

Titre: Modeling Urban Electric Vehicle Charging Under Pricing and Behavioral Heterogeneity Using an Agent-Based Simulation Framework
Title:

Auteur: Arsham Bakhtiari
Author:

Date: 2026

Type: Mémoire ou thèse / Dissertation or Thesis

Référence: Bakhtiari, A. (2026). Modeling Urban Electric Vehicle Charging Under Pricing and Behavioral Heterogeneity Using an Agent-Based Simulation Framework [Thèse de doctorat, Polytechnique Montréal]. PolyPublie.
Citation: <https://publications.polymtl.ca/76562/>

 **Document en libre accès dans PolyPublie**
Open Access document in PolyPublie

URL de PolyPublie: <https://publications.polymtl.ca/76562/>
PolyPublie URL:

Directeurs de recherche: Francesco Ciari, & Amir Reza Mamdoohi
Advisors:

Programme: Génie civil
Program:

POLYTECHNIQUE MONTRÉAL

affiliée à l'Université de Montréal

**Modeling Urban Electric Vehicle Charging Under Pricing and Behavioral
Heterogeneity Using an Agent-Based Simulation Framework**

ARSHAM BAKHTIARI

Département de Département des génies civil, géologique et des mines

Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*
Génie civil

Février 2026

POLYTECHNIQUE MONTRÉAL

affiliée à l'Université de Montréal

Cette thèse intitulée :

**Modeling Urban Electric Vehicle Charging Under Pricing and Behavioral
Heterogeneity Using an Agent-Based Simulation Framework**

présentée par **Arsham BAKHTIARI**

en vue de l'obtention du diplôme de *Philosophiæ Doctor*
a été dûment acceptée par le jury d'examen constitué de :

Genevieve BOISJOLY, présidente

Francesco CIARI, membre et directeur de recherche

Amirreza MAMDOOHI, membre et codirecteur de recherche

Alessia ZARZANI, membre

Jiangbo YU, membre externe

DEDICATION

*To Iran,
a land of culture and resilience,
and to its people,
who continue to move forward despite hardships . . .*

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to all the people who accompanied and supported me throughout my academic journey, from my earliest years of education to the completion of this thesis. I would especially like to thank my supervisors and professors for their guidance and support, as well as my friends and colleagues for their encouragement. My deepest gratitude goes to my parents and family for their love, trust, and unwavering support. This thesis is the result of a shared journey, made possible through the kindness and support of many people.

RÉSUMÉ

La croissance rapide de l'adoption des véhicules électriques (VE) constitue une étape essentielle vers la réduction des émissions de gaz à effet de serre du secteur des transports. Toutefois, elle engendre également de nouveaux défis pour les réseaux électriques urbains et les infrastructures de recharge. Contrairement aux charges électriques traditionnelles, la demande de recharge des VE est difficilement prévisible, car elle est étroitement liée aux comportements de mobilité et aux routines quotidiennes des usagers. Cette dépendance se traduit par une synchronisation temporelle des recharges et par une concentration spatiale des appels de puissance. Ainsi, les contraintes du système résultent davantage de la coordination collective des décisions de recharge au sein d'infrastructures partagées et spatialement limitées que du volume total d'énergie consommée. Comprendre et maîtriser ces dynamiques est donc essentiel pour assurer une intégration fiable et efficace des VE dans les systèmes urbains.

Bien que la gestion de la recharge des VE suscite un intérêt croissant, une grande partie de la littérature repose encore sur des représentations simplifiées ou statiques de la demande de recharge. Ces approches traitent souvent le comportement de recharge comme exogène ou supposent un accès illimité aux infrastructures. Elles peinent ainsi à rendre compte des phénomènes de congestion, de files d'attente et de contraintes locales sur le réseau électrique, ainsi que des adaptations des usagers face aux signaux tarifaires, à la disponibilité des infrastructures ou aux évolutions technologiques. En particulier, les effets combinés de la structure des activités quotidiennes, de la sensibilité des usagers à un faible niveau de charge de la batterie, de l'accessibilité aux bornes et des instruments de politique publique demeurent insuffisamment étudiés dans des cadres intégrés.

Cette thèse vise à combler ces lacunes en mobilisant un cadre de simulation multi-agents, fondé sur les comportements et les activités, dans lequel les décisions de recharge des VE émergent naturellement des déplacements individuels. S'appuyant sur la plateforme MATSim, le modèle est enrichi de modules spécifiques aux VE afin de représenter la recharge comme une composante intégrée des activités quotidiennes, en tenant compte de l'état de charge de la batterie, de l'accessibilité aux infrastructures de recharge et des signaux de politique publique. Le cadre est appliqué à la région métropolitaine de Montréal, permettant une analyse détaillée de la demande de recharge, de la consommation électrique et des phénomènes de congestion dans le temps et dans l'espace.

La recherche s'articule autour de trois dimensions principales de la performance des systèmes

de recharge des VE. Premièrement, le comportement de recharge est analysé dans un scénario de référence sans tarification, afin d'établir des profils temporels et spatiaux crédibles et de confronter les résultats du modèle à des données observées de recharge publique. Les résultats mettent en évidence des pics marqués de recharge résidentielle en soirée, ainsi qu'une demande bimodale pour la recharge publique, associée aux activités professionnelles et aux activités hors domicile. Ces motifs émergent directement de la structure des activités quotidiennes, confirmant que les routines de mobilité constituent le principal déterminant des comportements de recharge.

Deuxièmement, la thèse évalue des stratégies de gestion de la demande fondées sur la tarification, en particulier la tarification en fonction du temps d'utilisation (TOU) et la tarification différenciée spatialement. Les résultats montrent que la tarification TOU peut déplacer une partie de la recharge hors des périodes de pointe en soirée, notamment pour la recharge publique. Toutefois, l'ampleur de ce déplacement dépend fortement de l'accessibilité et de la disponibilité des infrastructures de recharge. Lorsque les options de recharge sont spatialement ou temporellement contraintes, la capacité des usagers à réagir aux signaux de prix demeure limitée. La tarification spatiale influence également la localisation de la recharge, mais ses effets sont étroitement liés à ceux de la tarification temporelle. Dans certains cas, les incitations spatiales peuvent même réorienter une partie de la demande vers des périodes de forte sollicitation, atténuant ainsi les effets du déplacement temporel induit par la tarification TOU. Ces interactions soulignent que les dimensions temporelle et spatiale de la tarification doivent être envisagées conjointement.

Troisièmement, la thèse examine des déterminants comportementaux et technologiques de la recharge, indépendamment de toute tarification. La sensibilité des usagers à un faible niveau de charge de la batterie est représentée à l'aide de fonctions continues d'anxiété d'autonomie. Les résultats indiquent qu'une anxiété accrue incite les usagers à recharger à des niveaux de charge plus élevés, augmentant la fréquence des recharges et la synchronisation des tentatives de recharge dans le temps et l'espace. Cette synchronisation comportementale engendre des files d'attente plus importantes aux bornes publiques, même en l'absence de signaux tarifaires. Par ailleurs, des scénarios technologiques et infrastructurels évaluent les effets de l'augmentation de la capacité des batteries, de la puissance des bornes et de la densité des infrastructures. Des batteries de plus grande capacité réduisent la fréquence de recharge et la congestion sans accroître la demande de pointe, tandis que les améliorations d'infrastructure facilitent l'accès et réduisent les temps d'attente, mais peuvent également intensifier les pics de puissance en permettant des recharges simultanées à forte puissance lors des périodes d'activité dominantes.

Dans l'ensemble, les analyses révèlent de fortes interactions endogènes entre le comportement des usagers, les contraintes d'infrastructure et les interventions de politique publique. Ni la tarification, ni les changements comportementaux, ni les améliorations technologiques ne suffisent, pris isolément, à gérer efficacement la demande de recharge. Les résultats montrent que les dynamiques du système émergent de l'interaction entre ces éléments, la levée de certaines contraintes pouvant conduire à une resynchronisation des comportements autour de périodes de recharge privilégiées.

En conclusion, cette thèse propose un cadre de modélisation intégré et des résultats empiriques qui approfondissent la compréhension des systèmes de recharge des VE en milieu urbain, au-delà des approches agrégées. En modélisant explicitement la recharge comme le produit des activités quotidiennes et de décisions adaptatives sous contraintes réalistes, ce travail met en évidence la nécessité de stratégies coordonnées combinant dynamiques comportementales, planification des infrastructures et conception des politiques publiques. Ces enseignements offrent des pistes concrètes pour les décideurs et les planificateurs souhaitant réduire la congestion, maîtriser les pointes de demande et soutenir une intégration durable et fiable des véhicules électriques dans les systèmes urbains de transport et d'énergie.

ABSTRACT

The rapid growth of electric vehicle (EV) adoption marks a crucial step toward reducing greenhouse gas emissions from transportation, but it also creates new challenges for urban electricity networks and charging infrastructure. Unlike traditional electrical loads, EV charging demand is hardly predictable as it closely follows individual mobility patterns and daily routines, resulting in synchronized timing and localized concentrations of power demand. Therefore, system stress is driven more by the collective timing of charging decisions within shared infrastructure and spatial limits than by total energy use. Understanding and managing these dynamics is vital for ensuring the reliable and efficient integration of EVs into city systems.

Although more focus is being placed on EV charging management, most existing studies depend on simplified or static models of charging demand. They often treat charging behavior as exogenous or assuming unconstrained access to infrastructure. Such approaches are limited in their ability to capture congestion, queuing, and local grid strain, as well as how users adapt to pricing changes, infrastructure availability, and technological advancements. Particularly, the combined impact of daily activity patterns, user sensitivity to low battery levels, ease of access to charging stations, and policy measures is not thoroughly examined in integrated models.

This thesis fills these gaps by using a behaviorally based, activity-driven agent simulation framework where EV charging decisions naturally arise from individual travel behavior. Building on the MATSim platform, it adds EV-specific features to model charging choices within daily activities, considering factors such as state of charge, access to charging infrastructure, and policy signals. The enhanced framework is applied to the Greater Montréal metropolitan area, allowing detailed analysis of charging demand, energy use, and queue patterns over time and space.

The research explores three key aspects of EV charging system performance. First, it analyzes baseline charging behavior without pricing policies to establish reliable temporal and spatial demand patterns and to validate model results against observed public charging data. Findings reveal clear evening peaks in residential charging and bimodal public charging demand linked to work-related and non-home activities. These patterns arise directly from daily activity structures, showing that charging behavior is mainly driven by mobility routines.

Second, the thesis examines pricing-based demand management strategies, focusing on time-of-use (TOU) pricing and spatially differentiated pricing. The findings indicate that TOU

pricing can shift charging demand away from peak evening hours, especially at public chargers. However, the extent of this shift is heavily limited by charger accessibility and availability. When charging options are restricted in space or time, users cannot fully respond to price incentives. Spatial pricing also influences where charging happens, but its effects are closely linked with those of temporal pricing. In some cases, spatial incentives partially redirect demand back to high-demand periods, reducing some of the temporal shifts caused by TOU pricing. These interactions show that temporal and spatial pricing must be considered together, as their combined impact depends on how users balance price, access, and timing within infrastructure constraints.

Third, the thesis explores behavioral and technological factors that influence charging habits independently of pricing. Behavioral sensitivity to low battery levels is shown through continuous range anxiety functions. The findings indicate that stronger range anxiety prompts users to start charging at higher state-of-charge levels, leading to more frequent charging and clustering of charging attempts at similar times and locations. This behavioral synchronization results in longer lines at public charging stations, even without pricing incentives. Simultaneously, scenarios involving technology and infrastructure assess the impact of larger battery capacities, higher charger power, and greater charger density. Larger batteries reduce the need for frequent charging and congestion without increasing peak power demand. Conversely, infrastructure improvements primarily enhance access and reduce waiting times but can also increase peak electricity demand, as faster, more numerous chargers allow many users to charge simultaneously during peak periods.

Across all analyses, the results show strong endogenous interactions among user behavior, infrastructure constraints, and policy interventions. Neither pricing strategies, behavioral shifts, nor technological improvements alone are enough to manage charging demand effectively. Instead, system-level outcomes result from the interaction of these factors, with relaxed constraints often leading to behavioral synchronization around preferred charging times.

Overall, this thesis offers a comprehensive modeling framework and empirical insights that deepen the understanding of urban EV charging systems beyond simple aggregate models. By explicitly modeling charging behavior as a function of daily activity patterns and adaptive decision-making under realistic constraints, the research emphasizes the need for integrated strategies that account for behavioral dynamics, infrastructure planning, and policy development. These findings guide planners and policymakers in efforts to reduce congestion, manage peak demand, and enable the scalable and reliable integration of electric vehicles into urban energy and transportation systems.

TABLE OF CONTENTS

DEDICATION	iii
ACKNOWLEDGEMENTS	iv
RÉSUMÉ	v
ABSTRACT	viii
LIST OF TABLES	xiii
LIST OF FIGURES	xiv
LIST OF SYMBOLS AND ACRONYMS	xvi
CHAPITRE 1 INTRODUCTION	1
1.1 Background and Motivation	1
1.2 EV Charging as a System-Level Problem	2
1.3 Modeling EV Charging Behavior	4
1.4 Behavioral Heterogeneity in Charging Decisions	5
1.5 Policy and Planning Strategies for EV Charging Systems	7
1.6 Research Gaps and Working Hypotheses	8
1.7 Thesis Structure	10
CHAPITRE 2 LITERATURE REVIEW	13
2.1 Agent-Based Modeling and Behavioral Representation of EV Charging	13
2.2 Behavioral Heterogeneity and Adaptive Charging Strategies	16
2.3 Pricing Mechanisms and Demand-Side Control in EV Charging	17
2.4 Battery Technology and Charging Infrastructure Trade-offs	19
2.5 Range Anxiety and Its Role in Electric Vehicle Charging Behavior	20
2.6 Synthesis of Literature and Research Objectives	22
CHAPITRE 3 METHODOLOGY	25
3.1 Methodology	25
3.1.1 Overview of the Modeling Framework	25
3.1.2 MATSim : Activity-Based and Agent-Based Simulation	27
3.1.3 EV-Contrib : Electrification and Energy Dynamics	29
3.1.4 Urban-EV Framework : Activity-Integrated Charging	29

3.1.5	Behavioral Architecture of Urban EV Charging	31
3.1.6	Summary of Model Components	32
3.1.7	Charging Decision Framework and Strategy Design	34
3.1.8	Charging Execution, Initial Conditions, and Cost Representation . .	38
3.1.9	Initial State of Charge (SOC)	40
3.1.10	Electricity Pricing Mechanisms	41
3.1.11	Utility Function Extensions and Range Anxiety	42
3.2	Study Area, Data, and Implementation	46
3.2.1	Study Area : Montreal Census Metropolitan Area	46
3.2.2	Synthetic Population Generation	47
3.2.3	Activity Location Assignment	47
3.2.4	Transportation Network and Public Transit	47
3.2.5	Charging Infrastructure and EV Fleet	48
3.2.6	Sampling Strategy and Computational Considerations	49
3.2.7	Scope and Limitations	50
CHAPITRE 4 FIRST THEME – BEHAVIORAL HETEROGENEITY IN EV CHAR-		
	GING	51
4.1	System-Wide Power Demand under Alternative Charging Logics	52
4.2	Queuing Dynamics and Charging Infrastructure Congestion	54
4.3	Temporal and State-of-Charge Patterns of Charging Initiation	55
4.4	Activity-Based Charging Patterns under Behavioral Heterogeneity	56
4.4.1	Charging Activity Context under Heterogeneous Behavior	57
4.4.2	Charging Logic and Daily Activity Complexity	59
4.4.3	Sociodemographic Patterns as Indirect Outcomes	60
4.5	Charging Logic, Activity Context, and Energy Outcomes	61
4.6	Synthesis and Implications of Behavioral Heterogeneity	64
4.6.1	Key Findings	64
4.6.2	Implications for the Working Hypotheses	65
4.6.3	Contribution of This Theme	66
CHAPITRE 5 SECOND THEME — PRICING, INFRASTRUCTURE CONSTRAINTS,		
	AND SPATIAL RIGIDITY IN URBAN EV CHARGING SYSTEMS	68
5.1	Simulation Framework and Baseline Behavior (Free Scenario)	68
5.2	Model Validation Against Observed Public Charging Data	71
5.3	Impact of TOU Pricing on Charging Behavior	74
5.3.1	Temporal Variation in Charging Demand	74

5.3.2	Utilized Charger Types	77
5.3.3	Queues at Charging Stations and User Experience	79
5.3.4	Spatial Variation of Charging Demands	81
5.3.5	Spatio-Temporal Distribution of Charging Demand	85
5.3.6	Constraints and System Bottlenecks	88
5.4	Unlimited-Charger Scenario	90
5.5	Area Pricing	92
5.6	Chapter Synthesis and its theme within the broader thesis framework.	95
5.6.1	Key Findings	96
5.6.2	Implications for the Working Hypotheses	96
5.6.3	Contribution of This Theme	97
CHAPITRE 6 THIRD THEME — BEHAVIORAL SENSITIVITY AND TECHNO- LOGICAL LEVERS IN EV CHARGING SYSTEMS		98
6.1	Impact of Range Anxiety on Charging Behavior	99
6.1.1	State of Charge at Charging Initiation	99
6.1.2	Temporal Distribution of Charging Initiation	101
6.1.3	Impacts of Range Anxiety on Power Demand	103
6.1.4	Queuing Effects at Public Charging Stations	105
6.2	Technology and Infrastructure Scenarios	106
6.2.1	Public Charging Power Demand under Technology and Infrastructure Scenarios	108
6.2.2	Queuing Dynamics under Battery and Infrastructure Scenarios	111
6.3	Synthesis and Contributions of the Chapter	112
6.3.1	Key Findings	113
6.3.2	Implications for the Working Hypotheses	113
6.3.3	Contribution of This Chapter	114
CHAPITRE 7 CONCLUSION		115
7.1	Summary of Works	115
7.2	Limitations	118
7.3	Future Research	119
REFERENCES		121

LIST OF TABLES

Tableau 2.1	Synthesis of EV Charging Modeling Literature and Identified Research Gaps	24
Tableau 3.1	Summary of key model components.	32
Tableau 4.1	Distribution of charging events, average charging duration, and SOC gain by activity type and charging logic in the heterogeneous scenario.	62
Tableau 6.1	Summary of battery and charging infrastructure scenarios	107

LIST OF FIGURES

Figure 1.1	Overview of Thesis.	12
Figure 3.1	MATSim’s iterative loop in this study.	26
Figure 3.2	Range-anxiety penalty as a function of state of charge for two values of the sensitivity parameter B : (top) $B = 15$, producing a sharp increase in penalty below approximately 30% SOC; and (bottom) $B = 7.5$, shifting behavioral pressure toward higher SOC levels around 50%.	45
Figure 3.3	Study area and spatial distribution of Home and Public chargers.	49
Figure 4.1	Total charging power demand by time of day for each charging logic.	53
Figure 4.2	Temporal distribution of queued EVs by hour of day across different charging logics.	54
Figure 4.3	Spatial distribution of chargers experiencing queuing under the SOC-Based scenario.	55
Figure 4.4	Probability of initiating a charging session by time of day and initial SOC, disaggregated by charging logic.	56
Figure 4.5	Aggregate share of charging events by activity type under the heterogeneous scenario, pooled across all charging strategies.	57
Figure 4.6	Share of charging events by activity type and charging logic under the heterogeneous scenario.	58
Figure 4.7	Distribution of charging logics by daily activity complexity under the Flat scenario.	59
Figure 4.8	Distribution of charging logics by income, age, and gender.	61
Figure 5.1	Temporal distribution of power demand in the Free scenario.	69
Figure 5.2	Spatial distribution of charging events in the Free scenario.	70
Figure 5.3	Temporal distribution of charging events’ start time in the Flat-priced scenario.	72
Figure 5.4	Temporal distribution of charging events’ duration in the Flat-priced scenario.	73
Figure 5.5	Temporal distribution of power demand for Home chargers across three scenarios.	75
Figure 5.6	Temporal distribution of power demand for Public chargers across three scenarios.	76
Figure 5.7	Total number and percentage of Home and Public chargers used in each scenario.	78

Figure 5.8	Charger types used in each scenario throughout the day.	79
Figure 5.9	Hourly queue share (bars) and median waiting time (lines) at public charging stations under Free, Flat-Priced, and TOU-Priced scenarios.	80
Figure 5.10	Spatial distribution of charging events.	82
Figure 5.11	Spatial distribution of power demands.	83
Figure 5.12	Refined spatial distribution of charging demand across pricing scenarios (home and public chargers).	84
Figure 5.13	Spatial distribution of charging energy during the morning period (06 :00–10 :00).	86
Figure 5.14	Spatial distribution of charging energy during the midday period (10 :00–16 :00).	87
Figure 5.15	Spatial distribution of charging energy during the evening period (16 :00–22 :00).	88
Figure 5.16	Total number of public chargers used in each scenario.	89
Figure 5.17	Temporal distribution of power demand for public chargers across four scenarios.	90
Figure 5.18	Total number of public chargers used in each scenario.	91
Figure 5.19	Spatial distribution of power demand for TOU-priced and area-priced scenarios.	93
Figure 5.20	Temporal variation of power demand for home chargers in TOU-priced and area-priced scenarios.	94
Figure 5.21	Temporal variation of power demand for public chargers in TOU-priced and area-priced scenarios.	94
Figure 6.1	Kernel density estimation of state of charge at charging initiation for two range anxiety thresholds.	100
Figure 6.2	Kernel density estimation of charging start times under two range anxiety thresholds.	101
Figure 6.3	Aggregated charging power demand under different range anxiety thresholds.	103
Figure 6.4	Hourly probability of queuing and average queue time at public charging stations under different range anxiety thresholds.	105
Figure 6.5	Aggregated public charging power demand across battery and charging infrastructure scenarios.	109
Figure 6.6	Hourly probability of queuing at public charging stations across battery and charging infrastructure scenarios.	111

LIST OF SYMBOLS AND ACRONYMS

EV	Electric Vehicle
BEV	Battery Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
SOC	State of Charge
MATSim	Multi-Agent Transport Simulation
EV-Contrib	Electric Vehicle Contribution Module in MATSim
Urban-EV	Urban Electric Vehicle Charging Framework
CMA	Census Metropolitan Area
OD	Origin–Destination
GTFS	General Transit Feed Specification
OSM	OpenStreetMap
IPF	Iterative Proportional Fitting
IPU	Iterative Proportional Updating
TOU	Time-of-Use
CMCLP	Capacitated Maximal Coverage Location Problem
KDE	Kernel Density Estimation

CHAPITRE 1 INTRODUCTION

1.1 Background and Motivation

Road transportation electrification is increasingly seen as a vital strategy for cutting greenhouse gas emissions and local air pollution in cities. Therefore, electric vehicles (EVs) have become a central part of national and regional climate plans. Several governments have set ambitious goals for adopting electric vehicles and have promised to phase out internal combustion engines in the coming decades (1; 2). As part of these commitments, Canada has made substantial investments in charging infrastructure, particularly in Ontario, British Columbia, and Quebec (1). As a result, large metropolitan areas are expected to see a swift rise in EV ownership.

This transition, however, introduces a range of challenges for both transportation systems and electricity networks that extend beyond vehicle technology alone (3). Unlike traditional vehicles, EVs rely on electrical energy supplied by charging infrastructure that has limited capacity, is unevenly distributed across areas, and is shared among multiple users. When many vehicles charge simultaneously—especially during periods of high electricity demand—local distribution networks can face significant strain (4; 5; 6). These impacts are often most pronounced in residential areas during evening hours when charging activity coincides with peak household electricity consumption (7).

At the same time, charging infrastructure plays a direct role in shaping EV users' daily experiences. Limited charger availability, insufficient charging power, and long waiting times can reduce the convenience of EV use and contribute to concerns about driving range (8; 9). Access to charging infrastructure also varies across cities, with public chargers often concentrated in downtown or wealthier neighborhoods, while other areas are underserved (10). As EV adoption continues to grow, ensuring that charging systems remain reliable and accessible across diverse urban contexts becomes a critical challenge for planners and policymakers.

A main challenge in tackling these issues is that charging demand cannot be viewed as a fixed or external factor. Instead, it results from individual choices about when to charge, where to do it, and how long to stay connected. These choices are influenced by daily routines, travel needs, infrastructure access, and user preferences and perceptions. Consequently, the same charging infrastructure can lead to very different congestion patterns and grid impacts, depending on how drivers collectively utilize the system.

One behavioral mechanism that plays a particularly important role in these decisions is drivers’ perception of remaining battery charge. As the state of charge (SOC) decreases, many users experience growing concern about completing planned trips or finding a charging station—a phenomenon commonly known as range anxiety. This concern may lead drivers to start charging earlier than necessary, charge more often, or choose locations they consider reliable. In this way, SOC is not just a technical feature of the vehicle, but also a behavioral signal that affects when, where, and how often drivers charge, with direct impacts on queues and electricity demand.

In response to the challenges mentioned above, a variety of policy and planning tools have been suggested. Pricing strategies such as time-of-use tariffs aim to shift charging away from peak hours, while spatial pricing or differentiated access policies aim to spread demand across locations (11; 12). In parallel, technological developments—including larger battery capacities, faster chargers, and denser charging networks—are often promoted as solutions to reduce pressure on both users and infrastructure (13; 14; 15). However, these measures do not operate independently, and their effectiveness depends critically on how users adapt their charging behavior in response to both policies and constraints.

This thesis aims to better understand how EV charging demand develops through the interaction of individual behavior, charging infrastructure, and power system limits in urban settings. Instead of viewing charging demand as just an overall profile, the thesis models it as the result of activity-based decisions made by diverse users operating within realistic constraints. By directly connecting behavioral factors—such as range anxiety—to technological and infrastructural conditions, the thesis hopes to provide insights that support more effective charging policies, balancing grid reliability, infrastructure efficiency, and user convenience as EV adoption grows.

1.2 EV Charging as a System-Level Problem

Electric vehicle charging is not just about energy use; it is a system-level interaction involving users, charging infrastructure, and the electricity grid. Unlike traditional refueling, which usually happens at specific locations within short, well-defined time frames, EV charging can occur at many different places for varying durations. This flexibility offers opportunities for more efficient energy management; however, it also adds significant complexity, making it harder to predict and control the charging demand.

At the system level, charging demand is jointly shaped by three interrelated dimensions : *time*, *location*, and *duration*. When a vehicle charges determines whether it contributes to

peak or off-peak electricity demand. Where charging occurs affects which components of the grid and which charging facilities are impacted. How long a vehicle remains connected influences charger availability and queuing conditions for other users. These factors are closely interconnected and are influenced by daily travel patterns, activity schedules, and infrastructure limitations. Importantly, charging decisions are not made in isolation. When combined across many users, individual charging choices collectively lead to system-level issues such as congestion at charging stations, limited charger availability, and localized power demand. These emergent conditions, in turn, shape the experience and subsequent decisions of individual drivers, who must deal with waiting times, restricted access, or increased perceived risk. EV charging systems, therefore, exhibit feedback loops in which individual behavior creates system outcomes that later constrain or modify future decision-making.

From the perspective of the electricity grid, charging demand presents challenges not only because of overall energy use but also because it is concentrated in both time and location. Even a modest number of EVs can create significant local loads if many users charge simultaneously at the same site, especially in residential areas during evening hours (16). Such localized peaks may exceed the capacity of distribution transformers or feeders, leading to congestion or necessitating costly grid reinforcements (16). These impacts cannot be adequately represented using system-wide averages; instead, detailed descriptions of charging behavior and infrastructure use are needed.

From the perspective of the charging infrastructure, competition among users adds an extra layer of complexity. Public charging stations are shared resources, and their performance depends on both charger capabilities and user behavior. Long charging times reduce charger turnover and lead to longer waits, while synchronized arrivals can cause sudden queues even when overall demand remains relatively low (17; 18). Users who encounter congestion may respond by delaying charging, switching to alternative locations, or adjusting travel plans, thereby redistributing demand across other parts of the system (19).

Once again, as noted earlier, these system-level effects are interconnected with individual decision-making. Charging demand stems from choices made by users within various constraints, rather than from external demand profiles. Users vary in their access to home charging, their patience for waiting, their responsiveness to electricity prices, and their willingness to change travel or charging habits. As a result, the same infrastructure and pricing conditions can lead to significantly different outcomes.

Taken together, these interactions highlight why EV charging must be analyzed as a connected transportation–energy system problem. Analyses that focus only on grid load, infrastructure supply, or individual behavior in isolation provide only partial insights. Understanding

how charging demand changes over time and across locations requires a modeling framework that can represent individual decisions, aggregate their effects across users, and explicitly account for operational constraints such as charger availability, congestion, and queuing. This system-level view directly supports the modeling approach used in this thesis, which links daily activity patterns, charging behavior, and infrastructure performance to evaluate their combined impacts on demand and congestion.

1.3 Modeling EV Charging Behavior

Understanding EV charging as a system-level issue requires analytical tools that can model individual decision-making while also capturing its overall impact on the charging infrastructure and electricity networks. Over the past decade, various modeling approaches have been developed to characterize charging demand and evaluate its operational and system-wide effects. These approaches vary significantly in the level of behavioral detail, data requirements, and their ability to represent interactions among users.

One class of methods relies on empirical charging data collected from existing EV fleets (20; 21). These data-driven approaches use historical charging records to identify statistical regularities in charging start times, session durations, and energy consumption. When large and representative datasets are available, such methods provide valuable insights into observed charging behavior and can support short-term demand forecasting. However, their scope is inherently limited to conditions that have already been observed. As a result, they are less suited to evaluating changes in charging infrastructure, pricing schemes, or vehicle technology, and they provide limited insight into why drivers behave the way they do.

Model-based approaches aim to address these limitations by explicitly modeling driving and charging decisions. In these models, charging demand arises naturally from assumptions about travel behavior, battery dynamics, and user preferences. Among these approaches, agent-based models have gained particular attention in analyzing EV charging systems (22; 23; 24). Within an agent-based framework, individual vehicles or drivers are modeled as autonomous agents that make decisions throughout the day while interacting with both the transportation network and the charging infrastructure.

Agent-based models are especially well suited to capturing the temporal and spatial dimensions of charging behavior. Because agents follow daily activity schedules, charging decisions can be directly linked to trip chains, activity durations, and location choices. This structure makes it possible to reproduce key features of real-world charging systems, including the clustering of charging at home or work locations, competition for public chargers, and

time-of-day effects driven by routine travel patterns. Importantly, agent-based models can also represent feedback mechanisms, such as queuing at chargers and behavioral adaptation in response to congestion or pricing signals.

Despite these advantages, many existing agent-based EV charging models rely on simplified behavioral assumptions. A common practice is to impose a single charging rule across all agents—for example, charging exclusively at home (25) or initiating charging once the battery state of charge falls below a fixed threshold (26). While such assumptions simplify the model, they implicitly treat all users as having identical behavior. This assumption of homogeneity conflicts with empirical evidence, which shows significant differences among EV users in access to private charging, daily travel patterns, sensitivity to costs and waiting times, and tolerance for low battery levels.

Beyond structural charging rules, behavioral responses to declining battery levels represent another important dimension of charging behavior. As SOC decreases, drivers may experience increasing discomfort or risk aversion—commonly referred to as range anxiety—which can influence both the timing and location of charging decisions (27). Empirical and experimental studies suggest that drivers do not respond to low SOC in a purely binary manner, but instead adjust their behavior progressively as perceived range risk increases (28; 29). Although SOC is behaviorally important, it is often oversimplified in charging models. Many approaches depend on fixed SOC thresholds to start charging or assume all users tolerate low battery levels equally. Such models ignore variations in risk perception and may not accurately reflect how charging demand changes as SOC drops under different conditions of infrastructure availability and congestion. As a result, models that assume uniform SOC responses can predict overall charging demand but miss the underlying behavioral factors influencing individual choices. This limitation becomes especially critical when assessing policies or infrastructure updates, as users with different sensitivities to low SOC tend to respond differently to the same incentives or restrictions.

1.4 Behavioral Heterogeneity in Charging Decisions

EV charging behavior varies substantially across users and contexts. While all EVs require electrical energy, the conditions under which drivers choose to charge are shaped by a combination of technical constraints, daily routines, and individual preferences (30). Treating charging behavior as uniform across a population, therefore, risks overlooking important mechanisms that influence both infrastructure use and system-level dynamics outcomes.

One of the most significant sources of heterogeneity is access to charging infrastructure. Some

users have reliable access to private home chargers, while others depend partially or entirely on public charging facilities (31). This distinction alone can lead to significantly different charging behaviors. Users with home charging typically prefer long overnight sessions, while those without such access often rely more on daytime charging at workplaces, commercial locations, or public fast-charging stations. These variations influence not only when charging happens but also where congestion and grid impacts are most likely to occur.

Beyond access, heterogeneity also manifests in the *charging rules* that users implicitly or explicitly follow when deciding whether to charge. Drivers vary in what causes them to start charging, such as reaching a certain state-of-charge threshold, arriving at a specific activity location, or planning for future travel. Some prefer to charge early to lessen uncertainty, while others wait until it’s absolutely necessary. These different charging strategies can result in varying frequencies, session lengths, and patterns of charging, even if infrastructure and prices are the same. Using a single, uniform rule to describe charging behavior can overlook important differences and misrepresent how charging demand develops across the system.

Battery-related factors further influence diverse behaviors. Users vary in how they manage the battery’s charge level, their comfort with low SOC levels, their initial SOC at the start of the day, and their perception of range-related risks. Some drivers prefer to keep SOC levels relatively high and charge often, even for short durations, while others wait to charge until the battery drops to a low threshold (32). These preferences affect charging frequency, session length, and sensitivity to congestion or waiting times. As a result, identical travel patterns can lead to different charging behaviors depending on users’ risk attitudes and charging strategies.

Daily activity patterns add an extra layer of diversity. Charging opportunities depend on how long activities last and their locations, which differ between people and across days. Longer activities such as staying at home, working, or attending school typically allow for longer charging sessions. In contrast, shorter activities like shopping or leisure outings provide fewer chances for effective energy transfer. Users with more complex routines may have more charging options but also encounter tighter timing constraints, creating trade-offs between convenience and reliability.

Behavioral heterogeneity also influences how users respond to policy interventions. Pricing signals, for example, may strongly impact users with flexible charging options or those who adopt opportunistic charging rules, while having little effect on those whose charging decisions are tightly constrained by access or scheduling limitations. Similarly, infrastructure upgrades such as faster chargers may mainly benefit users who rely on public charging, while offering limited additional value to those who already charge at home. Ignoring differences in charging

rules and behavioral strategies can therefore lead to policies that seem effective on average but perform poorly for specific user groups.

Taken together, these considerations show that EV charging demand does not come from a single typical behavior, but from the mix of different charging rules and strategies used by diverse users. Recognizing this diversity is crucial for understanding how charging demand changes over time and space, and for assessing policies aimed at managing grid impacts, reducing congestion, or enhancing user experience. This view supports modeling methods that allow multiple charging logics to exist and interact, instead of applying one behavioral rule to all users.

1.5 Policy and Planning Strategies for EV Charging Systems

A mix of policy tools and infrastructure choices will be needed to reduce the effects of widespread electric vehicle use. Because charging demand comes from individual actions influenced by technical and spatial limits, no single solution can fully handle grid stress, congestion, and user experience issues. Instead, charging systems are shaped by how pricing mechanisms, infrastructure features, and vehicle technology interact, each affecting how users charge in practice.

Pricing policies are among the most widely discussed tools for managing EV charging demand (33; 22; 34; 35; 36). Time-based electricity tariffs aim to encourage users to shift charging away from peak-demand periods, typically by offering lower prices during off-peak hours (11; 12). When users have sufficient flexibility in when they charge, such pricing schemes can reduce simultaneous charging and help flatten aggregate load profiles. Spatial pricing mechanisms extend this concept by differentiating charging costs across locations to redistribute demand toward underutilized areas or facilities (22; 34; 35). While these methods can influence behavior, their success largely depends on users' access to alternatives and their willingness to change charging routines. For users who depend on a limited number of charging spots or face strict time constraints, pricing signals may have only a minor impact.

Beyond pricing, the physical features of charging infrastructure play a key role in shaping overall system performance. Charger density determines how many users can be served in a specific area, while charger power affects how quickly vehicles can recharge and how long chargers are occupied. Increasing charger density can reduce waiting times but might also lead to higher total electricity demand if many chargers are used at once, while increasing charger power can shorten charging times and improve turnover but may also increase local grid strain (37). These trade-offs show that infrastructure expansion doesn't automatically

lead to better system performance and needs to be assessed based on user behavior and grid limitations.

Vehicle technology, particularly battery capacity, introduces an additional dimension to these trade-offs. Larger batteries extend driving range and reduce charging frequency, which can lower the burden on public charging infrastructure (38). At the same time, larger batteries may increase energy consumption per charging session and total electricity demand if charging activity remains synchronized with common peak periods of the day, such as morning arrivals or evening home charging. As battery technology continues to evolve, its interaction with charging behavior and infrastructure use becomes increasingly important for long-term planning.

It is important to recognize that these policy and design measures do not operate independently. Pricing incentives shape how infrastructure is used; infrastructure features influence how users respond to pricing; and vehicle technology changes both charging needs and behavioral flexibility. For instance, faster chargers may support pricing strategies by allowing users to shift charging without long wait times, while larger batteries may decrease users' sensitivity to short-term price signals. Therefore, assessing these interactions requires an integrated framework that can simultaneously account for behavioral responses, infrastructure limitations, and grid impacts.

1.6 Research Gaps and Working Hypotheses

Despite growing interest in EV charging behavior and charging infrastructure planning, the existing literature still has several important limitations.

First, there is still a lack of a comprehensive agent-based modeling framework that can simultaneously represent urban EV charging behavior, behavioral heterogeneity, pricing mechanisms, and infrastructure constraints within a single system. Although many studies focus on individual components of this issue, relatively few offer an integrated framework that enables individual charging decisions to interact dynamically with congestion, charger availability, and power demand at the system level. Without such an approach, it remains challenging to assess how behavioral diversity, economic incentives, and technological advancements collectively influence charging outcomes in realistic urban environments.

Second, even within agent-based approaches, charging behavior is often dictated by fixed or uniform rules rather than arising naturally from individual decision-making processes. This restricts models' ability to show how diverse users respond differently to the same infrastructure and policies, and how these differences affect overall system outcomes such as

congestion, queuing, and load distribution.

Third, pricing-based demand management strategies are often evaluated mainly by their ability to shift charging demand in time or space, with less focus on whether the existing charging infrastructure can support the resulting demand patterns. In particular, pricing incentives might move congestion elsewhere rather than eliminate it completely, especially when charger capacity limits and queuing effects are not explicitly considered.

Fourth, technological and infrastructure strategies—such as increasing battery capacity, charger power, or charger density—are often analyzed separately. Few studies systematically compare these options under consistent behavioral assumptions, making it hard to determine which combinations of interventions are most effective for supporting growing EV adoption while also limiting grid stress.

Finally, behavioral responses related to battery state of charge are usually represented in a very simplified way. The initial state of charge is often considered an external or secondary assumption in the model, and sensitivity to low SOC—often linked with range anxiety—is usually modeled using fixed thresholds or uniform rules. As a result, the degree to which different starting battery conditions and varying sensitivities to low SOC affect charging behavior, congestion, and power demand remains insufficiently understood.

Based on these gaps, this thesis is guided by the following working hypotheses :

- Charging demand patterns and system-level impacts are strongly influenced by behavioral heterogeneity, and models that assume homogeneous charging behavior may misrepresent congestion and grid effects.
- Pricing strategies alone are insufficient to manage charging demand effectively if infrastructure constraints and user responses are not explicitly considered.
- Improvements in battery technology or charging infrastructure can alleviate certain system pressures, but they also introduce trade-offs that depend on how users adapt their charging behavior.
- Initial battery state of charge and sensitivity to low SOC significantly influence early charging behavior and congestion dynamics, and simplifying these dimensions may bias simulation-based assessments of charging demand.

These hypotheses do not predict specific numerical results. Rather, they outline qualitative expectations that are tested through simulation in later chapters.

1.7 Thesis Structure

This thesis is organized into a series of chapters that collectively develop, apply, and evaluate a behaviorally grounded framework for modeling electric vehicle charging in urban environments.

Chapter 2 reviews relevant literature on EV charging behavior, infrastructure planning, and modeling methods used to evaluate grid and transportation impacts. It emphasizes agent-based and activity-based models, as well as the treatment of behavioral assumptions and heterogeneity in existing research. This review situates the thesis within the broader research landscape and highlights gaps that motivate the proposed approach.

Chapter 3 outlines the modeling framework developed in this thesis. It describes the agent-based simulation environment and explains how it represents daily travel activities, vehicle energy consumption, and charging infrastructure. The chapter also introduces the behavioral components of charging decision-making and details how charging actions are integrated with activity schedules and system-level process constraints.

Chapter 4 examines the role of behavioral heterogeneity in EV charging behavior. It introduces multiple charging logics that represent different behavioral strategies and analyzes how their coexistence affects power demand, queuing dynamics, and spatial charging patterns. In this chapter, charging strategies are viewed as adaptive outcomes of the simulation rather than fixed assumptions.

Chapter 5 focuses on pricing-based demand management strategies. Using time-of-use and location-based pricing scenarios, it examines how pricing influences charging timing and location, and assesses how effectively pricing mechanisms alone can decrease peak demand without causing excessive congestion at public charging stations.

Chapter 6 explores technology and infrastructure design strategies to support higher levels of EV adoption. It compares scenarios with larger battery capacities, higher charger power, higher charger density, and combinations of these factors. Additionally, it examines how behavioral sensitivity to battery state of charge—represented through different range-anxiety parameters—affects charging behavior, grid load, charger utilization, and overall user experience.

Finally, Chapter 7 synthesizes the thesis’s main findings, discusses their implications for policy and planning, and outlines directions for future research. The chapter also addresses the limitations of the modeling approach to clarify the scope and applicability of the results.

Figure 1.1 summarizes the overall structure and methodological framework of the thesis.

The research is organized around a progressive sequence that links theoretical foundations, modeling development, and policy-oriented analysis.

The top part of the framework presents the conceptual basis of the thesis, beginning with the introduction and literature review. The literature is structured around five key themes : agent-based modeling, charging behavior and rules, behavioral heterogeneity, pricing mechanisms, and charging infrastructure and battery technology. These elements collectively motivate the research gaps addressed in this work.

The central component of the framework is the methodological approach, which is based on the MATSim agent-based simulation platform. Daily travel plans serve as the primary input, representing individuals' activity schedules and mobility patterns. Within this framework, charging behavior is modeled through three distinct decision logics—Planned, SOC-Based, and Opportunistic—which are allowed to coexist and evolve through MATSim's iterative execution, scoring, and replanning process. Additional behavioral and policy dimensions, such as pricing and range anxiety, are incorporated to evaluate their effects on charging decisions.

The model generates detailed outputs at both the individual and system levels, including charging location, timing, duration, charger type, energy consumption, and state-of-charge dynamics. These outputs enable a comprehensive analysis of charging behavior and its implications for infrastructure usage and grid performance.

Building on this framework, the thesis investigates four main hypotheses. These hypotheses address the role of behavioral heterogeneity in shaping charging demand, the effectiveness of pricing strategies, the interaction between infrastructure and user behavior, and the influence of range anxiety on charging dynamics.

Finally, the framework culminates in a synthesis of results and policy implications, where the combined effects of behavioral, spatial, and temporal factors are evaluated to inform the design of more effective EV charging strategies.

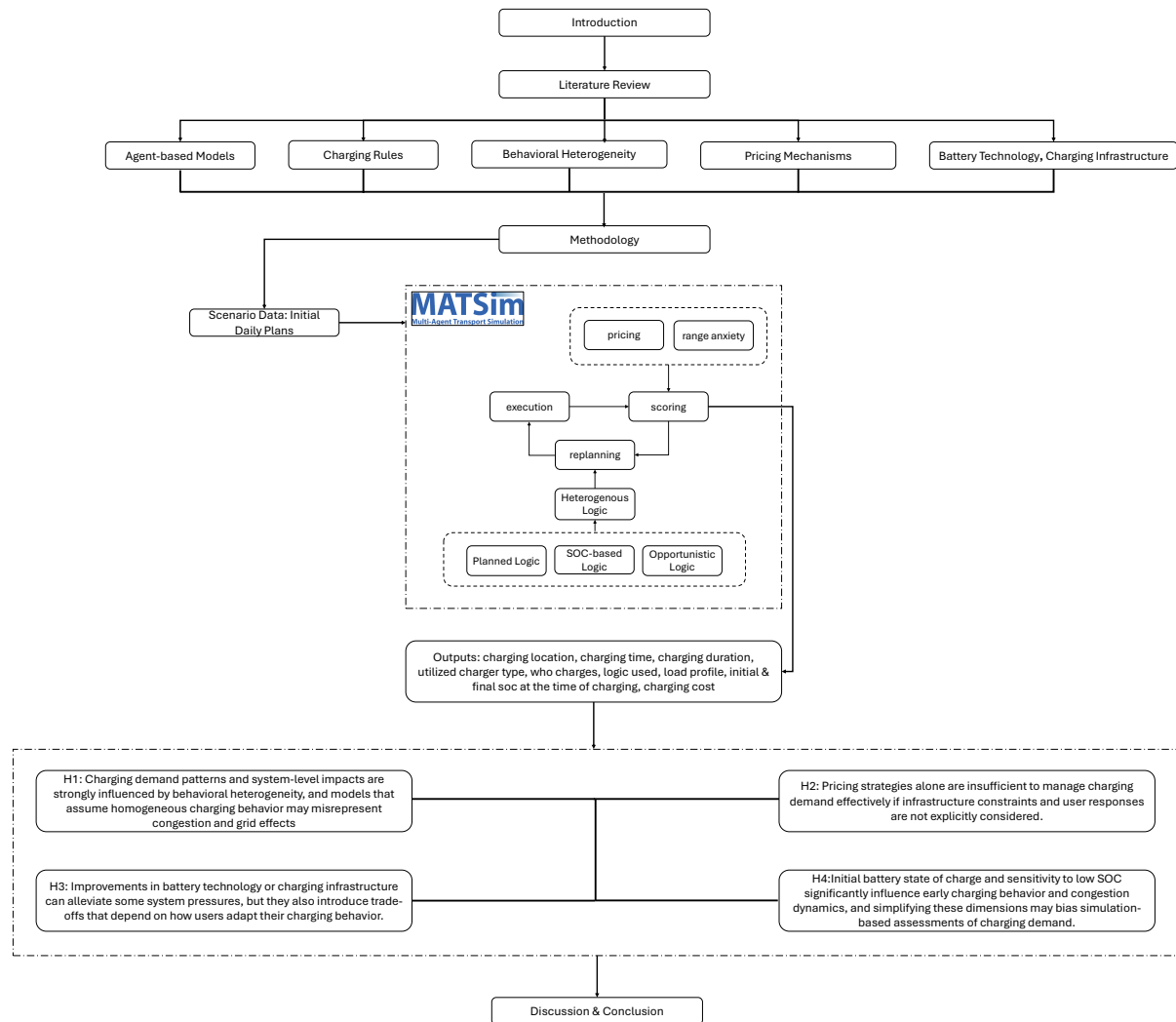


FIGURE 1.1 Overview of Thesis.

CHAPITRE 2 LITERATURE REVIEW

This chapter reviews the literature on modeling charging behavior, focusing on agent-based simulation frameworks, behavioral representations of charging decisions, and policy- and infrastructure-related interventions. As EV adoption accelerates in urban areas, charging demand has become a complex phenomenon shaped by individual mobility patterns, activity schedules, infrastructure availability, and interactions with electricity systems. Understanding this complexity has driven a growing body of research to move beyond simple load estimates toward more behaviorally grounded modeling approaches.

The goal of this review is not only to summarize existing modeling practices but also to critically examine the assumptions behind them, the aspects of behavior they represent, and the limitations that still exist. Instead of organizing the literature by specific tools or case studies, the review adopts a thematic structure that highlights key conceptual challenges in modeling urban EV charging. These include how to represent individual decision-making, address behavioral diversity and adaptation, incorporate pricing and policy tools, and understand the interaction between charging behavior and technological or infrastructural constraints.

The chapter is structured around five interrelated themes : (i) agent-based frameworks for EV charging analysis, (ii) representations of charging decision-making, (iii) behavioral heterogeneity and adaptive charging strategies, (iv) pricing mechanisms and demand-side control, and (v) technological and infrastructural dimensions of EV charging systems. Together, these themes provide a comprehensive foundation for situating the modeling approach developed later in the thesis.

2.1 Agent-Based Modeling and Behavioral Representation of EV Charging

The rapid growth of EV adoption has driven extensive research on modeling frameworks that can represent the interactions between travel behavior, charging decisions, and energy systems. Charging demand is influenced not only by vehicle technology and battery capacity but also by how individuals plan their daily activities, schedule trips, access charging stations, and respond to personal constraints. Capturing these interactions requires modeling approaches that combine mobility and charging within a single behavioral framework.

Early efforts to simulate EV charging demand often relied on stochastic or event-based approaches, including Monte Carlo simulations and simplified agent-based representations (39; 40; 41). While these models provided useful first-order insights into aggregate charging

patterns, charging was typically treated as a discrete event occurring at predefined locations. Continuous vehicle movement, activity schedules, and feedback between travel behavior and charging decisions were only partially represented, limiting the behavioral realism of these approaches.

More recent studies increasingly adopt microscopic, activity-based transport simulations, in which agents execute complete daily activity–travel plans on detailed transportation networks (42). Within these frameworks, vehicle energy consumption and SOC are continuously updated as agents travel, stop for activities, and access charging infrastructure. Charging decisions therefore emerge directly from daily activity patterns rather than being imposed as isolated post-trip events. This integration enables a more realistic representation of how charging demand evolves over time and space, and how it interacts with infrastructure availability and grid constraints.

Among the available modeling approaches, agent-based models (ABMs) have become one of the most widely used tools for analyzing EV charging behavior at urban and regional scales (22; 24; 23; 42). In ABMs, travelers and vehicles are represented as autonomous decision-making agents that interact with transportation networks and charging infrastructure (43). Internal states such as location, planned activities, energy consumption, and SOC can be tracked for each agent throughout the simulation. This structure allows ABMs to capture localized congestion, charging competition, demand peaks, and heterogeneous system responses.

Within this class of models, MATSim has emerged as one of the most widely adopted platforms for large-scale EV charging studies (22; 44; 45; 46; 47). Originally developed for activity-based travel demand modeling, MATSim has been extended to include vehicle energy consumption models and charging infrastructure representations. Its modular architecture allows researchers to test alternative charging rules, pricing mechanisms, and infrastructure layouts while maintaining computational tractability at the metropolitan scale. Other agent-based platforms, such as BEAM (48), CityMoS (49), and SEMSim (50), provide similar capabilities but are often applied to more specific use cases or smaller spatial domains.

While agent-based frameworks offer a strong technical foundation, simulation results are highly sensitive to how charging decisions are modeled. In most agent-based EV simulations, charging behavior hinges on two related choices : when to start charging and where to charge afterward. In many cases, these decisions are made together. Agents begin searching for a charging station when their battery SOC drops below a set threshold, and a charging location is then immediately chosen (46).

A dominant approach for modeling charging initiation relies on SOC-based triggers. Under

this paradigm, an agent initiates charging when the remaining battery level falls below a fixed threshold, typically between 20% and 60%. Variants include triggering charging when SOC is insufficient to complete the next planned trip or when additional safety margins are violated (51; 52; 53). For example, Bi et al. (51) tested multiple SOC-based rules in the CityMoS framework, including charging when SOC falls below 20% or when the vehicle cannot complete the next trip plus a safety margin, while always selecting the nearest available charging station. Similarly, Chaudhari et al. (53) assumed charging initiation when SOC approaches 25% or when future trips become infeasible.

SOC-based triggers provide a clear, computationally efficient mechanism for ensuring vehicle feasibility in simulations. However, they embed strong behavioral assumptions by framing charging primarily as a reactive response to low battery levels. Empirical evidence suggests that many EV users coordinate charging with long-duration activities, such as overnight parking at home or extended stays at work, rather than waiting until SOC reaches a critical level (54). As a result, threshold-based models may overemphasize synchronized charging events and under-represent routine-based or anticipatory charging behavior.

Once a charging trigger is activated, the choice of charging location is most commonly modeled using proximity-based heuristics. Vehicles are typically assigned to the nearest available charger, the station requiring the shortest detour, or the first feasible charger encountered along a planned route (25; 39; 55). For instance, Sweda and Klabjan (25) assumed universal access to home charging and did not explicitly define alternative charger selection mechanisms, while Trippe et al. (39) and Bischoff and Maciejewski (55) consistently selected the nearest feasible charging location. To reduce deterministic allocation effects, some studies introduce stochastic choice mechanisms or bounded choice sets that allow agents to select among multiple nearby chargers (56; 57). Nevertheless, these approaches capture only a subset of the factors influencing real-world charging decisions, such as waiting-time expectations, charger reliability, familiarity, and compatibility with activity duration (58).

Charging behavior is further shaped by assumptions regarding the initial SOC at the start of the simulation day. Initial SOC affects when users first perceive the need to charge, how charging activity accumulates over time, and when congestion emerges. Despite its behavioral relevance, initial SOC is often treated as a technical input, assigned randomly or fixed without systematic analysis (59; 60; 61). Similarly, range anxiety is often acknowledged as an important driver of charging behavior but is typically modeled implicitly through fixed SOC thresholds or conservative safety margins (27). Such representations fail to capture the gradual increase in concern as SOC declines or the substantial heterogeneity in user sensitivity to low battery levels.

The literature review highlights two main limitations. First, many agent-based EV charging models presume uniform charging behavior, applying identical logic to all agents regardless of individual user traits or daily circumstances. Second, charging start points are often determined by fixed SOC thresholds that ignore changing conditions like traffic jams, previous charging experiences, or upcoming activities. In urban settings, where daily travel usually stays within the vehicle’s range, users rarely face critically low SOC levels. Instead, charging is often pre-planned and influenced by external factors such as electricity prices, convenience, or long-duration tasks at home or work.

Overall, the literature presented in this section emphasizes the advantages and shortcomings of current agent-based EV charging models. While these frameworks provide detailed views of interactions between mobility and infrastructure, they often oversimplify charging behavior by using uniform, reactive decision rules. This highlights the need to explore behavioral diversity and adaptive charging strategies, which are discussed in the next section.

2.2 Behavioral Heterogeneity and Adaptive Charging Strategies

Increasingly, research shows that treating all electric vehicle users as if they charge in the same way undermines the realism and effectiveness of agent-based charging models. Studies repeatedly show significant differences in charging behavior, access to infrastructure, low battery tolerance, and responses to factors such as congestion, price, and daily routines. Consequently, many modeling approaches aim to include behavioral diversity to more accurately reflect real-world charging patterns and overall system results.

One common approach introduces heterogeneity through predefined user categories, with each category governed by a distinct charging rule. For example, some studies distinguish between *critical* and *non-critical* charging states, allowing only vehicles below certain SOC thresholds to initiate charging under constrained conditions (46). Other frameworks differentiate between compulsory and discretionary charging, depending on whether future trip feasibility is threatened (62). These categorical representations improve upon single-threshold models by allowing different responses under different conditions, but the behavioral types themselves are typically fixed. Agents do not transition between strategies, and heterogeneity is imposed exogenously rather than emerging from experience or context.

A smaller but growing set of studies models charging behavior as an adaptive process, allowing agents to adjust decisions based on past outcomes such as charging success, congestion, or low-SOC events (63; 64). In such frameworks, charging strategies develop over multiple simulation days, creating feedback loops between individual actions and overall system performance.

These methods are especially effective for capturing learning effects and path dependence, as users may adjust their charging timing or location choices after repeatedly facing unfavorable conditions. However, experience-based models are still relatively uncommon in large-scale urban applications due to added complexity, data needs, and calibration difficulties.

Despite these advances, most heterogeneous charging models still depend heavily on SOC thresholds and proximity-based charger selection. Even when learning or adaptation is incorporated, charging decisions are often seen mainly as responses to energy shortages rather than proactive choices integrated into daily routines. Other aspects of behavioral diversity—such as long-term habits, information uncertainty, social influence, or charging awareness—are rarely explicitly modeled and largely remain unexplored in urban-scale simulations.

Additionally, behavioral heterogeneity is not always dynamically connected to system performance. In many models, users are given different behaviors, but these behaviors do not change in response to congestion, queuing, or infrastructure use over time. As a result, the potential of behavioral diversity to smooth demand, spread charging spatially, or reduce peak congestion is not fully explored. These limitations emphasize the difficulty of representing charging behavior as both diverse and adaptive within computationally manageable urban-scale models.

2.3 Pricing Mechanisms and Demand-Side Control in EV Charging

As EV adoption accelerates, unmanaged charging demand raises concerns about peak electricity load, local grid congestion, and inefficient utilization of charging infrastructure. In response, a substantial body of research has investigated pricing mechanisms as demand-side control actions (DSCA) to influence when and where EV users charge. Rather than imposing direct operational constraints, pricing strategies seek to guide charging behavior by altering the relative cost of electricity across time and space.

TOU pricing is the most extensively studied pricing mechanism in the EV charging literature. By varying electricity prices throughout the day, TOU schemes encourage users to shift charging away from peak periods toward off-peak hours, such as overnight or midday (22; 34; 35). Numerous simulation-based studies report that TOU pricing can reduce evening demand peaks and smooth aggregate load profiles, particularly in residential charging contexts (65; 66). These findings have contributed to the widespread perception of TOU pricing as an effective and relatively simple tool for managing charging demand.

A detailed examination of the modeling assumptions reveals notable limitations behind these findings. Many studies treat pricing as either an external constraint or a fixed rule, rather

than as a central element influencing decision-making. In other words, many modeling efforts implement price effects in a simplified or static manner. In several studies, pricing is applied as a post-processing adjustment rather than being dynamically integrated into agents' charging decisions. For instance, Szinai et al. (34) combined the BEAM mobility simulator with the PLEXOS grid model to analyze unmanaged, TOU, and smart charging scenarios in California. While informative at the system level, their framework relied on fixed charging windows rather than adaptive, agent-level responses to time-varying prices. Similarly, Waraich et al. (22) used MATSim and PMPSS to study “dumb,” dual-tariff, and smart charging strategies, but treated charging as a post-processing module disconnected from travel behavior, excluded queuing and charger availability, and assumed that vehicles charge fully once connected.

Moreover, while TOU pricing can shift charging demand over time, it does not inherently address spatial concentration. When many users respond similarly to low-price periods, charging demand may become synchronized, potentially creating new peaks or congestion during incentivized time windows (67). For example, widespread early-morning charging encouraged by TOU pricing may overload workplace charging infrastructure if spatial capacity constraints are not explicitly considered. To address spatial imbalances in charging demand, several studies have proposed location-based or area-based pricing schemes, in which electricity prices vary across charging locations or zones (11; 12). The objective of these approaches is to steer users toward underutilized areas or away from constrained zones, thereby improving the spatial distribution of charging activity. Analytical models and small-scale simulation studies suggest that spatial price signals can influence charger choice under certain conditions (68). However, their effectiveness in realistic urban settings remains uncertain, as users' responses are constrained by activity schedules, trip purposes, familiarity with locations, and tolerance for additional travel time.

Infrastructure constraints are another recurring limitation. Although many studies show demand shifting from evening to morning under TOU incentives, they rarely examine whether existing public charging networks can accommodate the redistributed load. For example, early-morning charging at workplaces could overload specific zones if pricing strategies do not account for station capacity. Authors in (69) sought to address this by combining MATSim-based mobility simulation with a Capacitated Maximal Coverage Location Problem (CM-CLP) model for charger allocation, but their post-processing approach precluded behavioral feedback loops between charging congestion and travel decisions.

The literature identifies three ongoing gaps. Firstly, most pricing research mainly examines temporal demand shifts, with limited focus on the spatial concentration effects caused by uniform pricing signals. Secondly, few studies evaluate whether existing public charging in-

infrastructure can handle the redistributed demand during incentivized times. Thirdly, pricing responses are often modeled using simplified or post-processing methods that restrict charging activity to low-price periods, implicitly assuming all users are both willing and able to concentrate charging during these times. This overlooks activity constraints, infrastructure competition, and diverse behavioral responses.

2.4 Battery Technology and Charging Infrastructure Trade-offs

Alongside behavioral and policy research, a substantial amount of investigation focuses on technological and infrastructure strategies to increase electric vehicle adoption. These studies primarily examine battery capacity, charger power, and charger density, each affecting charging behaviors, infrastructure usage, and the electric grid in different ways. Although typically analyzed separately, these factors are interconnected, and their overall effect largely depends on how users interact with the charging infrastructure.

Advances in battery technology have led to steady increases in vehicle range, with larger battery capacities frequently cited as a means to reduce charging frequency and alleviate range anxiety (11; 70; 71). Vehicles equipped with larger batteries can complete a greater share of daily travel without mid-day charging, potentially reducing reliance on public infrastructure. However, the implications for electricity demand are not straightforward. Fewer charging events may be offset by larger energy transfers per session, particularly when users recharge during long-duration activities such as overnight parking at home or extended stays at work. As a result, increased battery capacity does not necessarily translate into lower peak demand or reduced congestion.

Another commonly proposed strategy is to increase charger power, particularly by deploying fast or high-power chargers. Higher charger power reduces charging duration and increases station throughput, improving convenience for users with limited access to home charging (72; 73). From an operational perspective, faster charging can mitigate queuing by reducing dwell times. At the same time, high-power chargers draw large instantaneous loads, which can exacerbate local grid stress even when total daily energy demand remains unchanged. Studies focusing on fast-charging hubs and corridors highlight the risk of localized power peaks that may exceed distribution-level capacity when multiple vehicles charge simultaneously (74).

Expanding charger density offers an alternative focus on spatial coverage instead of just charging speed. Adding more charging stations reduces the distance to the closest charger, improves redundancy, and spreads demand more evenly across areas. Studies indicate that, especially in dense urban settings, increasing charger density can be more effective at im-

proving accessibility and easing congestion than merely upgrading charger power (75; 76). However, higher charger density entails significant capital and maintenance costs, and without appropriate demand management, additional chargers may remain underutilized during off-peak periods while failing to fully alleviate congestion during peak times.

Although there has been extensive research on these aspects, most studies analyze battery capacity, charger power, and charger density separately. Few modeling approaches provide systematic comparisons of these strategies under consistent assumptions regarding user behavior, travel demand, and infrastructure limitations. Additionally, technological progress could alter charging behavior—such as encouraging users to delay charging or increasing reliance on fast chargers—forming feedback loops that are difficult to model without incorporating behavioral insights.

Overall, the literature emphasizes key trade-offs between technological and infrastructural strategies for promoting EV adoption. Enhancements such as increasing battery capacity, charger power, or charger density can boost certain system performance aspects but may impose new limitations in other areas. To fully grasp these trade-offs, modeling approaches need to integrate technological details with realistic portrayals of charging patterns and infrastructure utilization.

2.5 Range Anxiety and Its Role in Electric Vehicle Charging Behavior

Range anxiety is often described as the fear that an EV might run out of battery before reaching a destination or a charging station (77; 78). Although battery capacities and charging networks have steadily improved, this concern persists among EV users and is often seen as a key obstacle to EV adoption and promoting effective charging habits (77). The concern is especially strong among new drivers, those on long trips, or users in areas with unpredictable charging options (79).

Range anxiety significantly influences daily charging habits beyond its impact on adoption. The fear of battery depletion leads users to charge their vehicles earlier than necessary, even when they have enough battery for upcoming trips (46; 78). To minimize the risk of being stranded, drivers avoid low SOC levels, leading to more frequent opportunistic charging and a tendency to keep their batteries topped up whenever possible (46). As a result, charging choices are shaped not only by travel demands and energy needs but also by personal feelings of comfort and safety.

These behavioral responses directly influence when and how much electricity is used for EV charging. Early and precautionary charging often overlaps with peak-demand periods,

especially in residential areas, affecting overall load patterns and potentially worsening local grid congestion (77; 79). Correctly modeling this behavior is crucial for realistic estimation of EV-related electricity consumption and for assessing strategies to manage charging loads efficiently.

Several studies have explored the factors behind range anxiety and suggested ways to reduce its impact, such as expanding infrastructure, providing better information, and behavioral changes (77; 79; 80). However, in many modeling studies, range anxiety is either handled implicitly—by using fixed SOC thresholds that trigger charging—or completely ignored. These simplifications miss the point that range anxiety is a gradual and user-specific issue rather than a simple on-or-off condition that only occurs at very low SOC levels.

As mentioned, agent-based simulation frameworks such as MATSim are well-suited to modeling range anxiety because they allow individual agents to adjust their charging decisions over time based on past experiences and perceived risks. In earlier versions, the MATSim EV module allowed vehicles to operate even after their batteries were depleted. To fix this issue, Adenaw and Lienkamp added a fixed penalty to the agents’ utility when the battery reaches zero charge (46). Although this discourages full battery depletion, it applies the penalty only at failure and does not affect agent behavior during learning and replanning. Additionally, setting the penalty too high can hinder the simulation’s convergence.

In newer versions of MATSim, strict constraints prevent agents from completely running out of charge. However, this mechanism still only activates when the battery is fully drained and does not account for anticipatory charging behavior at higher SOC levels. As a result, current methods fail to capture the gradual development of range anxiety and its influence on charging decisions before critical battery levels are reached.

Meanwhile, pricing strategies, such as time-of-use tariffs, naturally discourage charging during expensive periods and are often suggested as tools to control electricity demand at charging stations. Conversely, range anxiety acts as a counterbalance by encouraging users to charge earlier and more often. Charging behavior, therefore, results from the interaction between economic incentives and psychological factors. To the authors’ knowledge, this combined influence of pricing and range anxiety has not been explicitly studied within agent-based EV charging simulations.

Modeling range anxiety explicitly within a simulation framework allows for a systematic analysis of its behavioral and system-wide effects. Treating range anxiety as a continuous, SOC-dependent factor—rather than a simple yes/no constraint—offers a more realistic view of how EV users navigate perceived risks, costs, and convenience when deciding to charge under uncertain conditions.

2.6 Synthesis of Literature and Research Objectives

The literature reviewed in this chapter shows significant progress in modeling electric vehicle charging behavior, particularly through the development of agent-based simulation frameworks that capture detailed travel patterns and charging processes. Activity-based models have enabled the integration of charging decisions within daily mobility routines, while extensions that include pricing mechanisms and infrastructure constraints have broadened the scope of policy and planning questions that can be explored. However, the review also highlights ongoing methodological and conceptual challenges that limit current approaches' ability to fully capture charging dynamics in complex urban settings.

A major limitation across much of the literature is how charging behavior is represented. Charging decisions are often based on simple or uniform rules, such as fixed SOC thresholds or proximity-based heuristics. While these representations make models feasible and efficient, they tend to see charging as merely a reactive response to energy shortages and neglect the influence of daily routines, habitual behaviors, and forward planning. Efforts to include behavioral diversity and learning are important steps forward, but they remain somewhat limited and are often implemented through predefined categories or narrowly focused adaptive mechanisms.

Pricing mechanisms, especially time-of-use and location-based pricing, have been extensively studied as tools to control demand. The literature indicates that pricing can affect charging demand, but its effectiveness depends heavily on behavioral assumptions and specific circumstances. Many studies assume uniform or highly responsive user behavior and pay limited attention to how charging demand interacts with infrastructure capacity, queuing, and user experience. Consequently, the overall feasibility and distributional effects of pricing-induced demand shifts are not yet well understood, particularly in dense urban areas.

Meanwhile, extensive research has explored technological and infrastructural strategies, such as boosting battery capacity, increasing charger power, and raising charger density. These studies reveal important trade-offs : gains in one area might ease certain constraints but worsen others, especially regarding peak power demand and local grid strain. Yet most evaluations examine these strategies separately and make simplified assumptions about behavior, which limits understanding of how technological progress interacts with charging habits and infrastructure use.

Overall, the literature highlights a broader challenge : although many studies examine individual components of EV charging systems, few provide comprehensive frameworks that integrate charging behavior, behavioral diversity, pricing strategies, and infrastructure limita-

tions into a single urban-scale simulation. Additionally, charging behavior is often treated as a fixed assumption rather than as an outcome of the interaction among users, infrastructure, and policy signals.

Against this background, the goal of this thesis is to develop and apply a behaviorally grounded modeling framework that enhances understanding of how electric vehicle charging demand arises in urban areas and how it responds to policies, infrastructure, and technology interventions. Charging is viewed not as an external demand profile, but as the result of individual decisions made within daily activity constraints, battery conditions, infrastructure availability, and system-level feedbacks.

More specifically, the thesis pursues the following research objectives :

- To represent EV charging behavior within an agent-based simulation framework that explicitly links charging decisions to daily activity patterns, vehicle energy dynamics, and charging infrastructure constraints.
- To examine how heterogeneity in charging behavior influences system-level outcomes, including electricity demand profiles, queuing at charging stations, and spatial patterns of infrastructure utilization.
- To assess the effectiveness and limitations of pricing-based demand management strategies, including time-based and location-based pricing, when behavioral diversity and infrastructure constraints are explicitly taken into account.
- To evaluate trade-offs between alternative technology and infrastructure strategies, such as increasing battery capacity, charger power, and charger density, under consistent assumptions regarding travel behavior and charging decision-making.
- To explore the sensitivity of charging behavior and system-level outcomes to assumptions regarding initial battery state of charge and to alternative representations of range anxiety within charging decision processes.

The contributions of this thesis follow directly from these objectives. First, it advances the modeling of EV charging behavior by treating charging strategies as behavioral outcomes that emerge from individual decision-making rather than as fixed assumptions. Second, it provides an integrated analytical framework in which behavioral, policy, and technological interventions can be examined consistently within the same urban context, allowing interactions and trade-offs to be identified explicitly. Third, by applying it to a large metropolitan case study, the thesis generates insights directly relevant to charging infrastructure planning and demand management as electric vehicle adoption increases.

TABLEAU 2.1 Synthesis of EV Charging Modeling Literature and Identified Research Gaps

Research Dimension	Common Modeling Practice	Key Limitation / Gap	Representative Studies
Agent-based frameworks	Activity-based agent-based models simulate travel behavior, SOC evolution, and charging processes, often using platforms such as MATSim or BEAM.	Lack of a comprehensive framework jointly representing pricing, heterogeneous charging behavior, infrastructure constraints, and range anxiety at metropolitan scale.	(22; 45; 48)
Behavioral homogeneity	Uniform charging rules (e.g., charging initiation and location choice) are commonly applied to all agents.	Heterogeneous charging strategies are rarely modeled explicitly or allowed to emerge endogenously through interaction with system conditions.	(46; 26; 81; 40; 52; 53; 25; 55; 39)
Time-based pricing (TOU)	Time-of-use pricing is shown to shift charging away from peak periods in residential and urban settings.	Often implemented as an external constraint assuming homogeneous compliance and ignoring congestion and behavioral feedback.	(22; 34; 35)
Spatial pricing	Location-based pricing influences charger choice in theoretical or small-scale simulations.	Rarely evaluated in large, activity-based urban models or combined with temporal pricing mechanisms.	(11; 68)
Infrastructure constraints	Some models include charger capacity limits, queuing, or power constraints.	Congestion effects are often treated exogenously and do not influence subsequent user decisions.	(69; 25)
Battery capacity improvements	Larger batteries reduce charging frequency but increase per-session energy demand.	System-level impacts are rarely evaluated jointly with behavioral responses and infrastructure constraints.	(71; 70)
Charger power and density	Fast chargers and denser networks improve accessibility and throughput.	Trade-offs between charger power, charger density, and grid stress are seldom compared under consistent behavioral assumptions.	(75; 73)
Range anxiety representation	Range anxiety is often represented implicitly through fixed SOC thresholds or conservative charging triggers.	Continuous, SOC-dependent behavioral pressure and sensitivity to low SOC are rarely examined systematically.	(60; 61; 27)
Integrated policy evaluation	Behavioral, pricing, and infrastructure interventions are typically studied in isolation.	Few frameworks jointly evaluate behavior, pricing, congestion, and infrastructure trade-offs within a unified urban model.	(33; 36)
This thesis	Develops a unified agent-based modeling framework in which charging behavior emerges endogenously from heterogeneous charging strategies, incorporates behavioral responses to pricing and congestion, and enables consistent comparison of pricing policies and infrastructure investment scenarios in large-scale urban systems.		

CHAPITRE 3 METHODOLOGY

3.1 Methodology

3.1.1 Overview of the Modeling Framework

This thesis develops an integrated agent-based modeling framework to analyze EV charging behavior in large urban systems under realistic behavioral, infrastructural, and pricing constraints. Consistent with the system-level perspective established in Chapter 1 and the research gaps identified in Chapter 2, charging demand is modeled as an emergent outcome of individual decisions embedded within daily activity and travel patterns, rather than as an exogenous input.

The modeling framework builds upon the *Multi-Agent Transport Simulation* (MATSim) platform (82), which provides a scalable, activity-based simulation environment capable of representing individual mobility decisions and their aggregate effects. EV charging functionality is implemented through a layered architecture consisting of three core components :

- the baseline MATSim system for daily activity-based mobility simulation,
- the EV-Contrib module for vehicle electrification and energy consumption modeling, and
- the Urban-EV framework for integrating charging directly into primary activities.

On top of this architecture, the present study introduces two behavioral extensions—electricity pricing and a range-anxiety penalty—that jointly shape charging decisions through MATSim’s utility-based learning process. These extensions address a key limitation identified in the literature : without explicitly balancing charging costs against battery-related risk, agent-based EV simulations may produce implausible charging patterns, such as excessive avoidance of charging under high prices or unrealistic battery depletion. The integration of pricing and range anxiety enables charging behavior to evolve as a trade-off between economic incentives and operational feasibility.

Figure 3.1 illustrates the overall simulation loop and the position of the proposed EV charging extensions within MATSim’s iterative structure. It illustrates the modified MATSim simulation loop as implemented in this study. While the overall structure follows the standard MATSim framework—comprising execution, scoring, and replanning phases—the model is extended to explicitly represent electric vehicle charging behavior and its interaction with daily activity schedules.

The key addition lies in the integration of a dedicated charging decision layer within the

replanning process. Instead of relying on a single deterministic rule, agents can select among multiple charging logics, namely Planned, SOC-Based, and Opportunistic strategies. These logics are embedded within the co-evolutionary learning process, allowing agents to adapt their charging behavior over successive iterations based on experienced outcomes.

Another important extension is the incorporation of behavioral and policy-related factors into the scoring function. Electricity pricing is introduced as a direct cost component influencing charging decisions, while a penalty function captures range anxiety by assigning increasing disutility to low state-of-charge levels. Together, these elements allow the model to represent both economic and behavioral drivers of charging behavior.

As a result, the simulation produces detailed charging-related outputs, including charging location, timing, duration, energy consumption, and state-of-charge dynamics. These outputs are then used in the analysis phase to evaluate system-level impacts such as demand patterns, congestion, and infrastructure utilization.

Overall, this extended framework enables a more behaviorally realistic representation of EV charging decisions, capturing the interaction between daily mobility patterns, infrastructure constraints, and adaptive user behavior.

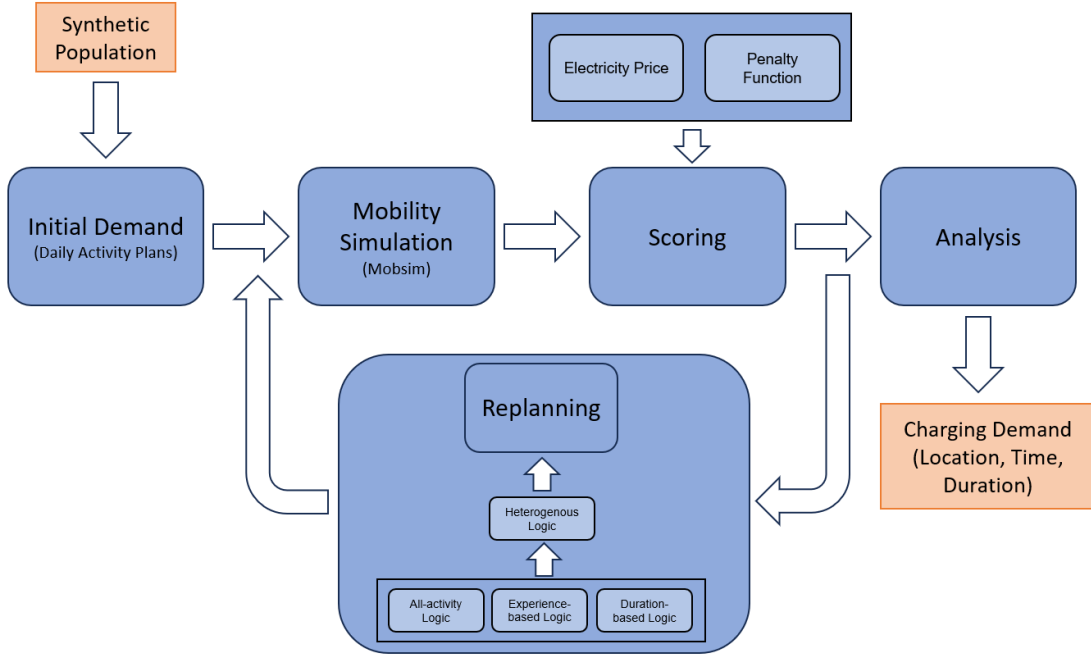


FIGURE 3.1 MATSim's iterative loop in this study.

3.1.2 MATSim : Activity-Based and Agent-Based Simulation

MATSim is an open-source, agent-based transport simulation framework designed to model daily mobility behavior at metropolitan scale through an iterative, co-evolutionary learning process (82; 83). Each traveler is represented as an autonomous agent equipped with one or more daily activity–travel plans. These plans define a complete sequence of activities—such as home, work, education, shopping, or leisure—along with their locations, desired durations, and the trips connecting them.

Initialization and Daily Plan Execution

At the beginning of the simulation, agents are initialized with daily plans derived from empirical data sources, described in Section 3.2. During each iteration, all agents execute their selected plans within the *mobility simulation* (mobsim). The mobsim explicitly models vehicle movements on the transportation network, accounting for link capacities, congestion, and interaction effects between agents. As a result, experienced travel times, delays, and congestion patterns emerge endogenously rather than being imposed exogenously.

This activity-based representation is particularly well suited for EV charging analysis. Because activities constrain when and where vehicles are parked, they define the feasible temporal windows during which charging can occur. Charging opportunities, therefore arise naturally from daily schedules, rather than being imposed independently of travel behavior.

In the present framework, key behavioral dimensions such as mode choice and route choice are modeled endogenously through the replanning process, allowing agents to adapt their decisions in response to network conditions, congestion, and charging-related factors.

However, daily activity patterns—including trip generation and destination choice—remain exogenous and fixed throughout the simulation. As a result, while the model captures behavioral adaptation in terms of how individuals travel and charge (e.g., when, where, and by which mode), it does not represent feedback effects on broader mobility patterns, such as changes in activity participation or destination selection in response to charging costs or infrastructure constraints.

Consequently, the results should be interpreted as reflecting adaptive operational decisions within a fixed activity system, rather than a fully integrated representation of transport–energy system co-evolution.

Scoring and Utility Formulation

After execution, each plan is evaluated using the utility function originally proposed by Charypar and Nagel (84). The total daily utility is expressed as the sum of activity-related utilities and travel-related (dis)utilities :

$$U_T = \sum_{i=1}^A U_{\text{act},i} + \sum_{i=1}^{Tr} U_{\text{travel},i}, \quad (3.1)$$

where $U_{\text{act},i}$ captures the utility of performing activity i , and $U_{\text{travel},i}$ represents the disutility associated with traveling between activities.

Travel disutility is typically expressed as :

$$U_{\text{travel},i} = \beta_{\text{travel},\text{mode}(i)} t_{\text{travel},i} + \beta_{d,\text{mode}(i)} d_{\text{travel},i} + \beta_m \Delta m_i, \quad (3.2)$$

where $t_{\text{travel},i}$ and $d_{\text{travel},i}$ denote travel time and distance, and Δm_i represents monetary costs. The coefficients β reflect marginal utilities calibrated to reproduce observed travel behavior.

This utility-based formulation plays a central role in the present study. Charging costs, congestion effects, and range-anxiety penalties are all incorporated as components of the utility function, ensuring that charging decisions are evaluated consistently with other mobility choices.

Replanning and Learning Dynamics

Following scoring, agents select plans using a logit-based choice model, in which plans with higher utility are chosen with higher probability. A configurable fraction of agents then enters a *replanning phase*, where new plans are generated by modifying elements such as routes, departure times, activity locations, or—in the context of this thesis—charging decisions.

Through repeated execution, scoring, and replanning, agents learn from experienced outcomes. Over successive iterations, this process drives the system toward a stochastic equilibrium that approximates Wardrop’s principle, in which no agent can improve its expected utility through unilateral changes (46). Importantly, equilibrium emerges from decentralized adaptation rather than centralized optimization, making MATSim well suited for analyzing behavioral responses to pricing, congestion, and infrastructure constraints.

3.1.3 EV-Contrib : Electrification and Energy Dynamics

Electric vehicle functionality is implemented using MATSim’s EV-Contrib module (82), which extends the base framework by introducing EV-specific components. These include a vehicle energy consumption model, continuous tracking of battery SOC, and charging infrastructure with defined power levels and availability constraints.

EV-Contrib models energy consumption dynamically as vehicles move through the transportation network. Energy use depends on vehicle motion, including speed and acceleration profiles, as well as auxiliary loads. Battery SOC is updated continuously, ensuring that vehicle operability is explicitly constrained by available energy. Charging infrastructure is represented as a set of charging stations with predefined power capacities and connector availability, and charging follows non-linear SOC-dependent curves reflecting physical battery limitations.

In its default configuration, EV-Contrib treats charging as a standalone activity triggered when SOC falls below a predefined threshold. While suitable for intercity contexts, this representation is less appropriate for dense urban environments, where EV users typically charge while performing other activities (45). This limitation motivates the adoption of the Urban-EV framework.

3.1.4 Urban-EV Framework : Activity-Integrated Charging

To represent urban EV charging behavior more realistically, this study adopts and extends the Urban-EV framework proposed by (46). In this framework, charging is integrated directly into primary activities rather than being treated as a separate event. When an agent arrives at an activity location equipped with charging infrastructure, the EV can be connected for the duration of that activity. Charging therefore occurs opportunistically during activity participation, constrained by both activity duration and charger availability.

In the present modeling framework, activity durations are not directly modified in response to charging needs. Daily activity schedules, including activity timing and duration, are generated as part of the travel demand model and remain fixed during the charging decision process. As a result, charging behavior is constrained by these predefined activity windows.

When an agent arrives at a location equipped with charging infrastructure, charging can only occur within the duration of the associated activity. Agents therefore adapt their charging decisions—such as whether to charge, when to charge, and where to charge—within the temporal and spatial constraints imposed by their activity schedules, rather than by extending or shortening activities to accommodate charging.

This assumption reflects a realistic modeling perspective in which most daily activities, such

as work, school, or scheduled appointments, have limited flexibility. While some degree of adaptation may occur in practice, incorporating endogenous activity duration adjustments would require a more complex joint modeling of activity scheduling and charging behavior, which is beyond the scope of this study.

Consequently, the model emphasizes how charging decisions adapt to existing mobility patterns, rather than how mobility patterns themselves change in response to charging needs.

Extensions Introduced in This Study

Two structural extensions are implemented to improve behavioral realism :

- **Realistic Charger Occupancy** : Once an EV is connected to a charger, it remains plugged in for the full duration of the underlying activity, even if the battery reaches full charge earlier. This captures real-world blocking behavior and ensures that charger availability reflects both charging demand and user activity patterns.
- **Dedicated Home Chargers** : Home chargers are assigned on a person-specific basis within each household. Only the resident agent can access the corresponding charger, preventing unrealistic sharing and ensuring that residential charging dynamics are consistent with observed practice.

These extensions are essential for reproducing congestion, queuing, and competition effects at public charging stations—phenomena that are central to the system-level questions addressed in this thesis.

Allowing non-blocking behavior—where vehicles disconnect from chargers once their battery is sufficiently charged—would significantly alter infrastructure utilization patterns. In such a case, charger turnover would increase, effectively expanding available capacity without requiring additional infrastructure. This would likely reduce both the probability and duration of queuing, particularly in high-demand locations.

However, non-blocking behavior introduces additional behavioral and operational complexity. It requires either active user intervention (e.g., returning to unplug the vehicle) or automated solutions such as smart charging systems. In practice, users may have limited willingness or ability to interrupt activities to move their vehicles, especially during long-duration activities such as work or overnight stays.

From a policy perspective, this behavior could be partially incentivized through pricing mechanisms. For example, time-based tariffs or idle fees applied after the completion of charging could encourage users to disconnect their vehicles and free up charging infrastructure. In this sense, pricing strategies may not only influence when users charge, but also how efficiently

charging infrastructure is utilized.

In the present study, blocking behavior is intentionally assumed to reflect a conservative and widely observed real-world pattern, where vehicles often remain connected beyond their active charging period. As a result, the model may overestimate congestion relative to an optimally managed system, but provides a realistic baseline for evaluating infrastructure performance under typical user behavior.

Similarly, activity locations are not endogenously modified in response to charging needs within the present modeling framework. Daily activity locations—such as home, work, and other destinations—are determined as part of the travel demand model and remain fixed during the simulation.

As a result, agents do not relocate activities (e.g., choosing a different grocery store or workplace) based on the availability of charging infrastructure. Instead, charging decisions are made conditional on the existing activity locations, reflecting a context in which mobility patterns are predetermined and charging behavior adapts within these spatial constraints.

This assumption is consistent with a short-term behavioral perspective, where most daily activities—particularly work and habitual destinations—are relatively inflexible. While some discretionary activities, such as shopping or leisure, may exhibit location flexibility in practice, modeling such adjustments would require integrating destination choice with charging behavior, which is beyond the scope of this study.

Consequently, the model captures how charging demand is shaped by existing urban activity patterns and infrastructure distribution, rather than how users might reorganize their spatial behavior to better accommodate charging needs.

3.1.5 Behavioral Architecture of Urban EV Charging

A central objective of this thesis is to represent EV charging behavior as an adaptive and heterogeneous decision-making process rather than as a fixed or purely reactive rule. As discussed in Chapters 1 and 2, charging demand in urban systems emerges from the interaction between daily activity patterns, infrastructure constraints, pricing signals, and users' tolerance for operational risk. Capturing these interactions requires a clear distinction between short-term charging reactions and longer-term behavioral adaptation.

Within the MATSim framework, this distinction is operationalized through two complementary decision layers : *within-day preplanning* and *between-day replanning*. Together, these mechanisms allow charging behavior to respond both to immediate conditions and to accumulated experience over repeated simulation iterations.

3.1.6 Summary of Model Components

TABLEAU 3.1 Summary of key model components.

Component	Description
State variables	SOC, location, activity type
Decision rules	Charging logic (Planned, SOC-Based, Opportunistic)
Action set	Charge / do not charge
Constraints	Activity duration, charger availability, walking distance
Pricing	Time-of-use and area-based electricity pricing
Behavioral factors	Range anxiety penalty function
Infrastructure	Charger type, capacity, and availability

Within-Day Preplanning : Reactive Charging Decisions

Preplanning refers to charging decisions made during the execution of a simulated day in response to the agent’s instantaneous state and local conditions. These decisions depend on variables such as current SOC, the availability of nearby charging stations, and the temporal feasibility of charging given the remaining activity schedule. Preplanning therefore captures real-time, reactive behavior, such as initiating charging when SOC becomes insufficient to safely complete upcoming trips.

In many existing agent-based EV models, charging behavior is governed almost exclusively by such reactive mechanisms. Charging is typically triggered once SOC falls below a predefined threshold, and a charging station is selected immediately based on proximity or feasibility constraints. While this approach ensures energy feasibility, it treats charging behavior as a purely technical response to battery depletion and ignores users’ ability to anticipate future conditions.

Under pricing regimes or congested infrastructure, reliance on preplanning alone leads to important limitations. Agents may repeatedly encounter high charging prices or long queues without modifying their behavior across days. As a result, charging demand may remain concentrated in time and space even when incentives exist to shift it. This limitation is particularly problematic in urban contexts, where charging opportunities are closely tied to recurring daily routines rather than isolated refueling events.

Between-Day Replanning : Experience-Based Adaptation

Replanning operates at the level of successive simulation iterations and enables agents to adapt their charging behavior based on experienced outcomes. After executing a daily plan,

agents evaluate its utility, which incorporates travel conditions, charging costs, delays, and penalties associated with low SOC. During the replanning phase, agents may modify elements of their plans—including charging-related decisions—before the next simulated day.

In the context of EV charging, replanning allows agents to internalize past experiences such as :

- repeatedly encountering high charging prices during specific time periods,
- experiencing congestion or queuing at particular charging stations,
- operating with low SOC and incurring range-anxiety penalties.

By adjusting charging timing, location, or strategy in response to these experiences, agents exhibit behavior that more closely resembles real-world adaptation. Users do not simply react to low SOC when it occurs; rather, they learn from previous days and proactively adjust charging routines to avoid undesirable outcomes.

This distinction is critical for evaluating policy interventions. Pricing mechanisms, in particular, are intended to influence behavior over time rather than instantaneously. Without replanning, pricing acts as a static disutility that agents endure repeatedly, whereas with replanning, pricing becomes a signal that reshapes charging strategies across iterations.

From Exogenous Rules to Endogenous Charging Behavior

A key limitation identified in the literature is that many EV charging models impose charging behavior exogenously through fixed rules or thresholds. Such representations restrict the range of behavioral responses and obscure the mechanisms through which charging demand adapts to policy and infrastructure conditions.

In this thesis, charging behavior is treated as an endogenous outcome of the utility-based learning process. Charging decisions are not hard-coded responses to SOC thresholds alone, but emerge from the interaction between :

- activity-based temporal constraints,
- charging costs and pricing signals,
- infrastructure availability and congestion,
- and behavioral penalties associated with low SOC.

Through MATSim’s iterative replanning process, agents evaluate alternative charging strategies and retain those that yield higher expected utility. Over successive iterations, this process produces a heterogeneous distribution of charging behaviors across the population, even under identical infrastructure and pricing conditions.

Importantly, heterogeneity is not imposed by assigning agents fixed behavioral types. Instead,

it emerges dynamically as agents respond differently to similar conditions based on their daily schedules, access to charging infrastructure, and accumulated experience. This endogenous emergence of diversity directly addresses the research gaps identified in Chapter 2.

Implications for Modeling Urban Charging Systems

By explicitly distinguishing between reactive preplanning and adaptive replanning, the proposed behavioral architecture enables a realistic representation of urban EV charging dynamics. Charging demand is no longer determined solely by technical feasibility, but by the trade-offs agents face between cost, convenience, and risk.

This architecture is particularly well-suited for analyzing :

- the effectiveness and limitations of pricing-based demand management strategies,
- the redistribution of charging demand under infrastructure constraints,
- and the interaction between behavioral heterogeneity and system-level congestion.

In the following sections, this behavioral foundation is operationalized through a structured charging logic framework. Charging strategies are defined not as fixed agent attributes, but as competing behavioral options that agents may adopt, abandon, or combine over successive iterations. This approach allows charging patterns to evolve endogenously while remaining grounded in empirically observed charging practices.

3.1.7 Charging Decision Framework and Strategy Design

Building upon the behavioral architecture described in Section 3.1.5, this study operationalizes EV charging behavior through a structured charging decision framework. The framework governs how agents identify feasible charging opportunities within their daily activity schedules and how they select among alternative charging strategies over successive simulation iterations.

Rather than prescribing a single charging rule for all agents, charging behavior is modeled as the outcome of strategic choice among multiple charging logics. This design directly addresses the limitations identified in the literature, in which homogeneous or static charging rules fail to reproduce the observed diversity in urban charging patterns.

Identification of Charging-Eligible Activities

The first step in the charging decision process is to identify which activities in an agent’s daily plan constitute feasible charging opportunities. Because EV charging in urban environments

is strongly constrained by activity participation, only activities that satisfy a set of behavioral and technical criteria are considered.

The filtering procedure follows three core principles :

- **Mode Consistency** : Only activities reached by an EV trip are eligible for charging. This condition ensures that the vehicle is physically present at the activity location and prevents assigning charging events to activities reached by other transport modes.
- **Non-Redundancy** : Activities already designated as plug-in or plug-out events in previous iterations are excluded. This prevents consecutive, unrealistic charging operations at the same location and ensures that each charging decision reflects a meaningful behavioral choice.
- **Temporal Plausibility** : Activities occurring at the beginning, middle, or end of the day are evaluated differently to reflect realistic daily mobility patterns and to avoid repeated charging at identical locations without intervening travel.

Activities satisfying these criteria form the set of *charging-eligible activities*. This set defines the feasible decision space within which agents may select charging opportunities. Importantly, this step does not determine whether charging occurs, but rather constrains where charging *could* occur given the agent’s daily schedule.

Treatment of Activity Position Within the Daily Schedule

The position of an activity within the daily plan affects its suitability for charging. To preserve behavioral realism, different rules are applied depending on whether an activity occurs at the start, middle, or end of the day.

First Activity of the Day The first activity is typically performed at home. An activity at the start of the schedule is considered eligible for charging only if it has not already been used as a charging event in previous iterations and if the preceding day’s plug-out operation does not imply that the vehicle remains at the same location. This prevents artificial repetition of home charging without intervening vehicle movement.

Middle Activities Activities occurring between the first and last activities are evaluated more flexibly. Any middle activity reached by an EV trip and not already marked as a charging event is considered eligible. This reflects the diversity of potential urban charging opportunities during work, shopping, leisure, or other discretionary activities.

Last Activity of the Day For the last activity, additional checks are performed to ensure that charging assignments remain plausible. If the second-to-last activity corresponds to a plug-out event and no vehicle relocation occurs before the final activity, charging at the last activity is not permitted. This avoids redundant charging sessions at identical locations and maintains consistency with realistic end-of-day behavior.

The complete activity filtering procedure is summarized in Algorithm 1.

Algorithm 1 Charging Activity Selection

```

1: Initialize ChargingActivities as empty list
2: for each activity in agent's daily plan do
3:   if activity is first in the schedule then
4:     if activity is not already a charging event then
5:       if trip to activity is made by EV then
6:         Add activity to ChargingActivities
7:       end if
8:     end if
9:   else if activity is last in the schedule then
10:    Check second-last and third-last activities
11:    if charging would be redundant then
12:      Skip activity
13:    else
14:      if trip to activity is made by EV then
15:        Add activity to ChargingActivities
16:      end if
17:    end if
18:   else
19:     if activity is not already a charging event then
20:       if trip to activity is made by EV then
21:        Add activity to ChargingActivities
22:       end if
23:     end if
24:   end if
25: end for

```

Charging Strategy Architecture

Once the set of charging-eligible activities is defined, agents must decide *how* to charge. This study introduces a charging strategy architecture composed of three empirically grounded charging logics, each representing a distinct behavioral archetype that we have anecdotal knowledge about.

Unlike previous studies that assign each agent a fixed charging rule, the proposed framework

allows agents to randomly select one charging logic at each iteration. This selection occurs prior to replanning and is evaluated through MATSim’s utility-based learning mechanism. Strategies that consistently yield higher utility are retained more frequently over successive iterations, allowing charging behavior to evolve endogenously.

Planned Charging Logic

The planned charging logic represents users who intentionally align charging with long-duration activities. From the set of charging-eligible activities, only activities exceeding two hours in duration are retained. Because home, work, and education activities typically span several hours, they naturally dominate this subset.

One activity is randomly selected from the filtered set for charging. This logic reflects charging behavior that prioritizes predictability, convenience, and compatibility with long parking durations. Empirical studies indicate that many EV users prefer such routine-based charging opportunities rather than relying on short or opportunistic stops (85).

SOC-Based Charging Logic

The SOC-based charging logic captures range-conscious behavior, where users initiate charging based on perceived battery insufficiency rather than purely on activity duration. Unlike threshold-based approaches commonly used in the literature, this logic incorporates information accumulated across previous simulation iterations.

For each charging-eligible activity, the average SOC at activity start—calculated from prior iterations—is evaluated. If this expected SOC falls below 30%, the activity is flagged as a candidate charging opportunity. The 30% threshold is widely reported as the level at which drivers begin to perceive battery state as critically low (39; 86). One flagged activity is then selected at random.

By relying on historical SOC information rather than instantaneous battery state, this logic reflects anticipatory behavior. Real-world EV users develop awareness of recurring travel patterns and plan charging accordingly, rather than reacting only when SOC becomes critically low.

Opportunistic Charging Logic

The opportunistic charging logic represents preventive charging behavior. All charging-eligible activities are considered valid, regardless of duration or expected SOC. One activity is selec-

ted at random for charging.

This logic captures users who prefer to maintain a high SOC buffer and charge whenever the opportunity arises. Such behavior is commonly observed in environments where charging infrastructure reliability is uncertain or where users prioritize risk avoidance over cost minimization.

Strategy Assignment and Endogenous Selection

Charging strategy selection is repeated independently for each agent and each iteration. The assignment procedure is summarized in Algorithm 2. Because strategies are evaluated through MATSim’s scoring and replanning process, the relative prevalence of each charging logic evolves endogenously over time.

Algorithm 2 Charging Strategy Assignment

```

1: Randomly assign one charging logic to the agent
2: if Planned Charging Logic then
3:   Filter activities with duration > 2 hours
4:   Prioritize home, work, and education activities
5:   Randomly select one activity for charging
6: else if SOC-Based Charging Logic then
7:   for each eligible activity do
8:     Retrieve historical mean SOC at activity start
9:     if SOC < 30% then
10:      Mark activity as candidate
11:   end if
12: end for
13:   Randomly select one candidate activity
14: else if Opportunistic Charging Logic then
15:   Randomly select one eligible activity
16: end if

```

This framework allows charging behavior to emerge as a population-level distribution rather than as a fixed assumption. Under identical infrastructure and pricing conditions, agents with different daily schedules and experiences adopt different charging strategies, producing heterogeneous and adaptive charging patterns consistent with empirical observations.

3.1.8 Charging Execution, Initial Conditions, and Cost Representation

Once a charging strategy and a corresponding activity are selected, charging behavior must be operationalized within the agent’s daily plan. This section describes how charging events

are executed in the simulation, how initial battery conditions are specified, and how pricing and behavioral penalties are incorporated into the utility function. Together, these elements translate abstract charging decisions into physically and behaviorally consistent system dynamics.

Operationalization of Charging Events

Charging execution is implemented by inserting explicit plug-in and plug-out events into the agent’s activity–travel plan. The exact structure of these events depends on the position of the selected charging activity within the daily schedule.

For charging occurring during the first or last activity of the day, charging typically takes place at the agent’s home location. If a dedicated home charger is available, the EV is connected directly upon arrival at home and remains plugged in until the corresponding plug-out event. If no home charger is available, the agent selects the nearest public charging station within a 1000 m radius of the home location. This distance threshold reflects a reasonable walking tolerance and prevents implausible long detours for residential charging. A walking distance threshold of 1000 m is assumed to define the maximum acceptable distance between an activity location and a charging station. This value is consistent with commonly used thresholds in the literature on pedestrian accessibility and transport modeling, where acceptable walking distances to access services or transit typically range between 500 m and 1000 m, depending on context and urban density (87; 88). It should be noted that this threshold is applied uniformly across all agents and activity types, and therefore does not capture potential variations in walking tolerance due to individual preferences, trip purpose, or environmental conditions.

In the context of EV charging, this threshold reflects a compromise between user convenience and infrastructure accessibility, particularly in dense urban environments where users may be willing to walk longer distances compared to suburban settings. It also aligns with findings suggesting that willingness to walk increases when activities involve longer durations, such as work or leisure.

For charging during middle activities, a more complex sequence is required. The agent first diverts to a nearby public charging station within a 1000 m radius of the activity location, plugs in the EV, and then walks to the primary activity location. After completing the activity, the agent returns to the charging station, unplugs the vehicle, and continues with the remaining daily schedule. This structure explicitly captures the interaction between charging infrastructure, pedestrian access, and activity participation.

Throughout the simulation, public charging stations are modeled as shared resources with finite capacity. When multiple agents attempt to use the same charger simultaneously, queuing and blocking effects emerge endogenously. Because vehicles remain plugged in for the full duration of the activity, charger occupancy reflects both charging demand and users' activity schedules, allowing congestion effects to propagate through the system.

Replanning and Behavioral Adjustment

After charging events are integrated into daily plans, MATSim's scoring and replanning mechanisms evaluate the resulting outcomes. Agents may respond to undesirable experiences—such as long waiting times, high charging costs, or strong range-anxiety penalties—by modifying future plans during replanning. Possible adjustments include :

- shifting charging to different activities or time periods,
- selecting alternative charging locations,
- modifying activity start times or durations,
- altering travel routes or modes,
- or eliminating unnecessary charging events.

This flexibility is essential for capturing adaptation under constrained infrastructure and pricing regimes. Charging behavior is therefore not fixed after a single decision, but evolves dynamically as agents accumulate experience across iterations.

3.1.9 Initial State of Charge (SOC)

Initial battery SOC is a critical yet often underexamined assumption in agent-based EV charging simulations. As highlighted in Chapter 2, many studies rely on simplified categorical assumptions to initialize the simulation, despite the fact that initial SOC strongly influences early charging demand, congestion formation, and system stabilization.

Empirical evidence suggests that EV users do not begin every day with fully charged batteries. Charging frequency varies across individuals, with battery electric vehicles typically charging every 1.5 days and plug-in hybrid vehicles charging even more frequently (89). As a result, initial SOC distributions should not be evenly considered among users.

Rather than imposing binary high/low SOC categories, this study adopts a stochastic initialization approach that captures a continuous range of battery states. The initial SOC of each EV is defined as :

$$\text{SOC}_{\text{initial}} = \text{SOC}_{\text{min}} + (1 - \text{SOC}_{\text{min}}) \times \text{rand}(0, 1), \quad (3.3)$$

where SOC_{min} represents a predefined minimum SOC threshold, and $rand(0, 1)$ is a uniformly distributed random variable.

This formulation ensures that all vehicles begin the simulation with feasible battery levels while preserving heterogeneity in initial conditions. By avoiding unrealistic concentration at either full or critically low SOC, the approach produces more gradual and realistic charging demand during the early iterations of the simulation. Initial SOC values are assigned as persistent vehicle attributes and are updated dynamically as the simulation progresses.

3.1.10 Electricity Pricing Mechanisms

Pricing plays a central role in shaping EV charging behavior by introducing explicit monetary trade-offs into agents' decision-making processes. In real-world contexts, electricity prices vary across time and location, reflecting demand patterns, grid constraints, and infrastructure costs. Capturing these variations is essential for evaluating pricing-based demand management strategies.

In this study, charging prices are incorporated through two complementary mechanisms : time-of-use (TOU) pricing and area-based pricing. Together, these mechanisms allow charging costs to vary both temporally and spatially.

Time-of-Use Pricing

TOU pricing is implemented using hourly price vectors defined for each charger type. Each vector specifies the cost of electricity for every hour of the day (0–23), allowing prices to increase during peak demand periods and decrease during off-peak hours. When a charging session spans multiple hours, the total cost is computed incrementally by applying the corresponding hourly rate to the energy delivered during each time interval.

Pricing levels also vary by charger type. Home chargers are assigned the lowest base rates, reflecting lower infrastructure and operational costs, while fast chargers are assigned higher rates due to their higher power demand and investment costs. This differentiation ensures that agents face realistic cost trade-offs when selecting charging locations and timing.

Area-Based Pricing

To capture spatial heterogeneity in charging demand and grid constraints, an area-based pricing mechanism is superimposed on the TOU structure. The study area is divided into a set of pricing zones, each represented by a centroid location. Every charging station is assigned

to the nearest zone, and a zone-specific multiplier is applied to its TOU price vector.

Zones characterized by high charging demand or grid stress receive higher multipliers, while zones with surplus capacity receive lower multipliers. This approach allows pricing to reflect localized congestion and infrastructure constraints without imposing hard access restrictions.

Pricing Scenarios

Three pricing scenarios are evaluated :

- **Free Scenario** : Charging is free of charge across all locations and times.
- **Flat-Priced Scenario** : A constant price is applied uniformly across all hours and locations.
- **TOU-Priced Scenario** : Prices vary by time and location. Off-peak hours (00 :00–14 :00) are priced at 50% of the base rate, while peak hours (15 :00–23 :00) are priced at 200% of the base rate. Area-based multipliers further adjust prices in high- and low-demand zones.

These scenarios allow the isolation of pricing effects and facilitate comparison between static and dynamic pricing regimes.

3.1.11 Utility Function Extensions and Range Anxiety

Charging prices are incorporated into MATSim’s utility framework through the monetary cost term. For EVs, the distance-based disutility associated with fuel consumption is replaced by the total electricity cost incurred during charging sessions. While this formulation enables agents to respond to electricity prices, pricing alone can generate implausible behavior if agents are allowed to postpone charging indefinitely in order to avoid monetary costs, even when battery levels become critically low.

In the default EV-Contrib implementation, this issue is typically addressed through hard SOC feasibility constraints or fixed penalty values that prevent vehicles from depleting their batteries. Although effective at maintaining energy feasibility, such formulations introduce discontinuities in the utility landscape : charging becomes suddenly mandatory once a critical SOC threshold is reached. As a result, agents do not receive a gradual behavioral signal that encourages anticipatory charging, limiting their ability to learn strategies that avoid entering low-SOC states in the first place.

To overcome this limitation, a continuous range-anxiety penalty is introduced to represent the discomfort and perceived risk associated with operating an EV at low state of charge. Rather than enforcing charging through abrupt constraints, the penalty progressively increases as

SOC declines, providing a smooth behavioral incentive that interacts directly with pricing in the utility function. The modified travel utility is expressed as :

$$U_{\text{travel},i} = \beta_{\text{mode},i} + \beta_{\text{travel},\text{mode}(i)} t_{\text{travel},i} + \beta_m \Delta m_i + \beta_{d,\text{mode}(i)} d_{\text{travel},i} + \beta_{\text{electricity}} + \beta_{\text{penalty}}. \quad (3.4)$$

The range-anxiety penalty is defined as :

$$\text{Penalty} = A \left(1 - e^{B(1-\text{SOC})} \right), \quad (3.5)$$

where parameter A controls the overall magnitude of the penalty and parameter B governs how rapidly discomfort increases as SOC decreases.

This functional form ensures that the penalty remains negligible at high SOC levels and increases smoothly as the battery depletes. Crucially, the penalty does not impose a fixed charging trigger. Instead, it provides a continuous gradient that guides MATSim’s co-evolutionary learning process, allowing agents to trade off electricity prices against the growing risk of operating at low SOC. In contrast to threshold-based formulations, agents can therefore adapt their charging behavior proactively, rather than reacting only once a critical SOC level has already been reached.

To explicitly examine how sensitivity to low SOC affects charging behavior, two alternative values of parameter B are evaluated. A higher value ($B = 15$) produces a steep increase in penalty below approximately 30% SOC, representing users who experience strong range anxiety once the battery reaches commonly perceived critical levels. A lower value ($B = 7.5$) shifts the onset of substantial penalty toward higher SOC levels (around 50%), capturing more risk-averse users who prefer to maintain a larger safety buffer and avoid operating at moderate battery levels altogether. Ideally these parameters should be calibrated through real observations, but since we don’t have access to real charger data, we try to figure the plausibility of a couple of values.

By comparing these two parameterizations, the analysis isolates the behavioral impact of range-anxiety sensitivity on charging timing, location choice, and congestion outcomes. Importantly, this design allows range anxiety to influence charging decisions throughout the simulation horizon, rather than acting as a binary constraint. The resulting framework enables agents to learn charging strategies that balance charging costs with operational reliability, which is essential for reproducing plausible behavior under dynamic pricing and constrained charging infrastructure.

Figure 3.2 illustrates the shape of the range-anxiety penalty function for $B = 15$ and $B = 7.5$,

respectively, highlighting how increased sensitivity shifts the onset of behavioral pressure toward higher SOC levels.

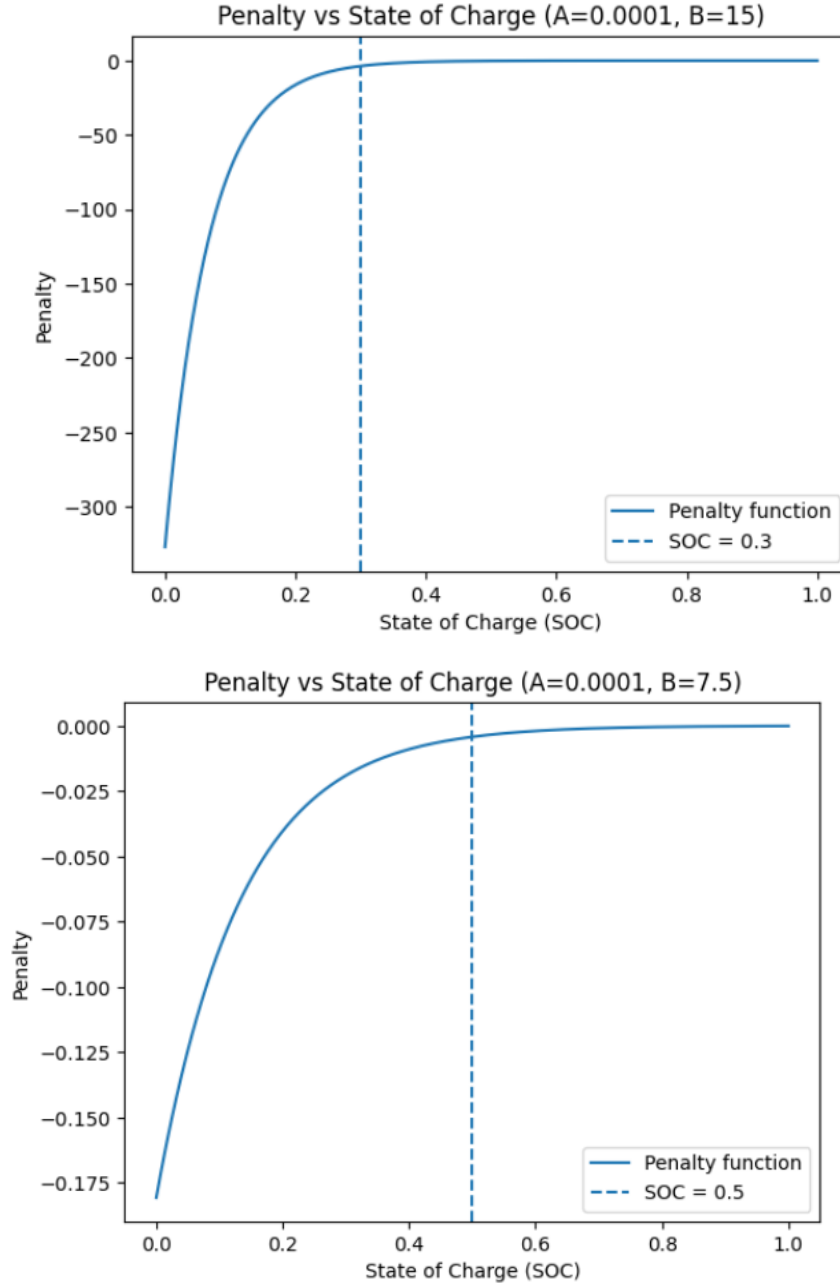


FIGURE 3.2 Range-anxiety penalty as a function of state of charge for two values of the sensitivity parameter B : (top) $B = 15$, producing a sharp increase in penalty below approximately 30% SOC; and (bottom) $B = 7.5$, shifting behavioral pressure toward higher SOC levels around 50%.

3.2 Study Area, Data, and Implementation

This section describes the study area, data sources, and implementation choices used to apply the proposed modeling framework. Consistent with the objectives of this thesis, the case study is designed to represent a large, complex urban environment in which EV charging behavior emerges from heterogeneous travel patterns, constrained infrastructure, and spatially differentiated demand.

3.2.1 Study Area : Montreal Census Metropolitan Area

The study area is the Montreal Census Metropolitan Area (CMA), one of the largest and most densely populated metropolitan regions in Canada. The Montreal CMA exhibits a combination of high travel demand, multimodal transportation infrastructure, and rapidly increasing EV adoption, making it a suitable context for analyzing system-level charging dynamics.

Montreal presents several characteristics that are particularly relevant for this research. First, daily travel patterns are highly heterogeneous, with substantial variation in trip lengths, activity schedules, and mode choice across the population. Second, access to private home charging is unevenly distributed, leading many EV users to rely partially or entirely on public charging infrastructure. Third, public charging stations are spatially concentrated in central areas, creating potential congestion and equity concerns as EV adoption grows.

These features align closely with the research questions of this thesis, which focus on how charging behavior emerges under realistic urban constraints and how pricing and infrastructure interventions interact with heterogeneous user behavior.

The analysis is conducted using a representative-day framework under average environmental conditions. Weather variability, including temperature effects on battery performance and travel behavior, is not explicitly modeled.

This simplification is particularly relevant in the Montreal context, where seasonal variation is significant. Cold temperatures can reduce battery efficiency, increase energy consumption, and affect charging duration, while adverse weather conditions may also influence travel patterns. As a result, the findings should be interpreted as conditional on stable environmental conditions.

3.2.2 Synthetic Population Generation

A synthetic population was constructed to represent the travel behavior of residents within the Montreal CMA. Population synthesis combines multiple data sources to generate disaggregate agents whose aggregate characteristics match observed population distributions.

The primary data sources used for population synthesis include :

- the 2016 Canadian Census (90),
- the 2018 Montreal Origin–Destination Survey (91),
- vehicle ownership data from the Société de l’assurance automobile du Québec (SAAQ) (92),
- and municipal property assessment rolls (93).

A Python-based synthesis workflow adapted from the EQASIM framework (94) was used to generate households and individuals. Iterative Proportional Fitting (IPF) (95) and Iterative Proportional Updating (IPU) (96) were applied to align synthetic microdata with marginal distributions for key socio-demographic attributes, including age, income, employment status, and vehicle ownership.

The PopGen module (97; 98) was then used to generate disaggregate agent profiles and assign daily activity chains based on observed travel behavior from the Origin–Destination survey. Each agent is associated with a household, an activity schedule, and one or more vehicles, enabling consistent modeling of travel and charging decisions.

3.2.3 Activity Location Assignment

Spatial coordinates for activities were assigned using municipal property assessment data, which provide detailed land-use classifications across the study area. Activity types such as home, work, education, shopping, and leisure were mapped to plausible land-use parcels, ensuring that simulated activities occur at realistic locations.

This approach keeps differences in where activities occur and allows charging demand to arise naturally from where people go and where chargers are located. It also makes it possible to examine mismatches between charging supply and activity demand, which are important for policy analysis.

3.2.4 Transportation Network and Public Transit

The transportation network was constructed using a combination of OpenStreetMap (OSM) geometry and General Transit Feed Specification (GTFS) data. The pt2matsim tool (99) was

used to integrate public transit services into the MATSim network, producing a multimodal representation that includes road links, transit routes, stops, and schedules.

Network links are characterized by attributes such as length, capacity, free-flow speed, and permitted modes. This detailed representation allows congestion effects to emerge endogenously during the simulation and ensures consistency between travel behavior and experienced travel conditions.

3.2.5 Charging Infrastructure and EV Fleet

Public charging infrastructure data were obtained from the *Circuit électrique* network (100). Each charging station is represented by its geographic location, power rating, and number of connectors. Three charger types are modeled : Level 2 chargers (20 kW), fast chargers (50 kW), and residential home chargers (10 kW). The modeled network includes a total of 2,655 Level 2 chargers and 278 fast chargers.

Consistent with observed North American charging patterns, 80% of EV-owning agents are assumed to have access to a dedicated home charger (99). Home chargers are assigned on a person-specific basis and cannot be shared. Public chargers, in contrast, are shared resources subject to congestion and queuing.

All EVs are assumed to have a battery capacity of 50 kWh, representing a mid-range electric vehicle. Initial SOC values are assigned stochastically as described in Section 3.1.9, introducing heterogeneity in battery state at the start of the simulation.

Figures 3.3 illustrate the study area together with the spatial distribution of different types of chargers.

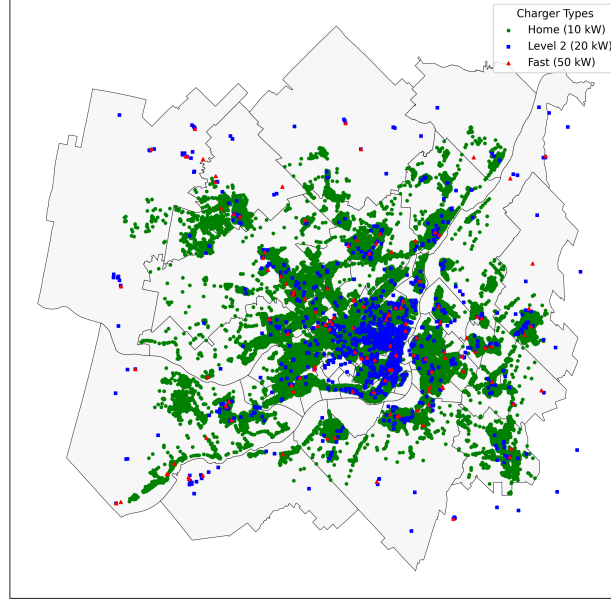


FIGURE 3.3 Study area and spatial distribution of Home and Public chargers.

3.2.6 Sampling Strategy and Computational Considerations

To balance behavioral realism with computational feasibility, the simulation is conducted on a 10% random sample of the full synthetic population. This sampling level is commonly used in large-scale MATSim applications and has been shown to provide reliable system-level results when demand and capacity are scaled consistently (101). The sampled population includes 300,664 agents and 149,783 vehicles, of which 75,625 are electric vehicles. This EV count corresponds to reported EV registrations in the Montreal CMA in 2023 (102).

To preserve consistency between demand and supply, network capacities and charging infrastructure capacities are scaled proportionally to the sampling rate. This approach maintains comparable congestion and utilization patterns while substantially reducing computational requirements.

The simulation is run for a sufficient number of iterations to allow charging behavior, congestion patterns, and utility values to stabilize. Results are analyzed after convergence, ensuring that reported outcomes reflect equilibrium behavior rather than transient initialization effects. In MATSim, the number of iterations is configurable and typically depends on model size and complexity, with urban simulations often requiring fifty to several hundred iterations to reach stability in travel behavior and network performance, even though smaller counts may be sufficient for preliminary convergence in simpler cases (82). In this study, convergence was assessed by monitoring the evolution of total utility across iterations. Based

on careful observation, total utility was found to stabilize by approximately 100 iterations, beyond which only marginal changes were observed.

3.2.7 Scope and Limitations

Several modeling assumptions are considered in this study. Battery capacities, charging power levels, and home charging access rates are fixed across scenarios to isolate the effects of behavioral heterogeneity, pricing, and infrastructure configuration. While this abstraction limits the representation of vehicle diversity, it allows clearer interpretation of system-level mechanisms.

In addition, learning and adaptation occur through MATSim’s iterative replanning rather than through explicit cognitive models. This choice reflects a focus on population-level equilibrium outcomes rather than individual-level learning processes.

Also, while the analysis explores multiple scenario dimensions—including pricing regimes, behavioral heterogeneity, infrastructure configuration, and range anxiety sensitivity—the interaction effects between these factors are only partially examined. In particular, combined extreme scenarios and infrastructure saturation conditions could reveal nonlinear system responses.

In addition, the stochastic nature of agent-based simulations implies that results may vary across runs. While the reported outcomes reflect stable patterns after convergence, further work could include formal uncertainty analysis or multiple-run variability assessment to strengthen the robustness of the findings.

Despite these limitations, the modeling framework is designed to capture the key interactions between travel behavior, charging decisions, pricing mechanisms, and infrastructure constraints. It therefore provides a robust platform for evaluating EV charging policies and planning strategies in large urban systems.

CHAPITRE 4 FIRST THEME – BEHAVIORAL HETEROGENEITY IN EV CHARGING

This chapter presents the first core contribution of the thesis and examines how behavioral heterogeneity in EV charging shapes system-level outcomes in urban environments. Building on the agent-based modeling framework introduced in Chapter 3, the analysis isolates the effects of different charging logics on electricity demand, queuing at charging stations, and activity-based charging patterns. The main idea of this chapter is that charging behavior is not just a minor modeling factor, but a key influence on grid impacts and infrastructure performance.

As discussed in Chapters 1 and 2, many existing EV charging studies rely on homogeneous or static representations of user behavior, often imposing a single charging rule across the entire population. While such assumptions simplify modeling, they risk masking important dynamics related to peak demand formation, queuing at public chargers, and the spatial distribution of charging load. This chapter directly addresses this limitation by explicitly modeling charging behavior as heterogeneous and adaptive, allowing multiple charging strategies to coexist and evolve endogenously through agents’ interactions with the system.

Three plausible charging logics are considered. *Planned charging* aligns with long-duration activities, such as at home and at work. *SOC-Based charging* reflects range-conscious behavior, in which users initiate charging only when the battery reaches a critically low state of charge. *Opportunistic charging* represents preventive or convenience-oriented behavior, where users charge whenever feasible opportunities arise. These logics are first analyzed independently under homogeneous scenarios to isolate their individual impacts. Then, a *heterogeneous* scenario in which all charging logics coexist, and agents dynamically select among them through MATSim’s utility-based learning process.

The objectives of this chapter are threefold. First, it demonstrates how assumptions about charging behavior fundamentally influence simulation outcomes, even when infrastructure supply, travel demand, and pricing conditions are held constant. Second, it evaluates whether behavioral diversity alone can mitigate grid stress and charging congestion in the absence of explicit control policies. Third, it examines how charging behavior interacts with daily activity patterns, revealing which activities and locations dominate charging demand under heterogeneous behavior.

4.1 System-Wide Power Demand under Alternative Charging Logics

Understanding how charging behavior converts into overall electricity demand is crucial for evaluating the operational effects of widespread EV adoption. Since charging demand in the proposed framework arises naturally from individual choices rooted in daily activities—such as travel patterns—differences in charging logic influence not only when charging occurs but also how often and whether it is necessary. Consequently, both the number of charging sessions and their timing together shape grid-level outcomes.

Figure 4.1 presents the total charging power demand throughout the day for the three homogeneous charging logic scenarios—*Planned*, *SOC-Based*, and *Opportunistic*—as well as for the *Heterogeneous* scenario. Each curve reflects a distinct behavioral mechanism and illustrates how individual decision rules aggregate into system-level demand profiles.

The **Planned charging logic** produces a strongly bimodal demand profile, with pronounced peaks during the **morning (06 :00–08 :00)** and **evening (17 :00–19 :00)** periods. Charging events are synchronized around long-duration home and work activities, resulting in highly concentrated demand. Peak load reaches approximately **62 MW**, representing the highest instantaneous demand across all scenarios. Although predictable, this pattern coincides with periods of elevated residential electricity consumption, implying substantial stress on local distribution networks.

The **Opportunistic charging logic**, despite allowing charging at all activities regardless of duration or SOC, generates a load profile that closely mirrors the Planned scenario. As shown in Figure 4.1, demand remains clustered around home and work periods, with limited redistribution toward midday hours. This outcome indicates that simply expanding the set of eligible charging opportunities does not necessarily diversify temporal demand. Long-duration activities continue to dominate charging behavior, while short stops often provide insufficient dwell time for meaningful energy transfer and are frequently underserved by charging infrastructure.

In contrast, the **SOC-Based charging logic** yields the lowest aggregate demand among the homogeneous scenarios and a comparatively flat load profile. Charging is initiated only when SOC falls below a critical threshold, resulting in fewer but longer charging sessions. Although modest morning and evening peaks remain, total demand is substantially reduced, and a mild midday shoulder appears as batteries are depleted during daytime travel. Under this logic, demand is therefore governed by battery-depletion dynamics rather than activity timing, producing a grid-friendly profile of total energy consumption.

The **Heterogeneous scenario** produces an intermediate but notably smoother outcome.

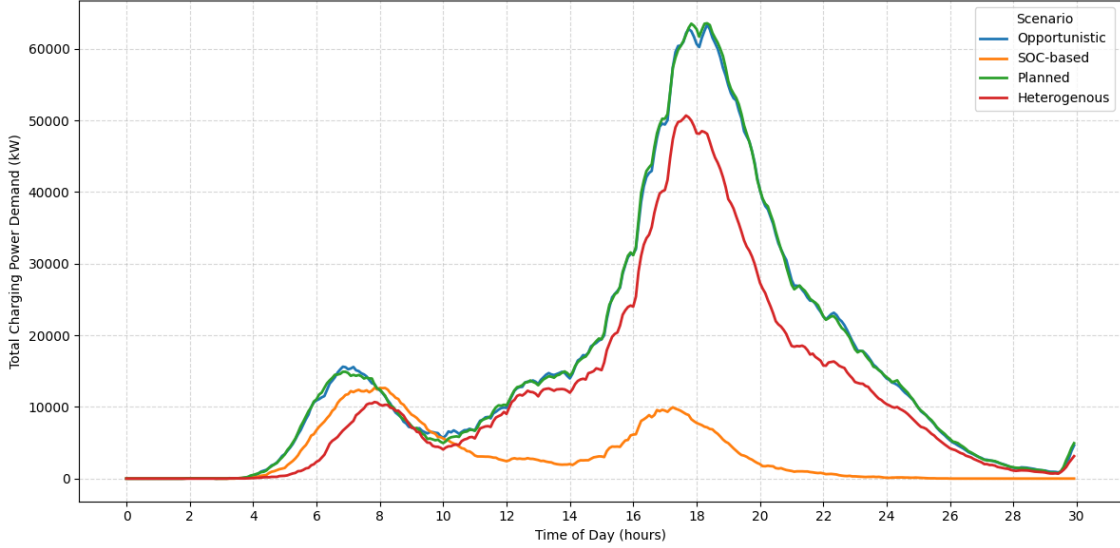


FIGURE 4.1 Total charging power demand by time of day for each charging logic.

Peak demand reaches approximately **50 MW**, corresponding to a reduction of about **20%** relative to the purely Planned scenario and, importantly, remaining below the SOC-Based peak during the morning period. While the total number of charging events in the heterogeneous scenario is indeed lower than in the homogeneous cases, this reduction is itself an endogenous behavioral outcome rather than an imposed assumption.

Specifically, behavioral heterogeneity allows agents to substitute between charging strategies over successive iterations. Agents who experience low marginal utility from charging—due to high prices (charging at expensive chargers), congestion, or sufficient residual SOC—may defer or eliminate redundant charging events altogether. Others shift charging to earlier or later periods, or rely on partial top-ups rather than full recharges. As a result, charging demand becomes both *less synchronized* and *less repetitive*, reducing the simultaneous activation of high-power chargers during peak periods.

This mechanism explains why the heterogeneous peak is lower even than the SOC-Based peak during the morning hours. Unlike SOC-Based charging, which concentrates demand among a smaller subset of users operating at critically low SOC, the heterogeneous population distributes charging decisions across multiple strategies and SOC ranges. This dispersion reduces the temporal alignment of charging sessions and lowers instantaneous load, even when some users continue to charge during traditional peak windows.

Crucially, this smoothing effect emerges without any explicit demand-control mechanism, pricing signal, or centralized coordination. It reflects the system-level consequence of adaptive

decision-making, where agents internalize past charging experiences and adjust both *whether* and *when* to charge. These results demonstrate that behavioral heterogeneity affects grid outcomes not only by shifting demand in time, but also by reducing unnecessary or poorly timed charging events altogether. As a result, models assuming homogeneous charging behavior may overestimate peak demand compared to real-world systems where heterogeneous and adaptive charging naturally smooths load profiles.

4.2 Queuing Dynamics and Charging Infrastructure Congestion

While aggregate demand characterizes grid impacts, queuing dynamics provide insight into charging infrastructure performance and user experience. Figure 4.2 shows the temporal distribution of queued charging attempts across charging logics.

Despite generating the lowest total charging demand, the **SOC-Based scenario** exhibits the highest peak queuing intensity, reaching approximately 7–8% during the 06 :00–09 :00 period. This outcome reflects two interacting mechanisms. First, charging sessions initiated at low SOC tend to be long, reducing charger turnover and prolonging congestion. Second, queuing is spatially concentrated in the urban core (Figure 4.3), where high activity density coincides with limited public charging capacity. At low SOC levels, strong range-anxiety penalties reduce users’ willingness to defer charging or seek alternative locations, reinforcing congestion at already stressed stations.

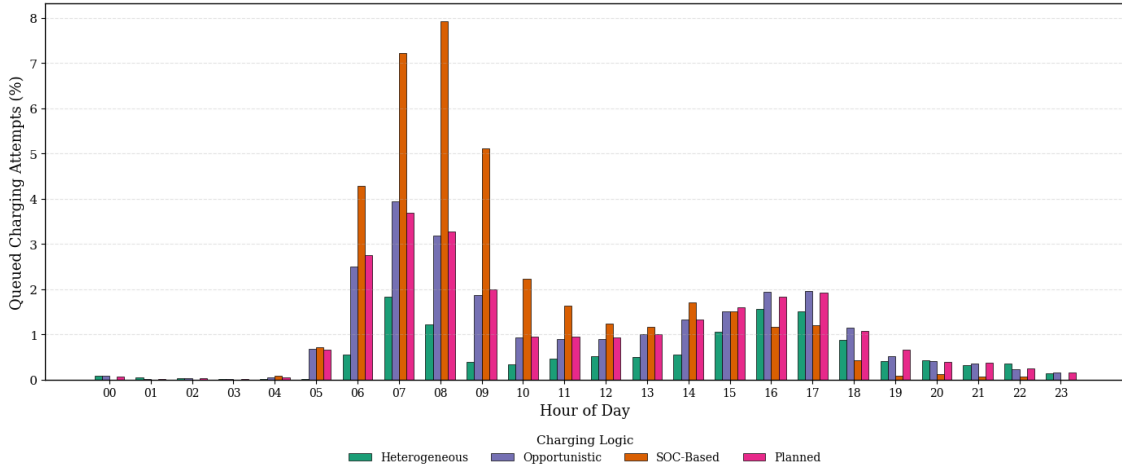


FIGURE 4.2 Temporal distribution of queued EVs by hour of day across different charging logics.

By contrast, the **Planned** and **Opportunistic** scenarios exhibit smoother queuing profiles, as users retain greater temporal and spatial flexibility. The **Heterogeneous scenario** pro-

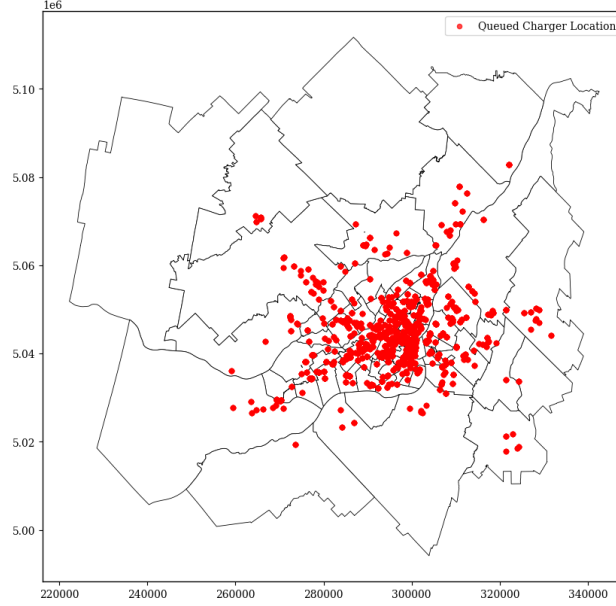


FIGURE 4.3 Spatial distribution of chargers experiencing queuing under the SOC-Based scenario.

duces the most balanced queuing pattern, with lower peaks and broader temporal dispersion, as behavioral diversity reduces synchronization in charging attempts.

4.3 Temporal and State-of-Charge Patterns of Charging Initiation

This section offers a detailed overview of the timing and SOC conditions triggering charging events for each logic. Its aim is to confirm that the strategies generate clear, consistent charging behaviors.

Figure 4.4 shows the probability of starting a charging session as a function of time of day (in two-hour intervals) and initial vehicle SOC, disaggregated by charging logic.

For the **Planned** logic, charging events are distributed relatively evenly across the day and span a wide range of SOC levels. This pattern is consistent with schedule-driven charging decisions, where charging is planned in advance and is not strongly tied to the immediate battery state.

In contrast, the **SOC-Based** logic exhibits a clear concentration of charging events at lower SOC levels, primarily below 40%. Charging initiation is more frequent during periods following major travel episodes, such as early morning and late afternoon. This behavior reflects the intended threshold-based mechanism, in which charging is triggered once the battery reaches a critical SOC level.

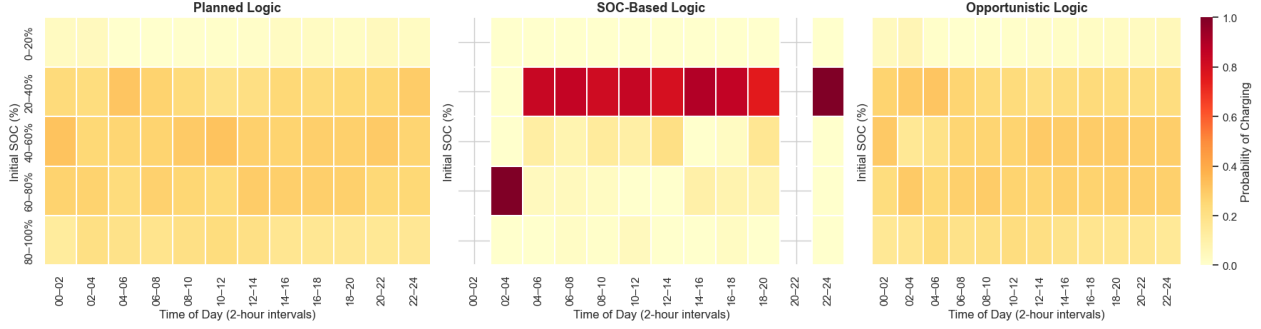


FIGURE 4.4 Probability of initiating a charging session by time of day and initial SOC, disaggregated by charging logic.

The **Opportunistic** logic shows a broad distribution across both time of day and SOC levels. Charging events frequently occur at intermediate and high SOC values, indicating top-up behavior during available activities rather than charging driven by necessity. As a result, no strong temporal or SOC concentration is observed for this logic.

Overall, the observed patterns confirm that each charging logic produces consistent behavioral tendencies aligned with its underlying decision mechanism. However, the distinction between Planned and Opportunistic charging remains relatively moderate in aggregate outcomes. While these strategies differ conceptually—one being anticipatory and the other reactive to opportunities—both are strongly anchored to long-duration activities, which results in similar temporal and spatial charging patterns at the system level.

4.4 Activity-Based Charging Patterns under Behavioral Heterogeneity

This section explores how endogenous strategy selection appears in daily life, specifically in the heterogeneous scenario where different charging strategies coexist and are adaptively chosen through co-evolutionary learning. Instead of externally prescribing charging behavior, this approach shows how such choices arise from the interplay between daily activity routines, temporal flexibility, and access to charging infrastructure.

The analysis unfolds in three steps. Initially, charging activity is analyzed across different activity types to pinpoint where charging happens under varied behaviors. Next, the influence of daily activity complexity is evaluated to understand how schedule structure influences charging strategy choices. Lastly, sociodemographic patterns are interpreted as indirect results of variations in activity structure and accessibility, rather than as innate behavioral preferences.

4.4.1 Charging Activity Context under Heterogeneous Behavior

Before disaggregating charging behavior by logic, it is useful to first examine the overall distribution of charging events across activity contexts in the heterogeneous system. Figure 4.5 reports the total share of charging events by activity type, aggregated across all charging logics.

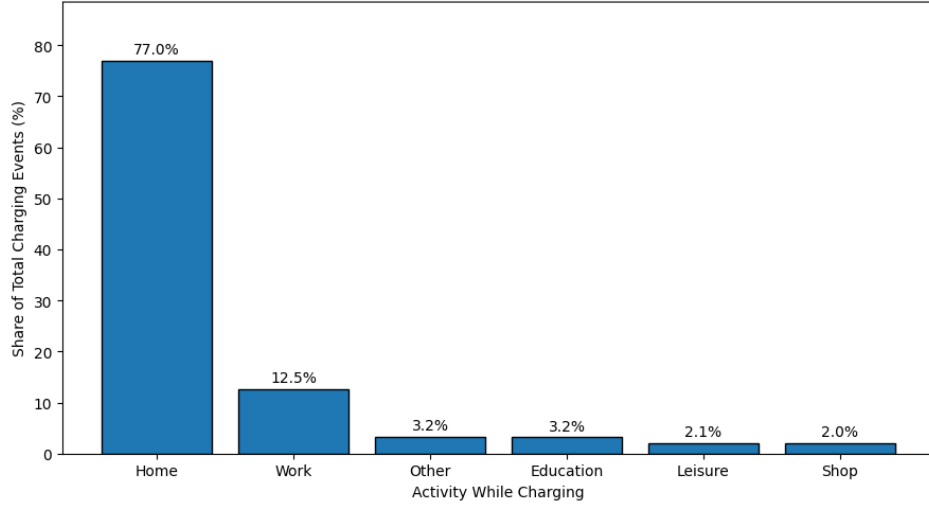


FIGURE 4.5 Aggregate share of charging events by activity type under the heterogeneous scenario, pooled across all charging strategies.

At the system level, charging is overwhelmingly concentrated at **home**, which accounts for approximately **77%** of all charging events. Work-related activities represent the second most common context (about **12–13%**), while education, leisure, shopping, and other intermediate activities collectively account for a relatively small share of charging. This aggregate pattern reflects the central role of long-duration residential parking in enabling EV charging opportunities within daily activity schedules. This result is fully consistent with empirical evidence reported in both the United States and Québec, where residential charging has been shown to account for roughly **80%** of electric vehicle charging activity (103; 104). The close alignment between these reported figures and the simulation outcomes provides external validation that the heterogeneous framework reproduces well-established real-world charging patterns, even within a dense urban context.

Figure 4.6 further disaggregates this aggregate distribution by charging logic, highlighting how different behavioral strategies interact with activity context under heterogeneous behavior.

For both the Planned and Opportunistic logics, approximately **79%** of all charging events

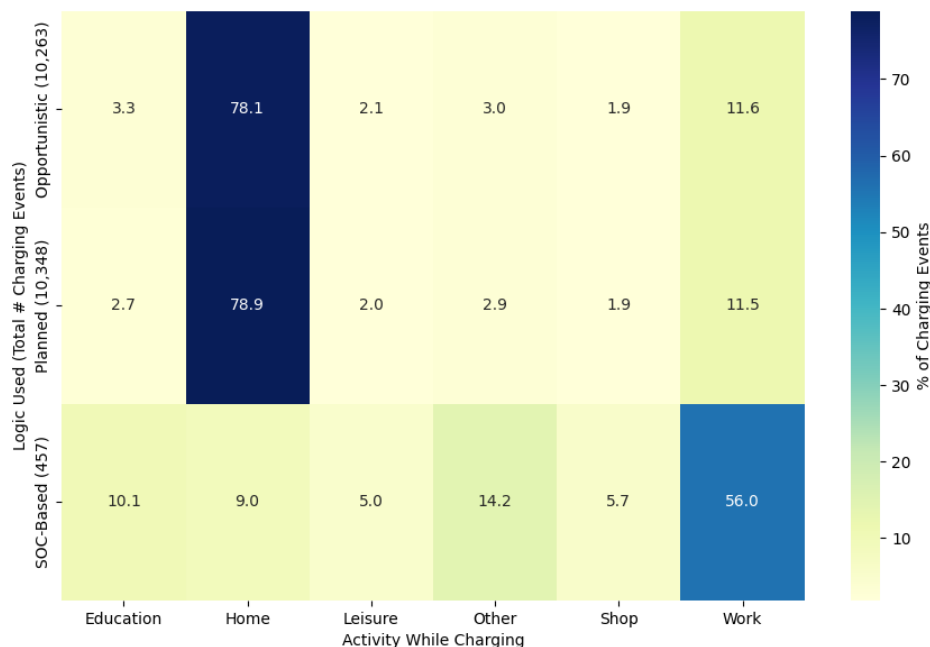


FIGURE 4.6 Share of charging events by activity type and charging logic under the heterogeneous scenario.

occur at home. Despite the greater behavioral flexibility of Opportunistic charging, charging activity remains strongly anchored to long-duration home (and, to a lesser extent, work) activities, indicating that long-duration, low-mobility periods continue to dominate charging choices even when agents are free to charge at any activity. This strong similarity suggests that, in practice, the distinction between Planned and Opportunistic charging is partially constrained by the structure of daily activities, which limits the extent to which opportunistic flexibility translates into fundamentally different system-level outcomes. It also reflects the central role of residential charging in daily EV use. In contrast, SOC-Based charging exhibits a markedly different activity context. Only about **9%** of SOC-Based charging events take place at home, with the majority occurring during work and other non-residential activities. This pattern reflects the reactive nature of SOC-Based behavior, in which charging is triggered only once battery levels fall below a critical threshold, often away from residential locations. As a result, SOC-Based users rely disproportionately on public charging infrastructure, helping to explain the elevated queuing and congestion observed for this logic in earlier sections.

Overall, these results demonstrate that activity context plays a central role in shaping charging outcomes even when charging strategies are selected endogenously. While residential charging remains the backbone of urban EV energy replenishment at the system level, different charging logics imply fundamentally different dependencies on residential versus public

charging infrastructure.

4.4.2 Charging Logic and Daily Activity Complexity

While activity type determines where charging occurs, daily activity *structure* determines how charging strategies are selected. Figure 4.7 examines how the complexity of individuals' daily schedules influences charging logic choice within the heterogeneous scenario. Activity complexity is defined by the total number of daily activities and categorized into *Simple* (3 activities), *Moderate* (4–7 activities), and *Complex* (8 or more activities).

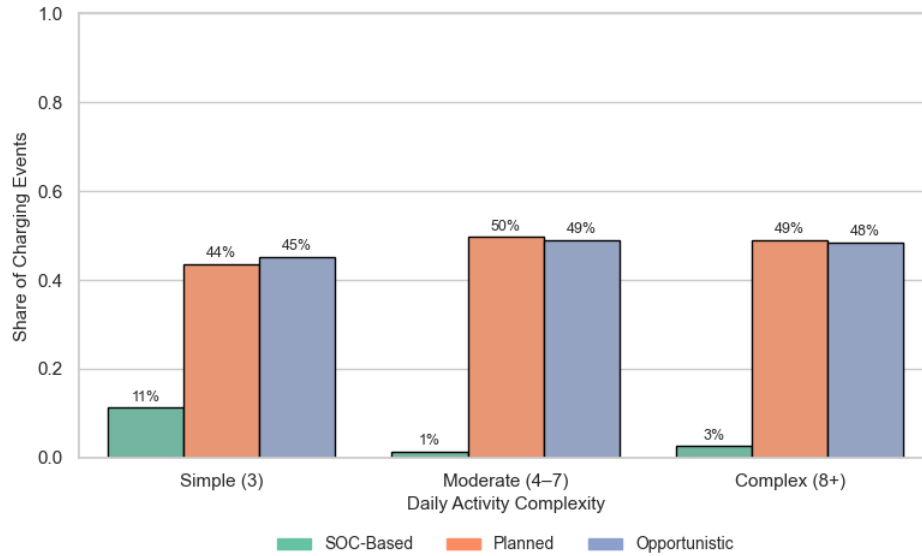


FIGURE 4.7 Distribution of charging logics by daily activity complexity under the Flat scenario.

Across all complexity levels, charging behavior is dominated by the **Planned** and **Opportunistic** logics, together accounting for nearly all charging events. However, the relative balance between these strategies—and the residual role of SOC-Based charging—varies systematically with daily schedule structure.

Among agents with *simple* daily schedules—typically corresponding to home–work–home routines—charging behavior remains more diverse than might be expected. Planned and Opportunistic charging account for comparable shares (approximately **44%** and **45%**, respectively), while SOC-Based charging represents a non-negligible share of about **11%**. This relatively higher presence of SOC-Based behavior arises from structural constraints embedded in the SOC-Based logic. Because the penalty associated with low state of charge increases sharply as SOC approaches the critical threshold, deferring charging until returning home

after work is often not feasible. Consequently, agents with simple home–work–home schedules tend to rely on work-based charging opportunities when available, using the long and predictable work parking duration to mitigate the risk of reaching critically low SOC levels before completing the return trip home. At the same time, when workplace charging is unavailable or constrained by queues, these agents can often still complete their daily travel without additional intermediate charging, given the limited complexity and spatial extent of their schedules.

As daily schedules become more *moderate* or *complex*, involving a larger number of intermediate and discretionary activities, the prevalence of SOC-Based charging declines sharply to **1–3%**. At the same time, charging behavior converges toward an even split between Planned and Opportunistic strategies (approximately **49–50%** each). Increased activity complexity expands the set of feasible charging opportunities, allowing users to avoid critical SOC levels through either planned or opportunistic charging.

Importantly, this shift is not driven by differences in pricing, risk preferences, or decision rules, as all agents are exposed to identical behavioral parameters in this scenario. Instead, the results suggest that the complexity of urban activity structures limits the appeal of strictly SOC-based charging, by offering drivers greater temporal flexibility in when and where they can charge. This helps explain why SOC-Based charging—while theoretically attractive from a grid perspective—remains uncommon in dense urban environments with diverse activity patterns.

4.4.3 Sociodemographic Patterns as Indirect Outcomes

Figure 4.8 reports the distribution of charging logics selected by agents in the heterogeneous scenario, disaggregated by gender, age group, and income level.

Across all sociodemographic dimensions, charging behavior is overwhelmingly dominated by the Planned and Opportunistic logics. Planned charging consistently accounts for approximately **45–52%** of charging events, while Opportunistic charging represents roughly **47–53%**. The SOC-Based logic remains marginal across all groups, accounting for only **1–3%** of charging events.

At first glance, the limited variation across sociodemographic groups might suggest that demographic attributes play only a minor role in shaping charging behavior. However, this apparent homogeneity is itself a meaningful result. In the present modeling framework, charging logic selection does *not* incorporate explicit demographic-specific behavioral parameters. All agents follow identical decision rules when exposed to identical activity contexts and

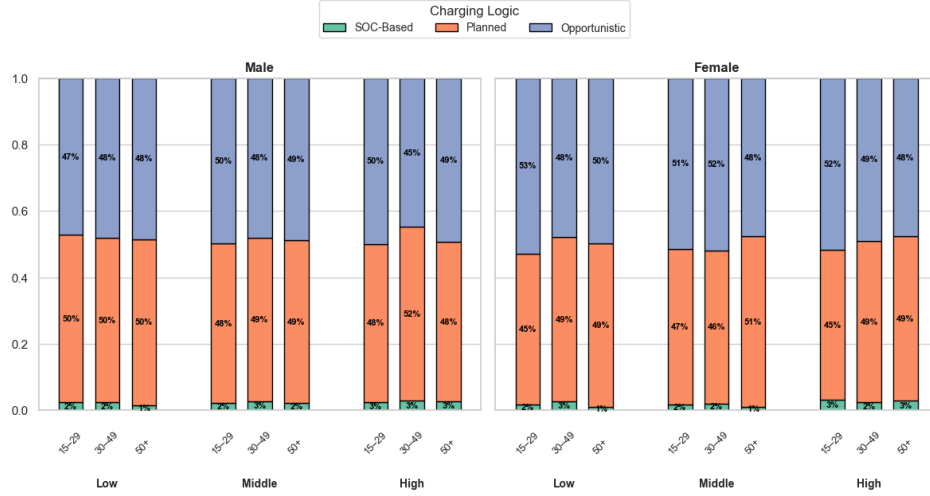


FIGURE 4.8 Distribution of charging logics by income, age, and gender.

infrastructure conditions. Consequently, any observed sociodemographic differences emerge *indirectly*, through correlations between demographic attributes, daily activity structure, and access to charging infrastructure.

Within this interpretation, the observed patterns are behaviorally consistent. Younger and lower-income agents exhibit slightly higher shares of Opportunistic charging, reflecting more fragmented daily schedules and greater exposure to intermediate activities. Older and higher-income agents show a modest shift toward Planned charging, consistent with more stable, long-duration home and work activities. Gender-based differences are minimal once activity context is accounted for.

From a policy perspective, these findings reinforce a central conclusion of this chapter : **charging behavior in heterogeneous urban populations is shaped primarily by daily activity patterns and charging accessibility rather than by sociodemographic characteristics per se**. As a result, interventions targeting the spatial and temporal availability of charging opportunities—such as residential, workplace, and destination charging—are likely to be more effective than demographic targeting alone.

4.5 Charging Logic, Activity Context, and Energy Outcomes

Table 4.1 summarizes the distribution of charging events by activity type and charging logic in the heterogeneous scenario, together with average charging duration and SOC gain. It must be noted that Table 4.1 summarizes how charging events are distributed across different activity types within the heterogeneous scenario, with each event classified by the charging

logic selected at that moment, whereas Figure 4.6 presents the distribution of activity types conditional on charging logic. Across all activity types, **home and work emerge as the dominant contexts for charging**. Users overwhelmingly initiate charging during long-duration activities, and within these settings the split between Planned and Opportunistic logic remains close to 50–50.

TABLEAU 4.1 Distribution of charging events, average charging duration, and SOC gain by activity type and charging logic in the heterogeneous scenario.

Activity Type	Charging Logic	Share (%)	Avg. Duration (h)	Avg. SOC Gain (%)
Education	Planned	43.0	8.25	37.2
	Opportunistic	50.3	7.83	36.6
	SOC-Based	6.7	6.74	49.5
Home	Planned	50.3	12.62	42.5
	Opportunistic	49.4	12.53	41.8
	SOC-Based	0.2	2.62	46.1
Leisure	Planned	43.1	3.86	39.3
	Opportunistic	50.3	3.40	36.5
	SOC-Based	6.6	3.18	50.2
Other	Planned	45.5	2.62	27.9
	Opportunistic	43.2	3.06	23.4
	SOC-Based	11.2	2.37	28.1
Shop	Planned	52.9	2.01	29.1
	Opportunistic	41.4	1.95	25.7
	SOC-Based	5.7	2.56	54.1
Work	Planned	45.1	9.12	37.5
	Opportunistic	44.9	9.17	37.4
	SOC-Based	10.0	9.10	54.6

By contrast, **SOC-Based charging** remains relatively rare but follows a distinct activity-related pattern. Its share is negligible at home (below 1%) but increases to approximately 6–11% across non-residential activities. SOC-Based charging events are characterized by shorter average durations than Planned and Opportunistic charging, while achieving substantially higher SOC gains. This pattern is consistent with a reliance on higher-power charging infrastructure, such as fast or rapid chargers, which enables significant energy transfer within limited time windows.

This observation also suggests that SOC-Based charging may be constrained by the availability of fast-charging infrastructure. Because SOC-Based users initiate charging primarily when their battery reaches a critical threshold, they face stronger incentives to restore driving range quickly, particularly during activities with limited dwell times. In dense urban environments, where fast chargers remain relatively scarce, this constraint likely limits the prevalence of SOC-Based behavior. At the same time, these results indicate that fast chargers are not strictly required to meet aggregate energy needs, as sufficient energy can be supplied through longer-duration activities using lower-power infrastructure, a finding consistent with previous work on charger location and type choice.

Short-duration activities—such as shopping, leisure, and other brief stops—exhibit a charging mix dominated by Planned and Opportunistic logics, with relatively short charging durations and modest SOC gains. These events primarily reflect opportunistic top-ups rather than full recharges. However, from an infrastructure perspective, such locations may also represent suitable candidates for targeted fast-charging deployment. Even limited fast-charging capacity at these sites could support SOC-Based charging when drivers reach low SOC levels away from home, potentially redistributing demand away from longer-duration activities and contributing to a more flexible charging profile.

Overall, the patterns in Table 4.1 highlight the strong interaction between activity structure, charging logic, and infrastructure availability. While long-duration activities naturally support planned and Opportunistic charging, short-duration activities may play a complementary role if equipped with appropriate charging power. Although SOC-Based charging remains rare under current infrastructure conditions, increasing the availability of fast chargers in strategic urban locations could encourage this behavior. In turn, such a shift may help reduce synchronized charging peaks by enabling drivers to respond more flexibly to low SOC conditions, underscoring the importance of infrastructure planning that considers not only aggregate demand but also behavioral responses shaped by the temporal and spatial organization of daily activities.

Across all activity types, home and work dominate charging contexts, with Planned and Opportunistic logics splitting nearly evenly. SOC-Based charging remains relatively rare but consistently achieves higher SOC gains over shorter durations, indicating reliance on high-power public chargers. Short-duration activities primarily host opportunistic top-ups with limited energy transfer.

4.6 Synthesis and Implications of Behavioral Heterogeneity

This chapter’s results show that behavioral diversity significantly influences system-level EV charging results. Assumptions regarding how people charge impact peak demand, queuing patterns, and infrastructure use. Even without pricing or central control, varied behaviors help decrease congestion and lower peak demand. These insights lay an essential groundwork for the following chapter, which explores if pricing strategies can further influence charging behavior and enhance the effects of diversity.

4.6.1 Key Findings

Several overarching findings emerge from the results of this chapter.

Firstly, the analysis of time and SOC dependency confirms that the implemented charging strategies exhibit clear and consistent behavioral patterns. Planned charging mostly functions independently of the battery’s current state, following routine schedules. SOC-Based charging mainly activates at low SOC levels, typically after trips when the battery is drained. Opportunistic charging occurs at various times and SOC levels, often during top-up opportunities. These distinct patterns demonstrate that the model effectively captures the specific behaviors linked to each charging strategy, thereby bolstering confidence in the subsequent analyses that rely on these behavioral mechanisms and strategies.

Second, assumptions regarding charging logic significantly influence electricity demand. Homogeneous scenarios showed markedly different load profiles even with the same travel demand and charging infrastructure. Planned charging led to distinct morning and evening peaks, causing the highest instantaneous grid load. In contrast, SOC-Based charging reduced overall demand and smoothed the load curve by basing charging on battery depletion rather than activity duration. Opportunistic charging, though flexible in theory, still resulted in demand patterns dominated by long-duration home and work activities, highlighting how daily schedules shape charging behavior. These findings illustrate that total power demand is highly sensitive to behavioral assumptions and cannot be inferred solely from infrastructure features.

Third, behavioral heterogeneity alone was shown to reduce peak electricity demand without any explicit pricing or centralized control policy. In the heterogeneous scenario, where agents chose charging strategies through experience-based utility learning, peak load decreased by about 20% compared to the purely Planned case. This smoothing effect arose naturally from the coexistence of different charging heuristics and variations in users’ daily activity patterns, demonstrating that overall grid impacts depend not only on infrastructure capacity but also

on how charging behaviors are distributed across the population.

Fourth, queuing dynamics highlighted key trade-offs between grid-focused and infrastructure-focused performance. While SOC-Based charging lowered overall power demand, it resulted in the highest queuing intensity, particularly during morning hours and at central public chargers. This indicates that low total demand does not necessarily mean low congestion. Charging habits that wait until SOC reaches critical levels tend to concentrate demand in specific areas and times, increasing competition for public chargers and making it harder for users to delay charging during congestion. Conversely, Planned and Opportunistic behaviors offered greater flexibility in timing and location, which led to more stable queuing patterns even when overall electricity demand was higher.

Fifth, activity context and daily schedule structure emerged as crucial factors affecting charging habits. Across all scenarios, the primary charging locations remained at home and work, underscoring the vital role of long-duration activities in urban EV charging. Nonetheless, SOC-Based charging showed a notable deviation from this pattern, mainly happening during non-residential activities and relying heavily on public charging infrastructure. The analysis of daily activity complexity indicated that SOC-Based charging becomes less frequent as schedules become more fragmented and flexible. Users with intricate activity chains tend to depend less on SOC thresholds and more on planned or opportunistic methods, which help prevent battery depletion from becoming the main trigger for charging. This highlights that greater flexibility in daily mobility reduces reactive, last-resort charging behaviors.

And finally, the analysis of sociodemographic patterns revealed limited direct differentiation in charging logic selection across income, age, and gender groups. Rather than indicating the absence of behavioral variation, this result clarifies that sociodemographic attributes influence charging behavior primarily *indirectly*, through their correlation with daily activity structure and access to charging infrastructure. Younger and lower-income agents exhibited slightly higher shares of opportunistic charging due to more fragmented schedules, while older and higher-income agents more often adopted planned charging aligned with stable routines. Gender-based differences were minimal once the activity context was accounted for. This finding underscores that charging behavior is driven more by how people move through the city than by demographic characteristics per se, within the scope of the modeled decision mechanisms.

4.6.2 Implications for the Working Hypotheses

The findings of this chapter directly support the first working hypothesis of this thesis : that charging demand patterns and system-level impacts are strongly influenced by behavioral

heterogeneity, and that models assuming homogeneous charging behavior may misrepresent both grid and infrastructure outcomes.

Homogeneous charging assumptions caused exaggerated grid peaks (Planned), underestimated infrastructure stress (SOC-Based), and led to misleading expectations of flexibility (Opportunistic). Allowing behavioral diversity to develop naturally produced more realistic outcomes, even without explicit policy intervention. Importantly, heterogeneity did not eliminate congestion or peak demand but redistributed them in ways that reduced extreme outcomes and highlighted trade-offs between grid load and charger availability.

This chapter also presents strong evidence for a second hypothesis : that system performance cannot be judged only by total electricity demand. Actions that seem beneficial from a grid perspective might worsen local congestion and queuing, while actions that boost overall demand can enhance infrastructure use by distributing charging more evenly across time and space. These findings emphasize the importance of integrated evaluation methods that include electricity demand, charger utilization, and user experience.

4.6.3 Contribution of This Theme

This chapter makes four main contributions. First, it empirically shows that charging behavior is a key determinant of system-level outcomes in urban EV charging systems, not just a secondary assumption. Second, it reveals that behavioral heterogeneity—emerging primarily from differences in daily activity patterns and accessibility within the current modeling framework, rather than from explicitly modeled demographic-specific parameters—can reduce grid stress even without pricing or technological changes. Third, the findings indicate that various charging behaviors, driven mainly by individual needs and constraints, lead to significantly different impacts on the power grid and charging infrastructure. These impacts result from users trying to meet their mobility needs, rather than responding to system-level goals. This analysis implicitly suggests which types of charging behavior are more compatible with grid stability, implying that supporting certain behaviors might benefit the system without limiting individual choices. Fourth, it clarifies the indirect role of sociodemographic variables within the modeling framework, where their influence is mediated through activity patterns and infrastructure access rather than explicitly represented in behavioral decision rules

By treating charging strategies as adaptive and allowing them to emerge through experience-based learning, this chapter advances the behavioral plausibility of agent-based EV charging models and provides a robust foundation for policy analysis that respects the diversity of urban mobility patterns.

While behavioral heterogeneity alone helps lower peak demand and redistributes congestion, it does not fully remove system stress. Peak loads and queuing remain across all scenarios, showing that additional strategies are needed to control charging demand as EV adoption rises. The next chapter builds on these findings by exploring pricing strategies and how time-based and location-based incentives influence diverse charging behaviors. By examining behavioral changes under different pricing regimes, it evaluates whether economic signals can better balance demand without causing congestion shifts to new locations or increasing inequalities among users and areas.

CHAPITRE 5 SECOND THEME — PRICING, INFRASTRUCTURE CONSTRAINTS, AND SPATIAL RIGIDITY IN URBAN EV CHARGING SYSTEMS

This chapter explores how pricing strategies, charging infrastructure limitations, and user behavior collectively influence urban EV charging outcomes at the system level. Building on the behaviorally grounded modeling framework introduced in Chapter 3, the analysis moves beyond aggregate demand profiles to investigate how charging demand emerges over time and space when heterogeneous users respond to pricing policies under real-world infrastructure limitations.

This chapter primarily aims to assess whether demand management strategies based on pricing, such as TOU and spatially differentiated (area) pricing, can effectively reduce peak electricity demand and charging congestion in real-world scenarios. Although pricing is frequently promoted as a flexible and economical policy instrument, its success largely relies on users' capacity to modify their charging behaviors, considering constraints like daily routines, charger accessibility, and spatial availability. As articulated in the working hypotheses of Chapter 1, pricing strategies alone may be insufficient if infrastructure constraints and behavioral responses are not explicitly accounted for.

To address this question, the chapter proceeds in a structured manner. First, a Free (no-pricing) scenario is analyzed to establish a behavioral baseline and to assess the plausibility of the simulated charging patterns relative to well-documented qualitative features of observed charging behavior. Next, the effects of TOU pricing are examined in detail, focusing on temporal shifts in charging demand, changes in charger types used, and congestion dynamics at public charging stations. The analysis then identifies system bottlenecks that limit the effectiveness of pricing and evaluates an Unlimited-Charger scenario to isolate the role of infrastructure capacity. Finally, an area pricing strategy is introduced to assess whether spatially differentiated prices can redistribute charging demand geographically and to explore potential trade-offs between temporal and spatial objectives.

5.1 Simulation Framework and Baseline Behavior (Free Scenario)

To establish a reference point for subsequent policy experiments, we begin by examining EV charging behavior under a Free scenario, in which users face no economic constraints. This scenario serves two purposes. First, it provides a behavioral baseline against which the

effects of pricing strategies can be evaluated. Second, it allows for an assessment of whether the agent-based simulation reproduces internally consistent charging patterns that align with theoretical expectations, while empirical plausibility under real-world pricing conditions is evaluated separately through the flat-priced scenario.

In the absence of pricing signals, charging decisions in this scenario are driven solely by individual activity schedules, the battery SOC, charger availability, and behavioral preferences embedded in the charging logic. As such, the resulting demand patterns reflect the natural interaction between daily mobility routines and infrastructure constraints, without any external incentive to shift charging in time or space.

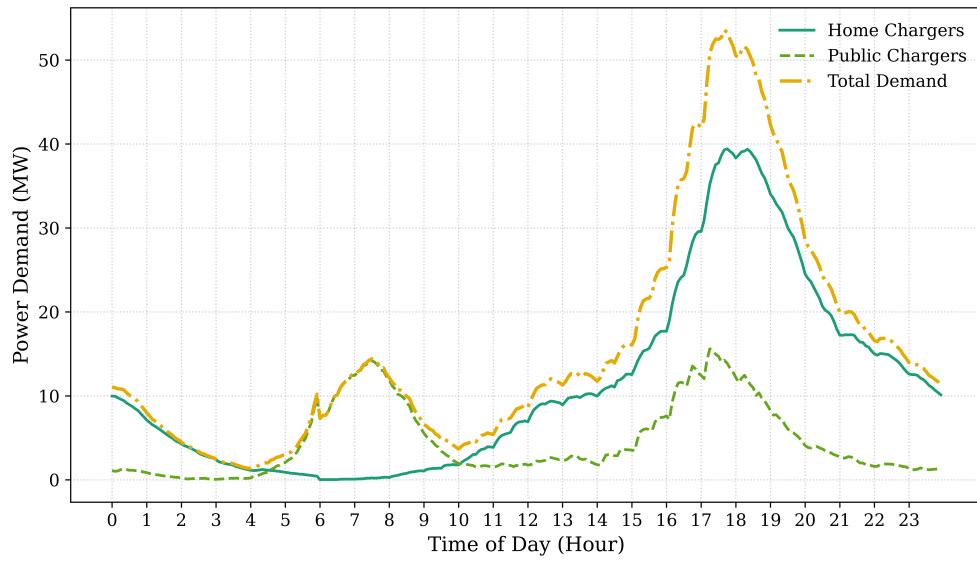


FIGURE 5.1 Temporal distribution of power demand in the Free scenario.

As shown in Figure 5.1, home charging demand in the Free scenario exhibits a pronounced evening peak, beginning around 6 :00 PM and reaching nearly 40 MW. This pattern is a direct consequence of activity-based behavior : most agents return home in the late afternoon or early evening and initiate charging during long-duration home activities. The concentration of charging during this period aligns with well-documented empirical findings that residential evening charging is a major contributor to peak electricity demand.

Public charging demand, by contrast, follows a bimodal temporal pattern, with two distinct peaks occurring in the morning (around 8 :00 AM) and in the late afternoon to early evening (around 5 :00 PM), each reaching approximately 15 MW. The morning peak is primarily associated with charging near workplaces or other non-residential activity locations, where agents arrive with partially depleted batteries and have sufficient activity duration to justify

charging. The evening public charging peak reflects charging during non-home activities such as shopping, dining, or recreational trips that occur before agents return home.

These temporal patterns are consistent with previous modeling and empirical studies (23; 105; 106), which similarly report an evening residential peak between 6 :00 PM and 7 :00 PM and a morning public charging peak around 8 :00 AM. The slightly earlier timing of the evening public charging peak relative to home charging can be explained by behavioral and spatial factors. Some users may charge at public stations near their residence and then walk the remaining distance home, while others charge during intermediate evening activities before returning home. These behaviors highlight the importance of explicitly modeling activity schedules and spatial accessibility when analyzing charging demand.

To further assess the simulation’s realism, the spatial distribution of charging events across super zones is examined in the Free scenario. Figure 5.2 illustrates that home charging events are predominantly located in residential zones, many of which are situated farther from the city center. In contrast, public charging events are more concentrated in central areas and high-activity zones, reflecting the clustering of workplaces, commercial destinations, and educational institutions. This spatial contrast between home and public charging is an emergent outcome of the model and aligns with expected usage patterns, further supporting the plausibility of the simulated charging behavior.

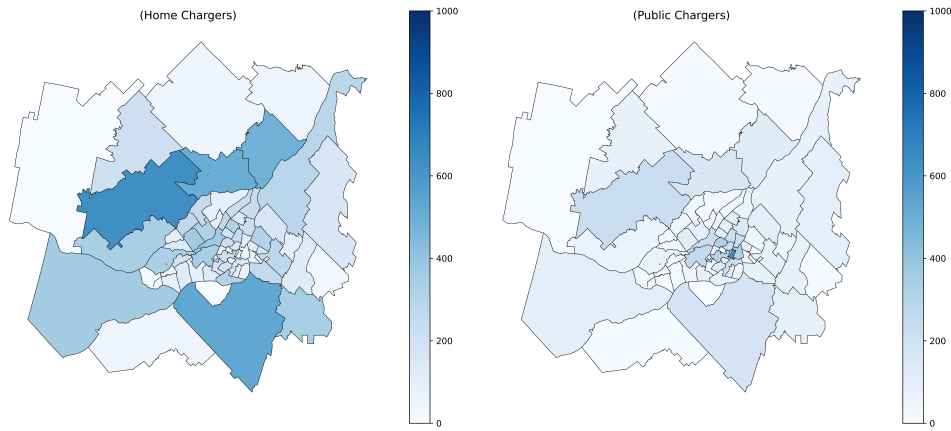


FIGURE 5.2 Spatial distribution of charging events in the Free scenario.

Taken together, the temporal and spatial patterns observed in the Free scenario establish a credible baseline for evaluating pricing and infrastructure interventions. The results confirm that, even in the absence of pricing, charging demand is highly concentrated in time and space, supporting the hypothesis introduced in Chapter 1 that system-level stress arises not from total energy consumption, but from the synchronization of individual charging decisions

under shared infrastructure constraints.

5.2 Model Validation Against Observed Public Charging Data

To assess the realism of the proposed agent-based simulation framework, a validation exercise was conducted by comparing simulated charging outcomes with observed data from public EV charging stations operated by Circuit Électrique in the Greater Montréal region. The objective of this validation is not to achieve a perfect point-by-point replication of observed behavior, but rather to evaluate whether the model reproduces key temporal patterns and aggregate magnitudes of public charging demand and charging durations under realistic assumptions.

Data Preparation and Processing. Observed charging records were cleaned and filtered to ensure consistency with the simulated system. Only charging sessions located within the Greater Montréal metropolitan area were retained, based on geographic coordinates. A representative weekday in October 2024 was selected to align with the period during which the origin–destination survey data used for activity modeling were collected, ensuring comparable seasonal activity patterns. This choice allows the validation to focus on a conservative operating scenario, as charging demand and electricity consumption tend to be higher during the fall than under average annual conditions.

For both observed and simulated datasets, charging sessions were selected by start time, and full session durations were preserved even when charging extended beyond midnight. Power demand was reconstructed at 5-minute resolution by summing charger power across all intervals when vehicles were actively charging. For observed data, effective charging duration was derived from the reported energy transferred and charger power, thereby accounting only for periods during which electricity was actually drawn from the grid. In contrast, plug-in duration was computed using the recorded start and end timestamps and was used exclusively for duration-based validation.

Simulation outputs were processed using the same temporal logic to ensure comparability. Only public charging sessions were retained; home charging events were excluded. Simulated power demand was reconstructed at the same 5-minute resolution, with appropriate handling for sessions extending beyond 24 hours. Plug-in durations were computed from simulated start and end times and aggregated by charging start hour, mirroring the observed data treatment.

Comparison of Power Demand Profiles. Figure 5.3 compares the simulated and observed public charging power demand profiles over the course of the day. Both datasets show a similar daily pattern, with a pronounced morning increase in charging activity and a do-

minant evening peak, reflecting common underlying drivers such as commuting patterns and activity scheduling. The simulation captures the relative magnitudes of these peaks and the overall temporal organization of public charging demand.

However, the simulated charging peaks occur approximately 1.5 hours earlier than those observed, indicating a systematic temporal offset rather than a close point-by-point match. Such a shift is not unexpected in large-scale agent-based simulations, where activity schedules are generated probabilistically and are not explicitly calibrated to observed clock-time distributions. As a result, departures, arrivals, and subsequent charging opportunities may occur earlier or later in the simulated day. Additional factors—including the random initialization of vehicle state of charge, probabilistic home-charging availability, and simplified representations of charger access—may further contribute to earlier charging decisions.

Despite this temporal offset, the consistency in peak ordering, relative intensity, and overall demand structure suggests that the simulation captures the dominant mechanisms shaping public charging demand, even if the exact timing differs from observed data.

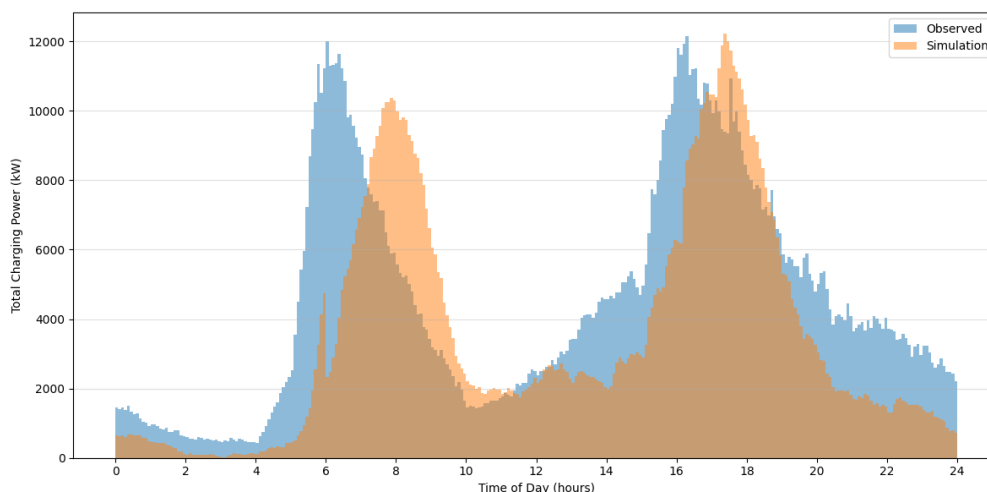


FIGURE 5.3 Temporal distribution of charging events' start time in the Flat-priced scenario.

This modest temporal shift may stem from several sources, including differences in the synthetic population generation process, simplified representations of daily activity timing, or stochastic assignment of the initial state of charge. Given the inherent variability of real-world charging behavior, the alignment observed at this aggregate level is considered satisfactory.

Comparison of Charging Durations. Figure 5.4 presents the average plug-in duration by charging start hour for both observed and simulated data. Despite the presence of sto-

chastic elements in the simulation—such as random initialization of battery state of charge, probabilistic home charger ownership, heterogeneous battery capacities, charger availability, and charger power losses—the model reproduces the main temporal trends in charging duration. Both datasets show longer average durations during daytime and early evening periods, with shorter sessions during late-night hours.

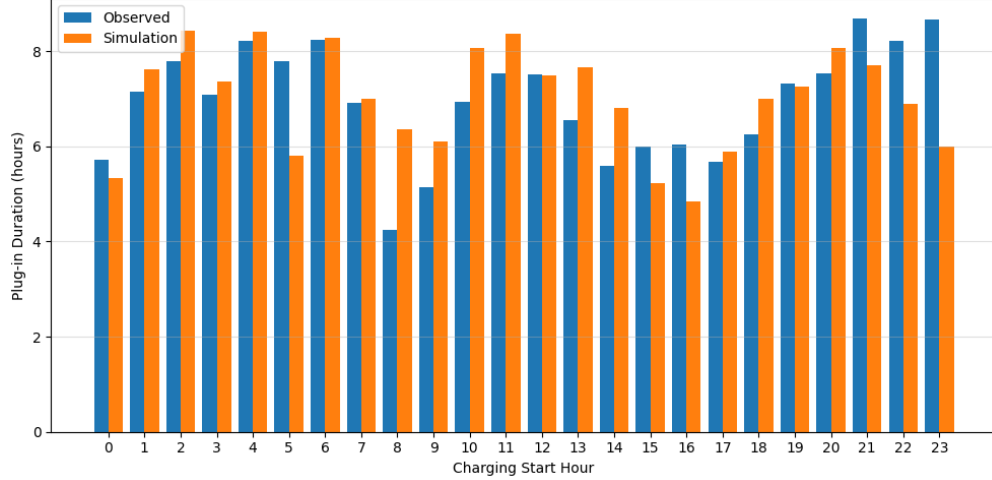


FIGURE 5.4 Temporal distribution of charging events’ duration in the Flat-priced scenario.

Discrepancies between observed and simulated durations are expected, particularly given the simplified representation of user patience and post-charging dwell time. Nevertheless, the close correspondence across most hours suggests that the model captures the dominant mechanisms governing charging duration at public stations.

Overall, the validation results indicate that the proposed modeling framework successfully produces realistic aggregate charging patterns for public infrastructure, even though it depends on stochastic behavioral elements and synthetic population data. The remaining gaps between observed and simulated results highlight areas for future enhancement, such as improved calibration of daily activity schedules, better modeling of dwell times after charging, and a more detailed account of charger availability constraints. Importantly, these discrepancies do not hinder the model’s ability to capture key system-level behaviors within the limited dimensions supported by empirical data. Although comprehensive validation across all outcomes is beyond this study’s scope, the partial consistency found offers tentative support for using the model as an exploratory tool for policy analysis and scenario testing.

5.3 Impact of TOU Pricing on Charging Behavior

This section evaluates how TOU pricing influences EV charging behavior when users are exposed to explicit temporal cost signals. Consistent with the policy discussion in Chapter 1, TOU pricing is designed to reduce charging activity during periods of high system stress—particularly evening hours—by increasing electricity prices during peak periods and/or lowering prices during off-peak times. In theory, such pricing schemes offer a flexible mechanism for flattening demand without requiring physical expansion of grid or charging infrastructure.

However, as emphasized in the working hypotheses, the effectiveness of TOU pricing depends on whether users possess sufficient behavioral and infrastructural flexibility to respond. Charging demand may shift over time only if users can adjust their charging decisions within the constraints imposed by daily activity schedules, charger availability, and spatial accessibility. The analysis below, therefore, focuses not only on aggregate demand shifts but also on how these shifts interact with charger type usage and congestion at public charging stations.

5.3.1 Temporal Variation in Charging Demand

To assess the behavioral response to TOU pricing, temporal charging demand profiles are compared across three scenarios : Free (no pricing), Flat-Priced, and TOU-Priced. These scenarios isolate the effect of temporal price variation by holding all other elements—travel demand, infrastructure, and charging logic—constant. The comparison allows for a direct evaluation of whether TOU pricing induces users to shift charging away from peak periods, as hypothesized.

Figure 5.5 presents the hourly power demand profiles for home chargers under the three scenarios, aggregated using one-hour intervals over a full day. Across all scenarios, home charging demand exhibits a consistent evening peak beginning around 6 :00 PM. This reflects the strong coupling between residential charging and daily activity schedules : regardless of pricing, most agents return home during this period and have long-duration activities that support charging.

Despite this structural similarity, important differences emerge in peak demand magnitude. In the TOU-Priced scenario, where the electricity price for home charging is doubled during peak hours, the maximum evening demand is reduced to approximately 75% of the peak observed in both the Free and Flat-Priced scenarios. This reduction indicates that TOU pricing successfully alters charging behavior among a subset of users, even in the presence of strong habitual tendencies toward home charging.

The observed reduction in home charging demand arises from several behavioral adaptations. Some users delay charging to later hours, others shift charging to public chargers during lower-cost morning periods, and some reduce EV usage altogether, potentially substituting alternative travel modes when electricity costs are perceived as high. Importantly, these adaptations occur endogenously within the simulation, rather than being imposed by rule-based constraints. This highlights the value of representing charging as an adaptive behavioral outcome rather than a fixed activity.

In contrast, the Flat-Priced scenario closely mirrors the Free scenario in both timing and magnitude of demand. This finding underscores a key insight : pricing mechanisms that do not introduce temporal differentiation offer little incentive for users to change their charging behavior. Constant prices may affect the overall charging frequency, but they do not address the core system-level issue of synchronized demand during peak periods.

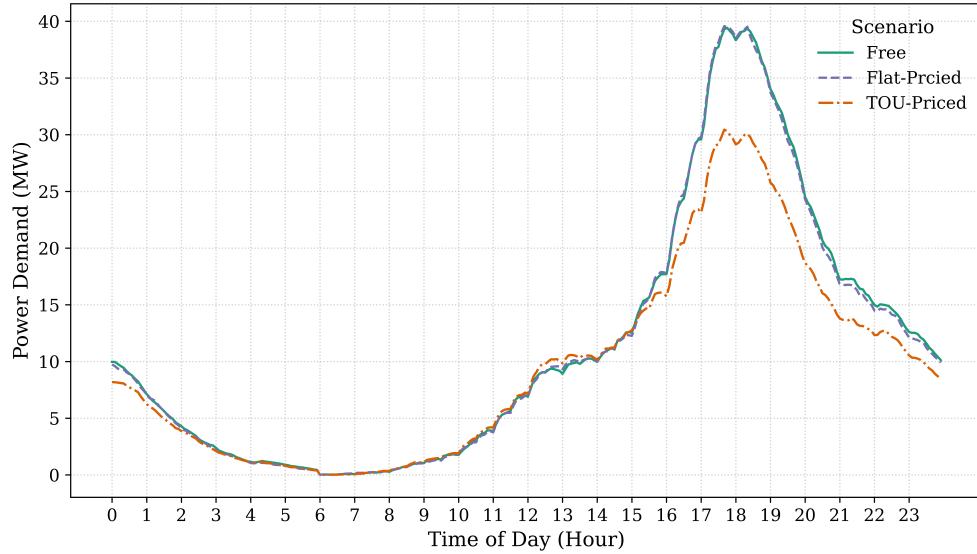


FIGURE 5.5 Temporal distribution of power demand for Home chargers across three scenarios.

Figure 5.6 shows the corresponding temporal demand profiles for public chargers. Unlike home charging, public charging exhibits a bimodal structure across all scenarios, with a morning peak (around 7–8 AM) and an evening peak (around 5–6 PM). These peaks correspond to charging associated with morning arrivals at workplaces and evening non-home activities, respectively.

In the Free scenario, public charging demand reaches approximately 15 MW in the evening and 14 MW in the morning. The Flat-Priced scenario exhibits slightly lower peaks, reflecting a modest reduction in overall charging events due to the introduction of cost. However, the

overall temporal structure remains unchanged, with the evening peak still dominant.

The TOU-Priced scenario, by contrast, exhibits a qualitatively different pattern. The morning peak increases to nearly 14 MW, while the evening peak is reduced by roughly half, dropping to approximately 7 MW. This inversion of peak dominance provides clear evidence that TOU pricing induces a temporal redistribution of public charging demand. Users respond to higher evening prices by advancing charging to earlier, lower-cost periods, particularly when charging opportunities coincide with morning activities.

This result confirms that pricing can influence charging demand to move away from peak times. However, it also highlights a key limitation : instead of removing peak demand, TOU pricing shifts it to other times. Demand reduced in the evening tends to resurface in the morning, potentially interacting with different infrastructure constraints. This redistribution hints at the congestion behaviors explored later in the chapter.

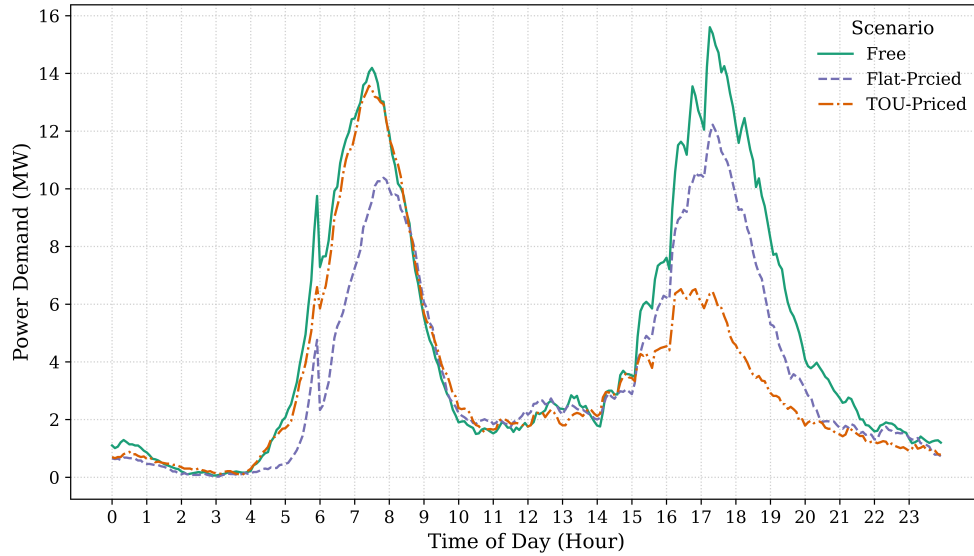


FIGURE 5.6 Temporal distribution of power demand for Public chargers across three scenarios.

Taken together, the temporal demand results demonstrate that TOU pricing is effective at altering the timing of charging behavior, particularly for public chargers where users exhibit greater temporal flexibility. This confirms the first-order behavioral response anticipated in the working hypotheses. However, the persistence of an evening peak in home charging and the emergence of a pronounced morning peak in public charging indicate that pricing alone does not eliminate peak demand—it merely shifts it.

These findings support a key argument of this thesis : charging demand is limited not only

by economic factors but also by patterns of daily activity and the spatial distribution of infrastructure. Users can only respond to pricing signals within the range of available charging options. Consequently, even well-designed pricing strategies may be less effective if the infrastructure’s capacity and accessibility do not align with the intended time shifts.

The subsequent sections expand on this insight by exploring how TOU pricing influences charger-type usage and congestion at public stations, and by highlighting infrastructure bottlenecks that ultimately constrain the effectiveness of demand management through pricing.

5.3.2 Utilized Charger Types

Beyond shifts in the timing of charging, pricing strategies may also influence *how* users charge—that is, which types of charging infrastructure they choose to rely on. Examining charger-type utilization, therefore, provides additional insight into the behavioral mechanisms through which pricing affects system-level outcomes. In particular, differences in charger power, charging speed, and cost may lead users to substitute between home chargers, public Level 2 chargers, and fast chargers when prices vary.

Figure 5.7 presents the total number and percentage of home and public chargers utilized in each pricing scenario. Across all scenarios, the overall number of charging events is highest in the Free scenario, followed by the Flat-Priced and TOU-Priced scenarios. This monotonic decline reflects the introduction of economic disutility : as charging becomes more costly, some users reduce the frequency of charging events or adjust travel behavior to avoid charging altogether.

Home charging remains the dominant mode of charging in all scenarios. Home chargers account for approximately 66.3%, 71.1%, and 71.7% of charging events in the Free, Flat-Priced, and TOU-Priced scenarios, respectively. The slightly lower share of home charging in the Free scenario is offset by greater use of public chargers, reflecting users’ preference for faster or more convenient charging opportunities when no cost is imposed.

These results are consistent with empirical evidence, which suggests that between 50% and 80% of EV charging events occur at home (78), while approximately 15–20% occur at workplaces and only a small fraction take place at other public locations (107). Together, these estimates indicate that roughly one-quarter of charging events occur outside the home, aligning closely with the public charging shares observed in this study.

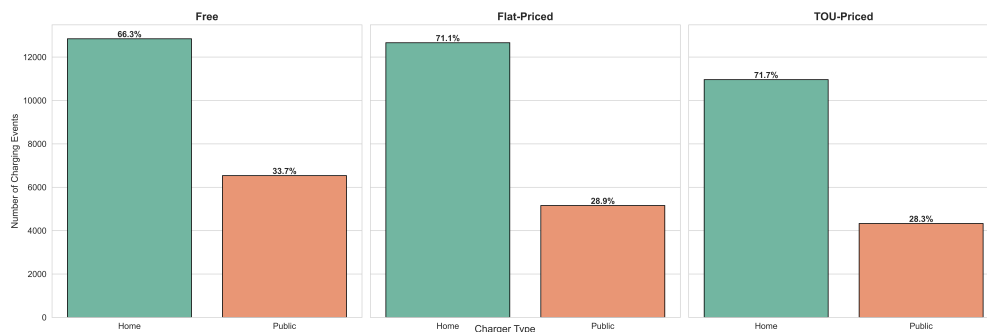


FIGURE 5.7 Total number and percentage of Home and Public chargers used in each scenario.

Figure 5.8 further disaggregates charger usage by charger type and time of day. Across all scenarios, Level 2 chargers are used more intensively in the morning than in the evening, reflecting charging during work and other daytime activities that offer sufficient duration for moderate-power charging. Home chargers, by contrast, dominate evening charging, consistent with long residential activity durations and habitual charging upon returning home. Nevertheless, a non-negligible share of users continue to rely on Level 2 chargers during evening hours,

Fast chargers exhibit a distinct usage pattern. Their utilization is highest in the Free scenario and declines noticeably under Flat-Priced and TOU-Priced conditions. This result reflects the trade-off faced by users between charging speed and cost. In the absence of pricing, fast chargers offer high utility by minimizing charging time and reducing inconvenience. When pricing is introduced—especially under TOU pricing—these benefits are offset by higher costs, leading users to substitute toward slower but cheaper alternatives when feasible.

This shift away from fast chargers under pricing regimes has important system-level implications. While reduced fast-charger usage may lower instantaneous power demand, it can also increase charger occupancy times at Level 2 stations, potentially exacerbating congestion during peak periods. These interactions illustrate how pricing can influence not only demand magnitude and timing, but also the operational performance of charging infrastructure.

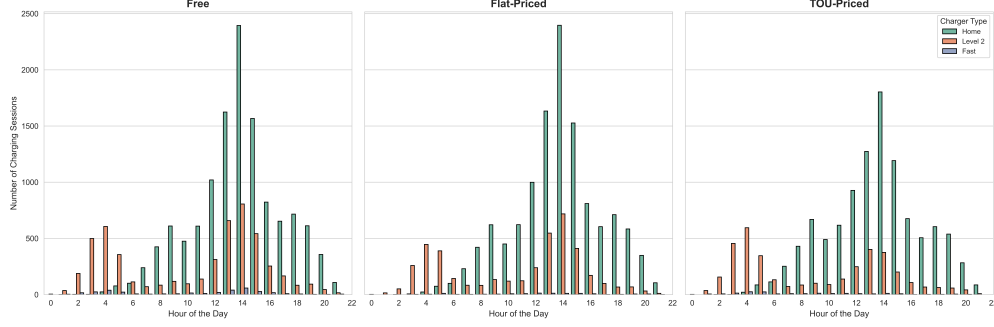


FIGURE 5.8 Charger types used in each scenario throughout the day.

5.3.3 Queues at Charging Stations and User Experience

In addition to altering charging demand and infrastructure usage, pricing strategies can significantly affect congestion dynamics at public charging stations. Because public chargers are shared resources, simultaneous arrivals and long charging sessions can lead to queuing even when total demand appears moderate. Understanding how pricing influences both the likelihood and severity of queuing is therefore critical for evaluating the practical effectiveness of demand management strategies.

Within the modeling framework, queuing occurs when all charging plugs at a station are occupied when an agent arrives. In such cases, agents are assumed to wait until a plug becomes available rather than immediately searching for an alternative station. This behavior reflects plausible, though potentially sub-optimal, real-world decisions, particularly in contexts where alternative chargers are not easily accessible.

At the same time, the model incorporates MATSim’s co-evolutionary learning process, through which agents adapt their future charging decisions based on experienced delays. Repeated exposure to congestion reduces the likelihood that agents will select the same crowded stations, resulting in a steady-state outcome that reflects typical congestion conditions rather than extreme cases.

Figure 5.9 presents both the share of users experiencing queues and the median waiting time across hours of the day for the three pricing scenarios. This combined representation provides a more comprehensive view of congestion, capturing not only how many users are affected but also how long they are delayed.

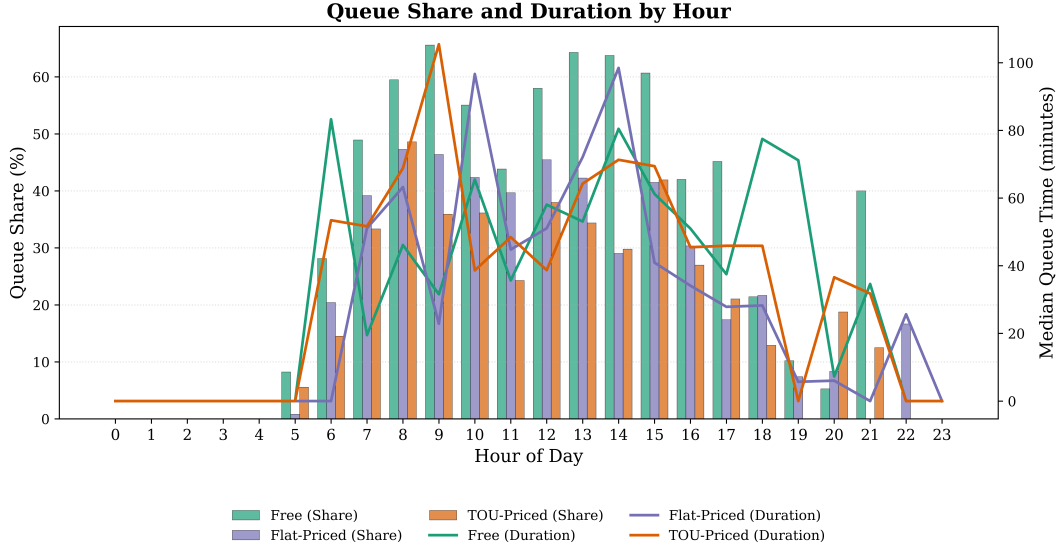


FIGURE 5.9 Hourly queue share (bars) and median waiting time (lines) at public charging stations under Free, Flat-Priced, and TOU-Priced scenarios.

The results reveal a clear temporal concentration of congestion. Across all scenarios, queuing emerges primarily during daytime hours, with the highest levels occurring between approximately 8 :00 AM and 3 :00 PM. The TOU-priced scenario shows a pronounced peak in the morning, both in terms of queue share and waiting time, indicating that lower prices during these hours incentivize synchronized charging behavior. This leads to a higher proportion of users experiencing queues, as well as longer waiting times compared to the other scenarios.

By contrast, during the late afternoon and evening period, the TOU-priced scenario generally exhibits lower queue shares and shorter waiting times relative to the Free and Flat-Priced scenarios. This suggests that TOU pricing can partially alleviate congestion during traditionally high-demand periods by shifting charging activity earlier in the day.

However, the results also highlight an important trade-off. While TOU pricing reduces congestion in some periods, it can exacerbate it in others by concentrating demand into low-price windows. This effect is particularly visible in the morning hours, where both the likelihood and duration of queuing increase simultaneously. In practical terms, this implies that some users may experience significant delays despite the presence of price incentives.

It is also important to interpret these findings in light of behavioral assumptions. In reality, users facing strict time constraints—such as morning commutes—may be less willing to wait and more willing to pay higher prices to avoid delays. In the model, this trade-off is represented through generalized cost functions, but may not fully capture all real-world

preferences. As a result, the observed queuing patterns should be interpreted as indicative of potential demand synchronization effects rather than precise forecasts.

An important spatial dimension underlies these congestion patterns. Despite the availability of numerous public chargers, queuing persists because many stations are not optimally located relative to users' activities. Agents tend to cluster around a subset of conveniently located chargers, leading to localized congestion even when total system capacity is sufficient.

Overall, the combined analysis of queue share and waiting time underscores a key system-level insight : pricing strategies alone are not sufficient to eliminate congestion. While they can effectively shift demand across time, they may also introduce new peaks in specific periods. Ensuring efficient system performance therefore requires not only well-designed pricing mechanisms but also adequate spatial distribution and capacity of charging infrastructure.

5.3.4 Spatial Variation of Charging Demands

While the preceding analysis focused on the temporal effects of TOU pricing, charging demand is equally shaped by its spatial distribution. Because charging infrastructure is unevenly distributed across Montreal, spatial concentration of demand can generate localized congestion and grid stress even when aggregate demand is reduced or temporally shifted. Understanding where charging occurs is therefore essential for evaluating the real-world effectiveness of pricing-based demand management strategies.

To examine spatial variation, the number of home and public charging events in each super zone is calculated and presented in Figure 5.10. The analysis is conducted at the level of ARTM sectors de pondération, which provide a consistent spatial framework aligned with demand modeling inputs. While finer spatial units could reveal additional local heterogeneity, this level of aggregation allows for robust comparison across scenarios and ensures statistical stability of results.

As expected, home charging events are concentrated in predominantly residential zones, many of which are located farther from the downtown core. These areas are characterized by longer home activity durations and higher rates of private charger access, making them natural focal points for residential charging demand.

Public charging events, by contrast, are more strongly concentrated in central and high-activity zones. These zones host dense clusters of workplaces, educational institutions, and commercial destinations, generating repeated opportunities for daytime and evening charging during non-home activities. This spatial separation between home and public charging reflects the activity-based nature of charging decisions and emerges endogenously from agents' daily

schedules and the spatial configuration of charging infrastructure.

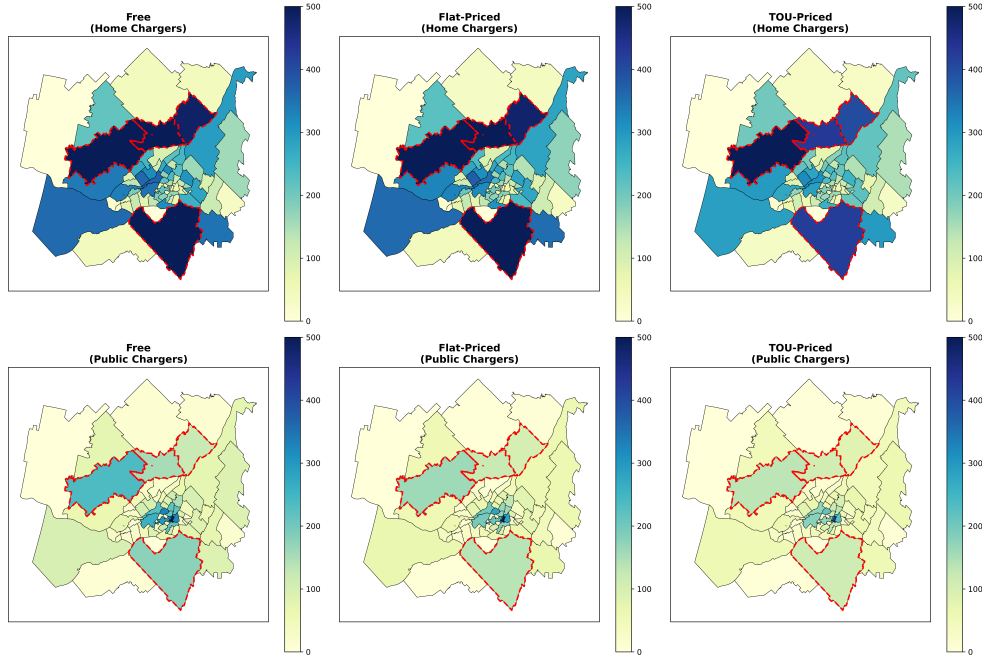


FIGURE 5.10 Spatial distribution of charging events.

Figure 5.11 presents the corresponding spatial distribution of total power demand, obtained by aggregating the power consumption of all charging events within each super zone. Although the total number of public charging events is substantially lower than that of home charging events, public chargers typically operate at higher power levels. As a result, in several central zones, public charging demand reaches levels comparable to—or even exceeding—those associated with home charging.

This finding highlights a key system-level dynamic : localized grid stress is driven not only by the number of charging events, but also by charger power and spatial clustering. In zones with dense activity and limited infrastructure redundancy, even a moderate number of public charging sessions can generate substantial instantaneous load.

A direct comparison between the spatial demand maps and the distribution of charging infrastructure (Figures 3.3, confirms that zones with high home charging demand correspond closely to areas with abundant residential chargers and home-based activities, while zones with high public charging demand align with areas containing dense public charger installations and non-home activity concentrations. Several super zones—highlighted in red in Figure 5.11—exhibit high demand for both home and public charging, suggesting mixed land-use environments where residential and non-residential activities coexist.

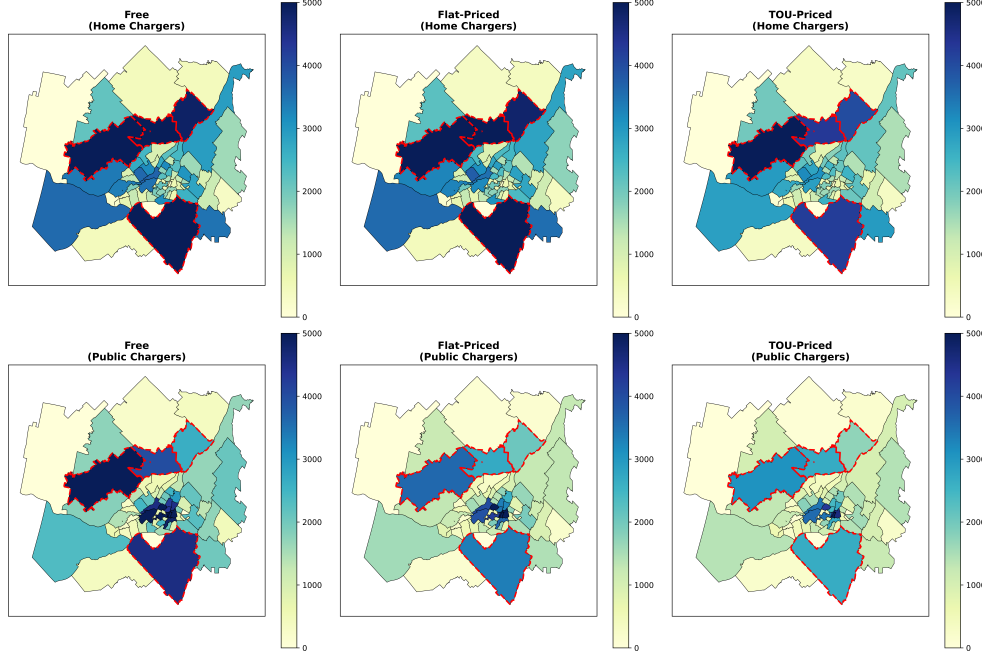


FIGURE 5.11 Spatial distribution of power demands.

To further investigate intra-urban spatial heterogeneity, a refined analysis was conducted using another zoning system, which provides a finer spatial resolution compared to the super-zone aggregation. This allows for a more detailed representation of localized charging patterns, particularly within the Island of Montreal, where aggregation effects are most pronounced.

Figure 5.12 presents the spatial distribution of charging demand at this finer scale across all pricing scenarios. Compared to the aggregated results, several localized clusters of high charging demand emerge more clearly, especially in central areas. These patterns are less distinguishable at the super-zone level, highlighting the importance of spatial resolution in capturing heterogeneity in charging behavior.

The comparison across scenarios confirms that, despite temporal shifts induced by pricing mechanisms, the spatial structure of charging demand remains largely unchanged. High-demand zones persist across Free, Flat-Priced, and TOU-Priced scenarios, reinforcing the strong dependence of charging behavior on activity locations.

The observed spatial structure is consistent with underlying urban characteristics. Central zones, characterized by higher employment density and limited access to private charging infrastructure, exhibit stronger concentrations of public charging demand. In contrast, peripheral zones display more dispersed patterns associated with residential land use and greater

availability of home charging.

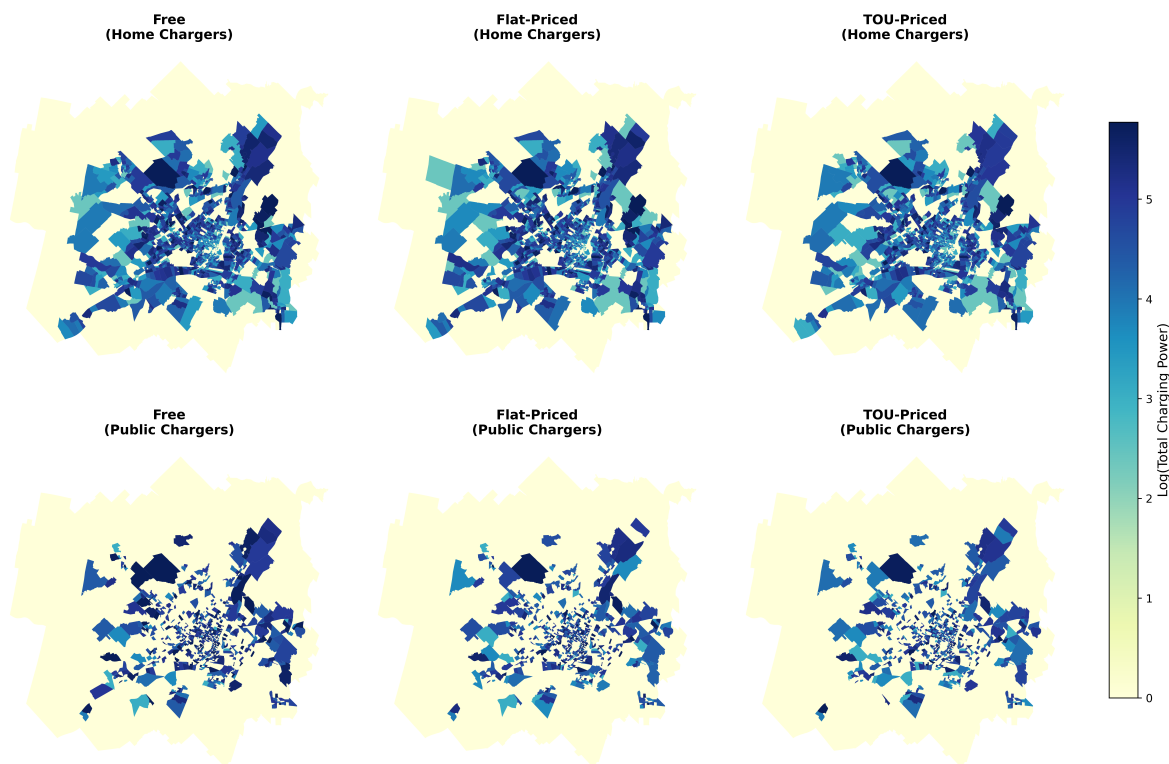


FIGURE 5.12 Refined spatial distribution of charging demand across pricing scenarios (home and public chargers).

A notable and policy-relevant result is that the spatial concentration of charging demand remains remarkably stable across the Free, Flat-Priced, and TOU-Priced scenarios. High-demand zones remain high-demand zones regardless of the pricing scheme applied. While TOU pricing successfully shifts demand in time, it does not substantially alter the geographic distribution of charging events.

This spatial rigidity reflects the strong coupling between charging behavior and daily activity locations. Users can adjust *when* they charge more easily than *where* they charge, particularly when activity locations such as home and work are fixed. This finding directly supports the hypothesis that pricing strategies targeting temporal behavior may have limited influence on spatial demand patterns unless users have realistic opportunities to relocate charging across zones.

The persistence of spatial concentration has important implications for infrastructure planning. Zones that experience high charging demand under baseline conditions continue to face pressure under pricing regimes, suggesting that spatial congestion and grid stress cannot be

addressed through temporal pricing alone. This insight motivates the subsequent analysis of system constraints and infrastructure bottlenecks.

5.3.5 Spatio-Temporal Distribution of Charging Demand

To further explore the interaction between spatial and temporal dynamics, charging demand was analyzed across different periods of the day, namely morning (06 :00–10 :00), midday (10 :00–16 :00), and evening (16 :00–22 :00). Figures 5.13, 5.14, and 5.15 present the spatial distribution of charging energy across these time periods for all pricing scenarios.

In the morning period, charging demand is primarily concentrated in central and high-activity zones, particularly for public chargers. This reflects the influence of work-related activities, where agents arrive at their destinations and initiate charging during the early part of the day.

During midday, this pattern becomes more pronounced, with strong clustering of public charging demand in central areas. This is consistent with the concentration of employment, commercial, and institutional activities, which generate sustained charging opportunities throughout the day.

In contrast, the evening period exhibits a clear shift in charging demand toward peripheral and residential zones, particularly for home chargers. This reflects the return of agents to their home locations and the increased reliance on private charging infrastructure during longer home-based activities. The spatial distribution becomes more dispersed compared to daytime periods, with higher intensity observed in suburban areas.

Across all time periods, the spatial structure of charging demand remains broadly consistent across pricing scenarios. While pricing mechanisms influence the timing of charging events, their effect on the spatial distribution remains limited. This further reinforces the strong coupling between charging behavior and activity locations, highlighting that temporal pricing strategies alone are insufficient to significantly alter spatial demand patterns.

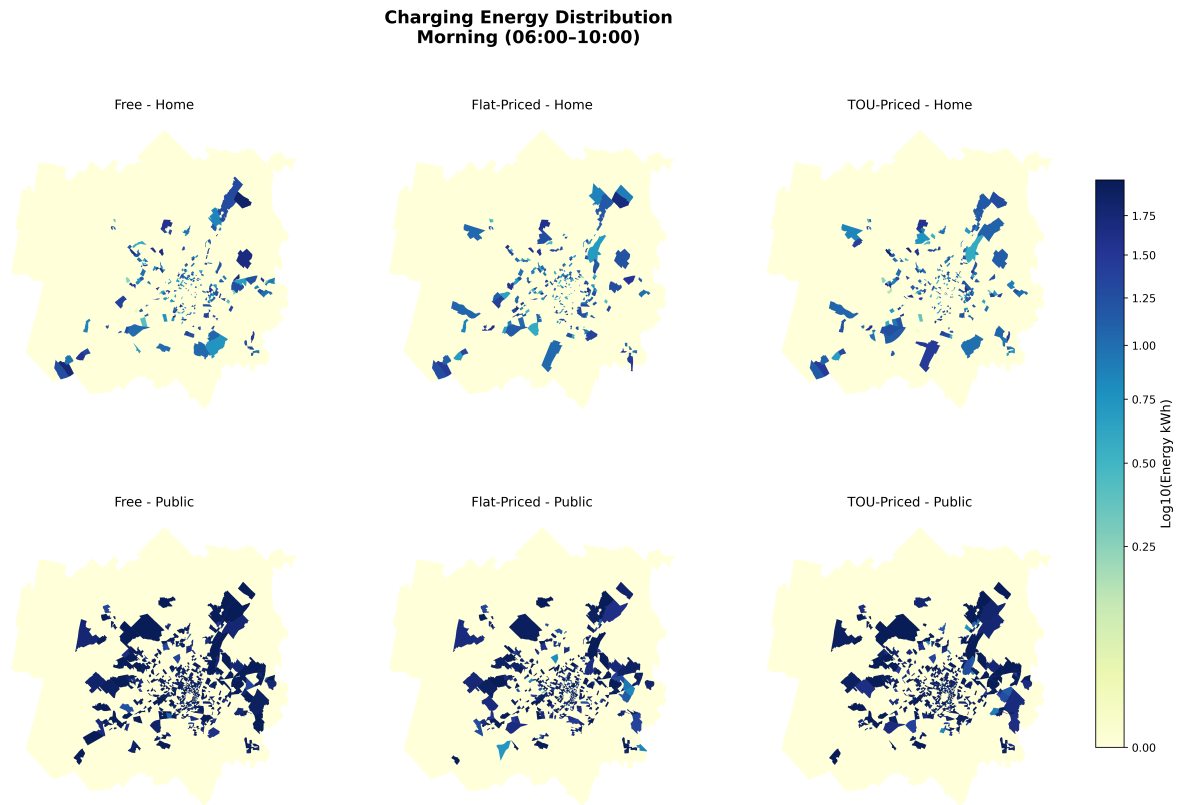


FIGURE 5.13 Spatial distribution of charging energy during the morning period (06 :00–10 :00).

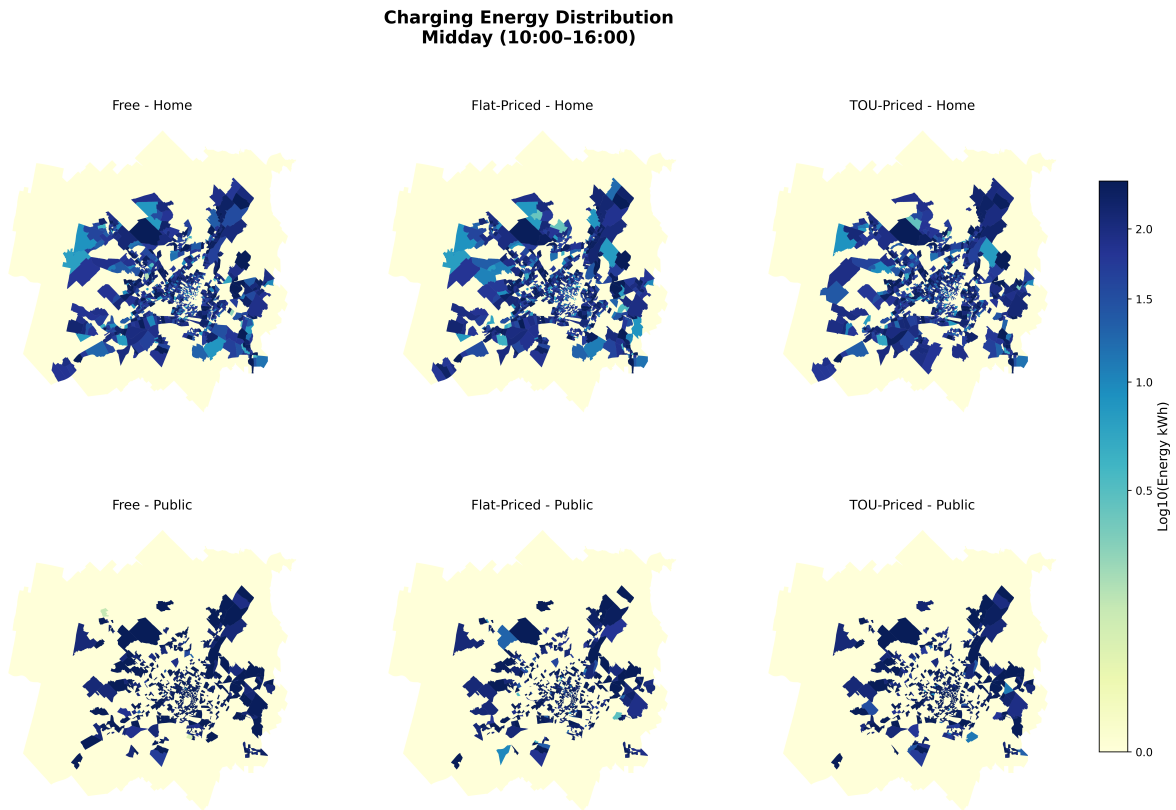


FIGURE 5.14 Spatial distribution of charging energy during the midday period (10 :00–16 :00).

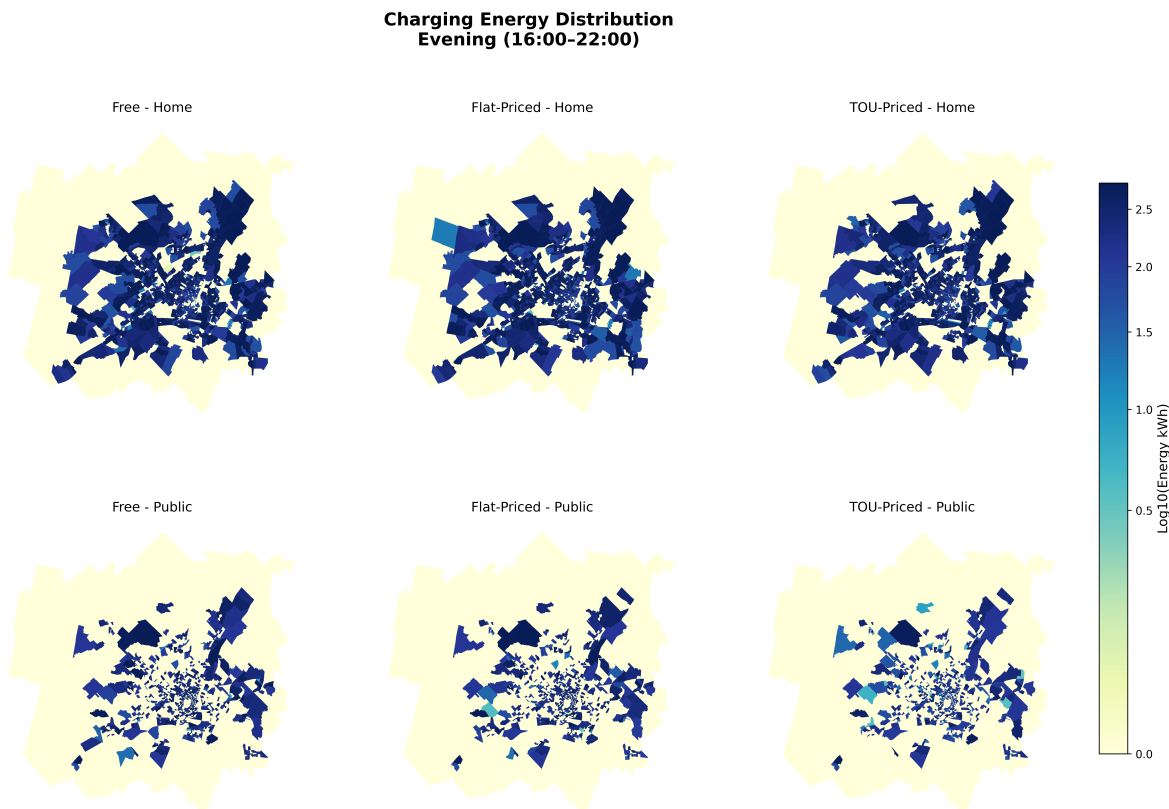


FIGURE 5.15 Spatial distribution of charging energy during the evening period (16 :00–22 :00).

5.3.6 Constraints and System Bottlenecks

The preceding sections demonstrated that TOU pricing can effectively redistribute charging demand from evening to morning hours, particularly for public charging. However, closer inspection of the temporal demand profiles reveals an important limitation. As shown in Figure 5.6, the morning peak in public charging demand under the TOU-Priced scenario reaches a level comparable to that observed in the Free scenario. This similarity suggests the presence of a binding capacity constraint during the morning period.

If sufficient charging capacity were available, one would expect the TOU-Priced scenario to exhibit a higher morning peak than the Free scenario, reflecting the successful relocation of suppressed evening demand. The absence of such an increase indicates that users intend to charge during low-cost morning hours but are prevented from doing so by infrastructure limitations.

Figure 5.16 provides further evidence of this constraint by comparing the total number of

public charging plugs used in each scenario with the overall number of available plugs in the network. Although approximately 2,934 public charging plugs exist across the system, only a subset of these chargers is actively utilized during the morning peak.

This discrepancy highlights a critical distinction between technical availability and practical accessibility. Many public chargers are located more than 1,000 meters from users' workplaces or non-home activity locations, making them impractical for routine use. As a result, agents concentrate charging demand around a limited set of stations that fall within acceptable walking distance, leading to localized congestion and underutilization elsewhere.

This spatial mismatch explains why pricing incentives alone cannot fully unlock latent charging capacity. Even when users are economically motivated to shift charging to off-peak hours, they can do so only at locations that are accessible within their daily activity constraints. Chargers that are technically available but spatially inconvenient remain unused, while accessible chargers become congested.

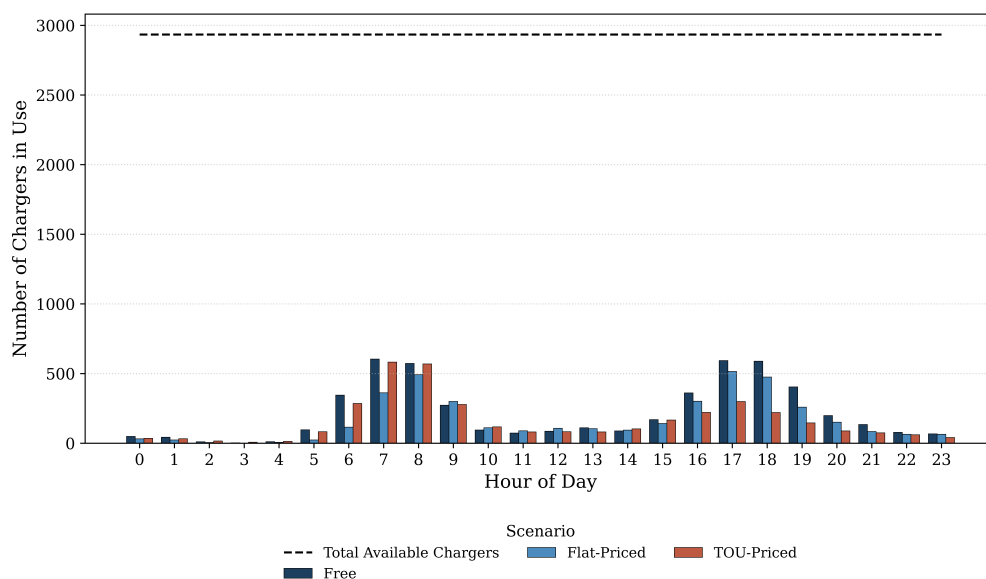


FIGURE 5.16 Total number of public chargers used in each scenario.

These results provide direct empirical support for one of the central working hypotheses of this thesis : pricing strategies alone are insufficient to manage charging demand effectively when infrastructure constraints and spatial accessibility are not explicitly addressed. While TOU pricing can successfully shift charging demand, its impact is capped by the physical configuration of the charging network.

In effect, TOU pricing reveals latent demand that cannot be accommodated under existing

infrastructure conditions. Rather than eliminating congestion, pricing shifts demand toward periods and locations where infrastructure becomes the new limiting factor. This observation motivates the introduction of an Unlimited-Charger scenario, designed to isolate the role of infrastructure capacity and to evaluate whether expanded charger availability can absorb redistributed demand more effectively.

5.4 Unlimited-Charger Scenario

To disentangle behavioral responses to pricing from physical infrastructure constraints, an Unlimited-Charger scenario is introduced in which the number of public charging plugs is increased tenfold. This counterfactual scenario does not represent a realistic deployment strategy, but rather serves as a diagnostic experiment that isolates the role of charger availability and accessibility in shaping charging demand. By removing capacity constraints, the analysis evaluates whether the demand shifts induced by TOU pricing are suppressed by infrastructure limitations or by behavioral rigidity.

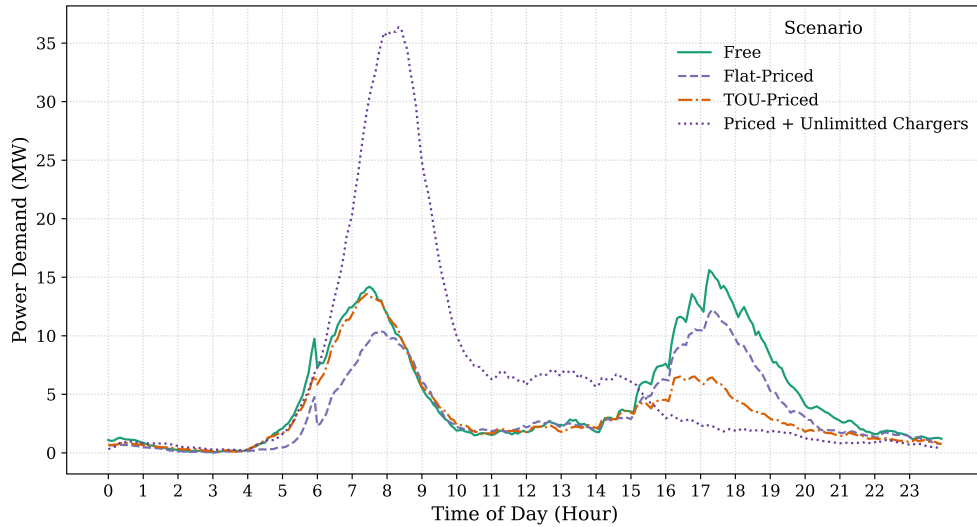


FIGURE 5.17 Temporal distribution of power demand for public chargers across four scenarios.

Figure 5.17 compares the temporal public charging demand profiles across all scenarios, including the Unlimited-Charger case. A striking change emerges in the morning period. Under the Unlimited-Charger scenario, the morning peak rises sharply, exceeding 35 MW—more than double the morning demand observed in both the Free and TOU-Priced scenarios. This confirms that users respond strongly to low morning prices when infrastructure constraints

are relaxed.

Importantly, the increase in morning charging demand is accompanied by a further reduction in evening charging. The evening public charging peak drops from approximately 7 MW in the TOU-Priced scenario to around 3 MW in the Unlimited-Charger scenario. This indicates that, when sufficient capacity is available, TOU pricing can achieve a much more effective redistribution of demand away from peak evening hours.

These results demonstrate that the limited morning response observed under the standard TOU-Priced scenario is not driven by a lack of behavioral willingness to shift charging, but rather by insufficient and poorly accessible infrastructure. Users intend to respond to price signals, but are prevented from doing so by spatial and capacity constraints.

Figure 5.18 further illustrates the number of public chargers utilized in each scenario, including the Unlimited-Charger case. The results show a substantial increase in the number of chargers used during the morning period, accompanied by a marked reduction in evening utilization. This pattern suggests that the existing charging network is not optimally aligned with users' activity locations and temporal needs.

Even with a large number of chargers available system-wide, utilization remains highly uneven. Chargers that are spatially accessible to key activity locations attract the majority of demand, while others remain underutilized. This reinforces the conclusion that charger placement—not just charger quantity—is a critical determinant of system performance.

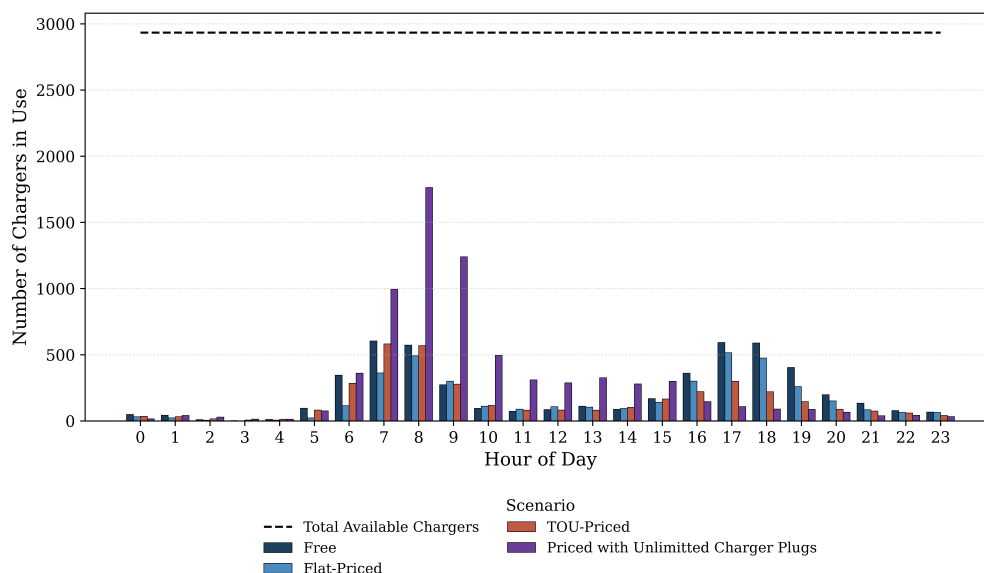


FIGURE 5.18 Total number of public chargers used in each scenario.

Taken together, the Unlimited-Charger scenario provides strong evidence in support of the second and third working hypotheses. Pricing strategies alone cannot fully resolve peak demand or congestion if infrastructure capacity and accessibility are binding. Conversely, infrastructure expansion without pricing would likely exacerbate peak demand rather than alleviate it. Effective demand management therefore requires an integrated approach in which pricing incentives are supported by sufficient and well-located charging infrastructure.

5.5 Area Pricing

The previous analyses demonstrated that TOU pricing can shift charging demand temporally, but that the spatial distribution of demand remains largely unchanged. High-demand zones continue to experience concentrated charging activity regardless of temporal pricing, suggesting that time-based incentives alone may be insufficient to address localized congestion and grid stress.

To address this limitation, an area pricing strategy is evaluated in which charging prices are increased in super zones that exhibit the highest demand under the TOU-Priced scenario, while prices in lower-demand zones remain unchanged. The objective of this policy is to influence not only when users charge, but also where charging occurs, encouraging spatial redistribution of demand across the network.

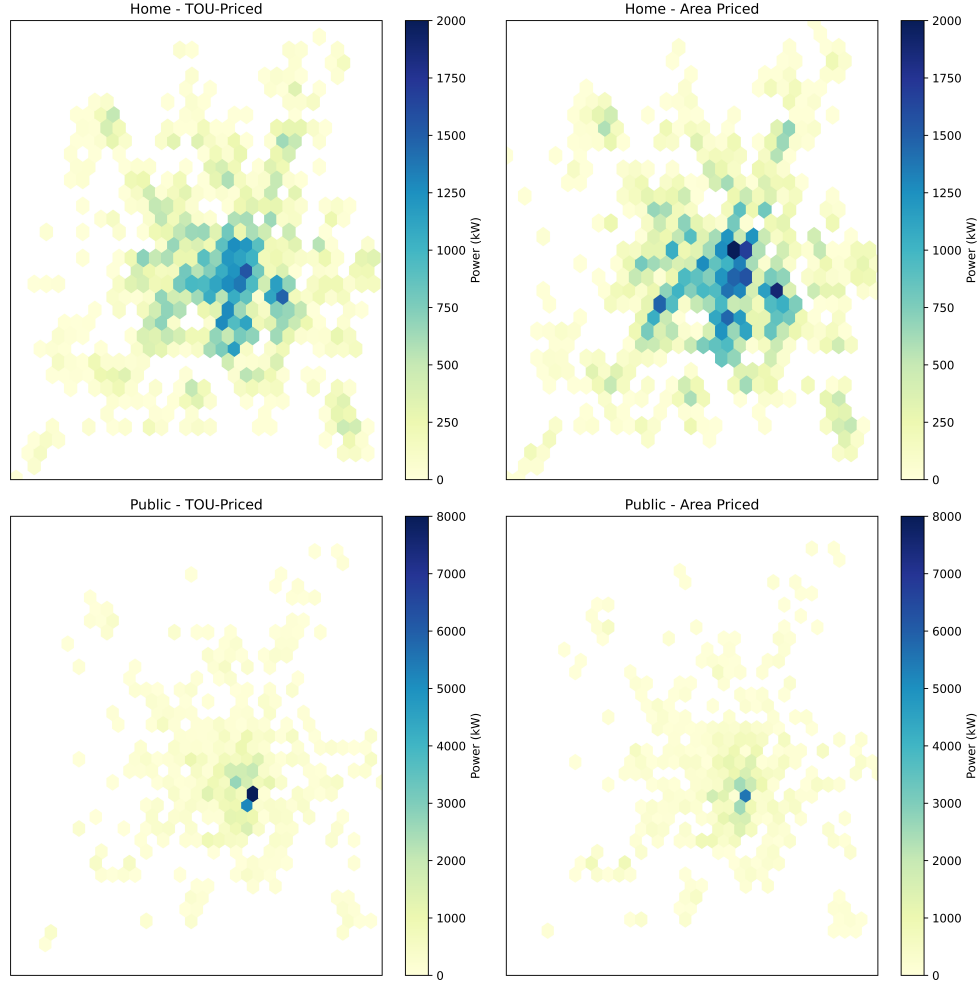


FIGURE 5.19 Spatial distribution of power demand for TOU-priced and area-priced scenarios.

Figure 5.19 compares the spatial distribution of power demand for home and public chargers under TOU pricing and area pricing. Several high-demand zones under the TOU-Priced scenario exhibit reduced demand under area pricing, while some lower-demand zones experience an increase. This shift indicates that area pricing can influence charging location choices for users who have access to multiple charging opportunities across zones.

However, the magnitude of spatial redistribution varies across users and charger types. For public charging, users with flexible daily schedules and access to multiple activity locations are more likely to relocate charging to lower-priced zones. Home charging, by contrast, is inherently less flexible. Users residing in high-priced zones have limited ability to relocate home charging unless alternative public chargers in lower-priced zones are conveniently accessible.

To verify that the observed spatial shifts are not simply the result of an overall reduction in

charging activity, the temporal demand profiles for home and public chargers are compared between the TOU-Priced and area-priced scenarios.

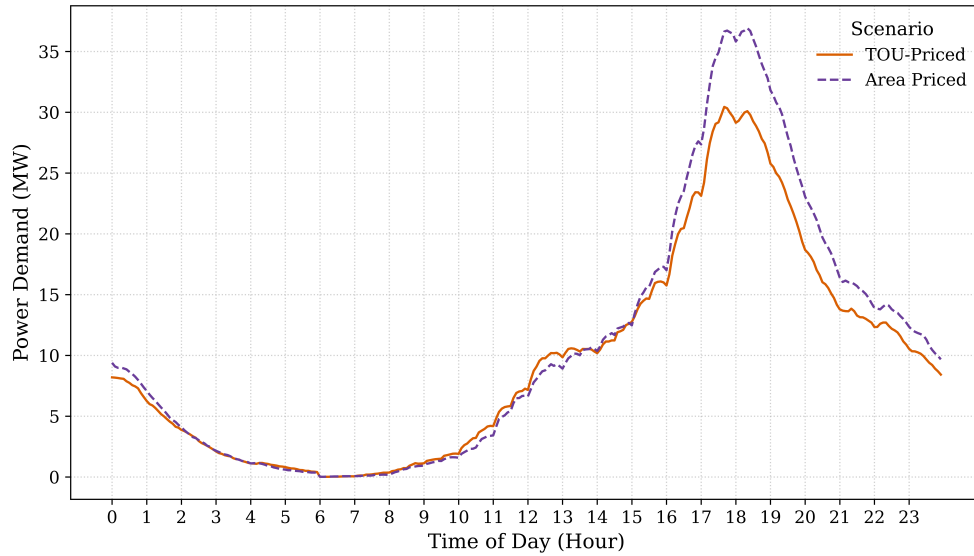


FIGURE 5.20 Temporal variation of power demand for home chargers in TOU-priced and area-priced scenarios.

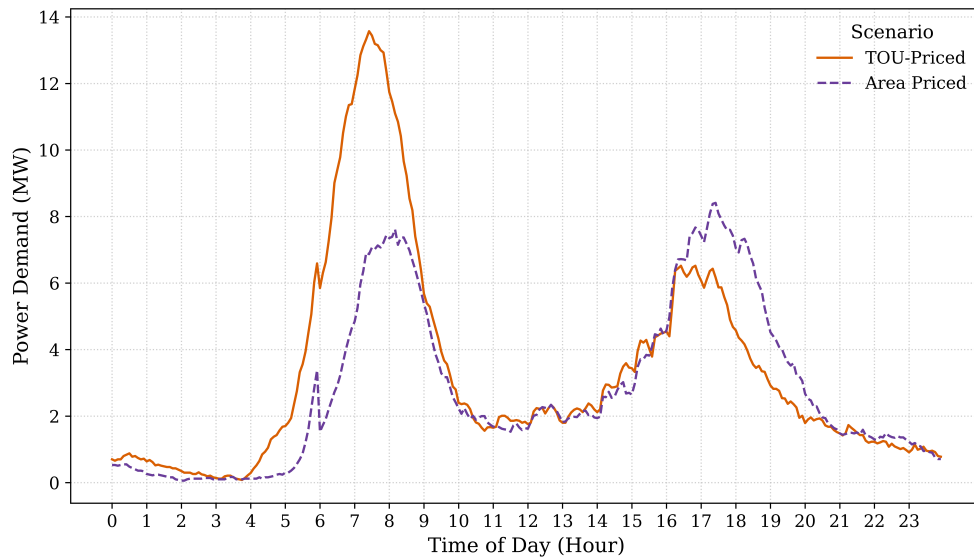


FIGURE 5.21 Temporal variation of power demand for public chargers in TOU-priced and area-priced scenarios.

The temporal profiles reveal an important trade-off. Under area pricing, the evening peak

for both home and public chargers increases relative to the TOU-Priced scenario, while the morning peak for public charging decreases. This shift reflects the interaction between spatial and temporal incentives. By increasing prices in high-demand zones during the morning, area pricing discourages some users from charging at that time and location, causing demand to shift back toward the evening or toward alternative zones.

This outcome illustrates a key limitation of spatial pricing strategies : while they can redistribute demand geographically, they may partially undermine the temporal load-shifting benefits achieved through TOU pricing. In other words, spatial and temporal pricing objectives can conflict if not carefully coordinated.

In summary, the pricing experiments reveal a nuanced picture of demand management in urban EV charging systems. TOU pricing is effective at shifting charging demand away from peak evening hours, particularly for public chargers, but its impact is constrained by infrastructure capacity and spatial accessibility. Area pricing can induce spatial redistribution of demand, but may also counteract temporal load-shifting benefits by discouraging off-peak charging in high-demand zones.

These findings provide support for the central hypothesis that no single policy instrument can fully resolve charging congestion and grid stress. Rather than prescribing specific policy designs, the analysis aims to improve understanding of the dynamic interactions between pricing, infrastructure availability, and user behavior. In this sense, the results are policy-relevant, as they highlight potential trade-offs and unintended effects, while identifying coordinated policies that optimize system-level performance metrics is left for future work.

5.6 Chapter Synthesis and its theme within the broader thesis framework.

This chapter combines insights on how pricing measures interact with behavioral differences and infrastructure limitations to influence EV charging outcomes at the system level. Instead of analyzing pricing mechanisms separately, it shows that charging demand is a dynamic process where individual behaviors, activity restrictions, and infrastructure access together shape congestion patterns over time and space. The chapter highlights that system effects such as peak shifting, ongoing congestion, or demand spreading are not caused solely by pricing signals but also result from the interaction between behavioral responses and the charging network’s physical capacity. The subsequent sections summarize the main findings, explore their implications for the hypotheses, and outline the specific role of this theme within the overall thesis.

5.6.1 Key Findings

This chapter explored how pricing strategies, user behavior, and charging infrastructure limitations shape urban EV charging patterns. Building on the earlier agent-based framework, charging demand was viewed as an emergent result of individual activity-driven choices constrained by time, space, and infrastructure. Instead of assuming static demand profiles, the analysis showed how users adjust their charging habits in response to pricing, leading to broader system-level patterns of electricity demand, congestion, and spatial clustering.

The Free scenario established a credible behavioral baseline, demonstrating that the model reproduces empirically consistent temporal and spatial charging patterns in the absence of pricing interventions. Charging demand was shown to be highly concentrated in both time and space, with pronounced evening peaks at home and bimodal demand at public chargers. These baseline results reinforced the system-level framing introduced in Chapter 1 : grid stress and congestion arise primarily from the synchronization of individual charging decisions around shared infrastructure, rather than from total energy consumption alone.

Introducing TOU pricing demonstrated user responsiveness to time-based price signals, especially during public charging. Evening charging dropped significantly, while morning charging increased, showing that pricing influences when users charge. Nevertheless, TOU pricing does not prevent congestion ; it shifts demand to different times and places where infrastructure limits are reached. Morning congestion at public chargers grew notably under TOU pricing, indicating that pricing can change where stress occurs but does not eliminate it.

The analysis of charger-type utilization further clarified the behavioral mechanisms underlying these shifts. Users switched between charger types in response to pricing, favoring slower but cheaper options as costs rose. These substitutions altered charger occupancy durations and amplified congestion dynamics, highlighting that pricing affects not only when charging occurs, but also how infrastructure is used operationally.

Finally, the area pricing experiment specifically focused on spatial distribution. While spatial pricing successfully redistributed some charging demand across zones, it also created trade-offs with temporal goals, partly undoing the off-peak load shifting achieved under TOU pricing. This highlights the close link between spatial and temporal pricing strategies and shows the risk of unintended demand rebounds when policy tools are used alone.

5.6.2 Implications for the Working Hypotheses

The results of this chapter provide strong empirical support for the working hypotheses articulated in Chapter 1. First, the findings confirm that charging demand patterns and congestion

outcomes are strongly shaped by behavioral heterogeneity and activity-based constraints. Users respond to price signals in ways that are mediated by daily schedules, charger accessibility, and charging opportunities, rather than purely by economic incentives.

Second, the analysis shows that relying solely on pricing strategies is inadequate for managing charging demand effectively when infrastructure capacity and spatial accessibility are limited. While TOU pricing uncovered hidden temporal flexibility in charging habits, this potential couldn't be fully utilized due to restricted charger access during incentive periods. The Unlimited-Charger scenario revealed that removing capacity constraints leads users to significantly shift charging toward cheaper times, confirming that infrastructure—rather than behavioral rigidity—is the main limiting factor.

Third, the findings suggest that spatial and temporal pricing goals can conflict when used separately. Area-based pricing reduced spatial concentration in some areas but somewhat weakened the temporal smoothing achieved with TOU pricing. This underscores the importance of considering how policy tools interact rather than evaluating them in isolation.

5.6.3 Contribution of This Theme

This theme contributes to the thesis by demonstrating that EV charging demand management is fundamentally a coupled behavioral–infrastructure problem. By embedding pricing mechanisms within an activity-based, agent-level simulation, the chapter moves beyond stylized demand-shifting assumptions and reveals how pricing interacts with real-world constraints such as charger availability, spatial accessibility, and congestion.

A significant insight is the clear identification of infrastructure constraints as a key factor limiting the effectiveness of pricing strategies. The analysis indicates that pricing incentives can only shape charging behavior within the set of choices made possible by infrastructure access. Consequently, infrastructure development and pricing policies should be seen as complementary tools : pricing reveals potential behavioral responses, while infrastructure availability determines whether those responses can be enacted.

This chapter broadens the literature by showing how individual responses to pricing lead to complex system-level results, such as congestion shifting and unexpected spatial impacts. These findings highlight the need for a coordinated policy that combines pricing, charger placement, and capacity expansion. They also prepare the way for the next part of the thesis, which moves from pricing strategies to examining how behavioral differences and charging logic influence system performance as EV adoption grows.

CHAPITRE 6 THIRD THEME — BEHAVIORAL SENSITIVITY AND TECHNOLOGICAL LEVERS IN EV CHARGING SYSTEMS

The previous chapter demonstrated that pricing strategies can influence the timing and location of EV charging, but that their effectiveness is fundamentally constrained by charging infrastructure capacity and spatial accessibility. Even when users respond rationally to electricity pricing, congestion, and peak demand may persist if such constraints exist. These findings highlight an important limitation of demand management policies that rely solely on external incentives.

This chapter shifts focus from pricing to two complementary dimensions that shape charging behavior more intrinsically : *behavioral sensitivity to low battery levels* and *technological characteristics of vehicles and charging infrastructure*. The chapter specifically explores how changes in range anxiety, along with advances in battery capacity and charging infrastructure, influence charging behaviors and system-wide results, even without pricing incentives.

By controlling conditions, the analysis separates behavioral responses from policy-driven demand changes. In the range anxiety experiments, the initial state of charge is randomly assigned to capture variability in daily vehicle states and to study how low SOC sensitivity affects charging behavior amid realistic uncertainty. Conversely, the technology and infrastructure scenarios start with all vehicles fully charged, so any changes in charging behavior can be linked directly to differences in battery size, charger power, or charger availability. This approach allows the chapter to analyze whether congestion and peak demand mainly result from behavioral sensitivity, technological limitations, or broader system constraints.

The chapter is organized into two main parts. The first part evaluates the role of range anxiety by comparing scenarios in which sensitivity to low SOC intensifies at different SOC thresholds. This analysis examines how the onset of range anxiety affects when and how often vehicles charge, the resulting power demand, and queuing at public charging stations.

The second part explores technological and infrastructure factors, such as increased battery capacity, more powerful chargers, higher charger density, and their combinations. These scenarios help evaluate how various investment strategies affect charging demand, congestion, and infrastructure use, while also revealing trade-offs between reducing peak power, alleviating queuing, and managing spatial demand.

6.1 Impact of Range Anxiety on Charging Behavior

Range anxiety is modeled in this study as a continuous penalty that increases as vehicle SOC declines, reflecting growing discomfort and perceived risk of battery depletion. Rather than imposing a fixed penalty term when the critical SOC occurs, this formulation allows charging decisions to respond gradually as the SOC declines.

To evaluate how the intensity and timing of range anxiety influence charging behavior, two scenarios are compared. In the first scenario, the penalty increases sharply once SOC falls below 30%, representing users who tolerate relatively low battery levels before experiencing significant anxiety. In the second scenario, the penalty increases earlier, at 50% SOC, indicating that more risk-averse users prefer to maintain higher battery levels.

Importantly, in these scenarios, the initial state of charge is assigned randomly across vehicles, reflecting heterogeneity in daily battery conditions at the start of the simulation. By holding all other elements of the system constant, this setup ensures that observed differences in charging behavior between these two scenarios arise from variations in sensitivity to low SOC rather than from differences in infrastructure, pricing, or travel demand.

6.1.1 State of Charge at Charging Initiation

Figure 6.1 presents kernel density estimates of vehicle SOC at the moment charging is initiated under two range anxiety scenarios. The first scenario represents a more risk-averse population in which the range anxiety penalty intensifies once SOC falls below 50%, while the second scenario assumes that anxiety escalates only at lower SOC levels, below 30%.

Kernel density estimation (KDE) is employed in this analysis because the SOC at the start of charging is a continuous variable. The goal is to compare how the overall distribution of charging decisions shifts under different range anxiety assumptions. Instead of just examining average SOC values, KDE captures changes in the distribution's shape, concentration, and spread across SOC levels. This approach is especially important for understanding how range anxiety influences charging behavior, which may affect not only the average timing of charging but also how sharply charging occurs near specific SOC thresholds. The resulting density curves are interpreted qualitatively, emphasizing relative shifts in concentration rather than precise probability values.

Each data point corresponds to an individual charging initiation event. For the SOC-based distributions, the recorded value is the vehicle's state of charge at the start of the charging session, whereas for the temporal distributions, which will be explained in the next section, the value corresponds to the clock time at which charging begins. The density estimates therefore,

represent the distribution of charging decisions across events, rather than aggregated or averaged quantities.

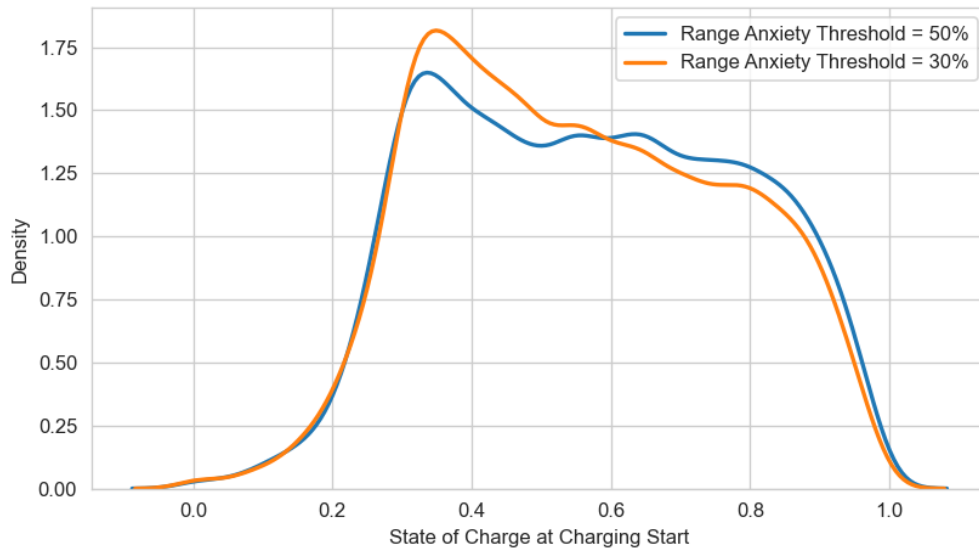


FIGURE 6.1 Kernel density estimation of state of charge at charging initiation for two range anxiety thresholds.

The distributions reveal a clear and systematic behavioral shift driven by sensitivity to low SOC. When range anxiety intensifies at the 50% SOC threshold, charging events become concentrated at higher battery levels compared to the 30% threshold scenario. This indicates that more risk-averse users initiate charging earlier, even when a substantial portion of usable driving range remains available. In contrast, when users tolerate lower SOC levels before experiencing range anxiety, charging initiation shifts toward lower SOC values. These users are willing to postpone charging until the battery approaches more critical levels, which could result in extracting more energy per charging session and reducing the overall frequency of charging events.

Importantly, these differences emerge despite identical travel demand, infrastructure configuration, and randomly assigned initial SOC distributions across scenarios. This confirms that the observed shift in charging initiation is not an artifact of early forced charging or initial battery conditions, but rather a direct consequence of behavioral sensitivity embedded in the charging decision process. The result highlights the importance of range anxiety in modeling formwork and how different approach can result in different outcome.

From a system-level perspective, earlier charging initiation has several implications. Charging at higher SOC levels increases the number of charging events per vehicle while reducing the

average energy transferred per session. This fragmentation of charging demand can reduce infrastructure efficiency by increasing competition for chargers and lowering charger turnover, particularly at public stations where availability is limited. As a result, heightened range anxiety may exacerbate congestion and queuing even in the absence of higher total energy demand.

From a policy standpoint, these findings suggest that range anxiety can significantly shape charging demand independently of pricing or infrastructure constraints. Policies or technologies that reduce perceived range risk—such as improved range estimation, more reliable real-time charger availability information, or increased visibility of nearby charging options—may therefore be as important as physical infrastructure expansion in managing congestion. Conversely, ignoring behavioral sensitivity in planning models may lead to underestimation of charging frequency and overestimation of infrastructure efficiency.

Overall, this analysis demonstrates that range anxiety is an important determinant of charging behavior. Even under randomized initial SOC conditions, increased sensitivity to low battery levels leads to earlier, more frequent charging, with direct consequences for system-level congestion and infrastructure utilization. This insight motivates the subsequent analysis of how technological and infrastructure improvements may mitigate—or amplify—the behavioral effects observed here.

6.1.2 Temporal Distribution of Charging Initiation

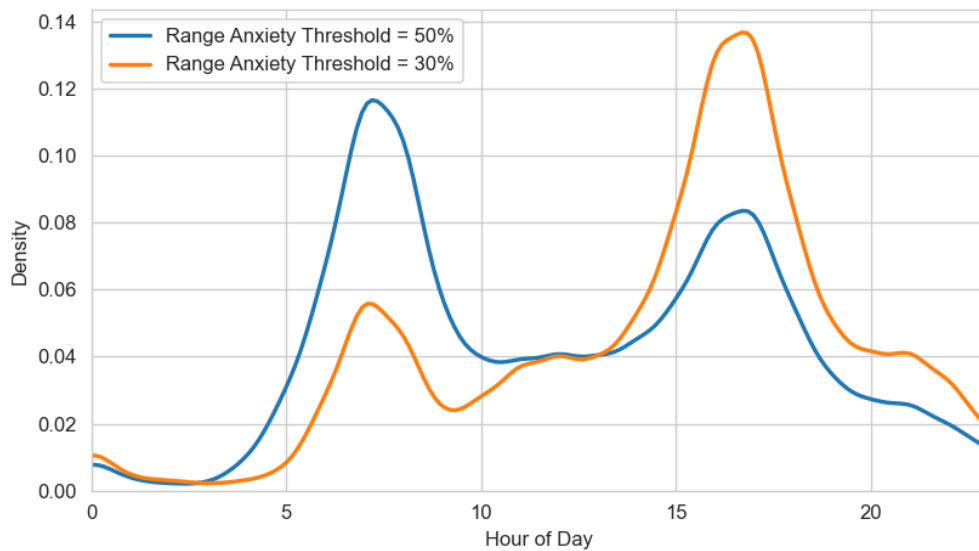


FIGURE 6.2 Kernel density estimation of charging start times under two range anxiety thresholds.

Figure 6.2 illustrates the temporal distribution of charging initiation for the two range anxiety scenarios using kernel density estimation. A clear shift in charging timing is observed as sensitivity to low state of charge increases.

When range anxiety intensifies at 50% SOC, charging initiation becomes strongly concentrated in the morning, with a pronounced peak around typical work arrival times (approximately 7–8 AM). This pattern reflects anticipatory charging behavior, whereby risk-averse users prefer to secure charging opportunities early in the day during long-duration daytime activities. Rather than waiting until battery levels approach critical thresholds, these users initiate charging proactively to reduce perceived risk and uncertainty.

In contrast, when anxiety escalates only at lower SOC levels (30%), charging initiation shifts toward later hours of the day, with a dominant peak in the late afternoon and early evening. This behavior is consistent with users delaying charging until battery depletion becomes more salient, resulting in charging that aligns more closely with post-work activities and home arrivals.

Importantly, this shift in charging timing does not mean that people charge less overall. Instead, it changes when charging begins during the day. When range anxiety is higher, drivers tend to start charging earlier, often during the morning or daytime, when many users follow similar work and activity schedules. This leads to more people trying to charge at the same time, increasing competition for public chargers—especially in busy areas such as workplaces and activity hubs.

When range anxiety is lower, drivers are more comfortable delaying charging until later in the day. As a result, charging demand shifts toward the evening, where it aligns more closely with residential activity patterns. While this reduces pressure on daytime public chargers, it can intensify evening demand and place additional stress on local electricity networks.

6.1.3 Impacts of Range Anxiety on Power Demand

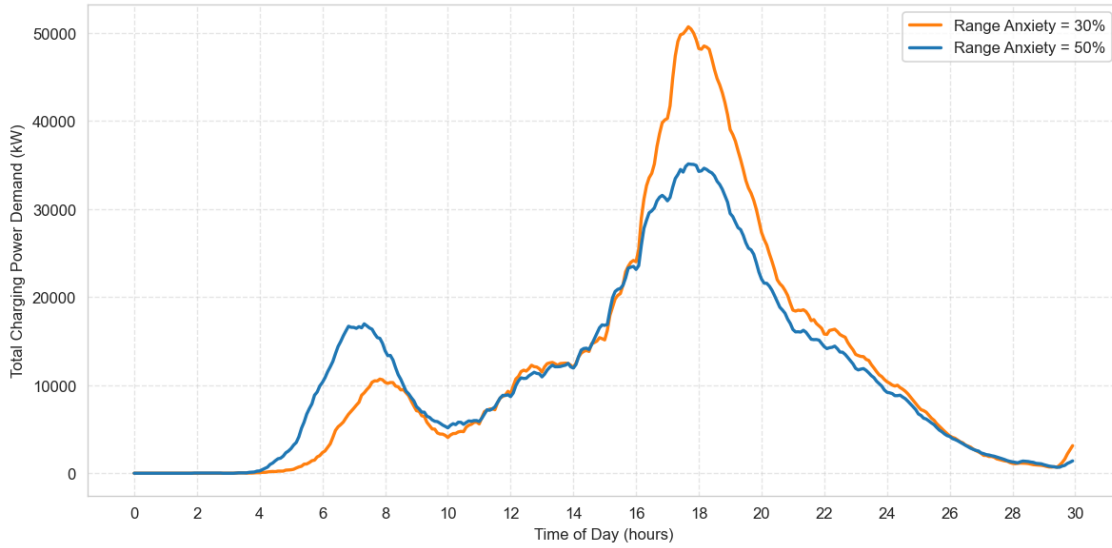


FIGURE 6.3 Aggregated charging power demand under different range anxiety thresholds.

Figure 6.3 compares the aggregated charging power demand profiles for the two range anxiety scenarios. Although both scenarios are characterized by similar daily travel demand and identical charging infrastructure, the temporal structure and magnitude of power demand differ substantially as a function of behavioral sensitivity to low state of charge.

When range anxiety intensifies at 30% SOC, charging demand exhibits a pronounced and sharply concentrated evening peak, reaching its maximum during typical post-work hours. This pattern reflects delayed charging behavior, whereby users tolerate lower battery levels throughout the day and initiate charging primarily upon returning home or during late-day activities. As a result, charging demand becomes highly synchronized in the evening, amplifying peak electricity loads during periods that already coincide with high residential consumption.

By contrast, when range anxiety escalates earlier, at 50% SOC, a significant portion of charging demand is shifted toward earlier hours of the day. The evening peak is noticeably reduced in magnitude, while a new morning peak emerges, corresponding to charging during early daytime activities. This redistribution reflects anticipatory charging behavior : risk-averse users prefer to secure charging opportunities earlier, even when substantial driving range remains available.

An additional feature of the 50% range anxiety scenario is that the reduction in evening peak demand exceeds the increase observed during morning hours. This indicates that charging is

not fully shifted from evening to morning, but rather redistributed across multiple charging events. More risk-averse users tend to initiate charging earlier in the day, often for shorter durations, while some subsequently recharge again later in the evening after additional travel. As a result, charging demand becomes less concentrated in a single peak period and more dispersed throughout the day, resulting in a net reduction in the evening peak without a proportional increase in morning demand.

From a policy perspective, these findings reveal that behavioral factors like range anxiety can influence peak demand patterns regardless of pricing or infrastructure changes. Promoting earlier charging could help lower evening peak loads. Nonetheless, this behavioral change might also lead to higher demand in the morning, potentially causing congestion at public chargers and putting additional stress on local grids.

These findings highlight the importance of coordinated policy strategies. Initiatives to lower range anxiety—like providing better real-time updates on charger availability or increasing battery sizes—should be assessed not just for how they enhance user experience but also for their effects on demand patterns over time. Without proper infrastructure planning, behavioral changes that seem positive during residential peak periods could just shift system stress to different times and areas.

Overall, the analysis shows that range anxiety is not just a user-experience concern but also a key factor affecting power demand profiles at the system level. Recognizing how behavioral sensitivity impacts charging timing is crucial for creating demand management strategies that ensure grid reliability, optimize infrastructure use, and maintain user confidence.

6.1.4 Queuing Effects at Public Charging Stations

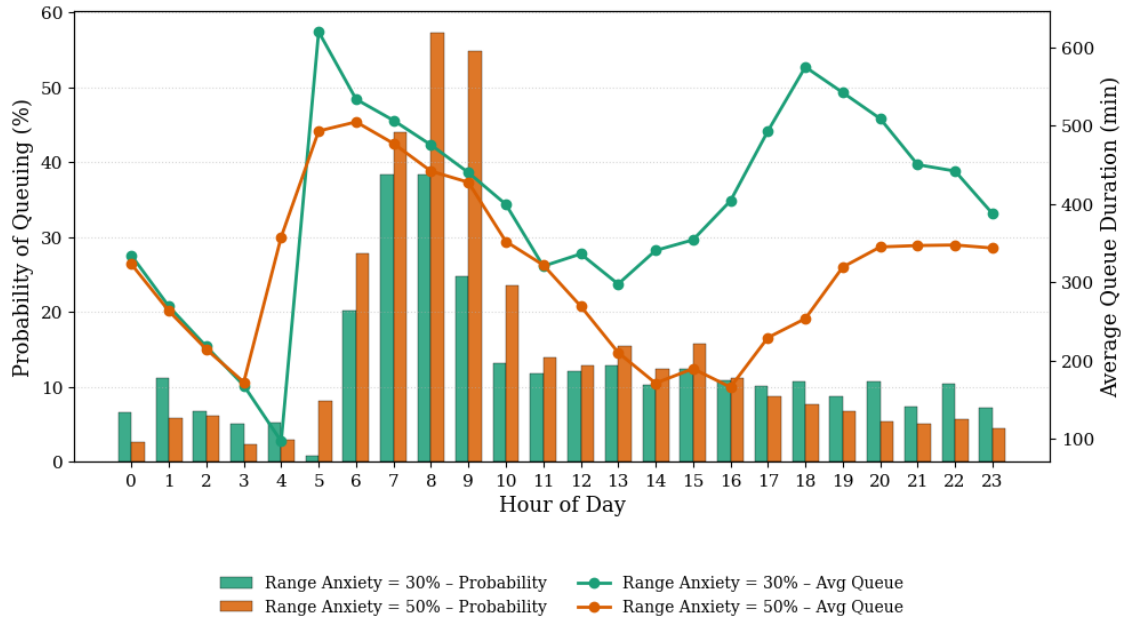


FIGURE 6.4 Hourly probability of queuing and average queue time at public charging stations under different range anxiety thresholds.

Figure 6.4 shows both the probability of experiencing queuing at public charging stations and the average queue duration across the day for the two range anxiety scenarios. The results illustrate how behavioral sensitivity to low state of charge affects not only when congestion occurs, but also how severe it becomes.

When range anxiety escalates earlier, at 50% SOC, queuing probability increases sharply during the morning hours, with peak values exceeding 50% between approximately 7:00 and 9:00 AM. This pattern is consistent with anticipatory charging behavior: more risk-averse users initiate charging earlier in the day, often at similar activity locations, leading to a high degree of temporal and spatial synchronization at a limited set of public chargers. Although queue durations during these hours remain moderate, the high probability of queuing indicates intense competition for charger access.

In contrast, when users tolerate lower SOC levels before experiencing anxiety (30% threshold), morning queuing is substantially lower. Charging activity is instead more concentrated in the late afternoon and evening. During this period, the queuing probability is lower than during the morning peak observed in the 50% scenario (because a large share of them probably charge at home), but average queue durations are noticeably higher. A plausible explanation

is that users in the 30% scenario arrive at chargers with lower remaining battery levels and therefore require longer charging sessions, increasing charger occupation times and prolonging queues even when fewer users are waiting.

Importantly, these differences emerge despite identical infrastructure capacity, travel demand, and pricing conditions. They are therefore driven by behavioral timing and charging intensity rather than by differences in total energy demand. Earlier charging, associated with higher range anxiety, increases the number of users competing for chargers simultaneously, while later charging, associated with lower anxiety, leads to fewer but longer charging sessions.

From a system perspective, these results highlight a trade-off between the timing and duration of congestion. Behavioral shifts that encourage earlier charging can reduce evening charging intensity but may generate severe morning congestion due to synchronized demand. Conversely, delayed charging reduces synchronization but increases average queue duration due to longer charging sessions. As a result, interventions aimed at influencing charging behavior—such as reducing range anxiety—must be evaluated alongside infrastructure capacity and charger power, as behavioral changes alone may alter the form of congestion rather than eliminate it.

It must be noted that while previous analyses presented in Figure 5.9 emphasized the share of users experiencing queues as a measure of overall congestion, the probability of queuing is used here to highlight the likelihood of encountering congestion at a given time. This representation is particularly useful when comparing behavioral scenarios, as it captures how changes in charging decisions—driven by range anxiety—affect the risk of queuing independently of the total number of charging events.

6.2 Technology and Infrastructure Scenarios

The previous section demonstrated that behavioral sensitivity to low state of charge can significantly reshape charging demand, congestion, and power profiles, even in the absence of pricing or infrastructure changes. While these behavioral effects are important, they also raise a critical question for planners and policymakers : to what extent can technological and infrastructure improvements mitigate the congestion and peak demand effects induced by heterogeneous charging behavior ?

To address this question, this section evaluates a set of battery and charging infrastructure scenarios designed to isolate the effects of vehicle technology and charger characteristics on system-level outcomes. Unlike the range anxiety analysis, all scenarios examined in this section assume a common initial condition in which vehicles begin the day fully charged.

This assumption ensures that observed differences in charging behavior and congestion arise from technological or infrastructure changes rather than from early forced charging due to low initial battery levels.

TABLEAU 6.1 Summary of battery and charging infrastructure scenarios

Scenario	Battery	Charger Power	Charger Density
<i>Baseline</i>			
Baseline B	50 kWh	12 / 20 / 50 kW	Current network
<i>Battery Scenarios (Infrastructure Fixed)</i>			
B1 : Medium Battery	75 kWh	Baseline power	Baseline density
B2 : Large Battery	100 kWh	Baseline power	Baseline density
<i>Charger Scenarios (Battery Fixed)</i>			
C1 : High Power	50 kWh	2× power	Baseline density
C2 : High Density	50 kWh	Baseline power	2× density
C3 : High Power + High Density	50 kWh	2× power	2× density
<i>Combined Improvement</i>			
D : Battery + Infrastructure Upgrade	100 kWh	2× power	2× density

The baseline scenario (B) represents current conditions in the Greater Montréal area, with a 50 kWh battery capacity and the existing configuration of charger power levels and spatial density. This scenario serves as the reference point for all subsequent comparisons.

The battery scenarios (B1 and B2) isolate the effect of increased vehicle battery capacity while holding charging infrastructure constant. These scenarios assess whether larger batteries—often proposed as a technological solution to range anxiety and charging congestion—reduce charging frequency, peak demand, and queuing without changes to the charging network.

The charger scenarios (C1–C3) isolate infrastructure-focused interventions by modifying charger power, charger density, or both, while keeping battery capacity fixed at the baseline level. Scenario C1 evaluates the effect of faster chargers, Scenario C2 examines the impact of increasing charger availability through higher density, and Scenario C3 explores the combined effect of power and density improvements.

Finally, the combined improvement scenario (D) represents an optimistic configuration in which both vehicle technology and charging infrastructure are upgraded simultaneously. While not intended as a realistic short-term deployment strategy, this scenario provides a

benchmark for evaluating the maximum achievable reduction in congestion and peak demand under coordinated investments.

The following subsections compare these scenarios in terms of charging behavior, power demand, queuing, and infrastructure utilization. By evaluating battery and infrastructure improvements both independently and in combination, the analysis aims to identify which levers are most effective at alleviating system-level constraints and which trade-offs emerge when different investment strategies are pursued in isolation.

6.2.1 Public Charging Power Demand under Technology and Infrastructure Scenarios

Before examining differences across technology and infrastructure scenarios, it is important to contextualize the magnitude of charging demand observed in this section. In contrast to the analysis, which assumed a random initial SOC and assignment, all scenarios examined here assume that vehicles begin the day with a fully charged battery. As a result, total charging demand is substantially lower than in scenarios with randomized initial SOC, where a portion of vehicles are forced to charge early in the simulation. This difference is clearly illustrated by comparing Figure 6.5 with Figure 5.6, highlighting the strong influence of initial SOC assumptions on aggregate power demand.

This comparison highlights an important modeling insight : initializing all vehicles with a full battery eliminates early, necessity-driven charging and isolates charging behavior that emerges endogenously from travel demand, infrastructure availability, and battery capacity. As a result, the power demand profiles presented in this section can be interpreted as a lower bound on charging demand under identical behavioral, technological, and infrastructural conditions.

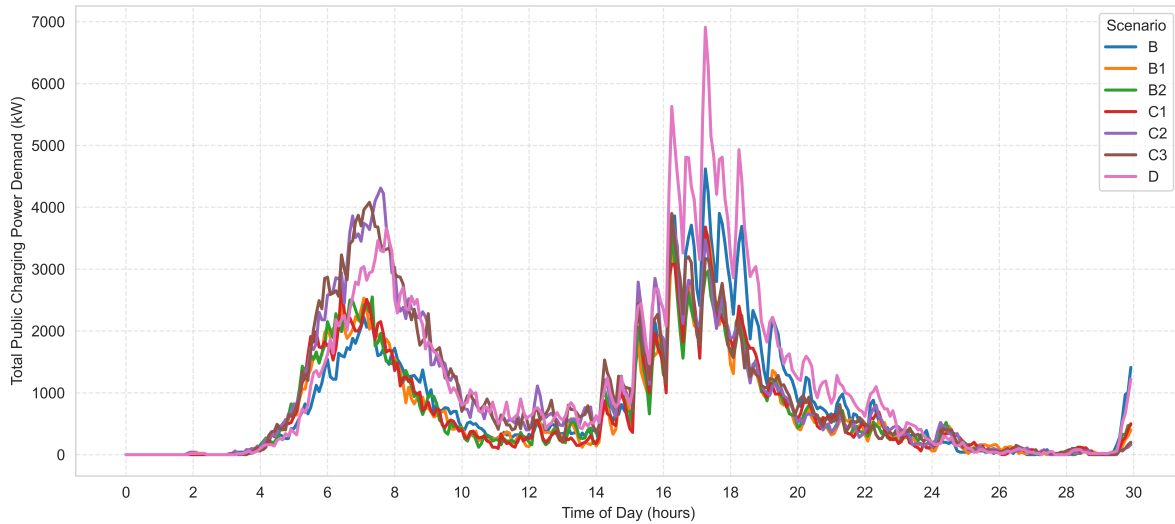


FIGURE 6.5 Aggregated public charging power demand across battery and charging infrastructure scenarios.

Figure 6.5 compares the temporal evolution of aggregated public charging power demand across battery and charging infrastructure scenarios. While overall demand levels vary across scenarios, clear differences emerge in the magnitude and relative balance of morning and evening peak demand as vehicle technology and infrastructure characteristics change.

The baseline scenario (B) exhibits two distinct demand peaks corresponding to morning and evening activity periods. In the battery capacity scenarios (B1 and B2), the morning peak remains comparable to—or slightly higher than—that of the baseline, whereas the evening peak is noticeably reduced. This asymmetry indicates that increasing battery capacity does not uniformly suppress peak demand across the day. Instead, larger batteries primarily reduce reliance on public charging during evening home-arrival periods, while morning charging demand remains largely intact. As battery capacity increases from 75 kWh to 100 kWh, this evening peak attenuation becomes more pronounced, confirming that battery improvements mainly reduce the frequency of discretionary evening charging rather than eliminating demand during structured morning activities.

Infrastructure-focused scenarios show a different pattern. Raising charger power (C1) causes a higher morning peak in public charging demand but reduces the evening peak compared to the baseline. Faster chargers enable vehicles to charge more quickly during the busy morning hours, increasing the instantaneous power when many users start charging simultaneously. Meanwhile, shorter and more efficient charging sessions decrease the need for long or repeated charges later in the day, lowering evening peak demand. Overall, improvements in charger

power shift power demand throughout the day, increasing morning loads while easing evening stress.

Increasing charger density (C2) produces a similar effect by relaxing spatial constraints on charging. Greater availability allows more vehicles to initiate charging simultaneously, increasing aggregate power demand during peak periods even as waiting times and queuing are reduced. The combined infrastructure scenario (C3) amplifies these effects, resulting in sharper and higher peaks due to the joint influence of increased accessibility and higher charging power.

The combined improvement scenario (D) exhibits the highest peak demand across all scenarios, particularly during the evening. Although larger batteries reduce the need for charging, the presence of fast, widely available chargers enables users to charge at their preferred times with minimal constraints. This leads to strong synchronization of charging activity around dominant daily routines, especially evening home arrivals, producing elevated instantaneous power demand. The resemblance between the baseline and combined scenarios in peak timing underscores that technological flexibility alone does not desynchronize charging behavior, and may even reinforce existing temporal preferences.

From a policy perspective, these findings highlight that battery and infrastructure investments affect power demand through fundamentally different pathways. Battery capacity improvements primarily suppress evening peak demand by reducing charging frequency, while infrastructure improvements reshape how charging is delivered and often increase instantaneous load. Consequently, strategies aimed at mitigating grid peaks should not rely solely on infrastructure expansion, but must be coordinated with vehicle-side improvements or complementary demand management mechanisms.

Overall, the results reinforce that technological improvements cannot be evaluated solely on user convenience or congestion reduction. Their implications for power system stress depend critically on how they interact with charging synchronization and activity-driven demand patterns.

6.2.2 Queuing Dynamics under Battery and Infrastructure Scenarios

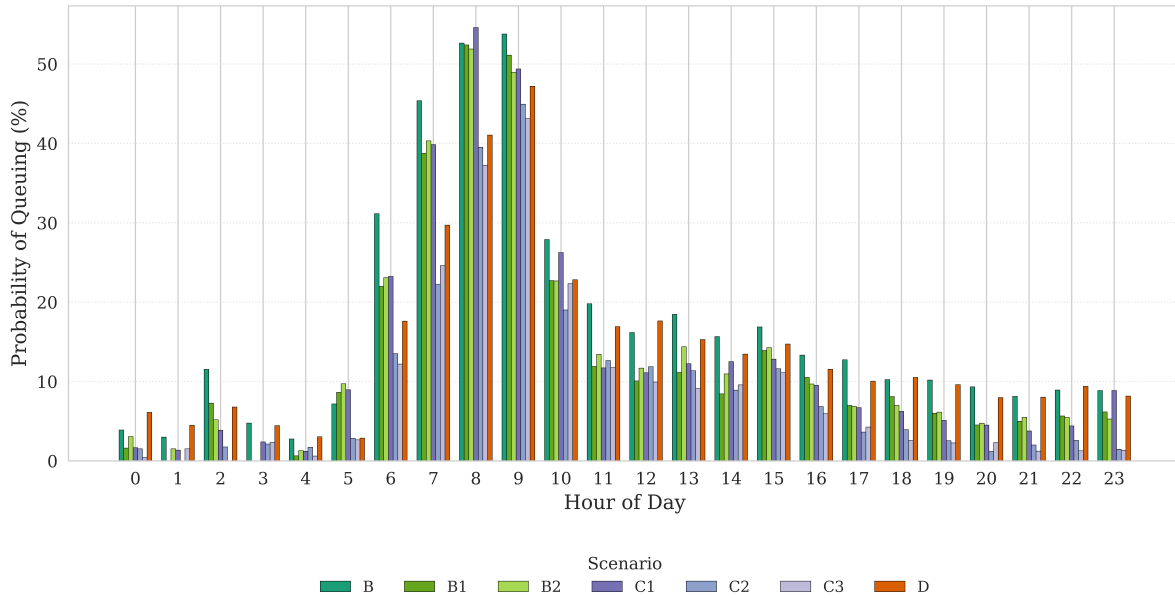


FIGURE 6.6 Hourly probability of queuing at public charging stations across battery and charging infrastructure scenarios.

Figure 6.6 compares the probability of experiencing queuing at public charging stations across the battery and infrastructure scenarios. The results reveal substantial differences in congestion dynamics that cannot be inferred from power demand alone, highlighting the importance of explicitly modeling queuing behavior.

The baseline scenario (B) exhibits pronounced morning congestion, with queuing probabilities exceeding 50% during peak arrival periods. This reflects the combined effects of synchronized travel demand and limited public charger availability, even under conditions where vehicles begin the day fully charged.

Increasing battery capacity (B1 and B2) leads to a systematic reduction in queuing across most hours of the day. Larger batteries reduce reliance on public charging during intermediate activities, thereby decreasing the number of simultaneous charging attempts. This effect is particularly evident during the morning peak, where queuing probabilities drop noticeably as battery capacity increases. Importantly, this congestion reduction occurs without increasing peak power demand, reinforcing the role of battery capacity as a demand-suppressing intervention.

Infrastructure-focused scenarios exhibit more nuanced effects. Increasing charger power alone (C1) reduces average waiting times but does not eliminate congestion during peak periods.

Although faster chargers improve turnover, synchronized arrivals still produce substantial queues when demand exceeds the number of available plugs. In some hours, queuing probabilities remain comparable to or even higher than the baseline, indicating that power upgrades alone are insufficient to resolve congestion.

Increasing charger density (C2) yields a more pronounced reduction in queuing. By increasing the number of available plugs, density improvements directly address the primary structural cause of queues. The combined infrastructure scenario (C3) further reduces congestion by jointly increasing service rate and availability, resulting in the lowest queuing probabilities among the infrastructure-only interventions.

The combined improvement scenario (D) presents a contrasting outcome. Despite offering the highest level of user flexibility through large batteries and upgraded infrastructure, queuing probabilities remain elevated during certain peak hours. This result reflects behavioral re-synchronization : when constraints are relaxed, users tend to converge on preferred charging times, partially offsetting infrastructure gains. As a result, even aggressive upgrades may fail to eliminate congestion without complementary demand management.

From a policy perspective, these findings emphasize that different investment strategies address congestion through distinct mechanisms. Battery capacity improvements reduce the need to charge and therefore suppress demand. Charger density directly increases system capacity and is the most effective infrastructure-based lever for reducing queues. Charger power improves service speed but offers limited congestion relief when demand is highly synchronized. Importantly, combining all improvements does not guarantee proportional reductions in queuing due to endogenous behavioral responses.

Overall, the queuing analysis reinforces a central conclusion of this chapter : alleviating charging congestion requires aligning behavioral incentives, vehicle technology, and infrastructure capacity. Focusing on a single dimension risks shifting or re-creating congestion elsewhere in the system.

6.3 Synthesis and Contributions of the Chapter

This chapter examines how behavioral sensitivity, vehicle technology, and charging infrastructure together influence electric vehicle charging patterns in urban settings. By carefully isolating behavioral, technological, and infrastructural factors in controlled scenarios, it shows that charging demand, congestion, and impacts on the power system result from the interplay between user behavior and structural constraints, rather than any single element. The following sections highlight the main findings, explore their implications for the working

hypotheses, and explain this chapter’s role within the overall thesis.

6.3.1 Key Findings

The initial section of the chapter examined how behavioral sensitivity to low state of charge influences user actions, using different range anxiety thresholds to measure this. The findings indicate that higher range anxiety prompts earlier and more frequent charging, shifts charging periods to daytime, and alters power demand away from evening hours. Nonetheless, this behavioral change does not prevent congestion; instead, it moves congestion to morning hours and busy activity areas, leading to increased queuing at public charging stations. These results highlight that psychological factors like range anxiety are crucial drivers of system-level charging behaviors, beyond just influencing user experience.

The second part of the chapter examined technological and infrastructure interventions, assuming all vehicles started the day fully charged. This approach separated natural charging behavior from early enforced charging and showed that initial state of charge assumptions significantly affect overall demand levels. When starting with a full initial SOC, the total charging demand was much lower, highlighting the importance of carefully interpreting simulation results that depend on initial conditions.

Across various technology and infrastructure scenarios, improvements in battery capacity primarily reduce charging frequency and alleviate congestion by decreasing reliance on public chargers. Larger batteries consistently lower queuing probabilities without increasing peak power demand, showing that vehicle-side enhancements serve as demand-reducing measures. Conversely, infrastructure-focused strategies impact how charging demand is managed rather than the total amount of charging. Increasing charger power and density enhances access and reduces wait times but often raises instantaneous power demand and, in some cases, fails to eliminate congestion due to synchronized charging behavior.

The combined improvement scenario revealed a key limitation of purely structural solutions. Even with significant increases in battery capacity and charging infrastructure, queuing and peak demand continued during times of highest activity. As restrictions were eased, users increasingly matched their charging choices with preferred activity periods, leading to internal behavioral synchronization that partly countered infrastructure improvements.

6.3.2 Implications for the Working Hypotheses

The findings of this chapter directly support the working hypotheses outlined in the Introduction. First, they confirm that charging demand and congestion are significantly influenced

by behavioral differences and psychological sensitivity, confirming the need for models based on actual behavior. Range anxiety, in particular, was shown to significantly impact charging timing, location choices, and congestion patterns.

Second, the results demonstrate that behavior-driven or pricing-induced shifts in charging timing are insufficient when infrastructure constraints remain binding. Although behavioral adaptations can redistribute demand across time and space, they cannot fully mitigate congestion when access to chargers is limited during key activity periods.

Third, the analysis reveals that technological and infrastructure improvements introduce important trade-offs that depend critically on how users adapt their behavior. While larger batteries reduce overall demand and congestion, increases in charger power and density may exacerbate peak loads or fail to resolve queuing if behavioral synchronization persists.

Finally, the results confirm that integrated strategies—combining behavioral understanding, vehicle technology, and infrastructure planning—are more robust than isolated interventions. Charging outcomes cannot be accurately predicted or managed without accounting for the mutual dependence between these elements.

6.3.3 Contribution of This Chapter

This chapter contributes to the thesis by showing that EV charging systems cannot be managed effectively with one-size-fits-all solutions. Charging demand is portrayed as an emerging result of behavioral choices made within technological and infrastructural limits. By separating behavioral sensitivity, vehicle capabilities, and infrastructure provision, the chapter explains how congestion and peak demand develop and continue.

From a policy and planning perspective, the results offer several actionable insights. Reducing range anxiety can reshape charging demand but may shift congestion elsewhere rather than eliminate it. Increasing battery capacity provides a strong way to suppress demand and decrease queues, while charger density stands out as the most effective infrastructure tool for easing congestion. Charger power enhances service speed but must be coordinated with grid capacity to prevent worsening peak loads. Importantly, all interventions need to be assessed in light of endogenous behavioral responses.

Overall, this chapter supports the main argument that EV charging demand management is primarily a behavioral-infrastructure problem. Recognizing and modeling this interaction is crucial for creating policies and investments that stay effective and adaptable as EV adoption increases. The next chapter expands on these ideas by analyzing how different behavioral models and policy options work with charging infrastructure under future demand scenarios.

CHAPITRE 7 CONCLUSION

Electric vehicle charging has become an increasingly important link between transportation and electricity systems. As EV adoption grows in urban areas, charging demand can no longer be treated as a minor or purely technical issue. Instead, it reflects how people travel, make decisions, and interact with the infrastructure and technology available to them in their daily lives. This thesis views EV charging not as a fixed load imposed on the power grid, but as a dynamic outcome of individual behavior shaped by urban activity patterns.

Across its three core themes, the thesis demonstrated that charging demand, congestion, and grid impacts cannot be adequately understood—or effectively managed—through isolated interventions or simplified behavioral assumptions. Instead, charging outcomes arise from the interaction of heterogeneous user behavior, spatially constrained infrastructure, pricing, and technological characteristics. The following sections synthesize the contributions of the thesis, highlight its limitations, and outline directions for future research.

7.1 Summary of Works

This thesis applies a behaviorally grounded agent-based modeling framework built on MATSim to analyze EV charging behavior in urban settings and at the metropolitan scale. Within this framework, the thesis develops and integrates several EV-specific extensions—including customized charging logic, pricing, range anxiety, person-specific home chargers, and infrastructure interaction modules—to represent urban EV charging behavior in detail. Rather than prescribing charging demand through static profiles or deterministic rules, charging behavior emerges from agents’ activity schedules, state-of-charge conditions, infrastructure accessibility, and learning-based responses to experienced costs and delays.

A central contribution of the thesis is the explicit treatment of charging behavior as a primary driver of system-level outcomes. In contrast to many existing studies that apply homogeneous charging rules for all agents, this work demonstrated that assumptions about charging logic fundamentally shape peak demand, congestion patterns, and infrastructure utilization. Even when travel demand, infrastructure supply, and pricing conditions are held constant, differences in charging behavior alone produce markedly different system outcomes.

The first theme examined behavioral heterogeneity in charging strategies, distinguishing between planned, SOC-based, and opportunistic charging logics. Planned charging targets long activities, SOC-based charging responds to low battery levels, and opportunistic charging

exploits any available opportunity to recharge. By analyzing both homogeneous and heterogeneous scenarios, the results showed that no single charging strategy is universally optimal. Planned charging concentrates demand during dominant home and work activities, producing predictable but highly synchronized peaks. SOC-based charging reduces total energy demand but intensifies congestion at public chargers by concentrating charging attempts among users operating at critically low SOC. Opportunistic charging offers greater temporal flexibility but remains structurally tied to long-duration activities.

Crucially, allowing these strategies to coexist and adapt endogenously led to lower peak demand and smoother queuing profiles. Behavioral heterogeneity reduced synchronization in charging decisions, demonstrating that diversity in user behavior can partially mitigate system stress.

Within the simulation, charging behavior is primarily shaped by daily activity structure rather than by sociodemographic attributes directly. Differences observed across income, age, or gender groups arise indirectly through their association with distinct travel patterns and activity chains, which constitute the main pathway through which sociodemographic information influences behavior in the current model configuration. Because charging preferences and decision rules do not explicitly vary by sociodemographic characteristics, the analysis does not imply that such attributes are irrelevant in real-world charging behavior. Instead, the results highlight that, under the present assumptions, activity patterns and infrastructure access act as the dominant mediators linking sociodemographics to charging outcomes, underscoring the importance of activity-based representations when analyzing EV charging dynamics.

The second theme evaluated pricing strategies as demand management instruments, focusing on TOU pricing and spatially differentiated pricing under real-world infrastructure constraints. The results confirmed that users do respond to temporal price signals, particularly for public charging, and that TOU pricing can significantly reduce evening charging demand. However, the analysis also showed that pricing alone does not eliminate congestion or peak demand; it redistributes them.

Under TOU pricing, suppressed evening demand reappeared as intensified morning charging, leading to new congestion peaks at public chargers. This redistribution effect was not driven by behavioral inflexibility, but by spatial and capacity constraints in the charging network. Even when users were economically motivated to shift charging, they could do so only at chargers that were practically accessible within their daily activity patterns. As a result, pricing revealed latent demand that could not be accommodated under existing infrastructure conditions.

The Unlimited-Charger scenario provided direct evidence that infrastructure constraints, rather than lack of behavioral responsiveness, limit the effectiveness of pricing. When capacity constraints were relaxed, users shifted charging more strongly toward low-cost periods, confirming that pricing and infrastructure are complementary.

Spatial pricing further illustrated the interdependence of policy objectives. While area-based pricing succeeded in redistributing charging demand across zones, it partially undermined the temporal load-shifting benefits achieved under TOU pricing. This trade-off highlights the risk of applying pricing instruments in isolation and reinforces the need for integrated evaluation of temporal and spatial effects.

The third theme examined behavioral sensitivity and technological levers, focusing on range anxiety, battery capacity, charger power, and charger density. By modeling range anxiety as a continuous SOC-dependent penalty rather than a fixed threshold, the analysis showed that psychological sensitivity to low battery levels is a first-order determinant of charging behavior. Increased range anxiety led to earlier and more frequent charging, shifting demand from evening to morning hours, and substantially increasing queuing at public chargers. Importantly, these effects emerged even under randomized initial SOC conditions and in the absence of pricing, demonstrating that behavioral sensitivity alone can reshape system-level outcomes. Reducing range anxiety may alleviate evening grid stress but can simultaneously intensify morning congestion if infrastructure capacity and spatial accessibility remain constrained.

Technological and infrastructure scenarios revealed distinct behavioral mechanisms. Increasing battery capacity primarily reduced charging frequency and suppressed congestion by decreasing reliance on public infrastructure. Larger batteries consistently reduced queuing without increasing peak power demand, indicating that vehicle-side improvements act as demand-reducing interventions. In contrast, infrastructure-focused interventions reshaped how charging demand is served rather than how much charging occurs. Increasing charger power and density improved accessibility and reduced waiting times, but often increased instantaneous power demand and failed to eliminate congestion due to synchronized charging behavior. The combined improvement scenario demonstrated endogenous behavioral resynchronization : when constraints are relaxed, users converge on preferred charging times, limiting the effectiveness of structural upgrades alone.

Taken together, the three themes demonstrate that EV charging systems are governed by coupled behavioral–infrastructure dynamics. Charging demand is not simply shifted or suppressed by individual interventions ; it adapts in response to changing constraints and incentives. Effective management therefore requires coordinated strategies that recognize the endogenous nature of charging behavior.

7.2 Limitations

While this thesis advances the modeling of urban EV charging systems, several limitations should be acknowledged.

First, charging behavior is modeled using predefined charging logic and utility-based adaptation, rather than through behavioral models directly derived from empirical data. While this method enables the analysis to reflect how overall charging patterns and grid impacts can arise from individual decisions, it also means that the resulting quantitative results should not be seen as exact predictions. The main value of the framework is in enhancing understanding of system dynamics and interaction mechanisms, not in delivering precise numerical estimates. Importantly, once empirically estimated individual charging models are incorporated, the aggregate outcomes may vary in scale or distribution, even if the core mechanisms identified in this thesis stay relevant.

Second, the representation of range anxiety, while continuous and behaviorally motivated, remains simplified. The penalty function captures sensitivity to declining SOC but does not explicitly model uncertainty, information asymmetry, or learning about charger reliability over longer time horizons. Real-world range anxiety is likely influenced by prior experiences, social factors, and information availability, which are only partially captured in the current framework.

Third, modeling of charging infrastructure assumes fixed charger locations and constant power characteristics within each scenario. While this enables straightforward comparison across policies and technology options, it does not account for long-term infrastructure investments, adaptive deployment strategies, or grid-side operational constraints such as transformer limits and voltage regulation.

Fourth, the analysis concentrates on a typical weekday and does not explicitly consider inter-day dynamics. In reality, charging decisions and battery states are closely connected across consecutive days, as charging cycles depend on what happened the day before and affect decisions the next day. While MATSim’s co-evolutionary learning captures adaptation in route and activity choices, the single-day scope limits the representation of multi-day charging cycles, cumulative battery depletion, and recovery effects. As a result, weekend travel, seasonal variations, extreme weather conditions, and long-term behavioral changes may create charging dynamics that are not fully reflected in this analysis.

Finally, while the Montréal metropolitan region offers a realistic and policy-relevant case study, the quantitative results from this thesis are inherently specific to its context. Variations in urban form, travel behaviors, and charging infrastructure across different cities mean that

the findings cannot be directly applied to other settings. Instead, the framework needs to be adapted with locally relevant data and network representations. At the same time, because the analysis emphasizes general behavioral mechanisms and activity-based constraints rather than city-specific preference models, the qualitative insights into how behavior, infrastructure, and charging dynamics interact may be applicable beyond the Montréal case.

7.3 Future Research

The findings of this thesis open several promising directions for future research, building on the exploratory insights developed in this work.

A first avenue concerns the transition from exploratory analysis to goal-oriented policy design. While this thesis focused on understanding the mechanisms through which behavior, pricing, infrastructure, and technology interact, future research could explicitly define system-level objectives—such as a desired spatial-temporal distribution of charging demand, reduced peak loads, or lower queuing—and test coordinated combinations of policy instruments to achieve these targets. Such work could move beyond single-lever experiments toward the evaluation and eventual optimization of integrated interventions combining pricing schemes, infrastructure deployment, and technological improvements.

A second direction involves deeper behavioral modeling. Future work could integrate empirically estimated charging choice models, incorporating stated- or revealed-preference data on charging timing, location choice, sensitivity to queues, range anxiety, and price. This would strengthen the behavioral grounding of the simulation and allow for a more explicit representation of heterogeneity in preferences beyond activity patterns alone.

Third, the treatment of range anxiety and information could be extended by incorporating uncertainty and information dynamics. Modeling imperfect knowledge of charger availability, real-time information provision, and learning across multiple days would enable the examination of how information systems and digital tools influence charging behavior, congestion, and user confidence.

Fourth, future research should extend the temporal scope of the analysis beyond a single day. Simulating charging behavior over multiple consecutive days or on a weekly basis would allow battery states, charging decisions, and congestion patterns to co-evolve over time. Such multi-day simulations could reveal stabilization effects, delayed charging responses, and cumulative impacts that cannot be captured in single-day analyses.

Fifth, longer-term dynamics could be explored by coupling the proposed framework with infrastructure investment and grid reinforcement models. This would enable the analysis of

co-evolution between charging demand, infrastructure deployment, and network constraints, supporting the evaluation of phased investment strategies and adaptive planning under uncertainty.

Sixth, future research could explore the sensitivity of model outcomes to the assumed walking distance threshold. In particular, varying this parameter would provide insight into how accessibility constraints influence charging station choice, spatial demand distribution, and congestion patterns. Incorporating heterogeneous walking preferences across users and activity types could further improve the behavioral realism of the model.

Finally, future studies could examine equity and distributional impacts in greater depth. While this thesis showed that charging behavior is primarily mediated by activity structure and access under the current model assumptions, unequal access to home charging and public infrastructure may have important implications for cost burden, convenience, and adoption. Explicit equity-focused analyses would support the design of more inclusive and socially robust charging policies.

Closing Remarks This thesis demonstrated that urban EV charging systems cannot be understood or managed through single-dimensional solutions. Charging demand is an emergent outcome of behavioral decisions made within technological and infrastructural constraints. Pricing, infrastructure expansion, and technological improvements each influence charging behavior, but none is sufficient in isolation. Recognizing and modeling the interaction between behavior, infrastructure, and policy is therefore essential for designing robust, efficient, and equitable charging systems.

By advancing a behaviorally grounded, system-level modeling framework, this thesis contributes to a more realistic understanding of EV charging dynamics and provides a foundation for integrated policy and planning under accelerating electrification.

REFERENCES

- [1] F. Razi et I. Dincer, “A review of the current state, challenges, opportunities and future directions for implementation of sustainable electric vehicle infrastructure in canada,” *Journal of Energy Storage*, vol. 56, p. 106048, 2022.
- [2] I. Burch et J. Gilchrist, “Survey of global activity to phase out internal combustion engine vehicles,” *Center of Climate Protection : Santa Rosa, CA, USA*, 2018.
- [3] P. Richardson, D. Flynn et A. Keane, “Optimal charging of electric vehicles in low-voltage distribution systems,” *IEEE Transactions on Power Systems*, vol. 27, n^o. 1, p. 268–279, 2011.
- [4] O. Sundstrom et C. Binding, “Flexible charging optimization for electric vehicles considering distribution grid constraints,” *IEEE Transactions on Smart grid*, vol. 3, n^o. 1, p. 26–37, 2011.
- [5] K. Clement-Nyns, E. Haesen et J. Driesen, “The impact of charging plug-in hybrid electric vehicles on a residential distribution grid,” *IEEE Transactions on power systems*, vol. 25, n^o. 1, p. 371–380, 2009.
- [6] A. R. Singh, P. Vishmuram, S. Alagarsamy, M. Bajaj, V. Blazek, I. Damaj, R. S. Rathore, F. N. Al-Wesabi et K. M. Othman, “Electric vehicle charging technologies, infrastructure expansion, grid integration strategies, and their role in promoting sustainable e-mobility,” *Alexandria Engineering Journal*, vol. 105, p. 300–330, 2024.
- [7] B. Borlaug, F. Yang, E. Pritchard, E. Wood et J. Gonder, “Public electric vehicle charging station utilization in the united states,” *Transportation Research Part D : Transport and Environment*, vol. 114, p. 103564, 2023.
- [8] G. Brückmann et T. Bernauer, “An experimental analysis of consumer preferences towards public charging infrastructure,” *Transportation Research Part D : Transport and Environment*, vol. 116, p. 103626, 2023.
- [9] J. S. Krupa, D. M. Rizzo, M. J. Eppstein, D. B. Lanute, D. E. Gaalema, K. Lakkaraju et C. E. Warrender, “Analysis of a consumer survey on plug-in hybrid electric vehicles,” *Transportation Research Part A : Policy and Practice*, vol. 64, p. 14–31, 2014.
- [10] C.-W. Hsu et K. Fingerman, “Public electric vehicle charger access disparities across race and income in california,” *Transport Policy*, vol. 100, p. 59–67, 2021.
- [11] Z. Hu, K. Zhan, H. Zhang et Y. Song, “Pricing mechanisms design for guiding electric vehicle charging to fill load valley,” *Applied Energy*, vol. 178, p. 155–163, 2016.

- [12] Z. Li et M. Ouyang, “The pricing of charging for electric vehicles in china—dilemma and solution,” *Energy*, vol. 36, n°. 9, p. 5765–5778, 2011.
- [13] International Energy Agency, “Electric vehicle charging – global ev outlook 2025,” 2025, ensuring a denser charging network helps address range anxiety and instil confidence in EV adoption. [En ligne]. Disponible : <https://www.iea.org/reports/global-ev-outlook-2025/electric-vehicle-charging>
- [14] P. Chakraborty *et al.*, “Addressing the range anxiety of battery electric vehicles with charging infrastructure deployment,” *J. Energy Storage*, 2022, dense and proximate fast chargers can alleviate range anxiety.
- [15] J. Sarda *et al.*, “A review of the electric vehicle charging technology, impact, and infrastructure,” *Renewable and Sustainable Energy Reviews*, 2024, comprehensive analysis of EV charging infrastructure and technology improvements.
- [16] A. Tayri *et al.*, “Grid impacts of electric vehicle charging : A review,” *Energies*, 2025, uncoordinated EV charging increases peak loads and stress on distribution grid components.
- [17] H. Masrur et A. T. Al-Awami, “Dynamics of an ev charging station considering queuing theory,” *Transportation Research Procedia*, vol. 84, p. 434–439, 2025.
- [18] W. Zhan, Y. Liao, J. Deng, Z. Wang et S. Yeh, “Large-scale empirical study of electric vehicle usage patterns and charging infrastructure needs,” *npj Sustainable Mobility and Transport*, vol. 2, n°. 1, p. 9, 2025.
- [19] A. Chattopadhyay et S. Kar, “Ideas : information-driven ev admission in charging station considering user impatience to improve qos and station utilization,” *arXiv preprint arXiv :2403.06223*, 2024.
- [20] S. Wang, Z. Y. Dong, F. Luo, K. Meng et Y. Zhang, “Stochastic collaborative planning of electric vehicle charging stations and power distribution system,” *IEEE Transactions on Industrial Informatics*, vol. 14, n°. 1, p. 321–331, 2017.
- [21] Y. Zhao, Z. Wang, Z.-J. M. Shen et F. Sun, “Data-driven framework for large-scale prediction of charging energy in electric vehicles,” *Applied Energy*, vol. 282, p. 116175, 2021.
- [22] R. A. Waraich, M. D. Galus, C. Dobler, M. Balmer, G. Andersson et K. W. Axhausen, “Plug-in hybrid electric vehicles and smart grids : Investigations based on a microsimulation,” *Transportation Research Part C : Emerging Technologies*, vol. 28, p. 74–86, 2013.
- [23] N. S. Lopez, A. Allana et J. B. M. Biona, “Modeling electric vehicle charging demand with the effect of increasing evses : A discrete event simulation-based model,” *Energies*,

- vol. 14, n°. 13, p. 3734, 2021.
- [24] C. Marmaras, E. Xydias et L. Cipcigan, “Simulation of electric vehicle driver behaviour in road transport and electric power networks,” *Transportation Research Part C : Emerging Technologies*, vol. 80, p. 239–256, 2017.
 - [25] T. Sweda et D. Klabjan, “An agent-based decision support system for electric vehicle charging infrastructure deployment,” dans *2011 IEEE Vehicle Power and Propulsion Conference*. IEEE, 2011, p. 1–5.
 - [26] M. Pagani, W. Korosec, N. Chokani et R. S. Abhari, “User behaviour and electric vehicle charging infrastructure : An agent-based model assessment,” *Applied Energy*, vol. 254, p. 113680, 2019.
 - [27] M. Thorhauge, J. Rich et S. E. Mabit, “Charging behaviour and range anxiety in long-distance ev travel : An adaptive choice design study,” *Transportation*, p. 1–23, 2024.
 - [28] X. Liu et Z. Bie, “Optimal allocation planning for public ev charging station considering ac and dc integrated chargers,” *Energy Procedia*, vol. 159, p. 382–387, 2019.
 - [29] T. Franke, I. Neumann, F. Bühler, P. Cocron et J. F. Krems, “Experiencing range in an electric vehicle : Understanding psychological barriers,” *Applied Psychology*, vol. 61, n°. 3, p. 368–391, 2012.
 - [30] M. Shariatzadeh, M. A. Lopes et C. H. Antunes, “Electric vehicle users’ charging behavior : A review of influential factors, methods and modeling approaches,” *Applied Energy*, vol. 396, p. 126167, 2025.
 - [31] I. Malabanan, P. Sauri Lavieri et I. Mateo-Babiano, “Electric vehicle charging disadvantage : a social justice perspective on charging with implications to accessibility,” *Transport Reviews*, vol. 45, n°. 5, p. 696–725, 2025.
 - [32] B. Chen, H. Guo, F. Zhou, Z. Hu, J. S. Huang, K. Wu, D. Meroux et S. Bao, “Electric vehicle users’ charging patterns and selection considerations at public charging stations,” *Transportation Research Part D : Transport and Environment*, vol. 149, p. 105081, 2025.
 - [33] A. Amin, W. U. K. Tareen, M. Usman, H. Ali, I. Bari, B. Horan, S. Mekhilef, M. Asif, S. Ahmed et A. Mahmood, “A review of optimal charging strategy for electric vehicles under dynamic pricing schemes in the distribution charging network,” *Sustainability*, vol. 12, n°. 23, p. 10160, 2020.
 - [34] J. K. Szinai, C. J. R. Sheppard, N. Abhyankar et A. R. Gopal, “Reduced grid operating costs and renewable energy curtailment with electric vehicle charge management,” *Energy Policy*, vol. 136, p. 111051, 2020.

- [35] S. Limmer et T. Rodemann, “Peak load reduction through dynamic pricing for electric vehicle charging,” *International Journal of Electrical Power & Energy Systems*, vol. 113, p. 117–128, 2019.
- [36] B. Palaniyappan, T. Vinopraba *et al.*, “Dynamic pricing for load shifting : Reducing electric vehicle charging impacts on the grid through machine learning-based demand response,” *Sustainable Cities and Society*, vol. 103, p. 105256, 2024.
- [37] Y. An, J. Y. Chow, S. Woo et J. Lee, “Urban public charging infrastructure planning for electric vehicles : A continuum approximation approach,” *Transportation Research Part D : Transport and Environment*, vol. 141, p. 104605, 2025.
- [38] Recurrent Auto, “A big ev battery is more about charging than range,” <https://www.recurrentauto.com/research/want-to-spend-less-time-charging-get-a-bigger-ev-battery>, 2025, accessed 2026-01-02.
- [39] A. E. Trippe, P. L. Hidalgo, M. Lienkamp et T. Hamacher, “Mobility model for the estimation of the spatiotemporal energy demand of battery electric vehicles in singapore,” dans *2015 IEEE 18th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2015, p. 578–583.
- [40] B. Jäger, F. M. M. Agua et M. Lienkamp, “Agent-based simulation of a shared, autonomous and electric on-demand mobility solution,” dans *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2017, p. 250–255.
- [41] Z. Liu, W. Yin, D. Feng et Y. Zhou, “A framework for analyzing the spatiotemporal distribution of urban electric vehicle charging load : A case study of shanghai,” *Sustainable Cities and Society*, vol. 124, p. 106392, 2025.
- [42] S. Wang, J. Pougala et T. Hillel, “Joint modelling of electric vehicle charging and daily activity scheduling,” *Transportation Research Part D : Transport and Environment*, vol. 147, p. 104911, 2025.
- [43] F. F. Bastariento, T. O. Hancock, C. F. Choudhury et E. Manley, “Agent-based models in urban transportation : review, challenges, and opportunities,” *European Transport Research Review*, vol. 15, n°. 1, p. 19, 2023.
- [44] T. Novosel, L. Perković, M. Ban, H. Keko, T. Pukšec, G. Krajačić et N. Duić, “Agent based modelling and energy planning—utilization of matsim for transport energy demand modelling,” *Energy*, vol. 92, p. 466–475, 2015.
- [45] J. Bischoff, F. J. Márquez-Fernández, G. Domingues-Olavarría, M. Maciejewski et K. Nagel, “Impacts of vehicle fleet electrification in sweden : A simulation-based assessment of long-distance trips,” dans *2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*. IEEE, 2019, p. 1–7.

- [46] L. Adenaw et M. Lienkamp, “Multi-criteria, co-evolutionary charging behavior : An agent-based simulation of urban electromobility,” *World Electric Vehicle Journal*, vol. 12, n° 1, p. 18, 2021.
- [47] J. Müller, M. Straub, A. Naqvi, G. Richter, S. Peer et C. Rudloff, “Matsim model vienna : Analyzing the socioeconomic impacts for different fleet sizes and pricing schemes of shared autonomous electric vehicles,” *Working Paper*, 2021.
- [48] H. Laarabi, Z. Needell, R. Waraich, C. Poliziani et T. Wenzel, “Beam : The modeling framework for behavior, energy, autonomy & mobility,” *arXiv preprint arXiv :2308.02073*, 2023. [En ligne]. Disponible : <https://arxiv.org/abs/2308.02073>
- [49] A. Siguenza-Torres, A. Wieder, Z. Meng, S. Narvaez Rivas, M. Gao, M. Grossi, X. Du, S. Bortoli, W. Cai et A. Knoll, “Enhance : Multilevel heterogeneous performance-aware re-partitioning algorithm for microscopic vehicle traffic simulation,” *ACM Transactions on Modeling and Computer Simulation*, vol. 35, n° 3, p. 1–26, 2025.
- [50] V. Viswanathan, D. Zehe, J. Ivanchev, D. Pelzer, A. Knoll et H. Aydt, “Simulation-assisted exploration of charging infrastructure requirements for electric vehicles in urban environments,” *Journal of Computational Science*, vol. 12, p. 1–10, 2016.
- [51] R. Bi, J. Xiao, V. Viswanathan et A. Knoll, “Influence of charging behaviour given charging station placement at existing petrol stations and residential car park locations in singapore,” *Procedia Computer Science*, vol. 80, p. 335–344, 2016.
- [52] H. Zhang, C. J. R. Sheppard, T. E. Lipman, T. Zeng et S. J. Moura, “Charging infrastructure demands of shared-use autonomous electric vehicles in urban areas,” *Transportation Research Part D : Transport and Environment*, vol. 78, p. 102210, 2020.
- [53] K. Chaudhari, N. K. Kandasamy, A. Krishnan, A. Ukil et H. B. Gooi, “Agent-based aggregated behavior modeling for electric vehicle charging load,” *IEEE Transactions on Industrial Informatics*, vol. 15, n° 2, p. 856–868, 2018.
- [54] C. Ziras, M. Thingvad, T. Fog, G. Yousefi et T. Weckesser, “An empirical analysis of electric vehicle charging behavior based on real danish residential charging data,” *Electric Power Systems Research*, vol. 234, p. 110556, 2024.
- [55] J. Bischoff et M. Maciejewski, “Agent-based simulation of electric taxicab fleets,” *Transportation Research Procedia*, vol. 4, p. 191–198, 2014.
- [56] N. Daina, A. Sivakumar et J. W. Polak, “Electric vehicle charging choices : Modeling and implications for smart charging services,” *Transportation Research Part C : Emerging Technologies*, vol. 81, p. 36–56, 2017.
- [57] J. Dong, C. Liu et Z. Lin, “Charging infrastructure planning for promoting battery electric vehicles : An activity-based approach using multiday travel data,” *Transportation*

Research Part C : Emerging Technologies, vol. 38, p. 44–55, 2014.

- [58] F. A. Bhat, G. Y. Tiwari et A. Verma, “Preferences for public electric vehicle charging infrastructure locations : A discrete choice analysis,” *Transport Policy*, vol. 149, p. 177–197, 2024.
- [59] M. El-Hendawi, Z. Wang, R. Paranjape, S. Pederson, D. Kozoriz et J. Fick, “Electric vehicle charging model in the urban residential sector,” *energies*, vol. 15, n°. 13, p. 4901, 2022.
- [60] C. D. Zuluaga-Ríos, D. F. Florián-Ceballos, M. Á. Rojo-Yepes et S. D. Saldarriaga-Zuluaga, “Review of charging load modeling strategies for electric vehicles : A comparison of grid-to-vehicle probabilistic approaches,” *Tecnura*, vol. 25, n°. 70, p. 108–125, 2021.
- [61] Y. Xing, F. Li, K. Sun, D. Wang, T. Chen et Z. Zhang, “Multi-type electric vehicle load prediction based on monte carlo simulation,” *Energy Reports*, vol. 8, p. 966–972, 2022.
- [62] Q. Jiang, N. Zhang, B. Y. He, C. Lee et J. Ma, “Large-scale public charging demand prediction with a scenario-and-activity-based approach,” *Transportation Research Part A : Policy and Practice*, vol. 179, p. 103935, 2024.
- [63] P. Michailidis, I. Michailidis et E. Kosmatopoulos, “Reinforcement learning for electric vehicle charging management : Theory and applications,” *Energies*, vol. 18, n°. 19, p. 5225, 2025.
- [64] P. Jamjuntr, C. Techawatcharapaikul et P. Suanpang, “Adaptive multi-agent reinforcement learning for optimizing dynamic electric vehicle charging networks in thailand,” *World Electric Vehicle Journal*, vol. 15, n°. 10, p. 453, 2024.
- [65] C. B. Jones, W. Vining, M. Lave, T. Haines, C. Neuman, J. Bennett et D. R. Scofield, “Impact of electric vehicle customer response to time-of-use rates on distribution power grids,” *Energy Reports*, vol. 8, p. 8225–8235, 2022.
- [66] S. Y. Yang, J. Woo et W. Lee, “Assessing optimized time-of-use pricing for electric vehicle charging in deep vehicle-grid integration system,” *Energy Economics*, vol. 138, p. 107852, 2024.
- [67] L. D. A. Bitencourt, B. S. Borba, R. S. Maciel, M. Z. Fortes et V. H. Ferreira, “Optimal ev charging and discharging control considering dynamic pricing,” dans *2017 IEEE Manchester PowerTech*. IEEE, 2017, p. 1–6.
- [68] J. Tan, F. Liu, N. Xie, W. Guo et W. Wu, “Dynamic pricing strategy of charging station based on traffic assignment simulation,” *Sustainability*, vol. 14, n°. 21, p. 14476, 2022.

- [69] Z. Yi, B. Chen, X. C. Liu, R. Wei, J. Chen et Z. Chen, “An agent-based modeling approach for public charging demand estimation and charging station location optimization at urban scale,” *Computers, Environment and Urban Systems*, vol. 101, p. 101949, 2023.
- [70] E. M. Szumska et R. S. Jurecki, “Parameters influencing on electric vehicle range,” *Energies*, vol. 14, n^o. 16, p. 4821, 2021.
- [71] X. He et Y. Hu, “Optimal mileage of electric vehicles considering range anxiety and charging times,” *World Electric Vehicle Journal*, vol. 14, n^o. 1, p. 21, 2023.
- [72] T. Yamada et A. Akisawa, “Effectiveness of high-power chargers at a quick-charging station for electric vehicles,” *Applied Energy*, vol. 377, p. 124623, 2025.
- [73] A. Zentani, A. Almaktoof et M. T. Kahn, “A comprehensive review of developments in electric vehicles fast charging technology,” *Applied Sciences*, vol. 14, n^o. 11, p. 4728, 2024.
- [74] Q. Yu, P. Zhao, J. Li, H. Wang, J. Yan et H. Zhang, “China’s urban ev ultra-fast charging distorts regulated price signals and elevates risk to grid stability,” *Nature Communications*, vol. 16, n^o. 1, p. 8451, 2025.
- [75] S. Á. Funke, F. Sprei, T. Gnann et P. Plötz, “How much charging infrastructure do electric vehicles need? a review of the evidence and international comparison,” *Transportation Research Part D : Transport and Environment*, vol. 77, p. 224–242, 2019.
- [76] D. Hall et N. Lutsey, “Emerging best practices for electric vehicle charging infrastructure,” *The international council on clean transportation (ICCT) : Washington, DC, USA*, vol. 54, 2017.
- [77] D. Pevec, J. Babic, A. Carvalho, Y. Ghiassi-Farrokhfal, W. Ketter et V. Podobnik, “Electric vehicle range anxiety : An obstacle for the personal transportation revolution?” dans *2019 4th International Conference on Smart and Sustainable Technologies (SpliTech)*. IEEE, 2019, p. 1–8.
- [78] T. Franke et J. F. Krems, “Understanding charging behaviour of electric vehicle users,” *Transportation Research Part F : Traffic Psychology and Behaviour*, vol. 21, p. 75–89, 2013.
- [79] N. Rauh, T. Franke et J. F. Krems, “Understanding the impact of electric vehicle driving experience on range anxiety,” *Human factors*, vol. 57, n^o. 1, p. 177–187, 2015.
- [80] T. Franke et J. F. Krems, “What drives range preferences in electric vehicle users?” *Transport Policy*, vol. 30, p. 56–62, 2013.
- [81] R. Bi, J. Xiao, D. Pelzer, D. Ciechanowicz, D. Eckhoff et A. Knoll, “A simulation-based heuristic for city-scale electric vehicle charging station placement,” dans *2017*

- IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2017, p. 1–7.
- [82] K. W. Axhausen, A. Horni et K. Nagel, *The Multi-Agent Transport Simulation MAT-Sim*. Ubiquity Press, 2016.
 - [83] W. Gao, M. Balmer et E. J. Miller, “Comparison of matsim and emme/2 on greater toronto and hamilton area network, canada,” *Transportation Research Record*, vol. 2197, n^o. 1, p. 118–128, 2010.
 - [84] D. Charypar et K. Nagel, “Generating complete all-day activity plans with genetic algorithms,” *Transportation*, vol. 32, n^o. 4, p. 369–397, 2005.
 - [85] F. S. Hoen, M. Díez-Gutiérrez, S. Babri, S. Hess et T. Tørset, “Charging electric vehicles on long trips and the willingness to pay to reduce waiting for charging : Stated-preference survey in norway,” *Transportation Research Part A : Policy and Practice*, vol. 175, p. 103774, 2023.
 - [86] S. M. Rezvanizani, Z. Liu, Y. Chen et J. Lee, “Review and recent advances in battery health monitoring and prognostics technologies for electric vehicle (ev) safety and mobility,” *Journal of Power Sources*, vol. 256, p. 110–124, 2014.
 - [87] K. T. Geurs et B. Van Wee, “Accessibility evaluation of land-use and transport strategies : review and research directions,” *Journal of Transport geography*, vol. 12, n^o. 2, p. 127–140, 2004.
 - [88] R. Daniels et C. Mulley, “Explaining walking distance to public transport : The dominance of public transport supply,” *Journal of Transport and Land use*, vol. 6, n^o. 2, p. 5–20, 2013.
 - [89] G. Tal, S. S. Raghavan, V. C. Karanam, M. P. Favetti, K. M. Sutton, J. H. Lee, C. Nitta, D. Chakraborty, M. Nicholas et T. Turrentine, “Advanced plug-in electric vehicle travel and charging behavior : Final report,” *California Air Resources Board Contract*, p. 12–319, 2020.
 - [90] Statistics Canada, “Census profile 2016,” 2016, accessed 2025-11-01. [En ligne]. Disponible : <https://www12.statcan.gc.ca/census-recensement/2016/dp-pd/prof/index.cfm?Lang=E>
 - [91] Ministère des Transports du Québec, “Origin–destination survey – montreal (2018),” 2018, accessed 2025-11-01. [En ligne]. Disponible : <https://www.transports.gouv.qc.ca/fr/ministere/Planification-transports/enquetes-origine-destination/montreal/2018/Pages/enquete-2018.aspx>
 - [92] Société de l’assurance automobile du Québec (SAAQ), “Données et statistiques 2016,” 2016, accessed 2025-11-01. [En ligne]. Disponible : <https://saaq.gouv.qc.ca/fileadmin/>

- documents/publications/donnees-statistiques-2016.pdf
- [93] Ville de Montréal, “Le rôle d’évaluation foncière et son contenu,” 2018, accessed 2025-11-01. [En ligne]. Disponible : <https://mtl.ged.montreal.ca/constellio/?collection=mtlca&portal=REPDOCVDM#!displayDocument/00000094015>
 - [94] S. Hörl et M. Balac, “Introducing the eqasim pipeline : From raw data to agent-based transport simulation,” *Procedia Computer Science*, vol. 184, p. 712–719, 2021.
 - [95] A. Durán-Heras, I. García-Gutiérrez et G. Castilla-Alcalá, “Comparison of iterative proportional fitting and simulated annealing as synthetic population generation techniques : Importance of the rounding method,” *Computers, Environment and Urban Systems*, vol. 68, p. 78–88, 2018.
 - [96] R. M. Pendyala, C. R. Bhat, K. G. Goulias, R. Paleti, K. C. Konduri, R. Sidharthan, H.-h. Hu, G. Huang et K. P. Christian, “Application of socioeconomic model system for activity-based modeling : Experience from southern california,” *Transportation Research Record*, vol. 2303, n^o. 1, p. 71–80, 2012.
 - [97] S. Hörl et M. Balac, “Synthetic population and travel demand for paris and île-de-france based on open and publicly available data,” *Transportation Research Part C : Emerging Technologies*, vol. 130, p. 103291, 2021.
 - [98] K. McNally, R. Cotton, A. Hogg et G. Loizou, “Popgen : A virtual human population generator,” *Toxicology*, vol. 315, p. 70–85, 2014.
 - [99] F. Poletti, “Public transit mapping on multi-modal networks in matsim,” *Master Thesis, IVT, ETH Zurich*, 2016.
 - [100] Electric Circuit, “Network,” 2022, accessed 2025-11-01. [En ligne]. Disponible : <https://lecircuitelectrique.com/en/>
 - [101] F. Hülsmann, R. Gerike et M. Ketzel, “Modelling traffic and air pollution in an integrated approach—the case of munich,” *Urban Climate*, vol. 10, p. 732–744, 2014.
 - [102] AVÉQ, “Statistiques — avéq : Électricité et mobilité,” 2025, consulted 7 Oct 2025. [En ligne]. Disponible : <https://www.aveq.ca/actualiteacutes/category/statistiques>
 - [103] U.S. Department of Energy, “Fotw #1214 : Most electric vehicle charging happens at home,” <https://www.energy.gov/eere/vehicles/articles/fotw-1214-most-electric-vehicle-charging-happens-home>, 2021, accessed : 2025-01.
 - [104] Government of Quebec, “Electric vehicle charging strategy,” <https://www.quebec.ca/en/government/policies-orientations/quebec-electric-vehicle-charging-strategy>, 2020, states that approximately 80% of personal EV charging occurs at home.

- [105] T. Qian, “Calculation of electric vehicle charging power based on spatial-temporal activity model,” dans *2018 China International Conference on Electricity Distribution (CICED)*. IEEE, 2018, p. 2884–2888.
- [106] J. Brady et M. O’Mahony, “Modelling charging profiles of electric vehicles based on real-world electric vehicle charging data,” *Sustainable Cities and Society*, vol. 26, p. 203–216, 2016.
- [107] M. Nicholas et G. Tal, “Charging for charging at work : Increasing the availability of charging through pricing,” Institute of Transportation Studies, UC Davis, Rapport technique, 2015.