS allocation should be driven by grid-support value rather than simple co-location with EVCS assets. The results show that placing BESS units at buses with greater influence on voltage conditions and local demand variability improves voltage performance, reduces losses, and increases the network's effective hosting capability. For practice, this means storage should be treated as a network-support asset, not merely a charger-adjacent resource.

A second insight is that EVCS planning based on representative daily demand patterns is more practical than relying on worst-case peak assumptions. The simulation results show that typical demand profiles can support realistic infrastructure sizing, while avoiding unnecessarily conservative investment decisions. This is particularly important in real-world deployment settings, where over-sizing the support infrastructure can undermine the economic viability of EV charging rollouts.

A third insight is that planning decisions alone are insufficient when charging demand deviates materially from the profile adopted during planning. The results under stressed-demand conditions show that adaptive BESS control is necessary to maintain acceptable voltage performance amid operational uncertainty. In practical terms, this implies that future-ready EVCS deployment strategies should include both a planning layer for infrastructure allocation and an operational layer for real-time corrective response.

The results also indicate that the framework is scalable and implementation-oriented. Its effectiveness on both the IEEE 33-bus and IEEE 123-bus systems suggests that the planning logic is transferable to networks of different sizes. In addition, the distributed voltage-based control scheme reduces communication and coordination requirements, which improves its suitability for staged deployment in real distribution systems.

From an industry deployment perspective, the main implication of RQ1 is clear: EVCS and BESS should be planned jointly, using realistic demand data and supported by local control capability. This integrated approach provides a technically reliable and operationally adaptive pathway for EV charging integration, while reducing the need for unnecessarily conservative network augmentation. These findings lay the foundation for the next stage of the research, in which the planning problem is extended beyond the distribution network to include transportation-driven charging demand and user accessibility.

Chapter 5

Traffic Informed EVCS Planning using Coupled Transport–Distribution Networks

This chapter addresses RQ2 by extending the planning logic of Chapter 4 from grid-oriented EVCS–BESS planning to a coupled PDN–TN setting. While Chapter 4 evaluated EVCS deployment primarily from the perspective of distribution-network feasibility and local BESS support, the present chapter introduces the transportation network as an explicit source of charging-demand formation. The central question is how EVCS planning changes when charging demand is no longer treated as an exogenous electrical load, but is instead derived from traffic-informed mobility patterns, accessibility conditions, and queueing behaviour.

The chapter, therefore, reformulates EVCS deployment as a coupled infrastructure planning problem. In the transportation layer, traffic activity, road impedance, travel distance, and service accessibility determine where and when EV charging demand emerges. In the power distribution layer, the resulting charging demand must be met without violating feeder capacity, voltage limits, or network performance requirements. The coupling between these layers creates a planning problem in which mobility-attractive locations are not necessarily electrically feasible, and electrically favourable locations are not necessarily attractive or accessible to EV users.

A key distinction in this chapter is between demand formation, infrastructure planning, and operational feasibility. Demand formation refers to the construction of time-varying EV charging demand from TN conditions. Infrastructure planning involves siting and sizing EVCSs and placing supporting BESS units. Operational feasibility refers to the ability of the PDN to accommodate the resulting charging demand while maintaining acceptable voltage, power loss, and service-capacity conditions. This separation is important because it prevents the coupled framework from becoming a black-box optimisation exercise and clarifies how transportation-side and power-side mechanisms influence the final planning outcome.

The proposed framework is organised around three connected components. First, a coupling architecture maps traffic-informed charging demand from TN nodes to candidate EVCS locations and corresponding PDN connection points. Second, an integrated multi-objective formulation captures infrastructure cost, technical grid performance, user travel cost, queueing effects, and cross-network feasibility constraints. Third, a hybrid GA–DDPG optimisation workflow is used to coordinate BESS and EVCS decisions under time-varying traffic-informed demand. The framework is evaluated using real Melbourne/Victoria traffic data coupled with a modified IEEE 33-bus distribution network, enabling the chapter to examine how traffic-informed demand affects infrastructure decisions compared with grid-only or simplified planning paradigms.

The chapter is organised as follows. Section 5.1 introduces the PDN–TN coupling architecture and defines how transportation-side demand is mapped into distribution-network planning. Section 5.2 presents the integrated multi-objective formulation, including cost, accessibility, service-capacity, and cross-network feasibility terms. Section 5.3 describes the hybrid GA–DDPG solution workflow and benchmark models. Section 5.4 presents the case-study results, benchmark comparisons, and mechanistic interpretation of coupling effects. Finally, Section 5.5 translates the findings into practitioner-oriented planning guidance and establishes the basis for the V2G and market-flexibility extensions developed in Chapter 6.

5.1 Coupling Architecture

The coupled planning problem considered in RQ2 arises because EV charging demand is generated in the TN but must be physically supplied through the PDN. The role of the present section is therefore to define the architecture that maps mobility-driven charging demand to PDN loading and infrastructure decisions.

The coupled planning problem considered in RQ2 arises because EV charging demand is generated within the TN but must be physically supplied through the PDN. The role of this section is therefore to define the architecture that maps mobility-driven charging demand to PDN loading and infrastructure decisions. From the PDN perspective, planning decisions must preserve voltage stability, reduce power loss, and respect feeder and storage operating limits. From the TN perspective, charging infrastructure must remain accessible, limit travel burden, and avoid excessive queueing delay. The coupled architecture, therefore, provides the basis for evaluating EVCS and BESS deployment decisions across both infrastructures rather than treating either network in isolation.

To capture these interactions, this work models the coupled system as two interacting graphs: a PDN that supplies energy to EVCS units and a TN that generates charging demand through traffic flows. The integration of these networks allows charging demand to propagate dynamically from traffic nodes to electrical buses, thereby enabling coordinated planning of EVCS placement and grid-support resources, such as BESSs.

This coupled representation provides the foundation for the multi-objective optimisation framework developed in this chapter. The framework integrates traffic-derived charging demand, grid operational constraints, and infrastructure investment costs to determine the optimal locations and capacities of EVCS and BESS units.

5.1.1 Power Distribution Network–Transportation Network Joint Modelling

Within the proposed architecture, the transportation and power networks are linked via a mapping mechanism that associates traffic intersections with candidate locations for charging infrastructure in the distribution network. In this representation, traffic nodes generate charging demand while electrical buses supply the corresponding charging power.

Through this mapping, charging demand originating from mobility patterns is translated into electrical load injections within the PDN. This mechanism ensures that EVCS placement decisions remain consistent with both transportation accessibility and electrical feasibility.

To ensure operational feasibility across the coupled system, several cross-network constraints must be respected. First, the voltage magnitude at each distribution bus must remain within the operational limits defined by grid codes. Second, the total charging demand assigned to each EVCS must remain within transformer and station capacity limits. Third, spatial constraints within the TN require that charging stations maintain minimum separation distances to avoid redundant infrastructure and inefficient use.

Within this architecture, modelling traffic dynamics and EV charging demand is a key component of the coupled planning framework. The following subsections, therefore, introduce the traffic network representation and the demand-generation model used to translate mobility activity into charging loads.

Modelling Traffic Network

Consistent with the common transportation-network representation defined in Chapter 3, the TN is modelled as a graph composed of intersections and connecting road segments. In this chapter, this representation is used to derive traffic-informed charging demand and to support the coupled EVCS planning problem. Formally, the traffic network (TN) is represented as

$$\begin{cases} TN = \{I, W, T\} \\ I = \{i_j \mid j = 1, 2, \ldots, n\} \\ W = \{w_{i,j} \mid i = 1, 2, \ldots, n,\ j = 1, 2, \ldots, n\} \\ T = \{t \mid t = 1, 2, \ldots, 48\} \end{cases} \tag{5.1}$$

where TN denotes the traffic network system, I represents the set of intersections, and n denotes the total number of intersections. W represents the road impedance matrix describing travel impedance between intersections, and T represents the set of time steps, where the daily operation horizon is discretised into 48 intervals corresponding to 30-minute periods [66].

Consider two connected intersections indexed as i and j. The traffic flow between these intersections can be estimated using the multi-parameter gravity model proposed in [59]

$$V_{i,j}^t = C\frac{N_i^\alpha N_j^\gamma}{W_{i,j}^t} \tag{5.2}$$

where $V_{i,j}^t$ denotes the traffic flow between intersections i and j at time step t. C represents a proportionality coefficient, while N_i and N_j denote the population sizes of the areas surrounding intersections i and j, respectively. The parameters α and γ represent application-specific scaling factors.

The road impedance term is calculated as

$$W_{i,j}^t = b_0 z_t^c + \sum_j b_j \times y_j \tag{5.3}$$

where z_t^c denotes the road saturation level during time step t, and y_j represents various infrastructure attributes that affect traffic conditions, including the number of traffic lights, bus stops, tram stations, train stations, and traffic lanes. Additional factors, such as road width, surface conditions, and weather, may also influence road impedance. The coefficients b and c represent normalised weighting factors that quantify the relative influence of each contributing parameter.

This representation allows the framework to capture both spatial heterogeneity in road infrastructure and temporal variation in traffic intensity across the TN.

Modelling EV Charging Demand

In the coupled RQ2 formulation, traffic flows alone are insufficient to determine charging demand. Charging demand must also reflect EV energy consumption behaviour and the evolution of battery SoC over the operating horizon.

For EVs, hourly driving mileage fluctuates throughout the day. Consequently, the hourly mileage as a percentage of total daily mileage can be represented using a mixed Gaussian probability density function [67]

$$f_s(x) = \sum_{k=1}^{K} \pi_k \times e^{-\left(\frac{x-\mu_k}{\sigma_k}\right)^2} \tag{5.4}$$

where π_k, μ_k, and σ_k denote the weight, mean, and variance of the kth Gaussian component, respectively, with $\sum_{k=1}^{K} \pi_k = 1$.

Based on this distribution, the cumulative driving mileage at time t can be expressed as

$$L(t) = L_0 \times \int_0^t f_s(x)\,dx = L_0 \times F_s(t) \tag{5.5}$$

where L_0 denotes the daily driving mileage.

Assuming that the initial SoC of an EV battery is β_0, the SOC at time t can be represented as

$$\mathrm{SOC}_t = \beta_0 - \frac{L(t)}{l_{\max}} \tag{5.6}$$

where $l_{\max}$ denotes the maximum driving range of the EV when fully charged.

The decision of EV drivers to initiate charging is modelled using a Weibull probability distribution:

$$f_{SOC}(x) = a \times b \times x^{b-1} \times e^{-ax^b} \tag{5.7}$$

The probability that an EV driver decides to charge when the SOC is β can therefore be calculated as

$$F_{\mathrm{SOC}}(\beta) = \int_0^{\beta} f_{\mathrm{SOC}}(x)\, dx \tag{5.8}$$

Accordingly, the probability that an EV requires charging while travelling at time t becomes

$$P_{\mathrm{charg}} = \int_0^{\beta_0 - \frac{L(t)}{l_{\max}}} f_{\mathrm{SOC}}(x)\, dx \tag{5.9}$$

Finally, the number of EVs requiring charging at intersection i during time step t is calculated as

$$N_i^t = V_i^t \times \alpha \times P_{\mathrm{charg}} \tag{5.10}$$

where α denotes the EV penetration level within the traffic network, and $V_i^t = \sum_j V_{i,j}^t$ represents the real-time traffic flow arriving at intersection i.

Through this formulation, the framework dynamically translates traffic activity into spatially and temporally distributed EV charging demand. In contrast to static demand representations rooted in classical location theory [68], this formulation reflects the fluctuating nature of EV charging requirements across the TN.

This dynamic demand coupling plays a central role in the coupled PDN–TN planning architecture. It ensures that charging infrastructure planning decisions remain aligned with real-world mobility behaviour, thereby improving both the practicality and the realism of EVCS deployment strategies.

5.2 Integrated Optimisation Formulation

Having established the coupled PDN–TN architecture and the traffic-informed demand propagation mechanism, this section formulates the RQ2 planning problem as an integrated multi-objective optimisation problem. The aim is to determine the locations and capacities of EVCS and BESS units such that the resulting infrastructure remains technically feasible for the distribution grid, economically justifiable for investors and operators, and practically efficient for EV users.

Unlike conventional EVCS planning models that prioritise a single stakeholder or a single infrastructure layer, the present formulation explicitly captures the interaction among three interdependent objective domains: grid-oriented technical performance, infrastructure-related economic cost, and user-oriented accessibility and service quality. As a result, the formulation evaluates not only the physical feasibility of EVCS deployment but also the trade-offs among power-system security, charging-service convenience, and investment efficiency.

Accordingly, the EVCS and BESS planning problem can be formulated as a multi-objective optimisation problem that determines the optimal siting and sizing of charging infrastructure while maintaining system feasibility across both the transportation and power networks. The decision variables, therefore, include the location and capacity of EVCS units, the siting and operational configuration of BESS units, and the corresponding operational states of the coupled PDN–TN system over the planning horizon. The resulting formulation simultaneously minimises technical grid impacts, infrastructure investment costs, and user travel-related costs subject to power system, service capacity, and operational constraints.

5.2.1 Infrastructure Cost Objectives

The goal of the proposed optimisation approach is to determine the optimal locations and sizes of EVCS units within a specified planning area, while accounting for the coupled objectives and constraints of the traffic and power networks. Accordingly, the proposed method is formulated as a multi-objective optimisation framework that minimises three main categories of cost functions: technical costs, annual investment costs, and annual travel-related costs.

Technical Costs

This study considers three technical objective functions, including power loss, voltage stability, and VD. These metrics collectively characterise the electrical impact of EVCS and BESS deployment on the distribution network and provide a physically meaningful representation of grid performance under traffic-driven charging demand.

Power Loss Power loss greatly affects distribution networks and is calculated as follows:

$$P_t^{LOSS} = \sum_{m=1}^{M} \sum_{n=1}^{N} \alpha_{mn}(P_m^t P_n^t + Q_m^t Q_n^t) + \beta_{mn}(Q_m^t P_n^t - P_m^t Q_n^t) \tag{5.11}$$

where

$$\alpha_{mn} = \frac{r_{mn}}{V_m V_n} \cos(\delta_m - \delta_n) \tag{5.12}$$

and

$$\beta_{mn} = \frac{r_{mn}}{V_m V_n} \sin(\delta_m - \delta_n) \tag{5.13}$$

In these equations, the sending and receiving buses are denoted by m and n, respectively. The branch impedance from bus m to n is given by $Z_{mn} = r_{mn} + jx_{mn}$, and P and Q represent the real and reactive powers of each bus. V_m and V_n denote the voltage magnitudes of buses m and n, respectively, while δ_m and δ_n denote their voltage angles. Here, α_{mn} and β_{mn} capture the contribution of real and reactive power flows, together with voltage-angle differences and line resistance, to feeder-level power loss.

Voltage Stability Index Because increasing and spatially concentrated charging demand can push the feeder toward voltage instability, a VSI is used to quantify proximity to voltage collapse and is therefore maximised. It is calculated as

$$VSI_{n,t+1} = (|V_{m,t}|^2 - 2P_{m,t}R_{m,t} - 2Q_{m,t}X_{m,t})^2 - 4(P_{m,t}^2 + Q_{m,t}^2)(R_{m,t}^2 + X_{m,t}^2) \tag{5.14}$$

$$VSI_{m,t} = \frac{1}{\min(vsi_{n,t+1})} \tag{5.15}$$

where $R_{m,t}$ and $X_{m,t}$ denote the branch resistance and reactance associated with the bus under analysis at time step t, respectively. A higher VSI indicates stronger voltage stability, whereas a lower value indicates greater vulnerability to voltage collapse under increased loading.

Voltage Deviation When integrating BESS and EVCS units in distribution networks, voltage regulation must be explicitly monitored:

$$VD_t = \sum_{m=2}^{M} |V_m^t - V_{ref}| \tag{5.16}$$

where V_m^t denotes the voltage of bus m after integrating BESS and EVCS units at time step t, and V_{ref} denotes the reference voltage. This objective captures the cumulative deviation of bus voltages from the desired operating point and is therefore used as an indicator of power-quality performance.

Taken together, these technical indices quantify complementary yet competing aspects of PDN performance. Reducing power loss improves electrical efficiency, improving VSI enhances voltage security, and minimising VD preserves power quality.

Annual Investment Cost

The annual investment cost comprises construction, maintenance, and loss costs. These costs capture the economic burden associated with the deployment and operation of charging infrastructure and therefore provide the economic counterpart to the grid-performance objectives. In contrast to the grid-oriented economic formulation of RQ1, the present chapter explicitly includes EVCS construction, maintenance, and loss-related costs because infrastructure deployment in the coupled PDN–TN setting must be evaluated from both grid and service-investment perspectives.

Construction Cost The construction cost C_{build} for EVCS k primarily comprises the expenses for purchasing equipment, land rental, and civil construction:

$$C_{\text{build}} = \frac{r_0(1+r_0)^{n_0}}{(1+r_0)^{n_0}-1}(N_k c_{\text{charg}} + S_k c_{\text{trans}} + A_k c_{\text{field}} + A_k c_{\text{roof}} + C_h) \tag{5.17}$$

where r_0, n_0, and N_k represent the discount rate, the lifespan of the EVCS, and the number of available charging piles at EVCS k, respectively. S_k denotes the transformer capacity at EVCS k (kW), c_{charg} and c_{trans} denote the cost per charging pile (\$) and the unit cost for transformer capacity (\$/kW), respectively, and A_k specifies the area size of EVCS k (m^2). Moreover, c_{field} and c_{roof} denote the land-rental cost and shed cost per unit area (\$/m^2), respectively, and C_h denotes the civil engineering cost of EVCS k (\$).

In contrast to studies that treat land, civil, and rental costs as constant parameters, the present formulation explicitly accounts for the location-dependent variability of c_{field}, c_{roof}, and C_h. As a result, the construction cost calculation more accurately reflects the realistic differences in siting conditions across candidate EVCS locations.

Maintenance and Operating Cost The labour and maintenance cost of EVCS equipment is treated as the operating and maintenance cost:

$$C_{mtn} = \gamma C_{build} \tag{5.18}$$

where γ denotes the ratio of labour and maintenance cost to construction cost, typically set to 9%.

Loss Cost For EVCSs, the loss cost C_{loss} primarily comprises line, charging, and transformer losses. Line loss refers to the power dissipated along the cable from the charging pile to the electricity metering point and is influenced by the cable length, conductor cross-section, and temperature. Charging loss refers to the standby and operating losses of the charging pile. Transformer loss includes both open-circuit loss and load loss:

$$C_{\text{loss}} = (P_{\text{line}} + P_{\text{charg}} + P_{\text{trans}})T_c P_c = (p_l \times l_{\text{cap}} + p_c \times c_{\text{cap}} + p_t \times t_{\text{cap}})T_c P_c \tag{5.19}$$

where P_{line}, P_{charg}, and P_{trans} denote the annual line loss, charging loss, and transformer loss, respectively (kW). These losses are calculated based on the corresponding loss rates (p_l, p_c, and p_t) and the capacities (l_{cap}, c_{cap}, and t_{cap}) of transmission lines, charging piles, and transformers. T_c denotes the annual operating hours (h), and P_c is the electricity price ($\$/kWh$).

These investment-related terms quantify the economic consequences of EVCS expansion and provide the necessary counterbalance to user-centric and grid-centric objectives.

5.2.2 Charging Service Accessibility

Because EVCS accessibility depends on drivers' time-varying locations within the TN, EVCS placement directly affects users' travel costs and service convenience. This component of the formulation explicitly links the transportation-layer dynamics introduced in Section 5.1 to infrastructure planning decisions in the power network. As EV drivers travel through the TN, their routing choices, travel distances, and waiting times collectively determine the effective accessibility of charging infrastructure.

Annual Travel Cost

Travel cost is composed of the electrical energy cost associated with reaching the assigned EVCS and the time cost associated with travelling and waiting:

$$C_k^2 = C_{kp} + C_{km} \tag{5.20}$$

The electrical energy cost for users, C_{kp}, is determined based on the distance from intersection i to EVCS k:

$$C_{kp} = \sum_{t=1}^{T}\sum_{i=1}^{I} \frac{d_{i,k} \times N_i^t}{l_0} \times P_c \tag{5.21}$$

The time cost for users, C_{km}, includes both the travel time from their current location to EVCS k and the queuing time at EVCS k:

$$C_{km} = \left[\sum_{t=1}^{T}\sum_{i=1}^{I} \frac{d_{i,k} \times N_i^t}{V_{i,k}^t} + \sum_{t} W_k^t\right] \times c_{time} \tag{5.22}$$

where $d_{i,k}$ denotes the driving distance from intersection i to EVCS k (km), N_i^t denotes the number of EVs requiring charging at intersection i during time step t, $V_{i,k}^t$ denotes the driving speed from intersection i to EVCS k (km/h), l_0 denotes the mileage per unit of electrical energy (km/kWh), c_{time} denotes the value of driver time in the planning area ($\$/h$), and P_c denotes the electricity price ($\$/kWh$).

This decomposition allows the optimisation to evaluate the mobility-side consequences of EVCS placement decisions explicitly.

5.2.3 Service Capacity

In addition to spatial accessibility, the practical performance of EV charging infrastructure depends strongly on the service capacity of charging stations and the waiting times experienced by EV users. Therefore, queueing dynamics are explicitly incorporated into the formulation.

The formulation assumes that EVCSs are equipped with two types of charging piles: fast and slow. The EV charging process follows a first-come, first-served policy. Using the Markov transition process and the dynamic M/M/C queueing model [60, 61], the queuing time at charging station k during time period t is determined as

$$W_k^t = W_{k,f}^t + W_{k,s}^t \tag{5.23}$$

where $W_{k,f}^t$ denotes the queuing time for users opting for fast charging at EVCS k during time period t:

$$W_{k,f}^t = \frac{P_{0,f}}{(N_{k,f}-1)!} \times \left(\frac{\lambda_{f,t}}{\mu_{f,t}}\right)^{N_{k,f}} \times \frac{\mu_{f,t}}{N_{k,f}\mu_{f,t}-\lambda_{f,t}} \tag{5.24}$$

$$P_{0,f} = \left[\sum_{n=0}^{N_{k,f}-1} \frac{1}{n!}\left(\frac{\lambda_{f,t}}{\mu_{f,t}}\right)^n + \frac{1}{N_{k,f}!}\left(\frac{\lambda_{f,t}}{\mu_{f,t}}\right)^{N_{k,f}} \times \left(\frac{N_{k,f}\mu_{f,t}}{N_{k,f}\mu_{f,t}-\lambda_{f,t}}\right)\right]^{-1} \tag{5.25}$$

Similarly, the queuing time for users opting for slow charging is

$$W_{k,s}^t = \frac{P_{0,s}}{(N_{k,s}-1)!} \times \left(\frac{\lambda_{s,t}}{\mu_{s,t}}\right)^{N_{k,s}} \times \frac{\mu_{s,t}}{N_{k,s}\mu_{s,t}-\lambda_{s,t}} \tag{5.26}$$

$$P_{0,s} = \left[\sum_{n=0}^{N_{k,s}-1} \frac{1}{n!}\left(\frac{\lambda_{s,t}}{\mu_{s,t}}\right)^n + \frac{1}{N_{k,s}!}\left(\frac{\lambda_{s,t}}{\mu_{s,t}}\right)^{N_{k,s}} \times \left(\frac{N_{k,s}\mu_{s,t}}{N_{k,s}\mu_{s,t}-\lambda_{s,t}}\right)\right]^{-1} \tag{5.27}$$

where $\lambda_{f,t}$ and $\lambda_{s,t}$ represent the numbers of EVs selecting fast and slow charging, respectively, during time period t:

$$\lambda_{f,t} = N_k^t \alpha \tag{5.28}$$

$$\lambda_{s,t} = N_k^t (1-\alpha) \tag{5.29}$$

where α denotes the probability of an EV opting for fast charging, this value varies over time, being higher during the day and lower at night. To better simulate real driver behaviour, the proposed method assigns different values of α across time steps. From 8 AM to 8 PM, α is set to 0.5, indicating equal probability of choosing fast and slow charging. From 8 PM to 8 AM, α is set to 0.2, indicating that EV drivers are less likely to choose fast charging during the night. $N_{k,f}$ and $N_{k,s}$ denote the numbers of fast and slow charging piles at EVCS k, respectively, while $\mu_{f,t}$ and $\mu_{s,t}$ denote the corresponding service rates during time period t.

These queueing relationships enable the framework to evaluate service performance under varying demand levels and explicitly capture the operational effect of charging congestion on user cost.

5.2.4 Cross-network Operational Feasibility

While the objective functions evaluate economic, technical, and service-oriented performance, candidate solutions must also satisfy operational constraints derived from the physical behaviour of the PDN and the service structure of the TN. These constraints ensure that charging demand from transportation activity can be safely accommodated by the electrical infrastructure without violating network stability limits.

The coupled nature of RQ2 requires that planning decisions remain feasible not only within each network but also across the networks' operational interactions.

Constraints of Power Distribution Network

The proposed method satisfies three key constraints related to power balance, voltage regulation, and BESS operation.

Power Constraint To ensure realistic simulation and practical operation, the total active and reactive power balance is enforced, preventing arbitrary power from entering or leaving the distribution network. Therefore, the total power at each bus, accounting for power losses and EV charging demand, must satisfy

$$\sum_{m=1}^{M}\left(p_m^{LOSS}+p_m^{LOAD}+p_m^{CH}\right)+\sum_{m=1}^{M}\sum_{p\in EP}p_{p,m}^{EVCS}=\sum_{m=1}^{M}p_m^{DG}+\sum_{m=1}^{M}p_m^{Dis} \tag{5.30}$$

where P_m^{LOSS}, P_m^{LOAD}, and P_m^{CH} denote real power loss, load, and BESS charging power at bus m, respectively. In addition, P_m^{DG} and P_m^{Dis} denote the real power generated by PV and the real power discharged by BESS at bus m.

Voltage Constraint To preserve power quality, the voltage magnitude of each bus m must remain within the allowable range:

$$V_{\min}\leq V_m\leq V_{\max} \tag{5.31}$$

where the lower and upper voltage bounds are set to 0.95 pu and 1.05 pu, respectively.

BESS Constraint The SoC of each BESS is updated as

$$SOC_i(t+1)=SOC_i(t)+T\times P_i(t) \tag{5.32}$$

where $P_i(t)$ and $SOC_i(t)$ denote the charge/discharge rate and SoC of the BESS at bus i and time t, respectively. Since SOC is expressed in kWh and the data resolution is 30 minutes, T is set to 0.5. To protect the BESS from overcharging and deep discharge, the following bounds are enforced:

$$SOC_{\min}\leq SOC_i(t)\leq SOC_{\max} \tag{5.33}$$

where $SOC_{\max}$ and $SOC_{\min}$ are set to 0.9 and 0.2 of the BESS capacity, respectively.

Constraints of Transportation Network

The planning of charging stations must also consider constraints arising from customer demand, road-network configuration, and service quality. These restrictions are implemented to ensure that: (i) queueing time during peak hours remains within acceptable limits, (ii) EVs can access nearby charging stations without excessive detours, and (iii) charging-station spacing avoids redundant and inefficient infrastructure clustering.

Waiting Time Constraint Let $w(t)$ denote the waiting time of drivers at the EVCS during time step t, and let $w_{\max}$ denote the maximum allowable queueing time:

$$w(t)\leq w_{\max} \tag{5.34}$$

Distance between EVCS and Intersection Let l_{ik} denote the distance from traffic intersection i to EVCS k, and let $l_{\max}$ denote the maximum driving distance of EVs when access to a charging station is needed:

$$\min(l_{ik})\leq l_{\max} \tag{5.35}$$

Distance between EVCSs When d_{ik}, the distance between EVCSs i and k, becomes excessively short, it can lead to a high vacancy rate among charging piles and, therefore, to inefficient use of infrastructure resources. Consequently, the spacing between two EVCSs must exceed the minimum distance $d_{\min}$:

$$d_{ik}\geq d_{\min} \tag{5.36}$$

Based on the relevant planning policies in Victoria, the minimum distance between EVCSs is set to 5 km.

These PDN- and TN-side constraints ensure that the electrical network can physically and operationally support the charging demand generated from the TN without violating voltage, storage, accessibility, or service-quality limits.

Overall, the integrated multi-objective formulation presented in this section establishes the mathematical foundation for analysing the coupled planning problem introduced in RQ2. By simultaneously capturing grid operational performance, infrastructure investment costs, and user-oriented charging accessibility, the formulation enables a comprehensive evaluation of EV charging infrastructure deployment within interconnected transportation and power systems. The next section builds on this formulation and introduces a hybrid optimisation strategy to compute coordinated BESS and EVCS planning decisions in the coupled PDN–TN environment.

5.3 Proposed Methodology

The integrated formulation of RQ2 defines a coupled planning problem in which charging demand emerges from transportation dynamics, while the operational behaviour of the PDN constrains the feasibility of the infrastructure. Solving this problem directly as a monolithic optimisation model is challenging because the decision space contains heterogeneous variables, nonlinear network interactions, time-varying demand states, and competing objective functions across two infrastructure layers.

To address this complexity, the chapter adopts a hybrid solution architecture composed of two complementary modules: a BESS integration module and an EVCS integration module. The first determines grid-support configurations for BESS deployment and operation, while the second determines the location and sizing of EVCS units under the coupled PDN–TN environment. This decomposition is not merely computationally convenient; it also reflects the physical structure of the planning problem, since BESS units primarily serve as grid-support resources, whereas EVCS units serve as the interface through which transportation-side demand enters the electrical network.

Accordingly, a GA is used for the BESS planning layer, and a DDPG algorithm is used for the EVCS planning layer. The two methods are integrated sequentially: BESS decisions first shape the feasible operating region of the PDN, after which EVCS siting and sizing decisions are optimised under traffic-informed demand and grid-aware constraints.

Methodologically, this section serves two purposes. First, it explains how the mathematical formulation of RQ2 is translated into a computational workflow that can be executed over the 48-step planning horizon. Second, it clarifies why the proposed hybrid structure is appropriate for a problem that requires handling discrete siting variables, continuous operating decisions, sequential demand evolution, and cross-network feasibility simultaneously.

5.3.1 Optimisation Architecture

This section introduces the computational architecture for implementing the coupled RQ2 planning framework. As illustrated in Fig. 5.1, the framework consists of two modules: the BESS integration module and the EVCS integration module. First, the BESS integration module identifies optimal locations and charge/discharge rates for BESS units, taking into account the PDN's objectives and constraints. Second, the EVCS integration module determines the optimal locations and sizes of EVCS units, taking into account the BESS integration module's output and the objectives and constraints of both the PDN and TN. This process is repeated at each time step to maintain dynamic coordination across the coupled system. To match the heterogeneous decision structure of the coupled PDN–TN problem, a hybrid GA–DDPG scheme is adopted. GA addresses the BESS layer, where discrete siting variables and nonlinear power-flow constraints make feasibility-preserving global search particularly important. DDPG addresses the EVCS layer, where deployment decisions must adapt over time steps in response to evolving traffic and charging demand states and involve continuous sizing actions alongside state-dependent trade-offs. The two methods therefore complement each other: GA establishes a feasible grid-support configuration that constrains and regularises the downstream

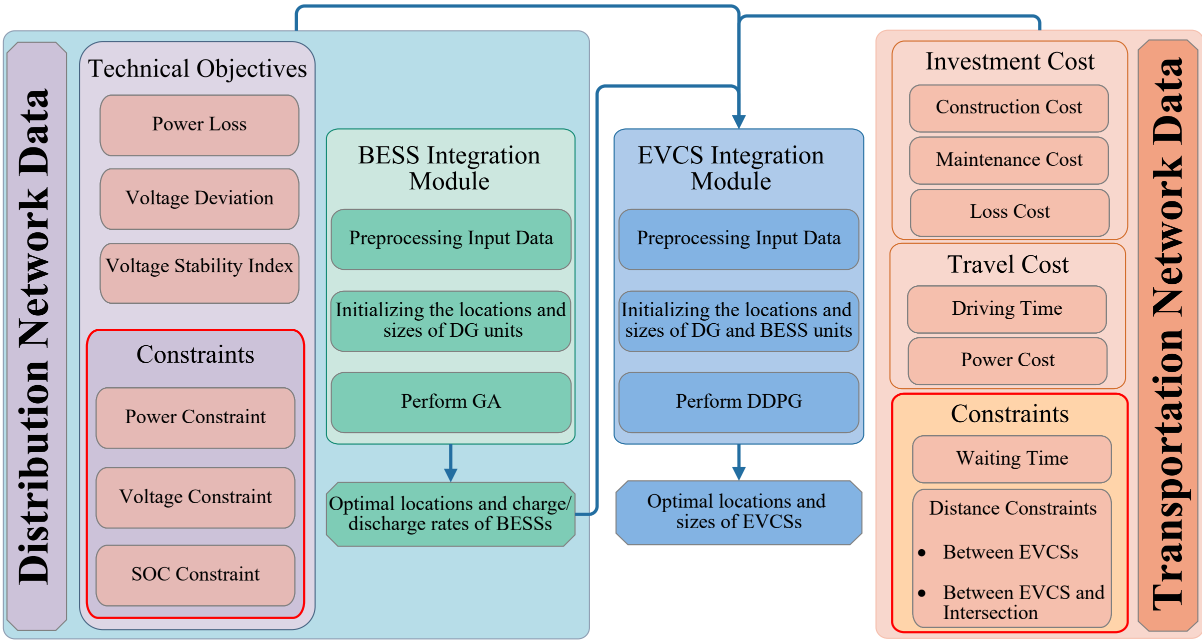


Figure 5.1: Proposed framework for traffic-informed EVCS–BESS planning in coupled PDN–TN environments.

decision space, while DDPG learns an adaptive state–action policy within this bounded space, thereby capturing spatiotemporal coupling without repeatedly re-solving the full mixed decision problem.

In practical terms, the proposed architecture can be viewed as a two-layer planning engine. The first layer assesses electrical feasibility by determining where storage support is required and how it should operate over the time horizon. The second layer uses the feasible electrical envelope to allocate charging infrastructure in ways that respond to evolving traffic demand, user accessibility requirements, and queueing behaviour. This separation is particularly useful in a coupled infrastructure setting because it avoids forcing a single algorithm to simultaneously solve fundamentally different decision types under a single search mechanism.

From a thesis perspective, the importance of this architecture lies in how it operationalises the coupled formulation in RQ2. The TN is not treated as an external post-processing layer, and the power network is not treated as a static feasibility check. Rather, both layers interact through time-indexed demand propagation, BESS support, and adaptive EVCS planning. This architecture, therefore, provides a concrete computational realisation of the research hypothesis that traffic-informed EV infrastructure planning must be solved as a coupled power–transport decision problem rather than as two decoupled planning tasks.

5.3.2 Hybrid GA–DDPG Optimisation Workflow

Pseudocode 1 summarises the operational flow of the proposed method. The algorithm begins by initialising the parameters of the GA and DDPG modules and generating the initial GA population. At each time step, the GA module searches for feasible BESS siting and operating solutions that satisfy PDN objectives and constraints. Once the BESS configuration is extracted, the transportation-side demand is updated using the gravity-based traffic model and the charging-demand model. Then, the DDPG module iteratively interacts with the environment to determine EVCS locations and sizes under the coupled PDN–TN objectives and constraints.

The workflow, therefore, follows a sequential logic. For each time step, the electrical side of the problem is stabilised first, after which the transportation-driven charging demand is mapped into the constrained electrical environment. This order is deliberate. Since EVCS decisions induce additional time-varying load on the PDN, the BESS layer must first determine the grid-support capacity available to absorb that demand. The EVCS layer can then optimise deployment decisions within a system state that already accounts for power-system limits.

Algorithm 1: Hybrid GA–DDPG workflow for traffic-informed EVCS–BESS planning

Input : Data of PDN and TN
Output: Locations and charge/discharge rates of BESSs, locations and sizes of EVCSs

```
Initialize GA and DDPG parameters
Generate the initial population for GA
for each timestep do
    while i ≤ iterations do
        pop = Run GA considering objective functions and constraints of PDN
        i ← i + 1
    end
    BESS_Locations, rate of charge/discharge = extract from pop
end
for each timestep do
    Calculate traffic flow per road using Eq. 5.2
    Calculate road impedance per road using Eq. 5.3
    Calculate the number of EVs that need to be charged using Eq. 5.9
    while i ≤ numberOfEpisodes do
        state = environment.reset()
        while j ≤ numberOfActions do
            action = agent.act(state)
            Evaluate objective functions and constraints of PDN and TN
            nextState, reward = action.step(action)
            agent.remember(state, action, reward, nextState)
            state = nextState
            j ← j + 1
        end
        agent.replay()
        i ← i + 1
    end
    EVCS_Locations, EVCS_Sizes = extract from agent
end
return BESS_Locations, rate of charge/discharge, EVCS_Locations, EVCS_Sizes
```

In Algorithm 1, the symbols `state`, `action`, and `reward` correspond to the reinforcement-learning representation of the EVCS planning problem. The state contains the time-indexed system information required for decision-making, including traffic-demand conditions and grid-relevant operating information. The action corresponds to EVCS deployment and sizing decisions, while the reward captures the combined effect of PDN and TN objectives under the imposed constraints. The replay mechanism enables the DDPG agent to learn from stored experiences rather than from only consecutive transitions, thereby improving training stability.

This workflow highlights the sequential yet interdependent structure of the proposed solution approach. BESS decisions first shape the feasible electrical operating region, after which EVCS decisions are optimised to remain responsive to traffic-derived charging demand. In this sense, the hybrid workflow is not merely an algorithmic choice; it is a direct computational translation of the coupled planning philosophy introduced in RQ2.

5.3.3 BESS Integration Module

The BESS integration module uses GA to determine time-resolved BESS siting and charge/discharge profiles that satisfy the objectives and constraints defined in Section 5.2. The BESS-related decisions are dominated by the need to preserve feasibility under nonlinear power-flow constraints and mixed discrete–continuous variables, which motivates the use of a GA for robust global exploration of the constrained solution space.

This module performs two key tasks. First, it identifies BESS locations and operating profiles that preserve PDN feasibility by minimising power losses and enhancing voltage stability while respecting operational constraints, including SOC limits and network topology. Second, given these grid-support configurations, the GA computes corresponding charge/discharge schedules in response to net-load variations and evolving grid conditions. This formulation enables effective grid-support-oriented energy management while maintaining voltage and operational security. This module incorporates temporal demand profiles, smart-meter-informed net demand, and operational constraints, such as SoC thresholds and voltage limits, to construct a realistic grid-support envelope for the coupled planning problem [38].

The GA is particularly well-suited to this module because the BESS planning subproblem involves discrete siting choices and nonlinear electrical feasibility constraints. Population-based search enables the method to simultaneously explore multiple candidate storage placements and retain those that provide robust voltage support under time-varying demand. In this sense, the BESS module not only optimises storage placement but also constructs the feasible operating envelope within which EVCS planning can proceed.

From the perspective of Chapter 5, the BESS module is not merely an auxiliary component. Its role is foundational because the grid-support capacity it provides directly influences how much transportation-derived charging demand can be accommodated without violating PDN constraints. In other words, BESS deployment expands the feasible region of the coupled planning problem, allowing the EVCS module to search for charging-station configurations that would otherwise be electrically infeasible.

5.3.4 EVCS Integration Module

The EVCS integration module employs the DDPG algorithm, an RL approach, to optimise EVCS deployment and sizing decisions under spatiotemporal variations in traffic and charging demand. By integrating traffic flow dynamics, the module jointly addresses PDN- and TN-related objectives, including minimising user travel time, queuing delays, and infrastructure investment costs. The spatial and temporal evolution of EV charging demand is modelled using a gravity model and Gaussian probability density functions, enabling state-dependent demand characterisation.

Within a multi-objective Markov decision process framework, DDPG learns an adaptive state–action policy that efficiently handles high-dimensional decision spaces and sequential trade-offs. The actor network generates candidate EVCS deployment and capacity decisions based on observed system states, while the critic network evaluates these actions against grid operational limits and user-centric performance metrics. The critic's feedback iteratively refines the actor policy, facilitating stable convergence under stochastic operating conditions and continuous control requirements.

Through the experience replay mechanism, DDPG improves sample efficiency and mitigates policy instability, thereby promoting stable convergence under stochastic operating conditions.

To further enhance training stability, both actor and critic components incorporate corresponding target networks, denoted as θ_A^t and θ_C^t, which are updated using soft update rules [63, 69, 64]:

$$\theta_A^t \leftarrow \Gamma\theta_A + (1-\Gamma)\theta_A^t \tag{5.37}$$

$$\theta_C^t \leftarrow \Gamma\theta_C + (1-\Gamma)\theta_C^t \tag{5.38}$$

When an action A_t is performed from state S_t, it generates a transition tuple $\{S_t, A_t, R_t, S_{t+1}\}$ that is stored in a replay buffer D. This buffer is then randomly sampled in mini-batches to train the actor and critic networks. For a continuous and unbounded domain, the critic network learns to evaluate the policy π by minimising the following loss function:

$$i = \frac{1}{T}\sum_{t\in\mathcal{T}} \left(y_t - C(S_t, A_t \mid \theta_C)\right)^2 \tag{5.39}$$

where

$$y_t = R_t + \gamma \max_{a_{t+1}\in\mathcal{A}} Q(S_{t+1}, a_{t+1} \mid \theta_A) \tag{5.40}$$

In this structure, the actor network generates candidate actions in the continuous EVCS decision space, while the critic network evaluates whether those actions improve the long-term planning objective under coupled PDN–TN conditions. The use of DDPG is motivated by two features of the problem: EVCS sizing decisions are naturally continuous, and the value of a candidate EVCS configuration depends on its sequential interaction with future traffic and charging states rather than on a single static snapshot.

This learning structure enables the EVCS module to adaptively search for deployment policies that satisfy both technical and user-centric constraints, including grid capacity, voltage stability, travel convenience, and queueing performance. In contrast to static planning heuristics, the RL-based structure is particularly well-suited to the time-varying and state-dependent nature of traffic-informed charging demand.

Within the thesis progression, this represents a methodological extension beyond the more grid-centred planning logic of Chapter 4. Whereas Chapter 4 focused on the electrical consequences of EVCS and BESS planning, the present module explicitly models how charging demand evolves over space and time as a function of mobility behaviour and then learns planning decisions that remain feasible across those changing demand conditions.

5.3.5 Computational Implementation

The computational implementation follows the common data environment and modelling assumptions defined in Chapter 3, with the RQ2-specific coupling logic applied to the Melbourne-based TN and the IEEE 33-bus PDN case study. The principal RQ2 case study integrates traffic data from 60 intersections and 95 roadways with a modified IEEE 33-bus distribution network. Each bus supplies 20 households with a heterogeneous mix of DERs, and the traffic layer is aggregated into 48 time steps to align with the daily optimisation horizon.

All simulations were executed on an AWS EC2 `r7i.16xlarge` (C36 Memory Optimised) instance running Windows Server, equipped with 64 vCPUs, 512 GB RAM, and a 512 GB EBS SSD. Under this configuration, the complete 48-time-step simulation of the proposed framework on the IEEE 33-bus network converged within approximately 5–8 minutes, corresponding to roughly 6–10 seconds per time step. This runtime remains consistent with engineering-level computational requirements for time-indexed planning studies.

From a computational perspective, the proposed GA–DDPG framework benefits from modular decomposition between feasibility-oriented planning (GA) and policy-based learning (DDPG), thereby avoiding direct joint optimisation over the full coupled PDN–TN decision space and mitigating combinatorial growth. Based on the implementation settings, including a state/action dimension of $48 \times 33 = 1584$ and a replay memory size of 2000 transitions, the replay buffer storage requirement is estimated at approximately 0.15–0.25 GB, including Python overhead. The overall peak RAM footprint observed during the full 48-step run is conservatively estimated to remain within 3–6 GB, dominated by DDPG components such as replay memory and actor-critic network parameters, and therefore negligible relative to the available system memory. The GA module incurs minimal additional memory overhead due to its moderate population size and number of generations.

The computational setup is reported not merely as a hardware detail but as an indicator of the method's practical tractability. In infrastructure-planning studies, solution quality alone is insufficient if the computational burden prevents the repeatable analysis of scenarios. The current runtime and memory profile indicate that the framework can be executed repeatedly for comparative planning studies, sensitivity tests, and scenario-based analyses without requiring impractical computing resources.

Collectively, these computational characteristics demonstrate a favourable balance between runtime efficiency, memory usage, and solution quality. More importantly, they support the practical applicability of the proposed framework for real-world EV infrastructure planning studies in coupled power and TNs. This matters from an industry-facing perspective because a planning framework that is theoretically rigorous but computationally impractical would be difficult to translate into operational or policy settings.

5.3.6 Benchmark Models

A strong methodological contribution requires not only proposing a new solution framework but also demonstrating why it performs differently from alternative planning paradigms. For this reason, the present chapter evaluates the proposed GA–DDPG strategy against several comparative configurations that highlight both the benefits and the limitations of different planning logics.

First, two deployment scenarios are considered to examine the effect of BESS support on coupled EVCS planning. In the first scenario, four BESS units are installed, and the number of EVCSs ranges from 5 to 13. In the second scenario, five BESS units are installed, and the number of EVCSs ranges from 9 to 17. In both scenarios, the nominal size of the EVCS units decreases as the number of stations increases, thereby reflecting the trade-off between station count and station capacity.

These two scenarios serve an important analytical purpose. They allow the study to distinguish between improvements arising from denser EVCS deployment and those arising from stronger grid support through additional BESS integration. As a result, the framework can reveal whether transportation-side accessibility gains are achieved solely by increasing charging-station density or also depend on electrical support from strategically placed storage units.

Second, the proposed multi-objective optimisation framework is benchmarked against two alternative planning paradigms for a common EVCS configuration:

- a PDN-oriented single-objective formulation (SO-PDN),
- a Pareto-based multi-objective baseline using NSGA-II,
- the proposed GA–DDPG multi-objective optimisation framework (MOO).

The SO-PDN baseline primarily focuses on grid-centric objectives, such as power loss and VD. It is useful for illustrating the limitations of planning strategies that prioritise electrical performance while treating user accessibility and queueing performance as secondary or implicit concerns. The NSGA-II baseline represents a conventional Pareto-based multi-objective planning approach. It provides a stronger benchmark because it accounts for both PDN and TN objectives, albeit without the same sequential learning-based treatment of time-indexed demand evolution. The proposed MOO framework, by contrast, explicitly models the sequential interactions between transportation demand and distribution-grid feasibility, thereby providing a more adaptive decision structure for the coupled planning problem.

From a thesis standpoint, these benchmark models are essential because they allow the contribution of RQ2 to be articulated more precisely. The point is not merely that the proposed method achieves lower costs under one particular configuration; rather, it shows that once traffic-informed, time-varying, and cross-network interactions are made explicit, simpler grid-only or static Pareto approaches are less capable of delivering balanced system-wide solutions.

Accordingly, the comparative analysis in the next section is designed to answer three questions. First, how does EVCS expansion interact with BESS support across the coupled network? Second, how do transportation-side and PDN-side objectives trade off under different deployment patterns? Third, to what extent does the proposed GA–DDPG structure provide more decision-ready and balanced outcomes than conventional benchmark methods?

Overall, the solution method presented in this section translates the multi-objective formulation of RQ2 into a computationally tractable and physically meaningful planning workflow. By combining grid-support-oriented search with adaptive charging-infrastructure learning, the framework enables coordinated decision-making across the PDN and TN layers while remaining practical enough for repeated scenario analysis. The next section addresses the three comparative questions above by presenting the case study design, optimisation outcomes, and cross-scenario analysis associated with RQ2.

5.4 Results and Discussion

This section evaluates the proposed traffic-informed planning framework under the coupled PDN–TN environment introduced in the preceding sections. The analysis is organised to answer RQ2 from four complementary perspectives progressively: the realism of the case-study design and input data, the behaviour of the optimal planning outcomes under different BESS-enabled deployment scenarios, the comparative performance of the proposed method against benchmark planning paradigms, and the broader mechanistic and practical insights that emerge from the coupled results.

Rather than treating the results as a simple numerical comparison, this section interprets them in relation to the central thesis of RQ2: namely, that EV charging infrastructure planning becomes materially different once charging demand is explicitly derived from traffic dynamics and once the distribution network is required to absorb that demand without violating technical feasibility. Accordingly, the discussion emphasises not only the optimal solutions themselves, but also why those solutions emerge and what they imply for decision-makers designing EV infrastructure in realistic urban settings.

5.4.1 Case Study

The common data environment, traffic-network construction, and feeder assumptions have already been defined in Chapter 3. Accordingly, this subsection summarises only the RQ2-specific elements of the coupled case study necessary to interpret the planning results. The principal RQ2 case study integrates Melbourne TN data with a modified IEEE 33-bus PDN to evaluate EVCS planning under explicit, traffic-informed demand. The transportation layer uses real-world traffic measurements from 60 intersections and 95 roadways, aggregated into 48 time steps to align with the daily optimisation horizon. The electrical layer follows the common household, PV, and BESS assumptions established earlier in the thesis.

Traffic records from VicRoads [55] are processed to construct time-indexed mobility demand, and are spatially mapped to the TN using geographic proximity and road connectivity. Basic

Table 5.1: Key parameters, charging-service assumptions, and optimisation settings used in the coupled PDN–TN case study.

Parameters	**Value**
Fast-charger rate $\mu_{f,t}$	60 kW
Slow-charger rate $\mu_{s,t}$	15 kW
Value of travel time c_{time}	20 $/h
Station lifetime	20 years
Electricity price (fast charge)	0.75 $/kWh
Electricity price (slow charge)	0.50 $/kWh
Maximum queue time for each EV w_{max}	20 min
Maximum drive distance l_{max}	30 km
Minimum distance of stations d_{min}	5 km
Rate of discount r_0	0.15
Electricity price p_c	0.13 $/kWh
Mileage per unit electrical energy l_0	4.1 km/kWh
The penetration level of EVs on the road α	0.5
Voltage temperature coefficient	0.1 °C
Current temperature coefficient	0.05 °C
Threshold voltage	230 V
Rated voltage	12.66 kV
Minimum of Voltage	216 V
Maximum of Voltage	253 V
DDPG actor/critic layer size	(400, 300)
DDPG (batch size, learning rate)	(64, 0.001)
GA (population size, max generations)	(20, 50)
GA (crossover rate, mutation rate)	(0.9, 0.1)

data screening is applied to remove missing or implausible entries and to enforce nonnegative traffic counts across time steps.

Figures 3.3 and 3.4 provide the temporal and spatial verification of the constructed charging-demand profiles, respectively. In particular, the extracted demand patterns reproduce the expected weekday peak-hour behaviour (7:30 AM–5:30 PM) and the concentration of high demand around the CBD, supporting the plausibility of the spatiotemporal mapping from traffic intensity to charging demand. The EV population at each intersection over time steps was derived from publicly available Victorian Government statistics [56] and spatially allocated to intersections using population density and traffic intensity proxies consistent with the adopted gravity-model structure.

The parameters used in the road-impedance formulation in (5.3) were calibrated using real-world traffic and infrastructure datasets obtained from publicly available sources, such as the number of lanes, road width, and surface type (asphalt, ultra-thin asphalt, concrete, and stone), the number of traffic lights [55], speed limits [56], the number of bus/train/tram stops [57], and weather conditions (sunny or rainy) [56]. To ensure reproducibility, all impedance-related attributes were first normalised to a common scale and then combined to form time-varying road impedance coefficients, thereby preserving the expected monotonic relationships (e.g., higher congestion indicators lead to higher impedance). This calibration procedure enables the impedance model to reflect both spatial heterogeneity (road geometry and infrastructure) and temporal variability (traffic flow and operating conditions) in Melbourne.

The parameters and model configurations used throughout the simulations are summarised in Table 6.1. These settings define the electrical, economic, queueing, and optimisation characteristics of the case study and are selected to preserve consistency with realistic planning assumptions and practical infrastructure limits.

The RQ2 case study adopts the following planning assumptions:

1. Each EVCS has up to 8 EV charging piles.
2. EVCS configurations include two types of charging units: a 120 kW DC fast charger with a maximum charging time of 90 minutes and a 7.7 kW AC slow charger with a charging time of 4 hours.
3. Waiting time for EVs at charging stations is capped at 20 minutes.
4. The time cost for drivers is calculated at $20 per hour, based on the average local wage. We use this to calculate the cost in Equation 5.22.

Additionally, the parameters for the optimisation model are derived from Table 6.1. These parameters include charging efficiency, which represents the energy conversion efficiency. The parameters in Equation 5.4 were calibrated using empirical traffic behaviour data, and the two Gaussian components were adopted from the empirically validated study in [11] to represent typical temporal patterns in charging demand:

- First component: $\pi_1 = 0.078$, $\mu_1 = 14.86$, $\sigma_1 = 5.31$.
- Second component: $\pi_2 = 0.051$, $\mu_2 = 8.75$, $\sigma_2 = 3.11$.

For the Weibull distribution, which models the SOC of EVs during charging, the parameters are estimated as $a = 6.31$ and $b = 1.67$ based on [11].

This real-data case-study environment ensures that the planning outcomes discussed next are grounded in realistic urban traffic and grid conditions rather than in fully synthetic demand assumptions.

5.4.2 Optimal Planning Outcomes Across BESS-enabled Scenarios

Using the modelled temporal and spatial charging demands, the optimisation framework identified EVCS locations and sizes under two scenarios. In the first scenario, four BESS units were installed, with the number of EVCSs ranging from 5 to 13. In the second scenario, five BESS units were installed, with the number of EVCSs ranging from 9 to 17. In both scenarios, the nominal size of EVCS units decreased as station count increased, reflecting a practical trade-off between charging-station density and individual-station capacity. This design choice is important because it reveals how the spatial distribution of charging infrastructure changes system performance under a constrained planning logic, rather than simply increasing total installed capacity.

As shown in Table 7.3, increasing the number of EVCSs in both scenarios leads to a clear reduction in driver-related costs. Travel time, energy consumption, and queuing time decreased significantly as the number of charging stations increased and their spatial density improved. For instance, in Scenario 1, increasing the number of EVCSs from 5 to 13 reduced total travel cost by nearly 16.7%. Similarly, in Scenario 2, increasing the number of EVCSs from 9 to 17 yielded a comparable reduction in travel and queueing burdens.

Figures 5.2–5.5 further illustrate these transportation-side improvements. Figures 5.2 and 5.3 show the reduction in total travel costs as the number of EVCSs increases under Scenarios 1 and 2, while Figures 5.4 and 5.5 show the corresponding decline in travel-plus-queue costs.

These trends highlight the fundamental balance in planning between supply-side investment and user-side convenience. Strategically increasing EVCS deployment reduces users' costs by minimising driving distances and waiting times, particularly during peak traffic hours (7:30 AM–5:30 PM). However, beyond a critical EVCS density threshold, the additional investment and maintenance costs outweigh the incremental reductions in user costs, thereby increasing total system expenditure. This confirms that charging-station expansion cannot be evaluated

Table 5.2: Performance comparison of EVCS and BESS planning strategies across cost, service-quality, and network-performance metrics.

Optimisation Results			PDN			TN ($\times 10^5$\$)				
Battery (Location)	EVCS	Size	P_loss	VSI	VD	Travel cost	Travel and queue time	Construction cost	Operation and maintenance cost	Loss cost
	5	250	8091.31, 8298.21	0.0781, 0.0801	0.5407, 0.9104	19.31	4.87	20.70	1.90	5.60
	6	250	8086.37, 8282.29	0.0782, 0.0801	0.5361, 0.8998	17.81	4.77	22.10	2.00	5.56
4	7	200	8064.92, 8286.98	0.0785, 0.0801	0.4895, 0.8881	17.20	4.58	26.50	2.40	5.63
	8	200	8033.80, 8289.38	0.0791, 0.0801	0.4314, 0.8753	17.20	4.25	29.80	2.70	5.69
(12, 15,	9	200	7930.24, 8292.53	0.0795, 0.0800	0.3639, 0.8513	16.21	3.55	32.70	2.90	5.73
20, 30)	10	175	7932.06, 8287.94	0.0798, 0.0802	0.2415, 0.8332	11.13	2.75	40.80	3.70	5.74
	11	175	7929.46, 8248.12	0.0797, 0.0802	0.2989, 0.8083	8.63	2.21	43.90	4.00	5.78
	12	150	7926.27, 8245.89	0.0799, 0.0802	0.2471, 0.8064	8.49	1.47	46.40	4.20	5.82
	13	150	7923.28, 8241.90	0.0799, 0.0804	0.1989, 0.8133	6.72	1.08	50.30	4.50	5.80
	9	200	7927.17, 8291.05	0.0794, 0.0801	0.3512, 0.8475	15.25	3.28	33.70	3.00	5.73
	10	175	7926.25, 8280.25	0.0798, 0.0802	0.2355, 0.8330	10.60	2.55	40.70	3.80	5.71
5	11	175	7925.25, 8243.77	0.0799, 0.0802	0.2515, 0.8050	8.20	2.05	44.70	3.98	5.77
	12	150	7923.05, 8240.22	0.0801, 0.0802	0.2311, 0.8034	7.39	1.25	46.80	4.32	5.78
(4, 14, 18,	13	150	7920.46, 8229.63	0.0801, 0.0804	0.1775, 0.8088	6.26	1.09	49.60	4.65	5.80
19, 31)	14	150	7918.32, 8222.55	0.0803, 0.0807	0.1685, 0.8001	6.15	1.05	54.30	4.90	5.87
	15	150	7922.51, 8218.50	0.0804, 0.0808	0.1672, 0.7950	5.64	0.99	59.50	5.40	5.88
	16	150	7916.88, 8215.45	0.0804, 0.0808	0.1600, 0.7901	5.20	0.97	64.10	5.80	5.92
	17	150	7908.45, 8210.15	0.0804, 0.0810	0.1586, 0.7873	4.20	0.92	65.40	5.90	5.97

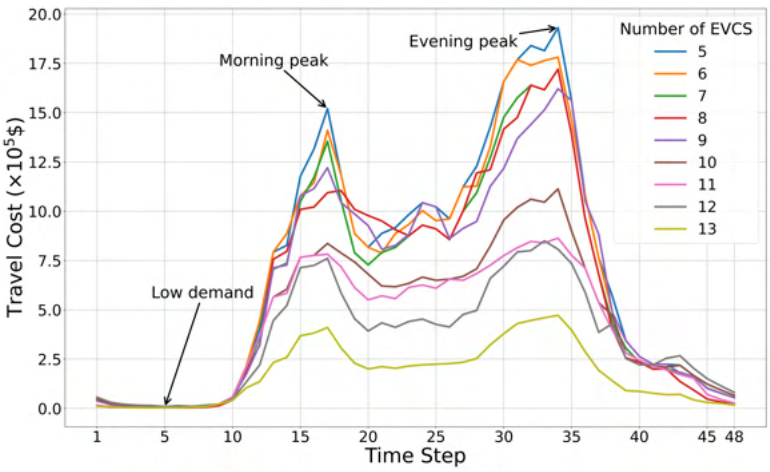


Figure 5.2: Travel-cost distribution under the four-BESS deployment scenario.

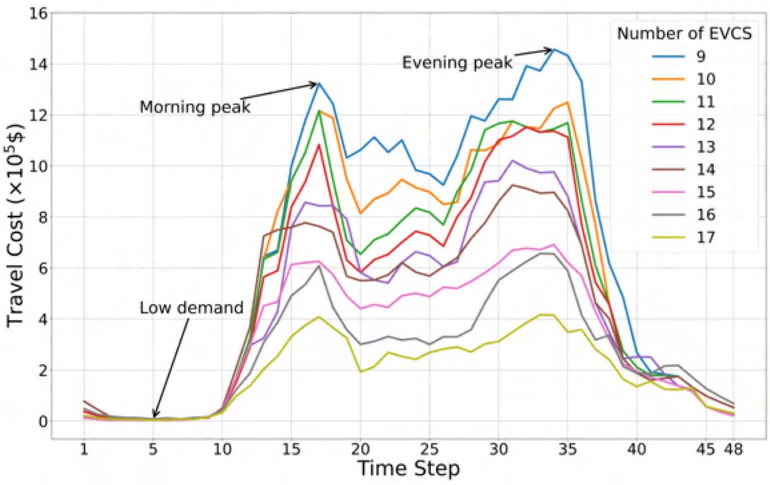


Figure 5.3: Travel-cost distribution under the five-BESS deployment scenario.

solely in terms of accessibility; it must also be assessed in relation to infrastructure cost and grid feasibility. Stated differently, more charging stations do not automatically imply a better planning solution unless the added service benefit remains proportionate to the corresponding

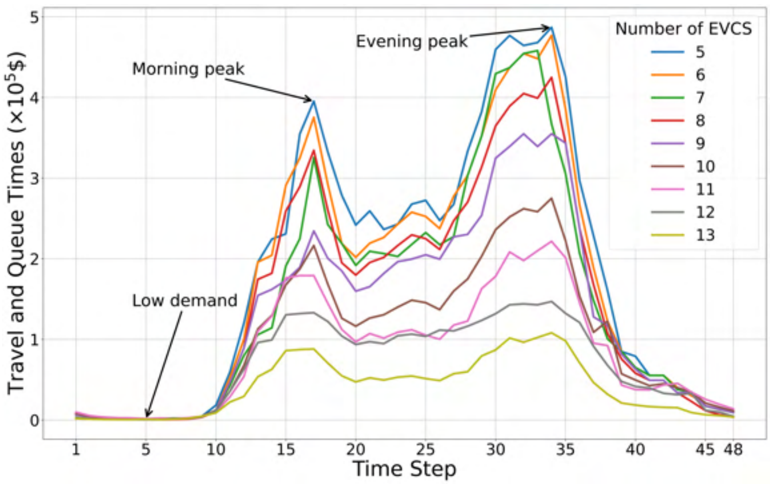


Figure 5.4: Travel and queueing times under the four-BESS deployment scenario.

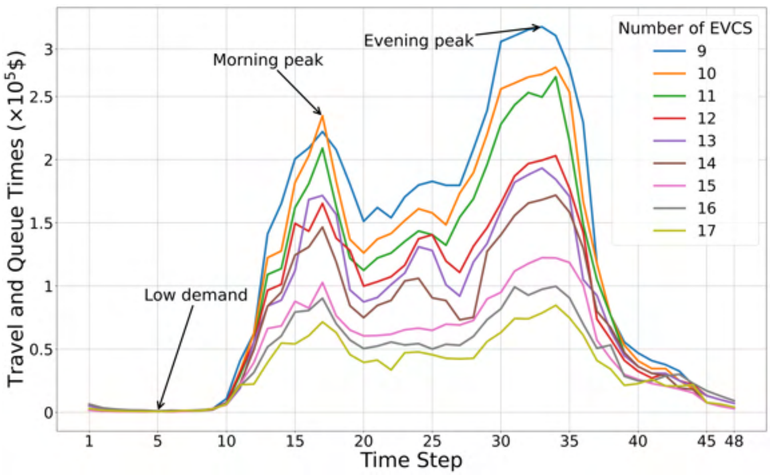


Figure 5.5: Travel and queueing times under the five-BESS deployment scenario.

economic and electrical burden.

In addition to transportation-side benefits, the results also demonstrate notable improvements in PDN performance. As shown in the first three PDN columns of Table 7.3, the coordinated integration of BESS and EVCS units enhances grid operation by reducing power loss and VD while improving voltage stability. These improvements emerge because the strategically placed BESS units regulate voltage levels, balance active and reactive power flows, and alleviate feeder loading under time-varying charging demand. This is particularly important during periods of concentrated charging activity, when the interaction between mobility-driven demand peaks and local grid constraints becomes most severe.

When comparing the common EVCS configurations across the two scenarios (9–13 stations), Scenario 2 consistently yields lower travel and queueing costs and better PDN-side metrics. This indicates that the additional BESS unit in Scenario 2 not only supports electrical performance but also improves transportation-side service by enabling smoother charging availability during peak demand. Among the shared configurations, the 13-EVCS case in Scenario 2 provides a particularly balanced trade-off. Across all tested configurations, however, the best overall outcome is achieved in Scenario 2 with five BESS units and 17 EVCSs, representing the strongest system-wide solution of the proposed framework.

The maximum-state network topologies associated with the two scenarios are illustrated in Figures 5.6 and 5.7. These figures show the optimal locations of BESS and EVCS units and pro-

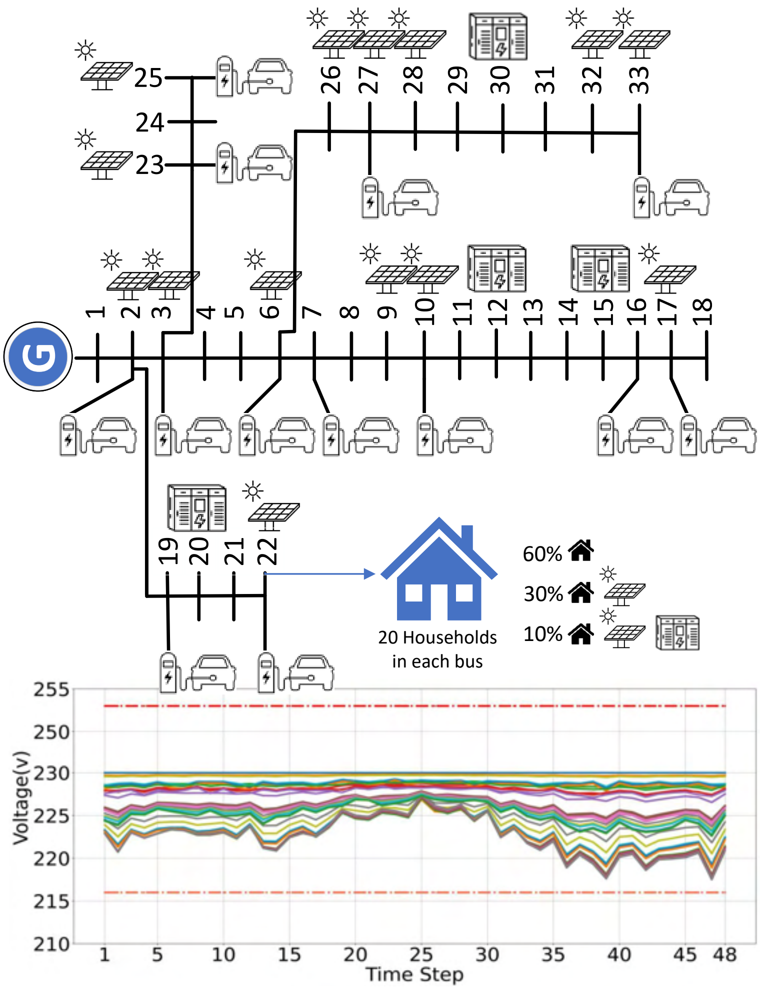


Figure 5.6: Network topology and voltage profile for the maximum-EVCS deployment case under the four-BESS scenario.

vide a spatial interpretation of how the proposed framework redistributes charging infrastructure and grid-support resources across the network.

Based on the results of the integration and optimisation outlined in Table 6.1, the placement and operation of BESSs and EVCSs within the PDN for both scenarios in the maximum state are illustrated in Figures 5.6 and 5.7. For each EVCS, a realistic load profile was assigned to reflect actual consumer behaviour patterns and to evaluate network performance under practical operating conditions. The voltage analysis demonstrates that all node voltages remained within acceptable limits across both scenarios. In the first scenario, the most significant voltage drop occurred between 5:30 PM and 1:00 AM, whereas in the second scenario, it occurred between 5:30 PM and 7:30 AM. These findings validate the effectiveness of the proposed integration and optimisation framework in maintaining voltage stability under varying operational conditions. They also show that the planning outcomes are not only economically and spatially attractive, but also operationally admissible from a power-system perspective.

Taken together, these scenario-based results directly answer the first layer of RQ2. Once traffic-informed charging demand is introduced into the planning model, the jointly optimal deployment of EVCS and BESS becomes a strongly coupled design problem in which grid support and service accessibility must be co-optimised rather than treated independently.

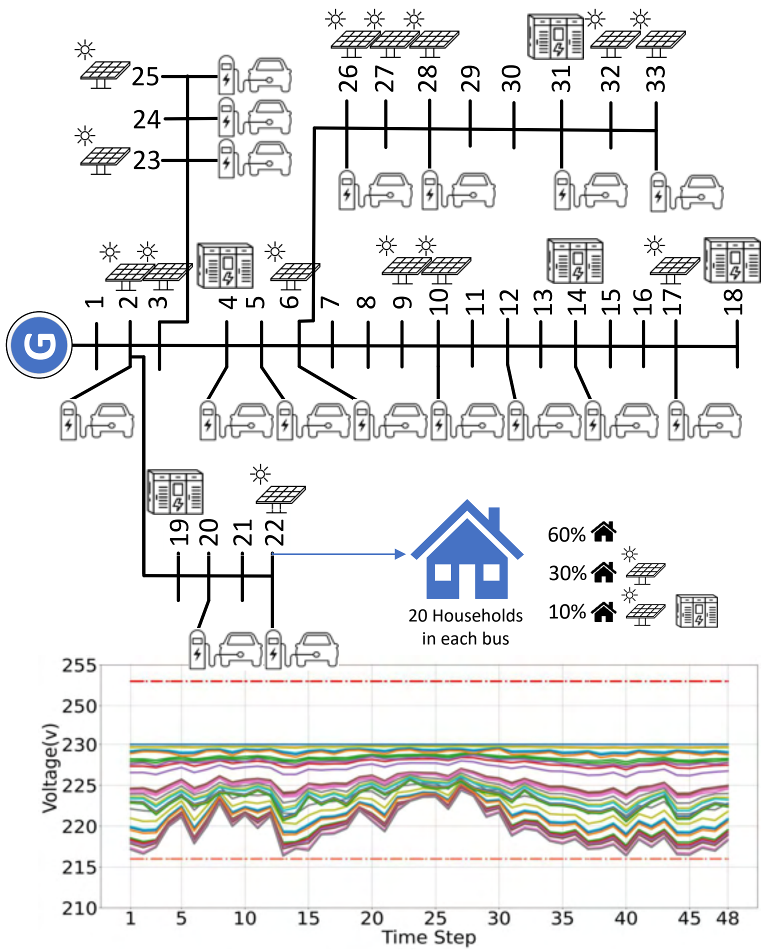


Figure 5.7: Network topology and voltage profile for the maximum-EVCS deployment case under the five-BESS scenario.

5.4.3 Benchmark Comparison

To further assess the value of the proposed method, Table 5.3 compares three planning paradigms for the standard 13-EVCS configuration: a PDN-oriented single-objective formulation (SO-PDN), a Pareto-based multi-objective baseline (NSGA-II), and the proposed GA–DDPG framework (MOO).

Table 5.3: Benchmark comparison among single-objective optimisation, NSGA-II, and the proposed multi-objective framework for the 13-EVCS configuration. (S1 and S2 denote scenarios with four and five BESS units, respectively; N_{CS} denotes the number of deployed EV charging stations; Trav., T+Q, Const., and O&M denote travel, travel-and-queue-time, construction, and operation-and-maintenance costs, respectively.)

Scenario	Config.		PDN						TN Cost ($\times 10^5$\$)				
	N_{CS}	Size	P_{loss} Min	P_{loss} Max	VSI (%) Min	VSI (%) Max	VD Min	VD Max	Trav.	T+Q	Const.	O&M	Loss
S1-SO-PDN	13	150	7915.12	8221.25	8.01	8.05	16.91	80.09	12.21	2.76	32.16	3.61	5.71
S1-NSGA-II	13	150	7921.41	8237.78	7.99	8.03	19.85	81.27	8.45	1.49	46.15	4.18	5.78
S1-MOO	13	150	7923.28	8241.90	7.99	8.04	19.89	81.31	6.72	1.08	50.30	4.50	5.80
S2-SO-PDN	13	150	7914.75	8219.15	8.03	8.08	16.55	79.53	10.97	2.61	39.52	3.85	5.70
S2-NSGA-II	13	150	7918.31	8227.15	8.01	8.04	17.48	80.58	8.28	1.45	47.55	4.25	5.79
S2-MOO	13	150	7920.46	8229.63	8.01	8.04	17.75	80.88	6.26	1.09	49.60	4.65	5.80

The SO-PDN formulation marginally improves grid-centric metrics such as power loss and

VD, but yields highly unbalanced outcomes, with travel and travel-plus-queue costs increasing by approximately 75–155% relative to the proposed MOO framework across both scenarios. This result is critical because it shows that optimising only the electrical layer can produce technically acceptable but user-unfriendly charging networks. Such a result may still appear attractive from a purely utility-centred viewpoint. Still, it is not appropriate for practical public-charging deployment, where user accessibility and service quality are central design criteria.

NSGA-II provides a more balanced solution than SO-PDN because it explicitly considers both PDN and TN objectives and seeks a Pareto-optimal compromise. However, it still underperforms the proposed MOO framework on user-centric metrics, particularly travel cost and travel-plus-queue cost. The reason is that NSGA-II treats the problem as a static multi-objective search, whereas the proposed GA–DDPG structure learns decisions under sequential, time-indexed demand evolution and therefore better captures how charging demand and service pressure unfold over the day. In other words, once time dependency becomes structurally important, a static Pareto search is less able to preserve the causal sequence between demand emergence, service congestion, and electrical feasibility.

The proposed MOO framework achieves the most balanced overall performance. Although it does not always produce the absolute minimum for each isolated grid-centric index, it consistently yields superior system-level trade-offs across both infrastructures. This is a more meaningful outcome from both a planning and an industry standpoint because the practical objective is not to optimise a single metric in isolation but to design a charging system that remains technically feasible, economically rational, and operationally accessible to users.

This benchmark analysis, therefore, precisely strengthens the thesis contribution of RQ2: the value of the proposed framework lies not merely in numerical improvements, but in its ability to produce more decision-ready and cross-network-balanced solutions than simpler grid-only or static Pareto-based alternatives. It also demonstrates that once traffic-informed, time-varying demand is explicitly modelled, the choice of solver becomes part of the planning contribution rather than merely a computational implementation detail.

5.4.4 Coupling Effects

Beyond the numerical comparisons, the results reveal several important mechanisms that help explain why coupled planning produces materially different solutions from decoupled approaches.

First, the results confirm that denser EVCS deployment reduces user-side burden by shortening average access distances and lowering queueing delays. Although this is expected from a transportation perspective, the coupled framework shows that the benefit is not unlimited. As the number of charging stations continues to increase, capital and operating costs rise more rapidly than the marginal gains in accessibility. The optimal solution, therefore, emerges from a balance between improving accessibility and infrastructure expenditure, rather than simply maximising station count.

Second, the results show that BESS integration does more than improve PDN technical indices. By smoothing charging availability and reducing voltage-related bottlenecks, BESS units also indirectly improve transportation-side performance. This is a key cross-network effect of RQ2: electrical flexibility changes mobility-side service outcomes. In other words, the TN benefits not only from more stations but also from a more supportive electrical environment that allows those stations to operate under heavy demand without degrading service quality. This cross-effect is one of the main reasons why coupled planning cannot be reduced to the independent optimisation of each network.

Third, the benchmark comparison demonstrates that traffic-informed planning changes the geometry of the planning problem. Once time-varying demand and user movement are explicitly modelled, the solution space is no longer adequately represented by static grid-centric or static Pareto logic. The proposed sequential GA–DDPG framework is better suited to this setting because it preserves the temporal ordering of demand emergence and infrastructure response. In this sense, the method aligns with the physics and service logic of the problem rather than merely serving as an alternative optimiser.

From an infrastructure planning perspective, these mechanisms imply that the best charging-station layout is not simply the one that minimises electrical stress or geographic travel distance. Rather, it is the one that mediates the interaction between spatial demand concentration, temporal queue formation, and electrical feasibility across the entire system. This is precisely the central insight that distinguishes RQ2 from the more PDN-oriented planning logic of Chapter 4.

5.4.5 Practical Planning Insights and Scope of Applicability

The results of this chapter provide several practical planning insights that are particularly relevant to EV infrastructure deployment in real-world urban settings.

First, EVCS planning should not be performed independently of traffic-demand Modelling. The results show that charging demand derived from real traffic conditions leads to materially different infrastructure decisions than would be obtained from static or spatially averaged demand assumptions. This has direct implications for utilities, charging-network operators, and transport planners, particularly in metropolitan regions where peak-hour movement patterns strongly shape the needs of charging services.

Second, BESS integration should be viewed as a planning enabler rather than merely an operational add-on. In the present study, additional BESS support improves not only voltage quality and loss reduction but also travel and queueing outcomes, because it enlarges the feasible and effective operating region of the charging network. This means that storage deployment can play a strategic role in supporting higher-density charging infrastructure in constrained urban grids.

Third, the results suggest that planning decisions should be evaluated in terms of balanced system performance rather than single-metric optimality. The proposed framework demonstrates that a modest sacrifice in isolated grid-centric indices can yield substantial gains in user accessibility and service quality while maintaining acceptable electrical performance. Such trade-offs are highly relevant in real-world planning, where infrastructure must serve multiple stakeholders simultaneously. For practice, this means that planners should interpret “optimality” as a compromise among coordinated systems rather than as the minimisation of a single electrical or transport metric.

At the same time, the present study remains focused on planning. It therefore does not explicitly model rare disruptive events such as major traffic incidents, feeder outages, or resilience-oriented emergency operations. The proposed framework captures spatiotemporal dynamics through time-indexed optimisation over 48 time steps using real traffic measurements and probabilistic charging-demand models, and the RL-based EVCS module learns under varying but typical operating conditions. However, rare disruptive events would require dedicated fault or incident datasets and a more explicit robust or stochastic resilience formulation. These extensions are important directions for future work, but are not necessary for the present planning-focused study targeting normal weekday operating variability.

Overall, the results confirm that EVCS expansion improves transportation efficiency, while coordinated BESS integration strengthens voltage regulation and PDN stability. More importantly, the interaction between these two layers reveals a clear coupled-planning effect: transportation performance and electrical feasibility improve together only when both traffic dynamics and grid-support capabilities inform infrastructure planning. These findings provide a direct answer to RQ2 and establish the basis for the flexibility-oriented extensions developed in the next chapter.

5.5 Practitioner-Oriented Planning Guidance

The findings of RQ2 suggest that EV charging infrastructure planning in urban environments should be treated as a coupled infrastructure design problem rather than as an isolated siting exercise. Once charging demand is derived from real traffic activity, the optimal placement and sizing of EVCS units become strongly dependent on both transportation accessibility and PDN feasibility. Accordingly, planning decisions that ignore either network are unlikely to remain efficient under realistic operating conditions.

From a distribution-system perspective, the results show that BESS deployment should not be viewed solely as a voltage-support or peak-shaving asset. In the coupled planning setting developed in this chapter, BESS units also enable charging-service expansion by expanding the feasible operating region for EVCS deployment. For practitioners, this implies that storage investment can be justified not only by grid performance metrics but also by its indirect contributions to service accessibility and charging-network effectiveness.

From a charging infrastructure perspective, increasing the number of EVCS units improves user accessibility. It reduces queueing burden, but only up to the point where the associated construction and operating costs outweigh the marginal service benefit. The planning implication is therefore not to maximise charging-station density but to identify a balanced deployment frontier where accessibility gains, grid feasibility, and infrastructure costs remain aligned. In practical terms, this favours coordinated medium-density deployment supported by strategically located BESS units over purely aggressive station expansion.

For utilities, charging-network operators, and transport planners, the main actionable insight is that traffic-informed demand modelling materially changes infrastructure decisions. Station locations derived from static or spatially averaged demand assumptions may appear acceptable in simplified studies, yet can become inefficient once peak-hour traffic concentration, queue formation, and local electrical constraints are explicitly represented. The use of spatiotemporal traffic data is therefore not an optional refinement; it is a necessary condition for realistic planning in dense metropolitan networks.

Overall, RQ2 establishes that effective EVCS planning requires a coordinated treatment of mobility demand, charging service quality, and grid support capability. This chapter, therefore, extends the planning logic of Chapter 4 from a primarily grid-oriented design problem to a coupled power–transport planning problem grounded in real traffic behaviour. The next chapter builds on this foundation by examining how the planning framework can be further extended when EV charging infrastructure is treated not only as a load-serving asset, but also as a flexible resource within the broader operational ecosystem.

Chapter 6

V2G Participation and Market-Driven Flexibility

This chapter addresses RQ3 by extending the coupled PDN–TN planning framework developed in Chapter 5 to account for V2G participation and market-driven flexibility explicitly. While the earlier chapters treated EVs primarily as electricity consumers whose charging demand must be accommodated within the coupled power–transportation system, the present chapter considers EVs as conditional flexibility resources capable of both consuming and supplying energy under suitable technical, behavioural, and market conditions.

The central challenge is that the practical value of V2G is not determined solely by bidirectional hardware capability. Although bidirectional chargers create the technical capability for energy exchange, this capability does not automatically translate into usable system flexibility. The practically available V2G contribution depends on where EVs are connected, how likely users are to participate, when vehicles are available, whether sufficient battery reserve exists, whether market activation is triggered, and whether local grid conditions allow bidirectional exchange. Therefore, the planning problem is not simply to locate V2G-capable EVCSs, but to identify where bidirectional infrastructure can provide reliable and operationally useful flexibility under behavioural, technical, and market constraints.

A central distinction in this chapter is therefore made among V2G capability, V2G availability, behavioural participation, market activation, and operational control. V2G capability refers to the physical presence of bidirectional charging infrastructure. Availability refers to whether vehicles with sufficient battery reserve are connected at suitable times and locations. Behavioural participation represents the willingness of EV users or fleet operators to provide grid-support services under incentive and mobility constraints. Market activation determines whether the available flexibility is actually committed and used within the planning framework. Operational control then determines whether the resulting charging and discharging behaviour can be managed without violating network-security limits. This layered interpretation prevents V2G from being treated as a guaranteed resource and provides the conceptual basis for the modelling framework developed in this chapter.

Accordingly, this chapter introduces a behaviour-aware and flexibility-aware planning framework composed of three interacting layers: (i) V2G infrastructure and bidirectional capability modelling, (ii) charging-demand and V2G participation modelling under behavioural uncertainty, and (iii) market-driven flexibility representation within a coordinated planning and control architecture. In this way, the chapter extends the coupled planning logic of Chapter 5 by embedding user-dependent and activation-dependent flexibility directly into EVCS deployment decisions.

The overall planning and control structure adopted in this chapter is illustrated in Fig. 6.1. The remainder of the chapter is organised as follows. Section 6.1 presents the modelling of V2G infrastructure and bidirectional capability. Section 6.2 develops EV charging demand in the presence of V2G, including utility-based participation and heterogeneous V2G profiles. Section 6.3 introduces market-driven flexibility activation and participation uncertainty. Section 6.4 presents the proposed multi-module optimisation framework. Section 6.5 reports and interprets the simulation results, and the chapter concludes with practical implications for industry and grid planning.

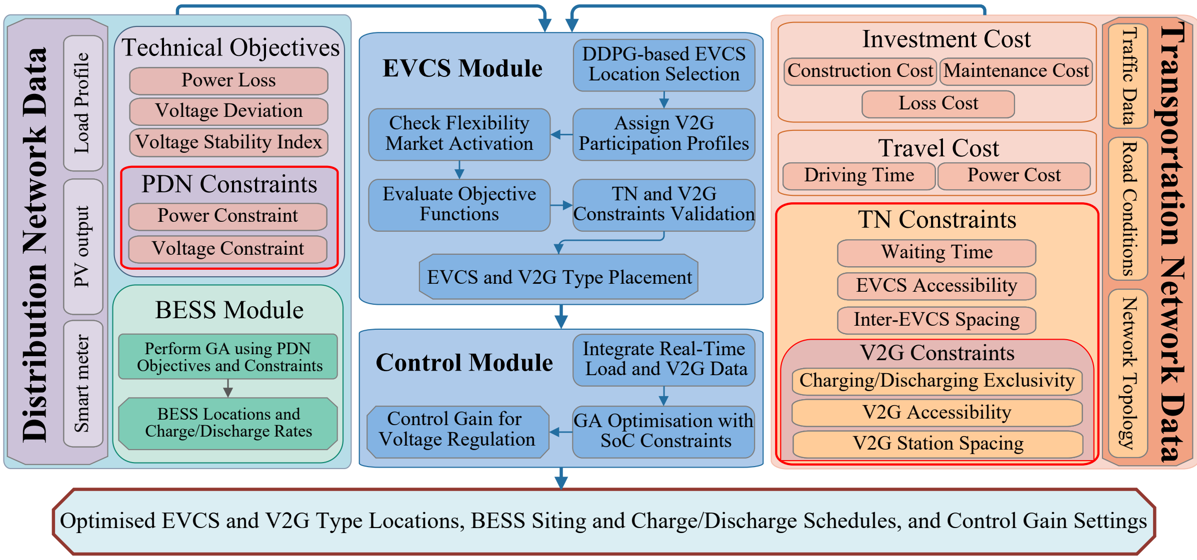


Figure 6.1: Proposed framework for V2G-aware EVCS–BESS planning with participation modelling, market-driven flexibility activation, and adaptive control.

6.1 V2G Infrastructure and Bidirectional Capability Modelling

The increasing deployment of bidirectional charging technologies enables EVs to exchange energy with the grid in both charging and discharging modes. From a planning perspective, this changes the operational role of the charging infrastructure. Instead of acting solely as electricity demand points, V2G-enabled EVCSs can also operate as distributed flexibility resources that support voltage regulation, reduce peak loading, and provide localised energy injection when required [47, 48, 49, 50].

Within the proposed framework, bidirectional charging capability is embedded in the coupled PDN–TN planning problem through explicit modelling of both G2V charging demand and V2G discharging supply. This representation ensures that EVCS planning decisions are evaluated not only in terms of charging service provision but also in terms of EV fleets' potential to provide grid support under realistic operational constraints. In this way, bidirectional charging is treated as a planning variable with direct implications for both infrastructure adequacy and operational flexibility.

6.1.1 Bidirectional Charging Representation

In the proposed framework, the net electrical interaction between EVs and the PDN is modelled by distinguishing charging and discharging operations. Let $p^{G2V}_{pr,m}$ and $p^{V2G}_{pr,m}$ denote, respectively, the charging and discharging power associated with EVs under V2G participation profile pr at bus m. The net EVCS demand at bus m is therefore given by

$$p^{EVCS}_{pr,m} = p^{G2V}_{pr,m} - p^{V2G}_{pr,m} \tag{6.1}$$

where the charging and discharging components are expressed as

$$p^{G2V}_{pr,m} = \left(N^{G2V}_{\mathrm{pr},m} \times R_{\mathrm{ch}}\right), \qquad p^{V2G}_{pr,m} = \left(N^{V2G}_{\mathrm{pr},m} \times R_{\mathrm{dis}}\right) \tag{6.2}$$

Here, $N^{G2V}_{\mathrm{pr},m}$ and $N^{V2G}_{\mathrm{pr},m}$ denote the number of EVs charging and discharging under profile pr at bus m, while R_{ch} and R_{dis} denote the charging and discharging rates, respectively.

This bidirectional representation is central to the chapter because it embeds EV charging and discharging directly into the PDN power-balance relationships and allows EVCS planning decisions to be evaluated in terms of both service provision and flexibility potential.

6.1.2 Operational Constraints

The ability of EV fleets to provide V2G services is constrained not only by technical charging capability but also by infrastructure deployment decisions and operational feasibility requirements. First, charging and discharging cannot occur simultaneously for the same EV. This exclusivity condition is expressed as

$$x_{i,u}^{\text{charge}} + x_{i,u}^{\text{discharge}} \leq 1, \qquad \forall i, u \tag{6.3}$$

where $x_{i,u}^{\text{charge}}, x_{i,u}^{\text{discharge}} \in \{0,1\}$ indicate whether the EV at node i and time interval u is charging or discharging.

Second, not all charging stations are V2G-enabled, and therefore, the effective participation of EV users in V2G depends on the accessibility of eligible stations. To represent this, the effective V2G access distance for user i is defined as

$$\mathcal{D}_i^{\text{V2G}} = \sum_{k \in \mathcal{S}_{\text{EVCS}}} \omega_{ik}\, \psi_k\, \mathcal{D}_{ik_{V2G}} \tag{6.4}$$

where $\omega_{ik} \in \{0,1\}$ indicates whether user i is assigned to station k, $\psi_k \in \{0,1\}$ indicates whether station k is V2G-enabled, and $\mathcal{D}_{ik_{V2G}}$ is the travel distance from user location i to station k. To preserve practical accessibility, this effective V2G distance is constrained by

$$\mathcal{D}_i^{\text{V2G}} \leq \mathcal{D}_{\max}^{\text{V2G}}, \qquad \forall i \tag{6.5}$$

Third, to avoid overconcentration of V2G-capable stations and to promote spatial coverage of flexibility resources, a minimum spacing requirement is imposed between V2G-enabled stations.

$$D_{kk'} \geq D_{\text{V2G}}^{\min}, \qquad \forall k \neq k', \text{ where } \psi_k = 1,\ \psi_{k'} = 1 \tag{6.6}$$

where $D_{kk'}$ denotes the distance between stations k and k', and $D_{\text{V2G}}^{\min}$ is the planning-defined minimum distance between V2G-enabled stations.

Together, these constraints ensure that V2G participation is not treated as an unconstrained virtual resource. Instead, it is represented as a location-dependent and infrastructure-dependent flexibility service whose availability is shaped by both physical deployment decisions and operational feasibility requirements. This distinction is important because it ensures that the flexibility value of V2G is evaluated within a physically meaningful and deployment-consistent planning space.

6.2 Modelling V2G Participation and Behavioural Uncertainty

While the previous section established the physical and infrastructural basis for bidirectional charging, the practical value of V2G depends on whether EV users actually participate in charging and discharging services under realistic operating conditions. In real charging ecosystems, EVs do not participate uniformly in charging and discharging services. Charging demand emerges from time-varying travel behaviour, whereas V2G participation depends on incentives, schedule flexibility, battery availability, and locational accessibility.

This behavioural layer is essential because uncertainty in participation directly affects the planning value of V2G-enabled infrastructure. If all bidirectional chargers are assumed to be fully available for grid support, the resulting planning model may overestimate improvements in hosting capacity and underestimate the need for complementary flexibility resources such as BESS. Conversely, if V2G participation is represented probabilistically, the optimisation framework can distinguish between installed bidirectional capacity and the portion of that capacity that is realistically available for operational support.

Accordingly, this section develops the behavioural layer of the proposed framework. It first represents EV charging demand as a probabilistic function of traffic activity and SOC dynamics in the presence of V2G capability. It then introduces a utility-based participation model to estimate the likelihood that EV users engage in V2G services. Finally, heterogeneous V2G participation profiles are defined to reflect the coexistence of public, commercial, and depot-based charging ecosystems. Collectively, these elements translate bidirectional capability into a user-dependent and context-dependent source of flexibility.

6.2.1 EV Charging Demand in the Presence of V2G

Consistent with the common transportation-network representation established in Chapter 3 and the coupled charging-demand logic developed in Chapter 5, the RQ3 framework uses a graph-based TN model to estimate time-varying EV charging demand and V2G availability across the planning horizon.

$$\begin{cases} \mathcal{T} = \{\mathcal{I}, \mathcal{E}, \mathcal{U}\} \\ \mathcal{I} = \{i \mid i = 1, 2, \dots, n\} \\ \mathcal{E} = \{e_{ij} \mid i = 1, 2, \dots, n, \quad j = 1, 2, 3, \dots, n\} \\ \mathcal{U} = \{u \mid u = 1, 2, \dots, 48\} \end{cases} \tag{6.7}$$

where $\mathcal{I}$ denotes the set of intersections, $\mathcal{E}$ the set of impedance-weighted roads, and $\mathcal{U}$ the set of 48 half-hour intervals across the 24-hour horizon. The traffic flow between nodes i and j at time interval u is estimated using an adapted gravity model [11, 59]

$$F_{ij}^u = C \times \frac{N_i^\phi \times N_j^\psi}{\Omega_{ij}^u} \tag{6.8}$$

where F_{ij}^u is the predicted vehicle flow from node i to node j, C is a scaling constant, N_i and N_j denote local population densities around the two intersections, and ϕ and ψ are scaling exponents. The road impedance is modelled as

$$\Omega_{ij}^u = b_0 \left(z_{ij}^u\right)^c + \sum_{r=1}^{R} b_r y_{ij,r} \tag{6.9}$$

where z_{ij}^u represents the saturation level of road link (i, j) at time interval u, $y_{ij,r}$ denotes the rth road-attribute variable, and b_r and c are calibrated impedance coefficients.

Based on these traffic patterns, EV charging demand is represented probabilistically. As EVs travel through the network, their charging needs depend on the cumulative travel distance, the initial SOC, and the driving range. Following the formulation adopted in the journal paper, the SOC at time interval u is approximated as

$$\mathrm{SOC}_u = \beta_0 - \frac{L(u)}{l_{\max}} \tag{6.10}$$

where β_0 is the initial SOC, $L(u)$ is the cumulative driving distance up to time interval u, and $l_{\max}$ is the maximum EV driving range.

The probability that an EV initiates charging is modelled using a Weibull-based decision mechanism [67, 11]. Accordingly, the expected number of EVs requiring G2V charging at intersection i and time interval u is

$$N_i^{\mathrm{G2V},u} = V_i^u \, \alpha \, P_{\mathrm{charg}} \tag{6.11}$$

where V_i^u denotes the traffic volume at node i, α is the EV penetration level, and P_{charg} is the probability of charging at the corresponding SOC level.

This representation provides the demand-side basis for the subsequent V2G participation estimates. Before the model can evaluate which EVs are likely to discharge energy back to the grid, it must first identify where and when charging demand emerges across the coupled transportation system.

Although V2G capability may be technically available, actual participation in bidirectional energy exchange is uncertain. EV users may participate in V2G only when the perceived benefits outweigh the inconveniences associated with battery discharge, reduced mobility reserve, or a detour to a V2G-enabled charging location. To represent this, the proposed framework adopts a utility-based logistic participation model.

The probability that an EV driver at intersection i participates in V2G is defined as

$$P_i^{\mathrm{V2G}} = \gamma \times \frac{1}{1 + \exp\left(-U_i^{\mathrm{V2G}}\right)} \tag{6.12}$$

where $\gamma \in [0, 1]$ denotes the maximum proportion of EV users willing to engage in V2G. Following [70], this chapter sets

$$\gamma = 0.3 \tag{6.13}$$

The latent utility is given by

$$U_i^{\mathrm{V2G}} = \beta_1 \times \pi_i - \beta_2 \times d_{\mathrm{V2G}} + \beta_3 \times f_i + \beta_4 \times (1 - \mathrm{SOC_{arrival}}) + \beta_5 \times \mathrm{TOD}(u) \tag{6.14}$$

where π_i denotes the discharge incentive in \$/kWh, d_{V2G} is the distance to the nearest V2G-capable charging station, f_i denotes schedule flexibility, $\mathrm{SOC_{arrival}}$ is the battery SOC upon arrival, and $\mathrm{TOD}(u)$ is a time-of-day indicator defined as

$$\mathrm{TOD}(u) = \begin{cases} 1, & \text{if } u \in \{33, 34, \ldots, 48\} \\ 0, & \text{otherwise} \end{cases}$$

The expected number of EVs participating in V2G at node i and time interval u is then.

$$N_i^{\mathrm{V2G},u} = N_i^{\mathrm{available},u} \times P_i^{\mathrm{V2G}} \tag{6.15}$$

where $N_i^{\mathrm{available},u}$ denotes the number of EVs with sufficient battery energy to support discharging. Only EVs arriving with $\mathrm{SOC_{arrival}} \geq 0.5$ are considered available, i.e.,

$$N_i^{\mathrm{available},u} = \sum_{e \in \mathcal{E}_i^u} \begin{cases} 1, & \text{if } \mathrm{SOC}_{e,\mathrm{arrival}} \geq 0.5, \\ 0, & \text{otherwise}, \end{cases} \tag{6.16}$$

This formulation prevents unrealistic overestimation of V2G participation by restricting grid-support services to EVs with adequate energy reserve and by treating participation as conditional rather than assumed. It also provides a more realistic bridge between user behaviour and system planning because charging demand, V2G availability, and discharging participation are represented within the same behaviour-aware demand layer.

6.2.2 V2G Participation Profiles

In practical charging ecosystems, V2G participation is heterogeneous rather than uniform. Different charging locations and user groups exhibit distinct temporal and operational characteristics. To reflect this diversity, the proposed framework defines three V2G participation profiles.

$$\text{PR} = \{\text{Normal, Marketplace, Depot}\} \tag{6.17}$$

1) Normal V2G: This profile represents public EVCSs where participation is voluntary and user-driven. The probability of participation is directly given by the utility-based model above, i.e., P_i^{V2G}.

2) Marketplace V2G: This profile represents EVs parked in commercial or workplace areas for extended daytime periods. In this case, V2G participation is active only during specific occupancy windows.

$$P_{\text{V2G},i}^{\text{Market}} = \begin{cases} P_i^{\text{V2G}}, & \text{if } u \in \{19, 20, \ldots, 32\} \\ 0, & \text{otherwise} \end{cases} \tag{6.18}$$

3) Depot V2G: This profile represents fleet-oriented or scheduled charging facilities such as depots, where discharging can be centrally coordinated. In this case, participation is modelled deterministically as

$$P_{\text{V2G},i}^{\text{Depot}} = 1, \qquad \text{if node } i \text{ is a depot with scheduled discharge} \tag{6.19}$$

These three profiles jointly capture voluntary, semi-structured, and centrally managed V2G behaviour. From the perspective of RQ3, this heterogeneous representation is essential because it allows infrastructure planning decisions to be evaluated not only with respect to technical charging capacity, but also with respect to the type, reliability, and timing of V2G participation that different charging locations can realistically provide. As a result, the framework can distinguish between nominal V2G capability and practically usable flexibility.

6.3 Market-driven Flexibility in EV Charging Infrastructure

The previous section established that V2G availability is both behaviour-dependent and profile-dependent. However, the existence of technically and behaviourally available EVs does not imply that flexibility will always be activated. In practice, EVCS operators may commit to providing flexibility services in future operations, but real-time V2G contributions depend on both market feasibility and EV availability. Consequently, this chapter distinguishes between behavioural availability and market-driven activation.

In this chapter, market-driven flexibility is interpreted as a planning-level activation mechanism that represents whether technically and behaviourally available V2G capacity is called upon for grid-support operation. It does not model a full electricity market-clearing process; rather, it captures the practical distinction between installed bidirectional capability and the flexibility that is actually activated under market-facing operating conditions.

6.3.1 Flexibility Activation Mechanism

To represent the activation of market-driven flexibility, binary variables $\rho_k \in \{0, 1\}$ are defined for each participation profile $\theta \in PR$:

$$\rho_k = \begin{cases} 1, & \text{if EVCS } k \text{ participates in next-day operation} \\ 0, & \text{if EVCS } k \text{ does not participate} \end{cases} \tag{6.20}$$

These variables determine whether the flexibility associated with a given V2G participation profile is activated within the planning and control framework. In other words, even if a charging location is technically capable of supporting V2G and the corresponding users are behaviourally willing to participate, the profile may remain inactive unless it is selected for market-oriented operation.

This activation mechanism provides a tractable representation of the conditional nature of V2G flexibility in practical planning environments. Rather than assuming that all available flexibility is dispatched, the model enables profile-specific flexibility to be selectively activated in response to operational and market conditions. This distinction is especially important in market-facing settings, where committed flexibility and realised flexibility are not always identical.

6.3.2 Market Participation Uncertainty

The binary activation variables ρ_θ also provide a compact representation of market participation uncertainty. In practical charging ecosystems, EVCS operators may intend to participate in flexibility markets, yet real-time participation may fail because of insufficient EV availability, reduced user willingness, or a mismatch between expected and actual charging station activity.

By incorporating ρ_θ into the proposed framework, the model captures this uncertainty in a planning-relevant form. The flexibility value of a given EVCS location is therefore determined not only by the nominal V2G capability of its connected EVs, but also by the likelihood that the corresponding participation profile can be activated in operation. This prevents the planning model from systematically overestimating the usable flexibility contribution of EV fleets.

From a planning perspective, this distinction is important. Behavioural participation describes who can participate, whereas market-driven activation determines which forms of participation are actually used. The combination of the two provides a more realistic representation of future charging ecosystems, especially in settings where flexibility provision is coordinated by aggregators or activated through market arrangements rather than directly by individual EV users. It therefore strengthens planning realism by aligning nominal infrastructure capability with operationally deliverable flexibility.

6.4 Proposed Multi-Module Optimisation Framework

This section presents the sequential three-stage optimisation framework adopted in RQ3 for the coordinated planning and operation of EV charging infrastructure in coupled PDN–TN systems. As illustrated in Fig. 6.1 and summarised in Algorithm 2, the framework integrates long-term infrastructure planning with short-term operational control. The three stages reflect the heterogeneous structure of the problem: BESS planning for grid-support feasibility, traffic-aware EVCS deployment under V2G participation and market-driven flexibility, and real-time BESS control for voltage support under stochastic charging and discharging conditions.

6.4.1 Stage I: BESS Planning Module

The first stage employs a GA to determine BESS locations and time-resolved charge/discharge profiles. This module addresses the feasibility-oriented electrical layer of the problem, where decisions are dominated by nonlinear AC power-flow relationships, mixed discrete–continuous variables, and voltage/SOC constraints. GA is adopted because it can search the resulting nonconvex solution space while preserving feasibility under PDN operating constraints [38, 62].

Candidate BESS configurations are evaluated across all time steps using power loss, VD, and voltage stability indices. In this way, the BESS module determines the grid-support envelope within which downstream EVCS planning can proceed. The outputs of this stage are the selected

BESS locations and their corresponding charging/discharging schedules. These outputs also provide the foundation for the electrical feasibility of the subsequent EVCS deployment stage.

6.4.2 Stage II: Traffic-aware EVCS Deployment Module

The second stage optimises EVCS deployment under coupled PDN–TN conditions using a DDPG algorithm. The problem is formulated as a multi-objective Markov Decision Process (MDP), in which the state includes traffic intensity, estimated G2V/V2G demand, existing grid loading, BESS support, and the current status of the charging infrastructure. The actions correspond to EVCS siting and sizing decisions, and the reward captures technical and user-centric performance, including power loss, travel cost, queuing time, and voltage feasibility.

In addition to the EVCS deployment problem itself, this stage includes modelling V2G participation profiles and activating market-driven flexibility. Hence, the DDPG policy learns deployment decisions that are not only traffic-aware and grid-feasible but also responsive to heterogeneity in V2G participation and profile-dependent activation. By doing so, the deployment policy accounts for both where charging demand occurs and where usable flexibility is most likely to emerge.

6.4.3 Stage III: Real-Time Control Module

The third stage addresses voltage regulation under dynamic operating conditions, following the infrastructure decisions from Stages I and II. A GA-based local control strategy is employed to optimise the control gains $K_i(u)$ that regulate BESS charge/discharge behaviour in response to VDs arising from EV charging, V2G discharging, and real-time uncertainty.

The control law is defined as

$$P_i(u) = K_i(u)\,[V_i(u) - V_{th}] \tag{6.21}$$

where $V_i(u)$ denotes the voltage magnitude at bus i and time interval u, $K_i(u)$ is the optimised local control gain, and V_{th} is the voltage threshold. If the local voltage falls below the nominal level because of heavy EVCS loading, the BESS discharges to provide support. Conversely, under surplus-voltage conditions, for example, due to reverse power flow, the BESS shifts toward charging mode.

This stage ensures that the planning decisions from the first two modules remain operationally robust when faced with stochastic EV behaviour and real-time V2G variability. In this sense, the control layer acts as the operational safeguard that preserves the validity of planning decisions under non-ideal conditions.

Algorithm 2: Sequential optimisation framework for coordinated BESS planning, EVCS/V2G deployment, and real-time control in RQ3

Input : PDN and TN data
Output: BESS locations and operating schedules, EVCS and V2G-enabled locations, optimal control gains $K_i(u)$

foreach *time step* u **do**
  while $i \leq$ *iterations* **do**
    Run GA to minimise technical costs (Eqs. 3.4–3.8) subject to constraints (Eqs. 5.30–5.33, 6.1, 6.2)
    Update population, $i \leftarrow i + 1$
  end
  Extract BESS location and rate of charge/discharge
end
foreach *intersection* i*, time* u **do**
  Compute traffic features (Eqs. 5.2, 5.3)
  Compute $N_i^{G2V,u}$ and $N_i^{V2G,u}$
  Assign EVCS and V2G type profile
end
foreach *time step* u **do**
  while $i \leq$ *episodes* **do**
    while $j \leq$ *actions* **do**
      action ← agent.act(state)
      Run DDPG for EVCS and V2G placement under TN constraints
      if *EVCS constraints satisfied* **then**
        Enforce V2G constraints and activate ρ_θ under market flexibility
      end
      state ← nextState
    end
  end
  Extract EVCS and V2G-enabled locations
end
Integrate real-world datasets (EVCS demand, active V2G participation types)
foreach *time step* u **do**
  while $i \leq$ *iterations* **do**
    Run GA to minimise VD by optimising $K_i(u)$ subject to SOC constraints
    Update population, $i \leftarrow i + 1$
  end
  Extract optimal $K_i(u)$ for all buses
end
return

Overall, the proposed multi-module framework combines global feasibility-oriented storage planning, adaptive traffic-aware charging infrastructure deployment, and localised voltage control. In doing so, it translates the behavioural and flexibility-oriented concepts of RQ3 into a computationally executable planning architecture. More importantly, it links infrastructure design, user behaviour, and operational control into a single, coordinated decision-making process.

Table 6.1: Key parameters, V2G participation assumptions, and optimisation settings used in the V2G-aware coupled PDN–TN case study.

Parameters	**Value**
Loss rates (G2V / V2G)	0.05 / 0.10
Cost of power from the substation	5 $/kWh
V2G pile cost rate (slow/fast)	1.2
Value of travel time c_{time}	20 $/h
DC charging pile capacity	120 kW
DDPG actor/critic layer size	[400, 300]
DDPG (batch size, learning rate)	(64, 0.001)
Electricity prices (S/F/Grid)	0.50/0.75/0.13 $/kWh
GA parameters (pop., gen., cross., mut.)	(20, 50, 0.9, 0.1)
Lifetime of each station	20 years
Max. V2G travel distance $\mathcal{D}_{\max}^{\text{V2G}}$	30 km
Mileage per energy unit l_0	4.1 km/kWh
Min. V2G station distance $D_{\text{V2G}}^{\min}$	2 km
Voltage limits (minimum / nominal)	216 V, 230 V
EV penetration level α	0.5

6.5 Results and Discussion

This section evaluates the RQ3 framework in a Melbourne-based coupled PDN–TN environment to examine how V2G participation behaviour and market-driven flexibility affect EVCS planning, transportation performance, and distribution-network stability. The common data environment, feeder assumptions, and traffic-network construction have already been established in Chapters 3 and 5; accordingly, only the RQ3-specific elements of the simulation setting are summarised here. This avoids reintroducing the common experimental backbone and keeps the chapter's focus on the additional behavioural, market-activation, and V2G-control layers introduced for RQ3.

The results are interpreted from a planning perspective rather than as isolated operational simulations. The key question is how V2G participation and market-driven flexibility reshape the feasible planning envelope for EVCS deployment while maintaining acceptable grid performance and transportation-side service quality. Therefore, the analysis focuses on three linked outcomes: the extent to which V2G reduces electrical stress, the extent to which participation uncertainty limits this benefit, and the extent to which coordinated control can utilise the available flexibility without masking structurally weak planning decisions.

The principal case study integrates a modified IEEE 33-bus radial distribution system with a Melbourne TN represented using real-world traffic data. The electrical layer follows the common household, PV, and BESS assumptions established earlier in the thesis, while the transportation layer uses 60 intersections and 95 roads aggregated into 48 half-hour intervals. Figures 3.2, 3.3, and 3.4 summarise the smart meter profile and the resulting temporal and spatial distributions of charging demand.

RQ3 extends this common case-study environment by introducing V2G participation profiles, utility-based participation behaviour, and market-driven activation of flexibility. Key chapter-specific parameters are reported in Table 6.1.

RQ3-specific demand and participation behaviour are parameterised using the Gaussian, Weibull, and utility-based formulations introduced earlier in the chapter, while the common electrical and transportation assumptions remain consistent with Chapters 3 and 5. Chapter-specific parameters are summarised in Table 6.1. All simulations were executed in a fixed computational environment to ensure repeatability across scenario studies.

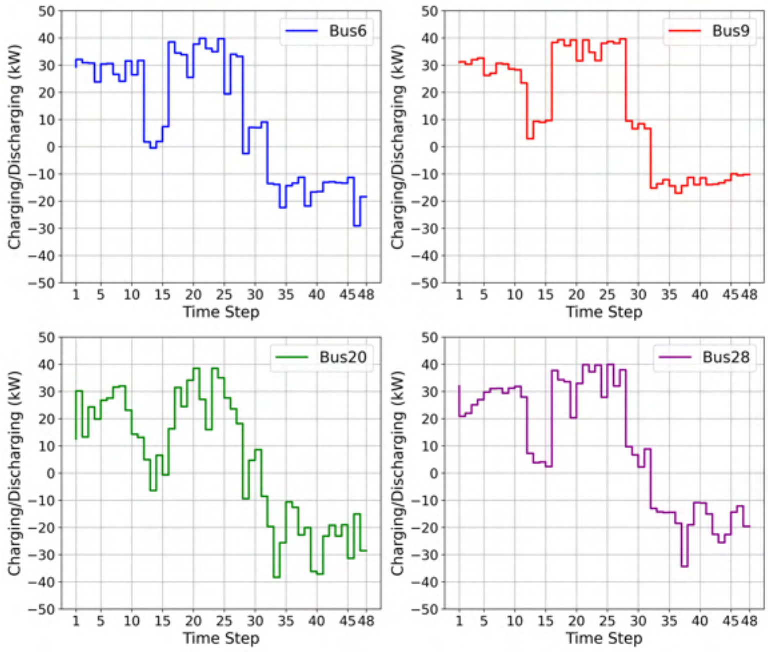


Figure 6.2: BESS charge/discharge profile over the 24-hour planning horizon for the IEEE 33-bus case study.

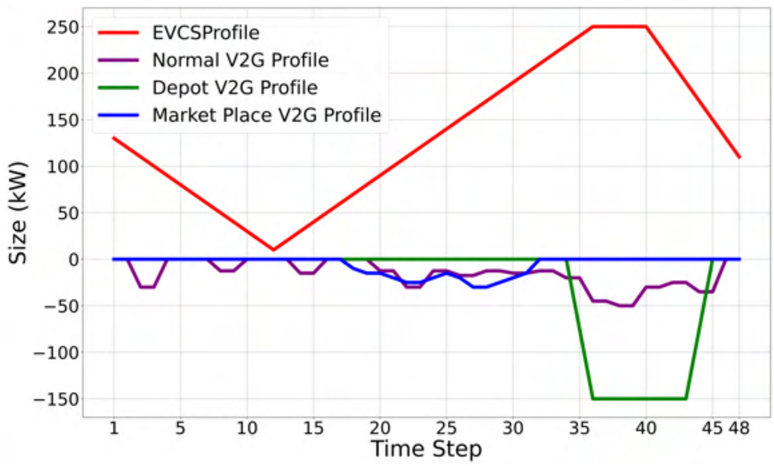


Figure 6.3: Daily EVCS load profiles under different V2G participation types and fixed EVCS deployment patterns.

6.5.1 Planning Performance under V2G Participation

Planning begins with GA-based siting and scheduling of BESS units. As shown in Fig. 6.2, the BESS units follow dynamic charging/discharging patterns across the 48 time steps to mitigate power loss and VD under varying load and PV conditions.

EVCS siting is then handled by the DDPG agent, which interacts with the coupled PDN–TN environment. Fig. 6.3 shows the EVCS power-consumption pattern together with three representative V2G participation profiles. To evaluate the combined effects of V2G participation and market engagement, four scenarios are considered:

- **Scenario 1:** Full V2G with 100% participation;
- **Scenario 2:** Partial V2G with full participation;

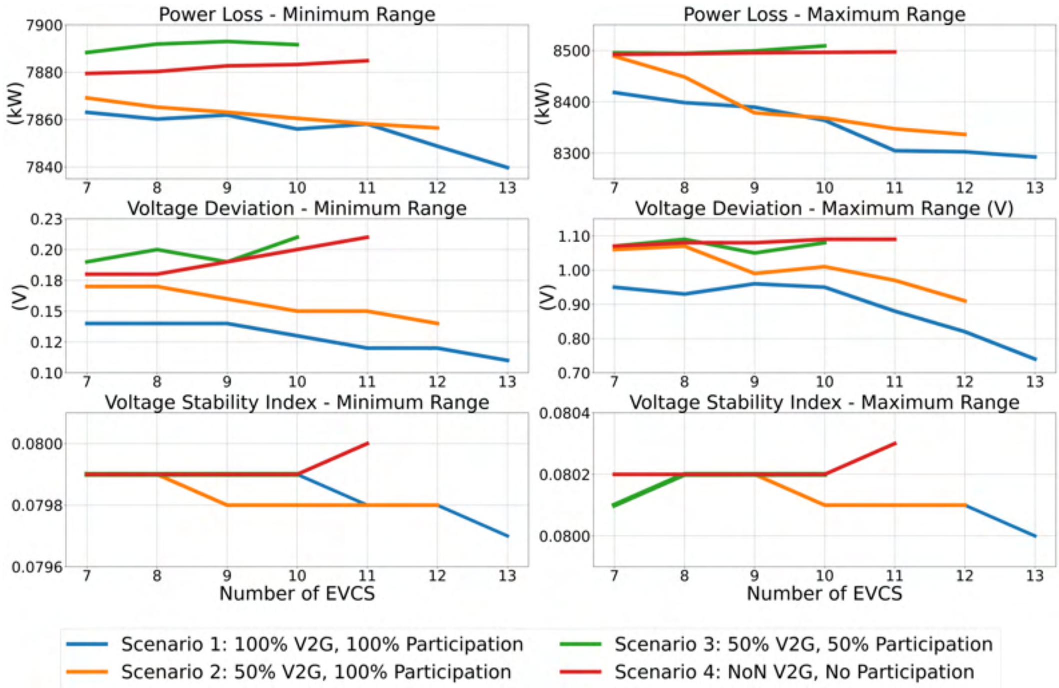


Figure 6.4: Comparison of technical performance costs under different V2G participation and market-activation scenarios.

- **Scenario 3:** Partial V2G with 50% participation;
- **Scenario 4:** Baseline without V2G.

Here, full V2G participation implies that the V2G centre can provide the committed export profile to the grid, whereas in the 50% participation case, the actual contribution is only half of the committed amount.

The system-level outcomes of these scenarios are summarised in Figs. 6.4 and 6.5. From the PDN perspective, Scenario 1 consistently provides the strongest performance, reducing power loss by approximately 0.6%, reducing the aggregate VD index by around 0.10 pu, and maintaining the strongest voltage-stability performance among the evaluated scenarios. Scenario 2 also improves performance, but its gains are smaller because fewer V2G-enabled stations are available. Scenario 3 performs noticeably worse despite nominal V2G support, because reduced participation and spatial concentration limit the practical value of available flexibility. In several metrics, this weak participation profile performs comparably to or worse than the non-V2G baseline (Scenario 4). The results, therefore, show that technical V2G capability alone is insufficient; effective participation matters materially. They also indicate that the planning value of V2G is strongly shaped by participation reliability rather than by bidirectional hardware alone.

6.5.2 Impact of Market Flexibility

The difference between Scenarios 2 and 3 is especially important for interpreting the role of market-driven flexibility. Both scenarios include V2G-enabled infrastructure, yet the level of effective participation differs. Scenario 2 reflects a case in which the available V2G profile can be fully activated, whereas Scenario 3 reflects a more constrained market-response condition in which only half of the committed flexibility is effectively available.

This comparison demonstrates that the value of V2G-ready infrastructure depends on the ability to activate operational flexibility. When participation and activation are strong, the charging network functions as a significant distributed flexibility resource. When activation is

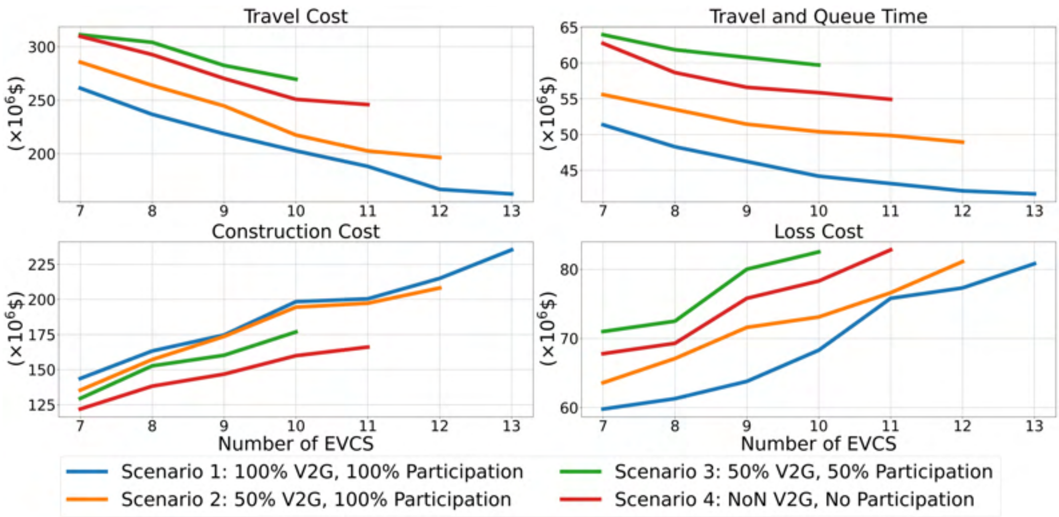


Figure 6.5: Comparison of annual investment and user travel costs under different V2G participation and market-activation scenarios.

limited, the same infrastructure provides materially weaker system support. In other words, the planning value of V2G capability is not captured solely by installing bidirectional chargers; it depends on whether those chargers can mobilise meaningful flexibility under profile-dependent and market-dependent conditions.

A further insight is that the gains in Scenario 1 begin to saturate beyond approximately 10 EVCSs. This suggests that while greater EVCS density improves accessibility and flexibility coverage, the marginal technical benefit diminishes once sufficient spatial support is in place. This saturation behaviour is relevant for practice because it suggests that the most effective V2G-oriented deployment is not necessarily the densest possible, but rather one that balances flexibility value, participation quality, and infrastructure cost.

These findings highlight an important distinction between V2G capability and V2G deliverability. Installing bidirectional EVCSs increases the theoretical flexibility embedded in the charging infrastructure, but market activation determines how much of that flexibility can be called upon in practice. From a planning perspective, this means that EVCS deployment strategies based only on installed V2G capacity may overstate network-support benefits unless participation and activation constraints are explicitly represented. Market-driven flexibility, therefore, acts as a realism filter that converts technical capability into an operationally credible planning resource.

6.5.3 Transportation System Performance

From the transportation system perspective, Fig. 6.5 shows that Scenario 1 yields the greatest reductions in travel cost and queuing time. Specifically, travel costs are reduced by up to 48% and queuing time by up to 75% relative to less effective participation scenarios, owing to the combination of well-distributed EVCS locations and effective V2G scheduling. Scenario 2 provides intermediate gains. Scenario 3 performs worse because low participation and weaker spatial coverage produce local service bottlenecks and dilute the benefits of V2G-enabled deployment. Scenario 4, while operationally simpler, lacks the additional flexibility that helps maintain charging service quality under heavy demand.

As the number of EVCSs increases, transportation performance generally improves because travel detours and queuing pressure decline. However, the benefits again saturate as station count rises, and this saturation aligns with the cost increases observed in Fig. 6.5. Hence, the transport-side results reinforce the broader thesis-level conclusion that optimal EVCS plan-

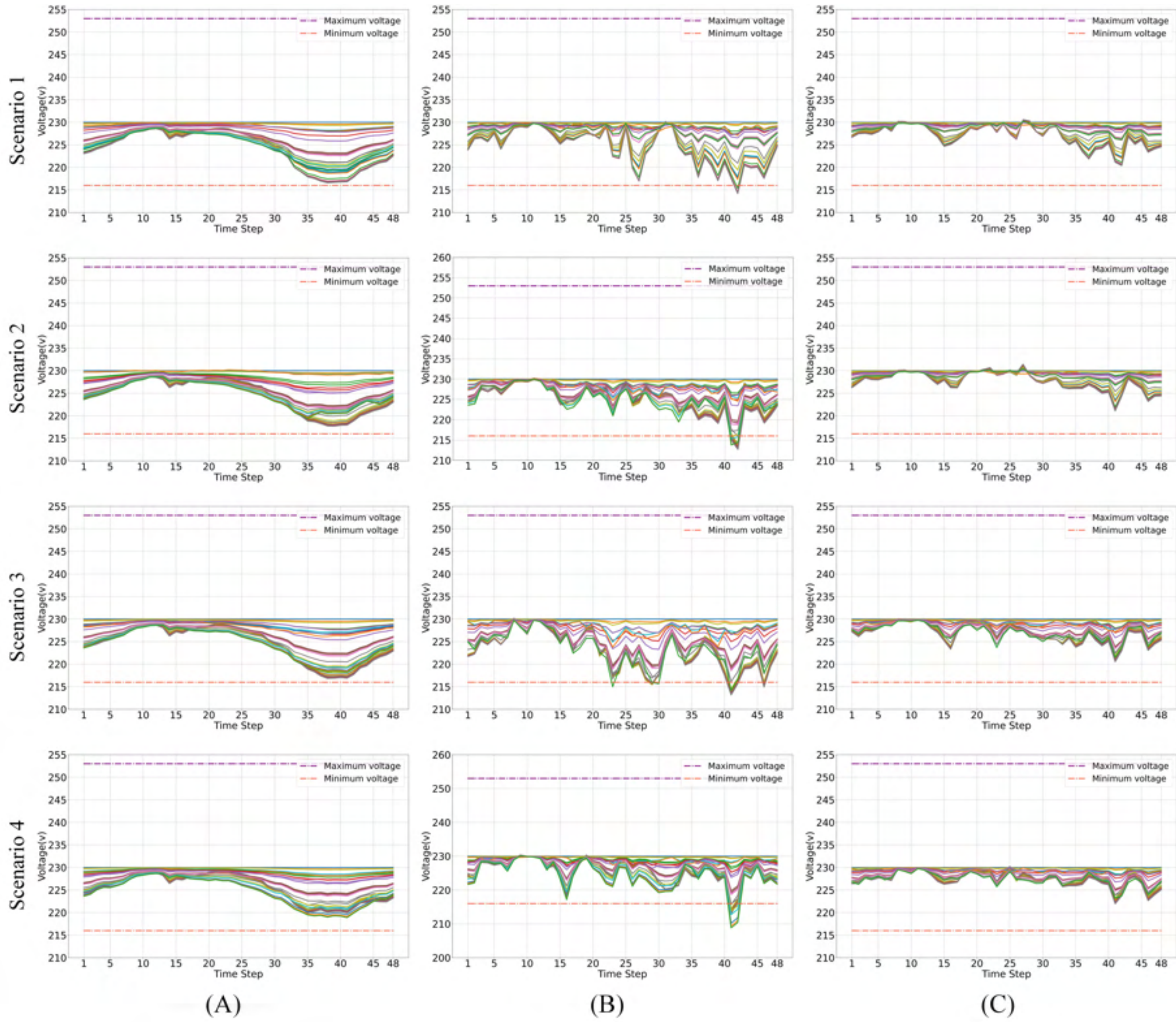


Figure 6.6: Voltage profiles under fixed, real-data, and controlled EVCS–V2G operating conditions across the planning scenarios.

ning must balance accessibility gains against cost and electrical feasibility rather than simply maximising station count.

An additional system-wide insight emerges from feasible hosting capacity. Scenario 1 supports up to 13 feasible EVCS deployments, whereas the baseline without V2G (Scenario 4) supports only 11. Scenario 3 performs the worst, enabling only 10 stations due to poor V2G spatial distribution and limited participation, thereby weakening the network's ability to absorb additional charging infrastructure. This result is important because it shows that strong V2G participation not only improves operations at fixed infrastructure levels but also expands the feasible planning space. In this sense, the quality of participation affects not only operational outcomes but also the size of the infrastructure deployment envelope.

6.5.4 Voltage Stability

Voltage robustness under real-time uncertainty is examined using the Control Module. Fig. 6.6 compares voltage profiles across the four scenarios under three conditions: (A) fixed EVCS/V2G patterns from the planning stage, (B) injection of real EVCS/V2G data to simulate operational volatility, and (C) activation of the control module using optimised BESS gains.

Under the fixed planning patterns in Fig. 6.6(A), all scenarios remain within acceptable voltage limits, indicating that the planning layer itself is technically sound. However, once real EVCS/V2G data are introduced in Fig. 6.6(B), voltage violations appear, especially in Scenario 4, which lacks V2G support, and in Scenario 3, where participation is limited and spatially uneven. This confirms that planning results alone are insufficient when actual operating conditions deviate from nominal assumptions.

After the Control Module is activated in Fig. 6.6(C), voltage stability is restored across all scenarios. The GA-optimised local gains adjust BESS behaviour in real time, compensating for both voltage drops and surplus-voltage conditions induced by charging and V2G activity. Scenario 1 remains the most stable, but even Scenario 4 benefits substantially from localised control despite lacking bidirectional EV support.

To further examine the robustness of the proposed framework, a brief sensitivity analysis was conducted with respect to several key operational parameters influencing V2G-enabled charging infrastructure. In particular, three factors were considered: the effective V2G loss rate, the maximum permissible queuing time at EVCS locations, and the operational SOC limits of BESS units.

First, increasing the V2G charge/discharge loss rate from 10% to 15% resulted in a modest increase in network power losses and associated operating costs. However, the relative performance ranking of the planning scenarios remained unchanged, with Scenario 1 consistently providing the strongest voltage support and overall system performance. This indicates that the technical benefits of coordinated V2G participation are not overly sensitive to moderate variations in conversion losses.

Second, relaxing the maximum queuing-time constraint from 20 minutes to 30 minutes slightly increased the flexibility of EVCS placement within the TN. While this relaxation improved siting feasibility in certain high-demand areas, it also increased the travel-related user cost due to longer waiting times. The overall planning outcomes, therefore, reflect a trade-off between user service quality and flexibility in infrastructure placement.

Third, narrowing the allowable BESS state-of-charge operating range from [0.2, 0.9] to [0.3, 0.8] reduced the effective energy flexibility available for real-time voltage regulation. Under these tighter SOC bounds, the system exhibited slightly higher VDs during high-demand periods. Nevertheless, the control module remained capable of maintaining voltage stability within acceptable limits.

Overall, these sensitivity observations confirm that the proposed coordinated planning and control framework remains operationally robust under realistic variations in key technical and service parameters. While parameter changes affect the magnitude of certain performance metrics, the fundamental conclusion of the chapter, namely, that strong V2G participation, combined with coordinated control, significantly improves PDN stability and EVCS planning feasibility, remains unchanged.

Taken together, the results provide the core answer to RQ3. Full and effective V2G participation yields the strongest combined gains in PDN performance, transport accessibility, and feasible EVCS hosting capacity, whereas weak or partially activated participation substantially limits the practical value of V2G-ready infrastructure. The chapter therefore shows that the benefits of bidirectional charging depend not only on technical capability, but also on participation behaviour, activation conditions, and real-time operational support. More broadly, the results demonstrate that robust EVCS planning in future smart grids requires the coordinated treatment of infrastructure design, participation realism, and operational controllability.

The voltage results also clarify the role of operational control within the proposed planning framework. Coordinated control improves the utilisation of BESS and V2G flexibility after infrastructure locations and capacities have been determined; however, it should not be interpreted as a substitute for structurally sound planning. If EVCSs are deployed at electrically weak locations or if V2G support is assumed to be fully available despite uncertain participation, real-time control can only partially mitigate the resulting voltage stress. Thus, operational control is most effective when it complements, rather than compensates for, feasible siting and sizing decisions.

6.6 Practitioner-Oriented Guidance for V2G-enabled Infrastructure Planning

The results of this chapter provide direct planning and operational insights for stakeholders involved in EV charging infrastructure deployment, electricity network operations, and flexibility market design.

For practical deployment, the results indicate that V2G-enabled EVCS planning should be treated as a co-design problem involving charging infrastructure, local grid flexibility, user participation, and market access. A technically optimal EVCS location may not be operationally valuable if participation is weak, market activation is limited, or local voltage constraints restrict bidirectional exchange. Conversely, locations with moderate charging demand may become strategically valuable if they combine adequate feeder hosting capacity, predictable parking behaviour, and reliable flexibility participation.

Implications for Distribution Network Operators and DNSPs: The results show that V2G-enabled EV fleets can act as distributed flexibility resources for voltage support and peak-load mitigation. This means that, under sufficiently strong participation and activation conditions, network operators can treat EVCSs not only as new electrical loads but also as potential support assets. In practical terms, strategically located V2G-enabled EVCSs can reduce feeder stress, improve voltage quality, and postpone or reduce the need for conventional network reinforcement.

Implications for EV charging infrastructure developers and operators: The results demonstrate that the value of charging infrastructure increases when EVCS deployment is aligned with both mobility demand and flexibility potential. Traffic-informed EVCS siting reduces travel and queueing burdens, while bidirectional capability creates additional revenue and system-value pathways by providing flexibility. However, these gains are not automatic; they depend on the quality of participation associated with each site type. Therefore, charging developers should distinguish between public, commercial, and depot-style locations when evaluating the business and operational value of V2G-ready charging assets.

Implications for aggregators and flexibility-market participants: The comparison between strong and weak participation scenarios shows that the practical value of V2G depends on the ability to deploy operational flexibility rather than merely on the presence of bidirectional hardware. This implies that aggregators and market-facing operators should prioritise charging locations with more reliable participation profiles and a greater probability of effective activation. In other words, infrastructure that is technically V2G-ready but behaviourally or operationally weak should not be valued as equivalent to infrastructure that provides consistent, dispatchable flexibility.

Implications for policy and integrated urban planning: The results also highlight the need for coordinated planning between transport electrification strategies and distribution-network development. From a policy perspective, support for V2G-ready infrastructure should be coupled with regulatory and market arrangements that enable the effective activation of flexibility, including clear participation frameworks, aggregator integration pathways, and data-sharing mechanisms among transport authorities, charging operators, and electricity system operators. Without such coordination, a substantial portion of the theoretical flexibility value of EV fleets may remain unrealised.

Overall, the chapter shows that future EV charging networks should be planned not merely as energy supply facilities, but as coordinated energy–mobility assets whose system value depends on location, participation behaviour, activation conditions, and controllability. For industry decision-makers, the central message is clear: the benefits of V2G-enabled charging infrastructure are real, but conditional. The highest value is obtained when traffic-informed deployment, strong participation profiles, market-oriented activation, and real-time control are designed together rather than in isolation.

Chapter 6, therefore, extends the thesis beyond traffic-informed EVCS siting and sizing by showing that flexibility-aware planning must distinguish between installed bidirectional capacity and realisable operational support. This distinction provides the foundation for the cross-study synthesis in Chapter 7, where V2G, BESS, uncertainty, control, and market participation are interpreted as structural planning dimensions within the design of integrated energy–mobility infrastructure.

Chapter 7

Decision-Centric Synthesis of EVCS Planning Frameworks

This chapter provides a decision-centric synthesis of EVCS planning frameworks in coupled PDN–TN systems and positions the thesis contributions within this broader methodological landscape. Rather than functioning as a conventional literature review, the chapter examines how infrastructure-planning decisions are formulated, sequenced, and coupled with operational mechanisms. This perspective is necessary because EVCS planning performance is not governed by the optimisation algorithm alone; it is also shaped by the decision architecture that links traffic-driven demand, grid-feasibility assessment, flexibility resources, operational control, and participation mechanisms.

The motivation for this synthesis is that the coupled PDN–TN EVCS planning literature remains fragmented not only by methodological diversity, but also by inconsistent decision structures, heterogeneous coupling assumptions, and uneven integration of planning and operational layers. Two studies may employ similar optimisation techniques yet reach different planning outcomes if they differ in how charging demand is generated, how transportation states are translated into electrical loading, how grid constraints are enforced, or how flexibility and control are embedded in the planning process. Therefore, this chapter compares planning frameworks through their structural decision logic rather than through solver categories alone.

Within the overall thesis, this chapter's role is interpretive rather than developmental. Chapters 4–6 introduced progressively enriched planning frameworks for EVCS deployment, moving from grid-aware EVCS–BESS planning, to traffic-informed coupled PDN–TN planning, and finally to V2G-enabled planning under participation and flexibility constraints. The purpose of the present chapter is to interpret this progression within the broader research landscape and to clarify how different modelling assumptions, coupling mechanisms, and operational features reshape the feasible EVCS deployment frontier. In this sense, the chapter links the thesis contributions to a wider question: how should EVCS planning frameworks be structured so that accessibility, electrical feasibility, flexibility utilisation, and deployment realism are assessed within a coherent decision architecture?

A key distinction adopted in this chapter is the separation between planning-layer and operation-layer decisions. Planning-layer decisions are long-horizon, capital-intensive, and largely irreversible choices, including EVCS siting, charger capacity sizing, BESS placement, and infrastructure readiness for V2G participation. Operation-layer decisions, by contrast, involve short-horizon adaptive mechanisms such as BESS dispatch, V2G activation, charging management, voltage regulation, pricing response, and queue-aware service coordination. The thesis connects these two layers, but does not collapse them into a single monolithic optimisation problem. This distinction preserves the interpretability of infrastructure-planning decisions while allowing their operational feasibility to be evaluated under realistic conditions for traffic, demand, flexibility, and participation.

Accordingly, the chapter has three objectives. First, it organises the EVCS planning literature through a decision-structure-oriented taxonomy that distinguishes among different planning architectures, methodological families, and planning-operation interfaces. Second, it evaluates the maturity of advanced planning features, including PDN–TN coupling, data-driven demand representation, uncertainty modelling, BESS coordination, V2G participation, market-enabled flexibility, operational control, accessibility, and resilience. Third, it uses the thesis case-study progression to interpret how these features act as structural planning dimensions that reshape hosting capacity, service accessibility, flexibility utilisation, and the feasible EVCS deployment frontier.

The analytical boundary of this chapter follows the scope established in Chapters 1 and 2. The focus is on EVCS infrastructure planning in coupled PDN–TN environments, where charging demand is treated as a mobility-driven quantity that must be translated into spatially and temporally varying electrical demand on distribution feeders. The synthesis, therefore, emphasises studies that connect infrastructure siting and sizing decisions with transportation-driven charging demand, feeder-level feasibility constraints, flexibility resources, and operational coordination. Particular attention is given to demand-to-grid translation mechanisms, because the practical value of a coupled planning framework depends on whether traffic-derived charging demand is mapped to enforceable PDN constraints rather than treated as an exogenous demand profile. Purely operational charging-control studies are considered only when they materially affect infrastructure planning decisions.

To achieve these objectives, the chapter proceeds through a sequence of analytical steps. Section 7.1 introduces a methodological taxonomy that categorises existing studies into distinct planning paradigms, while Section 7.2 evaluates the maturity of advanced planning features embedded in these frameworks. Section 7.3 then provides a comparative synthesis of methodological trends and modelling characteristics across the reviewed literature. Building on this qualitative synthesis, Section 7.4 develops a deployment-oriented scenario analysis that interprets how uncertainty, BESS, V2G participation, coordinated voltage control, and market-driven flexibility reshape the feasible EVCS deployment frontier under a common analytical framework. Section 7.5 consolidates the resulting insights and identifies structural research gaps, while Section 7.6 maps the thesis RQs to the broader methodological landscape. Finally, Section 7.7 discusses the implications of integrated EVCS planning for infrastructure development, electricity markets, transportation systems, and deployment-oriented decision-making.

7.1 Methodological Families of EVCS Planning Frameworks

Building on the research-domain boundaries established in the previous sections, this part of the chapter introduces a structured methodological taxonomy of EVCS planning frameworks for coupled PDN–TN environments. The objective is not merely to classify prior studies, but to organise them according to their underlying planning logic and decision architecture. Establishing such a taxonomy is essential for a doctoral-level synthesis because it enables the literature to be interpreted through a consistent analytical lens, thereby revealing methodological patterns, structural assumptions, and limitations across the research landscape.

Within the context of this thesis, the classification of planning frameworks is particularly important. The research contributions developed in the subsequent chapters build on progressively richer planning architectures that integrate traffic-aware demand modelling, distribution network feasibility, infrastructure flexibility, and coordinated operational mechanisms. Understanding how existing studies structure the EVCS planning problem, therefore, provides the conceptual foundation to position the thesis contributions relative to the current state of the art.

To support this objective, the chapter adopts the methodological classification framework illustrated in Fig. 7.1. The reviewed studies are grouped into six methodological families according to their core decision structure: FTO, LTO, Graph-based Candidate Screening (GCS), Plan-Operate-Learn (POL), Bi-Level optimisation (BLO), and Simulation-Based optimisation (SBO). Each family reflects a distinct philosophy for integrating predictive models, optimisation techniques, and system interactions in EVCS planning.

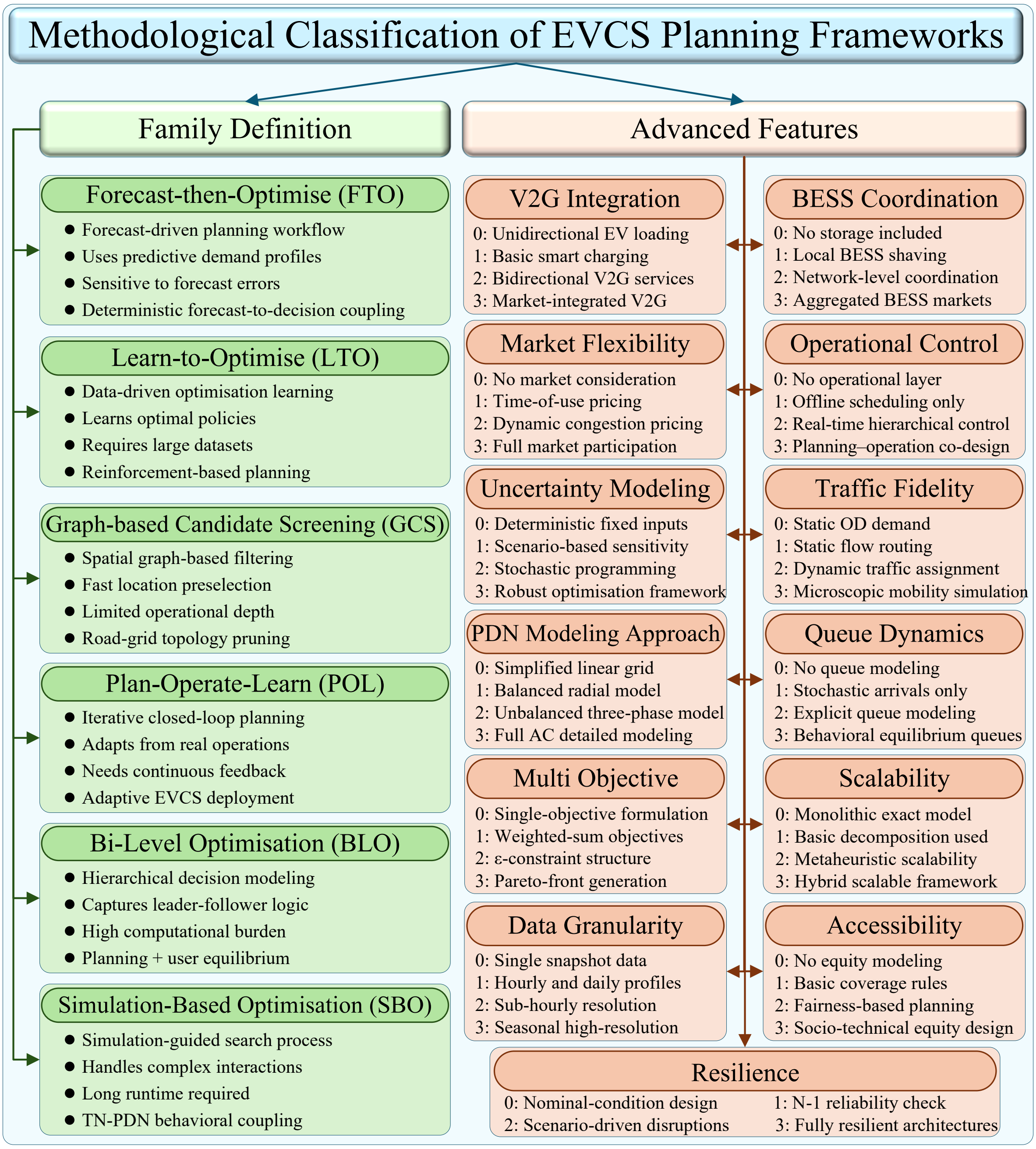


Figure 7.1: Proposed taxonomy for positioning reviewed studies across methodological classes and modelling dimensions in coupled PDN–TN EVCS planning.

Rather than grouping studies solely by application area or optimisation objective, this taxonomy emphasises the planning architecture through which infrastructure decisions are formulated and coordinated across the coupled energy–mobility system. This perspective is particularly important because different methodological families implicitly embed different assumptions about how uncertainty is treated, operational feedback, scalability, and cross-domain coupling.

Collectively, the six methodological classes represent distinct planning paradigms that capture the methodological evolution of EVCS planning research. Early approaches relied primarily on deterministic optimisation under forecasted demand, whereas more recent studies incorporate learning-based policies, large-scale screening strategies, and closed-loop planning architectures that explicitly account for system feedback and uncertainty.

7.1.1 Forecast-then-Optimise (FTO)

The FTO paradigm is among the earliest and most widely adopted planning structures for EVCS deployment. In this framework, uncertain inputs such as charging demand, renewable generation, or electricity prices are first estimated using forecasting models and then treated as fixed parameters in an optimisation problem that determines EVCS siting, sizing, or operational decisions.

This separation between prediction and optimisation improves transparency and computational tractability and aligns closely with conventional infrastructure planning workflows used in industry. Forecasting components are typically implemented using statistical models, including regression-based or diffusion-based demand estimation methods [71, 72], or learning-based approaches designed to predict mobility patterns and charging arrivals [73, 74]. Once these forecasts are generated, mathematical optimisation techniques are used to identify infrastructure configurations that satisfy grid constraints and planning objectives.

Despite its practicality, the FTO paradigm exhibits an inherent structural limitation. Because forecasts are treated as deterministic inputs to the optimisation stage, errors in the forecasting process propagate directly into planning outcomes. Furthermore, the absence of feedback between prediction and decision stages restricts the model's ability to adapt to evolving mobility patterns or changing grid conditions in coupled PDN–TN systems.

Nevertheless, a large body of literature demonstrates the effectiveness of FTO in integrating predictive modelling with optimisation-based EVCS planning. Early studies combined mobility and PV generation forecasts to design V2G-oriented charging infrastructures [73]. Subsequent research incorporated traffic-flow prediction and voltage-aware demand estimation to balance infrastructure cost, accessibility, and distribution grid performance [71, 72]. More recent work extended these models through multi-agent demand estimation [74], congestion-aware spatial allocation [75, 76], and land-use–driven demand evolution [77]. Collectively, these studies establish FTO as a mature data-driven paradigm that systematically translates predictive insights from mobility, grid, and renewable energy domains into EVCS planning decisions.

7.1.2 Learn-to-Optimise (LTO)

The LTO paradigm represents a shift from explicit optimisation pipelines toward data-driven policy learning. In contrast to FTO frameworks, LTO approaches learn a direct mapping from observed system states to planning or operational actions, thereby reducing reliance on repeated solution of complex optimisation models.

This paradigm is particularly attractive in nonlinear, high-dimensional, coupled PDN–TN environments, where RL and deep learning techniques can capture behavioural feedback among traffic congestion, grid conditions, and charging demand. In these models, agents observe system states such as voltage levels, station utilisation, or traffic congestion and learn policies that determine decisions on infrastructure siting, pricing, or operational control.

Once trained, learning-based policies enable rapid online inference and can support multi-objective coordination across mobility and energy systems. However, these approaches remain sensitive to the quality of the training data, simulator fidelity, reward design, and hyperparameter selection. Moreover, learning-based models often lack the interpretability and theoretical guarantees associated with traditional optimisation methods.

Recent literature illustrates the growing application of LTO frameworks in EVCS planning. Early studies simulated competitive market environments in which infrastructure operators learn pricing and investment strategies under grid constraints [78, 79]. Later work employed deep RL techniques such as the Soft Actor-Critic to optimise charging prices and routing responses jointly in multi-level market settings [45]. Additional studies formulated EVCS siting as a Markov decision process, enabling agents to learn investment policies directly from system interactions

[80]. More advanced approaches utilise recurrent neural networks and attention mechanisms to generate station placement and capacity decisions while capturing temporal mobility patterns [81]. Together, these developments demonstrate that LTO is emerging as a learning-driven paradigm capable of coordinating energy–mobility decisions in complex, data-rich environments.

7.1.3 Graph-based Candidate Screening (GCS)

The GCS addresses the dimensionality challenge associated with large-scale EVCS planning. In metropolitan-scale networks, thousands of potential infrastructure locations may exist, making direct optimisation computationally intractable. GCS methods, therefore, introduce a preprocessing stage that reduces the set of candidate locations before detailed optimisation is performed.

In these frameworks, the integrated PDN–TN system is represented as a graph, where nodes correspond to candidate charging locations and edges capture transportation connectivity or the electrical network structure. Network science metrics such as centrality, coverage, and clustering are then applied to identify nodes that are simultaneously attractive from both mobility and electrical perspectives.

By filtering candidate locations before optimisation, GCS approaches significantly improve scalability while preserving spatial and electrical realism. However, the heuristic nature of screening procedures may inadvertently exclude globally optimal solutions if the filtering criteria are overly restrictive.

The GCS literature has progressively evolved toward more sophisticated screening techniques. Early studies introduced K-shortest-path and delay-aware heuristics to account for congestion, grid capacity, and user accessibility [82, 83]. Subsequent research incorporated multi-demand charging contexts, including en-route and destination charging [84]. Later work introduced robustness-oriented screening methods based on voltage sensitivity analysis and distributionally robust formulations [85, 86]. More recent developments integrate AC power-flow-constrained optimisation, graph partitioning techniques, and hybrid metaheuristic frameworks to improve screening accuracy and scalability [87, 88, 89]. These developments position GCS as a scalable preprocessing strategy that bridges network analytics and optimisation in large-scale EVCS deployment.

7.1.4 Plan-Operate-Learn (POL)

The POL paradigm adopts a closed-loop perspective on EVCS infrastructure development. Rather than assuming static planning conditions, POL frameworks explicitly link long-term infrastructure design with operational feedback and learning processes.

In this paradigm, planning decisions such as station siting and capacity sizing are implemented in real or simulated systems. Operational interactions with users, markets, and grid infrastructures generate performance data that can subsequently be used to update demand forecasts, behavioural models, and infrastructure planning assumptions. By incorporating operational feedback into the planning cycle, POL frameworks improve robustness under uncertainty and support adaptive infrastructure evolution.

Early POL studies incorporated GIS-based screening techniques and fuzzy multi-criteria decision analysis to refine infrastructure planning based on operational performance indicators [90, 91]. Subsequent research incorporated pricing signals, traffic equilibria, and power-flow constraints into iterative planning updates [92, 93, 94]. More recent developments have expanded POL frameworks to include data-driven diagnostics, multi-agent coordination, and profitability-based expansion strategies [95, 96, 97, 98]. These studies illustrate how POL enables EVCS planning frameworks to evolve dynamically in response to real-world system performance.

7.1.5 Bi-Level optimisation (BLO)

BLO provides a structured approach for modelling hierarchical interactions between long-term infrastructure planning decisions and short-term operational responses. In BLO formulations, upper-level decision makers determine EVCS siting or investment strategies, while lower-level models represent transportation equilibrium, user charging behaviour, or power system operation.

By embedding equilibrium-based models such as user-equilibrium traffic assignment and optimal power flow, BLO frameworks capture endogenous feedback between infrastructure deployment, user behaviour, and grid performance. This capability makes BLO particularly well-suited for analysing the interactions among accessibility, congestion, and electrical feasibility in EVCS planning.

The primary advantage of BLO lies in its analytical rigour and interpretability, which allow planners to evaluate policy interventions such as pricing schemes, charging tariffs, or regulatory incentives. However, bilevel formulations are often computationally challenging because they result in nonconvex optimisation problems that must be reformulated as MINLPs or mathematical programs with equilibrium constraints (MPECs).

Research on BLO-based EVCS planning has progressively become more complex and realistic. Early studies introduced leader–follower models linking infrastructure investment to traffic equilibrium and grid feasibility [99]. Later work incorporated renewable integration, environmental objectives, and branch-flow power system models [79, 8, 100]. Additional developments interpreted EVCS planning as a Stackelberg game between planners and EV users [101]. Recent research has focused on improving scalability through decomposition methods and temporal coupling strategies while extending the framework to wireless charging infrastructure and multi-level decision environments [102, 103, 104, 105]. These developments position BLO as one of the most influential paradigms for modelling hierarchical EVCS planning problems.

7.1.6 Simulation-Based optimisation (SBO)

SBO integrates high-fidelity simulation environments with optimisation algorithms to address complex EVCS planning problems that are difficult to represent analytically. In SBO frameworks, detailed simulators, such as traffic simulators, power-flow models, or agent-based mobility platforms, are used to evaluate system performance under candidate infrastructure configurations. optimisation algorithms, then iteratively explore the decision space to identify improved solutions.

This paradigm is particularly well-suited to nonlinear, stochastic, and strongly coupled PDN–TN systems for which analytical formulations are intractable. By embedding realistic simulators within the optimisation process, SBO frameworks enable planners to evaluate infrastructure performance under diverse operating conditions, including congestion dynamics, stochastic demand patterns, and grid disturbances.

The primary advantage of SBO lies in its modelling flexibility and ability to capture complex system behaviour. However, this realism comes at the cost of significant computational effort, as each candidate solution requires a full simulation run. Therefore, convergence speed and solution quality depend heavily on the chosen metaheuristic or surrogate-based optimisation algorithm.

The SBO literature has evolved toward increasingly sophisticated simulation environments. Early work integrated metaheuristic search algorithms with simulator-in-the-loop architectures to jointly optimise service quality and grid performance [106]. Subsequent studies incorporated stochastic demand modelling, swarm-based algorithms, and power-flow-validated search strategies [107, 108, 109]. More recent research has extended SBO frameworks to city-scale planning environments, incorporating queuing dynamics, reliability analysis, V2G coordination, and hybrid simulation–learning architectures [110, 111, 51, 112]. These developments position SBO as a powerful paradigm for bridging analytical planning models and high-fidelity digital-twin environments for EVCS infrastructure planning.

7.2 Advanced Planning Features in Coupled Infrastructure Models

Beyond the methodological families introduced in the previous section, EVCS planning frameworks in coupled PDN–TN environments can also be differentiated by the depth, consistency, and structural role of the advanced planning features embedded within their formulations. Within the context of this thesis, these features are not treated as peripheral extensions but as core modelling components that directly shape planning realism, infrastructure feasibility, scalability, and deployment relevance. This section, therefore, evaluates the reviewed literature from a feature-oriented perspective, focusing on the extent to which key planning capabilities are explicitly represented and structurally integrated within coupled energy–mobility models.

In addition to the methodological taxonomy introduced in Section 7.1, the literature is assessed here through a complementary analytical lens that emphasises the maturity of advanced planning features. The objective is not merely to determine whether particular features are present, but to examine how transparently, consistently, and materially they are embedded in the planning architecture. This distinction is important because the technical value of an EVCS planning framework depends not only on the inclusion of advanced capabilities, but also on whether these capabilities meaningfully influence the representation of charging demand, grid feasibility, operational flexibility, and cross-domain interactions in coupled PDN–TN systems.

Accordingly, the analysis examines a set of advanced functional dimensions that capture the dominant dynamics of integrated EVCS planning, including bidirectional V2G interaction, BESS coordination, market-based flexibility, uncertainty representation, operational control, traffic fidelity, PDN modelling depth, queue dynamics, multi-objective optimisation, solution scalability, data granularity, accessibility, and resilience. By shifting the emphasis from solution techniques alone to the explicit representation of coupled-system behaviour, this perspective enables a more rigorous assessment of technical maturity, planning coherence, and practical readiness across the reviewed literature. The following subsections discuss each of these features in turn and evaluate their role in shaping next-generation EVCS planning frameworks.

7.2.1 V2G Integration

V2G technology transforms EVs from passive loads into distributed energy resources that can provide ancillary services such as voltage support, peak shaving, and frequency regulation, thereby enhancing grid flexibility and facilitating the integration of renewable energy. Practical deployment, however, remains constrained by battery degradation, communication and interoperability requirements, cybersecurity concerns, and incentive design, leading most implementations to rely on hierarchical control, aggregator-based coordination, and market-oriented participation mechanisms.

From a planning perspective, V2G integration within EVCS frameworks follows a clear progression in the depth of interaction. At the most basic level, EVs are modelled as unidirectional G2V loads, which simplifies grid-constrained siting but ignores their potential for flexibility [11]. Subsequent stochastic and multi-objective formulations expose latent flexibility by incorporating voltage limits, uncertainty, and cost–service trade-offs [113, 114]. More advanced models make charging responsive to tariffs and renewable availability, enabling peak mitigation without full bidirectional exchange [115, 116, 117]. Explicit V2G control then enables coordinated voltage regulation, congestion relief, and load balancing through aggregated fleets [118, 119]. At the highest level of integration, V2G is embedded in market-clearing and coordination mechanisms, enabling EV fleets to participate in dynamic pricing, routing, and ancillary service provision through Pareto-based optimisation and learning-enabled formulations [48, 120]. Overall, the literature reflects a clear transition from static charging assumptions toward adaptive, market-coupled, and V2G-enabled EVCS planning.

7.2.2 Battery Energy Storage System Coordination

Coordinating BESS with EVCS planning improves reliability, flexibility, and cost efficiency in coupled PDN–TN systems. By buffering renewable variability and stochastic charging demand, BESS supports feeder voltages, smooths intermittency, reduces peak-induced stress on transformers and lines, and can defer network reinforcement while aligning charging demand with renewable availability. Storage can also provide fast operational support, including voltage regulation and contingency backup, although its deployment is constrained by capital costs, degradation, uncertain revenue streams, and the difficulty of coordinating dispatch under mobility-driven demand. As a result, recent frameworks increasingly adopt multi-objective planning and PDN–TN co-simulation to balance investment, grid performance, and service quality, and, in more advanced settings, connect storage-enabled stations to demand-response and ancillary-service value streams.

BESS integration in EVCS planning can be categorised into four maturity levels. First, charging stations are modelled as grid-only loads without storage, which can amplify peak demand and voltage stress [75, 121]. Second, limited local mitigation is introduced without explicit energy buffering, for example, through reactive power compensation [122]. Third, station-level BESS is explicitly modelled, often in combination with renewable generation, to provide buffering, peak shaving, congestion relief, and uncertainty management [123, 124, 125]. Finally, coordination extends to feeder-level or system-level co-planning of EVCS and BESS, sometimes within aggregator- or market-based structures, enabling hosting-capacity enhancement, loss reduction, upgrade deferral, and participation in demand response and ancillary services [126, 127, 128, 129].

7.2.3 Market Flexibility

Market and pricing flexibility shape EVCS planning by linking charging demand, energy costs, and operational adaptation in coupled power–transport systems. Mechanisms such as time-of-use tariffs, locational pricing, and ancillary-service participation allow operators to respond to spatial–temporal grid conditions and user behaviour, thereby enabling load shifting, congestion mitigation, and improved asset utilisation. Incorporating such signals moves EVCS planning beyond static engineering design toward cyber-economic co-optimisation that jointly accounts for technical feasibility, user response, and financial viability. Practical effectiveness, however, depends on credible price signals, real-time communication, and careful treatment of user heterogeneity, since excessive price volatility can reduce accessibility and public acceptance.

From a planning standpoint, market flexibility evolves as the interaction between economic signals and system operation becomes progressively tighter. At the most basic level, EVCS deployment follows spatial, traffic, or engineering criteria with no explicit price adaptation, treating stations as passive assets subject to reliability or accessibility constraints [130, 131, 132]. A second line response introduces fixed or time-of-use tariffs, enabling limited temporal shifting and simplified revenue–cost balancing while remaining only weakly coupled to real-time grid states [133, 134]. More advanced formulations incorporate dynamic or locational pricing to couple charging costs with congestion and marginal energy costs, thereby inducing coordinated spatial–temporal charging responses [72]. At the most advanced stage, EVCSs become market-active assets that monetise flexibility through arbitrage and ancillary services under uncertainty-aware market mechanisms, including data-driven valuation, robust optimisation, and chance-constrained formulations [135, 136, 137, 138].

7.2.4 Operational Control

The operational control layer links long-term EVCS planning with real-time coupled PDN–TN dynamics. Because charging demand, grid conditions, and traffic states evolve jointly, embedding control within planning is essential to maintain voltage security, operational reliability, and service quality under uncertainty. Recent frameworks, therefore, adopt hierarchical designs in which siting and sizing decisions interact with distributed controllers that regulate charging rates, voltages, and load balancing in response to grid, traffic, and price signals. Model predictive control (MPC), Volt/VAR regulation, and multi-agent coordination enable anticipatory operation. They can reduce losses while unlocking flexibility and ancillary services through smart charging and V2G, albeit at the cost of greater communication, monitoring, and computational requirements.

From a planning perspective, operational control integration typically progresses through four stages. First, planning-only models determine EVCS locations and capacities under static assumptions, without explicit operational feedback [95]. Second, offline scheduling is added after siting using historical or forecast profiles for peak shaving and utilisation balancing, while control remains open-loop [139, 84, 89, 108, 109]. Third, planning is coupled with online hierarchical or distributed control to adapt charging decisions based on traffic-load feedback and space-time coordination [140, 141]. Finally, closed-loop co-design integrates predictive and distributed control while accounting for queueing, traffic equilibrium, and uncertainty to support robust joint planning and grid services [142, 143].

7.2.5 Uncertainty Modelling

Explicit uncertainty modelling is central to EVCS planning because EV adoption, charging demand, renewable output, and PDN–TN interactions are inherently stochastic. Purely deterministic formulations are therefore fragile under coupled variability in traffic, prices, and renewable generation. Uncertainty-aware frameworks use probabilistic descriptions, scenario analysis, and risk-aware formulations to limit voltage violations, congestion, and service degradation. Although robustness increases computational burden and data dependence, tractability is often maintained through scenario reduction, decomposition, or surrogate approximations. Overall, stochastic, Monte Carlo, and distributionally robust methods shift planning away from forecast-driven design toward performance-preserving decisions under realistic variability.

Methodologically, uncertainty integration progresses through four stages. Deterministic formulations fix traffic, demand, and price inputs, remaining computationally efficient but highly sensitive to forecast errors [96]. Sampled uncertainty, for example, through Monte Carlo simulation or structured scenarios, then supports risk-exposure analysis while keeping uncertainty generation largely external to the optimiser [144, 81]. Stochastic programming internalises uncertainty by embedding scenario probabilities to balance expected performance and risk across realisations, including behavioural heterogeneity [145]. Finally, robust and distributionally robust formulations provide worst-case or ambiguity-aware protection, sustaining feasibility under extreme conditions while incorporating high-fidelity power-flow constraints, scenario reduction, and data-driven variability [146, 147, 148, 149].

7.2.6 Traffic Fidelity

TN modelling fidelity governs the accuracy with which EVCS planning captures driver behaviour, congestion, and spatio-temporal mobility dynamics. Charging demand is inherently endogenous: station placement reshapes route choice and accessibility, while congestion and queueing vary with the timing and location of EV charging. Higher-fidelity TN models, therefore, improve demand and congestion estimation and help verify that siting outcomes remain consistent with realistic mobility behaviour. The trade-off is increased data requirements and higher computational overhead, especially when dynamic traffic assignment, microscopic simulation, or agent-based mobility models are employed.

Traffic modelling maturity in EVCS planning can be interpreted through four layers. Layer 1 uses static origin–destination demand, capturing aggregate patterns but neglecting congestion feedback and adaptive routing [150]. Layer 2 adopts equilibrium-based routing to redistribute flows in response to EVCS placement and network conditions [86, 79]. Layer 3 applies dynamic traffic assignment to resolve time-varying congestion and short-horizon variability, linking accessibility and charging demand through queueing arrivals, gravity/OD structures, and K-shortest-path routing [111, 151, 83]. Layer 4 employs microscopic or agent-based simulation with high-resolution mobility data to represent individual decisions, queue formation, and adaptive rerouting, thereby enabling fully dynamic PDN–TN coupling [73, 152].

7.2.7 PDN Modelling Approach

PDN modelling fidelity determines the electrical realism of integrated EVCS planning, namely how accurately voltages, thermal limits, and phase imbalance are represented in coupled power–transport analyses. This modelling choice directly influences hosting-capacity estimation and operational feasibility because charging demand interacts nonlinearly with feeder voltages, transformer loading, and reactive power behaviour. High-fidelity tools such as OpenDSS, GridLAB-D, and PowerFactory enable three-phase AC analysis and grid–traffic co-simulation, improving engineering validity at the expense of greater data requirements and computational complexity. Linearised models scale well for screening and exploratory planning but may understate voltage/VAR constraints and phase imbalance, thereby producing optimistic or infeasible infrastructure designs. The central objective is therefore to select the minimum model fidelity that preserves technical feasibility.

The literature reveals a four-layer progression in PDN realism. Layer 1 uses linear or DC-style approximations under balanced assumptions, often complemented by ex-post feasibility checks [142]. Layer 2 adopts balanced time-series DistFlow formulations to capture temporal variability in loads, renewables, and charging demand with moderate complexity [73]. Layer 3 employs unbalanced three-phase AC models to resolve phase-specific voltages and reactive flows under heterogeneous charging behaviour [141, 117]. Layer 4 couples full three-phase AC power flow with thermal, protection, and hosting-capacity constraints for mobility-aware co-optimisation and deployment-oriented validation, including V2G-enabled operation [91, 74, 94, 153].

7.2.8 Queue Dynamics

Queue-aware charging models are central to advanced EVCS planning because they capture user choice, traffic evolution, and grid operations in ways that static "fixed-demand" assumptions cannot. Arrivals are stochastic and state-dependent: mobility schedules, SoC, and perceived service availability all influence when and where charging occurs. Explicit queueing enables evaluation of waiting time, utilisation, and accessibility, while also revealing the feedback loop through which congestion and expected delay influence station choice and demand redistribution. When embedded in traffic–power co-simulation or agent-based platforms such as SUMO or MATSim, queue dynamics provide time-resolved evidence for charger sizing, operational efficiency, and resilience, albeit with substantially higher data and computational requirements.

Queue-aware EVCS planning has progressed through four layers of behavioural realism. The first assumes exogenous or instantaneous demand, so congestion and delay effects are not explicitly observed [88, 150]. The second introduces probabilistic arrivals and SOC heterogeneity to reflect temporal variability while still approximating service as effectively instantaneous [8, 126, 131]. The third model is cast as a finite stochastic service system, enabling direct assessment of waiting time, utilisation, and reliability, and supporting formulations that couple congestion with routing decisions [132, 120]. The most integrated layer endogenises queues within routing and station-choice mechanisms, closing the loop between congestion, user behaviour, and grid feasibility through dynamic assignment or agent-based simulation [154, 78].

7.2.9 Multi-Objective Optimisation

Multi-objective optimisation is fundamental to integrated EVCS planning because it makes trade-offs among cost, grid security, and sustainability explicit in coupled power–transport systems. Rather than collapsing performance into a single metric, it jointly captures investment and operating costs, voltage and thermal impacts, renewable utilisation, and user accessibility and delay, thereby enabling stakeholder-defensible compromise solutions. For this reason, evolutionary and swarm-based methods such as NSGA-II, MOEA/D, and PSO variants are widely used to approximate Pareto sets and reveal cost–service–reliability frontiers.

This paradigm has matured through increasingly structured formulations. Early studies optimise a single objective such as cost, losses, or VD, prioritising tractability while ignoring competing criteria [8, 88]. Scalarization methods, including weighted-sum and goal-programming approaches, then enable multi-criteria treatment but introduce sensitivity to subjective weighting choices [88]. More structured formulations use ε-constraint and lexicographic methods to enforce minimum thresholds for service, accessibility, or reliability while optimising a primary objective [83, 119]. The most mature frameworks explicitly construct non-dominated solution fronts through Pareto-based evolutionary or learning-enhanced methods, supporting systematic visualisation and interpretation of compromise solutions across economic, technical, and sustainability dimensions [155, 92].

7.2.10 Solution and Scalability

Solution methods and scalability are central challenges in integrated EVCS planning because PDN–TN coupling produces high-dimensional, nonlinear problems whose complexity grows rapidly with network size and temporal resolution. Under high EV penetration, the simultaneous treatment of power-flow constraints and stochastic traffic dynamics renders monolithic city-scale optimisation impractical. Recent frameworks, therefore, emphasise scalable architectures capable of delivering feasible solutions within acceptable runtimes, even at the expense of limited losses in theoretical optimality and interpretability.

This evolution can be summarised through four solution layers. First, direct MILP/MINLP models, when solved by commercial solvers, provide transparency and precision but scale poorly as network size and temporal detail increase [130]. Second, decomposition and coordination strategies partition the coupled PDN–TN problem into tractable submodules that exchange boundary variables or dual information, improving parallelism at the cost of additional tuning sensitivity [76]. Third, metaheuristics such as GA and PSO provide rapid, approximate solutions in large, nonlinear search spaces where exact solvers become impractical [112]. Fourth, hybrid and hierarchical pipelines combine constrained programming with heuristics, relaxations, and learning-based accelerators, often together with candidate pruning, to preserve feasibility while maintaining urban-scale practicality [156, 157].

7.2.11 Data Granularity

Temporal resolution and data granularity directly govern the fidelity of integrated EVCS planning by determining how well time-varying mobility, charging demand, and PDN dynamics are represented in coupled power–transport models. Finer temporal resolution captures diurnal traffic variation, renewable intermittency, and rapid load ramps, thereby improving siting, sizing, and scheduling decisions, but it also increases data volume and computational burden. Excessive aggregation, by contrast, can mask short-duration congestion and voltage violations that ultimately drive reliability limits. To balance fidelity and tractability, many studies compress time using representative-period clustering, hybrid sampling, and data-driven dimensionality reduction, seeking to preserve essential dynamics without inflating problem size. As mobility traces and telemetry continue to expand, planning frameworks are increasingly shifting toward adaptive, time-resolved decision models that better reflect operational variability.

Methodologically, data granularity has progressed through increasing temporal resolution. Early studies rely on snapshot or coarsely segmented models that capture average behaviour while masking short-term dynamics [114, 145]. Representative-period and clustering approaches then retain diurnal variability with reduced dimensionality [121]. More advanced studies adopt sub-hourly time slicing, typically 15–30 minutes, to resolve demand surges, congestion propagation, and operational constraints, often together with queue-aware modelling [158, 41]. The highest-fidelity frameworks extend to multi-day or seasonal horizons and synchronise feedback from mobility, renewables, and markets through high-resolution equilibrium or tri-level formulations that support predictive validation and near-real-time coordination [87, 159, 105, 9, 115].

7.2.12 Accessibility

Accessibility and equity are increasingly recognised as core dimensions of EVCS planning, reflecting a shift beyond purely techno-economic optimisation toward spatially balanced and socially acceptable deployment. In coupled power–transport settings, accessibility captures users' ability to reach charging services, including travel time, coverage, and demand satisfaction. At the same time, equity concerns the fair provision of services across locations and user groups. Embedding these criteria mitigates over-concentration in high-profit areas, reduces the number of underserved regions, and can improve public acceptance, even when it relaxes strict cost optimality.

A four-level maturation of accessibility and equity modelling is evident in the literature. At the first level, planning is primarily driven by cost, grid performance, and demand intensity, often resulting in uneven spatial coverage [77]. The second level introduces minimum-access constraints, such as coverage-distance limits or service thresholds, to guarantee baseline availability [160]. The third level treats fairness as an explicit objective through equity indices, such as spatial balance or service-equality metrics, typically supported by population-weighted GIS data and multi-objective formulations [161, 104, 162, 85]. At the most integrated level, equity and accessibility are co-modelled with socioeconomic attributes, land-use heterogeneity, and behavioural patterns within coupled PDN–TN frameworks, enabling socio-technical siting strategies that balance profitability, service quality, and user experience, including waiting-time equity and user satisfaction [163, 139, 164].

7.2.13 Resilience

Resilience and reliability have become central EVCS planning objectives because coupled power–transport systems must maintain charging service under failures, disturbances, and extreme events. Electrically, resilience concerns voltage stability, load balance, and continuity under contingencies; from the mobility side, it depends on route redundancy and adaptive accessibility during congestion or disruption. Treating these domains jointly reduces cascading effects in which localised grid or traffic shocks propagate into broader service disruption. As a result, resilience-oriented planning increasingly combines redundancy-aware siting, adaptive operation, and cross-domain dependency modelling. PV–battery hybrids and V2G-capable stations can further enhance local autonomy and recovery capability, albeit at a higher investment cost.

Resilience-oriented EVCS planning evolves through four integration layers with increasing disturbance awareness. First, solutions optimise cost and efficiency under nominal conditions, yielding designs that are vulnerable to disruption [45, 80]. Second, electrical robustness is enforced through contingency-aware constraints, such as N-1 tolerance, to protect against single-component failures [75, 98]. Third, transportation-side disruptions and broader uncertainty are incorporated through stochastic or scenario-based evaluation to assess service continuity under mobility stress [41, 110]. Fourth, system-wide resilience is pursued by embedding DERs, microgrids, and V2G-enabled fleets while explicitly modelling interdependent power–transport failures to sustain charging availability and accelerate recovery [103, 116, 84, 132].

Table 7.1: Comparative taxonomy of reviewed EVCS planning studies by methodological family and advanced-feature maturity level.

Ref	Year	Family	AF_1	AF_2	AF_3	AF_4	AF_5	AF_6	AF_7	AF_8	AF_9	AF_{10}	AF_{11}	AF_{12}	AF_{13}
[159]	2018	BLO-FTO	1	1	1	2	2	1	2	2	2	3	2	0	1
[9]	2018	BLO-SBO	1	1	2	3	3	2	2	3	2	3	3	1	1
[155]	2019	SBO-BLO	1	0	2	3	3	2	2	3	3	3	3	1	1
[154]	2019	BLO-SBO	2	1	2	3	3	2	2	3	3	3	3	1	1
[157]	2019	BLO-SBO	0	0	2	3	2	2	1	3	2	3	2	0	1
[151]	2019	BLO-SBO	1	0	2	3	3	2	2	3	3	3	3	1	1
[156]	2019	BLO-SBO	0	0	2	2	2	1	2	2	2	3	2	0	0
[149]	2019	BLO-SBO	1	2	2	3	3	3	2	3	2	3	3	1	1
[83]	2019	BLO-GCS	1	1	2	3	3	2	2	3	2	3	2	0	1
[142]	2020	SBO-BLO	0	0	1	3	3	3	0	3	3	3	3	1	1
[143]	2020	BLO-SBO	0	0	2	3	3	3	2	3	3	3	3	1	1
[91]	2020	BLO-POL	1	1	3	3	3	3	2	3	3	3	3	2	1
[78]	2020	BLO-LTO	1	1	2	3	3	2	2	3	3	3	3	1	1
[137]	2020	BLO-SBO	2	2	3	3	3	3	3	3	3	3	3	1	1
[138]	2020	BLO-SBO	2	2	3	3	3	3	3	3	3	3	3	2	1
[136]	2020	SBO-BLO	2	0	2	3	3	3	2	3	3	3	3	2	1
[146]	2020	BLO-SBO	1	3	0	2	2	2	3	3	2	3	2	1	2
[84]	2020	BLO-GCS	0	0	0	1	2	2	3	1	2	3	2	2	3
[86]	2020	GCS	0	0	0	1	3	1	2	1	1	2	2	0	1
[145]	2020	SBO-GCS	0	0	0	0	1	1	1	2	1	2	0	0	0
[123]	2021	BLO-SBO	2	1	3	3	3	3	2	3	3	3	3	2	1
[119]	2021	BLO-FTO	2	0	0	1	3	1	1	1	2	2	1	1	0
[8]	2021	BLO	0	1	0	1	3	2	2	1	1	2	2	1	1
[139]	2021	FTO-GCS	0	0	0	1	1	2	2	3	3	3	2	3	1
[134]	2021	FTO-SBO	0	0	1	2	2	3	3	2	2	3	2	2	1
[99]	2021	BLO	1	0	0	2	1	2	2	3	2	2	1	1	1
[129]	2021	GCS-SBO	0	3	0	3	3	2	3	2	3	3	3	2	2
[79]	2021	BLO	1	0	0	2	2	2	2	3	3	2	1	2	1
[85]	2021	GCS	0	0	0	1	1	2	2	3	3	2	1	2	2
[71]	2022	FTO	0	3	1	1	1	2	2	3	3	2	3	0	0
[163]	2022	GCS	0	0	0	1	1	1	2	0	2	2	1	2	0
[164]	2022	BLO	0	1	2	2	2	2	2	1	1	2	2	1	1
[124]	2022	GCS-SBO	0	1	1	1	2	2	2	2	2	2	2	2	1
[101]	2022	BLO	1	2	2	2	1	2	1	2	0	2	2	0	0
[107]	2022	SBO	0	2	0	0	1	2	2	0	2	2	2	0	0
[72]	2022	FTO-POL	0	2	1	2	2	1	3	2	2	3	3	0	1
[165]	2023	SBO-FTO	0	1	1	2	1	2	1	1	1	2	2	0	0
[102]	2023	BLO	0	0	1	1	1	2	2	1	1	3	1	0	0
[80]	2023	LTO	0	0	0	1	1	1	2	2	1	3	1	0	0
[41]	2023	SBO	0	0	1	1	2	2	2	2	2	2	1	0	1
[98]	2023	POL-BLO	0	0	3	2	2	1	2	2	2	2	1	0	1
[126]	2023	FTO-SBO	1	2	1	1	3	2	2	1	2	2	2	0	1
[87]	2023	GCS	0	0	1	1	1	2	2	2	2	2	1	0	0
[111]	2023	SBO	1	3	1	1	3	1	2	2	3	2	3	0	1
[74]	2023	FTO	0	0	0	2	3	3	2	2	1	2	3	0	1

Continued on next page

Table 7.1: Comparative taxonomy of reviewed EVCS planning studies (continued).

Ref	Year	Family	AF_1	AF_2	AF_3	AF_4	AF_5	AF_6	AF_7	AF_8	AF_9	AF_{10}	AF_{11}	AF_{12}	AF_{13}
[140]	2023	FTO-SBO	0	0	0	2	2	3	3	3	3	3	3	0	1
[104]	2023	BLO	2	2	3	3	2	3	3	2	3	3	2	1	2
[110]	2023	SBO	0	1	1	2	2	3	3	2	3	3	3	0	1
[162]	2023	FTO	1	3	2	2	2	2	2	2	3	2	2	1	1
[158]	2024	SBO	0	0	1	1	1	1	2	2	2	2	1	0	0
[51]	2024	SBO	3	0	0	1	1	0	3	1	2	3	1	0	0
[131]	2024	FTO-SBO	1	0	0	1	3	2	2	1	3	2	2	0	1
[48]	2024	BLO-POL	3	2	1	3	2	3	3	2	3	3	2	0	2
[132]	2024	BLO-SBO	0	0	0	1	3	3	3	2	3	2	2	0	3
[77]	2024	FTO-BLO	0	1	1	2	2	3	3	3	3	3	3	0	2
[122]	2024	BLO-FTO	0	0	0	1	2	2	3	1	3	2	2	0	1
[76]	2024	FTO-BLO	0	0	0	1	2	3	2	1	2	2	3	0	1
[152]	2024	FTO	0	0	1	2	3	3	3	2	3	3	3	0	1
[125]	2024	GCS-SBO	1	1	1	3	3	3	3	3	3	3	2	0	2
[117]	2024	GCS-FTO	1	0	1	3	3	3	1	2	3	3	3	0	1
[105]	2025	BLO	0	0	1	2	2	3	3	1	3	3	2	0	1
[103]	2025	BLO	3	1	2	2	2	3	3	1	3	2	2	0	2
[116]	2025	FTO-SBO	1	1	1	2	3	2	3	3	3	2	2	0	2
[113]	2025	GCS-SBO	0	2	1	2	2	2	2	2	3	2	2	0	1
[127]	2025	BLO-FTO	0	2	3	2	2	3	3	2	3	2	2	0	1
[147]	2025	SBO	1	2	1	2	2	2	2	2	3	2	2	1	1

7.3 Comparative Methodological Trends in EVCS Planning

Building on the advanced-feature analysis presented in the previous section, this section provides a comparative synthesis of the distribution of methodological paradigms, feature maturity levels, and modelling abstractions across the reviewed EVCS planning literature. The objective is not to introduce additional feature categories, but to examine how the previously identified methodological families and advanced planning features manifest in practice across studies published in the coupled PDN–TN planning domain. In this way, the section serves as an evidence-based bridge between the feature-level review and the subsequent synthesis of insights from the literature and unresolved research gaps.

To support this analysis, Table 7.1 consolidates the reviewed studies by mapping each work to its methodological family and corresponding advanced-feature (AF) maturity levels. This table provides the analytical basis for the comparative observations reported in this section and enables a structured interpretation of how the field has evolved in terms of methodological composition, modelling depth, and planning realism.

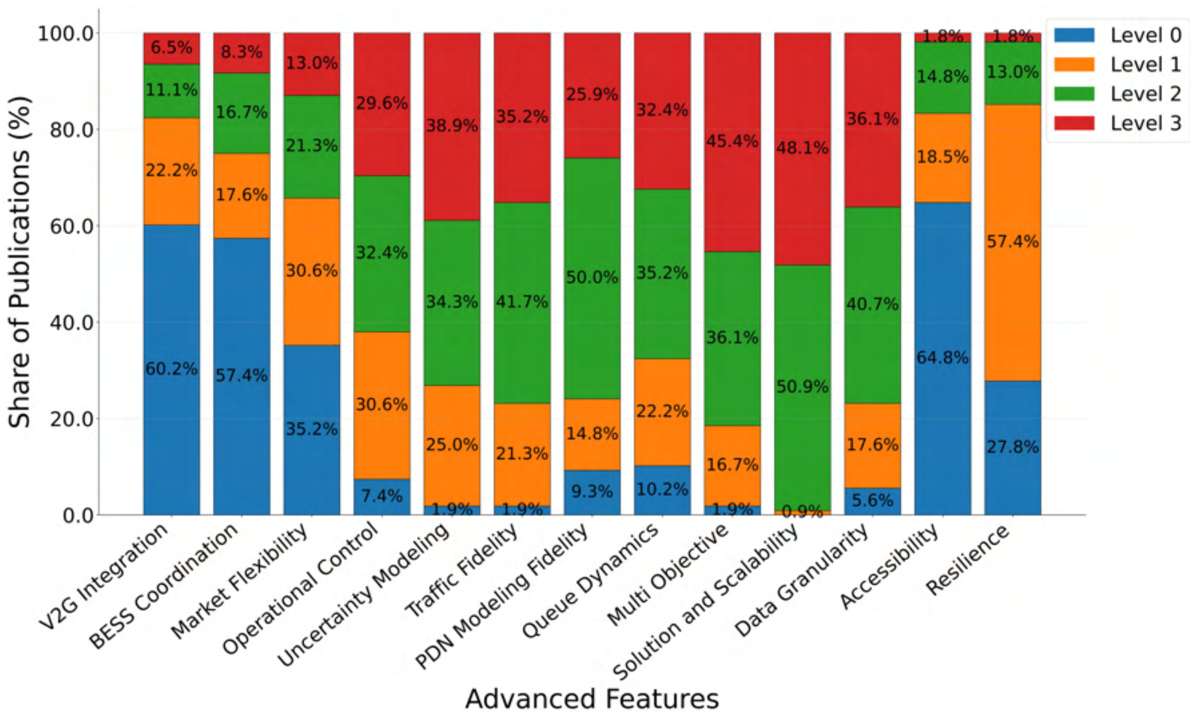


Figure 7.2: Distribution of advanced-feature maturity levels across reviewed EVCS planning studies.

Across the reviewed corpus ($N = 108$ studies published between 2018 and 2025), AF maturity exhibits a clearly uneven distribution, as shown in Fig. 7.2. Features associated with tractability, robustness, and baseline coupled-system representation dominate the literature. Solution scalability appears in all reviewed studies, while uncertainty modelling and traffic fidelity are nearly ubiquitous, indicating that the field has strongly prioritised computational manageability and traffic-aware demand representation. Operational control is also widely represented, suggesting that EVCS planning has progressively moved beyond purely static allocation toward models that acknowledge the operational consequences of infrastructure deployment.

By contrast, the comparative distribution of AF levels also reveals that flexibility-enabled and user-centric planning dimensions remain less mature. V2G integration and accessibility exhibit substantially lower adoption levels than scalability-, uncertainty-, and traffic-related features, indicating that most studies continue to prioritise feasibility and technical performance over bidirectional flexibility, equitable access, and service-oriented deployment quality. Market flexibility occupies an intermediate position, suggesting that economic coordination is increasingly recognised but has not yet become a consistently embedded structural component of EVCS planning architectures.

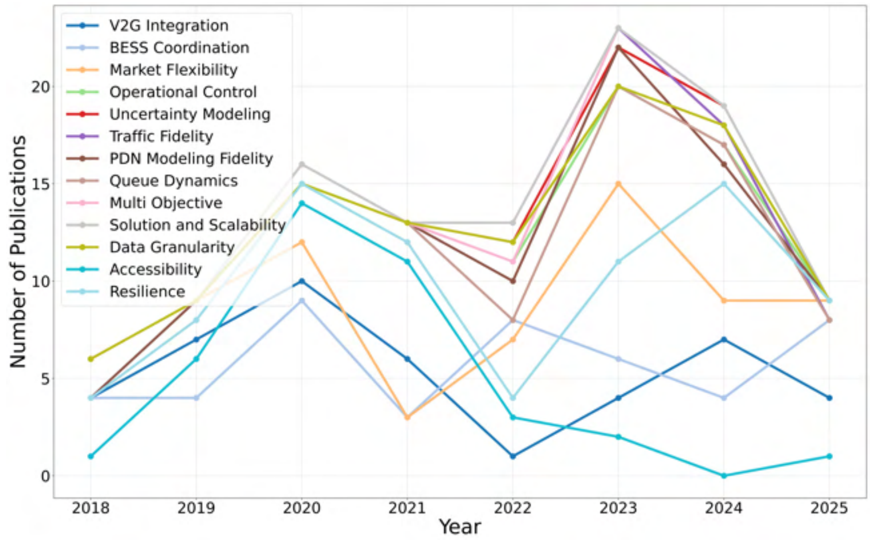


Figure 7.3: Temporal evolution of advanced-feature adoption in EVCS planning literature from 2018 to 2025.

The temporal evolution shown in Fig. 7.3 reinforces these observations. Publication activity peaks around 2023, coinciding with the strongest concentration of studies incorporating traffic fidelity, uncertainty representation, PDN modelling, and scalability-oriented design. This pattern indicates that the literature has matured most rapidly in features necessary to make coupled PDN–TN planning computationally viable and structurally defensible. In contrast, the adoption of V2G-related and market-oriented features grows more gradually over time, suggesting that these capabilities are entering the literature as second-stage enhancements rather than as foundational elements of mainstream EVCS planning models.

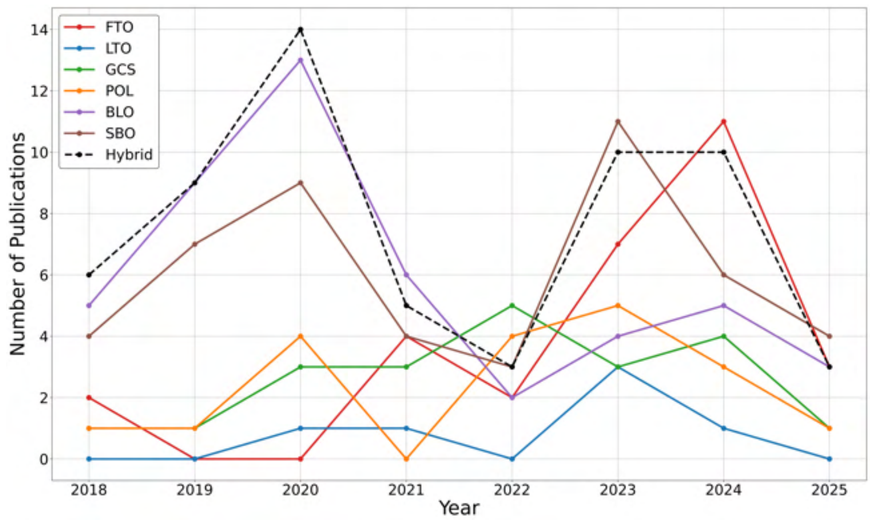


Figure 7.4: Temporal evolution of methodological families in EVCS planning studies.

A similar transition is visible in the methodological-family distribution reported in Fig. 7.4. The literature shows a clear movement away from single-paradigm planning formulations toward composite and hybrid architectures. Hybrid configurations dominate in most years, while Bi-Level Optimisation (BLO) and Simulation-Based Optimisation (SBO) remain persistently important across the review period. Purely isolated long-horizon or single-layer planning paradigms appear much less frequently. This shift suggests that EVCS planning is increasingly being treated as a layered infrastructure problem in which planning decisions, operational behaviour, and transportation-grid interactions must be coordinated rather than optimised in isolation.

This methodological diversification is important because it reflects a broader structural transition in the field. As EVCS planning problems became more coupled, dynamic, and multi-objective, single-method formulations became less capable of preserving realism across both infrastructure layers. The rise of hybrid approaches, therefore, signals not only methodological experimentation but also a recognition that no single modelling paradigm is sufficient to simultaneously address siting, sizing, uncertainty, traffic interactions, and grid feasibility requirements.

The adopted modelling abstractions provide further evidence of the trade-off between realism and tractability. As shown in Fig. 7.5, the majority of the reviewed studies rely on computationally convenient PDN representations, including simplified radial feeders, reduced-network models, or surrogate-style abstractions. By comparison, fully detailed AC-based or higher-fidelity feeder formulations remain relatively limited. This indicates that although grid-awareness is now common in EVCS planning, electrical realism is often simplified to preserve solvability, especially in large-scale or multi-period planning settings.

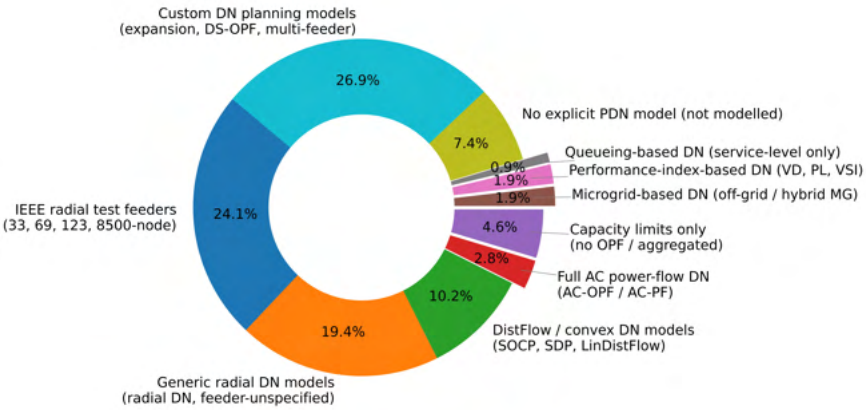


Figure 7.5: PDN modelling approaches adopted in reviewed EVCS planning studies.

From the transportation perspective, Fig. 7.6 shows that equilibrium-based abstractions and simplified mobility representations remain dominant, whereas studies using real-world mobility datasets remain comparatively limited. This imbalance is methodologically significant. It suggests that although the literature increasingly acknowledges the importance of transportation network effects, many EVCS planning studies still rely on stylised or aggregated traffic representations rather than high-resolution behavioural or empirical mobility data.

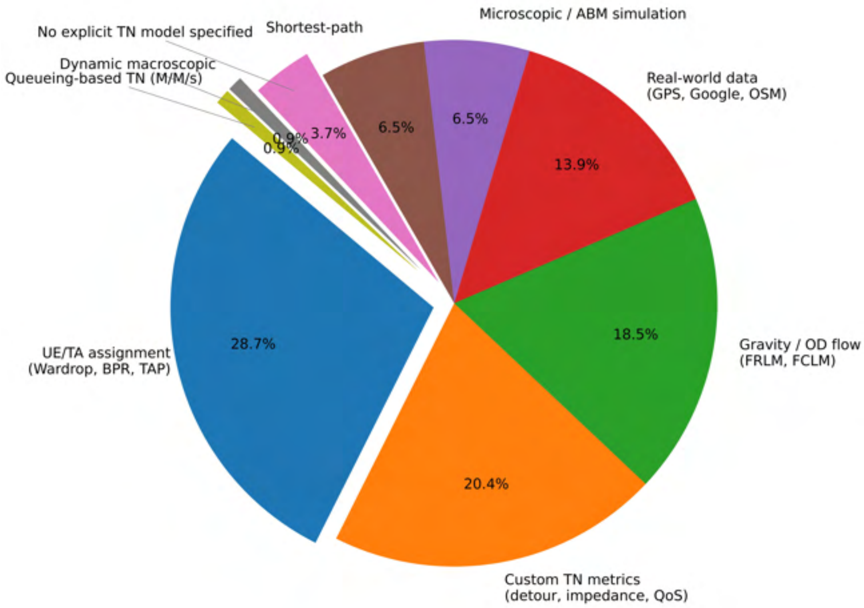


Figure 7.6: TN modelling sources and abstractions adopted in reviewed EVCS planning studies.

The temporal structure of planning models shows a comparable limitation. As illustrated in Fig. 7.7, a large proportion of studies remain based on static, snapshot, or short-horizon formulations, while only a relatively small subset adopts multi-stage or long-term planning horizons. This is a notable structural weakness because EVCS infrastructure is inherently a long-lived asset whose value depends on the evolution of demand, network loading, technology adoption, and participation in flexibility over time. The continued dominance of short-horizon modelling, therefore, indicates a mismatch between infrastructure lifetimes and analytical time representations in a significant portion of the current literature.

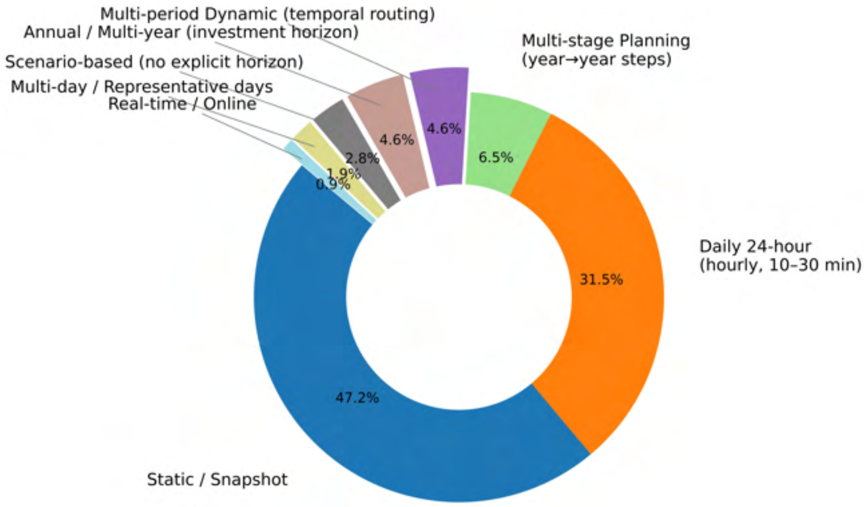


Figure 7.7: Planning horizons and temporal resolutions adopted in reviewed EVCS planning studies.

Taken together, the comparative evidence presented in this section shows that the EVCS planning literature has achieved substantial maturity in three areas: scalable solution design, uncertainty-aware formulation, and traffic-informed demand representation. At the same time, it remains constrained by simplified PDN models, limited empirical transportation inputs, shallow temporal depth, and comparatively weaker integration of V2G, accessibility, and market-enabled flexibility. In other words, the field has advanced considerably in making coupled EVCS planning solvable, but less consistently in making it fully representative of deployment.

These observations naturally motivate a deeper examination of how advanced planning features affect infrastructure deployment outcomes in practice. The next section, therefore, introduces a deployment-oriented scenario synthesis that uses a common analytical framework to interpret how uncertainty modelling, flexibility integration, coordinated control, and market participation influence feasible EVCS deployment and system-level behaviour in coupled PDN–TN environments.

7.4 Deployment-Oriented Scenario Synthesis of Advanced Planning Features

This section complements the methodological taxonomy and comparative trend analysis developed in the preceding sections by providing a deployment-oriented scenario synthesis of advanced planning features within a common coupled PDN–TN environment. The purpose is not to introduce a new planning framework, but to illustrate how the advanced planning features identified in Sections 7.2 and 7.3 translate into distinct system-level behaviours, feasible deployment boundaries, and industry-relevant planning implications when examined under consistent conditions.

In line with this chapter's synthesis-oriented role, the analysis is structured as an interpretive extension of the literature review rather than a standalone methodological contribution. Accordingly, the section uses a common reference framework to support scenario-based comparison and to clarify how uncertainty treatment, physical flexibility, coordinated control, and market activation alter the balance between electrical feasibility and charging accessibility in coupled EVCS planning.

The comparative synthesis developed in this section serves two complementary objectives. First, it provides an evidence-based interpretation of the advanced planning features reviewed earlier by examining their effects on system behaviour within a unified analytical framework. Second, it strengthens the positioning of the thesis contributions by demonstrating why deeper feature integration yields more deployment-relevant planning outcomes in coupled power–transportation environments.

Rather than redefining the entire planning architecture in detail, this section builds on the most comprehensive framework developed in Chapter 6, which integrated V2G participation, market-driven flexibility, and adaptive control into a coupled PDN–TN planning model. The scenario-based analysis presented here, therefore, uses the framework from Chapter 6 as the analytical reference and progressively interprets its behaviour through a hierarchy of feature-enriched scenarios. This avoids unnecessary repetition while preserving continuity between the RQ3 contribution and the broader systematic synthesis of Chapter 7.

7.4.1 Scenario Framework and Design

The reference analytical basis adopted in this section is the integrated planning and control framework developed in Chapter 6, as illustrated in Fig. 6.1 and formulated through the coupled PDN–TN representations, the V2G participation model, the market activation mechanism, and the coordinated control structure introduced therein. In the present chapter, that framework is not repeated in full; instead, it serves as a common comparative platform for interpreting the incremental implications of advanced planning features.

To provide a structured and transparent evaluation of advanced planning and operational features in EV charging infrastructure, a progressive scenario hierarchy is adopted, comprising five scenarios that represent successive levels of modelling richness. Starting from a baseline coupled representation, additional assumptions related to uncertainty exposure, physical flexibility integration, coordinated operational control, and market-driven activation are introduced incrementally. This staged design ensures that each scenario extends the previous one without altering the underlying network configuration, allowing the individual and combined impacts of advanced features to be examined systematically under consistent conditions and enabling observed performance differences to be attributed directly to the activated modelling elements. All scenarios are evaluated assuming a fixed configuration of four BESS units.

Five scenarios are considered, with their formal definitions summarised in Table 7.2. Scenario S1 establishes a deterministic baseline under nominal operating conditions, capturing the fundamental trade-off between grid constraints and charging accessibility in a coupled PDN–TN setting. Scenario S2 extends this baseline by explicitly introducing uncertainty across both network domains. Variations in electrical loading reflect uncertainty in aggregated demand and behind-the-meter behaviour, while traffic-demand variability captures fluctuations in mobility patterns and congestion. This scenario is intended to evaluate the robustness of planning outcomes rather than to enhance nominal performance.

Building on this uncertainty-aware formulation, Scenario S3 incorporates physical energy flexibility via BESS integration and bidirectional charging. This stage isolates the extent to which local flexibility can alleviate charging-induced stress and expand the feasible deployment space without assuming active coordination. Scenario S4 augments this configuration by introducing coordinated operational control, enabling an assessment of how active regulation interacts with flexibility to influence voltage behaviour, network losses, and overall system feasibility. Finally, Scenario S5 introduces market-driven activation by varying the participation level of flexible charging resources, reflecting practical constraints on availability, user adoption, and economic engagement.

In this way, the scenario hierarchy does not create a separate experimental framework; rather, it provides an interpretable synthesis layer through which the planning significance of the reviewed feature categories can be examined in deployment-oriented terms.

The parameter values, data environment, and coupled urban test setting used to support this comparative synthesis remain consistent with those introduced in Chapter 6. In particular, the analysis inherits the Melbourne-based transportation context, the modified IEEE 33-bus PDN representation, the probabilistic EV charging and V2G participation structure, and the multi-module planning and control architecture established for RQ3. This common basis allows the scenario results to be interpreted as feature-dependent variations within a stable deployment-oriented reference setting.

7.4.2 Comparative Behaviour Across Feature-Enriched Scenarios

This section delivers a system-level critical analysis of the scenario-based results, examining how the incremental integration of uncertainty, flexibility, coordinated control, and market participation influences

Table 7.2: Scenario definitions and activated planning features used for the deployment-oriented synthesis of EVCS planning in coupled PDN–TN systems.

Scenario		Description
S1		Baseline deterministic coupled PDN–TN planning under nominal operating conditions
S2 Uncertainty-Aware	$S2_1$	Low electrical load uncertainty (0.5 × base load profile)
	$S2_2$	High electrical load uncertainty (4 × base load profile)
	$S2_3$	Low traffic demand variability (0.5 × baseline traffic demand)
	$S2_4$	High traffic demand variability (2 × baseline traffic demand)
S3 Flexibility-Enabled	$S3_1$	Baseline scenario with BESS coordination
	$S3_2$	$S3_1$ with V2G integration
S4 Control-Enhanced	$S4_1$	$S3_1$ with coordinated voltage control
	$S4_2$	$S3_2$ with coordinated voltage control
S5 Market-Activated	$S5_1$	$S3_2$ with market flexibility (low participation: 25%)
	$S5_2$	$S3_2$ with market flexibility (moderate participation: 50%)
	$S5_3$	$S4_2$ with market flexibility (low participation: 25%)
	$S5_4$	$S4_2$ with market flexibility (moderate participation: 50%)

coupled PDN–TN planning outcomes. The analysis focuses on comparative trends in transportation accessibility, electrical feasibility, and achievable EVCS penetration, drawing on the numerical results summarised in Table 7.3 to assess how different modelling features shape planning performance across scenarios.

The scenario synthesis in this section is not intended to introduce a new optimisation algorithm or to re-evaluate the thesis case studies as isolated numerical experiments. Instead, it uses a fixed coupled PDN–TN analytical backbone to interpret how successive activation of modelling features changes the feasible EVCS deployment envelope. By retaining consistent network data, demand assumptions, and evaluation metrics across scenarios, the analysis isolates whether observed changes arise from exposure to uncertainty, physical flexibility, coordinated control, or market-driven participation, rather than from changes in solver structure or input assumptions.

Table 7.3 should therefore be interpreted as a structured diagnostic table rather than as a standalone numerical ranking of scenarios. The objective is to examine how the maximum feasible EVCS deployment frontier changes as additional modelling features are progressively activated. Lower-deployment configurations are not the primary focus of the comparison; instead, the table emphasises the upper bounds of feasible deployment under each scenario so that the marginal effects of uncertainty, flexibility, coordinated control, and market participation can be interpreted more clearly.

Table 7.3: Scenario-based comparison of EVCS and BESS planning outcomes across cost, service-quality, and network-performance metrics. S and N_{CS} denote the scenario and number of deployed EVCS, respectively; Trav., T+Q, Const., and O&M denote travel, travel-and-queue-time, construction, and operation-and-maintenance costs, respectively.

Config.		PDN						TN Cost ($\times 10^5$\$)				
S	N_{CS}	P_{loss} Min	P_{loss} Max	VSI (%) Min	VSI (%) Max	VD Min	VD Max	Trav.	T+Q	Const.	O&M	Loss
$S1$	7	9076	9725	6.65	6.69	0.23	1.32	340.70	77.18	97.55	8.78	81.36
	8	9099	9728	6.63	6.68	0.24	1.33	321.96	73.32	118.58	10.67	83.16
	9	9105	9732	6.61	6.66	0.24	1.35	297.38	70.76	125.42	11.29	90.96
	10	9117	9735	6.60	6.66	0.26	1.36	275.96	69.81	135.94	12.23	93.96
$S2_1$	7	5219	5592	7.22	7.26	0.15	0.86	337.22	75.25	97.55	8.78	46.78
	8	5232	5593	7.19	7.25	0.16	0.86	318.15	71.49	118.58	10.67	47.82
	9	5235	5595	7.17	7.23	0.16	0.88	295.31	68.99	125.42	11.29	52.30
	10	5242	5597	7.16	7.23	0.17	0.88	273.55	68.06	135.94	12.23	54.03
$S2_2$	7	16337	17506	5.65	5.69	0.36	2.08	356.03	83.74	97.55	8.78	146.45
	8	16378	17510	5.64	5.68	0.38	2.09	336.45	79.55	118.58	10.67	149.69
	9	16389	17517	5.62	5.66	0.38	2.13	310.76	76.77	125.42	11.29	163.73
	10	16412	17523	5.61	5.66	0.41	2.14	288.38	75.74	135.94	12.23	169.13
$S2_3$	7	7261	7780	6.92	6.96	0.21	1.19	204.42	27.40	97.55	8.78	65.09
	8	7279	7782	6.90	6.95	0.22	1.20	193.18	26.03	118.58	10.67	66.53
	9	7284	7785	6.87	6.93	0.22	1.22	178.43	25.12	125.42	11.29	72.77
	10	7294	7788	6.86	6.93	0.23	1.22	165.58	24.78	135.94	12.23	75.17
$S2_4$	7	12707	13615	6.28	6.32	0.27	1.55	459.95	158.22	97.55	8.78	113.90
	8	12738	13619	6.27	6.31	0.28	1.56	434.65	150.31	118.58	10.67	116.42
	9	12747	13625	6.25	6.29	0.28	1.59	401.46	145.06	125.42	11.29	127.34
	10	12765	13629	6.24	6.29	0.31	1.60	372.55	143.11	135.94	12.23	131.54
$S3_1$	7	8478	9109	7.32	7.36	0.21	1.20	325.22	69.46	109.75	9.88	74.58
	8	8489	9110	7.31	7.35	0.21	1.21	307.33	65.99	133.41	12.01	76.23
	9	8494	9113	7.30	7.34	0.22	1.22	283.87	63.68	141.10	12.70	83.38
	10	8500	9115	7.30	7.34	0.23	1.23	263.42	62.83	152.93	13.76	86.13
	11	8508	9117	7.29	7.34	0.24	1.23	250.13	60.76	162.97	14.67	90.78
$S3_2$	7	8170	8763	7.65	7.69	0.17	1.07	293.26	60.41	126.71	11.41	67.19
	8	8174	8754	7.65	7.68	0.17	1.07	272.08	57.13	148.33	13.35	68.77
	9	8177	8751	7.64	7.68	0.18	1.09	251.27	54.95	157.88	14.21	73.59
	10	8178	8739	7.64	7.68	0.18	1.09	233.07	53.50	175.66	15.81	77.22
	11	8183	8711	7.63	7.67	0.18	1.05	219.17	51.95	181.69	16.35	83.29
	12	8165	8668	7.63	7.67	0.16	0.94	191.24	50.23	192.91	17.36	87.01
	13	8156	8658	7.62	7.66	0.14	0.85	186.33	49.72	211.11	19.00	90.95
$S4_1$	7	7879	8492	7.99	8.02	0.18	1.07	309.73	61.74	121.94	10.97	67.80
	8	7880	8493	7.99	8.02	0.18	1.08	292.69	58.66	148.23	13.34	69.30
	9	7882	8495	7.99	8.02	0.19	1.08	270.35	56.60	156.78	14.11	75.80
	10	7883	8496	7.99	8.02	0.20	1.09	250.88	55.85	169.92	15.29	78.30
	11	7884	8497	8.00	8.03	0.21	1.09	245.96	54.92	176.06	15.85	82.80
$S4_2$	7	7863	8418	7.99	8.02	0.14	0.95	261.29	51.36	143.67	12.93	59.80
	8	7860	8398	7.99	8.02	0.14	0.93	236.83	48.28	163.26	14.69	61.30
	9	7861	8389	7.99	8.02	0.14	0.96	218.67	46.22	174.65	15.72	63.80
	10	7856	8363	7.99	8.01	0.13	0.95	202.73	44.17	198.38	17.85	68.30
	11	7858	8304	7.98	8.01	0.12	0.88	188.20	43.14	200.41	18.04	75.80
	12	7848	8302	7.98	8.01	0.12	0.82	166.75	42.12	214.98	19.35	77.30
	13	7839	8292	7.97	8.00	0.11	0.74	162.47	41.69	235.27	21.17	80.80

Continued on next page

Table 7.3: Scenario-based comparison of EVCS and BESS planning outcomes across cost, service-quality, and network-performance metrics (continued).

Config.		PDN						TN Cost ($\times 10^5$\$)				
S	N_{CS}	P_{loss} Min	P_{loss} Max	VSI (%) Min	VSI (%) Max	VD Min	VD Max	Trav.	T+Q	Const.	O&M	Loss
$S5_1$	7	7875	8473	7.99	8.02	0.17	1.04	297.62	59.15	127.37	11.46	65.80
	8	7875	8469	7.99	8.02	0.17	1.04	278.73	56.06	151.99	13.68	67.30
	9	7877	8468	7.99	8.02	0.18	1.05	257.43	54.01	161.25	14.51	72.80
	10	7876	8463	7.99	8.02	0.18	1.06	238.84	52.93	177.04	15.93	75.80
$S5_2$	7	7871	8455	7.99	8.02	0.16	1.01	285.51	56.55	132.81	11.95	63.80
	8	7870	8445	7.99	8.02	0.16	1.01	264.76	53.47	155.74	14.02	65.30
	9	7872	8442	7.99	8.02	0.17	1.02	244.51	51.41	165.72	14.91	69.80
	10	7869	8430	7.99	8.02	0.17	1.02	226.80	50.01	184.15	16.57	73.30
	11	7871	8400	7.99	8.02	0.17	0.99	217.08	49.03	188.23	16.94	79.30
	12	7862	8398	7.99	8.02	0.17	0.93	195.63	48.01	202.81	18.25	80.80
$S5_3$	7	7868	8444	7.99	8.02	0.15	0.99	278.25	54.99	136.06	12.25	62.60
	8	7867	8431	7.99	8.02	0.15	0.98	256.38	51.91	158.00	14.22	64.10
	9	7869	8426	7.99	8.02	0.16	1.00	236.76	49.86	168.40	15.16	68.00
	10	7865	8410	7.99	8.01	0.15	1.00	219.58	48.26	188.42	16.96	71.80
$S5_4$	7	7865	8429	7.99	8.02	0.15	0.97	268.55	52.91	140.41	12.63	61.00
	8	7863	8412	7.99	8.02	0.15	0.95	245.21	49.84	161.00	14.49	62.50
	9	7865	8405	7.99	8.02	0.15	0.98	226.42	47.78	171.97	15.48	65.60
	10	7860	8383	7.99	8.01	0.14	0.97	209.95	45.92	194.11	17.47	69.80
	11	7862	8333	7.98	8.01	0.13	0.91	196.87	44.91	196.76	17.71	76.85
	12	7852	8331	7.98	8.01	0.13	0.85	175.41	43.88	211.33	19.02	78.35

The scenario comparison indicates that EVCS densification improves transportation-side accessibility, but only up to the point where electrical hosting constraints become binding. Under passive coupled planning, this limit is reached without any mechanism to expand the feasible deployment boundary. Load and traffic uncertainty alter the severity of operating conditions, but they do not by themselves increase feasible EVCS capacity. In contrast, physical flexibility through BESS and V2G shifts the boundary by increasing the admissible loading range, while coordinated voltage regulation determines how effectively this additional flexibility can be utilised. Market-driven participation then introduces a practical availability constraint, converting technically available V2G capability into a smaller but more realistic flexibility contribution.

These results suggest that EVCS deployment in coupled PDN–TN systems follows a constrained expansion mechanism. Accessibility improvements create the planning incentive for denser charging infrastructure, but the achievable deployment frontier is governed by electrical hosting capacity, flexibility availability, control effectiveness, and participation realism. Consequently, advanced features such as BESS, V2G, coordinated control, and market participation should not be treated as isolated operational add-ons. They act as structural planning variables that determine whether additional EVCS deployment is technically feasible, operationally usable, and practically reliable.

Baseline Coupled PDN–TN Planning ($S1$)

Scenario $S1$ establishes the passive benchmark of coupled PDN–TN planning and quantifies the intrinsic accessibility–security trade-off. Within the feasible range of seven to ten EVCSs, transportation performance improves monotonically: increasing station density enhances spatial coverage and disperses demand, reducing travel cost and travel-and-queue time by around 20% through shorter access distances and lower local congestion.

These accessibility gains are accompanied by increasing PDN stress. Power losses rise modestly, whereas VD increases more sharply near the feasibility boundary, and VSI declines steadily, indicating progressive erosion of voltage margins under uncoordinated charging growth. As a result, feasible deployment in $S1$ saturates at ten EVCSs, directly exposing the baseline coupling limit.

Sensitivity to Load and Traffic Uncertainty ($S2$)

Scenario $S2$ tests robustness under uncertainty while retaining the passive structure of $S1$. Two independent sources of uncertainty are evaluated across four sub-scenarios: PDN load variability ($S2_1$–$S2_2$) and TN traffic variability ($S2_3$–$S2_4$).

On the PDN side, $S2_1$ (reduced load) improves VD and losses by increasing voltage headroom, whereas $S2_2$ (high-stress loading) degrades VD and stability with increasing EVCS penetration. In both cases, transportation metrics remain nearly unchanged, confirming that PDN-side uncertainty primarily shifts electrical feasibility rather than accessibility.

TN-side uncertainty produces the opposite pattern. Under reduced traffic in $S2_3$, travel-and-queue time decreases markedly because of lower congestion and queueing delay, while travel cost declines more moderately. Under higher traffic in $S2_4$, travel-and-queue time grows near-superlinearly as congestion intensifies, whereas travel cost increases more gradually as users adapt routes and station choices. Electrical metrics remain largely invariant across $S2_3$ and $S2_4$, indicating weak back-coupling from traffic variability to PDN operation in the passive configuration.

Overall, $S2$ shifts absolute performance levels but does not relax the baseline accessibility–security frontier: electrical uncertainty governs voltage quality and losses, while traffic uncertainty predominantly reshapes congestion and waiting time.

Effect of Physical Flexibility Integration ($S3$)

Scenario $S3$ introduces physical flexibility to mitigate charging-induced electrical stress and to expand PDN hosting capacity. Scenario $S3_1$ enables BESS coordination, while $S3_2$ adds bidirectional operation through V2G.

In $S3_1$, storage systematically reduces power loss and VD relative to $S1$, thereby increasing electrical operating margin without changing the TN structure. In $S3_2$, V2G discharging further strengthens this effect, yielding substantially lower VD than the passive benchmark and extending feasible EVCS deployment from ten to thirteen, as shown in Table 7.3.

On the transportation side, the expanded feasible siting space supports denser deployment, thereby reducing travel costs and travel-and-queue times, especially at higher penetration levels, where congestion relief is most sensitive to station availability. Overall, $S3$ shifts the planning frontier by decoupling accessibility gains from proportional electrical penalties.

Role of Coordinated Voltage Regulation ($S4$)

Scenario $S4$ evaluates whether coordinated voltage regulation can systematically amplify the benefits of physical flexibility. Scenario $S4_1$ adds active voltage control to storage-enabled operation, while Scenario $S4_2$ combines coordinated control with full V2G capability.

In Scenario $S4_1$, VD is reduced relative to Scenario $S3_1$, indicating that feedback-based regulation more effectively targets voltage-quality objectives than storage scheduling alone. Power loss also decreases modestly, reflecting improved power-flow coordination. Scenario $S4_2$ delivers the strongest PDN performance among the non-market configurations: compared to uncontrolled V2G operation, VD improves further while preserving feasibility for thirteen EVCSs with enhanced stability margins. Transportation performance improves indirectly in both cases because relaxed electrical constraints enable denser, more balanced EVCS placement. Overall, Scenario $S4$ suggests that while V2G expands the available flexibility pool, coordinated voltage regulation governs how efficiently that flexibility is translated into system-level performance gains.

Market Activation Under Partial Participation ($S5$)

Scenario $S5$ examines market-driven activation under partial participation. To avoid redundancy, extreme cases are excluded: zero participation reduces to the non-market controlled configuration, whereas full participation corresponds to the fully coordinated V2G case. The analysis, therefore, focuses on intermediate participation levels.

Four sub-scenarios are considered: $S5_1$–$S5_2$ represent 25% participation without and with coordinated control, while $S5_3$–$S5_4$ represent 50% participation under the same control assumptions. Increasing participation from 25% to 50% expands the effective flexibility pool and reduces power loss and VD.

Adding coordinated control yields a further reduction in VD, clarifying that participation determines the availability of flexibility, while control determines utilisation efficiency.

Across the $S5$ configurations, $S5_4$ delivers the strongest overall outcome and approaches the technical performance of the fully coordinated V2G case, whereas $S5_1$ performs the worst due to limited activation and a lack of coordination. Consistently, higher participation, combined with control, supports larger feasible EVCS deployment, whereas partial participation constrains dense siting. Overall, $S5$ shows that market mechanisms can recover a substantial share of V2G benefits, but only when sufficient participation is paired with coordinated regulation.

7.4.3 System-Level Planning Implications

Across all scenarios, transportation accessibility improves systematically with EVCS density: travel-related costs decline within the passive-feasible range and improve further when flexibility and coordinated operation enable denser deployment. These gains are driven primarily by improved spatial coverage and demand redistribution rather than by scenario-specific assumptions alone.

By contrast, PDN hosting capacity varies sharply with the activated features. In $S1$, feasibility saturates at ten EVCSs because of voltage-quality limits; $S2$ shifts performance but does not relax this boundary. Flexibility fundamentally reshapes the trade-off: $S3_2$ extends feasibility to thirteen EVCSs, and $S4$ further improves voltage quality and reduces losses at comparable penetration levels. Market-activated cases refine this upper bound under realistic adoption constraints: low-participation configurations yield intermediate performance and limited expansion, whereas $S5_4$ recovers much of the benefit of fully coordinated V2G and supports expansion to twelve EVCSs with manageable grid impact. Overall, flexibility defines the achievable deployment envelope, while coordinated control and market participation determine how efficiently that envelope is utilised in practice.

These comparative findings are fully consistent with the RQ3 results reported in Chapter 6, but their role here is different. In Chapter 6, the framework was introduced and validated as the thesis contribution addressing V2G participation and market-driven flexibility. In the present chapter, the same framework is used as a synthesis reference to demonstrate more broadly why the deeper integration of advanced planning features yields more realistic, scalable, and industry-relevant EVCS planning outcomes in coupled PDN–TN systems.

From a broader methodological perspective, the scenario-based interpretation presented above also clarifies why several limitations identified in the literature remain structurally important. While many studies incorporate advanced features at the individual level, such as uncertainty modelling, flexibility integration, or coordinated control, these capabilities are often introduced in isolation rather than as part of a coherent planning architecture. The scenario hierarchy illustrates that the practical value of these features emerges primarily through their combined interaction within a unified planning framework. This observation reinforces the need for EVCS planning models that simultaneously capture transportation dynamics, electrical feasibility, distributed flexibility, and operational coordination.

The following section, therefore, synthesises the key insights emerging from the literature review and the scenario-based interpretation and identifies the principal research gaps that motivate the methodological developments proposed in this thesis.

7.5 Synthesis of Literature Insights and Identified Research Gaps

The preceding sections provided a structured synthesis of EVCS planning research from both methodological and feature-oriented perspectives. In addition to the comparative literature analysis, the deployment-oriented scenario synthesis presented in Section 7.4 offered an interpretive evaluation of how advanced planning features influence system-level behaviour in a common coupled PDN–TN environment.

Taken together, these analyses indicate that EVCS planning research has evolved from early transportation-centric station-placement models toward increasingly integrated formulations that recognise charging infrastructure as a coupling layer between mobility systems, PDNs, and emerging flexibility markets. Despite this methodological progression, the current state of the art remains structurally uneven. Several critical limitations continue to constrain the realism of deployment and the system-level robustness of existing EVCS planning frameworks.

The principal research gaps identified in the literature are summarised as follows.

- **Incomplete representation of bidirectional PDN–TN interactions**

  Many existing studies incorporate both TNs and PDNs within a single framework; however, the interaction between them is frequently simplified to one-directional demand transfer or coarse spatial aggregation. Transportation behaviour is often represented through static origin–destination demand patterns, while electrical feasibility is evaluated using simplified power-flow models. In practice, EVCS deployment simultaneously reshapes mobility flows and electrical loading conditions: charging-station accessibility influences route choice and station utilisation, while the resulting charging demand affects voltage profiles, transformer loading, and feeder congestion. Planning models that do not preserve this reciprocal interaction may therefore produce infrastructure configurations that appear optimal under stylised assumptions but perform poorly under realistic system conditions.

- **Separation between infrastructure planning and operational dynamics**

  A large portion of the literature determines EVCS siting and sizing decisions under static or weakly dynamic assumptions, whereas real charging systems operate under rapidly changing mobility demand, renewable variability, electricity prices, and network states. Without explicit links between planning decisions and operational coordination mechanisms, such as smart charging, demand response, voltage regulation, and congestion management, planned infrastructure may not sustain acceptable performance once deployed. Although integrated planning–operation formulations have begun to emerge, they remain fragmented and often treat operational control as a post-planning adjustment rather than as a structural component of long-term infrastructure design.

- **Limited structural integration of flexibility resources**

  The growing availability of distributed flexibility resources, including EV batteries, stationary storage, and bidirectional charging technologies, creates opportunities to transform EVCS infrastructure from passive electrical loads into active energy assets. Technologies such as V2G and BESS can support peak shaving, voltage regulation, loss reduction, and ancillary-service provision. Nevertheless, many planning models continue to represent charging stations primarily as demand nodes. Even when flexibility mechanisms are included, they are frequently treated as operational refinements rather than endogenous planning variables, thereby underestimating their role in expanding hosting capacity and shaping feasible deployment envelopes.

- **Fragmented treatment of multi-domain uncertainty**

  EV adoption trajectories, charging demand patterns, renewable generation, traffic congestion, and electricity market conditions all introduce substantial uncertainty into EVCS planning decisions. While stochastic and robust optimisation methods have been explored, their application in fully integrated PDN–TN planning remains limited. In many studies, uncertainty is addressed only within individual subsystems, such as charging demand or renewable generation, without capturing the cross-domain feedback mechanisms through which transportation behaviour and electrical response influence one another. This fragmented treatment weakens the robustness of planning outcomes and reduces confidence in long-term infrastructure investment decisions.

- **Scalability challenges in large-scale urban planning environments**

  As EV adoption increases, EVCS planning problems must increasingly be solved at the metropolitan scale with large candidate-location sets, fine temporal resolution, nonlinear grid constraints, and stochastic traffic dynamics. Under such conditions, exact optimisation formulations often become computationally intractable. Although metaheuristic methods, decomposition strategies, and simulation-based approaches have been proposed to address this challenge, the literature still lacks a broadly accepted balance between computational scalability, modelling fidelity, and solution robustness. Simplifying transportation behaviour improves tractability but reduces behavioural realism, while simplifying electrical models improves solvability but weakens feasibility assurance.

- **Lack of reproducible feature-level benchmarking**

  A further limitation is the lack of standardised benchmarking environments for isolating the marginal impact of advanced planning features. Existing studies often use different network models, demand assumptions, optimisation settings, and performance metrics, making it difficult to determine whether improved outcomes arise from a modelling feature, a solver choice, a dataset, or a case-specific assumption. This limits cumulative methodological progress and reduces the comparability of EVCS planning frameworks. Reproducible feature-level benchmarking is therefore necessary to evaluate how uncertainty modelling, BESS coordination, V2G participation, market activation, and operational control, individually and jointly, affect the feasibility of infrastructure deployment.

- **Underrepresentation of user-oriented service objectives**

  Most EVCS planning studies prioritise techno-economic objectives such as investment costs, power losses, VD, and network efficiency. In contrast, user-oriented service dimensions, including accessibility, spatial equity, waiting-time distribution, and charging-service reliability, remain comparatively underdeveloped. From a deployment perspective, however, charging infrastructure must provide equitable and behaviourally credible access across urban environments. Planning frameworks that focus solely on engineering efficiency may therefore yield infrastructure configurations that result in uneven coverage or underserved mobility corridors.

Taken together, these limitations indicate that the next generation of EVCS planning frameworks must move beyond simplified infrastructure-allocation models toward integrated, flexibility-aware, uncertainty-resilient, and operationally credible planning architectures. In particular, future models must preserve the reciprocal interaction between transportation demand and distribution-network feasibility, embed distributed flexibility resources as structural planning components, incorporate uncertainty across both mobility and electrical domains, and remain computationally scalable for large urban systems.

Addressing these challenges is essential if EVCS planning is to support not only theoretical optimisation performance but also the practical deployment of charging infrastructure that underpins electrified, resilient, and decarbonised transport systems.

7.6 Mapping the Thesis Research Questions to the Identified Methodological Landscape

The preceding sections established a structured analytical perspective on the EVCS planning literature by combining two complementary dimensions: methodological architecture and advanced-feature maturity. Section 7.1 categorised existing studies into distinct planning paradigms, while Sections 7.2 and 7.3 examined how critical modelling capabilities, including traffic representation, uncertainty handling, grid realism, and operational coordination, are embedded within these paradigms. The synthesis presented in Section 7.5 further demonstrated that, despite substantial methodological progress, the current literature remains characterised by several structural imbalances in the way coupled PDN–TN planning problems are formulated.

These observations provide the conceptual foundation for the RQs addressed in this thesis. Rather than emerging as isolated technical challenges, the RQs arise directly from the methodological patterns and limitations identified across the reviewed literature. In particular, the comparative analysis reveals four recurring structural gaps in the current EVCS planning landscape: incomplete representation of traffic-driven charging demand formation, limited integration of distributed flexibility resources within infrastructure planning, weak coordination between long-term planning and operational dynamics, and the absence of unified evaluation environments capable of systematically assessing the impact of advanced planning features.

Within this context, the RQs of the thesis are formulated to address these gaps by progressively extending EVCS planning architectures in coupled PDN–TN systems. Instead of focusing solely on algorithmic improvements within a fixed model structure, the thesis investigates how the planning architecture itself can be systematically enriched to represent better the physical, behavioural, and operational interactions that characterise large-scale energy-mobility systems.

The first stage of this research trajectory focuses on grid-aware infrastructure planning and operational support within the distribution network. As discussed in the literature synthesis, many existing studies either neglect the role of distributed flexibility in supporting EVCS integration or treat planning and operation as largely separate activities. The first RQ therefore examines how EVCS and BESS resources can be jointly planned and operationally coordinated to maintain grid feasibility under time-varying charging demand. Chapter 4 addresses this objective by developing a coordinated planning-and-operation framework in which BESS siting, operating schedules, EVCS placement, and adaptive control are considered together within the PDN.

Building on this grid-aware foundation, the second stage of the thesis addresses the structural role of traffic-driven charging demand in infrastructure planning. As the literature review has shown, many existing models continue to rely on simplified or exogenous assumptions about charging demand, even when both network domains are nominally represented. The second RQ, therefore, investigates how transportation dynamics can be incorporated explicitly so that charging demand emerges from mobility behaviour rather than being imposed as a fixed electrical input. Chapter 5 addresses this objective by extending the planning framework to a coupled PDN–TN environment in which traffic-informed charging demand, accessibility, travel cost, and queueing performance are integrated directly into EVCS planning.

The third stage of the thesis addresses the interaction between infrastructure planning, distributed flexibility, and realisable system support. As highlighted in the literature synthesis, many EVCS planning models still treat charging demand as unidirectional and represent flexibility resources either weakly or only as operational refinements. The third RQ, therefore, examines how V2G participation behaviour, heterogeneous user profiles, and market-driven flexibility mechanisms can be embedded within the planning architecture itself. Chapter 6 addresses this objective by introducing a V2G-enabled and market-aware planning framework in which participation-sensitive flexibility and coordinated operational control are incorporated into the coupled PDN–TN planning problem.

Beyond these individual modelling advancements, the thesis also addresses a broader methodological limitation identified in the literature: the lack of consistent evaluation environments for comparing EVCS planning architectures. Because existing studies employ heterogeneous datasets, modelling assumptions, and network configurations, it is often difficult to isolate the incremental value of specific modelling capabilities. To overcome this limitation, the thesis adopts a unified PDN–TN evaluation environment that allows successive planning architectures to be compared within a consistent analytical setting. This unified evaluation basis enables the incremental impact of grid-aware coordination, traffic-informed demand formation, flexibility integration, and operational control to be assessed systematically across Chapters 4–6.

Collectively, the RQs define a staged methodological progression through which the thesis advances EVCS infrastructure planning from isolated grid-oriented optimisation toward integrated, flexibility-aware energy–mobility decision support. Instead of developing a single all-encompassing framework, the thesis builds a sequence of increasingly comprehensive planning architectures within a unified evaluation environment, thereby addressing the lack of reproducible feature-level benchmarking identified in the literature. Chapter 4 first establishes the grid-aware foundation by coordinating EVCS and BESS planning with operational network constraints. Chapter 5 then extends this foundation to a coupled PDN–TN setting, in which traffic-informed charging demand and transportation-side accessibility are explicitly embedded in the planning process. Chapter 6 further extends the framework by incorporating V2G participation, market-driven activation of flexibility, and coordinated operational support, thereby linking infrastructure planning to realistic flexibility availability and deployment feasibility.

This progressive research design directly reflects the structural gaps identified in the literature synthesis and aligns the thesis contributions with the broader methodological evolution of EVCS planning research. By systematically strengthening the coupling between grid feasibility, transportation dynamics, distributed flexibility, and operational coordination, the thesis advances EVCS planning toward more realistic, scalable, and deployment-oriented infrastructure design frameworks for future energy-mobility systems.

7.7 Implications for Infrastructure Planning, Energy Markets, and Transport Systems

The integrated EVCS planning frameworks developed in this thesis have implications that extend beyond methodological optimisation. As demonstrated by both the comparative literature synthesis and the deployment-oriented scenario analysis presented earlier in this chapter, EV charging infrastructure operates at the interface between TNs and electricity systems, and its planning architecture directly influences the efficiency of infrastructure investment, grid feasibility, market participation capability, and mobility service performance. The implications discussed in this section, therefore, emerge not only from abstract modelling considerations but also from the consistent observation that deeper integration of traffic-informed demand representation, distributed flexibility resources, coordinated control, and participation-sensitive activation yields more deployment-relevant EVCS planning outcomes.

- **Implications for Infrastructure Planning**

The results highlight the limitations of isolated EVCS siting approaches that evaluate transportation demand and grid hosting capacity independently. Coordinated PDN–TN planning enables infrastructure allocation that simultaneously improves accessibility, grid compatibility, and station utilisation while reducing the risk of localised distribution-network overload.

- **Implications for Grid Operation and Flexibility Integration**

  Flexibility-enabled EVCS infrastructure can evolve from passive electrical loads into active grid-support assets. By integrating BESS and V2G capabilities within planning architectures, charging infrastructure can contribute to peak-demand mitigation, voltage stability, and distribution-network congestion management.

- **Implications for Electricity Markets**

  Charging infrastructure equipped with storage and V2G capabilities can participate in emerging flexibility markets by responding to price signals and system conditions. This enables EVCS installations to provide services such as demand response, energy arbitrage, and ancillary support, highlighting the need for market mechanisms that accommodate EV charging infrastructure as distributed energy resources.

- **Implications for Transportation Network Management**

  Charging infrastructure deployment directly affects route choice, congestion patterns, and the spatial distribution of charging demand. Traffic-aware planning frameworks enable infrastructure strategies that align with real-world mobility patterns, improving accessibility while avoiding congestion concentrations around specific charging locations.

- **Implications for Integrated Energy–Mobility Systems**

  The results demonstrate that EVCS planning should be treated as a multi-domain infrastructure design problem rather than a narrowly defined siting optimisation task. Integrated planning architectures provide a foundation for designing charging networks that support both transportation demand and power-system reliability.

From an industry-translation perspective, the synthesis implies that EVCS deployment should be co-designed with flexibility resources, operational control capabilities, and participation mechanisms rather than being treated as a standalone siting problem. For utilities, this means that hosting capacity assessment should be linked to BESS and V2G availability; for transport planners, accessibility improvements should be evaluated against grid feasibility; and for market participants, theoretical flexibility potential should be distinguished from realistically activatable support. This interpretation provides the basis for the decision-support framing developed in Chapter 8.

Overall, the synthesis confirms that the central contribution of this thesis is not limited to improving EVCS siting and sizing outcomes, but lies in demonstrating how EV charging infrastructure can be planned as an integrated, flexibility-aware, and deployment-oriented energy–mobility asset under realistic grid, traffic, and participation constraints.

Chapter 8

Conclusions, Industry Translation, and Future Work

This thesis addressed EV charging infrastructure planning as a progressively enriched decision-making problem spanning feeder-level technical feasibility, transportation-driven service demand, operational support, and participation in flexibility markets. Rather than treating EVCS deployment as a static siting task, the thesis developed a cumulative planning paradigm in which infrastructure decisions were progressively reformulated across three stages: coordinated EVCS–BESS planning and operation in distribution networks, traffic-informed planning in coupled PDN–TN environments, and flexibility-aware planning under heterogeneous V2G participation and market-driven activation.

Taken together, the thesis supports a central conclusion: EV charging infrastructure planning becomes materially more realistic, robust, and deployment-relevant when it moves beyond static, grid-only formulations toward coordinated, data-driven, and system-level decision structures. The principal contribution of the thesis is therefore not a single algorithmic novelty in isolation, but a coherent planning architecture that links electrical feasibility, mobility-driven demand formation, conditional flexibility availability, and operational support within a unified infrastructure decision-support perspective.

The purpose of this final chapter is threefold. First, it consolidates the thesis's main scientific contributions and robust findings. Second, it translates the methodological outcomes into deployment-oriented guidance for utilities, charging infrastructure operators, transport planners, policymakers, and flexibility-market participants. Third, it identifies the limitations, validity boundaries, and future research opportunities required to advance the proposed framework toward broader practical use.

8.1 Summary of Contributions

The thesis makes five principal contributions that collectively address the three research questions developed in Chapter 2.

First, in response to RQ1, it developed a coordinated planning-and-operation framework for integrating EVCS and BESS infrastructure in PDNs. This contribution established that charging infrastructure should not be planned independently of feeder-level operating behaviour. By jointly considering EVCS deployment, BESS siting, time-varying network conditions, and adaptive operational support, the thesis showed that infrastructure adequacy depends not only on nominal feasibility but also on the system's ability to remain stable under realised demand variability.

Second, in response to RQ2, the thesis extended EVCS planning from a grid-only setting to a coupled power–transportation setting. Charging demand was reformulated as an endogenous consequence of traffic conditions, accessibility, travel cost, and queueing exposure rather than as an externally imposed electrical load. This changed the structure of the planning problem by showing that mobility-attractive infrastructure can be electrically fragile, whereas feeder-attractive infrastructure can be behaviourally ineffective if poorly aligned with real charging-service demand.

Third, in response to RQ3, the thesis incorporated V2G participation, behavioural heterogeneity, and market-driven flexibility into the planning framework. This shifted the role of EVs beyond passive charging demand, treating them as conditional distributed flexibility resources whose value depends on participation likelihood, temporal availability, activation logic, and deployment context. By avoiding deterministic assumptions about V2G availability, the thesis provided a more credible basis for flexibility-aware EVCS planning.

Fourth, the thesis grounded the proposed framework in real Melbourne and Victoria datasets. Residential demand, rooftop PV generation, traffic measurements, road-network information, and probabilistic charging-demand modelling were integrated to construct a case-study environment that is both methodologically transparent and relevant to Australian urban planning conditions. This empirical grounding strengthened the practical credibility of the results and supported the interpretation of the framework as a decision-support tool rather than a purely theoretical optimisation model.

Fifth, the thesis contributed a decision-centric interpretation of EVCS planning research. Through the systematic synthesis in Chapter 7 and the deployment-oriented consolidation developed in this final chapter, the work clarified how planning-layer choices, mobility assumptions, flexibility mechanisms, and operational support interact to shape infrastructure outcomes. This shifts the evaluation of EVCS planning from algorithm-only comparison toward deployment-oriented decision logic.

8.2 Key Findings and Robust Insights

While the previous section summarised the thesis's methodological contributions, this section consolidates the main insights that emerged from applying those contributions across the three research stages.

The first finding is that EVCS deployment cannot be reduced to a narrow location–allocation problem. Across all three research stages, infrastructure performance depended on the interaction among spatial demand, feeder constraints, service accessibility, and operational support. This means that technically feasible planning outcomes should be judged not only by cost or nominal placement quality but also by robustness, controllability, and practical usefulness.

The second finding is that coordinated BESS integration materially improves the feasibility and quality of EVCS deployment in distribution networks. Strategically placed BESS units reduced VD, improved voltage stability, and mitigated the growth of technical losses under time-varying charging demand. The addition of adaptive operational control strengthened this result by showing that local support can preserve planning validity when realised demand departs from nominal expectations.

The third finding is that traffic-informed demand formation materially changes infrastructure decisions. Once charging demand is linked explicitly to accessibility, travel burden, traffic concentration, and queueing conditions, the resulting infrastructure layout differs meaningfully from grid-only solutions. This indicates that static or exogenous electrical representations of EV demand are structurally insufficient for deployment-relevant planning.

The fourth finding is that V2G-enabled flexibility creates real value, but only under aligned technical, behavioural, and market conditions. When participation is sufficiently credible and appropriately timed, V2G can improve both grid-side and service-side outcomes, including power loss, voltage performance, travel cost, and queueing behaviour. However, these gains are not automatic consequences of bidirectional hardware. They depend on participation behaviour, temporal availability, activation logic, and spatial infrastructure design. A central practical insight of the thesis is therefore that flexibility should be planned as a realisable capability, not assumed as a guaranteed resource.

The fifth finding is that operational control is most effective when it complements sound infrastructure planning rather than compensates for weak planning. Control improves robustness, mitigates short-term variability, and helps preserve security margins, but it cannot systematically rescue infrastructure decisions that are fundamentally inconsistent with feeder feasibility or mobility-driven demand formation.

At the thesis level, these findings support a unifying insight: EVCS planning becomes most decision-relevant when it is treated as a layered system problem defined by three interacting dimensions:

- electrical feasibility, which determines whether the distribution network can support infrastructure;
- mobility-driven service demand, which determines where infrastructure is practically valuable and how it is used;
- flexibility-enabled operational adaptability, which determines how robustly infrastructure can respond to variability and uncertainty.

This three-dimensional perspective provides the conceptual backbone of the thesis and explains why the progression from RQ1 to RQ3 produced not merely richer models, but more realistic infrastructure-deployment logic.

8.3 Unified Decision Support Framework for Industry Translation

The methodological contribution of the thesis can be interpreted as a unified decision-support framework for planning EV charging infrastructure in coupled energy–mobility systems. The purpose of this framework is not to replace detailed utility planning studies or site-specific engineering validation. Rather, it provides a structured planning logic through which electricity-network constraints, mobility-driven demand, service quality, flexibility availability, and operational support can be evaluated together.

The framework is therefore best interpreted as an offline decision-support layer for scenario testing, candidate-site screening, infrastructure portfolio comparison, and flexibility-readiness assessment. Its role is not to prescribe a single fixed deployment solution, but to provide a structured analytical environment in which technically feasible, service-effective, and flexibility-aware infrastructure options can be compared before detailed implementation decisions are finalised.

8.3.1 Framework Structure

At the system level, the proposed framework is organised around four interacting layers: data inputs, functional modules, decision outputs, and feedback-driven decision points. Together, these layers establish a traceable pathway from multi-domain observations to infrastructure and operational decisions that can be interpreted in practical planning settings.

Data Inputs. The input layer combines the core data streams introduced in Chapter 3, including:

- time-series load and distributed-generation data derived from residential demand and PV records;
- feeder topology, electrical limits, and network-operating constraints for the PDN;
- traffic-flow information, road-network attributes, and intersection-level mobility patterns for the TN;
- EV behavioural descriptors, including charging likelihood, state-of-charge evolution, accessibility response, and flexibility participation assumptions.

The importance of this layer lies less in the volume of data than in its structural fidelity. The thesis shows that planning quality depends on retaining sufficient spatial and temporal granularity to preserve how charging demand forms, where it materialises, and how it affects feeder-level technical performance.

Functional Modules. The inputs are processed through four coupled modules:

- a network-constrained planning module, which determines EVCS and BESS siting and sizing under technical, economic, and environmental objectives;
- a demand-formation module, which transforms traffic dynamics, accessibility, and behavioural assumptions into spatially and temporally resolved charging demand;
- a flexibility and V2G module, which models bidirectional capability, heterogeneous participation profiles, and market-conditioned flexibility activation;
- an operational control module, which provides adaptive BESS support to preserve voltage performance under realised deviations from nominal planning assumptions.

These modules do not operate as isolated sequential blocks. Demand formation changes the effective electrical loading seen by the feeder. Infrastructure placement changes service accessibility and queueing conditions. V2G participation changes the balance between passive charging burden and active flexibility support. Operational feedback then reveals whether the planning solution remains credible under realised system conditions. The framework is therefore decision-coupled rather than merely data-coupled.

Decision Outputs. The output layer is aligned with stakeholder-facing performance indicators and planning needs. It includes:

- optimal locations and capacities of EVCS and BESS assets;
- time-resolved charging-demand allocation across candidate sites;
- network-performance indicators such as power loss, VD, and voltage stability;
- service-side indicators such as accessibility, travel cost, and queueing exposure;
- operational signals associated with BESS support and, where applicable, V2G-enabled flexibility activation.

These outputs are interpretable not only within the thesis's simulation environment but also in practical planning discussions concerned with feasibility, utilisation, and deployment quality.

Decision Points and Feedback Loops. A defining characteristic of the framework is the presence of explicit decision feedback. Planning outcomes are not treated as valid by construction. Instead, they are tested against operational response, demand variability, and realised system stress. When voltage security weakens, queueing becomes excessive, or flexibility participation underperforms, the planning outcome serves as the basis for iterative refinement. This closed-loop logic is important for practical deployment because it reduces the risk of treating nominally optimal but operationally fragile solutions as decision-ready infrastructure strategies.

8.3.2 Operational and Planning Use Cases

The proposed framework is designed for environments in which infrastructure decisions are distributed among multiple actors with partially aligned yet distinct responsibilities. It therefore does not assume a single decision-maker. Instead, it supports interpretation across utility, operator, and planning workflows through a shared representation of demand, network capability, and flexibility.

For **distribution network operators and DNSPs**, the framework provides a more realistic basis for assessing the technical implications of EVCS deployment than conventional maximum-demand screening. Because charging demand arises from mobility and accessibility dynamics rather than being imposed as an exogenous static load, the framework enables feeder-level assessment that is more consistent with how demand is likely to emerge in practice. This supports more targeted identification of hosting-capacity limitations, local voltage-support needs, and the circumstances under which BESS integration can defer or reduce the need for conservative reinforcement responses.

For **charging infrastructure operators and developers**, the framework provides deployment logic that links utilisation potential to network feasibility. Candidate locations are no longer assessed only by travel demand or commercial attractiveness. They are evaluated through a combined techno-economic lens that considers expected utilisation, service quality, queueing exposure, and grid capability. This matters because the thesis repeatedly shows that traffic-attractive locations are not necessarily feeder-feasible, while electrically attractive locations are not necessarily service-effective.

For **strategic planners, transport agencies, and policy actors**, the framework functions as a scenario-evaluation tool for long-horizon infrastructure strategy. It enables comparison of deployment portfolios under alternative assumptions about accessibility targets, flexibility participation, EV uptake, local buffering needs, and market activation. In this role, the framework helps shift EVCS planning away from isolated site selection toward coordinated urban infrastructure design.

For **aggregators and flexibility-market participants**, the framework clarifies that infrastructure value is not determined solely by the presence of bidirectional hardware. Flexibility value depends on whether the site can attract available vehicles, whether participation is behaviourally credible, whether activation aligns with operational needs, and whether the resulting service can be delivered reliably. This distinction is essential for avoiding inflated estimates of V2G value in planning studies.

The strongest practical value of the framework lies in the alignment it creates across these stakeholder perspectives. When utilities, operators, and planners evaluate infrastructure through disconnected assumptions, predictable failures emerge: technically feasible but poorly utilised stations, commercially attractive but feeder-constrained sites, or flexibility-enabled assets whose assumed value never materialises in operation. By structuring the problem through a unified decision-support architecture, the thesis provides a more credible path from data to deployment.

8.4 Cross-Study Design Principles

The three RQs of the thesis should be read as a cumulative progression in planning logic rather than as three stand-alone studies. When interpreted together, they show that EVCS planning is not adequately captured by static siting under exogenous demand. Instead, it should be treated as a coupled infrastructure problem in which network feasibility, mobility-driven utilisation, and operational adaptability are jointly relevant.

The integrated findings of the thesis can be expressed as a set of practical design principles that support deployment-oriented interpretation beyond the specific case studies:

- EVCS siting should be filtered by feeder feasibility at the candidate-selection stage rather than after demand-based site attractiveness has already been established.
- BESS deployment is most effective when treated as a local network-support asset in constrained areas, not merely as a generic add-on to charging infrastructure.
- Accessibility should be embedded directly into the optimisation problem because it changes both realised utilisation and the spatial burden placed on the grid.
- Charging-demand representation should remain time-resolved because static or over-aggregated demand assumptions conceal queueing effects, charging coincidence, and local stress concentration.
- V2G should be modelled as conditional and probabilistic because installed bidirectional capability and practically realisable flexibility are not equivalent.
- Planning assumptions should remain consistent with available operational control capability because infrastructure solutions that depend on idealised control responses are unlikely to remain credible in practice.
- Excessive spatial concentration of EVCS deployment should generally be avoided unless strong feeder conditions or local support resources justify it.
- Iterative planning with operational feedback is preferable to one-shot optimisation in fast-changing electrification environments.

These principles do not replace the formal optimisation framework. Their value lies in translating the thesis's deeper logic into compact deployment guidance for practitioners who may not operate at the full methodological level of the research chapters.

8.5 Deployment and Implementation Roadmap

The methodological strength of a planning framework does not by itself guarantee practical uptake. Translation into real planning environments depends on whether the framework can be supported by available data, implemented within tractable computational structures, and trusted under uncertainty. This section, therefore, outlines the practical conditions required to move from an analytical planning framework to deployable decision-support logic.

Implementation of the proposed framework requires coordinated access to multi-domain data. At a minimum, four broad classes of information are needed: power-network topology, operating limits, and feeder-level technical constraints; time-series demand and distributed-generation data with sufficient temporal resolution; traffic-flow, road-network, and accessibility-related mobility data; and behavioural parameters relevant to charging demand, queueing response, and flexibility participation. These inputs are not optional additions. They define the minimum information base required to preserve the coupling among mobility-driven demand, feeder-level feasibility, and flexibility-enabled operation.

The practical challenge lies not only in data availability but also in data interoperability. In most deployment settings, electrical, mobility, and behavioural datasets are maintained by different institutions, collected at different temporal resolutions, and structured for different operational purposes. The framework, therefore, requires a consistent spatial and temporal mapping layer through which traffic-originating charging demand can be translated into feeder-relevant infrastructure decisions. Without this mapping layer, transport-side demand estimates and power-system feasibility assessments remain disconnected, weakening the reliability of deployment recommendations.

Data governance is equally important. Some of the most valuable input classes, particularly smart-meter demand, mobility traces, and charging-use records, may be commercially sensitive, privacy-sensitive, or institutionally fragmented. Practical use of the framework therefore requires anonymisation, controlled aggregation, explicit access arrangements, and clear responsibility for data validation and refresh cycles. In deployment terms, governance is not an auxiliary administrative issue; it is one of the enabling conditions for coordinated EVCS planning.

From a computational perspective, the framework combines non-convex optimisation, time-indexed simulation, and learning-based decision components. As model fidelity, network size, and scenario breadth increase, computational burden becomes a real implementation issue. Practical deployment should therefore rely on a clear separation between offline planning and online operational support. Infrastructure siting, sizing, scenario comparison, and portfolio design can be performed offline using larger computational budgets and broader scenario ensembles. Operational support, by contrast, should remain lightweight enough to respond to local conditions without re-solving the full planning problem in real time. This distinction is consistent with the structure established in Chapters 4–6, where planning and control are connected but not computationally collapsed into a single monolithic process.

The computational practicality of the framework can be supported through architectural decomposition rather than by assuming unlimited computational capacity. Candidate-site screening, selective spatial aggregation, representative-scenario construction, modular optimisation, and parallel evaluation can reduce the computational burden while preserving the framework's main decision logic. These measures make the framework more usable in planning environments where transparency, runtime, repeatability, and auditability are operational requirements in their own right. Importantly, such measures should be interpreted as implementation strategies for maintaining computational tractability, not as evidence of unrestricted applicability to all network sizes or planning contexts.

The deployability of the framework ultimately depends on whether its outputs can be trusted under uncertainty. In practical terms, planning recommendations must remain credible when demand, behaviour, network conditions, and the availability of flexibility deviate from nominal assumptions. Three implementation risks are particularly important. First, charging demand may be overestimated, leading to underutilised infrastructure and inflated investment requirements. Second, feeder constraints may be underestimated, leading to hidden voltage-security risks or excessive reliance on future reinforcement. Third, flexibility may be overestimated, especially where V2G participation is assumed more strongly than behavioural, market, or operational conditions justify. These are not merely modelling uncertainties; they are translation risks that can weaken otherwise sophisticated planning frameworks in real deployment environments.

Operational validation should therefore extend beyond numerical convergence or algorithmic feasibility. It should include consistency checks between assumed and realised system response, conservative treatment of uncertain flexibility, sensitivity testing around key behavioural and technical parameters, and periodic recalibration as EV penetration, charging behaviour, traffic patterns, and participation conditions evolve. Reliability, in this context, is not only a matter of technical performance under nominal operation. It is the consistency between what the planning layer assumes and what the operating environment can actually deliver.

Overall, the deployment pathway for the proposed framework should be staged. In its first practical use, the framework is most suitable as an offline decision-support tool for scenario analysis, candidate-site screening, EVCS–BESS portfolio comparison, and flexibility-readiness assessment. With improved data access, institutional coordination, and validation against local operating conditions, selected components can then be integrated into utility, charging-operator, or municipal planning workflows. More advanced operational use, particularly involving real-time flexibility activation or adaptive control, should only be pursued where observability, communication infrastructure, and market participation arrangements are sufficiently mature. This staged pathway preserves the technical value of the framework while recognising the practical constraints that shape implementation in real planning environments.

8.6 Planning and Policy Implications

The findings of the thesis imply that EVCS deployment should be treated as a cross-domain planning problem rather than as a grid add-on or a transport convenience measure considered in isolation. In Australian urban contexts, and especially in Melbourne and Victoria, this implication is particularly strong because high distributed PV penetration, growing EV uptake, and increasing interest in flexibility services create a planning environment in which temporal demand shifts and local hosting conditions matter directly.

The stakeholder relevance of this conclusion extends across the Australian energy and transport ecosystem. For DNSPs, the framework supports network-aware EVCS planning, hosting capacity assessment, and the identification of local voltage support needs. For system and market institutions, it clarifies how distributed charging demand and conditional EV flexibility may affect future demand profiles and coordination of flexibility. For charging infrastructure developers and operators, it supports candidate-site screening using demand, accessibility, queueing exposure, feeder feasibility, and flexibility-readiness indicators together. For transport agencies, local governments, and planning authorities, it links charging deployment to urban mobility patterns, service accessibility, and public charging needs. For policy bodies, it supports evidence-based coordination between EV uptake, charging infrastructure readiness, and integrated energy–mobility planning.

The first implication concerns siting. Candidate locations cannot be judged solely by mobility demand or feeder strength. High-demand sites are not automatically optimal if they coincide with constrained electrical locations, and technically favourable sites may remain strategically weak if they impose excessive travel burden or poor accessibility. The practical implication is that EVCS siting should remain a constrained coordination problem from the outset.

The second implication concerns capacity. EVCS and BESS sizing should be based on time-resolved operational conditions rather than static peak-demand reasoning. Across the thesis, time variation in charging demand, PV support, traffic intensity, and local flexibility materially change what constitutes adequate infrastructure capacity. Peak-based design can therefore become systematically conservative and economically inefficient when temporal diversity is ignored.

The third implication concerns V2G readiness. The thesis supports infrastructure readiness for bidirectional flexibility where feasible, but it does not support treating future flexibility as guaranteed support. Infrastructure design should clearly distinguish between enabling V2G capability and operationally relying on V2G value. Bidirectional hardware, communication readiness, and interoperability are necessary conditions, but not sufficient ones. Realisable value still depends on participation behaviour, incentive structures, activation timing, and site-specific deployment conditions.

The fourth implication concerns accessibility and service coverage. Accessibility is not a secondary service metric; it is a structural determinant of where charging demand forms and how infrastructure performs in practice. Travel distance, travel time, and queueing exposure affect whether an EVCS portfolio is merely installed or actually useful. Improving accessibility through denser or more strategically distributed EVCS deployment can reduce user burden and improve service quality, but it can also intensify local network stress if the electrical layer is not coordinated accordingly. Conversely, restricting infrastructure to only the strongest feeder locations may reduce immediate technical risk but degrade service coverage and weaken the practical value of the charging network.

For planners and policymakers, these implications indicate that siting, sizing, accessibility, and flexibility readiness should be aligned during infrastructure planning rather than handled as separate technical, commercial, and policy processes. In the Australian context considered in this thesis, better coordination between electricity-sector planning, transport planning, and local infrastructure strategy is therefore not an optional enhancement. It is a necessary condition for avoiding fragmented, inequitable, and operationally inconsistent rollout.

These implications connect directly to the Australian infrastructure context established in Chapter 1. Australia's EV transition is no longer only a matter of expanding charger numbers; it also requires planning methods that ensure charging infrastructure is electrically supportable, spatially accessible, operationally reliable, and capable of using distributed flexibility under realistic participation conditions. By grounding the analysis in Melbourne and Victoria data, this thesis shows how traffic patterns, residential demand, rooftop PV generation, BESS coordination, and conditional V2G participation can be evaluated within a single decision-support logic. The resulting contribution is a transferable planning perspective for aligning charger rollout, distribution-network readiness, user accessibility, and flexibility activation in future Australian energy–mobility systems.

8.7 Limitations and Translation Boundaries

Despite its contributions, the thesis should be interpreted within clearly defined boundaries of validity and translation. Stating these boundaries strengthens, rather than weakens, the credibility of the work because it clarifies what the framework can reliably support and what remains outside its present scope.

A first limitation concerns temporal scope. The case studies are based on representative weekday operation over a 24-hour horizon with 48 half-hour intervals. This resolution is appropriate for planning-oriented analysis because it captures the principal daily interactions among traffic flow, residential demand, PV generation, and EV charging. However, it does not explicitly model rare but consequential events such as prolonged outages, emergency charging surges, multi-day weather anomalies, or severe traffic disruptions.

A second limitation concerns behavioural abstraction. Although the thesis incorporated a richer behavioural representation than many conventional EVCS planning studies, including SOC-dependent charging probability, queueing effects, heterogeneous V2G participation, and market-activation logic, user behaviour was still represented probabilistically rather than through survey-calibrated microsimulation or full agent-based behavioural calibration. The resulting findings should therefore be interpreted as system-level planning insights rather than exact predictions of individual user actions.

A third limitation concerns network abstraction and geographic representation. On the electrical side, the framework used modified IEEE 33-bus and 123-bus feeders populated with real Victorian data rather than proprietary utility feeder models. On the transportation side, the Melbourne case study was represented as a graph-based mobility structure rather than a complete microscopic traffic simulation. These choices are methodologically appropriate for strategic infrastructure planning, but they define the scale at which the findings should be generalised.

A fourth limitation concerns uncertainty in future conditions and data dependency. The framework depends on the availability, preprocessing, and quality of multi-domain datasets, including load profiles, PV output, traffic conditions, and behavioural assumptions. Future EV uptake, charger standards, tariff structures, and market participation may evolve in ways that alter the precise quantitative outcomes of infrastructure planning. The thesis should therefore be interpreted as providing a structured planning framework that can be adapted to comparable contexts, rather than a fixed forecast of future infrastructure layouts.

A fifth limitation concerns computational intensity. Although the modular GA–DDPG architecture remained computationally tractable under the case-study conditions, larger real networks, richer scenario ensembles, and higher-fidelity behavioural layers may impose substantial runtime and model-management burdens. This does not weaken the conceptual framework, but it makes computational design an important part of practical translation.

A sixth limitation concerns adoption readiness. The framework is reproducible in a practical engineering sense because its modelling structure, data-processing logic, decision sequence, and optimisation settings are explicitly documented throughout the thesis. However, reproducibility should not be interpreted as identical numerical replication under all conditions. Because the framework includes stochastic optimisation and RL, some run-to-run variation is expected unless all seeds, environments, and initial states are fixed identically. The more relevant point is that the framework can be reconstructed, tested, and re-applied under equivalent assumptions. These limitations also define how the thesis should be interpreted beyond the specific case-study environment.

Transferability follows the same principle. What transfers across settings is the decision structure: the coupling of network feasibility, mobility-driven demand, flexibility participation, and operational support. What does not transfer automatically are case-specific calibrated values, traffic intensities, feeder-specific hosting margins, or participation profiles. Application in a new region, therefore, requires recalibration rather than direct numerical reuse. The framework should be understood as an adaptable planning architecture, not as a fixed template of universally valid parameter values.

Taken together, these limitations define the conditions under which the findings are valid: strategic, data-informed planning of EV charging infrastructure under realistic daily urban conditions, with explicit treatment of cross-domain interactions, conditional flexibility, and operational feasibility.

8.8 Future Research and Translation Opportunities

The results of the thesis point to several important directions for future work.

The first concerns long-term infrastructure planning under uncertainty. The present thesis focused on representative daily operating environments, which are appropriate for studying time-varying interactions among demand, traffic, and flexibility. A natural extension is multi-year planning in which EV uptake, PV penetration, tariff structures, charging technologies, and flexibility participation evolve. Such extensions would strengthen the framework's usefulness for staged rollout, investment timing, and infrastructure expansion under uncertainty.

The second concerns computational acceleration. Because the integrated planning problem combines time-indexed simulation, non-convex optimisation, and learning-based components, future work should explore surrogate-assisted optimisation, decomposition approaches, machine-learning-based approximations, and parallel computing strategies to improve runtime efficiency for larger, more detailed scenario-based applications.

The third concerns richer behavioural modelling. Although the thesis moved materially beyond static charging assumptions, future work could incorporate survey-calibrated user-preference models, dynamic station-choice behaviour, agent-based mobility simulation, and finer segmentation of charging purposes across residential, workplace, retail, depot, and freight contexts. This would further strengthen the realism of both charging-demand estimation and V2G participation modelling.

The fourth concerns deeper integration between markets and aggregators. The present framework incorporated market-driven flexibility activation and participation uncertainty, but future research could more explicitly represent aggregator strategies, settlement logic, dynamic pricing, ancillary-service participation, and commercial coordination. This would improve the direct interpretability of the V2G value under realistic regulatory and market arrangements.

The fifth concerns resilience-oriented and digital-twin extensions. Future work could test the framework under feeder contingencies, communication failures, renewable intermittency shocks, and transport disruption scenarios, thereby extending the present logic toward resilience analysis. Similarly, adaptation to utility-specific feeder models, GIS-linked planning systems, and digital-twin environments would strengthen the framework's translational pathway for operational planning practice.

The sixth concerns broader adaptation and industry adoption. Because the framework is modular and data-driven, it is suitable for adaptation to other Australian metropolitan regions and, with appropriate recalibration, to international urban settings facing similar electrification pressures. Practical applications include DNSP planning studies, charging network rollout analysis, municipal infrastructure strategy, and flexibility readiness assessment. Future work should therefore advance not only the methodological sophistication of the framework, but also its integration into real planning workflows.

8.9 Final Remarks

This thesis began with a practical question: how should EV charging infrastructure be planned when electricity networks, transportation systems, user behaviour, and flexibility resources interact in ways that conventional single-domain planning cannot adequately represent? The answer developed throughout the thesis is that EVCS planning must be treated as a coordinated infrastructure design problem rather than a static siting task.

By progressing from grid-aware EVCS–BESS planning to traffic-informed coupled PDN–TN planning, and finally to V2G- and market-aware flexibility integration, the thesis showed that increasing modelling realism materially changes infrastructure decisions, stakeholder trade-offs, and the meaning of a good planning outcome. Electrical feasibility, accessibility, and flexibility are not optional additions to charging infrastructure planning; they are structural determinants of deployment quality.

The final contribution of the thesis is therefore broader than the sum of its individual studies. It provides a coherent, data-driven, and practically interpretable decision framework for EV charging infrastructure planning in future smart energy and mobility systems. Within the scope defined in this thesis, that framework offers a credible basis for more robust, efficient, and industry-relevant infrastructure decisions under the evolving conditions of urban electrification.

Bibliography

[1] M. J. Sajid, Q. Cao, and W. Kang, "Transport sector carbon linkages of eu's top seven emitters," *Transport Policy*, vol. 80, pp. 24–38, 2019.

[2] M. Yang, Y. Chen, S. Huang, and L. Chen, "Recent advances in coordination and optimization of power-transportation systems: An overview," *Renewable and Sustainable Energy Reviews*, vol. 220, p. 115786, 2025.

[3] J. Li, A. Chew, and H. Wang, "Investigating state-of-the-art planning strategies for electric vehicle charging infrastructures in coupled transport and power networks: A comprehensive review," *Progress in Energy*, 2024.

[4] M. Kumar, A. Kumar, A. M. Soomro, M. Baloch, S. T. Chaudhary, and M. A. Shaikh, "A comprehensive review of optimizing multi-energy multi-objective distribution systems with electric vehicle charging stations," *World Electric Vehicle Journal*, vol. 15, no. 11, p. 523, 2024.

[5] S. Shao, M. Pipattanasomporn, and S. Rahman, "Grid integration of electric vehicles and demand response with customer choice," *IEEE transactions on smart grid*, vol. 3, no. 1, pp. 543–550, 2012.

[6] S. Tirunagari, M. Gu, and L. Meegahapola, "Reaping the benefits of smart electric vehicle charging and vehicle-to-grid technologies: Regulatory, policy and technical aspects," *IEEE Access*, vol. 10, pp. 114 657–114 672, 2022.

[7] K. E. Adetunji, I. W. Hofsajer, A. M. Abu-Mahfouz, and L. Cheng, "An optimization planning framework for allocating multiple distributed energy resources and electric vehicle charging stations in distribution networks," *Appl. Energy*, vol. 322, p. 119513, 2022.

[8] R. Sa'adati, M. Jafari-Nokandi, and J. Saebi, "Allocation of ress and pev fast-charging station on coupled transportation and distribution networks," *Sustainable Cities and Society*, vol. 65, p. 102527, 2021.

[9] X. Wang, M. Shahidehpour, C. Jiang, and Z. Li, "Coordinated planning strategy for electric vehicle charging stations and coupled traffic-electric networks," *IEEE Transactions on Power Systems*, vol. 34, no. 1, pp. 268–279, 2018.

[10] J. Liu, J. Sun, and X. Qi, "Optimal placement of charging stations in road networks: A reinforcement learning approach with attention mechanism," *Applied Sciences*, vol. 13, no. 14, 2023.

[11] Y. Wang, Y. Zhao, S. Gan, K. Li, Y. Chen, and J. Lai, "Optimization of charging stations integrated with dynamic transportation systems in metropolises," *Transportation Research Part D: Transport and Environment*, vol. 119, p. 103726, 2023.

[12] Department of Climate Change, Energy, the Environment and Water, "National Electric Vehicle Strategy: Increasing the Uptake of EVs to Reduce Our Emissions and Improve the Wellbeing of Australians," https://www.dcceew.gov.au/energy/transport/national-electric-vehicle-strategy, 2023, australian Government, accessed: 18 May 2026.

[13] Australian Energy Market Operator Learning Academy, "NEM Operational Forecasting Overview," AEMO Learning Academy online training material. Available: https://www.aemolearningacademy.aemo.com.au/, 2026.

[14] Australian Energy Market Operator, "National Electricity Market Overview," AEMO Learning Academy online training material. Available: https://www.aemolearningacademy.aemo.com.au/, 2026.

[15] Department of Climate Change, Energy, the Environment and Water, "National Electric Vehicle Strategy Annual Update 2024–25," https://www.dcceew.gov.au/energy/transport/national-electric-vehicle-strategy, 2025, australian Government, accessed: 18 May 2026.

[16] Electric Vehicle Council, "State of EVs 2025," https://electricvehiclecouncil.com.au/, 2025, accessed: 18 May 2026.

[17] S. G. Motlagh, J. Oladigbolu, and L. Li, "A review on electric vehicle charging station operation considering market dynamics and grid interaction," *Applied Energy*, vol. 392, p. 126058, 2025.

[18] T. Yuvaraj, K. Devabalaji, J. A. Kumar, S. B. Thanikanti, and N. I. Nwulu, "A comprehensive review and analysis of the allocation of electric vehicle charging stations in distribution networks," *IEEE access*, vol. 12, pp. 5404–5461, 2024.

[19] W. Gan, M. Shahidehpour, M. Yan, J. Guo, W. Yao, A. Paaso, L. Zhang, and J. Wen, "Coordinated planning of transportation and electric power networks with the proliferation of electric vehicles," *IEEE Trans. Smart Grid*, vol. 11, no. 5, pp. 4005–4016, 2020.

[20] Y. Hou, C. Zhao, C. Xue, Y. Wang, Y. Liang, J. Hu, Y. Hou, J. Chen, and H. Zhao, "Coordinated control method of photovoltaic energy storage charging integrated charging station," in *Third International Conference on Mechanical, Electronics, and Electrical and Automation Control (METMS 2023)*, X. Yuan and G. Wu, Eds., vol. 12722, International Society for Optics and Photonics. SPIE, 2023, p. 127222N.

[21] J. G. E. C. A. E. S. P. A. H. B. M. D. M. Keen, Jeremy and F. Eldali, "Distribution capacity expansion: Current practice, opportunities and decision support," *CO: National Renewable Energy Laboratory*, 2022.

[22] A. Pratap, P. Tiwari, R. Maurya, and B. Singh, "Minimisation of electric vehicle charging stations impact on radial distribution networks by optimal allocation of dstatcom and dg using african vulture optimisation algorithm," *Int. J. Amb. Energy*, vol. 43, no. 1, pp. 8653–8672, 2022.

[23] R. M. Arvind Pratap, Prabhakar Tiwari and B. Singh, "A novel hybrid optimization approach for optimal allocation of distributed generation and distribution static compensator with network reconfiguration in consideration of electric vehicle charging station," *Electric Power Comp. Syst.*, vol. 51, no. 13, pp. 1302–1327, 2023.

[24] Y. Zhang, S. Ren, Z. Y. Dong, Y. Xu, K. Meng, and Y. Zheng, "Optimal placement of battery energy storage in distribution networks considering conservation voltage reduction and stochastic load composition," *IET Gen., Trans. & Dist.*, vol. 11, no. 15, pp. 3862–3870, 2017.

[25] K. Balu and V. Mukherjee, "Optimal deployment of electric vehicle charging stations, renewable distributed generation with battery energy storage and distribution static compensator in radial distribution network considering uncertainties of load and generation," *Appl.Energy*, vol. 359, p. 122707, 2024.

[26] O. Erdinç, A. Taşcıkaraoğlu, N. G. Paterakis, I. Dursun, M. C. Sinim, and J. P. Catalão, "Comprehensive optimization model for sizing and siting of dg units, ev charging stations, and energy storage systems," *IEEE Trans. Smart Grid*, vol. 9, no. 4, pp. 3871–3882, 2017.

[27] A. Pal, A. Bhattacharya, and A. K. Chakraborty, "Placement of public fast-charging station and solar distributed generation with battery energy storage in distribution network considering uncertainties and traffic congestion," *J. Energy Storage*, vol. 41, p. 102939, 2021.

[28] C. Li, L. Zhang, Z. Ou, Q. Wang, D. Zhou, and J. Ma, "Robust model of electric vehicle charging station location considering renewable energy and storage equipment," *Energy*, vol. 238, p. 121713, 2022.

[29] Y. T, S. T D, U. Meyyappan, B. Aljafari, and S. B. Thanikanti, "Optimizing the allocation of renewable dgs, dstatcom, and bess to mitigate the impact of electric vehicle charging stations on radial distribution systems," *Heliyon*, vol. 9, no. 12, p. e23017, 2023.

[30] A. Eid and M. Abdel-Salam, "Management of electric vehicle charging stations in low-voltage distribution networks integrated with wind turbine–battery energy storage systems using metaheuristic optimization," *Engineering Optimization*, vol. 56, no. 9, pp. 1335–1360, 2024.

[31] J. J. Saldanha, A. Nied, R. Trentini, and R. Kutzner, “Ai-based optimal allocation of bess, ev charging station and dg in distribution network for losses reduction and peak load shaving,” *Electric Power Syst. Res.*, vol. 234, p. 110554, 2024.

[32] L. A. Wong, V. K. Ramachandaramurthy, S. L. Walker, P. Taylor, and M. J. Sanjari, “Optimal placement and sizing of battery energy storage system for losses reduction using whale optimization algorithm,” *J. Energy Storage*, vol. 26, p. 100892, 2019.

[33] S. Deb, K. Tammi, X.-Z. Gao, K. Kalita, and P. Mahanta, “A hybrid multi-objective chicken swarm optimization and teaching learning based algorithm for charging station placement problem,” *IEEE Access*, vol. 8, pp. 92 573–92 590, 2020.

[34] K. Balu and V. Mukherjee, “Optimal allocation of electric vehicle charging stations and renewable distributed generation with battery energy storage in radial distribution system considering time sequence characteristics of generation and load demand,” *J. Energy Storage*, vol. 59, p. 106533, 2023.

[35] A. Eid, O. Mohammed, and H. El-Kishky, “Efficient operation of battery energy storage systems, electric-vehicle charging stations and renewable energy sources linked to distribution systems,” *J. Energy Storage*, vol. 55, p. 105644, 2022.

[36] P. Ray, C. Bhattacharjee, and K. R. Dhenuvakonda, “Swarm intelligence-based energy management of electric vehicle charging station integrated with renewable energy sources,” *Int. J. Energy Res.*, vol. 46, no. 15, pp. 21 598–21 618, 2022.

[37] N. Kumar, T. Kumar, S. Nema, and T. Thakur, “A multiobjective planning framework for ev charging stations assisted by solar photovoltaic and battery energy storage system in coupled power and transportation network,” *Int. J. Energy Res.*, vol. 46, no. 4, pp. 4462–4493, 2022.

[38] S. Çelik and Şeyda Ok, “Electric vehicle charging stations: Model, algorithm, simulation, location, and capacity planning,” *Heliyon*, vol. 10, no. 7, p. e29153, 2024.

[39] R. Saadati, M. Jafari-Nokandi, and J. Saebi, “Allocation of ress and pev fast-charging station on coupled transportation and distribution networks,” *Sustainable Cities and Society*, vol. 65, p. 102527, 2021.

[40] M. Campaña and E. Inga, “Optimal deployment of fast-charging stations for electric vehicles considering the sizing of the electrical distribution network and traffic condition,” *Energy Reports*, vol. 9, pp. 5246–5268, 2023.

[41] M. Campaña and E. Inga, “Optimal deployment of fast-charging stations for electric vehicles considering the sizing of the electrical distribution network and traffic condition,” *Energy Reports*, vol. 9, pp. 5246–5268, 2023.

[42] T. Schettini, M. dell’Amico, F. Fumero, O. Jabali, and F. Malucelli, “Locating and sizing electric vehicle chargers considering multiple technologies,” *Energies*, vol. 16, no. 10, 2023.

[43] W. Wang, Y. Liu, W. Wei, and L. Wu, “A bilevel ev charging station and dc fast charger planning model for highway network considering dynamic traffic demand and user equilibrium,” *IEEE Trans. Smart Grid*, vol. 15, no. 1, pp. 714–728, 2024.

[44] C. Li, D. Carta, and A. Benigni, “Ev charging station placement considering v2g and human factors in multi-energy systems,” *IEEE Trans. Smart Grid*, vol. 16, no. 1, pp. 529–540, 2025.

[45] Y. Li, J. Wang, W. Wang, C. Liu, and Y. Li, “Dynamic pricing based electric vehicle charging station location strategy using reinforcement learning,” *Energy*, vol. 281, p. 128284, 2023.

[46] H. Yao, Y. Xiang, C. Gu, and J. Liu, “Optimal planning of distribution systems and charging stations considering pv-grid-ev transactions,” *IEEE Trans. Smart Grid*, vol. 16, no. 1, pp. 691–703, 2025.

[47] F. Ahmad, A. Iqbal, I. Ashraf, M. Marzband, and I. Khan, “Optimal location of electric vehicle rapid charging stations in power distribution network and transportation network with v2g strategies,” in *2021 IEEE Transportation Electrification Conference (ITEC-India)*. IEEE, 2021, pp. 1–5.

[48] Z. Liang, T. Qian, M. Korkali, R. Glatt, and Q. Hu, "A vehicle-to-grid planning framework incorporating electric vehicle user equilibrium and distribution network flexibility enhancement," *Applied Energy*, vol. 376, p. 124231, 2024.

[49] M. Bilal and M. Rizwan, "Integration of electric vehicle charging stations and capacitors in distribution systems with vehicle-to-grid facility," *Energy sources, part a: recovery, utilization, and environmental effects*, vol. 47, no. 1, pp. 7700–7729, 2025.

[50] C. Li, D. Carta, and A. Benigni, "Ev charging station placement considering v2g and human factors in multi-energy systems," *IEEE transactions on smart grid*, vol. 16, no. 1, pp. 529–540, 2024.

[51] I. A. Soliman, V. Tulsky, H. A. Abd el Ghany, and A. E. ElGebaly, "A comprehensive simultaneous allocation algorithm of charging stations and vehicle to grid operation in radial networks," *Computers and Electrical Engineering*, vol. 120, p. 109836, 2024.

[52] I. A. Soliman, V. Tulsky, H. Abd el Ghany, and A. E. ElGebaly, "Efficient allocation of capacitors and vehicle-to-grid integration with electric vehicle charging stations in radial distribution networks," *Applied Energy*, vol. 377, p. 124745, 2025.

[53] D. Liu, P. Zeng, S. Cui, and C. Song, "Deep reinforcement learning for charging scheduling of electric vehicles considering distribution network voltage stability," *Sensors*, vol. 23, no. 3, p. 1618, 2023.

[54] K. Bachiri, A. Yahyaouy, H. Gualous, M. Malek, Y. Bennani, P. Makany, and N. Rogovschi, "Multi-agent ddpg based electric vehicles charging station recommendation," *Energies*, vol. 16, no. 16, p. 6067, 2023.

[55] VicRoads Open Data, "Vicroads open data portal," https://vicroadsopendata-vicroadsmaps.opendata.arcgis.com/, accessed: 2025-07-18.

[56] DataVic, "Victorian government data directory," https://discover.data.vic.gov.au/, accessed: 2025-07-18.

[57] Melbourne Transport Map, "Comprehensive public transport map for greater melbourne and geelong," https://melbournetransportmap.com/, accessed: 2025-07-18.

[58] PVOutput.org, "Free solar power monitoring and community platform," https://www.pvoutput.org, accessed: 2025-07-18.

[59] S. Erlander and N. F. Stewart, *The gravity model in transportation analysis: theory and extensions*. Vsp, 1990, vol. 3.

[60] B. Vahdani, R. Tavakkoli-Moghaddam, M. Modarres, and A. Baboli, "Reliable design of a forward/reverse logistics network under uncertainty: A robust-m/m/c queuing model," *Transportation Research Part E: Logistics and Transportation Review*, vol. 48, no. 6, pp. 1152–1168, 2012.

[61] Z. Moghaddam, I. Ahmad, D. Habibi, and Q. V. Phung, "Smart charging strategy for electric vehicle charging stations," *IEEE Trans. Transport. Electri.*, vol. 4, no. 1, pp. 76–88, 2018.

[62] C. A. Griffiths, C. Giannetti, K. T. Andrzejewski, and A. Morgan, "Comparison of a bat and genetic algorithm generated sequence against lead through programming when assembling a pcb using a six-axis robot with multiple motions and speeds," *IEEE Trans. Ind. Inf.*, vol. 18, no. 2, pp. 1102–1110, 2021.

[63] K. E. Adetunji, I. W. Hofsajer, A. M. Abu-Mahfouz, and L. Cheng, "A two-tailed pricing scheme for optimal ev charging scheduling using multiobjective reinforcement learning," *IEEE Trans. Ind. Inf.*, 2023.

[64] W. Pinthurat, T. Surinkaew, and B. Hredzak, "Simultaneous voltage regulation and unbalance compensation in distribution systems with an information-driven learning approach," *IEEE Trans. Ind. Inf.*, 2023.

[65] Z. L. E. R. L. S. L. M. S. L.-S. E. W. Yanbo Ge, D-Y Lee and F. Yang, "Modeling future demand for ev charging infrastructure," *CO: National Renewable Energy Laboratory*, 2023.

[66] A. Pal, A. Bhattacharya, and A. K. Chakraborty, "Placement of public fast-charging station and solar distributed generation with battery energy storage in distribution network considering uncertainties and traffic congestion," *Journal of Energy Storage*, vol. 41, p. 102939, 2021.

[67] L. Calearo, M. Marinelli, and C. Ziras, "A review of data sources for electric vehicle integration studies," *Renewable and Sustainable Energy Reviews*, vol. 151, p. 111518, 2021.

[68] M. Daskin, "Network and discrete location: Models, algorithms and applications," *Journal of the Operational Research Society*, vol. 48, 01 1996.

[69] M. Alizadeh, A. M. Amani, L. Meegahapola, M. Jalili, and O. Hill, "Optimal integration of ev charging stations into distribution network planning and operation," *IEEE Transactions on Industrial Informatics*, 2025.

[70] E. Bakhuis, J. A. Annema, K. Vringer, and B. van Wee, "Exploring user willingness to adopt vehicle-to-grid (v2g): A statistical analysis in the netherlands," *Energy Policy*, vol. 185, p. 113090, 2025.

[71] N. Kumar, T. Kumar, S. Nema, and T. Thakur, "A comprehensive planning framework for electric vehicles fast charging station assisted by solar and battery based on queueing theory and non-dominated sorting genetic algorithm-ii in a co-ordinated transportation and power network," *Journal of Energy Storage*, vol. 49, p. 104180, 2022.

[72] Y. Tao, J. Qiu, S. Lai, X. Sun, and J. Zhao, "Adaptive integrated planning of electricity networks and fast charging stations under electric vehicle diffusion," *IEEE Transactions on Power Systems*, vol. 38, no. 1, pp. 499–513, 2022.

[73] M. Schläpfer, H. J. Chew, S. Yean, and B.-S. Lee, "Using mobility patterns for the planning of vehicle-to-grid infrastructures that support photovoltaics in cities," *ArXiv*, vol. abs/2112.15006, 2021. [Online]. Available: https://api.semanticscholar.org/CorpusID:245634568

[74] M. W. Mudiyanselage, F. H. Aghdam, S. M. Kazemi-Razi, K. Chaudhari, M. Marzband, A. Ikpehai, A. Abusorrah, and G. Harris, "A multiagent framework for electric vehicles charging power forecast and smart planning of urban parking lots," *IEEE Transactions on Transportation Electrification*, vol. 10, no. 2, pp. 2844–2857, 2023.

[75] T. Wu, Z. Li, G. Wang, X. Zhang, and J. Qiu, "Low-carbon charging facilities planning for electric vehicles based on a novel travel route choice model," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 6, pp. 5908–5922, 2023.

[76] D. S. Govind and M. Fozdar, "Integrated infrastructure strategy for sustainable electrical vehicles charging stations and transportation networks," in *2024 IEEE 11th Power India International Conference (PIICON)*. IEEE, 2024, pp. 1–6.

[77] Y. Chen, S. Hu, Y. Zheng, S. Xie, Q. Hu, and Q. Yang, "Coordinated expansion planning of coupled power and transportation networks considering dynamic network equilibrium," *Applied Energy*, vol. 360, p. 122789, 2024.

[78] Y. Zhao, Y. Guo, Q. Guo, H. Zhang, and H. Sun, "Deployment of the electric vehicle charging station considering existing competitors," *IEEE Transactions on smart grid*, vol. 11, no. 5, pp. 4236–4248, 2020.

[79] H. Zhang, J. Qiu, and Y. Wang, "Planning strategy of fast-charging stations in coupled transportation and distribution systems considering human health impact," *International Journal of Electrical Power & Energy Systems*, vol. 133, p. 107316, 2021.

[80] Z. Zhao, C. K. Lee, and J. Huo, "Ev charging station deployment on coupled transportation and power distribution networks via reinforcement learning," *Energy*, vol. 267, p. 126555, 2023.

[81] Q. Zhao, Z. Wei, H. Liu, Y. Han, and J. Wang, "Optimal semi-dynamic traffic and power flow assignment of coupled transportation and power distribution systems for electric vehicles," *IET Electrical Systems in Transportation*, vol. 13, no. 1, p. e12064, 2023.

[82] Y. Zhang, J. Chen, L. Cai, and J. Pan, "Ev charging network design with transportation and power grid constraints," in *IEEE INFOCOM 2018-IEEE conference on computer communications*. IEEE, 2018, pp. 2492–2500.

[83] X. Zhang, P. Li, J. Hu, M. Liu, G. Wang, J. Qiu, and K. W. Chan, "Yen's algorithm-based charging facility planning considering congestion in coupled transportation and power systems," *IEEE Transactions on Transportation Electrification*, vol. 5, no. 4, pp. 1134–1144, 2019.

[84] D. Mao, J. Tan, and J. Wang, "Location planning of pev fast charging station: An integrated approach under traffic and power grid requirements," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 1, pp. 483–492, 2020.

[85] S. Deb, K. Tammi, X.-Z. Gao, K. Kalita, P. Mahanta, and S. Cross, "A robust two-stage planning model for the charging station placement problem considering road traffic uncertainty," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 7, pp. 6571–6585, 2021.

[86] B. Zhou, G. Chen, T. Huang, Q. Song, and Y. Yuan, "Planning pev fast-charging stations using data-driven distributionally robust optimization approach based on ϕ-divergence," *IEEE Transactions on Transportation Electrification*, vol. 6, no. 1, pp. 170–180, 2020.

[87] H. Yang, X. Li, J. Ge, P. Huang, and G. Zhou, "Planning of fast-charging stations considering heterogeneous charging patterns in electrified transportation networks," in *2023 8th Asia Conference on Power and Electrical Engineering (ACPEE)*. IEEE, 2023, pp. 312–316.

[88] M. Hosseini, A. Rahmani, and F. Hooshmand, "A robust model for recharging station location problem," *Operational Research*, vol. 22, no. 4, pp. 4397–4440, 2022.

[89] L. Li, Y. Zhang, C. Cheng, H. Du, and S. Liu, "A heuristic algorithm for deploying electric taxi charging stations to enhance service quality," *Applied Sciences*, vol. 14, no. 18, p. 8536, 2024.

[90] M. Erbaş, M. Kabak, E. Özceylan, and C. Çetinkaya, "Optimal siting of electric vehicle charging stations: A gis-based fuzzy multi-criteria decision analysis," *Energy*, vol. 163, pp. 1017–1031, 2018.

[91] W. Gan, M. Shahidehpour, M. Yan, J. Guo, W. Yao, A. Paaso, L. Zhang, and J. Wen, "Coordinated planning of transportation and electric power networks with the proliferation of electric vehicles," *IEEE Transactions on Smart Grid*, vol. 11, no. 5, pp. 4005–4016, 2020.

[92] T. Qian, C. Shao, X. Li, X. Wang, and M. Shahidehpour, "Enhanced coordinated operations of electric power and transportation networks via ev charging services," *IEEE Transactions on Smart Grid*, vol. 11, no. 4, pp. 3019–3030, 2020.

[93] S. Lv, Z. Wei, G. Sun, S. Chen, and H. Zang, "Optimal power and semi-dynamic traffic flow in urban electrified transportation networks," *IEEE Transactions on Smart Grid*, vol. 11, no. 3, pp. 1854–1865, 2019.

[94] H. Zhang, Z. Hu, and Y. Song, "Power and transport nexus: Routing electric vehicles to promote renewable power integration," *IEEE Transactions on Smart Grid*, vol. 11, no. 4, pp. 3291–3301, 2020.

[95] A. Golab, S. Zwickl-Bernhard, T. Perger, and H. Auer, "Spatio-temporal charging model for the identification of bottlenecks in planned highway charging infrastructure for passenger bevs," *e & i Elektrotechnik und Informationstechnik*, vol. 139, no. 8, pp. 693–711, 2022.

[96] C. Shao, K. Li, T. Qian, M. Shahidehpour, and X. Wang, "Generalized user equilibrium for coordination of coupled power-transportation network," *IEEE Transactions on Smart Grid*, vol. 14, no. 3, pp. 2140–2151, 2022.

[97] L. Affolabi, M. Shahidehpour, F. Rahimi, F. Aminifar, K. Nodehi, and S. Mokhtari, "Hierarchical transactive energy scheduling of electric vehicle charging stations in constrained power distribution and transportation networks," *IEEE Transactions on Transportation Electrification*, vol. 9, no. 2, pp. 3398–3409, 2022.

[98] R. Saadati, M. Jafari-Nokandi, J. Saebi, and S. H. Hosseini, "Optimal location of fast charging stations alongside pricing design from distribution company viewpoint considering renewable energy resource: A modified capacitated flow-capturing location model," *Sustainable Energy, Grids and Networks*, vol. 34, p. 100989, 2023.

[99] S. Sun, X. Zhou, H. Zhu, W. Meng, and Z. Zhang, "Optimal planning of pev fast charging stations considering transportation-power network couplings," in *2021 IEEE 4th International Electrical and Energy Conference (CIEEC)*. IEEE, 2021, pp. 1–6.

[100] G. Ferro, R. Minciardi, L. Parodi, and M. Robba, "Optimal planning of charging stations in coupled transportation and power networks based on user equilibrium conditions," *IEEE Transactions on Automation Science and Engineering*, vol. 19, no. 1, pp. 48–59, 2021.

[101] X. Duan, Z. Hu, Y. Song, K. Strunz, Y. Cui, and L. Liu, "Planning strategy for an electric vehicle fast charging service provider in a competitive environment," *IEEE Transactions on Transportation Electrification*, vol. 8, no. 3, pp. 3056–3067, 2022.

[102] G. Zhou, Q. Dong, Y. Zhao, H. Wang, L. Jian, and Y. Jia, "Bilevel optimization approach to fast charging station planning in electrified transportation networks," *Applied Energy*, vol. 350, p. 121718, 2023.

[103] M. Yuan, K. Ji, Y. Liu, S. Chen, T. Jin, and C. Li, "Coordinated planning of charging stations and distribution networks with v2g interaction and line capacity margin considerations," in *2025 6th International Conference on Electrical Technology and Automatic Control (ICETAC)*. IEEE, 2025, pp. 241–245.

[104] F. Xia, H. Chen, M. Yan, W. Gan, Q. Zhou, T. Ding, X. Wang, L. Wang, and L. Chen, "Market-based coordinated planning of fast charging station and dynamic wireless charging system considering energy demand assignment," *IEEE Transactions on Smart Grid*, vol. 15, no. 2, pp. 1913–1925, 2023.

[105] J. Zheng, X. Wei, Z. Zhang, J. Xue, R. Chen, and S. Xie, "A tri-level planning strategy for integrated power and transport systems incorporating ev elastic charging behaviors," *Applied Energy*, vol. 396, p. 126207, 2025.

[106] F. Ahmad, A. Iqbal, I. Ashraf, M. Marzband *et al.*, "Optimal location of electric vehicle charging station and its impact on distribution network: A review," *Energy Reports*, vol. 8, pp. 2314–2333, 2022.

[107] V. Vijayalakshmi, P. Arumugam, A. Ananthi Christy, and R. Brindha, "Simultaneous allocation of ev charging stations and renewable energy sources: An elite rernn-m2mpa approach," *International Journal of Energy Research*, vol. 46, no. 7, pp. 9020–9040, 2022.

[108] S. Raval, T. Natarajan, and S. Deb, "A novel levy-enhanced opposition-based gradient-based optimizer (le-ob-gbo) for charging station placement," *Electronics*, vol. 12, no. 7, p. 1522, 2023.

[109] F. Ahmad and M. Bilal, "Allocation of plug-in electric vehicle charging station with integrated solar powered distributed generation using an adaptive particle swarm optimization," *Electrical engineering*, vol. 106, no. 3, pp. 2595–2608, 2024.

[110] A. Kapoor, V. S. Patel, A. Sharma, and A. Mohapatra, "Optimal planning of fast ev charging stations in a coupled transportation and electrical power distribution network," *IEEE Transactions on Automation Science and Engineering*, 2023.

[111] N. Kumar, T. Kumar, S. Nema, and T. Thakur, "Reliability oriented techno-economic assessment of fast charging stations with photovoltaic and battery systems in paired distribution & urban network," *Journal of Energy Storage*, vol. 72, p. 108814, 2023.

[112] K. Nareshkumar, N. Sikder, and D. Das, "Optimal planning of battery swapping stations for e-taxis in a coupled transportation-distribution network," in *2025 IEEE Energy Conversion Congress & Exposition Asia (ECCE-Asia)*. IEEE, 2025, pp. 1–5.

[113] B. V. Kumar and A. Farhan, "Multi-objective planning of charging stations and shunt capacitors considering driving range-based traffic flow in distribution networks," *Journal of Energy Storage*, vol. 138, p. 118585, 2025.

[114] Y. Guo, X. Zhang, D. Li, C. Gu, C. Lu, T. Ji, and Y. Wang, "Multiobjective electric vehicle charging network planning considering chance-constraint on the travel distance for charging," *IET Electrical Systems in Transportation*, vol. 2023, no. 1, p. 6690544, 2023.

[115] L. Geng, Z. Lu, L. He, J. Zhang, X. Li, and X. Guo, "Smart charging management system for electric vehicles in coupled transportation and power distribution systems," *Energy*, vol. 189, p. 116275, 2019.

[116] K. Nareshkumar and D. Das, "Economic planning of ev charging stations and renewable dgs in a coupled transportation-reconfigurable distribution network considering ev range anxiety," *Electrical Engineering*, vol. 107, no. 5, pp. 5787–5806, 2025.

[117] J. Zhu, F. Chen, S. Liu, Y. An, N. Wu, and X. Zhao, "Multi-objective planning optimization of electric vehicle charging stations with coordinated spatiotemporal charging demand," *IEEE Transactions on Intelligent Transportation Systems*, 2024.

[118] S. Sun, Q. Yang, J. Ma, A. J. Ferré, and W. Yan, "Hierarchical planning of pev charging facilities and dgs under transportation-power network couplings," *Renewable Energy*, vol. 150, pp. 356–369, 2020.

[119] A. Pal, A. Bhattacharya, and A. K. Chakraborty, "Allocation of electric vehicle charging station considering uncertainties," *Sustainable Energy, Grids and Networks*, vol. 25, p. 100422, 2021.

[120] T. Qian, Z. Liang, S. Chen, Q. Hu, and Z. Wu, "A tri-level demand response framework for evcs flexibility enhancement in coupled power and transportation networks," *IEEE Transactions on Smart Grid*, vol. 16, no. 1, pp. 598–611, 2024.

[121] S. F. Keleshteri, T. Niknam, M. Ghiasi, and H. Chabok, "New optimal planning strategy for plug-in electric vehicles charging stations in a coupled power and transportation network," *The Journal of Engineering*, vol. 2023, no. 3, p. e12252, 2023.

[122] F. Keramati, H. R. Mohammadi, and G. R. Shiran, "Determining optimal location and size of pev fast-charging stations in coupled transportation and power distribution networks considering power loss and traffic congestion," *Sustainable Energy, Grids and Networks*, vol. 38, p. 101268, 2024.

[123] P. Tadayon-Roody, M. Ramezani, and H. Falaghi, "Multi-objective locating of electric vehicle charging stations considering travel comfort in urban transportation system," *IET Generation, Transmission & Distribution*, vol. 15, no. 5, pp. 960–971, 2021.

[124] R. Saadati, J. Saebi, and M. Jafari-Nokandi, "Effect of uncertainties on siting and sizing of charging stations and renewable energy resources: A modified capacitated flow-refueling location model," *Sustainable Energy, Grids and Networks*, vol. 31, p. 100759, 2022.

[125] K. Nareshkumar and D. Das, "Optimal location and sizing of electric vehicles charging stations and renewable sources in a coupled transportation-power distribution network," *Renewable and Sustainable Energy Reviews*, vol. 203, p. 114767, 2024.

[126] A. Pal, A. Bhattacharya, and A. K. Chakraborty, "Planning of ev charging station with distribution network expansion considering traffic congestion and uncertainties," *IEEE Transactions on Industry Applications*, vol. 59, no. 3, pp. 3810–3825, 2023.

[127] R. S. Ferraz, R. S. Ferraz, A. C. Rueda-Medina, and J. F. Fardin, "Novel variable charging pricing strategy applied to the multi-objective planning of integrated fast and slow electric vehicle charging stations and distributed energy resources," *Electric Power Systems Research*, vol. 241, p. 111293, 2025.

[128] T. Boonseng, A. Sangswang, and S. Naetiladdanon, "Optimal design of battery-supported fast-charging systems on australian highways," in *2022 IEEE Transportation Electrification Conference & Expo (ITEC)*. IEEE, 2022, pp. 935–940.

[129] A. Pal, A. Bhattacharya, and A. K. Chakraborty, "Placement of public fast-charging station and solar distributed generation with battery energy storage in distribution network considering uncertainties and traffic congestion," *Journal of Energy Storage*, vol. 41, p. 102939, 2021.

[130] T. Xu, L. Li, and A. Li, "Hydrogen station allocation under stochastic user-equilibrium network flow," *International Journal of Hydrogen Energy*, vol. 49, pp. 1154–1165, 2024.

[131] M. Abdelaziz, A. Ali, R. Swief, and R. Elazab, "A reliable optimal electric vehicle charging stations allocation," *Ain Shams Engineering Journal*, vol. 15, no. 7, p. 102763, 2024.

[132] H. Li, Y. He, W. Fu, and X. Li, "Bi-level planning of electric vehicle charging station in coupled distribution-transportation networks," *Electric Power Systems Research*, vol. 232, p. 110442, 2024.

[133] R. Xie, W. Wei, M. E. Khodayar, J. Wang, and S. Mei, "Planning fully renewable powered charging stations on highways: A data-driven robust optimization approach," *IEEE transactions on transportation electrification*, vol. 4, no. 3, pp. 817–830, 2018.

[134] F. Xia, H. Chen, M. Shahidehpour, W. Gan, M. Yan, and L. Chen, "Distributed expansion planning of electric vehicle dynamic wireless charging system in coupled power-traffic networks," *IEEE Transactions on Smart Grid*, vol. 12, no. 4, pp. 3326–3338, 2021.

[135] Z. Danping, L. Juan, C. Yuchun, C. Zhongjian, and L. Liping, "Research on electric vehicle charging stations planning based on traffic destination heat data and charger usage data," in *2020 IEEE 5th International Conference on Intelligent Transportation Engineering (ICITE)*. IEEE, 2020, pp. 407–410.

[136] M. Lokhandwala and H. Cai, "Siting charging stations for electric vehicle adoption in shared autonomous fleets," *Transportation Research Part D: Transport and Environment*, vol. 80, p. 102231, 2020.

[137] S. N. Hashemian, M. A. Latify, and G. R. Yousefi, "Pev fast-charging station sizing and placement in coupled transportation-distribution networks considering power line conditioning capability," *IEEE Transactions on Smart Grid*, vol. 11, no. 6, pp. 4773–4783, 2020.

[138] B. Zhou, G. Chen, Q. Song, and Z. Y. Dong, "Robust chance-constrained programming approach for the planning of fast-charging stations in electrified transportation networks," *Applied energy*, vol. 262, p. 114480, 2020.

[139] M. Asna, H. Shareef, P. Achikkulath, H. Mokhlis, R. Errouissi, and A. Wahyudie, "Analysis of an optimal planning model for electric vehicle fast-charging stations in al ain city, united arab emirates," *IEEE Access*, vol. 9, pp. 73 678–73 694, 2021.

[140] F. Zargari, Y. Li, H. Jiang, and Y. Li, "Electric-vehicle charging station optimization in power-traffic coupled networks: Problem formulations and a three-stage iterative algorithm," *IEEE Transactions on Transportation Electrification*, vol. 10, no. 3, pp. 7174–7190, 2023.

[141] J. Wu, Q. Li, Y. Bie, and W. Zhou, "Location-routing optimization problem for electric vehicle charging stations in an uncertain transportation network: An adaptive co-evolutionary clustering algorithm," *Energy*, vol. 304, p. 132142, 2024.

[142] J. Fu, L. Lin, and X. Gao, "Comprehensive qos analysis of urban public charging network in topology and capacity with its application in optimization," *IEEE Access*, vol. 8, pp. 53 636–53 648, 2020.

[143] L. Guo, F. Wen, and K. Wang, "Coordinated planning between charging facilities of electric vehicles and concerned distribution system considering random risk cost," in *2020 International Conference on Smart Grids and Energy Systems (SGES)*. IEEE, 2020, pp. 1027–1032.

[144] J. Li, X. Xu, Z. Yan, H. Wang, and Y. Chen, "Dynamic flow equilibrium of transportation and power distribution networks considering flexible traveling choices and voltage quality improvement," *CSEE Journal of Power and Energy Systems*, 2024.

[145] S. Ge, K. Shen, and H. Liu, "Charging station planning considering user's travel characteristics and construction of distribution network lines," in *2020 23rd International Conference on Electrical Machines and Systems (ICEMS)*. IEEE, 2020, pp. 2030–2034.

[146] C. Shao, T. Qian, Y. Wang, and X. Wang, "Coordinated planning of extreme fast charging stations and power distribution networks considering on-site storage," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 1, pp. 493–504, 2020.

[147] V. Murali and D. B. Raj, "Optimizing electric vehicle charging stations and distributed generators in smart grids: A multi-objective meta-heuristic approach," *IEEE Latin America Transactions*, vol. 23, no. 11, pp. 1022–1035, 2025.

[148] H. Jiang, Y. Zhang, Y. Chen, C. Zhao, and J. Tan, "Power-traffic coordinated operation for bi-peak shaving and bi-ramp smoothing–a hierarchical data-driven approach," *Applied energy*, vol. 229, pp. 756–766, 2018.

[149] A. Pahlavanhoseini and M. S. Sepasian, "Scenario-based planning of fast charging stations considering network reconfiguration using cooperative coevolutionary approach," *Journal of Energy Storage*, vol. 23, pp. 544–557, 2019.

[150] M. Bilal, F. Ahmad, A. Mohammad, and M. Rizwan, "Techno-economic evaluation and sensitivity analysis of renewable energy based designing of plug-in electric vehicle load considering load following strategy," *Applied Energy*, vol. 377, p. 124557, 2025.

[151] A. Shukla, K. Verma, and R. Kumar, "Multi-objective synergistic planning of ev fast-charging stations in the distribution system coupled with the transportation network," *IET generation, transmission & distribution*, vol. 13, no. 15, pp. 3421–3432, 2019.

[152] B. He, B. Yang, Y. Han, Y. Zhou, Y. Hu, H. Shu, S. Su, J. Yang, Y. Huang, J. Li *et al.*, "Optimal evcs planning via spatial-temporal distribution of charging demand forecasting and traffic-grid coupling," *Energy*, vol. 313, p. 133885, 2024.

[153] S. Xie, Z. Hu, and J. Wang, "Two-stage robust optimization for expansion planning of active distribution systems coupled with urban transportation networks," *Applied Energy*, vol. 261, p. 114412, 2020.

[154] Q. Cui, Y. Weng, and C.-W. Tan, "Electric vehicle charging station placement method for urban areas," *IEEE Transactions on Smart Grid*, vol. 10, no. 6, pp. 6552–6565, 2019.

[155] A. Pan, T. Zhao, H. Yu, and Y. Zhang, "Deploying public charging stations for electric taxis: A charging demand simulation embedded approach," *IEEE Access*, vol. 7, pp. 17 412–17 424, 2019.

[156] A. Shukla, K. Verma, and R. Kumar, "Planning of ev fast charging stations for distribution system coupled with transportation network," in *2019 IEEE Power & Energy Society General Meeting (PESGM)*. IEEE, 2019, pp. 1–5.

[157] Y. Zhang, J. Chen, L. Cai, and J. Pan, "Expanding ev charging networks considering transportation pattern and power supply limit," *IEEE transactions on smart grid*, vol. 10, no. 6, pp. 6332–6342, 2019.

[158] V. Vijay, C. Venkaiah, and D. V. Kumar, "Multi objective queue theory based optimal planning of rapid charging stations and distributed generators in coupled transportation and distribution network," *Energy Storage*, vol. 6, no. 1, p. e484, 2024.

[159] H. Zhang, S. J. Moura, Z. Hu, W. Qi, and Y. Song, "Joint pev charging network and distributed pv generation planning based on accelerated generalized benders decomposition," *IEEE transactions on transportation electrification*, vol. 4, no. 3, pp. 789–803, 2018.

[160] J. Wang, H. D. Kaushik, and J. Zhang, "Optimal planning of electric vehicle charging stations: Integrating public charging networks and transportation congestion," in *2024 IEEE Kansas Power and Energy Conference (KPEC)*. IEEE, 2024, pp. 1–6.

[161] Y. Ji, Y. Zhang, L. Chen, J. Zuo, W. Wang, and C. Xu, "The optimal dispatch for a flexible distribution network equipped with mobile energy storage systems and soft open points," *Energies*, vol. 18, no. 11, p. 2701, 2025.

[162] J. Lin, J. Qiu, Y. Tao, and X. Sun, "Planning of electric vehicle charging stations with pv and energy storage using a fuzzy inference system," *IEEE Transactions on Transportation Electrification*, vol. 10, no. 3, pp. 5894–5909, 2023.

[163] S. Pawar, V. Kalkhambkar, and R. Kumar, "Charging station placement for electric vehicles," in *2022 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES)*. IEEE, 2022, pp. 1–6.

[164] C. Shao, K. Li, Z. Hu, and M. Shahidehpour, "Coordinated planning of electric power and natural gas distribution systems with refueling stations for alternative fuel vehicles in transportation system," *IEEE Transactions on Smart Grid*, vol. 13, no. 5, pp. 3558–3569, 2022.

[165] A. Soltanpour, M. Ghamami, M. Nicknam, M. Ganji, and W. Tian, "Charging infrastructure and schedule planning for a public transit network with a mixed fleet of electric and diesel buses," *Transportation Research Record*, vol. 2677, no. 2, pp. 1053–1071, 2023.

Appendix

This appendix brings together two forms of supporting material for the thesis. First, it documents the publications produced during the candidature and maps them to the relevant research questions, thesis chapters, and candidate contributions. Second, it records the computational implementation, data traceability, module interfaces, and reproducibility boundaries supporting the numerical studies. The appendix is intended to support transparency, research-output declaration, and technical auditability without repeating the detailed formulations, results, or discussion already presented in the main chapters.

Publications and Contribution Map

The research undertaken during this PhD has resulted in a portfolio of journal articles, conference papers, and related collaborative outputs addressing EV charging infrastructure planning, coupled power–transportation systems, V2G-enabled flexibility, and flexibility-market coordination. The publication trajectory follows the same intellectual progression as the thesis itself: from grid-aware EVCS–BESS planning, to coupled PDN–TN planning, and finally to V2G-enabled, participation-aware, and market-aware infrastructure design.

This publication record reflects a deliberate research pathway in which each stage builds upon the limitations and insights of the previous one. The early conference work established the initial grid-oriented planning formulation, the journal extensions developed more mature planning and operational frameworks, and the later outputs advanced the research toward traffic-informed, V2G-enabled, and flexibility-aware EVCS planning. In addition, the review manuscript supports the thesis's broader positioning by synthesising the EVCS planning literature from decision structure and deployment relevance perspectives.

Journal Articles

1. **M. Alizadeh**, A.M. Amani, L. Meegahapola, M. Jalili, and O. Hill, "A Data-Driven Comparative Analysis of Electric Vehicle Charging Infrastructure Planning Frameworks in Coupled Power–Transportation Networks," Energy and AI, 2026. (Under Review)
2. **M. Alizadeh**, A.M. Amani, L. Meegahapola, M. Jalili, and O. Hill, "Traffic-Informed Planning of V2G-Enabled EV Charging Infrastructure Under Participation Uncertainty," IEEE Transactions on Intelligent Transportation Systems, 2026. (Under Review)
3. **M. Alizadeh**, A.M. Amani, L. Meegahapola, and M. Jalili, "Coordinated V2G Control for Transient Voltage-Frequency Support in Renewable Microgrids," Renewable Energy Focus, 2026. (Revised)
4. **M. Alizadeh**, A.M. Amani, L. Meegahapola, M. Jalili, and O. Hill, "Optimal Traffic-Informed Design and Operation of EV Charging Stations in Power Distribution Grids," IEEE Transactions on Transportation Electrification, 2025. DOI: 10.1109/TTE.2026.3670484. (Published)
5. **M. Alizadeh**, A.M. Amani, L. Meegahapola, M. Jalili, and O. Hill, "Dynamic Planning Mechanism for Allocating Electric Vehicle Charging Stations in Distribution Networks," IEEE Transactions on Industrial Informatics, 2025. DOI: 10.1109/TII.2025.3574435. (Published)

Conference Articles

1. M.H. Nikkhah, **M. Alizadeh**, S. Koushkbaghi, R. Taguelmimt, S. Aknine, and M. Jalili, "Optimizing Electric Vehicle Flexibility via a State-of-Charge-Based Strategy for the Market Operator," 2026 IEEE 24th International Conference on Industrial Informatics (INDIN), 2026. (Accepted)
2. **M. Alizadeh**, M.H. Nikkhah, A.M. Amani, L. Meegahapola, and M. Jalili, "Optimal Traffic-Informed Integration of V2G-Enabled Charging Infrastructure in Power Distribution Network," 2025 IEEE International Conference on Energy Technologies for Future Grids (ETFG), 2025. DOI: 10.1109/ETFG61999.2025.11401068. (Published)

3. M.H. Nikkhah, **M. Alizadeh**, A.M. Amani, M. Jalili, and X. Yu, "A Novel Approach for Flexibility Market Management Using Coordination of Electric Vehicles and Battery Systems," IECON 2025–51st Annual Conference of the IEEE Industrial Electronics Society, 2025. DOI: 10.1109/IECON58223.2025.11221318. (Published)
4. **M. Alizadeh**, L. Meegahapola, A.M. Amani, M. Jalili, and A. Seilsepour, "Optimal Planning Framework for Battery Energy Storage Systems and Electric Vehicle Charging Stations in Distribution Networks," Proceedings of the 2024 IEEE International Conference on Industrial Technology (ICIT), 2024. DOI: 10.1109/ICIT58233.2024.10540935. (Published)

Thesis Contribution Map

The publications are integrated into the thesis as a coherent research program rather than as isolated outputs. Their relationship to the thesis chapters, research questions, and supporting research activities is summarised below.

Direct Thesis Contributions

- **RQ1 / Chapter 4: Integrated EVCS–BESS Planning and Operation in Distribution Networks**

  The ICIT 2024 conference paper established the initial grid-aware EVCS–BESS planning formulation by examining the coordinated allocation of BESS and EVCS assets in distribution networks. This work provided the preliminary methodological basis for RQ1.

  The IEEE Transactions on Industrial Informatics journal article extended this initial formulation into a more mature planning–operation framework by incorporating real-world Victorian smart-meter and PV data, coordinated BESS deployment, EVCS allocation, and local voltage-based operational control. This publication forms the main technical basis of Chapter 4.

- **RQ2 / Chapter 5: Traffic-Informed Planning in Coupled PDN–TN Systems**

  The IEEE Transactions on Transportation Electrification journal article extended the thesis from distribution-network planning to traffic-informed EVCS planning in coupled PDN–TN systems. This publication incorporated transportation network effects, charging accessibility, travel costs, queueing behaviour, EVCS service capacity, and distribution network feasibility into a unified planning framework. It forms the main technical basis of Chapter 5.

- **RQ3 / Chapter 6: V2G Participation, Market-Driven Flexibility, and Operational Coordination**

  The ETFG 2025 conference paper established the initial V2G-enabled extension of the traffic-informed planning framework by examining the integration of V2G-capable EVCS infrastructure in distribution networks. This work provided the preliminary basis for the flexibility-aware planning stage of the thesis.

  The submitted IEEE Transactions on Intelligent Transportation Systems journal manuscript develops the mature RQ3 framework by incorporating V2G participation uncertainty, behavioural heterogeneity, market-driven flexibility activation, and coordinated operational support. This publication forms the main technical basis of Chapter 6.

Synthesis and Positioning Contributions

- **Review and comparative synthesis / Chapters 2 and 7:**

  The submitted Energy and AI manuscript supports the thesis at the synthesis and positioning levels. It contributes to the classification of EVCS planning studies from a decision-structure perspective and helps identify the methodological gaps that the proposed frameworks address. Within the thesis, this work informs the literature foundation in Chapter 2 and the systematic synthesis and positioning of the thesis contributions in Chapter 7.

Related and Supporting Research Outputs

- **Microgrid V2G control and transient support:**

  The revised manuscript for the journal Renewable Energy, focusing on coordinated V2G control for transient voltage-frequency support in renewable microgrids, is a related research output developed during the PhD. Although it is not directly mapped to the main sources of Chapters 4–6, it supports the broader thesis theme by investigating how V2G-enabled resources can contribute to voltage and frequency support under dynamic operating conditions. This work strengthens the candidate's broader contribution to V2G control and the integration of flexibility.

- **Flexibility-market coordination and EV participation:**

  The IECON 2025 conference paper on flexibility market management using coordination of EVs and battery systems and the INDIN 2026 conference paper on state-of-charge-based EV flexibility for the market operator are related collaborative outputs developed during the later stages of the PhD. These works complement the thesis by addressing market-side coordination of EV and battery flexibility. They are particularly relevant to the market-aware, flexibility-enabled direction of RQ3, although they are treated as supporting outputs rather than as primary thesis chapters.

This mapping is consistent with the thesis structure. Chapter 4 addresses integrated EVCS–BESS planning and operation in distribution networks, Chapter 5 extends the framework to coupled distribution–transportation planning with traffic-informed demand, and Chapter 6 incorporates V2G participation, market-driven flexibility, and operational coordination. Chapters 2 and 7 provide the literature foundation, research-gap synthesis, and contribution positioning that connect the publication outputs to the broader EVCS planning field. The additional microgrid and flexibility-market publications demonstrate the broader research trajectory developed during the candidature and reinforce the thesis focus on deployable, flexibility-aware energy–mobility systems.

Original Contribution Statement

The candidate is the primary contributor to the publications arising from this thesis. The candidate led the conceptual development of the research, the mathematical formulation of the optimisation problems, the modelling of coupled PDN–TN systems, the design and implementation of the computational frameworks, the processing and integration of real-world datasets, the simulation studies, the analysis of results, and the preparation of the manuscripts. The co-authors contributed through scholarly supervision, technical discussion, critical feedback, and manuscript review.

The originality of the thesis lies in the progressive integration of four elements that are often treated separately in the literature: infrastructure planning, operational coordination, transportation-driven demand formation, and flexibility-aware EV participation. Rather than contributing a single isolated optimisation model, the thesis establishes a structured planning pathway that evolves from distribution-network feasibility, to coupled power–transport interaction, and finally to V2G-enabled and market-aware infrastructure design under realistic operating conditions.

Accordingly, the contribution of this thesis should be understood in terms of planning architecture and system integration. The work moves EVCS planning beyond static, single-network, and load-imposed formulations toward a data-driven, deployment-oriented decision framework that is directly relevant to utilities, charging infrastructure planners, transport agencies, flexibility-market participants, and integrated energy–mobility system design.

Computational Implementation, Data Traceability, and Reproducibility

This appendix documents the computational implementation supporting the thesis. The main chapters present the research motivation, literature gaps, mathematical formulations, scenario results, discussion, and industry-facing interpretation. Therefore, this appendix does not repeat the full optimisation models, numerical results, or deployment claims. Instead, it provides a compact technical record of how the computational studies were structured, how real-world data were converted into model inputs, how the main modules exchanged information, and how numerical feasibility and consistency were checked.

The implementation was developed using research notebooks that tracked the thesis's progressive stages. These notebooks represent a research-grade computational workflow rather than deployment-ready software. Their purpose is to document the computational pathway by which the Melbourne and Victoria datasets, benchmark distribution feeders, traffic-informed charging demand, EVCS–BESS optimisation, V2G participation logic, queueing assessment, and power-flow-based validation were integrated into a reproducible modelling process.

The appendix is organised around four technical traceability questions: (i) what data and computational artefacts support each research stage; (ii) how real-world data are transformed into time-indexed power and transportation inputs; (iii) how optimisation, simulation, and feasibility-checking modules interact; and (iv) what conditions are required for numerical replication and transfer to another case-study environment.

Computational Artefacts and Research Stages

Table A.1 maps the main computational artefacts to the research stages of the thesis. The purpose is to document the basis for implementing each research question rather than to repeat the publication mapping or the detailed results reported in the main chapters.

Table A.1: Computational artefacts supporting the research stages of the thesis.

Stage	**Computational role**	**Main artefacts**	**Traceability purpose**
RQ1	Grid-aware EVCS–BESS planning and voltage-support assessment.	Smart-meter/PV profiles; modified IEEE feeder; EVCS and BESS decision variables; power-flow outputs; BESS control-gain tests.	Traces infrastructure decisions to feeder-level voltage, loss, and storage feasibility.
RQ2	Traffic-informed PDN–TN planning.	Traffic aggregation; road impedance; charging-demand allocation; TN–PDN mapping; queueing model; GA–DDPG workflow.	Links mobility-driven demand to grid-constrained EVCS siting and sizing.
RQ3	V2G-aware planning under participation uncertainty.	G2V/V2G profiles; participation logic; availability and SOC filters; scenario-specific flexibility activation; post-planning validation.	Separates installed bidirectional capability from realised V2G flexibility.
Reporting layer	Numerical output, visualisation, and evidence generation.	Saved arrays for voltage, loss, travel, queueing, EVCS, BESS, and V2G outputs; plotting scripts; comparison tables.	Ensures consistency between simulations, figures, tables, and interpretation.

This artefact-based view is important because the thesis is not based on a single isolated simulation. Instead, it progressively connects data processing, network modelling, optimisation, operational assessment, and scenario comparison. The computational artefacts, therefore, provide the technical bridge between the conceptual framework developed in the main chapters and the numerical evidence supporting the thesis's findings.

Data-to-Model Traceability

A central feature of the thesis is the conversion of heterogeneous real-world data into time-indexed planning inputs. The computational workflow integrates residential demand, rooftop PV generation, traffic measurements, road network information, EV charging assumptions, and V2G participation logic. Table A.2 summarises how the main data categories are converted into model inputs.

This traceability is necessary because the thesis relies on coupled modelling layers. A change in traffic allocation can alter charging demand at candidate EVCS locations; a change in charging demand can alter feeder voltage and loss outcomes; and a change in V2G participation can alter the effective operational value of bidirectional charging. The data-to-model pathway, therefore, provides the basis for interpreting the results as system-level planning outcomes rather than isolated numerical outputs.

Table A.2: Data-to-model traceability in the computational workflow.

Data category	Processing role	Model input	Integrity check
Residential demand	Cleaned, aligned, and aggregated to feeder buses.	48-step bus-level active-load profiles.	Valid time index, nonnegative load, and bus-allocation consistency.
Rooftop PV generation	Aligned with demand and assigned to PV-enabled buses.	48-step PV injections and net-demand profiles.	Profile length, sign convention, and load–PV consistency.
Traffic measurements	Aggregated and mapped to TN nodes and links.	48-step traffic-intensity profiles.	Missing-data screening, nonnegative flow, and temporal alignment.
Road-network attributes	Converted into distance and impedance measures.	Distance matrix, impedance factors, and access-cost indicators.	Valid node/link indexing and consistent impedance definition.
EV charging assumptions	Combined with traffic, trip distance, SOC probability, and service capacity.	Spatiotemporal charging demand at candidate EVCSs.	Nonnegative demand and valid TN–EVCS mapping.
V2G participation assumptions	Filtered by profile, SOC, access distance, availability, and activation.	Participation-weighted V2G flexibility profiles.	Nominal capacity is separated from usable flexibility.

Execution Topology of the Computational Workflow

The most complete implementation follows a staged workflow rather than a single monolithic optimiser. This structure reflects the modelling logic of the thesis: data are prepared and aligned, the PDN and TN representations are constructed, charging demand and V2G participation are generated, infrastructure decisions are optimised, feasibility checks are applied, and final outputs are exported for interpretation. Table A.3 summarises this execution topology.

Table A.3: Execution topology of the computational workflow.

Workflow block	Implementation role	Audit relevance
Configuration and data loading	Sets horizon, network size, EVCS/BESS bounds, V2G settings, optimisation parameters, and input paths.	Defines an explicit and repeatable experiment setup.
PDN construction	Builds the feeder model with buses, lines, grid connection, loads, PV, EVCS, BESS, and V2G injections.	Links planning decisions to power-flow feasibility.
TN construction	Defines traffic nodes, road links, distances, impedance factors, and accessibility indicators.	Preserves the spatial basis of charging-demand allocation.
Charging and queueing modules	Estimate charging demand and waiting time from traffic, SOC probability, station capacity, and service rates.	Prevents EV demand from being treated as a fixed electrical load.
Optimisation modules	Apply GA-based BESS/control decisions and DDPG-based EVCS allocation under coupled constraints.	Screens candidates against electrical and service-quality criteria.
V2G and validation layer	Applies participation, availability, activation, and post-planning voltage-control checks.	Verifies usable flexibility rather than installed capability alone.
Result export and plotting	Stores asset locations, objectives, costs, voltage profiles, BESS/V2G profiles, and scenario outputs.	Traces reported figures and tables to saved simulation arrays.

This topology is important because the thesis combines modelling layers that can become inconsistent if handled independently. The staged structure ensures that each layer produces an explicit output that becomes the input to the next layer. This also supports debugging, scenario reconstruction, and result verification.

Module Interfaces and Feasibility Checks

The computational workflow is organised around module interfaces. These interfaces define how information passes from data preparation to transportation modelling, power-flow evaluation, optimisation, and operational validation. Table A.4 summarises the principal module interfaces used in the implementation.

Table A.4: Principal module interfaces and feasibility checks.

Module	**Inputs**	**Outputs**	**Feasibility or validation check**
Traffic-demand module	Traffic flow, TN nodes, distances, EV penetration, trip distance, and charging probability.	Time-indexed charging demand at candidate locations.	Valid node mapping, nonnegative demand, and 48-step alignment.
Queueing module	Arrival rate, service rate, charger type, station size, and EVCS action.	Waiting-time and service-quality indicators.	Queue stability and waiting-time limit compliance.
TN–PDN mapping	Candidate EVCS locations, TN nodes, PDN buses, and mapping rules.	EVCS demand is assigned to feeder buses.	No unmapped station and no invalid bus assignment.
Power-flow evaluation	Feeder topology, load, PV, EVCS demand, BESS action, V2G injection, time step.	Voltage profile, losses, convergence status, and operating variables.	Power-flow convergence and voltage-limit compliance.
BESS planning/control	Candidate buses, charge/discharge action, SOC state, voltage deviation, operating bounds.	BESS schedule, SOC trajectory, and corrective control action.	SOC, power limits, and voltage-response validity.
EVCS allocation environment	System state, candidate action, demand map, feeder condition, and service indicators.	EVCS location/size vector, reward, next state, feasibility flag.	Voltage, distance, spacing, queueing, and power-flow constraints.
V2G participation module	Profile type, SOC, access distance, availability, time step, activation signal.	Usable V2G flexibility and bidirectional charging adjustment.	Participation, SOC, distance, and activation feasibility.
KPI extraction	Final decisions, technical outputs, service outputs, and cost parameters.	Loss, voltage, travel, queueing, investment, and O&M indicators.	Consistency between exported arrays, tables, and plots.

This interface-based view clarifies that the optimisation result is only meaningful after it has passed both technical and service-quality feasibility checks. A candidate solution may appear attractive in one objective while being infeasible in another domain. For example, an EVCS placement may reduce travel cost but create voltage violations, or a V2G-enabled scenario may appear beneficial only if installed bidirectional capability is incorrectly treated as fully available flexibility. The module interfaces, therefore, provide a computational safeguard against internally inconsistent interpretations.

Scenario Reconstruction Logic

The thesis evaluates different infrastructure configurations and operating assumptions across its research stages. The purpose of this section is to clarify how scenarios can be reconstructed computationally without repeating the numerical results reported in the main chapters. Table A.5 summarises the main reconstruction logic.

Table A.5: Scenario reconstruction logic used across the computational studies.

Stage	Scenario variable	Computational reconstruction	Key check
RQ1	EVCS/BESS deployment and control settings.	Modify locations, sizes, and BESS control parameters while preserving common feeder and time-series inputs.	Voltage, loss, SOC, and convergence feasibility.
RQ2	EVCS density, BESS count, and traffic-informed demand allocation.	Re-run the coupled PDN–TN workflow with scenario-specific infrastructure counts and demand mapping.	Travel cost, queueing, spacing, voltage, and feeder feasibility.
RQ3	V2G mode, profile type, and participation level.	Switch between G2V, full V2G, partial V2G, and reduced-participation cases using scenario-specific flexibility profiles.	Installed V2G capacity must not be treated as fully dispatchable flexibility.
Control validation	Operational uncertainty and corrective BESS response.	Apply post-planning control checks under dynamic EVCS and V2G operating conditions.	Voltage correction without violating BESS limits.

This reconstruction logic is included because the thesis uses scenario-based comparison to interpret infrastructure planning outcomes. The scenarios are not independent experiments with unrelated assumptions; rather, they are controlled modifications of the same computational pathway. This allows the effect of EVCS density, BESS support, V2G capability, participation level, and control action to be interpreted within a consistent modelling structure.

Implementation-Specific Quality Controls

Several implementation controls were used to reduce hidden inconsistency across the notebook-based workflow. These controls are not new assumptions and do not change the mathematical formulation. They define how the computational experiments should be reconstructed and audited. Table A.6 summarises the main quality controls.

Table A.6: Implementation-specific quality controls for computational auditability.

Control	Purpose
Time-step integrity	Checks that demand, PV, traffic, EVCS, BESS, V2G, and control arrays follow the same 48-step operating horizon.
Unit-conversion discipline	Prevents scaling errors between kW/MW, kWh/MWh, per-unit voltage, minutes, hours, and monetary cost units.
Network-state reconstruction	Ensures each time step uses the correct load, PV, EVCS, BESS, and V2G state before power-flow evaluation.
Constraint-first validation	Rejects or penalises candidates violating voltage, SOC, spacing, distance, queueing, or convergence constraints.
Scenario isolation	Prevents carry-over of scenario-specific variables such as EVCS count, BESS count, V2G mode, participation level, or control status.
Stochastic reconstruction	Requires documented seeds, stable package versions, and fixed hyperparameters when exact numerical replication is required.
Output preservation	Stores numerical arrays before plotting so that tables, figures, and interpretation are generated from the same data source.

These controls are included because the implementation combines stochastic optimisation, learning-based action selection, time-indexed power-flow simulation, and traffic-driven demand generation. Without explicit implementation controls, two simulations may appear methodologically equivalent yet produce different numerical outputs due to hidden changes in random initialisation, scenario settings, unit conversions, or time-index alignment.

Numerical Sanity Checks

Before interpreting optimisation outputs, each simulation run should satisfy a set of numerical sanity checks. These checks are quality-control tests rather than additional results. They clarify the computational standards used to distinguish feasible planning outcomes from artefacts of simulation, scaling, or plotting. Table A.7 summarises the main checks.

Table A.7: Numerical sanity checks for optimisation and simulation outputs.

Output category	**Sanity check**
Power-flow convergence	Feasible operating points must converge. Non-convergent cases are treated as infeasible or penalised.
Voltage profiles	Reported feasible cases must satisfy voltage limits after EVCS, BESS, and V2G interactions are applied.
BESS SOC trajectory	SOC must remain within bounds after every charge/discharge update and control action.
EVCS demand response	Higher charging demand should not increase feeder stress unless allocation, BESS, V2G, or control actions change accordingly.
Traffic and queueing response	Higher station density should generally reduce travel or queueing burden unless constrained by spatial concentration or insufficient service capacity.
V2G contribution	V2G-enabled cases should improve performance only when participation, SOC, availability, access, and activation conditions are satisfied.
Cost consistency	Additional stations, storage, or bidirectional capability should be reflected in investment, O&M, or loss-related costs unless explicitly excluded.
Plot–table consistency	Figures and tables must be generated from the same saved numerical arrays.

These checks are particularly important for coupled EVCS planning. A solution may reduce travel cost by increasing station density while violating feeder voltage constraints; similarly, a V2G-enabled case may appear highly beneficial if installed bidirectional capability is incorrectly treated as fully available flexibility. The checks in Table A.7 reduce the risk of such internally inconsistent interpretations.

Computational Environment and Runtime Notes

The computational studies were implemented as research notebooks using Python-based workflows for optimisation, simulation, and plotting. The power-flow evaluations were performed using a time-indexed reconstruction of the distribution feeder so that each operating interval reflected the corresponding demand, PV, EVCS, BESS, and V2G conditions.

Where high-memory computation was required, simulations were executed on a cloud computing instance with sufficient memory and processor capacity for repeated optimisation and 48-step time-series simulations. The purpose of this computational setup was not to demonstrate production-grade software deployment, but to ensure that the coupled PDN–TN optimisation workflow could be executed repeatedly under consistent scenario settings.

Exact numerical replication requires the same input datasets, package versions, random seeds, optimisation hyperparameters, scenario configuration files, and computational environment. In contrast, engineering-level reproducibility requires reconstruction of the workflow logic, data-processing steps, module interfaces, and feasibility checks documented in this appendix.

Reproducibility Boundary and Transferability

The thesis is reproducible in a practical engineering sense: the modelling structure, data-processing logic, module interfaces, feasibility checks, objective categories, scenario definitions, and computational workflow are documented sufficiently for the studies to be reconstructed under equivalent assumptions. Exact numerical replication, however, requires the same input files, software package versions, random seeds, initial optimisation populations, neural-agent settings, and computational environment.

The transferable element of the thesis is the decision architecture: the integration of feeder-level feasibility, mobility-driven charging demand, service-quality constraints, BESS support, V2G participation, and operational validation. The non-transferable elements are the case-specific traffic intensities, feeder hosting margins, behavioural parameters, V2G participation profiles, cost assumptions, and scenario values. Application to another city, utility, or charging-market environment, therefore, requires recalibration and validation rather than direct numerical reuse.

This appendix is deliberately limited to computational implementation and support for reproducibility. It does not repeat the thesis formulations, literature synthesis, results, publication map, impact statement, or industry-translation discussion. Its role is to clarify the thesis's computational basis, make it more auditable, and facilitate extension without unnecessary conceptual repetition.