ABSTRACT

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| Title of the Document: | INTEGRATED PLANNING OF RESIDENTIAL AND COMMERCIAL ELECTRIC VEHICLE CHARGING INFRASTRUCTURE: A STRATEGIC BI-LEVEL OPTIMIZATION AND QUEUING FRAMEWORK APPROACH |
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Electric vehicles (EVs) have gained significant popularity, becoming an attractive option for cleaner transportation systems. The market adoption of different types of EVs in the USA has grown significantly over the years. A critical challenge for this expanding market is the limited charging infrastructure available in both residential and commercial spaces. This research aims to study the optimal number, placement, and management of charging stations required to accommodate EVs at both residential and commercial locations, considering varying market penetration rates, household adoption of charging infrastructure, and the constraints posed by power network capacities.

The developed model is applied to the Baltimore Metropolitan Statistical Area (MSA) to determine the optimal number and distribution of charging stations. This study integrates real-world Origin-Destination (OD) trip data with census data to investigate the relationship between residential and commercial EV charging infrastructures. Furthermore, advanced queuing theory models are employed to analyze and manage congestion at commercial charging stations, evaluating system

performance indicators such as waiting times, blocking probabilities, and station utilization under realistic, stochastic demand conditions.

Scenario analysis illustrates the shifting landscape of charging infrastructure demands for both current (0.09%, 0.75%, and 1.61%) and future market penetration rates (5%, 7.5%, and 10%), reflecting Maryland's current adoption levels and future growth projections driven by policy initiatives and technological advancements in EV infrastructure. The findings reveal a clear inverse relationship between the availability of residential charging facilities and the necessity for commercial chargers. Utilizing a bi-level optimization model, this research balances investor interests with EV user satisfaction by maximizing profits and minimizing user charging costs. Additionally, the queuing simulation highlights critical operational insights, illustrating how variations in arrival rates, service times, and charger availability impact overall system efficiency and user experience.

These combined insights emphasize the importance of integrating residential and commercial charging infrastructure planning with congestion management strategies. Policymakers, utility providers, and infrastructure investors can utilize these findings to formulate sustainable EV charging strategies, considering market penetration rates, household charger adoption, optimal State of Charge (SoC) management, and operational efficiency through queuing management. This comprehensive framework provides robust guidance for stakeholders aiming to develop resilient, sustainable, and efficient EV charging networks, promoting greater EV adoption and contributing to environmental sustainability.

# INTEGRATED PLANNING OF RESIDENTIAL AND COMMERCIAL ELECTRIC VEHICLE CHARGING INFRASTRUCTURE: A STRATEGIC BI-LEVEL OPTIMIZATION AND QUEUING FRAMEWORK APPROACH

By

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# Dedication

To my girlfriend, Swastika Bera, my father, Dr. Jayanta Tarafdar, and my mother, Srabani Tarafdar

for their love and support.

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## Chapter 1: Introduction

### *1.1 Research Background*

Electric vehicles (EVs) have gained significant popularity and have become an attractive option for cleaner transportation systems. The market adoption of different types of EVs in the USA has grown significantly over the years. One of the challenges for such a growing market is the limited charging infrastructure in both residential and commercial spaces. This paper aims to study the optimal number and placement of charging stations required to accommodate EVs at both residential and commercial locations, depending on the market penetration rate and the adoption of charging infrastructure in households.

The transportation sector's increasing energy consumption and subsequent environmental pollution have led to a growing focus on promoting more sustainable and energy-efficient vehicles. Both government and private sectors are exploring EVs as a viable solution, offering energy efficiency (Albatayneh et al., 2020; Hofman & Dai, 2010) and low emissions (Verma et al., 2022) compared to conventional fossil fuel vehicles. The market offers several types of EVs (Sanguesa et al., 2021), including Hybrid Electric Vehicles (HEVs), Battery Electric Vehicles (BEVs), and Plug-In Hybrid Electric Vehicles (PHEVs). The latter two types can also be classified as Plug-In Electric Vehicles (PIEVs). PIEVs provide the convenience of charging from electric outlets. Despite having larger battery capacities and more powerful electric motors than traditional HEVs, PIEVs still face limitations in driving range due to battery capacity and energy efficiency constraints (Anderman, 2004). Moreover, drivers' anxiety about driving range significantly influences the adoption of EVs (Neubauer & Wood, 2014; Noel et al., 2019). Therefore, expanding the existing charging infrastructure and establishing additional charging facilities is crucial to meet the growing demand (Matanov & Zahov, 2020). As the number of EVs continues to grow, there is an urgent need to enhance the charging infrastructure to accommodate the increasing charging requirements (T. Chen et al., 2020; Wolbertus et al., 2020).

EV charging infrastructure is typically categorized as residential and commercial. Residential charging has served as a practical, efficient, and cost-effective solution, particularly for early EV adopters when commercial charging infrastructure was not widespread. On the other hand, commercial charging facilities benefit EV users by providing fast charging and extended driving range. Previous studies have separately investigated the impact of EV Charging Stations (EVCS) in both commercial and residential settings. However, the availability of residential charging options can influence the demand for commercial charging stations. Despite this, there remains a significant gap in research qualifying and quantifying the impact. Therefore, this paper aims to address this crucial gap by analyzing how the presence or absence of residential charging facilities could impact the demand for commercial charging infrastructure, considering various charging patterns. The case study utilizes traffic networks and EV profiles in Baltimore, Maryland, U.S., to derive insights into this matter. The results will also provide a preliminary understanding of the impacts of different market penetration rates of EVs.

The planning of EV charging stations involves three main steps: EV charging demand forecasting, charging station locating and sizing modeling, and planning model solving. Existing methods for forecasting EV charging demand include the Monte Carlo load forecasting model based on the charging period (M. Li et al., 2019), forecasting models based on trip chains considering temporal and spatial distribution (Nguyen & Hansen, 2017), and statistical load forecasting models based on charging probability (Z. Chen et al., 2018). Some studies analyze search behavior, navigation behavior, and usage patterns of EV users, proposing a charging demand evaluation method based on Bayesian reasoning (J. Li et al., 2018).

Regarding charging station locating and sizing models, research has considered stakeholders such as charging station investors, EV owners, and the distribution network. Various models aim to maximize annual traffic flow captured by fast charging stations while minimizing total investment cost and energy loss (S. Wang et al., 2018), establish multi-objective bi-level planning models (Suo et al., 2016), and optimize the economy considering distribution network security and power quality constraints (Yu et al., 2015). Solution methods for these models include grid and Voronoi diagram algorithms (Xiufan et al., 2017), particle swarm optimization algorithms (Othman et al., 2020), and genetic algorithms (M. Chen et al., 2019).

However, practical problems require consideration beyond the return to investors; the cost of charging, influenced by EV user preferences, charging queue times, travel distance, power, and charging prices, also significantly impacts overall economic benefits and service satisfaction. Addressing these gaps, this study proposes a bi-level optimization model integrating the interests of both charging station investors and EV users. The upper level aims to maximize the profit of charging stations, while the lower level aims to maximize user satisfaction by minimizing charging costs and optimizing charging schedules.

The previous phase of this research determined the required number of commercial charging stations based on the percentage of the population with access to residential charging facilities and their charging behavior (Tarafdar, Gong, et al., 2024; Tarafdar, Zhang, et al., 2024). This study, representing the second phase, focuses on optimally locating these charging stations using a bi-level optimization approach. The bi-level programming model developed ensures efficient charging infrastructure utilization, balancing EV users' needs and the charging stations' operational constraints. This approach integrates the interests of both charging station investors and EV users, optimizing global economic costs while improving user satisfaction with the charging service.

The developed model is applied to the Baltimore Metropolitan Statistical Area (MSA) to determine the optimal number of charging stations. This study integrates real-world Origin-Destination (OD) trip data with census data to investigate the relationship between residential and commercial EV charging infrastructures. The study illustrates the shifting landscape of charging infrastructure demands through scenario analysis for market penetration rates of 0.09%, 0.75%, 1.61%, 5%, 7.5%, and 10%. The 0.09% rate represents the lowest EV market penetration in Maryland, observed in Somerset County. The 0.75% rate reflects the state average, while 1.61% represents the highest penetration found in Montgomery County. For future market projections, penetration rates of 5%, 7.5%, and 10% were chosen to align with ambitious growth targets set by policymakers and the expected expansion of EV adoption driven by technological advancements, infrastructure development, and government incentives. These higher rates simulate potential market conditions as EV adoption continues to grow, helping to understand the long-term impact on charging infrastructure needs. The findings reveal a clear inverse relationship between the availability of residential charging facilities and the need for commercial chargers.

In addition, this study investigates the optimal placement and distribution of commercial EV charging stations within the Baltimore MSA, focusing on a market penetration rate of 0.7%, representing 15,350 EVs and 7,600 households with EVs. Utilizing a bi-level optimization model, the study aims to balance the interests of charging station investors with the satisfaction of EV users by maximizing profits and minimizing charging costs. The analysis reveals significant reductions in the need for commercial charging stations as household adoption of residential chargers increases, particularly at a higher State of Charge (SoC).

These insights highlight the importance of balancing residential and commercial charging infrastructure to meet the evolving needs of EV users. While this research utilizes realistic datasets and advanced modeling techniques, it is important to acknowledge certain limitations concerning input accuracy and data assumptions. Due to the inherently complex and dynamic nature of electric vehicle (EV) adoption, user behavior, traffic patterns, and power grid interactions, the inputs used in the analyses cannot be guaranteed as entirely accurate or exhaustive. Real-world EV charging dynamics involve numerous uncertainties, including fluctuating consumer behavior, variability in traffic conditions, diversity in vehicle battery capabilities, and rapidly evolving technological and infrastructure developments. Capturing all these factors with absolute precision would require extremely detailed, high-resolution datasets, extensive computational resources, and continuous updates to reflect real-time changes, constituting a comprehensive research endeavor beyond the scope of this dissertation. Instead, this study adopts a strategic, approximate estimation approach, aiming primarily to identify general trends, potential infrastructural gaps, and operational challenges associated with the deployment and operation of EV charging infrastructures. The central objective is not exact numerical precision but rather capturing overarching patterns to proactively anticipate key issues in infrastructure planning, power grid management, and service delivery. By highlighting critical points of congestion, infrastructural deficiencies, and operational limitations, the findings provide valuable insights and strategic guidelines for stakeholders such as policymakers, urban planners, utility providers, and infrastructure investors. Future studies can expand upon this foundational research by employing more detailed datasets, dynamic real-time modeling, and sophisticated analytical frameworks to further refine these insights and enhance planning accuracy. Policymakers and utility providers can use these findings to formulate sustainable EV charging strategies, considering market penetration rates, household adoption of charging facilities, and optimal SoC management to reduce reliance on commercial infrastructure. This comprehensive approach provides a robust framework for policymakers and stakeholders to develop sustainable EV charging networks, fostering greater EV adoption and contributing to environmental sustainability.

## *1.2 Objectives*

In the context of rapid EV adoption, ensuring that charging infrastructure evolves to meet user demand and grid capacity is crucial. This research addresses the complexities of designing and deploying a robust charging network, balancing between residential and commercial infrastructure while maintaining grid stability and economic feasibility. The following key questions guide this investigation:

- How does the adoption of residential chargers affect the demand for commercial charging stations?

- What is the optimal method for distributing commercial charging stations to maximize both user access and operational efficiency?

- How can the integration of power grid constraints be optimized to ensure system reliability at different EV market penetration levels?

- How do changes in pricing and charger availability influence user behavior, and how can this be effectively modeled?

- What are the future infrastructure requirements for different levels of EV market penetration, and how can scenario analysis inform these needs?

- How can advanced queuing models be leveraged to effectively manage congestion and optimize the performance of EV charging stations?

By addressing these questions, the research aims to provide a comprehensive framework that integrates user behavior, charging demand, queuing dynamics, and grid constraints into a unified optimization and simulation model. This integrated model will yield critical insights into how residential and commercial EV infrastructure can coexist, adapt, and efficiently manage congestion as the market evolves.

The primary objectives of this research are:

- Develop a predictive model to understand how residential charger adoption impacts the need for commercial charging infrastructure, considering both current and future market penetration rates.

- Formulate a bi-level optimization model for the strategic placement and distribution of commercial charging stations, balancing user convenience and economic feasibility for investors.

- Integrate power grid constraints into the optimization model to ensure that the growing charging demand does not exceed grid capacity, with a particular focus on voltage stability and load management.

- Develop a user behavior simulation model that predicts how pricing strategies and charger availability influence charging patterns, incorporating dynamic pricing and time-of-use rates to shape user behavior.

- Perform scenario analysis to project future infrastructure requirements for different levels of EV market penetration, enabling the anticipation of charging station demand under various adoption scenarios.

- Construct and validate an advanced queuing simulation model to evaluate station performance, analyze congestion dynamics, and optimize charger utilization, facilitating effective management of charging station resources under stochastic demand conditions.

### *1.3 Organization*

To achieve the research objectives, this study has organized the primary research tasks into eight chapters. The core of those tasks and their interrelations are illustrated in **Figure 1**.

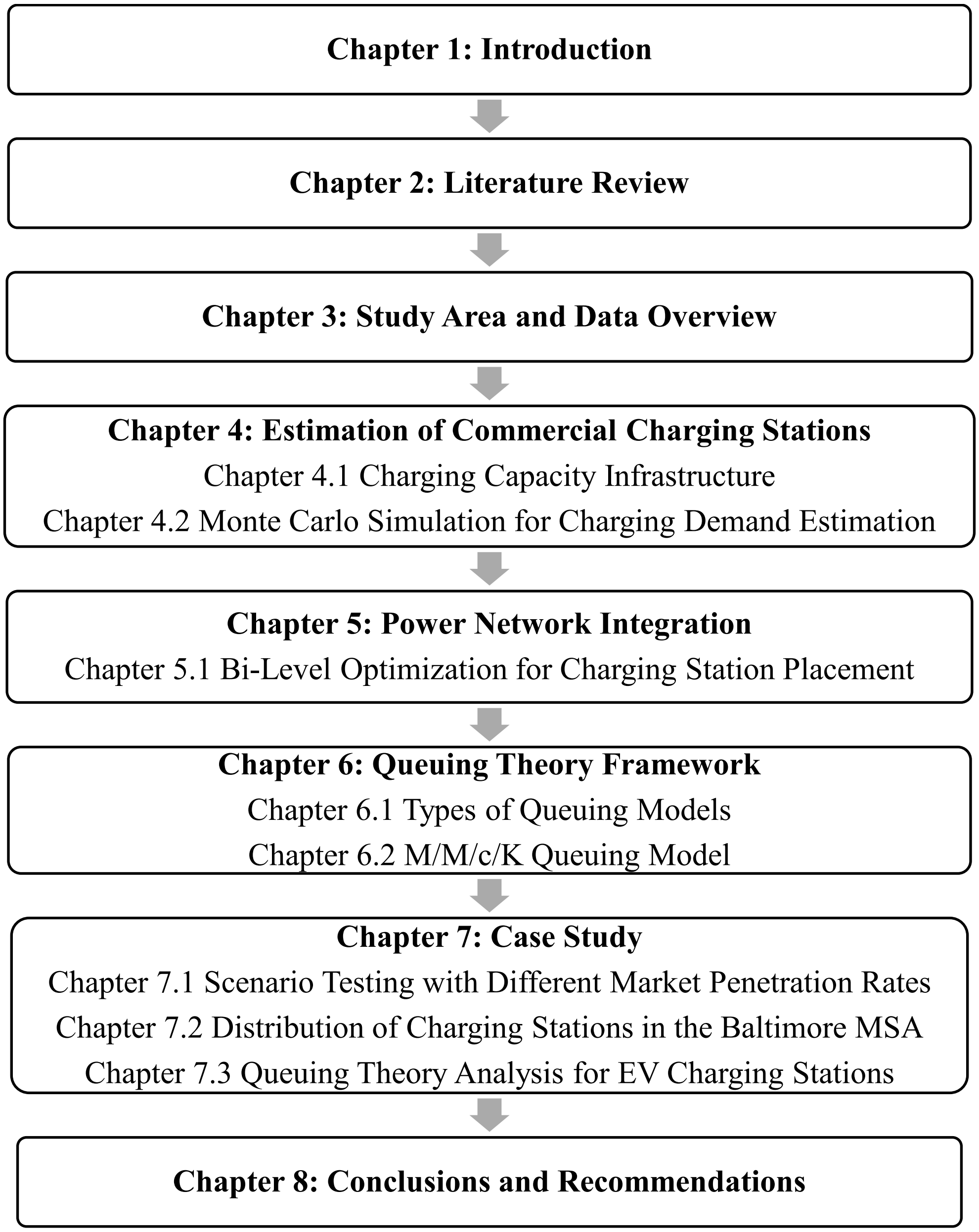


**Figure 1 Dissertation Organization**

As shown in **Figure 1**, this dissertation is structured across seven chapters, each progressively building on the previous to create a comprehensive understanding of the interaction between residential and commercial EV charging infrastructure.

- **Chapter 1** introduces the research background, objectives, and organization of the dissertation. It sets the stage by discussing the challenges of EV infrastructure development in the context of increasing EV adoption rates and presents the main research questions.

- **Chapter 2** provides a detailed literature review on electric vehicle charging infrastructure, focusing on both residential and commercial settings. It examines existing methods for forecasting charging demand, charging station placement models, and strategies for optimizing the integration of these infrastructures. The chapter also explores different optimization techniques used in EV infrastructure planning, including bi-level optimization, dynamic programming, and grid management approaches.

- **Chapter 3** discusses the characteristics of the study area, with a specific focus on the Baltimore MSA. The chapter presents the data sources used, including OD trip data, census information, and grid capacity data. It outlines how these datasets are integrated into the analysis to assess travel demand, EV usage patterns, and the current charging infrastructure landscape. Additionally, it discusses the assumptions made regarding user behavior, EV penetration rates, and charger usage patterns.

- **Chapter 4** presents the methodology for estimating the number of commercial charging stations required based on residential charger adoption rates. It begins with a detailed overview of the Monte Carlo Simulation (MCS) process used to account for the uncertainty in user behavior and charging patterns. The chapter also describes the different market penetration scenarios (e.g., 5%, 7.5%, and 10%) used to generate demand estimates for charging stations and the probability distributions assigned to key variables, such as charging frequency and trip distances. The model also integrates behavioral insights, such as the likelihood of users opting for residential charging over public charging in different urban settings, and the impact of tariff structures on charging decisions. The outputs of this process form the basis for the placement strategy developed in subsequent chapters.

- **Chapter 5** introduces the bi-level optimization model developed for charging station placement. The upper level focuses on maximizing investor profit by strategically locating commercial charging stations while considering factors such as land acquisition costs, proximity to high-demand areas, and competition with other charging stations. The lower-level model is user-centric, optimizing individual charging behavior by minimizing travel time to charging stations and charging costs. This chapter also delves into the technical formulation of the bi-level optimization problem, including the decision variables (e.g., station locations, pricing, user schedules), constraints (e.g., grid capacity, voltage stability, user travel times), and the solution approach. Advanced dynamic programming methods are employed to handle uncertainties in user behavior, grid load, and market fluctuations. Additionally, the model accounts for variations in electricity demand and EV usage, providing a more robust solution for long-term infrastructure planning.

- **Chapter 6** presents an advanced queuing simulation model tailored to analyze the operational dynamics and performance of EV charging stations. Employing an $M/M/c/K$ queuing framework, the chapter focuses on evaluating key performance indicators such as blocking probability, average waiting times, queue lengths, and server utilization. The model explicitly considers stochastic arrival patterns and variable charging durations, enabling a realistic assessment of congestion and station efficiency. Critical system constraints—including stability, capacity limitations, and dynamic pricing impacts—are integrated into the simulation. Additionally, the chapter explores various scenario analyses, such as improvements in charging speeds, higher EV adoption rates, and infrastructure scaling, providing strategic insights into future charging station operations and infrastructure investments.

- **Chapter 7** presents the results of the model simulations, providing a detailed analysis of infrastructure needs under varying market penetration rates, ranging from current levels (e.g., 0.09%) to projected future levels (e.g., 5%, 7.5%, 10%). The chapter discusses the sensitivity of the model to different user adoption rates of residential chargers and evaluates the optimal number and distribution of commercial charging stations under different pricing and charging behavior scenarios. Additionally, it explores the impact of residential charger adoption on reducing the overall demand for commercial charging infrastructure while balancing this against the potential strain on the power grid. The chapter also evaluates the performance of the bi-level optimization model under various grid constraints, including load balancing, voltage stability, and energy pricing fluctuations. Furthermore, the simulation results include a comparison of different dynamic pricing strategies to assess their effectiveness in shaping user charging behavior and mitigating peak demand.

- **Chapter 8** summarizes the key findings, contributions, and practical implications of the research. It also outlines the ongoing work necessary for dissertation completion, particularly in refining the integration of dynamic pricing and real-time data into the optimization model. The chapter concludes with a discussion of potential extensions of the model, such as the incorporation of heavy-duty vehicle charging infrastructure or the expansion to a nationwide level.

# Chapter 2: Literature Review

## *2.1 EV Charging Infrastructure*

EV charging infrastructure is typically categorized as residential and commercial. Residential charging has served as a practical, efficient, and cost-effective solution, particularly for early EV adopters when commercial charging infrastructure was not widespread. This type of charging offers convenience, allowing users to recharge their vehicles overnight without the need for frequent visits to public stations, making it especially appealing for those with access to private garages or driveways. On the other hand, commercial charging facilities benefit EV users by providing fast charging options and extending driving range, which is essential for long-distance travel or for users who do not have access to residential charging. Studies indicate that between 50% to 80% of all PIEV charging events occur at home, underscoring its predominance in the EV charging landscape (Franke & Krems, 2013). Residential charging infrastructure primarily consists of Level 1 (**Figure 2**) and Level 2 (**Figure 3**) charging systems, each catering to different needs; Level 1 typically provides slower charging speeds suitable for overnight use, while Level 2 offers faster rates appropriate for faster charging during shorter parking periods (Nicholas & Tal, 2017).

**Figure 2 Level 1 Charging Infrastructure** (Evenflow Home and Commercial Services, 2024)

**Figure 3 Level 2 Charging Infrastructure** (Mlot, 2016)

The preference for residential charging is primarily driven by its convenience and cost-effectiveness, further supported by installation subsidies (LaMonaca & Ryan, 2022) and time-of-use electricity tariffs, which make overnight charging more economical (Bailey et al., 2015; Dunckley & Tal, 2016). Many countries provide subsidies to encourage EV owners to install residential chargers. For instance, the Maryland Energy Administration (MEA) offers the Maryland EV Charging Station Rebate Program (Maryland Energy Administration, 2023), which offers rebates for acquiring and installing eligible EV charging stations. However, the feasibility of installing residential charging is contingent upon the driver having access to dedicated off-street parking, such as a driveway or garage.

Introducing widespread residential charging infrastructure might pose challenges, as charging patterns could concentrate during peak hours, potentially straining the power grid (Azin et al., 2021; Datta et al., 2020; Roy et al., 2023; Sundstrom & Binding, 2010). Furthermore, difficulty accessing the charging facilities may arise due to traffic constraints (G. Wang et al., 2013), power constraints (Affolabi et al., 2022), or both (Huang et al., 2018; Xiang et al., 2016). Despite the focus on residential charging, the deployment of commercial infrastructure remains crucial, especially for long-range BEV owners who depend on the availability of fast charging along travel corridors to alleviate range anxiety during longer trips (Dong et al., 2014; Figenbaum & Kolbenstvedt, 2016; Neaimeh et al., 2017).

Commercial charging facilities are typically located at sites where vehicles are parked for extended periods, such as shopping centers, airports, hotels, government offices, and various commercial establishments (Alternative Fuels Data Center, 2023). Additionally, fast commercial chargers are commonly found along highway corridors (Erdoğan et al., 2022; Sathaye & Kelley, 2013). These facilities play an important role in shaping the landscape of EV adoption by offering fast and convenient charging solutions for EV owners. The evolution of commercial charging infrastructure (**Figure 4**) is critical to the widespread adoption of EVs. Studies have explored various strategic approaches to optimize commercial electric EVSE placement and economics, such as clustering techniques and flow-capturing location models, to maximize EV accessibility and usage of charging stations (Berman, 1995; Berman et al., 1992; Hodgson, 1990; Ip et al., 2010; Momtazpour et al., 2014). These studies underscore the importance of strategic site selection in metropolitan areas to enhance service coverage and operational efficiency (Kuby & Lim, 2005; Shukla et al., 2011; Upchurch et al., 2009). Moreover, real-world driving data has been used to simulate recharging demands, aiming to minimize missed trips and optimize the commercial charging network (Andrews et al., 2012; Dong et al., 2014). These strategies emphasize the critical need for strategic placement of charging facilities to cater effectively to the growing number of BEV users. Furthermore, recognizing the importance of integrating behavioral responses into planning, some studies have explored activity-based approaches to refine the location strategy of commercial chargers, considering potential users' daily routines and route choices (Jee E Kang & Recker, 2009; Jee Eun Kang & Recker, 2015; Schneider et al., 2014). This understanding aids in developing a charging infrastructure that aligns with current demand and anticipatory growth patterns.

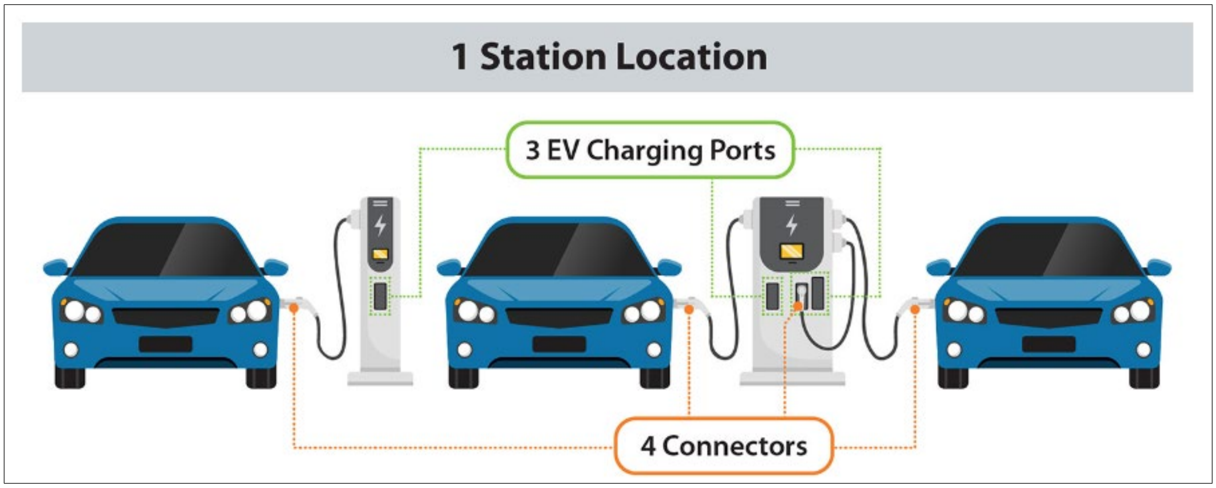


**Figure 4 Commercial EV Charging Infrastructure** (Alternative Fuels Data Center, 2020)

Despite their higher cost compared to residential charging options, commercial charging facilities are essential in addressing the increasing demand for EV charging infrastructure, particularly in urban areas with higher EV adoption rates. In the United States, urban or densely populated regions tend to have concentrated EV ownership, where approximately 82% of all EV sales in 2015 took place within the fifty most populous metropolitan areas (Lutsey et al., 2016). This urban concentration poses a challenge, especially for urban residents living in apartment-style housing, as access to off-street parking and residential EV charging may be limited, hindering EV adoption (Chia et al., 2012). However, the limited availability of commercial charging facilities remains a significant obstacle to widespread EV adoption (Engel et al., 2018). To address this challenge, governments have recently enacted legislation to accelerate the expansion of commercial charging infrastructure in urban areas, intending to meet the growing demand for EV charging and enable efficient system management (Schott et al., 2015). Governments aiming to promote the development of commercial charging networks must strategize efficient ways to invest in the necessary infrastructure while being mindful of the challenge of achieving profitability. As mentioned earlier, a significant portion of EV charging currently takes place at home. However, this trend may shift as commercial charging infrastructure becomes more readily accessible and as EV utilization grows, leading to changes in driver needs and behaviors. Empirical studies have demonstrated that the utilization of various charging infrastructures changes notably as EV adoption increases (Illmann & Kluge, 2020; Narassimhan & Johnson, 2018; Schulz & Rode, 2022; Zou et al., 2020). Therefore, analyzing driver profiles and behaviors is crucial to making informed decisions regarding charging investments.

The impact of EV owners on the charging system has led to the development of incentive programs (X. Li et al., 2020; H. Wang et al., 2023; Zhou et al., 2019). However, substantial groundwork is required to ensure that charging system management caters to the needs of both service providers and consumers. A significant body of different and separate studies on EV networks and charging systems examines the EVCS site selection based on multiple qualitative and quantitative factors (Hosseini & Sarder, 2019). This body of work provides valuable insights into various aspects of EV charging infrastructure, including system design, management strategies, stakeholder engagement, and incentive programs. These studies give a deeper understanding of the challenges and opportunities of establishing a robust and sustainable EV charging ecosystem.

## *2.2 EV Charging Station Location Placement*

EV commercial charging station site selection has become a significant research area due to the necessity of charging infrastructure to support EV adoption and mitigate range anxiety. The siting problem is approached from multiple perspectives, including company-driven and government-driven initiatives. From the company perspective, Location Routing Problems (LRP) integrate routing plans with charging station locations. For instance, Yang and Sun (Yang & Sun, 2015) introduced an LRP for battery swap stations, while Li-ying and Yuan-Bin (Li-ying & Yuan-bin, 2015) explored multiple charging station LRPs with time windows. Goeke et al. (Goeke et al., 2015) improved solutions for battery swap station LRPs using adaptive variable neighborhood search algorithms. The government perspective focuses on deploying commercial recharging infrastructure to boost EV market penetration. Mak et al. (Mak et al., 2013) developed robust optimization models for battery-swapping infrastructures, and Xi et al. (Xi et al., 2013) applied a simulation-optimization model to locate EV chargers in central Ohio. Other studies (Cai et al., 2014; Dong et al., 2014; Namdeo et al., 2014) utilized large-scale trajectory data and geospatial modeling to evaluate and develop commercial charging infrastructure. Li et al. (S. Li et al., 2016) developed a multi-period, multi-path refueling location model to expand commercial EV charging networks, dynamically satisfying growing origin-destination trips in the EV market (Hu, Martinez, et al., 2017; Hu, Zou, et al., 2017).

Different optimization techniques have been employed to tackle the charging station siting problem. Meng et al. (Meng et al., 2020) utilized geographic area theory to analyze regional layout characteristics for planning charging station locations, providing insights into spatial distribution patterns. Wu et al. (Y. Wu et al., 2017) proposed a Triangular Intuitionistic Fuzzy Number (TIFN)-based structure considering economic, social, environmental, and planning factors. Ademulegun et al. (Ademulegun et al., 2022) developed a strategy incorporating technical-physical-socio-economic factors, which demonstrated the importance of a holistic approach to planning. He et al. (S. Y. He et al., 2016) compared models like the ensemble coverage model and the p-median model, with the p-median model demonstrating superior results in optimizing station locations for maximum coverage. While these studies contributed significantly to EV charging infrastructure planning, several limitations persisted, including the inability to incorporate dynamic traffic flows, handle large real-time datasets, and address multiple conflicting objectives. This study addresses these challenges by combining real-world Origin-Destination (OD) data with Monte Carlo Simulation (MCS) to model charging behavior dynamically, incorporating power load constraints and employing a multi-objective bi-level optimization approach to balance profitability and charging costs.

Pan et al. (Pan et al., 2020) created a siting model to maximize EV drivers' current activities, and Cao et al. (Cao et al., 2021) used a probability calculating model to forecast charging load and minimize user travel costs. Bai et al. (Bai et al., 2019) applied a non-dominated ranking genetic algorithm (NSGA-II) combined with linear programming and neighborhood search, achieving high efficiency in multi-objective optimizations. Krol and Sierpinski (Król & Sierpiński, 2022) used a genetic algorithm and fuzzy logic for a medium-sized city case study, underscoring the need for a flexible, heuristic-based approach. While these studies provided valuable insights into user-centric optimization and heuristic methods, their application was limited when scaling to larger metropolitan areas, handling the complexity of multi-objective systems, and integrating both residential and commercial charging needs. This study addresses these challenges by employing a scalable bi-level optimization model that integrates real-world OD data, balancing system profitability and user satisfaction, and incorporating both residential and commercial charging demands.

Yi et al. (Yi et al., 2022) developed a modified geographic PageRank (MGPR) model to estimate charging demand based on trip origin-destination (OD) and social parameters. Wang et al. (Xu Wang et al., 2018) utilized artificial intelligence (AI) to evaluate urban EV driving routes and determine charging station locations. Bi-level optimization has also been prominently featured in EV charging station siting research. For instance, Janjic et al. (Janjić et al., 2021) used a p-median approach with hierarchical analysis to optimize construction cost, charging station distance, parking, and distribution network. Hodgson (Hodgson, 1990) and Kuby and Lim (Kuby & Lim, 2005) introduced flow capture models considering EV range constraints, although they faced limitations with fixed service radii and single-objective optimizations. Despite the contributions of these studies, limitations remain in terms of reliance on static demand estimates, high computational requirements, and single-objective optimizations. This study addresses these limitations by adopting dynamic demand models, utilizing MCS for demand estimation to ensure computational efficiency, and employing a bi-level optimization framework that balances investor profits with user satisfaction through multiple objectives, optimizing both profitability and user convenience under different market penetration scenarios.

Recent studies aim to address these gaps by integrating multiple subjects and objectives—for example, Meng et al. (Meng et al., 2020) proposed an asymptotic coverage model, and a multi-objective NSGA-II was used to maximize system benefits and coverage level. Multiple studies (Liu et al., 2021; Sadeghi-Barzani et al., 2014; Wei et al., 2017; Xiang et al., 2016; Zhang et al.,

2019) investigated various factors in planning EV charging stations, considering traffic constraints, EV user distribution, and the relationship between traffic flow data, the grid, and the traffic network.

Incorporating renewable energy sources and storage devices into EV charging infrastructure planning has gained traction. Previous research (Amer et al., 2021; Domínguez-Navarro et al., 2019; Erdinç et al., 2017; Hadian et al., 2020; Ji et al., 2020; Shojaabadi et al., 2016; Tao et al., 2019; S. Wang et al., 2020; W. Wang et al., 2020) explored integrating photovoltaic (PV) and wind power, reducing operating costs and improving renewable energy consumption rates. Moreover, fast charging technology has driven the need for comprehensive planning of charging stations with varying rates. However, these studies did not fully explore the implications of integrating renewable sources with power grid constraints and EV charging patterns, a gap that this study seeks to address by factoring power load constraints directly into the bi-level model. This ensures that charging stations can operate efficiently under different energy-sourcing conditions while maintaining grid stability.

Zeb et al. (Zeb et al., 2020) focused on this by planning three-level charging posts. Mixed-Integer Quadratic Constraint Programming (MIQCP) models have been proposed to coordinate traffic and distribution networks, energy storage systems, and fast charging stations (Gan et al., 2020). As proposed by Zeng et al. (Zeng et al., 2020), bi-level programming models have also emerged, employing Karush-Kuhn-Tucker (KKT) conditions, McCormick relaxation, and Big M methods to solve these problems effectively. He et al. (C. He et al., 2019) further extend functionality with integrated power station models. While these studies have made significant contributions, limitations remain in addressing real-time grid fluctuations, computational complexity, and dynamic EV usage patterns. This study addresses these issues by incorporating dynamic pricing, simplifying constraints for faster computation, and integrating real-time traffic data and energy storage systems to optimize charging station placement and operation.

The extensive body of research highlights the need for sophisticated optimization techniques and multi-faceted approaches to plan and deploy EV charging infrastructure effectively. Addressing user preferences, economic factors, renewable energy integration, and advanced optimization methods remains crucial for advancing EV adoption and infrastructure development.

### *2.3 EV and Power Grid Network*

The integration of EVs into modern transportation systems has sparked a growing body of research addressing various aspects of charging infrastructure, user behavior, and grid interaction. Researchers have examined charging patterns and the strategies for optimal EV scheduling (Brady & O'Mahony, 2016; Shepero & Munkhammar, 2018; F. Wu & Sioshansi, 2017), along with dynamic pricing models designed to balance the costs for users and providers (Subramanian & Das, 2019; Xu et al., 2020). Investigations into the impacts of charging behavior on power grids highlight the challenges posed by increased electricity demand (Kapustin & Grushevenko, 2020). Complementing these technical studies, work has also focused on EV market development (Y. He et al., 2017) and the behavioral drivers behind customer adoption (Cui et al., 2021; X.-W. Wang et al., 2021).

As the EV industry continues to expand, the interaction between EVs and the power grid becomes increasingly complex. Hariri et al. (Hariri et al., 2021) analyzed the reliability of smart grids, incorporating the stochastic nature of plug-in hybrid EV usage. Similarly, Zheng et al. (Zheng et al., 2021) proposed a vehicle-to-grid (V2G) framework that explored various operational modes, contributing to more efficient peak load management. On a broader scale, Stiasny et al. (Stiasny et al., 2021) investigated how EV charging demand affects low-voltage distribution networks while also identifying gaps in control strategies that could stabilize grid performance.

In the quest for enhancing grid-EV coordination, optimization methods have emerged as vital tools. For example, Su et al. (J. Su et al., 2020) introduced a rolling horizon scheduling model, leveraging genetic algorithms to manage both EV charging schedules and electricity market profits. Hierarchical optimization models, such as the one developed by DeForest et al. (DeForest et al., 2018), have provided further insights into balancing daily EV charging with energy market participation. Alinejad et al. (Alinejad et al., 2021) designed a model aimed at managing the interaction between parking operators and EV owners by optimizing pricing and usage behavior and introducing penalties to guide efficient charging behavior.

Despite these advancements, some models encounter practical limitations when applied on a larger scale. Subramanian and Das (Subramanian & Das, 2019) proposed a two-layer optimization model that addresses both grid management and user behavior, but the computational complexity of the approach presents implementation challenges. Wu and Sioshansi (F. Wu & Sioshansi, 2017) expanded on this by developing a two-stage stochastic model that integrates centralized EV charging control with MCS techniques to efficiently address uncertainties in user behavior and grid load. However, one critical area that remains underexplored is how different pricing strategies might influence user charging habits and behaviors.

A key focus of recent studies has also been the integration of renewable energy into EV charging systems. Sterchele et al. (Sterchele et al., 2020) found that controlled charging strategies, coupled with flexible EV battery management, significantly enhance the integration of renewable energy sources like wind and solar into the grid. These strategies have the potential to reduce overall system costs by aligning charging schedules with periods of high renewable generation. Expanding on this, Sun (Sun, 2021) introduced a dynamic charging model that incorporates time-of-use (TOU) pricing to optimize the placement of EV charging stations and improve the utilization of renewable energy systems.

However, challenges remain when modeling real-world EV user behaviors. For instance, Welzel et al. (Welzel et al., 2021) proposed a non-linear optimization model for managing EV charging within a mixed energy system, including a photovoltaic setup, but the actual charging behaviors captured in the model were overly simplistic. In contrast, Lee et al. (Lee et al., 2019) leveraged real-world data from the adaptive charging dataset (ACN-data) to study EV user behaviors, although limitations in data collection point to the need for more comprehensive arrival and departure time distributions.

To address the increasing complexity of renewable energy and EV grid interactions, Jovanovic et al. (Raka Jovanovic et al., 2021) developed a bi-objective model that optimizes flexible EV charging demand in a way that mitigates the effects of the "duck curve" caused by fluctuating solar power generation. This model utilized quadratic programming to optimize the ramp-up requirements of the grid while also maximizing charging station profits. Through careful management of EV charging and discharging behaviors, these optimization strategies have demonstrated the potential to stabilize grid loads, reduce peak demand, and promote load-shifting behaviors that align with renewable energy availability (R Jovanovic et al., 2020).

In conclusion, as the penetration of renewable energy sources increases, EV charging strategies and infrastructure must evolve to accommodate grid fluctuations and renewable intermittency. While significant progress has been made in optimizing charging schedules and infrastructure locations, the challenge lies in designing models that more accurately reflect real-world behaviors and pricing mechanisms. Future research must continue to explore how these systems can be scaled while maintaining grid reliability and promoting renewable energy integration.

### *2.4 Queuing Models in EV Charging Infrastructure Analysis*

The rapid proliferation of EVs poses significant challenges to existing electric grid infrastructures, primarily due to increased congestion at charging stations. To address these challenges, researchers have extensively leveraged queuing theory to analyze EV charging patterns, congestion management, and resource optimization. Queuing models, such as the $M/M/c/K$ frameworks, are particularly suited for EV charging scenarios due to their effectiveness in handling random arrival patterns and varying charging durations.

A common approach in queuing theory applications is the assumption of a Poisson arrival process for EVs, which effectively captures the stochastic nature of vehicle arrivals at charging stations (Aveklouris et al., 2017; Liang et al., 2014; Xudong Wang et al., 2017). This Poisson-based approach provides a realistic representation of independent arrival events occurring randomly over time, making it ideal for modeling unpredictable demand patterns at charging stations (Clement-Nyns et al., 2009; Esmailirad et al., 2021; G. Li & Zhang, 2012).

Charging duration variability is often modeled using an exponential distribution, reflecting the broad diversity in vehicle battery states and charging needs. Esmailirad et al. (Esmailirad et al., 2021) explored an extended $M/M/K/K$ queuing model to assess the profitability and operational efficiency of multiservice EV charging stations, highlighting how queuing theory can accommodate multiple services, including battery swapping and discharging, in addition to regular charging. Their findings underscore the effectiveness of multi-dimensional queuing models in evaluating economic viability and managing service demand in complex charging environments.

To manage fair resource allocation among multiple charging points, Wang et al. (Xudong Wang et al., 2017) developed a multi-server generalized processor sharing (MGPS) model. This framework addresses fairness by equitably distributing electricity among vehicles, ensuring balanced utilization of charging resources. Their model, termed physical multi-server generalized processor sharing (pMGPS), emphasizes fairness but faces practical limitations due to its fluid-flow model assumptions. To overcome this, they further proposed a packetized approach—physical start-time fair queuing (pSTFQ)—which maintains a balance between fairness and practical applicability by scheduling discrete charging tasks effectively.

Another critical aspect studied through queuing theory is the impact of EV charging on distribution grids. Sortomme et al. (Sortomme et al., 2010) proposed coordinated charging strategies to minimize distribution system losses. By integrating queuing models with dynamic electricity tariffs, this strategy effectively manages grid stress while optimizing consumer convenience and operational cost-effectiveness. The incorporation of dynamic pricing within queuing models offers a mechanism for demand management, aligning charging patterns with periods of low grid stress and lower energy costs.

Several studies have introduced advanced analytical approaches, such as fluid and diffusion approximations, to enhance model realism and scalability. Remerova et al. (Remerova et al., 2014) applied fluid limits to manage large-scale EV charging systems, facilitating computational efficiency when exact solutions become impractical. Similarly, Kempker et al. (Kempker et al., 2016) emphasized optimizing EV charging strategies within smart grids by employing diffusion models, allowing for effective management of stochastic demand and capacity constraints.

Aveklouris et al. (Aveklouris et al., 2017) further analyzed congestion issues by introducing equilibrium queuing models, emphasizing dual congestion—availability of charging spaces and power constraints. They proposed models considering random parking and energy demands, contributing valuable insights into both infrastructure planning and policy development. Their work closely parallels processor-sharing queues with impatience, highlighting scenarios where EVs might leave without fully charging due to extended wait times (Garnett et al., 2002; Gromoll et al., 2006; Larson & Sasanuma, 2007).

Bayram et al. (Bayram et al., 2013) discussed the social optimization of charging strategies through queuing theory, presenting gradient schedulers that minimize delay and optimize social welfare. These models are particularly useful for managing fast-charging station networks, providing strategic insights into scheduling and capacity planning (Fleming et al., 1994; Turitsyn et al., 2010; Yudovina & Michailidis, 2014).

The interplay between fairness, resource limitations, and user behavior was explored by Zeltyn and Mandelbaum (Zeltyn & Mandelbaum, 2005), who analyzed customer impatience in queueing systems. Their insights can significantly influence EV charging strategies, informing infrastructure developers on minimizing customer dissatisfaction and optimizing service performance (Pang et al., 2007; W. Su & Chow, 2011).

Further advanced queueing network analyses proposed by Carvalho et al. (Carvalho et al., 2015), Liang et al. (Liang et al., 2014), Li & Zhang (G. Li & Zhang, 2012), and additional studies such as Clement-Nyns et al. (Clement-Nyns et al., 2009), Pang et al. (Pang et al., 2007), and Larson & Sasanuma (Larson & Sasanuma, 2007), addressed critical behavior in charging networks, underscoring how network topology and user interactions significantly impact congestion management.

Moreover, layered queuing networks have been introduced to analyze interactive congestion at multiple levels, where entities have dual roles as both customers and servers. These studies, such as those by Aveklouris et al. (Aveklouris et al., 2017), emphasize how EV chargers simultaneously act as consumers of grid resources, highlighting complex interdependencies between infrastructure layers (Aveklouris et al., 2017; G. Li & Zhang, 2012; Zeltyn & Mandelbaum, 2005).

## Chapter 3: Overview and Characteristics of the Study Area

### *3.1 Baltimore Metropolitan Statistical Area (MSA)*

To model the impacts of residential charging facilities on the demands of commercial charging infrastructure, the Baltimore-Columbia-Towson MSA, commonly referred to as the Baltimore MSA, is selected as the study site. The Baltimore MSA comprises six counties and one independent city, namely Anne Arundel, Baltimore City and County, Carroll, Harford, Howard, and Queen Anne's, with a combined population of approximately 3 million (Wikipedia, 2023). **Figure 5** illustrates the study area.

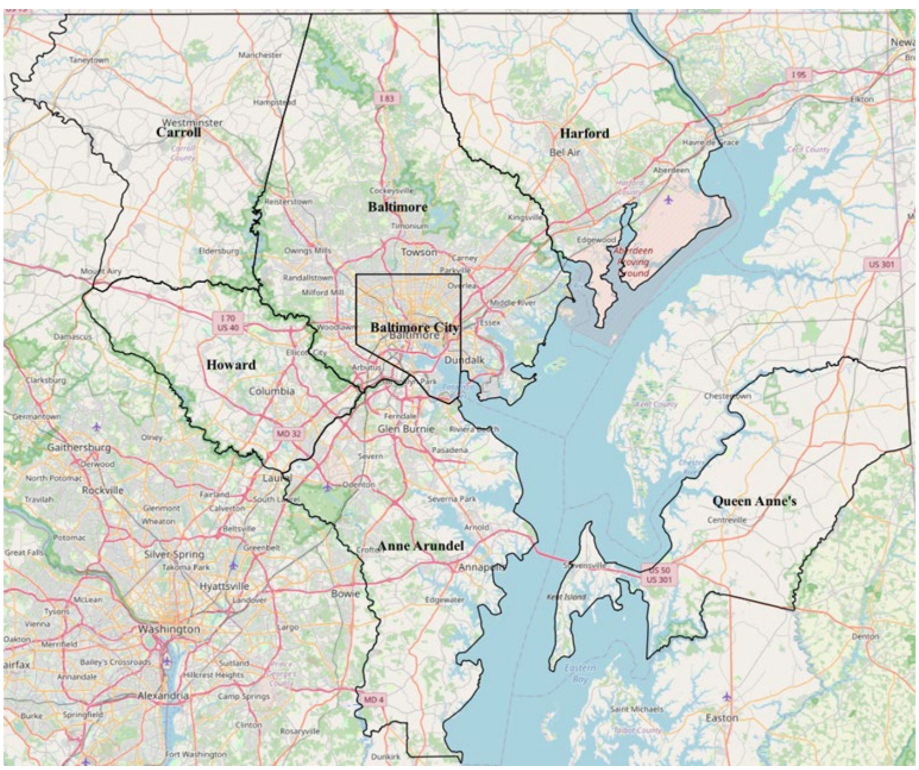


**Figure 5 Study Area**

### *3.2 Travel Demand*

The OD trip data from the Regional Integrated Transportation Information System (RITIS) (The Center for Advanced Transportation Technology (CATT) Laboratory at the University of Maryland, 2017) were employed in this study to model the demand for EV charging. RITIS is a multifunctional platform catering to various transportation stakeholders. The system hosts various data types, ranging from traffic volume, speed, and vehicle class data from sensors to crowdsourced information from platforms such as Waze. This OD trip data obtained from RITIS offers insights into trip origins, destinations, and, in some cases, the routes taken. To ensure privacy, private data aggregator services anonymize the OD data.

The study collected OD data for all 1397 Traffic Analysis Zones (TAZs) in the Baltimore MSA. This dataset spans all seven days of the week, from 8 AM to 8 PM, covering 2018 through 2022, focusing specifically on Light and Medium-Duty Vehicles. The OD data is integrated with the Baltimore Round 10 Cooperative Forecast (Bolton, 2022) to gain further insights into the population movement within the study area. This forecast provides population, household, and employment forecasts at the TAZ 2020 level, thereby enhancing the understanding of how the population moves within the study area. **Table 1** below shows some of the key information utilized in the analysis based on the forecast data. The integrated OD-Forecast data enables the modeling of travel patterns in the subsequent MCS.

**Table 1 Round 10 Cooperative Forecasts Attributes** (Bolton, 2022)

| **Field** | **Description** |
|---|---|
| STATEFP20 | State Federal Information Processing System (FIPS) code |
| COUNTYFP20 | County FIPS code |
| NAME | 2020 TAZ name |
| TAZ20 | 2020 Baltimore Metropolitan Council Traffic Analysis Zone number |
| Pop20 | 2020 Population |
| HHs20 | 2020 Number of households |
| Emp20 | 2020 Number of jobs |

### *3.3 EV Profile*

According to the Baltimore Round 10 Cooperative Forecast data, the Baltimore MSA has 1,097,265 households. Estimations for the total number of vehicles in this area are derived from a 2013 paper (Cirillo & Liu, 2013), which calculates the vehicle ownership percentages in the State of Maryland using the data from the 2009 National Household Travel Survey (NHTS) (Federal Highway Administration (FHWA), 2009). **Table 2** below shows vehicle ownership in Maryland.

This ownership distribution yields a total of 2,216,476 vehicles within the study area. The EV market penetration rate determines the number of EVs.

**Table 2 Vehicle Ownership Data in the State of Maryland (2009)** (Cirillo & Liu, 2013)

| **Vehicle Ownership** | **2009 Percentages** |
|---|---|
| 0 car households | 4.92 |
| 1 car households | 24.92 |
| 2 car households | 43.39 |
| 3 car households | 19.08 |
| 4+ car households | 7.69 |
| Total | 100 |
| Average car ownership per household | 2.02 |

A comparative analysis will be conducted to examine various scenarios of current EV market penetration rates within the study area, drawing on a study by PlugInSites (Lanny, 2021) comparing Maryland's PIEV adoption by county. The study highlighted significant differences in the number of PIHVs registered per 100,000 residents, particularly between suburban counties and more rural areas. Montgomery and Somerset counties have the highest (1.61%) and lowest (0.09%)

percentages of PIEVs (**Figure 6**), respectively, with 0.75% representing the state average EV adoption rate.

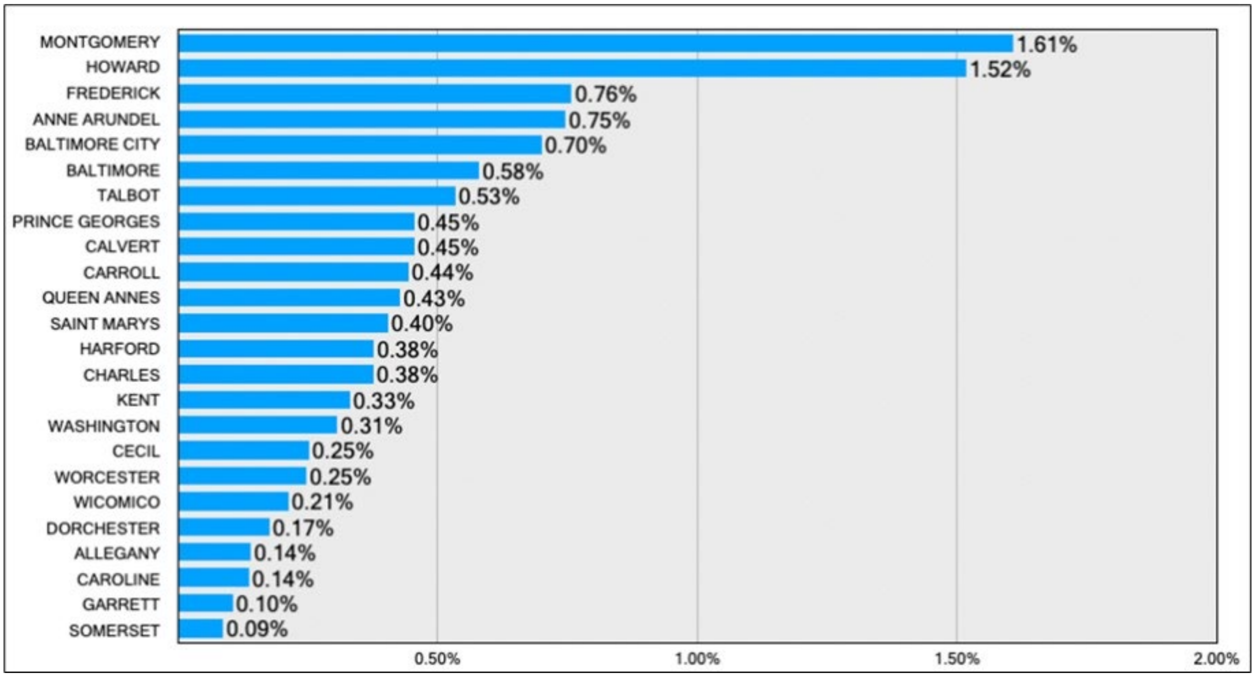


**Figure 6 PIEVs as a Percentage of All Vehicles Registered in Each Maryland County as of August 2021** (Lanny, 2021)

The study will further explore the implications of hypothetical market penetration rates of 5%, 7.5%, and 10% to forecast future trends in charging facility requirements. **Table 3** below summarizes the estimated number of EVs for each market penetration rate based on the spreadsheet data:

**Table 3 Total Number of EVs for Different Market Penetration Rates in the Baltimore MSA**

| Market Penetration Rate (%) | Number of EVs | Market Penetration Rate (%) | Number of EVs |
|---|---|---|---|
| 0.09 | 1,974 | 5 | 109,250 |
| 0.75 | 16,450 | 7.5 | 164,125 |
| 1.61 | 35,305 | 10 | 219,281 |

## Chapter 4: Estimation of Commercial Charging Stations

This study employs Monte Carlo Simulation (MCS) to model the stochastic EV charging demand using static travel demand and EV profiles. This approach addresses the inherent complexity and stochasticity arising from diverse travel patterns, EV characteristics, and the capacity of charging infrastructure. The EV travel demand is determined using collected real-world Origin-Destination (OD) trip data, travel surveys, and travel demand forecasting models. EV profiles, such as EV market penetration rate, EV driving range, and charging infrastructure capacity, are obtained from relevant standards and literature. **Figure 7** below provides an overview of the modeling, along with the datasets employed in this study.

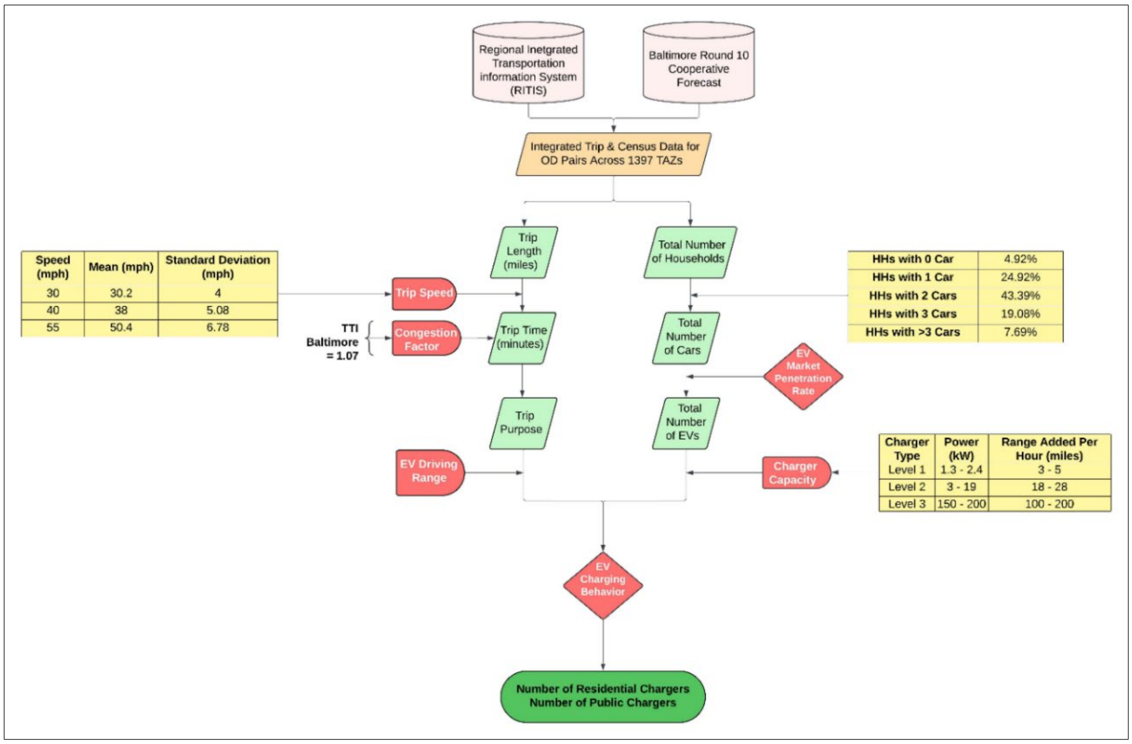


**Figure 7 Model Overview**

*4.1 Charging Infrastructure Capacity*

In the USA, various types of EV charging equipment offer different charging rates. The common EV charging equipment rating system includes Level 1 for slow charging (1.3 – 2.4 kW), Level 2 for semi-fast to fast charging using AC power (3 – 19 kW), and Level 3 (150 – 200 kW) for DC fast charging (DCFC) (U.S. Department of Transportation, 2023). Level 1 chargers, utilizing a standard residential 120-volt AC outlet, typically require around 40 to more than 50 hours to fully charge a BEV to 80% from empty or 5 to 6 hours for a PHEV. Level 2 chargers, commonly found at home, workplaces, and commercial charging stations, provide faster charging through 240V (residential) or 208V (commercial) electrical service, capable of charging a BEV to 80% in 4 to 10 hours or a PHEV in 1 to 2 hours. Conversely, DCFC equipment installed along busy routes can charge a BEV to 80% in 20 minutes to an hour, although most PHEVs are incompatible with DCFC chargers. The driving range added per hour is 3-5 miles, 18-28 miles, and 100-200 miles for levels 1, 2, and 3 chargers, respectively (FreeWire Technologies, 2024).

Commercial charging facilities are assumed to provide Level 2 and Level 3 chargers. This study considers sample vehicles with an average driving range of around 205 miles (Alternative Fuels Data Center, 2024). Vehicles in the study follow a stochastic process to select charging facilities along their route based on their state of charge (SoC) and trip length. It is assumed that only one EV can charge at home, while commercial charging facilities can simultaneously charge at least four EVs (Federal Highway Administration (FHWA) & U.S. Department of Transportation (DOT), 2024).

*4.2 Monte Carlo Simulation for Charging Demand Estimation*

Recent studies have employed probabilistic models to explore EV charging patterns (Argade et al., 2012; Ul-Haq et al., 2018). In contrast to the conventional deterministic approach, probabilistic models recognize the inherent stochastic nature of EV users' travel behavior and charging patterns, providing a more realistic representation of real-world scenarios. Extensive testing and comparisons with deterministic approaches have confirmed the superior performance and accuracy of the probabilistic model in capturing the true nature of EV charging patterns. As one model incorporating stochastic elements, EV trips and charging events are generated using MCS by sampling from probability distributions for key parameters. This approach enables the simulation to capture a wide range of possible scenarios, allowing for flexibility in modeling diverse trip characteristics, charging strategies, and charging system configurations. Several important factors are considered in MCS, including travel frequency, trip length, vehicle speed, trip purpose, trip departure times, availability of residential charging options, etc.

Using travel demand data, the MCS first estimates the total number of daily EV trips as a percentage of the total trips, acknowledging that not all EVs make trips every day. The travel distances and times are determined for each trip purpose, and the likelihood of Home-Based Non-Work (HBNW) and Home-Based Other (HBO) trips following Home-Based Work (HBW) trips is incorporated. The simulation then computes travel distances for each category. Departure and arrival times are generated within 24 hours using random sampling techniques considering peak-hour congestion, reflecting realistic traffic conditions. This comprehensive approach allows for an in-depth analysis of daily EV travel patterns and charging requirements. Charging durations and locations—whether residential or commercial—are simulated using stochastic factors, such as charging power levels.

By executing the MCS iteratively for a large number of trials, a comprehensive understanding of EV behavior and charging infrastructure utilization is attained. **Figure 8** below outlines the process. The MCS outputs two key sets of EV charging events: one for charging events at home and another for charging at commercial charging facilities along the travel routes. Each set captures diverse charging behaviors and their implications on the demand for commercial charging infrastructure. The simulation also explores the impacts of different levels of EV market penetration.

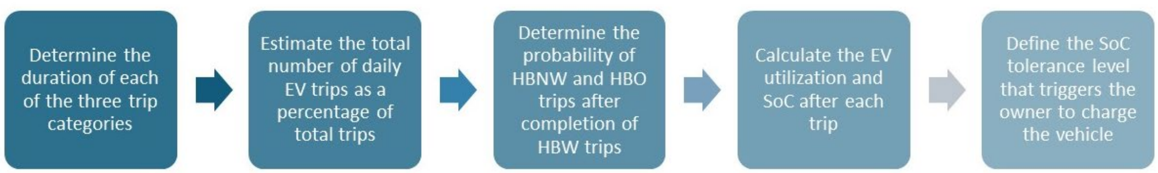


**Figure 8 Flowchart Depicting EV Load Estimation in the Daily Routine Estimation Process**

The first step is understanding trip duration, which is crucial for determining the battery usage of EVs. The integrated OD-Forecast data enables the calculation of trip lengths based on trip purposes, as different types of trips often vary in travel distance or time. Commuting trips to work or school typically exhibit shorter durations, while longer trips are commonly associated with leisure and vacation activities. Household travel survey datasets are utilized to facilitate this categorization of daily trips based on their purpose (Stopher & Greaves, 2007). For this study, three broad categories of trips originating from residential locations are considered:

1. HBW: This category includes trips to work or school, primarily routine trips. The average duration of these trips tends to be shorter than other categories.

2. HBNW: Trips falling under this category are routine, including shopping or running errands. The average length of these trips is typically longer than HBW trips.

3. HBO: This category primarily covers leisure and vacation-related trips. Trips in this category are the longest among the three mentioned above.

The Euclidean distances between the OD pairs are used to measure trip length, given the lack of detailed route data in the study area. Because the exact purposes of trips (such as work or non-work) cannot be determined from the available data, this study organizes trips by their distances. For practical purposes, trips shorter than 15 miles are categorized as HBW, between 15 and 30 miles as HBNW, and those over 30 miles as HBO. This approach is based on the assumption that shorter trips are likely for daily commutes or routine activities, while longer trips could serve other purposes. This method offers a logical way to group trips based on length without more specific data about their purpose. The geographical coordinates of TAZ centroids are used to calculate these trip distances. Intra-zone trips, resulting in zero-mile distances, are filtered out before the remaining trips are categorized into HBW, HBNW, and HBO.

Similarly, vehicle speeds are assumed to follow a normal distribution (Berry & Belmont, 1951) for each trip category, with means speeds of 30, 40, and 55 mph, respectively. The rationale behind this assumption is that since most HBW trips are short, they predominantly traverse local roads with lower speed limits. In contrast, HBNW and HBO trips traverse highways with higher speed limits to some extent. The study employs these speeds to calculate travel times based on travel distances, which are used later in estimating departure times, arrival times, and other important information for the MCS.

The subsequent step involves determining the number of EV trips daily (Ul-Haq et al., 2018). This study assumes that EVs have the possibility to undertake multiple trips within a single day. Therefore, the total number of EVs within the study area may not equal the number of charging events occurring within the same timeframe. To address this, MCS incorporates risk factors into the quantitative analysis. This approach facilitates the consideration of uncertainties by generating distributions that represent probable outcome values. The probabilities associated with specific trip purposes are formulated using Equations (1) and (2).

$$\mathrm{N}_{(\mathrm{u})} = EV_{tot} * N_{avg} * \prod_{r=1}^{U} \rho_{(r)} \tag{1}$$

where $\rho_{(r)}$ is the probability of a trip occurring with the purpose $r$; $U$, $N$, and $N_{avg}$ represent the number of trip purpose categories, the number of trips for the category $u$, and average daily trips, respectively. $EV_{tot}$ denotes the total number of EVs in the study area.

The departure, arrival, and travel times are computed for each trip simulated by the MCS. A congestion factor will be incorporated into the travel time to account for increased travel times during peak periods (8-9 AM and 5-6 PM). This factor is estimated using the travel time index for the Baltimore MSA (Bureau of Transportation Statistics 2024). Upon the completion of a trip, the State of Charge (SoC) of an EV is reduced due to the energy consumed during the trip. The SoC after the trip is then estimated based on the initial SoC and the total travel time. For EV owners with residential charging options, two scenarios with different initial SoCs (i.e., the SoC before the daily trips) of 80% or 50% of the full charge are assumed. The 80% SoC reflects the optimal charge level that balances battery health and driving range (Craig Cole, 2024), while 50% SoC represents a typical threshold for ensuring sufficient charge for immediate trips without causing range anxiety (Azin et al., 2021). For those without residential charging options, the initial SoC is assumed to be 50%, considering the cost and time required for charging at commercial stations. The comparison between the remaining charge in the EV battery and the EV owner's charge threshold determines whether the vehicle can continue with other trips or requires charging at commercial charging facilities before the next trip. This study assumes that EVs with less than 30% (Azin et al., 2021) charge will actively seek out commercial charging facilities to recharge. As a result, the number of EV charging events at commercial facilities along the route can be calculated.

Ultimately, the required number of commercial chargers needed under various residential EV charging infrastructure adoption scenarios is determined. Firstly, scenarios with various "residential charging percentages," representing the percentage of EV owners installing residential chargers, ranging from 0% to 100%, are examined. For each residential charging percentage, the proportion of households with EVs is computed using the EV penetration rate and the total number of households. As discussed earlier, the initial SoC for residential charging is set to either 80% or 50% for each scenario. Subsequently, the total number of residential chargers is obtained by multiplying the number of EV-owning households by the corresponding residential charger percentage, reflecting the expected deployment of residential charging infrastructure.

Once the number of residential chargers is determined, the remaining EV charging events requiring commercial charging are identified. This includes charging events at commercial facilities along the route due to low SoC, and originally, residential charging events were replaced by commercial charging due to the absence of residential charging options. Charging at commercial facilities involves selecting the charger level, with 82% using Level 2 chargers and 18% using Level 3 chargers. The range added per hour is calculated based on the selected charger level. The required charging time to reach the next trip or to full capacity is then calculated. Finally, the total number of commercial chargers is computed by dividing the EV charging events necessitating commercial charging by the chosen charging capacity.

**Table 4** below provides the pseudocode of the MCS.

**Table 4 MCS Pseudocode for EV Charging Algorithm**

```
Define Parameters
Market Penetration Rate ← x%
Total Number of Vehicles ← N
Total EVs ← x% × N
Results for Home and Public Charging ← []
```

```
Simulate Charging:
   for i in range(length(Departure Times)) do
      Select Charging Power and Range Added per Hour
      Charging Time ← EV Driving Range / Range Added per Hour
      Adjust Departure and Arrival Times
   end for
Perform MCS for EVs:
   for i in range(Total EV Trips per Day) do
      Departure Times, Arrival Times, Travel Times ← Estimate Departure Arrival Travel Time()
      Results for Home and Public Charging.append((Departure Times, Arrival Times, Travel Times))
   end for
Charging EVs after Trips:
   Initialize Home Charging Count, Public Charging Count
   Set Home Charger Percentages ← [0, 0.5, 0.6, 0.7, 0.8, 0.9]
   for home charger percentage in Home Charger Percentages do
      Set Probability of Home Charging ← home charger percentage
      Set Probability of Public Charging ← 1 - home charger percentage
      Initialize SoC to either 0.8 or 0.5
      for result in Results for Home and Public Charging do
         Departure Times, Arrival Times, Travel Times ← result
         for i in range(length(Travel Times)) do
            SoC After Trip ← Initial SoC - Travel Times[i] × n
            if SoC After Trip ≥ 0.3 then
               Home Charging Count++
               Initial SoC ← SoC After Trip
            else
               Public Charging Count++
               Select charger level (82% Level 2, 18% Level 3)
               Calculate range added per hour and charging times
               if i+1 < len(Departure Times) then
                  Adjust Initial SoC based on Gap between Trips and Charging Time
                  Adjust Travel Times based on Peak Traffic Congestion Hours
               end if
            end if
         end for
      end for
   end for
Handle exceptions:
   for result in Results for Home and Public Charging do
      Departure Times, Arrival Times, Travel Times ← result
      try:
         Execute the loop
```

```
        except:
            continue
    end for
```

Ultimately, the first phase of this research, which involves modeling travel demand and charging requirements using MCS, provides a comprehensive understanding of EV behavior and charging infrastructure utilization. This foundation sets the stage for the second phase of the research: developing a bi-level optimization framework to determine the optimal locations for commercial EV charging stations. This framework will balance user convenience, economic factors, and infrastructure costs, ensuring effective deployment of charging infrastructure to meet growing EV demand.

# Chapter 5: Power Network Integration

## *5.1 Bi-level Optimization for Charging Station Placement*

This study focuses on deriving an optimal construction plan for an EV charging infrastructure within a designated area comprising multiple zones. The primary goals are to determine the scale, i.e., the number of charging piles required for each charging station, and to optimize the charging schedule based on predicted or actual charging demand. The model incorporates time-of-use electricity prices and users' flexible charging time windows. A significant aspect of this research is the coexistence of residential and commercial charging facilities, which potentially influences charging behaviors and demand patterns differently compared to scenarios with only commercial charging stations. A bi-level programming model is constructed to address the problem of selecting the location and scale of EV charging stations and scheduling their operation. The model operates on a weekly time scale, ensuring that all prices and demands are calculated accordingly over a one-week period.

### 5.1.1 Sets and Parameters

- **Block Set $\boldsymbol{N}$:** The entire area under study is divided into $N$ blocks for easier management and modeling. Each block represents a potential location for charging station placement, and the blocks are indexed as $N = \{1,2,\dots,n\}$. The division allows the model to account for varying demand and availability of space in different parts of the city.

- **Position of Each Alternative Charging Station $\boldsymbol{l_{station}}$:** This set includes the geographical coordinates (longitude and latitude) for all potential charging station locations. It is represented as:

$$l_{station} = \{\left[ls_{1_{longi}}, ls_{1_{lati}}\right], \left[ls_{2_{longi}}, ls_{2_{lati}}\right], \dots, \left[ls_{n\_longi}, ls_{n\_lati}\right]\}$$

These positions define the spatial location where each charging station can be placed, which is critical for ensuring the station serves local demand efficiently.

- **Charging Demand Set $\boldsymbol{M}$:** This set defines the demand in terms of the number of vehicles requiring charging, represented as $M = \{1,2, \dots, m\}$, where m is the total number of charging requests or events.
- **Charging Amount Set $\boldsymbol{Q}$:** $Q = \{q_1, q_2, \dots, q_m\}$represents the amount of energy required for charging each EV. Each value $q_m$ corresponds to a particular EV and is a function of the SoC and the battery capacity.
- **Charging Time Window Set $\boldsymbol{T_m}$:**

  $T_m = \{[t_{1\_start}, t_{1\_end}], [t_{2\_start}, t_{2\_end}], \dots, [t_{m\_start}, t_{m\_end}]\}$ defines the preferred time window for each EV $m$ during which the vehicle should be charged. This set helps ensure that vehicles are charged within the user specified availability of the user, improving user satisfaction.

- **Charging Demand Position $\boldsymbol{p_m}$:** The position of each EV in need of charging is captured in this set as: $p_m = \{[p_{1_{longi}}, p_{1_{lati}}], [p_{2_{longi}}, p_{2_{lati}}], \ldots, [p_{m\_longi}, p_{m\_lati}]\}$. These coordinates are critical for mapping demand to the nearest available charging station.

5.1.2 Decision Variables

- $\boldsymbol{x_i}$**:** A binary decision variable indicating whether a charging station is placed in block $i$ ($x_i = 1$); otherwise, ($x_i = 0$). This variable controls the placement of charging stations within the network.
- $\boldsymbol{y_i}$**:** An integer decision variable representing the number of charging piles at the charging station $i$. This controls the capacity of each selected station, ensuring sufficient resources to meet the expected demand.
- $\boldsymbol{z_{imt}}$**:** A binary variable indicating if EV $m$ will be charged in the charging station $i$ at time $t$; if yes, $z_{imt} = 1$; otherwise $z_{imt} = 0$. This variable captures the allocation of charging slots to vehicles across time windows.

5.1.3 Upper-Level Model

The upper-level model aims to maximize the profit generated by the EV charging infrastructure by accounting for both revenue and cost components. The overall objective is to maximize profit:

$$\text{maximize } F = P - C_{op} - C_{con} - C_p - C_l \tag{2}$$

Where $P$is the charging profit (difference between revenue and cost), and the other terms represent operating costs, construction costs, equipment costs, and land-use costs, respectively.

- **Charging Profit $\boldsymbol{P}$:** The charging profit is calculated as:

$$P = R_{charging} - C_{charging} \tag{3}$$

With $R_{charging}$ being the total revenue from users and $C_{charging}$ being the operational costs of providing charging services.

- **Charging Revenue $\boldsymbol{R_{charging}}$:** The revenue is calculated as:

$$R_{charging} = \sum_{i=1}^{n} \sum_{t}^{T} \sum_{m}^{M} z_{imt} * p_e(t) \tag{4}$$

Where $p_e(t)$ is the charging price for users at the time $t$. Charging prices are typically time-dependent (higher during peak hours and lower during off-peak). $C_{charging}$ is the charging cost, which is calculated at the lower level.

- **Charging Cost $\boldsymbol{C_{charging}}$:** The charging cost is the expense incurred in powering the charging stations, calculated as:

$$C_{charging} = \sum_{i=1}^{n} \sum_{i'=1}^{n'} \sum_{t}^{T} \sum_{m}^{M} G_{ii'} \left(V_i^2 - V_{i'}^2 - 2V_i V_{i'} \cos(\theta_{ii'})\right) * z_{imt} * \left(D_s * \frac{(SoC_m^d - SoC_m^a) * B_m}{\eta}\right) * p_e(t) \tag{5}$$

$$p_e(t) = \begin{cases} c_e(t) * (1 + Low\ Markup\ Percentage)\ if\ t \in off - peak\ hours \\ c_e(t) * (1 + High\ Markup\ Percentage)\ if\ t \in peak\ hours \end{cases} \quad (6)$$

Where the unit electricity price at the time $t$ is $c_e(t)$ which is the time-of-use price. This accounts for the electricity drawn from the grid based on the state of charge and power demands.

- **Operating Costs $C_{op}$:** This represents the ongoing costs of operating the charging stations.

$$C_{op} = \sum_{i=1}^{n} x_i * c_{op\_i} \quad (7)$$

Where $c_{op\_i}$ is the operation cost in a station $i$. $C_{con}$ is the construction cost, representing the costs of building the charging stations. It accounts for maintenance, management, and staffing expenses.

- **Construction Costs $C_{con}$:** Construction costs represent the expenses for building new charging stations:

$$C_{con} = \sum_{i=1}^{n} x_i * c_{con} \quad (8)$$

$c_{con}$ is the construction cost for one charging station. $C_p$ is the cost to buy the EV chargers, representing the expenses to purchase the charging equipment.

- **Charger Equipment Cost $C_p$:** This cost covers the purchase of EV chargers, calculated as:

$$C_p = \sum_{i=1}^{n} x_i * y_i * c_p \quad (9)$$

Where $c_p$ is the cost to buy one charger (level 2 and level 3).

- **Land Use Cost $C_l$:** The land use cost represents the expense of acquiring land for the charging stations:

$$C_l = \sum_{i=1}^{n} x_i * c_{l\_i} \quad (10)$$

Where $c_{l\_i}$ is the land-use cost for the charging station selected in the block $i$.

5.1.4 Lower-Level Model

The lower-level model focuses on minimizing the total charging cost ($C_{charging}$), for EV users by providing an optimal charging schedule. The goal is to reduce the cost associated with electricity consumption at various times and optimize the scheduling of EVs.

**Objective Function $C_{charging}$:** The total charging cost to be minimized is

$$minimize\ C_{charging} = \sum_{i=1}^{n} \sum_{i'=1}^{n'} \sum_{t}^{T} \sum_{m}^{M} G_{ii'}\left(V_i^2 - V_{i'}^2 - 2V_iV_{i'} \cos(\theta_{ii'})\right) * z_{imt} * \left(D_s * \frac{(SoC_m^d - SoC_m^a) * B_m}{\eta}\right) * c_e(t) \quad (11)$$

Here, $i' = adj(i)$ indicates that the power flow or voltage effects at $i$ are influenced by bus $i'$, which is directly connected to $i$. This equation considers the cost of power delivered to the vehicles, factoring in the state of charge and the power flow in the grid.

*Use of Adjacent Bus in a Power Grid*

In power systems, buses (or nodes) are key points in the grid where various electrical components like loads (such as charging stations), generators, and transmission lines are connected. These buses are used to model the flow of electricity through the network, representing points where electrical quantities such as voltage and power are measured and controlled.

When analyzing power flow, it is important to consider how buses interact. Each bus $i$ is connected to other buses in the grid through transmission lines. These connections between buses $i$ and $i'$ allow for the transfer of electrical power. Therefore, the power demand at any given bus $i$, such as a charging station, affects not just the local bus but also the adjacent buses in the network. This is why the concept of "adjacent buses" written as $i' = adj(i)$, is essential.

**Why We Consider Adjacent Buses**

- **Influence on Power Flow**: When power is drawn at one bus (e.g., when electric vehicles charge at a station), it affects the entire grid. The flow of electricity from one bus to another depends on the network's configuration. In this way, bus $i'$, which is adjacent to bus $i$, is directly affected by the power demands at $i$, and vice versa.

- **Voltage Drops**: Voltage at any bus in the grid can be influenced by neighboring buses due to the nature of power flows. If a large amount of power is drawn at bus $i$ (the charging station), it can cause a voltage drop at adjacent bus $i'$. This is why power flow equations typically consider both $i$ and its adjacent bus $i'$ to model how power is distributed across the network.

- **Network Connectivity**: In a power grid, buses are interconnected in complex ways (through transmission lines or distribution systems), forming a network. These connections allow for the transfer of power between buses, which means that no bus operates in isolation. By accounting for the adjacent buses $i'$, we can model the interdependent nature of power systems, where the demand at one point affects other parts of the grid.

In the bi-level optimization context, $i$ represents the bus where the charging station is located, and $i' = adj(i)$ represents another bus that is directly connected to bus $i$. This allows us to consider how the power flow and voltage at bus $i$ are influenced by the power flow and voltage at adjacent buses $i'$.

**Detailed Example of Bus Interaction**

1. **Bus $\boldsymbol{i}$ and Charging Station $\boldsymbol{i}$**:

    - **Bus $\boldsymbol{i}$**: This represents the point in the power grid where charging station $i$ is connected. The power drawn by the charging station directly impacts the power demand at this bus. For instance, when EVs are charging at station $i$, the power consumption increases, raising the demand for bus $i$.

- **Charging Station $\boldsymbol{i}$**: The EV charging load at the station $i$ directly influences the grid by drawing power, which the grid must supply. This power comes from the adjacent buses, and the flow of power between buses is determined by the network's configuration and the loads connected to these buses.

2. **Bus $\boldsymbol{i'}$**:

   - **Adjacent Bus $\boldsymbol{i'}$**: Bus $i'$ is any bus directly connected to $i$ through a transmission line or other network elements. It represents a neighboring point in the power system that interacts with bus $i$. The power drawn at the bus $i$ affects the voltage and power of bus $i'$, and vice versa due to the interconnected nature of the grid.

**Relation Between Bus $\boldsymbol{i}$ and Bus $\boldsymbol{i'}$**

- **Connection through the Network**: Bus $i$, where the charging station is located, is connected to adjacent buses $i'$ via transmission lines. Power flows between buses based on the generation and load at these points. For example, if more power is drawn at bus $i$, the load on the adjacent bus $i'$ might increase, leading to changes in voltage and power flows between these buses.

- **Voltage and Power Flow**: The voltage at bus $i$ can influence and be influenced by the voltage at the adjacent bus $i'$. The power flow equations describe how power generated at one bus flows to another and how the voltage levels are affected across the network. This interaction is modeled by the power flow equations (such as active and reactive power constraints), which include terms involving the voltages $V_i$ and $V_{i'}$ and the angle difference between buses $i$ and $i'$.

**Example Scenario:**

- **Charging Station $\boldsymbol{i}$ at Bus $\boldsymbol{i}$**: Suppose a significant number of EVs are charging at a station $i$. The increased power demand for bus $i$ causes more electricity to flow through the network.

- **Impact on Other Buses $\boldsymbol{i'}$**: Due to the network's interconnected nature, the increased load on bus $i$ can cause a voltage drop at the bus $i'$, which is adjacent to the bus $i$. This means that as more EVs charge at station iii, not only does the power demand at bus $i$ increase, but there is also an impact on the voltage and power flow of the bus $i'$.

- **Power Flow Equations**: The power balance equations that involve the voltages $V_i$ and $V_{i'}$ describe how the power consumed by bus $i$ affects adjacent buses $i'$. This ensures that the system models how power flows through the network when multiple buses are involved and accounts for the interaction between these interconnected buses.

5.1.5 Constraints

*(i) Power Load Constraint:*

This constraint ensures that the total power demand from all charging activities at any given time $t$ does not exceed the power grid's maximum allowable load, $w_{max}$. The power demand at time $t$ is calculated as the sum of the power requirements from all vehicles charging at all selected stations:

$$W(t) = \sum_{i=1}^{n} \sum_{t}^{T} \sum_{m}^{M} z_{imt} * p_{imt} \tag{12}$$

Here, $p_{imt}$ represents the power demand of vehicle $m$ at station $i$ at time $t$. The sum of these individual power demands gives the total load on the grid at time $t$.

The constraint ensures that this total power demand $W(t)$ does not exceed $w_{max}$, the threshold that the grid can handle without overloading.

$$W(t) \leq \ w_{max} \, for \; all \; t \tag{13}$$

This constraint is vital for maintaining grid stability and preventing blackouts or disruptions caused by an excessive charging load at peak times. Violating this constraint could cause voltage fluctuations and strain on the grid, so the power distribution network must have sufficient capacity to accommodate the total EV charging demand at any given time.

*(ii) Time Window Constraint:*

The time window constraint ensures that each vehicle is charged within the specific time range requested by the user. This is especially important to account for user behavior, preferences, and convenience. Each EV has a preferred time window, represented as $[t_{m\_start}, t_{m\_end}]$ during which the charging must be completed.

The binary decision variable $z_{imt}$ indicates whether vehicle mmm is being charged at station $i$ at time $t$. This variable must satisfy the condition that the charging time $t$ falls within the user's specified time window:

$$t(z_{imt}) \in \left[t_{m_{start}}, t_{m_{end}}\right] \, for \; all \; m \tag{14}$$

This constraint ensures that each EV is charged only during its desired time slot, providing flexibility for the EV owner and helping to balance the charging demand throughout the day by avoiding simultaneous charging of all EVs at peak times. It helps manage demand and ensures the charging schedule meets user expectations.

*(iii) Facility Constraint:*

The facility constraint governs the capacity of each charging station to handle the number of vehicles that require charging at a given time. Each charging station $i$ has a fixed number of charging piles $y_i$, which limits the number of vehicles that can be charged simultaneously.

The constraint ensures that the total number of vehicles being charged at station $i$ at time $t$ does not exceed the number of available charging piles:

$$\sum_{m}^{M} z_{imt} \leq x_i y_i \, for \; all \; i \; and \; t \tag{15}$$

Here, $x_i$ indicates whether a charging station is active in block $i$, and $y_i$ represents the number of chargers available at that station. This constraint prevents overloading the station by ensuring that the number of vehicles being charged at any moment does not exceed the physical infrastructure capacity. It also helps determine how many chargers are needed at each station to meet demand, optimizing the placement of stations and their sizes.

*(iv) SoC of Battery Constraint:*

The SoC constraint ensures that the battery charge of each vehicle remains within a safe and operational range during the charging process. Charging the battery beyond safe limits can degrade its performance and lifespan.

This constraint sets the minimum and maximum SoC levels for the vehicles, ensuring that the battery is charged within this range:

$$25\% \leq SoC \leq 90\% \tag{16}$$

Charging a battery too low (below 25%) or too high (above 90%) can adversely affect battery health, leading to quicker wear and tear. Therefore, this constraint ensures the safety and longevity of EV batteries while also considering efficiency—since charging efficiency tends to drop at higher SoC levels.

*(v) Max Number of Stations per TAZ Constraint:*

The TAZ constraint limits the number of charging stations that can be placed within each TAZ. This ensures a balanced and optimized distribution of charging stations across the area, preventing an over-concentration of infrastructure in certain zones while leaving others underserved.

The constraint specifies that the number of stations in any TAZ cannot exceed a predefined maximum:

$$x_i \leq Max\ stations\ per\ TAZ \tag{17}$$

This practical constraint considers urban planning considerations, available space, and demand distribution. It helps ensure that EV infrastructure is deployed equitably across different zones.

*(vi) Voltage Constraint:*

This constraint ensures that the voltage at each bus in the power network remains within safe operating limits. Voltage fluctuations can harm electrical equipment and lead to inefficient power distribution.

The voltage at each bus $i'$ must be maintained within a specified range between $V_{i'}^{min}$ and $V_{i'}^{max}$ :

$$V_{i'}^{min} < V_{i'} < V_{i'}^{max} \tag{18}$$

This constraint helps in maintaining the stability and reliability of the power grid by ensuring that the voltage levels do not deviate too far from nominal values. If the voltage falls outside this range, it can lead to equipment damage, power losses, and potential blackouts.

*(vii) Power Inequality Constraint:*

This constraint ensures that the power generated and consumed at each bus remains within the allowable limits. It is divided into two parts—one for real power ($P_i$) and one for reactive power ($Q_i$).

The real power at each bus must be within the bounds of $P_i^{min}$ and $P_i^{max}$:

$$P_i^{min} \leq P_i \leq P_i^{max} \tag{19}$$

Similarly, the reactive power at each bus must stay within predefined limits:

$$Q_i^{min} \leq Q_i \leq Q_i^{max} \tag{20}$$

This constraint ensures that both real and reactive power levels are kept within safe operating limits for each bus, preventing grid instability and ensuring efficient operation. Maintaining proper reactive power balance is particularly important for voltage control and minimizing power losses in the system.

*(viii) Branch Current Constraint:*

Each branch (or transmission line) in the power grid has a maximum current capacity, and this constraint ensures that the current flowing through each branch does not exceed this limit.

The current in any branch $br$ is restricted to:

$$I_{br(i,i')} < I_{br(i,i')}^{max} \tag{21}$$

Exceeding the maximum current capacity can lead to overheating, damage to the infrastructure, and potential system failure. This constraint ensures that all branches operate within their designed capacities, protecting the grid from excessive loads and maintaining safe transmission of electricity across the network.

*(ix) Minimum Service Coverage Constraint:*

This constraint ensures that electric vehicle (EV) users in all demand locations are sufficiently covered by nearby charging stations. Specifically, for each EV $m \in M$, the cumulative influence or accessibility of all stations $i \in N$, scaled by the inverse of their distance $d_{im}$, must exceed a minimum threshold $S_{min}$. This represents a baseline level of accessibility to charging infrastructure that prevents demand points from being too far or poorly connected to available stations.

$$\sum_{i \in N} \frac{x_i}{d_{im}} \geq S_{min}, \forall m \in M \tag{22}$$

Where:

- $d_{im}$: Distance between the demand position $p_m$ and charging station $l_{station,i}$.
- $S_{min}$: Minimum required service coverage.

*(x) Accessibility Constraint:*

This constraint places a limit on the average distance EV users must travel to reach their assigned charging station. It is designed to enhance convenience and minimize user burden by reducing excessive detours or long access times, especially critical in urban areas where time and traffic congestion are factors.

$$\frac{\sum_{m\in M}\sum_{i\in N} d_{im} z_{imt}}{\sum_{m\in M}\sum_{i\in N} z_{imt}} \leq D_{max}, \forall t \in T \tag{24}$$

Where:

- $D_{max}$: Maximum allowable average travel distance.

*(xi) Population Proportionality Constraint:*

This constraint ensures that the spatial deployment of charging stations reflects the distribution of the population across blocks. The number of stations $x_i$ in each block $i$ must be proportional to the population $P_i$ in that block, controlled by a constant proportionality factor $\lambda$. This fosters population-based fairness in infrastructure allocation.

$$\sum_{i \in N} x_i \geq \beta Pop_i, \forall i \in N \quad (25)$$

Where:

- $Pop_i$: Population in block $i$.

- $\beta$: Proportionality factor.

The study utilizes various cost estimates and pricing data critical to the planning and implementation of EV charging infrastructure. Level 2 charging equipment costs range from $400 to $6500, with average installation costs around $3000. Level 3 chargers, on the other hand, can cost between $10,000 and $40,000, with an average installation cost of $21,000 (Mouravskiy, 2023). Electricity rates from the Baltimore Gas and Electric Company are $0.16 per kWh for flat rates, $0.33 per kWh during peak times, and $0.11 per kWh during off-peak hours (Baltimore Gas and Electric Company, n.d.). Additionally, the average EV consumes around 11.81 kWh per day, translating to approximately 353.3 kWh per month and 4,310.65 kWh per year (EVBox, n.d.). Transaction fees for commercial EVSE units using credit card payment systems range from 5% to 7.5% (U.S. Department of Energy, 2015). Permit costs for Level 2 chargers vary from $14 to $821, and network fees range from $100 to $900 annually, depending on the EVSE unit type (U.S. Department of Energy, 2015). Demand charges for electricity can increase monthly utility bills by up to $2,000 (U.S. Department of Energy, 2015). Additional costs include bollards or wheel stops ($200-$800 and $100-$200, respectively) and trenching costs, which can be $100 per foot. Trenching 50 feet costs around $5,000, and 100 feet costs about $10,000 (U.S. Department of

Energy, 2015). Suitable EV charging sites can be as small as half an acre (Bishop, 2024), with an acre of land in Baltimore County, Maryland, costing between $50,000 and $190,000 in 2024 (Guerilla, 2024). These numbers were crucial for making important numerical assumptions regarding the various costs associated with EV charging stations, including construction, land purchase, land use, and operating expenses.

# Chapter 6: Advanced Queuing Simulation Model Framework

The rapid growth of electric vehicle (EV) adoption introduces significant challenges in terms of infrastructure adequacy, particularly the efficient allocation and management of charging facilities. The charging process for EVs involves substantial power consumption, and as the EV penetration rate increases, it leads to intensified congestion, not only at individual charging stations but also throughout the entire electricity distribution network (Aveklouris et al., 2017). Addressing this congestion is crucial to ensuring the sustainable development of EV infrastructure and promoting widespread adoption.

Queuing theory, a mathematical approach that studies the behavior of waiting lines or queues, has emerged as a powerful tool to analyze, model, and optimize the complex interactions and service mechanisms inherent in EV charging infrastructure. This theoretical framework allows researchers and infrastructure planners to predict charging station performance, assess service capacity, optimize resource allocation, and evaluate the impacts of congestion at various scales, from individual stations to entire grids (Wang et al., 2017; Aveklouris et al., 2017).

Queuing theory is particularly suited to EV charging scenarios due to several unique characteristics of EV charging behavior and infrastructure constraints. Firstly, EV arrivals at charging stations are inherently stochastic, influenced by variables such as user driving patterns, charging preferences, state of charge (SOC) at arrival, and external factors like pricing strategies and incentives. Secondly, EV charging demands vary significantly in terms of energy requirements and charging durations, presenting heterogeneity similar to typical service demands in classic queuing systems.

Moreover, charging facilities are often limited by two main sources of congestion: spatial constraints (the number of available charging spots) and electrical constraints (available power capacity). The interaction between these constraints can severely impact charging performance and user satisfaction, necessitating sophisticated modeling approaches to balance service quality with infrastructure investment costs (Aveklouris et al., 2017; Wang et al., 2017).

### *6.1 Types of Queuing Models Applied to EV Charging*

Several queuing models have been effectively adapted for EV charging scenarios. Commonly utilized models include:

- **M/M/k/k Models:** These models represent scenarios with k charging servers (stations), where EV arrivals follow a Poisson distribution, and the service (charging) times are exponentially distributed. Such models are particularly relevant when modeling stations with limited parking spaces where arriving vehicles that find all chargers occupied immediately leave without waiting (blocking system) (Bayram et al., 2013).

- **Multi-server Generalized Processor Sharing (MGPS):** The MGPS models allocate charging resources proportionally among multiple servers, ensuring equitable distribution of power and minimizing the potential for overload or under-voltage in distribution transformers. MGPS addresses fairness concerns that arise when charging demand surpasses grid capacity, facilitating a controlled distribution of charging loads (Wang et al., 2017).

- **Processor-Sharing Queues with Impatience:** This model considers scenarios where EVs may leave charging stations before being fully charged due to time constraints or dissatisfaction with waiting times. Such models provide valuable insights into customer behavior dynamics and service level impacts of extended wait times (Aveklouris et al., 2017).

Incorporating queuing theory into EV charging station management facilitates strategic planning, policy formulation, and infrastructure scaling. Queuing models allow planners to simulate various operational scenarios, estimate the probability of station overload, predict waiting times, and evaluate the effectiveness of congestion mitigation strategies such as dynamic pricing, reservation systems, and demand-response schemes (Sortomme et al., 2011; Su and Chow, 2012).

Furthermore, advanced queuing simulations contribute significantly to evaluating and enhancing grid resilience by optimizing the distribution of charging loads over time and across multiple locations. By understanding queuing behavior at the station and grid levels, stakeholders can improve reliability, enhance customer satisfaction, and ensure sustainable energy consumption patterns (Wang et al., 2017; Aveklouris et al., 2017).

### *6.2 $M/M/c/K$ Model*

The $M/M/c/K$ queuing model was selected for this research due to several critical reasons. Firstly, the model accurately captures the real-world limitations and operational constraints of EV charging stations, including a finite number of charging spaces (servers) and a finite queuing capacity (K). Such limitations closely reflect practical conditions in public charging facilities where parking and charging resources are constrained.

Secondly, the assumption of exponential interarrival and service times aligns well with typical EV charging scenarios, where arrivals and service durations can be reasonably approximated by stochastic processes with memoryless properties. This simplicity and tractability allow the model to be effectively applied in large-scale simulations and real-time operational analyses.

Furthermore, the $M/M/c/K$ model explicitly addresses congestion by incorporating a blocking mechanism, where vehicles arriving at fully occupied stations are denied immediate service. This feature directly models the potential user dissatisfaction and infrastructure inefficiencies resulting from limited charging capacity, providing valuable insights into infrastructure planning and resource allocation.

Finally, adopting the $M/M/c/K$ model facilitates rigorous analytical derivation of performance metrics, such as blocking probability, average waiting times, and system throughput, which are critical for policy formulation and strategic infrastructure investments. Thus, the selection of this model ensures that the research outcomes are directly applicable to practical decision-making and infrastructure optimization.

### 6.2.1 System Description

This section provides a detailed explanation of the queuing model applied specifically to electric vehicle charging stations in this study. It introduces the fundamental characteristics, assumptions, and parameters associated with the chosen $M/M/c/K$ model, clearly defining each component involved in modeling the charging station operations and its performance metrics.

An $M/M/c/K$ queue is considered for modeling EV charging stations, characterized by the following:

1. **Queueing Type**: An $M/M/c/K$ queue is considered, where:

   - $M_a$: Assumes a Poisson arrival process, suitable for modeling randomly arriving EVs at charging stations.

   - $M_s$: Exponential service times represent the stochastic variability and memoryless property of EV charging durations.

   - $c$: Number of chargers or servers available at a charging station.

   - $K$: Maximum number of vehicles that can either be charging or waiting for service at the station. When this limit is reached, additional arriving vehicles are denied entry (blocked).

2. **Variables and Parameters**:

- $\lambda_s$: Arrival rate at station $s$ (vehicles/unit time), capturing how frequently EVs arrive for charging.

- $\mu$: Service rate per charger (vehicles/unit time), directly affecting the station's service capacity.

- $c_s$: Number of chargers at station $s$, directly affecting the station's service capacity.

- $K_s$: Total capacity of station $s$ (servers plus waiting spaces), defining the upper limit of vehicles accommodated by the station at any given moment.

- $\rho_s = \frac{\lambda_s}{\mu c_s}$: Utilization ratio of station $s$, indicating the fraction of station capacity actively used.

- $\Phi_n$: Probability of having exactly $n$ vehicles within the system at a given time.

- $\xi_{loss}$: The probability of the system being full represents the likelihood of new arrivals being rejected due to capacity constraints.

- $w_s$: Average waiting time experienced by vehicles at station $s$.

- $q_s$: Average queue length at station $s$, indicating the typical number of vehicles waiting for a charger.

6.2.2 Queueing Dynamics

This subsection details the queuing dynamics specific to the $M/M/c/K$ queue model, elaborating on the mathematical foundations and practical implications of key performance metrics. These dynamics allow for a comprehensive understanding of the charging station's operational characteristics, efficiency, and potential limitations.

**State Probabilities**: For an $M/M/c/K$ queue, the steady-state probability ($\Phi_n$) of having exactly $n$ vehicles in the system can be mathematically expressed through distinct cases depending on whether the number of vehicles $n$ is less than or equal to the number of available chargers $c_s$ or exceeds it. When the system has fewer vehicles than chargers available, all vehicles are being served immediately upon arrival. However, once the number of vehicles surpasses $c_s$, additional vehicles must wait, forming a queue. The state probabilities thus capture the likelihood of each potential system occupancy scenario.

$$\Phi_n = \begin{cases} \dfrac{\frac{(\lambda_S/\mu)^n}{n!}}{\sum_{k=0}^{c_S-1}\frac{(\lambda_S/\mu)^k}{k!}+\frac{(\lambda_S/\mu)^{c_S}}{c_S!}\sum_{k=c_S}^{K_S-c_S}(\frac{1}{c_S})^k}, 0 \leq n < c_s \\ \dfrac{\frac{(\lambda_S/\mu)^n}{c_S^{n-c_S}c_S!}}{\sum_{k=0}^{c_S-1}\frac{(\lambda_S/\mu)^k}{k!}+\frac{(\lambda_S/\mu)^{c_S}}{c_S!}\sum_{k=c_S}^{K_S-c_S}(\frac{1}{c_S})^k}, c_s \leq n < K_s \end{cases} \tag{26}$$

**Blocking Probability**: The blocking probability $\xi_{loss}$, indicates the probability that the system reaches its full capacity $K_s$. At this point, any additional arriving vehicle is denied entry and must leave the system immediately. This metric is essential for evaluating how often potential users might encounter a completely occupied charging station, influencing user satisfaction and operational efficiency.

$$\xi_{loss} = P_{K_s} \tag{27}$$

**Mean Queue Length**: The mean queue length $q_s$ is computed as the expected number of vehicles waiting to be charged, reflecting the average level of congestion within the station. Higher values of $q_s$ typically imply increased user dissatisfaction and longer waiting periods, directly impacting the station's perceived performance and necessitating strategies for congestion mitigation.

$$q_s = \sum_{n=c_s}^{K_s} (n - c_s)\Phi_n \tag{28}$$

**Mean Waiting Time**: The average waiting time $w_s$ represents the average duration vehicles spend waiting in the queue before beginning the charging process. This metric is critical for user satisfaction, as extended waiting periods can discourage station usage and impact the broader adoption of electric vehicles. It also assists in strategic planning, helping to determine optimal station sizing and resource allocation.

$$w_s = \frac{q_s}{\lambda_s(1-\xi_{loss})} \tag{29}$$

**Server Utilization**: The server utilization $\rho_s$ measures the proportion of total charger capacity actively used at the station $s$. High utilization rates indicate efficient resource usage but also suggest a higher likelihood of congestion. Conversely, low utilization rates point towards underutilization of available resources, potentially leading to inefficient capital expenditure. Balancing utilization is, therefore, crucial in optimizing infrastructure investment and ensuring high-quality service.

$$\rho_s = \frac{\lambda_s}{\mu c_s} \tag{30}$$

6.2.3 Performance Metrics

1. **Average Waiting Time**: The system-wide average waiting time $\overline{w}$ is computed as the weighted average of individual stations' waiting times, considering their respective arrival rates:

$$\overline{w} = \frac{\sum_{s \in S} w_s * \lambda_s}{\sum_{s \in S} \lambda_s} \tag{36}$$

2. **Average Queue Length**: The average queue length $\bar{q}$ across all stations is calculated by averaging individual station queue lengths:

$$\bar{q} = \frac{\sum_{s \in S} q_s}{|S|} \tag{37}$$

3. **Utilization Rate**: Overall server utilization rate $\bar{\rho}$ is obtained by averaging the utilization across all stations:

$$\bar{\rho} = \frac{\sum_{s \in S} \rho_s}{|S|} \tag{38}$$

4. **Blocking Probability**: Assessment of blocking probability $\xi_{loss}$ at each station provides insights into system performance under various load conditions, highlighting areas needing potential infrastructure investment or policy intervention.

### *6.3 Extension to a Multi-Station System Model*

While Sections 6.1 through 6.2 provided a detailed $M/M/c/K$ modeling framework for a single EV charging station, real-world deployments typically involve multiple stations distributed across a region. Each station may vary in terms of location, charger count, arrival rates, and capacities. Consequently, system-level considerations emerge, including the spatial distribution of EVs, total network congestion, and any blocking that may occur when vehicles cannot be served at their station of choice.

#### 6.3.1 Multi-Station Setup and Voronoi Partitioning

Suppose $N$ charging stations, indexed by $i = 1,2, \dots, N$, are located at positions $x_1, x_2, \dots, x_n$ in a region of interest. If the nearest-station rule is adopted (where an EV chooses the charging station nearest to its current location), the region can be divided into Voronoi cells $\{V_1, V_2, \dots, V_n\}$, defined by

$$V_i = \{x: \parallel x - x_i \parallel \leq \parallel x - x_j \parallel \ \forall j \neq i\} \tag{39}$$

Let $\Lambda(t, x)$ denote the spatial arrival rate (vehicles per unit area per unit time) at position $x$ and time $t$. Then, the arrival rate $\lambda_i(t)$ to station $i$ can be found by integrating over the Voronoi cell $V_i$:

$$\lambda_i(t) \; = \; \int V_i \Lambda(t, x) \, dx \tag{40}$$

Alternatively, if a high-level approach is sufficient, one may define $\alpha_i(t)$ as the fraction of the total regional demand $\lambda_{total}(t)$ that arrives at station $i$:

$$\lambda_i(t) = \alpha_i(t) \, \lambda_{total}(t) \tag{41}$$

Either formulation extends the basic single-station notion of $\lambda_s$ (from Section 6.2) to a network setting where arrival rates differ across stations based on location or demand patterns.

6.3.2 Queueing Model for Each Station

Even in a multi-station context, each individual station $i$ operates as its own $M/M/c/K$ queue, exactly as described in Section 6.2.1:

- **Poisson arrivals** at rate $\lambda_i(t)$ .
- **Exponential service times** with rate $\mu_i$ per charger.
- A **finite number** of chargers $c_i$ (servers).
- A **capacity limit** $K_i$, beyond which arriving vehicles are blocked.

Hence, the key single-station equations (for state probabilities $P_n$, blocking probability $P_{loss}$, mean queue length $q_i$, and average waiting time $i$) remain valid for station $i$, with the substitution $\lambda_s \to \lambda_i, \mu \to \mu_i$.

### 6.3.3 The System as a Continuous-Time Markov Chain (CTMC)

To study the overall network behavior, one can view the vector

$$X(t) \ = \ (X_1(t), X_2(t), \ldots, X_N(t)) \tag{42}$$

as the global state of the system, where $X_i(t)$ is the number of vehicles (in service or waiting) at station $i$ at time $t$. The process $\{X(t): t \geq 0\}$ evolves as a CTMC, meaning that future transitions depend only on the current state $X(t)$, not on how that state was reached (memoryless property).

#### *6.3.3.1 Transitions*

1. **Arrival at Station $\boldsymbol{i}$**: If $X_i(t) < K_i$, the next arrival to station $i$ occurs at rate $\lambda_i(t)$, causing the state to change from $X(t)$ to $X(t) + e_i$, where $e_i$ is a unit vector that increments the count for station $i$.
2. **Service Completion at Station $\boldsymbol{i}$**: If $X_i(t) > 0$, vehicles depart the queue at a rate $min\ (X_i(t), c_i)\mu_i$, corresponding to up to $c_i$ vehicles being served in parallel. Each service completion reduces $X_i(t)$ by one.

*6.3.3.2 Kolmogorov Forward Equations (Transient Analysis)*

For station $i$, let $p_{n,i}(t) = Pr\,[X_i(t) = n]$. In the general time-dependent (transient) case, the evolution of $p_{n,i}(t)$ follows:

$$\frac{d}{dt} p_{n,i}(t) = \lambda_i(t)\, p_{n-1,i}(t)\, 1_{\{n-1<K_i\}} \;+\; min\,(n+1, c_i)\, \mu_i\, p_{n+1,i}(t) \;-\; [\lambda_i(t)\, 1_{\{n<K_i\}} 1 \;+\; min\,(n, c_i)\, \mu_i]\, p_{n,i}(t) \tag{43}$$

for $n = 0,1, \dots, K_i$. Here, arrivals "birth" the state from $n-1$ to $n$, provided $n-1 < K_i$, and service completions "death" the state from $n+1$ to $n$. Although the joint distribution of $X(t)$ across all stations is higher-dimensional, each station can be treated independently if vehicles do not switch queues (no "station-hopping"), allowing direct application of the $M/M/c/K$ equations from Section 6.2.

6.3.4 System-Level Performance Metrics

Beyond station-specific indicators (see Section 6.2.5), the multi-station setup enables one to evaluate network-wide measures of effectiveness:

- **Total Queue Length Across All Stations:**

$$L_{system}(t) = \sum_{i=1}^{N} X_i(t) \tag{44}$$

representing the total number of vehicles (waiting or charging) in the entire region at time $t$.

- **System-Wide Blocking Rate:** If $\xi_{loss,i}(t)$ denotes the blocking probability at station $i$, then the overall blocking rate for the network can be computed as a weighted average:

$$\xi_{loss}^{(system)}(t) = \frac{\sum_{i=1}^{N} \lambda_i(t) \xi_{loss,i}(t)}{\sum_{i=1}^{N} \lambda_i(t)} \tag{45}$$

where $\sum_{i=1}^{N} \lambda_i(t)$ is the total regional arrival rate at time $t$. This quantity highlights how often EVs in the region fail to find an available station upon arrival.

- **Overall Mean Waiting Time:** A composite waiting time for the entire charging network can be defined similarly. Let $w_i(t)$ be the average waiting time at station $i$. Then,

$$w_{system}(t) = \frac{\sum_{i=1}^{N} \lambda_i(t)(1-\xi_{loss,i}(t))w_i(t)}{\sum_{i=1}^{N} \lambda_i(t)(1-\xi_{loss,i}(t))} \tag{46}$$

providing a throughput-weighted measure of how long a typical EV arriving in the region waits before charging.

- **Network Utilization:** As a parallel to the station-level utilization $\rho_s$ in Equation (32), one may average across all stations:

$$\bar{\rho}^{(system)} = \frac{1}{N} \sum_{i=1}^{N} \frac{\lambda_i(t)}{\mu_i c_i} \tag{47}$$

indicating how intensively the region's charging resources are used on average.

It is important to emphasize that the methodology and equations introduced in Section 6.2 form the conceptual foundation for the multi-station framework described here in Section 6.3. In Section 6.2, the $M/M/c/K$ queue model was thoroughly detailed for a single charging station, covering the assumptions of Poisson arrivals, exponential service times, and finite capacity leading to blocking when the system is full. Each station in the multi-station network still follows these identical queuing assumptions and uses the same state probability, blocking probability, and average waiting time derivations.

Concretely, the single-station performance metrics - such as the blocking probability $P_{loss}$ derived from Equation (29), the mean queue length $q_s$ from Equation (30), and the average waiting time $w_s$ from Equation (31) - continue to apply at every individual station $i$. The only difference is that each station now has its own parameters $\{\lambda_i, \mu_i, c_i, K_i\}$, which can be heterogeneous across the network. Consequently, all mathematical expressions in Section 6.2 can be reused without modification simply by replacing the single-station symbols $(\lambda_s, c_s, K_s)$ with the station-specific equivalents $(\lambda_i, c_i, K_i)$.

Building on these station-level results, Section 6.3 then introduces aggregate metrics - for instance, $L_{system}(t)$, $\xi_{loss}^{(system)}(t)$, and $w_{system}(t)$ - that sum or average the outcomes from multiple stations. This step involves additional notation (e.g., the Voronoi partitions $V_i$ and total regional arrival rate $\lambda_{total}(t)$ to handle how overall demand is partitioned among stations. Nevertheless, the underlying queuing calculations at each station remain strictly those from

Section 6.2. Hence, the mathematical formulations in Section 6.2 serve as building blocks that, when taken together for each station $i$, compose the larger system-level analysis.

# Chapter 7: Case Study

## *7.1 Commercial EV Charging Station Estimation*

### 7.1.1 Current Market Penetration

The analysis of current market penetration rates, including 0.09%, 0.75%, and 1.61%, provides valuable insights into the early stages of EV adoption and its implications for charging infrastructure. These market penetration rates were selected to represent the current adoption levels in the State of Maryland. The rates of 0.09%, 0.75%, and 1.61% were chosen to reflect the lowest, average, and highest EV market adoption levels in the state of Maryland, observed in Somerset County, the state average, and Montgomery County, respectively. An MCS approach is applied to simulate and estimate the required number of commercial EV charging stations for these market penetration levels. This probabilistic method accounts for uncertainties and variations in key factors affecting EV charging demand, such as charging behavior, travel patterns, and the availability of residential chargers.

MCS is particularly suited for this analysis because it models a wide range of possible outcomes by randomly sampling from predefined probability distributions that represent real-world variations. The simulation generates numerous potential scenarios based on varying EV user behaviors and infrastructure parameters to estimate the expected demand for commercial charging stations under different market penetration rates. The MCS process is outlined as follows:

1. **Input Variables and Distributions**:

- **EV Ownership**: For each market penetration rate, the total number of EVs in the region is estimated based on census data and EV registration trends.

- **Residential vs. Commercial Charging**: The percentage of EV users relying on residential charging versus those dependent on public commercial infrastructure is modeled. The availability of home chargers significantly influences the demand for public charging stations.

- **Charging Frequency**: EV users may charge their vehicles based on several factors, including daily commute distances, battery SoC, and access to charging stations. Probability distributions represent the variability in user behavior and charging frequency.

- **Geographic and Travel Patterns**: Using OD trip data, the simulation captures the spatial distribution of charging demand across different regions of the Baltimore MSA. Areas with higher traffic and longer commutes tend to generate more demand for public charging stations.

2. **Simulation of Scenarios**:

    - The MCS runs thousands of iterations, randomly sampling from the input distributions. Each iteration represents a possible scenario where different variables interact, such as the percentage of EV users without home charging, the geographic distribution of trips, and the frequency of charging sessions at public stations.

- The simulation outputs the number of required commercial charging stations for each iteration, providing a range of possible infrastructure needs for the current market penetration rates.

3. **Aggregating Results**:

    - After running the simulation across many iterations, the results are aggregated to estimate the average number of commercial charging stations needed to meet the demand at each market penetration rate. The simulation provides insight into the variability in infrastructure needs, indicating the upper and lower bounds of required charging stations based on different user behaviors and regional demand factors.

4. **Scalability and Adaptability**:

    - MCS offers a dynamic and adaptable framework. The model is easily scaled for different market penetration scenarios, ranging from early adoption rates to future projections. This method accounts for the inherent uncertainties in charging behavior and infrastructure deployment, ensuring robust estimates that can guide decision-making for both current and future market conditions.

By applying MCS, this study captures the inherent uncertainties and variations in EV user behavior and infrastructure demand, allowing for a comprehensive analysis of commercial charging station needs. This methodology not only estimates the required number of charging stations but also provides insight into how changing user patterns and charging preferences will impact infrastructure development as EV adoption increases.

*(i) 0.09% Market Penetration*

**Figure 9** illustrates the demand for residential and commercial EV charging facilities at a 0.09% market penetration rate, indicative of initial EV adoption. At a 0.09% market penetration, EV owners rely entirely on commercial infrastructure without any residential charging options, resulting in the peak demand of 229 commercial charging stations.

As household adoption of charging facilities increases, the need for commercial charging stations decreases significantly. When 50% of households have residential chargers, the required number of commercial chargers drops by 46.7%, from 229 to 122 stations. At 60% household adoption, the requirement for commercial chargers further declines by 55.9%, from 229 to 101 stations. This trend continues as 70% of households adopt residential chargers, reducing the number of required commercial stations by 65.1% to 80 stations. At 80% household adoption, the demand for commercial charging stations decreases even more dramatically, dropping by 74.2% to 59 stations. In addition to the influence of household adoption rates, the SoC also plays a role in determining the demand for commercial charging infrastructure. Although SoC management is not the primary focus, it provides context for optimizing commercial charging requirements. For a 50% SoC, the reductions in the number of required commercial chargers are significant as household adoption increases. However, maintaining a higher SoC (80%) consistently results in fewer required commercial charging stations than lower SoC levels (50%). For instance, at 50%

household adoption, the number of commercial chargers required for 80% SoC is 119, a 48.0% reduction compared to the initial 229 stations. At 60% household adoption, the requirement drops by 58.1% to 96 stations. When 70% of households have residential chargers, the number of required commercial stations for 80% SoC is reduced by 68.2% to 73 stations. At 80% household adoption, the requirement further decreases by 78.6% to 49 stations.

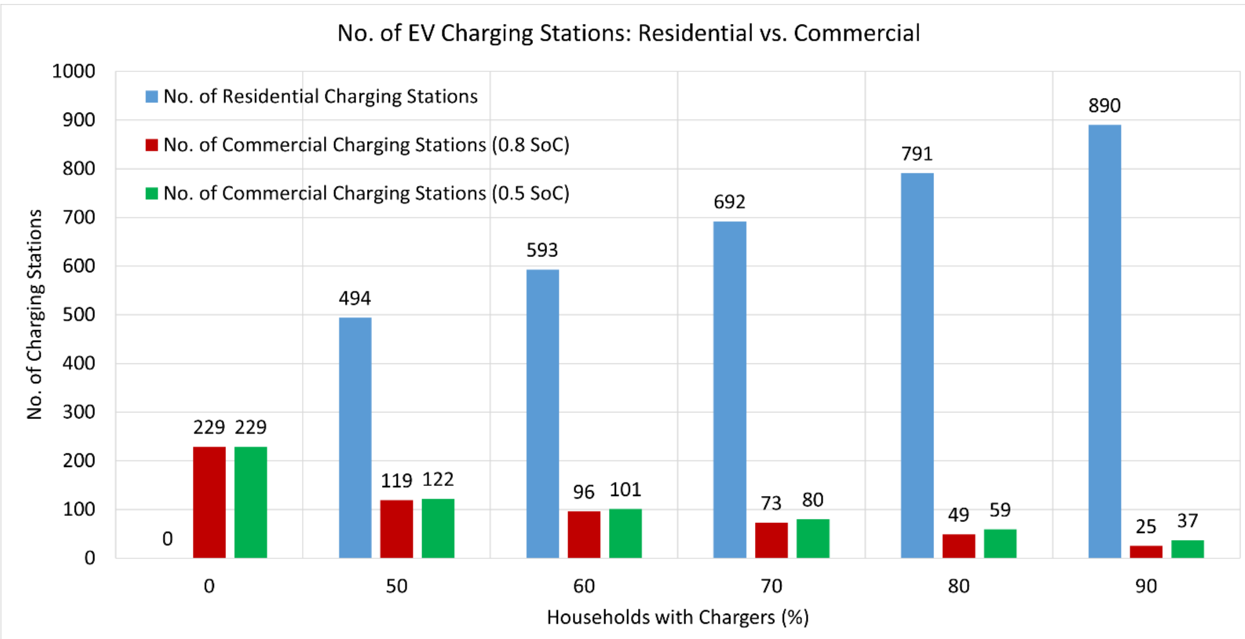


**Figure 9 Comparison of the Number of EV Chargers (Residential vs. Commercial) for EV Market Penetration Rate = 0.09%**

*(ii) 0.75% Market Penetration*

As depicted in **Figure 10**, the market penetration rate increases to 0.75%, reflecting a moderate adoption phase. At this level, the demand for commercial charging stations significantly decreases as the percentage of households with charging facilities rises. When no households have charging facilities, the demand remains at 1900 commercial charging stations for both 50% SoC and 80% SoC.

However, as household adoption reaches 50%, the need for commercial charging stations decreases. At 50% SoC, 1016 stations are required, while at 80% SoC, only 984 stations are needed, a 3.15% reduction. At 80% household adoption, the number of required commercial charging stations drops from 486 at 50% SoC to 404 at 80% SoC, a 16.9% reduction.

Overall, maintaining an 80% SoC results in a 41% decrease in the number of required commercial charging stations compared to a 50% SoC. This trend underscores the importance of increasing household adoption of residential chargers to reduce the strain on commercial charging infrastructure as market penetration grows.

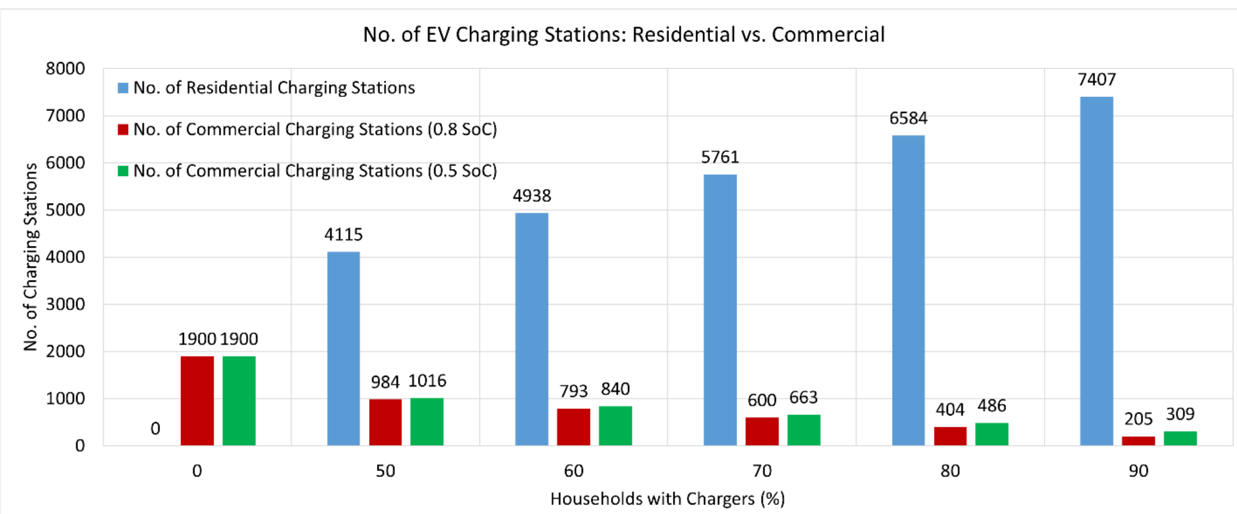

**Figure 10 Comparison of the Number of EV Chargers (Residential vs. Commercial) for EV Market Penetration Rate = 0.75%**

*(iii) 1.61% Market Penetration*

At 1.61% market penetration, illustrated in **Figure 11**, the demand for commercial charging stations significantly decreases with higher household adoption of charging facilities. When no households have charging facilities, 4,080 commercial charging stations are needed for both 50% SoC and 80% SoC.

At 50% household adoption, 50% SoC requires 2,182 stations, while 80% SoC needs 2,113 stations, a 3.2% reduction. At 60% household adoption, the requirement drops to 1,802 stations for 50% SoC and 1,703 stations for 80% SoC, a 5.5% decrease. At 70% household adoption, 50% SoC requires 1,423 stations, and 80% SoC requires 1,287 stations, a 9.5% reduction. At 80% household adoption, the need decreases to 1,043 stations for 50% SoC and 866 stations for 80% SoC, a 16.9% reduction. Finally, at 90% household adoption, 50% SoC requires 664 stations, while 80% SoC needs only 440 stations, a 33.7% decrease.

These comparisons highlight that as household adoption of residential chargers increases, the dependency on commercial charging infrastructure decreases significantly. Higher SoC levels further reduce the need for commercial charging stations.

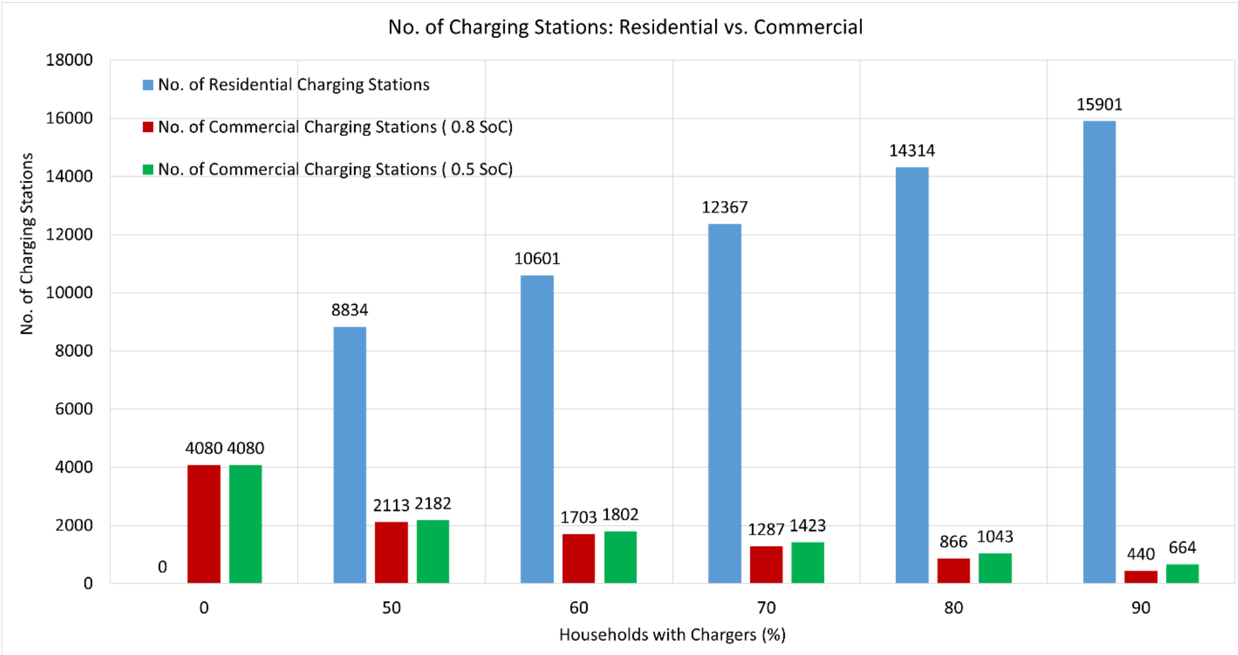


**Figure 11 Comparison of the Number of EV Chargers (Residential vs. Commercial) for EV Market Penetration Rate = 1.61%**

7.1.2 Future Market Penetration

The analysis of future market penetration rates, including 5%, 7.5%, and 10%, projects significant growth in EV adoption and its subsequent impact on charging infrastructure requirements. Higher penetration rates simulate the anticipated increase in EV adoption as policies, infrastructure, and technology improvements continue to drive market growth.

*(i) 5% Market Penetration*

At a 5% market penetration rate, EV adoption has reached a significant level, requiring substantial charging infrastructure (**Figure 12**). As household adoption of charging facilities increases, the need for commercial charging stations decreases markedly. With no households having charging facilities, both 50% SoC and 80% SoC require 12,669 commercial charging stations.

When 50% of households have charging facilities, the demand for commercial stations drops to 6,776 for 50% SoC and 6,560 for 80% SoC, a 3.2% reduction. At 60% household adoption, 50% SoC requires 5,598 stations, while 80% SoC needs 5,286 stations, a 5.6% decrease. When 70% of households have charging facilities, the number of required commercial stations decreases to 4,419 for 50% SoC and 3,997 for 80% SoC, a 9.5% reduction. At 80% household adoption, 50% SoC requires 3,240 stations, compared to 2,689 stations for 80% SoC, a 17% decrease. Finally, at 90% household adoption, the demand drops to 2,062 stations for 50% SoC and 1,365 for 80% SoC, a 33.8% decrease. These results highlight that higher household adoption of charging facilities and maintaining an 80% SoC significantly reduce the reliance on commercial charging infrastructure.

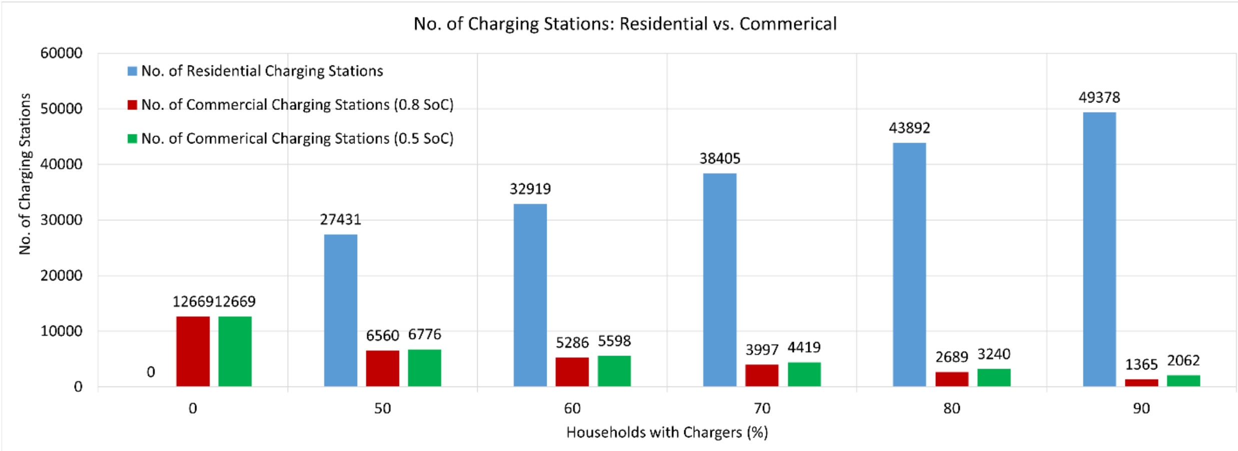


**Figure 12 Comparison of the Number of EV Chargers (Residential vs. Commercial) for EV Market Penetration Rate = 5%**

*(ii) 7.5% Market Penetration*

At a 7.5% market penetration rate (**Figure 13**), EV adoption becomes more prominent, demanding extensive charging infrastructure. The analysis reveals significant differences between maintaining a 50% SoC and an 80% SoC across various levels of household adoption of charging facilities. When no households have charging facilities, both 50% SoC and 80% SoC require 19,010 commercial charging stations. As household adoption increases to 50%, 50% SoC requires 10,170 commercial charging stations, while 80% SoC requires 9,845 stations, a 3.2% decrease. At 60% household adoption, 50% SoC necessitates 8,402 stations compared to 7,938 for 80% SoC, a 5.5% decrease. When 70% of households have charging facilities, 50% of SoC require 6,634 stations, while 80% of SoC need 5,998 stations, a 9.6% decrease. At 80% household adoption, 50% SoC requires 4,866 stations, compared to 4,033 stations for 80% SoC, a 17.1% decrease.

Finally, at 90% household adoption, 50% SoC demands 3,098 stations, while 80% SoC requires only 2,046 stations, a significant 34% decrease.

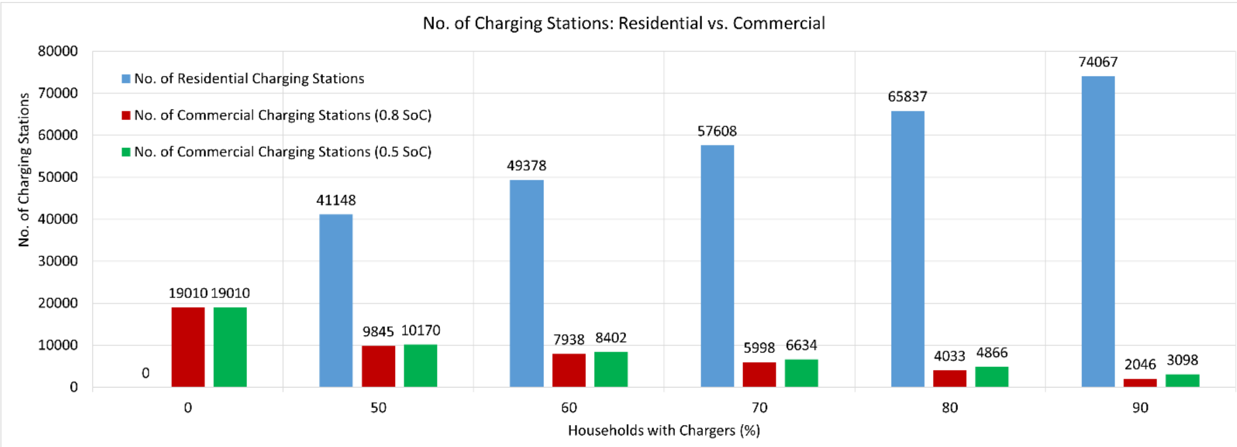


**Figure 13 Comparison of the Number of EV Chargers (Residential vs. Commercial) for EV Market Penetration Rate = 7.5%**

*(iii) 10% Market Penetration*

**Figure 14** depicts the scenario at a 10% market penetration rate, where the extensive adoption of EVs necessitates a robust charging infrastructure. The analysis highlights notable differences between maintaining a 50% SoC and an 80% SoC across varying levels of household adoption of charging facilities. With no households equipped with charging facilities, both 50% SoC and 80% SoC require 25,345 commercial charging stations. As household adoption reaches 50%, the need for commercial charging stations decreases to 13,558 for 50% SoC and 13,124 for 80% SoC, a reduction of 3.2%. At 60% household adoption, 50% SoC requires 11,200 stations, whereas 80% SoC reduces this to 10,580 stations, a 5.5% decrease. When 70% of households have charging facilities, 50% SoC necessitates 8,843 stations compared to 7,996 stations for 80% SoC, a 9.6% decrease. At 80% household adoption, 50% SoC demands 6,485 stations, while 80% SoC needs only 5,379 stations, a 17% reduction. Finally, at 90% household adoption, the requirement for commercial charging stations drops significantly to 4,128 for 50% SoC and 2,726 for 80% SoC, a 34% decrease.

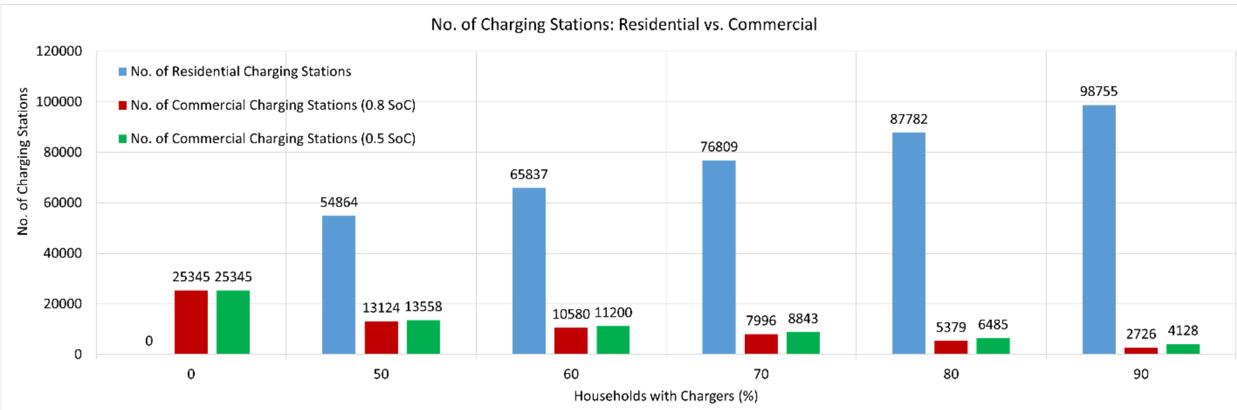


**Figure 14 Comparison of the Number of EV Chargers (Residential vs. Commercial) for EV Market Penetration Rate = 10%**

These comparisons illustrate that as more households are equipped with residential charging facilities, the dependency on commercial charging infrastructure diminishes significantly. The market penetration rate and the adoption of residential charging facilities are critical factors in optimizing commercial charging infrastructure. Higher market penetration rates increase the overall demand for chargers, but this demand can be effectively managed by increasing the percentage of households with residential charging facilities. This approach helps reduce the strain on commercial charging infrastructure and supports the efficient growth of the EV market.

The modeling results reveal a clear trend: as the adoption of residential charging facilities increases, the demand for commercial chargers decreases. This relationship holds true across both current and future market penetration scenarios. **Figure 15** below illustrates these trends, highlighting the critical role of residential charging infrastructure in shaping the overall charging landscape. Policymakers and stakeholders should consider enhancing access to residential charging solutions to reduce dependence on commercial infrastructure and support the broader adoption of EVs.

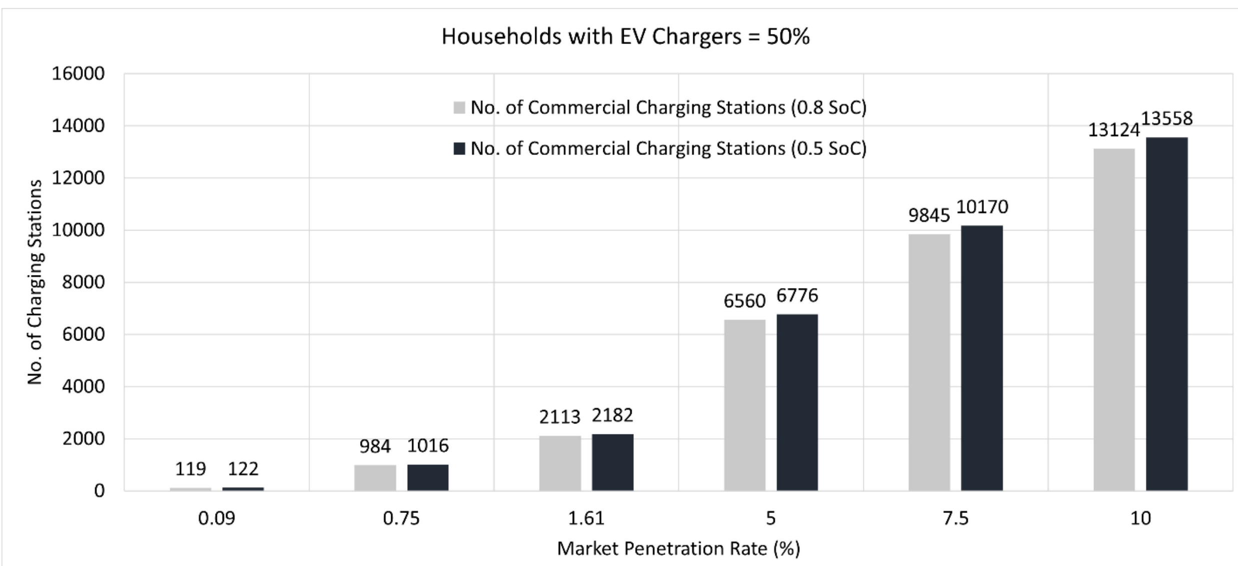


**Figure 15 Number of Commercial Charging Stations for Different Market Penetration Rates, Households with Chargers = 50%**

**Figure 15** depicts the number of commercial charging stations required at different market penetration rates, with 50% of households having EV charging facilities. Higher market penetration rates necessitate more infrastructure. For example, at a 10% market penetration rate, 13,558 public charging stations are needed at 50% SoC, which drops to 13,124 at 80%. Similarly, at a 7.5% market penetration rate, 10,170 public chargers are needed at 50% SoC, reducing to 9,845 at 80%.

Maintaining an 80% SoC is recommended for optimal EV battery health and reducing wear, whereas a minimum of 50% SoC is needed to avoid range anxiety. Higher SoC reduces the need for frequent charging stops, thus decreasing the demand for commercial chargers. This trend is consistent across different market penetration rates, highlighting the importance of optimal SoC management.

Both the public and private sectors must be prepared to meet the needs of EV users. The combined effort of public-private partnership will ensure a seamless transition to electric mobility, reduce range anxiety, and support the sustainable growth of the EV market. Preparing the necessary infrastructure, considering market penetration rates, household charging adoption, and SoC management, is essential for the successful adoption and use of EVs.

### *7.2 EV Power Network Integration for Current Market Penetration*

### 7.2.1 Current Market Penetration Rate

A bi-level optimization model is applied to analyze the current market penetration rates of 0.09%, 0.75%, and 1.61%. This model addresses the strategic and operational challenges of EV infrastructure deployment, providing a robust framework for balancing the interests of different stakeholders.

- **Upper Level:** The upper-level model focuses on determining the optimal number of commercial EV charging stations, ensuring that the infrastructure deployment meets the market demand while maximizing the profitability for station investors. The objective is to strategically place the stations to serve both urban and suburban areas while minimizing costs for investors.

- **Lower Level:** The lower-level model integrates power network considerations, optimizing grid management and dynamic pricing. This component ensures the power distribution system can handle the additional load from EV charging without overloading the grid. It also incorporates dynamic pricing to balance grid stability and operational efficiency, adjusting prices in real time based on demand.

The bi-level optimization model is well-suited for addressing the complexities of EV infrastructure planning, as it simultaneously considers both the market demand for charging stations and the operational constraints imposed by the power grid.

The selection of 0.09%, 0.75%, and 1.61% market penetration rates is based on the current EV adoption levels in Maryland. The 0.09% rate reflects the lowest observed penetration, found in Somerset County, while the 0.75% rate represents the state average. The 1.61% rate observed in Montgomery County represents the highest penetration in the state. These market penetration levels were chosen to provide insights into how different adoption rates influence the need for commercial charging infrastructure and how the power grid can be adapted to support these levels of EV ownership.

*(i) 0.09% Market Penetration Rate*

In this scenario, a market penetration rate of 0.09% was selected, which aligns with the EV adoption rate observed in Somerset County, Maryland, despite the fact that Somerset is not part of the study area. The intention behind using this penetration rate was to explore how such a low percentage of EV ownership would impact the infrastructure needs, even in regions where EV adoption has been slow.

At this 0.09% penetration rate, the required number of commercial charging stations varies depending on the percentage of households equipped with residential chargers and the SoC of the EVs.

In the scenario where 0% of households have access to residential charging infrastructure, the demand for commercial charging stations peaks, with 229 stations needed for both 50% SoC and 80% SoC levels. However, as the adoption of residential chargers increases, the requirement for public charging infrastructure declines. For instance, with 50% of households having residential chargers, the need for commercial stations drops to 122 for 80% SoC and 119 for 50% SoC, reflecting reductions of 46.7% and 48.0%, respectively.

At 60% household adoption, the number of commercial charging stations decreases further to 101 for an 80% SoC and 96 for a 50% SoC, resulting in reductions of 55.9% and 58.1%, respectively. For 70% household adoption, the required number of commercial stations falls to 80 for an 80% SoC and 73 for a 50% SoC, representing a reduction of 65.1% and 68.1%.

As residential charger adoption reaches 80%, the need for public charging infrastructure decreases significantly, with only 59 commercial stations required for an 80% SoC and 49 stations for a 50% SoC, showcasing reductions of 74.2% and 78.6%, respectively. At the highest level of residential adoption, 90%, the demand for commercial stations drops sharply to 37 stations for an 80% SoC and 25 stations for a 50% SoC, resulting in reductions of 83.8% and 89.1%, respectively.

While Somerset County was not part of the study area, this analysis provides valuable insights into how a low EV market penetration rate might impact charging infrastructure, particularly in regions where EV adoption is still in its early stages. The results demonstrate that even with lower EV ownership, the gradual adoption of residential chargers can significantly reduce the need for commercial charging infrastructure.

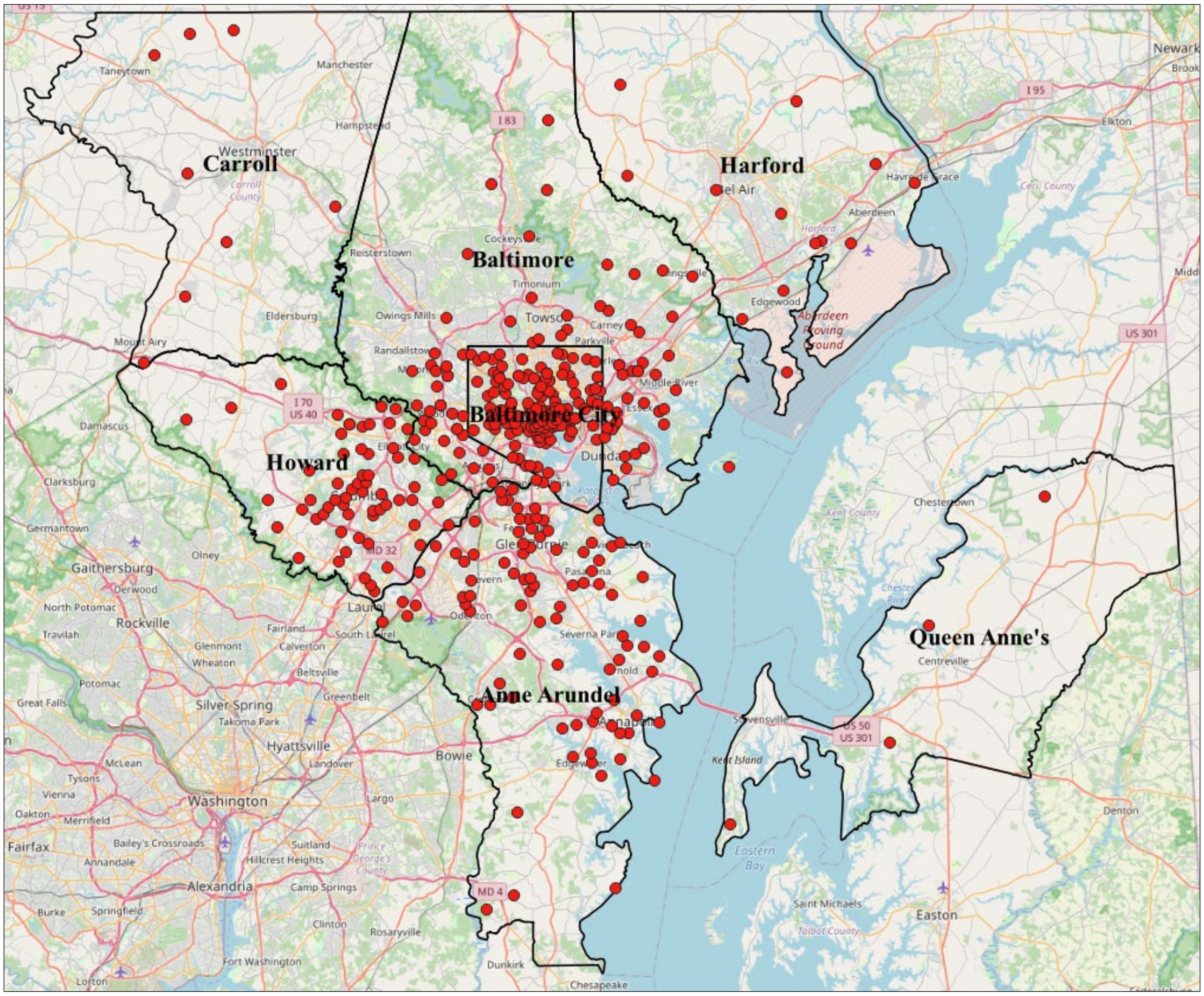


**Figure 16 Distribution of Commercial EV Charging Stations in Baltimore MSA for 0% Residential Charging Facilities 0% for 0.09% Market Penetration**

**Figure 16** illustrates the distribution of 229 commercial charging stations for a 0.09% market penetration rate, with 0% of households having residential chargers and an SoC of 0.5. This scenario assumes that no EV owners have access to home charging infrastructure, leading to a complete reliance on public commercial charging stations across the study area. Given the low penetration rate, the charging station network is notably sparse, with large geographic gaps between stations, especially in more rural or less densely populated regions.

1. **Baltimore City and Surrounding Areas:**

    - The densest concentration of commercial charging stations is observed in **Baltimore City**, which serves as the urban core of the region. Given the city's dense population and significant vehicle ownership, the demand for public charging infrastructure is higher here compared to surrounding areas. In this scenario, despite the low penetration rate, Baltimore City has a network of public charging stations distributed throughout its central and surrounding districts.

    - **Baltimore County** also shows a considerable number of charging stations, particularly in areas like Towson and along major transportation routes. However, even within the county, significant gaps exist between charging stations, particularly as one moves farther from the urban core.

2. **Suburban Counties:**

    - **Howard County** sees several charging stations, particularly near Columbia and along the I-95 corridor, but the stations are far more spaced out compared to the more densely populated Baltimore City. The charging station distribution here is more oriented toward commuters and travelers using the main highways, reflecting the more suburban nature of the county.

- **Anne Arundel County** similarly shows charging stations scattered along major routes, particularly near Annapolis and around Baltimore-Washington International Airport. However, large areas of the county remain uncovered, especially in the southern and eastern sections, indicating lower charging demand or accessibility in those regions.

3. **Less Populated and Rural Areas:**

   - **Carroll County** has a very sparse distribution of charging stations, with a few stations clustered near Westminster, the county seat, and along major roads leading into Baltimore County. The rural nature of the county results in fewer stations and larger gaps between them.

   - **Harford County** displays a somewhat similar pattern, with most charging stations located in and around Bel Air and along major highways such as I-95. The northern and more rural areas of Harford show minimal charging infrastructure, reflecting the reduced demand in these less densely populated regions.

   - **Queen Anne's County**, a largely rural county with small population centers, has very limited charging infrastructure. Only a few charging stations are placed near Centreville, the county seat, and along US Route 50, which serves as a major corridor for commuters and travelers heading to and from the Eastern Shore. The rest of the county, particularly its eastern regions, remains devoid of charging infrastructure, indicating a much lower demand for EV charging in this more remote area.

4. **Overall Sparse Distribution:**

   - The overall distribution of the 229 charging stations is quite sparse across the study area, with large gaps in coverage, particularly in rural areas. Charging stations are mostly concentrated around urban centers, commercial zones, and along major highways, where the likelihood of encountering EVs is higher. However, the lack of widespread infrastructure in more remote regions indicates that EV drivers in these areas would face challenges in accessing public charging, further underlining the importance of developing residential charging infrastructure.

   - Major commuter corridors, such as I-95, US 50, and I-70, have some coverage, ensuring that long-distance travelers have access to public charging stations. However, even along these routes, the number of available stations is limited, requiring careful planning by EV users to ensure they can recharge during their journeys.

This sparse distribution of charging stations highlights the challenges faced by regions with low EV adoption rates. In a scenario where 0% of households have residential chargers, the public infrastructure alone is insufficient to support widespread EV use, particularly in less urbanized areas. The need for more extensive infrastructure becomes even more pronounced when considering that EV users in rural and suburban areas may have to travel significant distances to reach a public charging station.

Additionally, while the major metropolitan areas like Baltimore City, Columbia, and Annapolis have reasonable coverage, the overall network does not extend far into rural areas, potentially limiting EV adoption in these regions. The current distribution also places a burden on commuters and travelers, as they are limited to a relatively small number of stations spread out along major roads.

This distribution also suggests that without residential charging options, many EV users in rural and suburban areas would face significant obstacles to transitioning to electric vehicles, as their access to charging infrastructure would be highly restricted. The limited number of stations in the 0.09% penetration rate scenario emphasizes the need for more robust public infrastructure or incentives for residential charger installation to better accommodate the growing EV population.

*(ii) 0.75% Market Penetration Rate*

For this scenario, a market penetration rate of 0.75% was selected, which aligns with the state average EV adoption rate for Maryland and represents a significant figure for Baltimore City. At this market penetration rate, approximately 16,450 EVs are estimated to be in the Baltimore MSA, with 7,600 households owning EVs. The number of commercial charging stations required in this context is highly dependent on the percentage of households equipped with residential chargers and the SoC levels of the EVs.

In scenarios where no households have access to residential charging facilities (0% adoption rate), the number of required commercial charging stations is at its highest, with 1,900 stations needed for both 50% and 80% SoC levels. As more households adopt residential chargers, the demand for commercial charging infrastructure decreases significantly. For example, with 50% of households having residential chargers, the number of required commercial stations decreases to 1,016 for an 80% SoC and 984 for a 50% SoC, representing reductions of 46.5% and 48.2%, respectively.

This trend continues with 60% household adoption, where the demand for commercial charging stations further reduces to 840 for an 80% SoC and 793 for a 50% SoC, showing a reduction of 55.8% and 58.2%, respectively. At 70% household adoption, the required number of commercial stations drops to 663 for an 80% SoC and 600 for a 50% SoC, which corresponds to a decrease of 65.1% and 68.4%. For 80% household adoption, the number of commercial charging stations falls to 486 for an 80% SoC and 404 for a 50% SoC, representing reductions of 74.4% and 78.8%, respectively. Finally, at 90% household adoption, only 309 commercial charging stations are needed for an 80% SoC and 205 for a 50% SoC, reflecting a significant reduction of 83.7% and 89.2%, respectively.

**Figure 10** illustrates the critical role that residential charging infrastructure plays in reducing the need for the deployment of commercial charging stations. As household adoption of residential chargers increases, the reliance on public commercial infrastructure decreases significantly, particularly at higher SoC levels.

For instance, transitioning from a 50% household adoption rate to a 90% adoption rate at an 80% SoC level reduces the need for commercial stations by 79.1%. Similarly, at a 50% SoC, the reduction is 69.5%. These results demonstrate the direct correlation between household charger adoption and the decreasing demand for commercial charging infrastructure, which has substantial implications for the cost and planning of future EV infrastructure development.

Moreover, when comparing 50% SoC to 80% SoC within the same household adoption rate, the reductions in required commercial chargers range from 1.6% to 33.6%, highlighting the impact that higher SoC levels have on lowering the demand for commercial stations. As EV adoption continues to rise, the results of this study underscore the importance of promoting residential charging solutions to minimize the strain on public charging infrastructure and enhance the overall efficiency of the EV charging ecosystem.

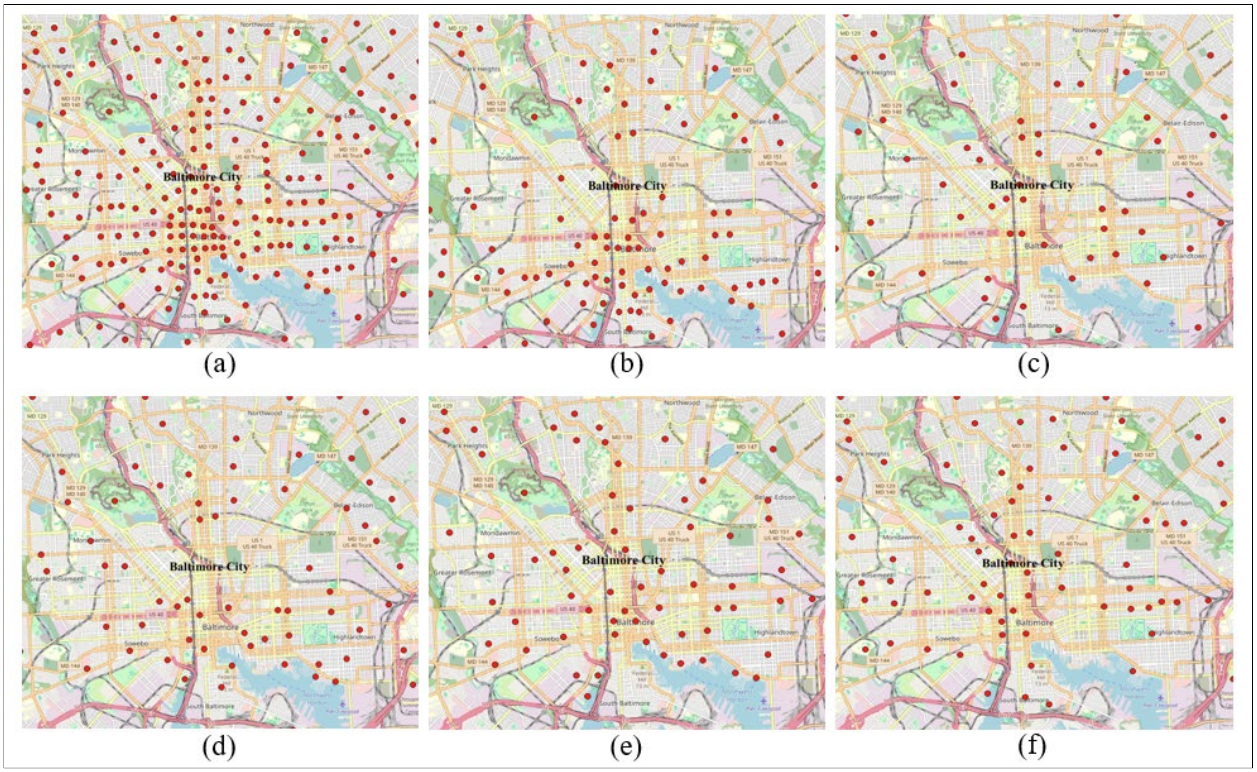


**Figure 17 Scenario Comparison for Commercial EV Charging Stations in Downtown Baltimore City for Residential Charging Facilities: (a) 0% (b) 50% (c) 60% (d) 70% (e) 80% and (f) 90% for 0.75% Market Penetration**

In **Figure 17** for Downtown Baltimore City, with a 0.75% market penetration rate and a State of Charge (SoC) of 0.05, we observe the strategic placement of commercial charging stations based on varying levels of residential charging infrastructure adoption. The six subfigures, (a) through (f), represent scenarios where different percentages of households have access to residential EV chargers, ranging from 0% to 90%.

- **Subfigure (a)** shows the densest distribution of commercial charging stations, reflecting a situation where 0% of households have residential chargers. In this case, EV users are highly dependent on commercial charging infrastructure, leading to widespread station placement throughout the city to meet the demand.
- **Subfigure (b)**, with 50% household adoption, demonstrates a moderate decrease in the number of commercial charging stations. As more households have access to residential chargers, the need for commercial stations lessens, and we see fewer stations clustered in residential areas.
- **Subfigures (c)** through **(f)** continue this trend, with 60%, 70%, 80%, and 90% household adoption, respectively. As the percentage of households with residential chargers increases, the number of required commercial charging stations diminishes. By 90% adoption in subfigure (f), the distribution of commercial chargers is more sparse and concentrated primarily in commercial zones or along major transportation corridors rather than dispersed across the city.

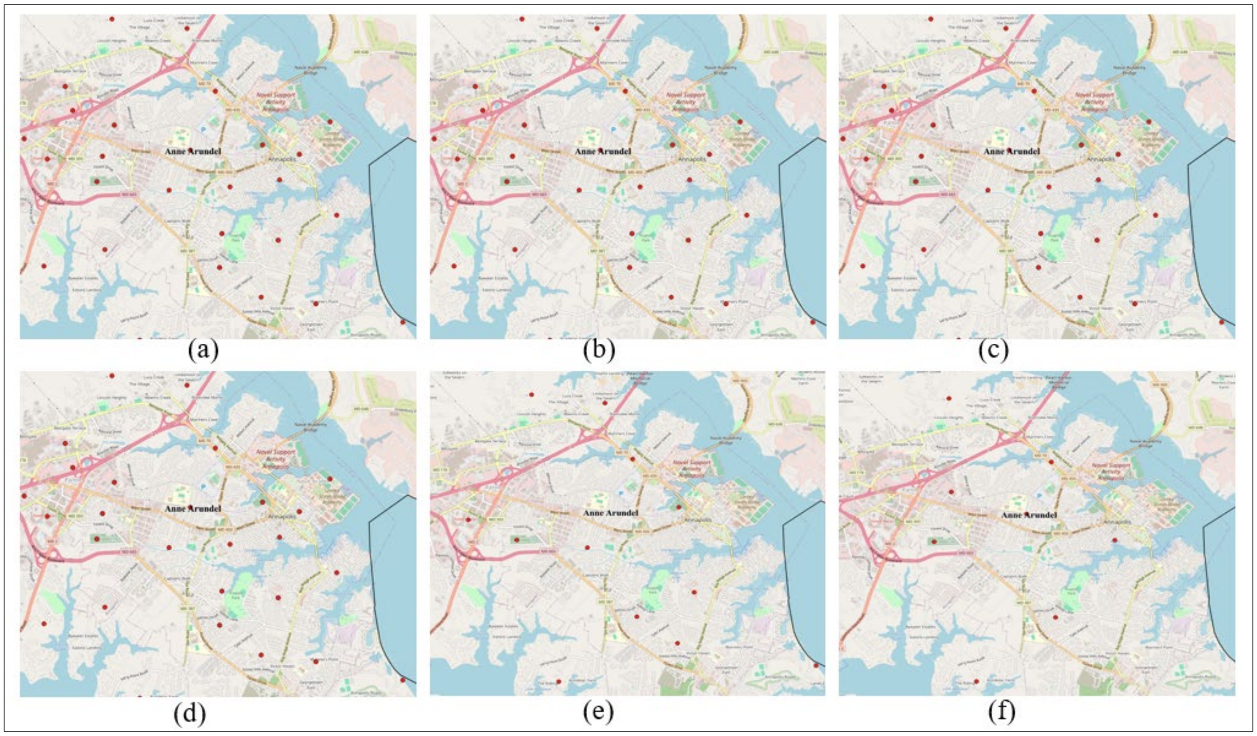


**Figure 18 Scenario Comparison for Commercial EV Charging Stations in Annapolis for Residential Charging Facilities: (a) 0% (b) 50% (c) 60% (d) 70% (e) 80% and (f) 90% for 0.75% Market Penetration**

In **Figure 18**, for Annapolis, we analyze the placement of commercial charging stations based on varying levels of residential EV charger adoption at a 0.75% market penetration rate, with the state of charge (SoC) at 0.05. The six subfigures, labeled (a) through (f), represent the same scenario structure as for Baltimore City, with household residential charger adoption ranging from 0% to 90%. Each subfigure reflects how the adoption rate of residential EV chargers influences the density and distribution of commercial charging stations in Annapolis.

- **Subfigure (a)**, where 0% of households have residential EV chargers, shows a sparse but relatively well-distributed network of commercial charging stations throughout Annapolis. Given the total dependence on commercial charging infrastructure, these stations are spread across residential areas and concentrated along major roads and highways, particularly near high-traffic zones like Anne Arundel.

- **Subfigure (b)**, where 50% of households have residential chargers, mirrors subfigure (a) in terms of charging station placement. Here, there is no notable reduction in the number of commercial charging stations, as the demand is still high, even though half of the households have access to home charging. This indicates that the existing network sufficiently meets the demand for public charging in this scenario.

- **Subfigure (c)** shows a scenario with 60% household adoption, and again, no significant changes are seen in the placement of commercial charging stations compared to the prior subfigures. The network remains stable, indicating that the reduced demand from residential charging at this level has not yet prompted any notable adjustments in commercial station deployment.

- **Subfigure (d)**, with 70% household adoption, similarly shows no changes in the commercial charging station distribution. This suggests that, up to this point, the infrastructure is robust enough to handle shifts in demand without major alterations. The network still provides sufficient coverage for EV users relying on public charging.

- **Subfigure (e)** marks the first visible change in the placement of commercial charging stations, as the household adoption rate reaches 80%. At this level, there is a noticeable reduction in the number of commercial charging stations, particularly in less central areas of Annapolis. The stations are now more concentrated along major transportation routes, such as highways and key commercial zones, as fewer EV users are reliant on public charging. The remaining stations are positioned to support long-distance travelers and those without access to residential chargers in more densely populated areas.

- **Subfigure (f)**, with 90% of households having residential chargers, shows the most significant reduction in commercial charging infrastructure. The number of stations is greatly reduced, with commercial chargers now only located in essential spots along highways and near major commercial centers. These stations cater primarily to transient users, such as visitors or commuters, as the vast majority of Annapolis households have shifted to residential charging. This demonstrates a significant reliance on home charging and reflects a major decline in the need for public infrastructure in residential zones.

The overall trend observed in the Annapolis comparison shows that, up to a household adoption rate of 70%, the distribution of commercial charging stations remains largely unchanged. It is only at the higher levels of residential charger adoption—80% and 90%—that we see notable reductions in the public infrastructure, with commercial stations becoming more concentrated along primary travel corridors. This transition illustrates the diminishing reliance on public charging stations as more households gain access to residential chargers, which helps alleviate the demand for commercial stations, particularly in suburban or residential areas.

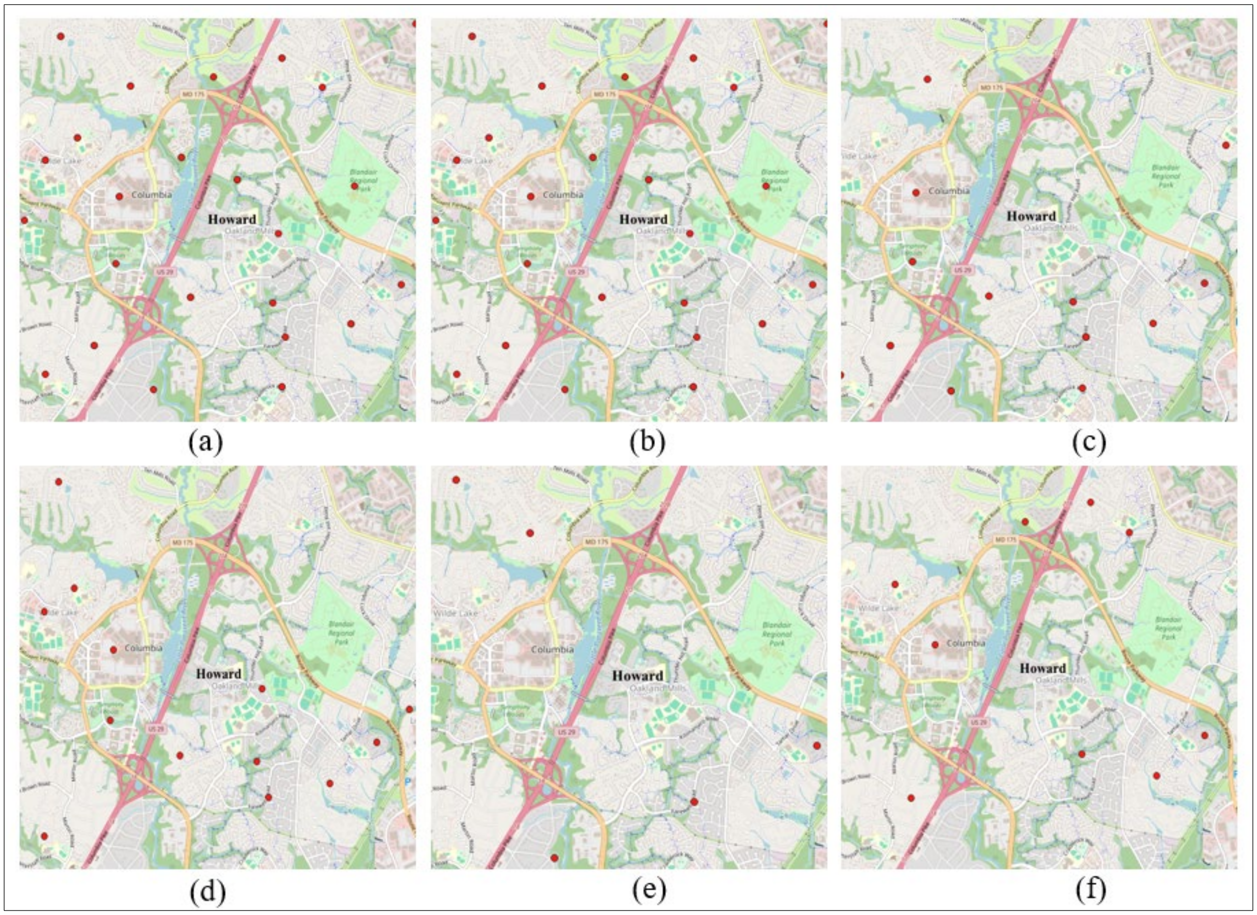


**Figure 19 Scenario Comparison for Commercial EV Charging Stations in Columbia for Residential Charging Facilities: (a) 0% (b) 50% (c) 60% (d) 70% (e) 80% and (f) 90% for 0.75% Market Penetration**

In the Columbia, MD area (**Figure 19**), the impact of household EV charger adoption on commercial charging station placement is clearly demonstrated through subfigures (a) to (f), illustrating how the network of commercial charging stations changes as the percentage of households with residential chargers increases from 0% to 90%. The variation across these subfigures is particularly notable as the changes in the distribution of commercial charging infrastructure become more pronounced with higher residential adoption rates.

- **Subfigures (a)** and **(b)** both represent scenarios where 0% and 50% of households, respectively, have residential chargers. In both cases, the distribution of commercial charging stations remains unchanged, indicating that at a 50% adoption rate, the commercial infrastructure is still highly utilized, and there is no significant reduction in public charging demand. The charging stations are spread across residential areas, key commercial zones, and major roads, ensuring that users without home charging access can conveniently charge their EVs. The network remains robust and widespread, covering a variety of locations in Columbia, particularly near high-traffic areas such as the Columbia Mall and along major highways like MD 175 and US 29.

- **Subfigure (c)**, where 60% of households have adopted residential chargers, starts to show a more concentrated distribution of commercial charging stations. The network shifts focus from residential neighborhoods to more central locations, particularly near commercial areas and along main transportation corridors. This reflects the growing reliance on residential chargers, as fewer EV owners depend on public stations, allowing for a reduction in less critical areas.

- **Subfigure (d)**, at 70% residential charger adoption, continues the trend of consolidation. The number of commercial charging stations decreases further, with the infrastructure now mainly centered along key highways and commercial hubs. Residential areas see a notable reduction in charging stations, emphasizing the diminishing need for public charging infrastructure as the majority of households now have access to home chargers.

- **Subfigure (e)**, representing 80% adoption of residential chargers, highlights a significant reduction in the number of public charging stations. The remaining stations are concentrated around the most trafficked areas, particularly along the major highways like US 29 and MD 175, as well as commercial centers. Residential areas are now almost entirely devoid of public chargers, showing that most daily charging needs are met at home. The remaining public infrastructure serves primarily long-distance travelers and those without access to residential charging.

- **Subfigure (f)**, with 90% household adoption, shows the most drastic reduction in commercial charging stations. The remaining infrastructure is sparse and concentrated solely on key highways and essential commercial centers. The significant drop in the number of public charging stations reflects the fact that, with 90% of households equipped with residential chargers, the demand for public infrastructure has diminished almost entirely. The few remaining stations cater to occasional or transient users, indicating a near-complete shift toward residential charging in the Columbia area.

The comparison of the Columbia scenario vividly illustrates how the availability of residential charging significantly influences the deployment of commercial charging stations. While there is no noticeable difference between subfigures (a) and (b), corresponding to 0% and 50% household adoption, the effects become increasingly clear starting from 60% adoption and beyond. By the time residential charger adoption reaches 90%, the commercial infrastructure is almost entirely focused on supporting long-distance travel and commuters, with very little demand remaining in residential zones. This transition underscores the powerful impact that residential charger availability has on shaping the future of EV infrastructure.

*(iii) 1.61% Market Penetration Rate*

In this scenario, a market penetration rate of 1.61% was selected, representing the highest EV adoption rate in Maryland, specifically observed in Montgomery County. At this penetration rate, approximately 35,305 EVs are estimated to be present within the Baltimore Metropolitan Statistical Area (MSA), with a significant number of households now owning electric vehicles. The required number of commercial charging stations in this scenario is heavily influenced by the percentage of households equipped with residential chargers and the State of Charge (SoC) levels of the vehicles.

In cases where 0% of households have residential charging access, the need for commercial charging stations reaches its peak, with 4,080 stations required for both 50% and 80% SoC levels. However, as more households gain access to residential chargers, the demand for public infrastructure decreases considerably. For example, when 50% of households have residential chargers, the number of commercial charging stations required drops to 2,182 for an 80% SoC and 2,113 for a 50% SoC, representing reductions of 46.5% and 48.2%, respectively.

This trend continues with 60% household adoption, where the demand further decreases to 1,802 for an 80% SoC and 1,703 for a 50% SoC, showing reductions of 55.8% and 58.2%, respectively. At 70% household adoption, the number of required commercial stations drops to 1,423 for an 80% SoC and 1,287 for a 50% SoC, reflecting decreases of 65.1% and 68.4%.

As residential charger adoption reaches 80%, the demand for commercial infrastructure decreases even further, with only 1,043 stations needed for an 80% SoC and 866 for a 50% SoC, representing reductions of 74.4% and 78.8%, respectively. Finally, at 90% household adoption, the need for public charging infrastructure declines dramatically, with only 664 commercial stations required for an 80% SoC and 440 stations for a 50% SoC, showcasing significant reductions of 83.7% and 89.2%, respectively.

This analysis demonstrates that as residential charging adoption increases, the demand for public commercial charging stations decreases sharply, especially at higher levels of residential charger deployment. The trend emphasizes the growing reliance on home charging as the dominant method of charging, particularly in areas with high EV adoption rates.

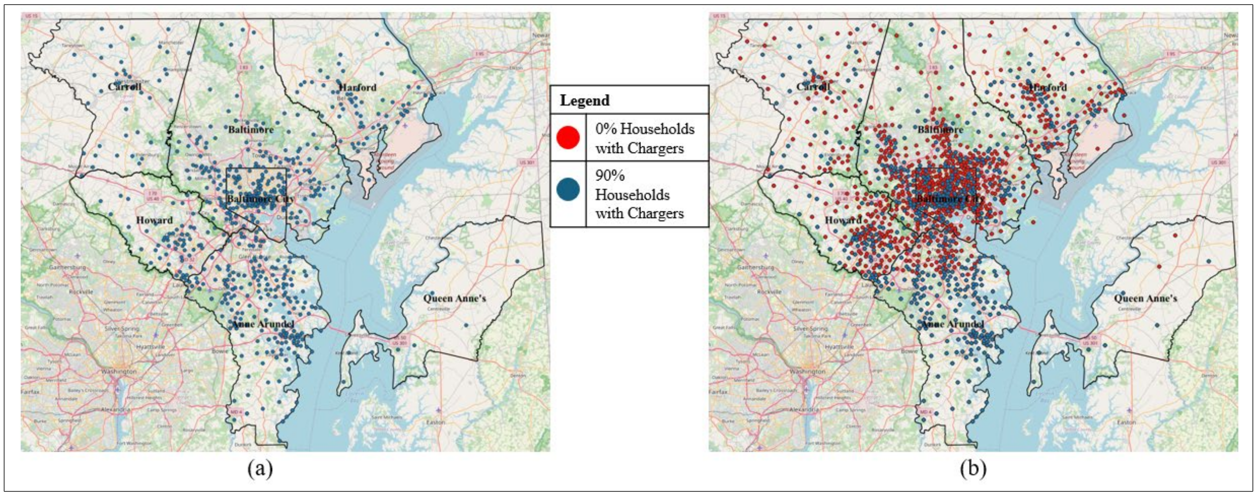


**Figure 20 Scenario Comparison for Commercial EV Charging Stations in Baltimore MSA for Residential Charging Facilities: (a) 0% (b) 90% for 1.61% Market Penetration**

**Figure 20** above presents an overall view of the Baltimore MSA for a 1.61% market penetration rate; the distribution of commercial charging stations is represented through red and blue dots. Red dots signify areas where 0% of households have residential chargers, meaning a greater reliance on public commercial infrastructure is necessary. Blue dots indicate areas where 90% of households have residential chargers, illustrating a significant reduction in the need for public charging infrastructure as the majority of charging happens at home. This comparison provides key insights into how the availability of residential chargers affects the deployment of public and commercial stations across the region.

**Metropolitan and Urban Coverage:**

The charging station distribution covers all the major metropolitan areas within the Baltimore MSA. These densely populated regions naturally require a significant number of commercial charging stations to meet the charging demands of EV users.

- **Baltimore City**: The urban core of Baltimore City is densely populated with charging stations in both scenarios, as it is the largest population center in the region. Given the high density of EV users and fewer available residential spaces for chargers, public infrastructure is crucial to meet demand. As expected, even with 90% of households having residential chargers, a high density of commercial stations remains concentrated in the downtown area, where transient users, visitors, and daily commuters heavily rely on public infrastructure.

- **Towson (Baltimore County)**: Towson, another major urban area, also shows significant coverage in both 0% and 90% scenarios. Towson's position as a major commercial and administrative hub north of Baltimore means it has a higher demand for public charging infrastructure. Here, too, even with substantial residential charger adoption, commercial charging remains essential, reflecting Towson’s role as a regional commuter destination.

**Suburban and Regional Coverage:**

Beyond the core urban centers, several suburban and regional areas also see substantial coverage of commercial charging stations, indicating that EV adoption is widespread even outside the city centers.

- **Westminster (Carroll County)**: In Westminster, we observe a solid presence of charging stations, particularly with 0% residential charger adoption. Westminster, a more rural and suburban area compared to Baltimore, still requires public charging stations for residents and commuters. However, with the rise in residential charger adoption, the number of required commercial stations decreases noticeably as the local population begins to rely more heavily on home charging.

- **Bel Air (Harford County)**: The county seat of Harford, Bel Air, also shows significant coverage of public charging infrastructure. Bel Air serves as a central hub for surrounding rural areas, and thus, the commercial charging stations provide essential services for users from both urban and rural settings. As residential adoption rises, commercial stations become concentrated in high-traffic areas, although a notable portion remains due to the commuter population and regional users without access to home charging facilities.

- **Columbia (Howard County)**: Columbia, a major planned community and one of the largest in the MSA is covered extensively by commercial charging stations. The region's high-density residential and commercial mix requires significant charging infrastructure, as Columbia serves both as a residential hub and a workplace for many commuters. Even with 90% of households having residential chargers, Columbia still retains a substantial number of public charging stations due to its centrality in the region's transportation network.

- **Annapolis (Anne Arundel County)**: Annapolis, the state capital, also has a substantial commercial charging infrastructure, reflecting its importance as a governmental and tourist center. With its high influx of visitors, the need for public charging remains high even as residential charger adoption increases. Commercial charging stations are concentrated near the downtown and waterfront areas to accommodate the transient population.

**Areas with Sparse Coverage:**

While the charging infrastructure is robust in the key metropolitan and suburban areas, some more rural or less densely populated regions see limited commercial charging infrastructure.

- **Centreville (Queen Anne's County)**: Centreville, located in the more rural Queen Anne's County, exhibits a much lower density of charging stations compared to other counties in the Baltimore MSA. The lower population density and fewer commuting demands reduce the need for public infrastructure. With 90% of households having residential chargers, the few commercial stations that do exist are concentrated near major highways and transit routes, reflecting the lower overall demand for public charging.

Overall, the distribution of charging stations across the Baltimore MSA demonstrates a well-developed network that covers all major urban and suburban areas, ensuring access to charging infrastructure for both residents and visitors. As the level of residential charger adoption increases, the reliance on public infrastructure decreases, particularly in less dense or rural areas like Centreville. However, in major cities and suburban hubs such as Baltimore, Towson, Columbia, and Annapolis, public charging remains essential, even with higher levels of residential charger adoption. These areas are critical not only for local residents but also for commuters and transient users, ensuring that EV drivers have access to charging infrastructure throughout the region. This analysis highlights the adaptability of the charging infrastructure network in the Baltimore MSA, emphasizing its ability to meet the growing needs of EV users while adjusting to the rise in residential charging capabilities.

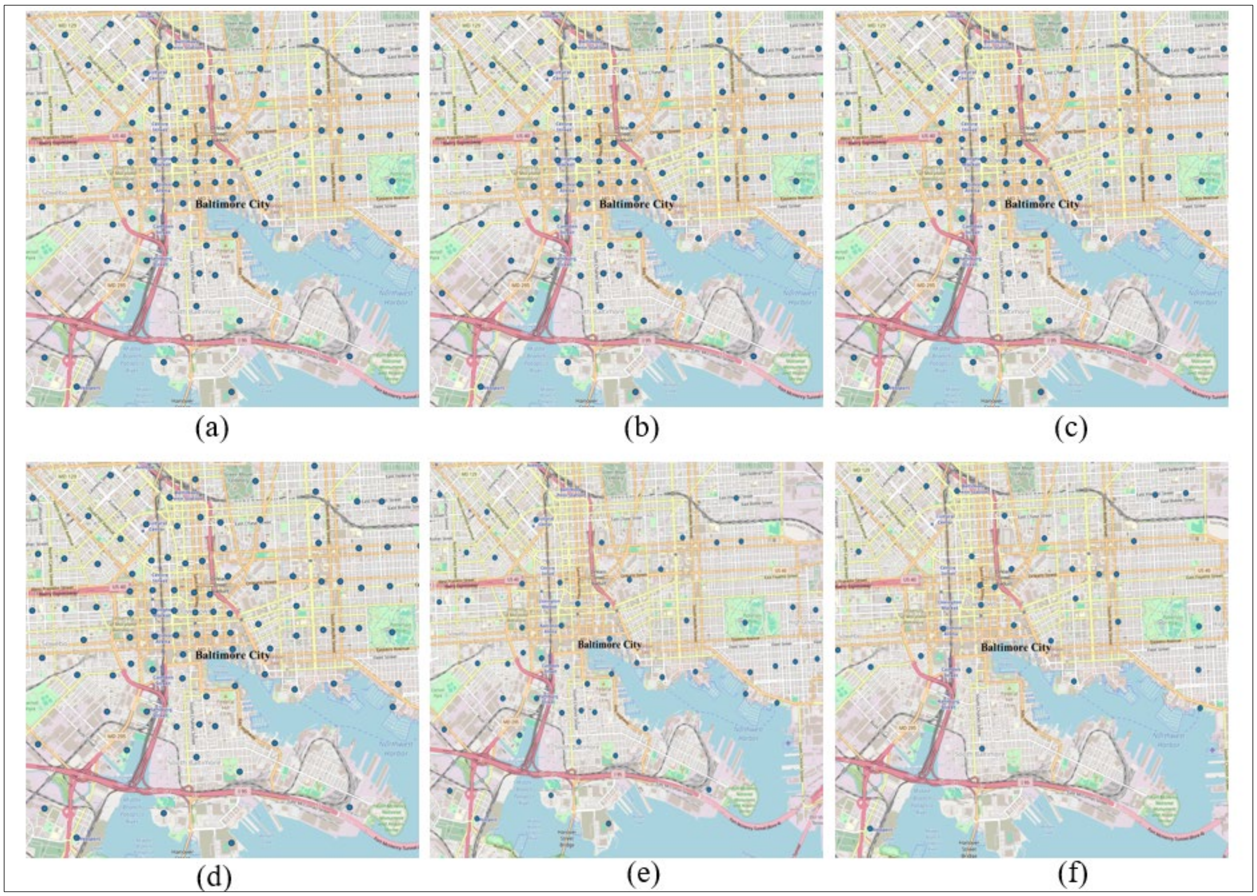


**Figure 21 Scenario Comparison for Commercial EV Charging Stations in Downtown Baltimore City for Residential Charging Facilities: (a) 0% (b) 50% (c) 60% (d) 70% (e) 80% and (f) 90% for 1.61% Market Penetration**

In Downtown Baltimore City (**Figure 21**), the impact of household EV charger adoption on commercial charging station placement is illustrated through subfigures (a) to (f), showing how the network of commercial charging stations adapts as the percentage of households with residential chargers increases from 0% to 90%. The variation across these subfigures is particularly notable as the distribution of commercial charging infrastructure remains static up to a certain point and only begins to change at higher adoption rates.

- **Subfigures (a)**, **(b)**, **(c)**, and **(d)** all represent scenarios where 0%, 50%, 60%, and 70% of households, respectively, have residential chargers. Across all four scenarios, the distribution of commercial charging stations remains unchanged. This indicates that even as residential adoption rises to 70%, the demand for commercial charging stations remains stable, and commercial infrastructure continues to be heavily utilized. The charging stations are evenly spread across downtown residential and commercial zones, as well as along major roads, ensuring broad access to public charging infrastructure for EV users. Even with 70% of households having residential chargers, the grid still requires a significant number of commercial stations to meet the charging demand, reflecting the importance of public infrastructure at these lower levels of household adoption.

- **Subfigure (e)**, where 80% of households have adopted residential chargers, shows the first notable changes in the commercial charging infrastructure distribution. At this level, the number of commercial charging stations starts to reduce slightly. Some of the stations in less central residential areas have been removed, indicating that a higher proportion of EV users now rely on residential charging infrastructure, thus lessening the strain on public stations. However, key locations, especially those along major travel corridors and commercial districts, continue to maintain public charging stations, highlighting the need for public infrastructure to support users who do not have home charging facilities or are traveling longer distances.

- **Subfigure (f)**, where 90% of households have adopted residential chargers, shows a more pronounced reduction in commercial charging stations. The infrastructure becomes increasingly concentrated along the busiest roads and in core commercial areas, with fewer stations available in residential neighborhoods. This reflects a major shift toward residential charging as the primary method of EV charging. The remaining public infrastructure is designed to serve occasional users, long-distance travelers, and those without access to residential chargers, indicating that public charging is now supplementary rather than essential.

This scenario comparison for Downtown Baltimore City emphasizes how residential charging adoption drastically influences the need for public infrastructure. While the network of commercial charging stations remains unchanged up to 70% residential charger adoption, the impact becomes more visible at 80% and 90%, where the reliance on commercial stations decreases significantly. By the time 90% of households have residential chargers, the public infrastructure is concentrated mainly in commercial areas and along travel routes, highlighting the transition to residential charging as the dominant charging method in this area. The shift underscores how increasing household charger adoption can reduce the strain on public infrastructure, enabling a more efficient deployment of commercial charging stations.

### *7.3 Queuing Simulation Results and Analysis for EV Charging Infrastructure*

This section presents detailed results from the advanced queuing simulation developed to analyze EV charging station performance under varying market penetration scenarios and different initial states of charge (SoC). As the adoption of electric vehicles continues to rise, managing congestion at charging stations becomes critical to ensure user satisfaction, infrastructure efficiency, and operational sustainability. Therefore, this analysis specifically evaluates key performance metrics such as average waiting time, server utilization, blocking probability, and average queue length, each carefully selected for their practical implications and strategic value in planning EV charging infrastructure.

The average waiting time is a critical indicator of user convenience and satisfaction. Longer waiting times directly correlate with reduced user satisfaction and could negatively affect the adoption of electric vehicles. Hence, quantifying and analyzing waiting times across different penetration rates and SoC scenarios allows infrastructure planners and policymakers to identify congestion issues proactively and implement necessary mitigation strategies.

Server utilization is evaluated to measure the efficiency of resource use within charging stations. High utilization rates indicate efficient usage of charging infrastructure but may also suggest an increased risk of congestion during peak demand. Conversely, low utilization rates may signify over-investment in charging facilities and poor capital resource management. Analyzing utilization across various market scenarios helps to balance infrastructure capacity and demand effectively, guiding optimal investment decisions.

Blocking probability is included to measure the likelihood that incoming vehicles are unable to access charging stations due to full occupancy, resulting in vehicles being turned away. A high blocking probability not only impacts user satisfaction negatively but also suggests severe capacity constraints. Evaluating this metric across different market penetration levels and SoC conditions helps identify critical thresholds for infrastructure expansion, ensuring that station capacity keeps pace with increasing demand.

The average queue length metric complements the blocking probability and waiting time analyses by providing insights into the typical number of vehicles waiting for charging at any given time. Long queues indicate insufficient capacity relative to demand, potentially discouraging EV adoption. By analyzing queue lengths under varying conditions, infrastructure managers can better understand demand patterns, anticipate future needs, and optimize queue management strategies to enhance user experience.

Together, these metrics provide comprehensive insights into charging infrastructure performance, enabling informed decisions to manage congestion effectively, optimize resource allocation, and enhance user satisfaction across various market penetration and SoC scenarios.

### 7.3.1 Current Market Penetration Rate

*(i) 0.09% Market Penetration Rate, SoC = 0.5*

Blocking Probability:

**Table 5 Blocking Probability Across Different Household Percentages for Market Penetration Rate = 0.09%, SoC = 0.5**

| Blocking Probability (%) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 109 | 91 | 77 | 54 | 34 |
| **5** | 4 | 0 | 0 | 0 | 0 |
| **10** | 2 | 0 | 2 | 2 | 0 |
| **15** | 2 | 0 | 0 | 0 | 0 |
| **20** | 1 | 1 | 0 | 1 | 0 |
| **30** | 1 | 0 | 0 | 0 | 0 |

This comparative analysis examines the simulated blocking probability across charging stations under varying household adoption levels (50%, 60%, 70%, 80%, and 90%) at a 0.09% EV market penetration rate and an initial State of Charge (SoC) of 50%.

The results indicate a clear trend where higher household adoption rates of residential chargers significantly reduce the likelihood of blocking at commercial charging stations. At 50% household adoption, most stations (109) reported minimal blocking probability, although there were notable exceptions, with a few stations experiencing blocking probabilities over 20% to 30%. As household adoption increased to 60%, the overall number of stations facing substantial blocking decreased, with the highest recorded blocking probability dropping to approximately 20%.

Further increasing the household adoption rate to 70% resulted in even fewer stations exhibiting significant blocking probabilities. At this level, only a handful of stations showed blocking probabilities between 6% and 12%, underscoring the effectiveness of increased residential charger availability in relieving commercial infrastructure congestion.

At the 80% adoption rate, the number of stations experiencing notable blocking further decreased, with the highest observed blocking probability reduced to approximately 20%. Finally, at the highest tested household adoption level of 90%, almost all stations showed minimal blocking, with only isolated instances of blocking probabilities between 8% and 14%.

<u>Average Waiting Time:</u>

**Table 6 Average Waiting Time Across Different Household Percentages for Market Penetration Rate = 0.09%, SoC = 0.5**

| Average Waiting Time (min) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 78 | 74 | 55 | 42 | 25 |
| **10** | 7 | 4 | 3 | 2 | 3 |
| **20** | 4 | 4 | 1 | 3 | 1 |
| **30** | 8 | 5 | 3 | 2 | 2 |
| **40** | 3 | 1 | 0 | 1 | 0 |

Similarly, average waiting time exhibits a clear relationship with household adoption rates. At 50% adoption, although most stations experienced minimal waiting times, notable instances exceeded 20 to 40 minutes, indicating significant congestion at certain locations. Increasing household adoption to 60% and 70% gradually reduced waiting times, with fewer stations experiencing extended waiting periods. At higher adoption rates of 80% and 90%, the average waiting time significantly improved, with most stations maintaining minimal to zero waiting time and only a few experiencing longer waits. This analysis further emphasizes the critical role that residential charging adoption plays in reducing congestion and improving overall charging station efficiency.

Average Queue Length:

**Table 7 Average Queue Length Across Different Household Percentages for Market Penetration Rate = 0.09%, SoC = 0.5**

| Average Queue Length (vehicles) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 0 | 1 | 1 | 0 | 0 |
| **1** | 38 | 38 | 31 | 17 | 11 |
| **2** | 56 | 42 | 33 | 31 | 19 |
| **3** | 13 | 8 | 8 | 4 | 3 |
| **4** | 9 | 10 | 6 | 6 | 4 |
| **5** | 4 | 2 | 1 | 0 | 0 |
| **6** | 2 | 0 | 0 | 1 | 0 |

Initially, at a 50% adoption rate, queue lengths were relatively higher, with many stations reporting an average queue length of 2-3 vehicles and some reaching as high as 5-6 vehicles. As residential charger adoption rose to 70% and beyond, average queue lengths significantly decreased. By 90% household adoption, the majority of stations reported queue lengths of 1-2 vehicles, clearly illustrating the impact of increased home charging capabilities in reducing queues at commercial charging stations.

Utilization:

**Table 8 Utilization Across Different Household Percentages for Market Penetration Rate = 0.09%, SoC = 0.5**

| Utilization Rate (%) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 0 | 1 | 1 | 0 | 0 |
| **10** | 2 | 2 | 3 | 9 | 7 |
| **20** | 7 | 7 | 10 | 14 | 4 |
| **30** | 15 | 15 | 7 | 11 | 10 |
| **40** | 10 | 9 | 18 | 22 | 8 |
| **50** | 5 | 2 | 2 | 2 | 0 |

| | | | | | |
|---|---|---|---|---|---|
| **60** | 8 | 4 | 4 | 3 | 3 |
| **70** | 5 | 3 | 2 | 3 | 2 |
| **80** | 2 | 0 | 0 | 0 | 0 |
| **90** | 0 | 0 | 0 | 1 | 0 |

Station utilization results show distinct distribution shifts with increasing adoption of household chargers. At 50% adoption, a pronounced peak at approximately 50% utilization is noticeable, with a diverse distribution across various utilization levels. As adoption climbs to 60% and 70%, utilization patterns start becoming more balanced, with significant station counts around 40-50%. By the 80% and 90% adoption thresholds, the utilization distribution flattens, with more stations experiencing lower utilization levels, signifying less demand at commercial stations due to widespread residential charging.

*(ii) 0.09% Market Penetration Rate, SoC = 0.8*

Blocking Probability:

**Table 9 Blocking Probability Across Different Household Percentages for Market Penetration Rate = 0.09%, SoC = 0.8**

| Blocking Probability (%) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0.0** | 111 | 87 | 63 | 46 | 19 |
| **2.5** | 2 | 3 | 3 | 1 | 2 |
| **5.0** | 1 | 1 | 1 | 0 | 1 |
| **7.5** | 1 | 0 | 1 | 1 | 0 |
| **12.5** | 2 | 2 | 1 | 1 | 1 |
| **17.5** | 2 | 1 | 0 | 1 | 0 |
| **20.0** | 0 | 0 | 1 | 0 | 1 |
| **32.5** | 0 | 0 | 1 | 0 | 0 |

The results indicate a general trend of decreasing the number of stations with zero blocking probability as household adoption rates increase. Specifically, at 50% adoption, 92.5% of stations show no blocking probability, declining significantly to 73.1% at 90% adoption. Stations experiencing non-zero blocking probabilities become relatively more frequent and severe, especially evident at higher adoption levels such as 90%, where blocking probabilities as high as 20% start to emerge, highlighting increased utilization and potential congestion at charging stations as residential charger adoption rises.

Average Waiting Time:

**Table 10 Average Waiting Time Across Different Household Percentages for Market Penetration Rate = 0.09%, SoC = 0.8**

| Average Waiting Time (min) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 89 | 67 | 51 | 30 | 15 |
| **5** | 10 | 7 | 4 | 5 | 2 |
| **10** | 4 | 7 | 3 | 3 | 2 |
| **15** | 1 | 0 | 1 | 2 | 0 |
| **20** | 4 | 1 | 2 | 0 | 2 |
| **25** | 2 | 2 | 2 | 1 | 0 |
| **30** | 1 | 2 | 0 | 1 | 1 |
| **35** | 3 | 1 | 0 | 1 | 0 |
| **40** | 0 | 0 | 0 | 0 | 1 |
| **45** | 0 | 0 | 0 | 0 | 1 |
| **60** | 0 | 0 | 1 | 0 | 0 |

As household adoption increases from 50% to 90%, the number of stations with minimal average waiting time (0 minutes) declines significantly—from 89 stations at 50% adoption to just 15 at 90% adoption. Concurrently, the number of stations experiencing nonzero waiting times grows slightly across categories from 5 to 45 minutes, with some stations reaching waiting times as high as 60 minutes at intermediate adoption levels. This shift indicates a gradual increase in congestion and wait times at charging stations as more households adopt EVs, even under a modest 0.75% market penetration and 50% SoC.

Average Queue Length:

**Table 11 Average Queue Length Across Different Household Percentages for Market Penetration Rate = 0.09%, SoC = 0.8**

| Average Queue Length (vehicles) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 0 | 0 | 1 | 0 | 0 |
| **1** | 51 | 34 | 24 | 12 | 9 |
| **2** | 51 | 43 | 32 | 25 | 7 |
| **3** | 6 | 7 | 5 | 7 | 3 |
| **4** | 7 | 9 | 7 | 3 | 4 |
| **5** | 4 | 3 | 2 | 2 | 1 |
| **6** | 0 | 0 | 1 | 0 | 1 |
| **7** | 0 | 0 | 1 | 0 | 0 |

Most stations show mean queue lengths between 1 to 2 vehicles, especially prominent at lower adoption rates (50% and 60%). As household adoption increases, the distribution shifts slightly towards longer queues, indicating more demand for charging stations. For instance, at 90% adoption, queue lengths of 4 or more vehicles are proportionally more noticeable. Queue lengths reaching up to 7 vehicles occur only once and exclusively at the 70% adoption rate. Lower adoption rates (50%-60%) maintain shorter queues consistently, illustrating less congestion compared to higher adoption rates (70%-90%).

Utilization:

**Table 12 Utilization Across Different Household Percentages for Market Penetration Rate = 0.09%, SoC = 0.8**

| Utilization Rate (%) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 0 | 0 | 1 | 0 | 0 |
| **10** | 5 | 5 | 3 | 1 | 3 |
| **20** | 14 | 17 | 10 | 7 | 3 |

| | | | | | |
|---|---|---|---|---|---|
| **30** | 0 | 0 | 0 | 0 | 4 |
| **40** | 25 | 24 | 12 | 14 | 1 |
| **50** | 1 | 0 | 0 | 0 | 0 |
| **60** | 2 | 2 | 4 | 1 | 1 |
| **70** | 3 | 5 | 3 | 4 | 2 |
| **80** | 0 | 0 | 1 | 0 | 0 |
| **90** | 0 | 0 | 1 | 0 | 1 |

As household adoption rates increase from 50% to 90%, the distribution of simulated station utilization shifts noticeably toward higher values. At lower adoption levels (50% and 60%), utilization is concentrated around 20% and 40%, indicating moderate usage across most stations. However, as adoption rises to 70%, 80%, and eventually 90%, this distribution broadens and flattens, with a growing number of stations experiencing utilization rates between 60% and 90%. Simultaneously, the number of stations operating at lower utilization levels declines, reflecting a system-wide intensification of demand. This progression highlights the increasing strain on infrastructure under higher residential adoption scenarios, underscoring the need for careful planning to maintain service quality.

*(iii) 0.75% Market Penetration Rate, SoC = 0.5*

Blocking Probability:

**Table 13 Blocking Probability Across Different Household Percentages for Market Penetration Rate = 0.75%, SoC = 0.5**

| Blocking Probability (%) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 109 | 88 | 75 | 61 | 42 |
| **10** | 17 | 13 | 13 | 9 | 5 |
| **20** | 26 | 20 | 19 | 18 | 18 |
| **30** | 21 | 16 | 17 | 10 | 6 |
| **40** | 36 | 35 | 27 | 26 | 20 |

| | | | | | |
|---|---|---|---|---|---|
| **50** | 27 | 19 | 17 | 13 | 9 |
| **60** | 20 | 16 | 12 | 8 | 6 |
| **70** | 16 | 10 | 8 | 7 | 4 |
| **80** | 8 | 6 | 6 | 5 | 3 |
| **90** | 5 | 4 | 2 | 2 | 2 |

As household adoption increases from 50% to 90% under a 0.75% market penetration rate and 50% SoC, there is a clear shift from low to higher blocking probabilities. At 50% adoption, 109 stations operate without any blocking, but that number declines steadily to 42 stations with 90% adoption. Conversely, the number of stations in higher blocking categories (30% and above) increases significantly. For example, stations experienced a 50% blocking rise from 27 to 9, while those in the 60%-90% range show a similar upward shift. These patterns indicate increasing network congestion, emphasizing the urgency of infrastructure enhancements to prevent service degradation and ensure equitable access as EV adoption continues to rise.

<u>Average Waiting Time:</u>

**Table 14 Average Waiting Time Across Different Household Percentages for Market Penetration Rate = 0.75%, SoC = 0.5**

| Average Waiting Time (min) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 4 | 3 | 3 | 2 | 2 |
| **10** | 14 | 12 | 12 | 12 | 11 |
| **20** | 40 | 31 | 20 | 19 | 17 |
| **30** | 36 | 28 | 19 | 18 | 10 |
| **40** | 29 | 26 | 16 | 14 | 13 |
| **50** | 22 | 20 | 14 | 12 | 13 |
| **60** | 21 | 18 | 14 | 11 | 13 |
| **70** | 18 | 15 | 12 | 9 | 11 |
| **80** | 13 | 9 | 7 | 6 | 6 |
| **90** | 5 | 3 | 3 | 2 | 3 |
| **100** | 11 | 1 | 1 | 1 | 2 |

As household adoption levels increase from 50% to 90% under a 0.75% EV market penetration rate and 50% SoC, a consistent trend of growing congestion is evident. At 50% adoption, 109 stations operate without any blocking, decreasing sharply to 88, 75, 61, and finally, 42 stations at higher adoption levels. This reduction in unblocked stations is accompanied by a rise in stations experiencing moderate to severe blocking, particularly beyond the 40% threshold. Similarly, the distribution of average waiting times indicates rising congestion. Stations with average waiting times below 20 minutes decline notably with adoption increase, while those facing 60 to 90+ minute waits rise progressively. For example, only 22 stations faced 50-minute waits at 50% adoption, but even as the number drops, higher waiting time bins like 60, 70, and 80 minutes become increasingly populated. These outcomes jointly underscore the growing strain on existing infrastructure and the critical need for capacity expansion and strategic planning to maintain acceptable service quality in the face of rising EV adoption.

Average Queue Length:

**Table 15 Average Queue Length Across Different Household Percentages for Market Penetration Rate = 0.75%, SoC = 0.5**

| Average Queue Length (vehicles) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 0 | 0 | 0 | 0 | 0 |
| **1** | 2 | 2 | 0 | 1 | 0 |
| **2** | 22 | 18 | 14 | 10 | 6 |
| **3** | 35 | 34 | 32 | 26 | 18 |
| **4** | 199 | 159 | 123 | 99 | 68 |
| **5** | 83 | 65 | 49 | 43 | 31 |
| **6** | 138 | 105 | 82 | 65 | 48 |
| **7** | 218 | 192 | 155 | 111 | 62 |
| **8** | 319 | 265 | 208 | 131 | 76 |

As household adoption of residential EV chargers increases from 50% to 90%, a consistent decrease in average queue lengths is observed across all vehicle categories. Stations experiencing the highest congestion — with average queue lengths of 7 or 8 vehicles — are notably more prevalent at lower adoption levels. At 50% household adoption, 218 stations report a queue length of 7, and 319 stations report 8, indicating substantial pressure on the commercial infrastructure. These figures drop significantly to just 62 and 76 stations, respectively, at 90% adoption.

Similarly, the mid-range categories (queue lengths of 5 and 6 vehicles) exhibit downward trends, falling from 83 and 138 stations at 50% adoption to 31 and 48 stations at 90%. Even the most frequently occurring category — 4 vehicles — declines from 199 stations at 50% to just 68 stations at 90%.

The absence of zero-queue stations across all adoption rates underscores that even with high residential charger adoption, commercial stations still experience baseline usage. However, the overall reduction in high queue lengths clearly illustrates that increasing household charger availability significantly alleviates congestion at commercial charging stations, enhancing system efficiency and user experience.

<u>Utilization:</u>

**Table 16 Utilization Across Different Household Percentages for Market Penetration Rate = 0.75%, SoC = 0.5**

| Utilization Rate (%) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 0 | 0 | 0 | 1 | 0 |
| **20** | 1 | 2 | 1 | 0 | 0 |

| | | | | | |
|---|---|---|---|---|---|
| **40** | 25 | 21 | 15 | 12 | 6 |
| **60** | 24 | 20 | 14 | 13 | 9 |
| **80** | 64 | 22 | 18 | 13 | 10 |
| **90** | 79 | 66 | 54 | 21 | 20 |

The distribution of station utilization rates demonstrates a clear shift toward lower-intensity usage as household charger adoption increases. At 50% household adoption, a significant number of stations operate at high utilization — 79 stations fall in the 90% utilization bracket and 64 in the 80% bracket. These figures sharply decline to just 20 and 10 stations, respectively, at 90% adoption. This reduction reflects a direct relief in station-level demand due to greater home-charging availability.

Moderate utilization categories, such as 60% and 40%, also show a declining pattern, with counts nearly halved from 50% to 90% adoption. For instance, 25 stations were operating at 40% utilization at 50% household adoption, but only six stations remain in that category at 90%. Interestingly, extremely low or idle stations (0%–20%) remain rare throughout, indicating continued baseline demand regardless of household charger penetration.

*(iv) 0.75% Market Penetration Rate, SoC = 0.8*

Blocking Probability:

**Table 17 Blocking Probability Across Different Household Percentages for Market Penetration Rate = 0.75%, SoC = 0.8**

| Blocking Probability (%) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 91 | 92 | 79 | 48 | 27 |
| **20** | 47 | 35 | 33 | 20 | 8 |
| **40** | 23 | 17 | 15 | 11 | 5 |

| | | | | | |
|---|---|---|---|---|---|
| **60** | 28 | 11 | 3 | 5 | 2 |
| **80** | 19 | 5 | 6 | 4 | 2 |

As household EV charger adoption rises, the distribution of blocking probabilities shows a strong shift toward lower congestion levels. At 50% household adoption, only 91 stations operate with a blocking probability of 0%, whereas this number declines progressively to just 27 stations at 90% adoption. This trend is accompanied by a clear reduction in the number of stations facing moderate to severe blocking.

Stations with 20% blocking probability drop from 47 at 50% adoption to only eight at 90%. Similarly, the number of stations experiencing 40% and 60% blocking probabilities decreases from 23 and 28 to just 5 and 2, respectively, by 90% adoption. Even in the highest congestion category (80% blocking probability), the number of stations drops from 19 to only 2.

This substantial reduction in high blocking probabilities across the adoption spectrum illustrates the critical impact of household infrastructure in redistributing charging demand. It enables a shift away from over-reliance on public stations, thereby alleviating bottlenecks and improving system reliability — even under more demanding energy requirements represented by 80% SoC scenarios.

Average Waiting Time:

**Table 18 Average Waiting Time Across Different Household Percentages for Market Penetration Rate = 0.75%, SoC = 0.8**

| Average Waiting Time (min) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 12 | 3 | 11 | 2 | 5 |

| | | | | | |
|---|---|---|---|---|---|
| **20** | 36 | 29 | 26 | 17 | 8 |
| **40** | 17 | 11 | 13 | 11 | 4 |
| **60** | 53 | 42 | 31 | 8 | 7 |
| **80** | 22 | 7 | 6 | 8 | 2 |
| **100** | 1 | 6 | 3 | 2 | 0 |
| **120** | 2 | 2 | 0 | 0 | 0 |

The distribution of average waiting times shows a clear downward trend as household charger adoption increases, particularly at higher wait time brackets. At 50% household adoption, 53 stations report average waiting times of 60 minutes, 36 stations report 20-minute waits and 22 stations fall in the 80-minute category — all reflecting considerable congestion. However, by 90% adoption, these figures drop to just 7, 8, and 2 stations, respectively, illustrating a significant reduction in delay.

The number of stations with extremely high waiting times — 100 and 120 minutes — also drops to zero by 90% adoption, reinforcing the benefit of residential infrastructure expansion. The most substantial improvement appears between the 50% and 80% adoption levels, where waiting times drop steeply across nearly all categories.

Interestingly, moderate wait times (20–40 minutes) initially decline and then stabilize, indicating that while some congestion remains, it becomes much more manageable as household adoption increases. Meanwhile, short waiting times of 0–20 minutes increase in frequency, signaling improved charging accessibility and reduced service delays.

This pattern highlights the importance of household charging adoption not only in reducing queue lengths and utilization but also in alleviating prolonged user delays — a key factor in ensuring user satisfaction and maintaining momentum for EV adoption at scale.

Average Queue Length:

**Table 19 Average Queue Length Across Different Household Percentages for Market Penetration Rate = 0.75%, SoC = 0.8**

| Average Queue Length (vehicles) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 0 | 0 | 0 | 0 | 0 |
| **1** | 2 | 2 | 0 | 1 | 0 |
| **2** | 18 | 18 | 16 | 5 | 7 |
| **3** | 31 | 36 | 28 | 22 | 7 |
| **4** | 166 | 159 | 112 | 87 | 36 |
| **5** | 83 | 59 | 46 | 27 | 14 |
| **6** | 131 | 98 | 87 | 51 | 27 |
| **7** | 227 | 173 | 131 | 94 | 53 |
| **8** | 326 | 250 | 180 | 107 | 61 |

The trend in average queue lengths continues to reflect reduced commercial station congestion as household charger adoption increases. The most heavily congested stations — those with an average queue length of 8 vehicles — show a sharp decline from 326 stations at 50% adoption to just 61 at 90%. Similarly, queue lengths of 7 vehicles decrease from 227 to 53 stations across the same range.

Mid-level congestion categories (e.g., queue lengths of 5 and 6) also see steady reductions. For instance, stations with a queue length of 5 falls from 83 at 50% adoption to just 14 at 90%, and those with a queue length of 6 drop from 131 to 27. Even at four vehicles — often considered a moderate but still impactful queue — the number of stations is more than halved, from 166 to 36.

Low queue categories such as 2 and 3 vehicles also decline, albeit less dramatically, reflecting the overall system relief. The absence of zero-queue stations across all adoption levels emphasizes that even with widespread residential infrastructure, commercial chargers maintain a necessary support role.

Overall, the reduction in queue lengths across the board indicates a tangible benefit of increased home charging availability, especially under higher SoC requirements. This supports the strategic value of enhancing household EV charging access to reduce system-wide wait times and improve charging experience reliability.

<u>Utilization:</u>

**Table 20 Utilization Across Different Household Percentages for Market Penetration Rate = 0.75%, SoC = 0.8**

| Utilization Rate (%) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 0 | 0 | 0 | 0 | 0 |
| **20** | 2 | 22 | 0 | 1 | 1 |
| **40** | 21 | 8 | 17 | 8 | 7 |
| **60** | 32 | 20 | 13 | 10 | 7 |
| **80** | 26 | 16 | 10 | 14 | 4 |
| **90** | 67 | 48 | 25 | 21 | 14 |

At a higher SoC threshold of 80%, the utilization rate patterns display a more balanced but still declining trend with increased household charger adoption. Stations operating at the highest utilization level (90%) declined from 67 at 50% household adoption to just 14 at 90%, highlighting reduced strain on public infrastructure. Similarly, 80% utilization stations drop from 26 to 4 over the same range.

Interestingly, the 60% utilization category also follows a declining trend — from 32 stations at 50% adoption to just seven at 90%. While some fluctuations appear in the 40% utilization group (e.g., a non-monotonic dip and rise), the general pattern indicates a dispersion of load and improved station availability as more EV owners shift to home charging.

Notably, the presence of stations in the 20% utilization bracket at 60% adoption (22 stations) may suggest transitional load redistribution effects. Overall, this shift reflects improved system efficiency and underscores the importance of household charger penetration in flattening commercial demand and minimizing congestion, even under higher state-of-charge requirements.

*(v) 1.61% Market Penetration Rate, SoC = 0.5*

<u>Blocking Probability:</u>

**Table 21 Blocking Probability Across Different Household Percentages for Market Penetration Rate = 1.61%, SoC = 0.5**

| Blocking Probability (%) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 13 | 11 | 12 | 9 | 3 |
| **20** | 52 | 41 | 30 | 19 | 18 |
| **40** | 29 | 29 | 22 | 15 | 16 |
| **60** | 56 | 47 | 22 | 26 | 14 |
| **80** | 18 | 20 | 16 | 13 | 6 |
| **100** | 1 | 1 | 1 | 1 | 0 |

At 1.61% market penetration and 50% SoC, blocking probabilities remain high across all household adoption levels, indicating severe congestion within the system. Only 13 stations experience no blocking at 50% adoption, and this number drops to just three at 90%. Stations with 60% or higher blocking probabilities account for over 35% of the network at lower adoption rates and only show modest improvement with increased household charger availability. This suggests that, under high market penetration, commercial infrastructure alone is insufficient without substantial residential adoption to prevent frequent service denials and access issues.

Average Waiting Time:

**Table 22 Average Waiting Time Across Different Household Percentages for Market Penetration Rate = 1.61%, SoC = 0.5**

| Average Waiting Time (min) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 1 | 4 | 2 | 2 | 1 |
| **20** | 12 | 18 | 8 | 8 | 5 |
| **40** | 27 | 25 | 21 | 12 | 11 |
| **60** | 53 | 47 | 37 | 34 | 18 |
| **80** | 42 | 35 | 30 | 27 | 28 |
| **100** | 9 | 5 | 8 | 2 | 3 |
| **120** | 5 | 5 | 3 | 3 | 2 |

At a 1.61% market penetration rate and 50% SoC, the distribution of average waiting times shows a consistently high system load, especially at lower levels of household charger adoption. Stations with waiting times of 80 minutes or more remain substantial even at 90% adoption, though they reduce in count. For instance, stations with 80-minute waits drop from 42 at 50% adoption to 28 at 90%, and those with 60-minute waits decrease from 53 to 18. While higher household adoption helps compress wait times across the board, persistent delays in the upper time ranges signal the need for further infrastructure scaling or demand management strategies.

Average Queue Length:

**Table 23 Average Queue Length Across Different Household Percentages for Market Penetration Rate = 1.61%, SoC = 0.5**

| Average Queue Length (vehicles) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 0 | 0 | 0 | 0 | 0 |
| **1** | 0 | 0 | 0 | 0 | 0 |
| **2** | 2 | 3 | 4 | 4 | 1 |
| **3** | 1 | 1 | 2 | 0 | 0 |
| **4** | 65 | 65 | 52 | 36 | 19 |
| **5** | 77 | 65 | 65 | 35 | 25 |
| **6** | 119 | 90 | 74 | 46 | 37 |
| **7** | 361 | 309 | 248 | 164 | 118 |
| **8** | 1557 | 1269 | 978 | 758 | 464 |

The queue length distribution at 1.61% market penetration and 50% SoC reflects significant system congestion, particularly at lower household adoption levels. At 50% adoption, 1,557 stations report average queues of 8 vehicles, with 361 stations in the 7-vehicle range. As household adoption increases, these numbers steadily decrease, with 8-vehicle queues falling to 464 and 7-vehicle queues to 118 by 90% adoption. This decline in queue intensity indicates the effectiveness of residential charging in alleviating pressure on public infrastructure and reducing overall system congestion.

Utilization:

**Table 24 Utilization Across Different Household Percentages for Market Penetration Rate = 1.61%, SoC = 0.5**

| Utilization Rate (%) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 0 | 0 | 0 | 0 | 0 |
| **20** | 1 | 0 | 2 | 2 | 1 |

| | | | | | |
|---|---|---|---|---|---|
| **40** | 1 | 1 | 2 | 2 | 0 |
| **60** | 17 | 21 | 4 | 2 | 1 |
| **80** | 69 | 64 | 50 | 40 | 27 |
| **90** | 203 | 163 | 133 | 94 | 70 |

At a 1.61% market penetration rate and 50% SoC, the majority of stations operate at high utilization levels, with 203 stations reaching 90% utilization at just 50% household adoption. As household adoption increases to 90%, high-utilization stations drop to 70, indicating reduced pressure on commercial infrastructure. Moderate utilization (60–80%) also decreases across the board, highlighting the positive impact of home charging availability in balancing system demand.

*(vi) 1.61% Market Penetration Rate, SoC = 0.8*

Blocking Probability:

**Table 25 Blocking Probability Across Different Household Percentages for Market Penetration Rate = 1.61%, SoC = 0.8**

| Blocking Probability (%) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 14 | 13 | 13 | 17 | 20 |
| **20** | 65 | 66 | 55 | 46 | 37 |
| **40** | 69 | 70 | 60 | 45 | 33 |
| **60** | 103 | 82 | 59 | 44 | 27 |
| **80** | 94 | 62 | 51 | 22 | 14 |
| **100** | 43 | 31 | 23 | 9 | 5 |

Blocking probability is notably high at low household adoption levels. At 50% adoption, 94 stations experience blocking in the 80% range, and 43 stations are fully blocked. As household adoption increases to 90%, both metrics drop sharply—only 14 stations face 80% blocking, and full blocking is down to just five stations. Simultaneously, stations with minimal blocking (0–

20%) rise from 79 at 50% adoption to 90 at 90% adoption, confirming significant improvement in system accessibility.

Average Waiting Time:

**Table 26 Average Waiting Time Across Different Household Percentages for Market Penetration Rate = 1.61%, SoC = 0.8**

| Average Waiting Time (min) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **0** | 6 | 8 | 13 | 15 | 21 |
| **20** | 45 | 58 | 47 | 36 | 37 |
| **40** | 124 | 128 | 107 | 74 | 66 |
| **60** | 246 | 235 | 194 | 138 | 113 |
| **80** | 101 | 74 | 72 | 61 | 50 |
| **100** | 6 | 6 | 7 | 6 | 3 |

Waiting times follow a clear decreasing trend with increasing household adoption. At 50% adoption, most stations fall into the 60–80 minute category, with 101 stations experiencing even higher wait times between 80 and 100 minutes. By the time adoption reaches 90%, the number of stations in this upper range nearly halves, and the number of stations with wait times under 40 minutes increases. The overall system becomes faster and more responsive as more households participate in the charging network.

Average Queue Length:

**Table 27 Average Queue Length Across Different Household Percentages for Market Penetration Rate = 1.61%, SoC = 0.8**

| Average Queue Length (vehicles) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **2** | 3 | 3 | 2 | 2 | 1 |
| **3** | 2 | 2 | 2 | 0 | 1 |

| | | | | | |
|---|---|---|---|---|---|
| **4** | 67 | 59 | 41 | 26 | 19 |
| **5** | 79 | 61 | 52 | 36 | 18 |
| **6** | 106 | 91 | 65 | 50 | 25 |
| **7** | 354 | 308 | 228 | 131 | 76 |
| **8** | 1502 | 1179 | 897 | 621 | 300 |

Queue lengths dramatically reduce as household adoption increases. At 50% adoption, the majority of stations report long queues of 7–8 vehicles, with 1502 stations peaking at a queue length of 8. By contrast, at 90% adoption, the count drops to 300. Simultaneously, lower queue lengths (2–5) become more prevalent, showing that higher adoption effectively spreads demand across the network and reduces congestion at individual charging locations.

<u>Utilization:</u>

**Table 28 Utilization Across Different Household Percentages for Market Penetration Rate = 1.61%, SoC = 0.8**

| Utilization Rate (%) | 50% Household Adoption | 60% Household Adoption | 70% Household Adoption | 80% Household Adoption | 90% Household Adoption |
|---|---|---|---|---|---|
| **20** | 2 | 2 | 2 | 1 | 1 |
| **40** | 7 | 6 | 5 | 4 | 4 |
| **60** | 28 | 21 | 17 | 15 | 13 |
| **80** | 484 | 438 | 356 | 331 | 248 |
| **90** | 323 | 318 | 285 | 240 | 189 |

Utilization remains high across all adoption levels, especially within the 80–90% range. Although stations operating at greater than 90% utilization decline slightly—from 323 at 50% adoption to 189 at 90%—this still reflects an efficient and well-utilized network. The gradual decline indicates better load distribution as more households have access to private chargers, reducing pressure on public infrastructure without compromising its effectiveness.

# Chapter 8: Conclusions

## *8.1 Research Summary and Contributions*

This study investigates the interrelationship between residential and commercial EV charging infrastructures, using the Baltimore MSA as the study area. The detailed OD trip data integrated with census data provides a comprehensive understanding of EV charging behaviors and infrastructure requirements. The analysis highlights the critical impact of residential charging facilities on the demand for commercial charging stations, revealing several key findings:

1. **Inverse Relationship**: A clear inverse relationship exists between the availability of residential charging facilities and the demand for commercial charging infrastructure. As the adoption of residential chargers increases, the necessity for commercial chargers decreases significantly. For example, at a 0.09% market penetration rate, with no households having charging facilities, 229 commercial chargers are required. However, as household adoption of residential chargers reaches 80%, the demand for commercial chargers drops significantly to 59 stations, demonstrating a 74.2% reduction.

2. **Impact of Market Penetration**: Different market penetration rates of EVs show consistent trends. The presence of residential chargers substantially reduces the demand for commercial charging facilities. This relationship holds across varying levels of EV adoption, from early stages to more developed markets. For instance, at a 5% market penetration rate, if no households have residential chargers, 12,669

commercial charging stations are needed. However, when 80% of households have residential chargers, the demand decreases to 2,689 stations, a 78.8% reduction. Comparatively, at a 7.5% market penetration rate, the number of commercial chargers required drops from 19,010 with no residential chargers to 4,033 with 80% household adoption, a similar 78.8% reduction. This illustrates that the presence of residential chargers consistently reduces commercial charging needs across different levels of market penetration.

3. **Impact of SoC**: The analysis underscores the critical role of residential charging infrastructure and optimal SoC management in shaping the overall charging landscape. As EV adoption rates increase from 0.09% to 10%, the dependency on commercial charging infrastructure diminishes significantly. For example, at a 10% market penetration rate with 90% household adoption, maintaining an 80% SoC requires only 1,365 commercial chargers compared to 2,062 for a 50% SoC, representing a 33.8% reduction. This trend highlights that maintaining higher SoC levels has the potential to reduce reliance on commercial infrastructure.

4. **Queuing Theory Integration and Service-Level Impacts**: The inclusion of queuing theory modeling significantly enhances the operational understanding of the EV charging network by evaluating metrics such as average waiting time, queue length, utilization, and blocking probability:

- **Queue Lengths** increase substantially at higher EV adoption levels and lower SoC thresholds, particularly under low household residential charger adoption. For instance, at 1.61% market penetration and 50% SoC, over 1500 stations experienced an average queue length of 8 vehicles.

- **Waiting Times** follow a similar trend, with 50% household adoption and high EV penetration resulting in average wait times clustering between 60–90 minutes, with some stations exceeding 100 minutes.

- **Utilization Rates** were heavily skewed toward 80–95% at higher adoption levels, indicating the potential for operational overload at key stations.

- **Blocking Probabilities** show marked variation: while 50% household adoption results in over 200 stations experiencing blocking rates above 80%, increasing adoption to 90% drastically reduces the number of such congested stations.

These findings underscore that without sufficient residential infrastructure, commercial charging stations are prone to severe congestion, reducing system reliability. Queuing analysis provides direct metrics for evaluating not just quantity but **quality of service**.

5. **Policy Implications**: Policymakers should focus on promoting residential charging solutions through incentives and subsidies. For instance, subsidies for residential charger installations can reduce the pressure on commercial infrastructure. As market penetration rates increase, the demand for commercial chargers can be significantly

alleviated if more households access residential charging facilities. For example, at higher market penetration rates like 10%, the presence of residential chargers and maintaining an optimal SoC (80%) can lead to substantial reductions in the need for commercial chargers. This approach encourages EV adoption and ensures the infrastructure is in place to support it, making the overall EV charging ecosystem more efficient and sustainable. Preparing the necessary infrastructure, considering market penetration rates, household charging adoption, and SoC management, is essential for the successful adoption and use of EVs.

Despite the comprehensive analysis, this study has certain limitations. The assumptions of EV travel behavior and charging patterns may not capture all real-world complexities. Additionally, the study focuses on a specific geographic area, and the findings may not be fully generalizable to other regions with different characteristics. Future research should explore dynamic models that consider real-time data on EV charging behavior and grid impacts. Integrating renewable energy sources with EV charging infrastructure could also provide valuable insights into creating a more sustainable and resilient system. Further, examining the economic aspects of charging infrastructure investments and their long-term benefits can help formulate effective policies and strategies for EV adoption.

This study provides a foundational understanding of the interplay between residential and commercial EV charging infrastructures. Leveraging detailed real-world OD trip data integrated with census data and advanced modeling techniques offers valuable insights for policymakers, researchers, and stakeholders in transitioning to a sustainable EV ecosystem. The findings underscore the critical importance of strategic planning and optimization in deploying EV charging infrastructure. Through applying a bi-level optimization model, this research has provided valuable insights into how different levels of residential charger adoption and SoC preferences can influence the number and placement of commercial charging stations.

The Baltimore MSA case study revealed that as residential charger adoption increases, the reliance on commercial charging stations decreases significantly. For instance, at a 70% household adoption rate, the number of required commercial stations for an 80% SoC was reduced by 68.4% compared to scenarios with no residential chargers. This trend was consistent across various SoC levels, highlighting the effectiveness of residential chargers in alleviating the demand on public infrastructure.

Furthermore, the study illustrated the economic viability of the proposed model. The calculated weekly profit of $233,607.66 for 192 charging stations aligns with industry standards when projected annually. This demonstrates the model's capability to balance profitability for operators while meeting user needs. The robust framework ensures that both high and low-demand areas are adequately serviced, optimizing resource allocation and enhancing the overall efficiency of the EV charging network.

Overall, this study contributes to the growing body of knowledge on EV infrastructure planning, offering a scalable and adaptable methodology for cities and regions aiming to support the transition to electric mobility. By addressing both economic and user-centric factors, the proposed bi-level optimization model paves the way for more effective and efficient deployment of EV charging stations, ultimately supporting the broader adoption of electric vehicles.

### *8.2 Limitations*

Although the analysis presented in this dissertation provides valuable insights into EV charging infrastructure needs and optimal deployment strategies, several limitations must be acknowledged to accurately interpret and apply the findings. The following are the key limitations associated with this research:

1. **Simplified User Behavior Modeling:** This study assumes simplified EV user behaviors and static charging patterns. Real-world scenarios involve dynamic user decisions influenced by real-time traffic conditions, road congestion, availability of alternative charging stations, pricing structures, personal convenience, and socio-economic factors. This research does not incorporate detailed modeling of rerouting behaviors, station-switching decisions, or multi-station interactions, which could significantly alter demand patterns and infrastructure requirements.
2. **Assumption of Homogeneity in EV Users and Charging Stations:** The models employed do not account for the heterogeneity in vehicle types, battery sizes, charging power capabilities, and compatibility constraints across different EV models and charging station types. Real-world implications of such heterogeneity—such as varying charging durations, fluctuating utilization rates, and diverse user preferences—can substantially impact the accuracy of demand estimations and infrastructure sizing.

3. **Static and Deterministic Optimization:** The optimization approaches utilized in the study primarily employ deterministic methodologies, neglecting uncertainties in user preferences, charging station reliability, operational disruptions, and dynamic grid availability. Real-world conditions inherently include stochastic variations and unforeseen disruptions that could significantly influence optimal station locations and the number of chargers required.
4. **Limited Consideration of Real-Time Traffic and Grid Dynamics:** This dissertation does not incorporate real-time fluctuations in traffic volumes, unexpected congestion, incidents, detours, or dynamic operational states of the power grid. Consequently, the proposed deployment strategies may underestimate or overestimate actual station utilization and congestion issues that could arise under real-world operational uncertainties.
5. **Queueing Model Assumptions:** The queueing analysis assumes memoryless (Poisson arrivals and exponential service times) behavior, which might not fully capture complex real-world arrival and service time distributions. Charging sessions in reality often exhibit dependencies and correlations, influenced by factors such as peak usage times, time-of-day variations, seasonal fluctuations, and specific local events. Thus, real-world queuing behavior may differ significantly from modeled predictions.
6. **Exclusion of Multi-Investor and Competitive Dynamics:** The analysis primarily focuses on a centralized decision-making scenario and does not consider competitive interactions or cooperative siting strategies involving multiple investors. Real-world market conditions,

investment decisions, and competitive behaviors can significantly affect the optimal placement and economic feasibility of charging stations.

7. **Absence of Detailed Economic and Regulatory Considerations:** Economic feasibility analyses presented are simplified and do not extensively explore detailed cost breakdowns, variable pricing structures, subsidies, regulatory constraints, and incentives. Comprehensive economic and policy considerations would provide more nuanced insights into the practical implications and sustainability of proposed infrastructure investments.
8. **Geographic and Data Generalizability Constraints:** The case study utilized data from the Baltimore MSA. While insightful, the geographic specificity and data constraints limit generalizability to other regions with potentially different demographic profiles, traffic patterns, EV adoption rates, and infrastructure maturity levels. Consequently, results may not directly translate to other urban, suburban, or rural contexts without region-specific adjustments.
9. **Limited Scenario and Sensitivity Analysis Scope:** Although multiple EV market penetration rates were considered, broader sensitivity analyses regarding critical input parameters, such as user adoption rates, charger utilization rates, and varying SoC conditions, were limited. Extensive sensitivity analyses could provide deeper understanding of robustness and variability of outcomes under diverse future conditions.
10. **Absence of Long-Term Evolution and Technology Trends:** The research does not explicitly model future technological advancements, such as improvements in battery technology, charger efficiency, or autonomous vehicle integration, which could profoundly impact future charging infrastructure requirements. Additionally, evolving regulatory

frameworks, grid modernization efforts, and emerging transportation innovations are not extensively accounted for in the modeling approach.

Clearly acknowledging these limitations is critical for interpreting the findings accurately and recognizing areas where future research can further refine and enhance the outcomes presented in this dissertation.

### *8.3 Future Research*

Building on the contributions of this dissertation, several avenues can be pursued to expand the framework:

1. **Integration of Dynamic Pricing Models**: While this study assumes fixed service rates, future work could include dynamic pricing strategies that respond to congestion levels, time-of-use demand, and grid constraints. This could create feedback loops between user behavior and service cost.

2. **Behavioral Mobility Models**: Enhancing the lower-level model with more granular user mobility data—such as trip chaining, destination choice, or activity-based travel patterns—could improve accuracy in estimating charger usage.

3. **Real-Time Data Feedback and IoT Integration**: Future research could incorporate real-time data streams from sensors, smart meters, and connected vehicles to update charging demand and availability in real time, enabling adaptive infrastructure planning.

4. **Multi-Objective Optimization**: Future extensions could include a multi-objective framework that balances cost, environmental impact, grid stability, and user convenience.

5. **Decentralized Energy Systems**: Incorporating vehicle-to-grid (V2G) interactions and distributed energy storage within the optimization and queuing models could simulate how EVs contribute to energy resilience.

6. **Equity and Accessibility**: Future models could consider demographic and geographic disparities in EV access and infrastructure provision to promote equitable planning.

7. **3D Spatial Modeling of Charger Locations**: Expanding beyond zip-code or regional data, using spatial microsimulation or GIS-based modeling could refine placement strategies down to the block level.

8. **Expanded Queuing Frameworks**: More complex queuing systems (e.g., multi-server, priority queues, and networked queues) could be used to simulate interdependent charging stations or hub-based systems.

9. **Long-Term Demand Forecasting**: Integrating demographic, technological, and policy trend projections could inform long-term planning horizons, allowing for staged infrastructure deployment.

10. **Game-Theoretic User Choice Models**: Introducing user choice behavior within the queuing system (e.g., route diversion, charger skipping) would make the model more dynamic and realistic.

## Appendix

### *Tables of Notations*

**Table 29 Notations for Monte Carlo Simulation (MCS)**

| Notation | Description | Type |
|---|---|---|
| $\mathrm{EV}_{\mathrm{tot}}$ | Total number of Electric Vehicles | Parameter |
| $\mathrm{N}_{\mathrm{avg}}$ | Average daily number of trips | Parameter |
| $\mathrm{N}_{(\mathrm{u})}$ | Total EV trips for the u-th scenario | Parameter |
| $\rho_{(\mathrm{r})}$ | Probability of a trip with purpose r (HBW, HBNW, HBO) | Parameter |
| $U$ | Number of trips | Parameter |

**Table 30 Notations for Bi-Level Optimization**

| Notation | Description | Type |
|---|---|---|
| $x_i$ | 1 if station placed in block $i$; 0 otherwise | Decision Variable |
| $y_i$ | Number of charging piles at station $i$ | Decision Variable |
| $z_{imt}$ | 1 if EV $m$ charges at station $i$ at time $t$ | Decision Variable |
| $V_i$ | Voltage at bus $i$ | Decision Variable |
| $P_i$ | Power calculated from $V_i$ | Parameter (Calculated) |
| $C_{op}$ | EVCS Operating cost | Parameter |

| | | |
|---|---|---|
| $C_{con}$ | EVCS Construction cost | Parameter |
| $C_p$ | EV Charger equipment cost | Parameter |
| $C_l$ | EVCS Land-use cost | Parameter |
| $p_e(t)$ | Charging price at time $t$ | Parameter |
| $c_e(t)$ | Electricity cost (Time-of-Use pricing) | Parameter |
| $G_{ii'}$ | Conductance between buses $i$ and $i'$ | Parameter |
| $\theta_{ii'}$ | Load angle difference | Parameter |
| $D_s$ | Total number of days | Parameter |
| $SoC_m^d$ | SoC at departure for EV $m$ | Parameter |
| $SoC_m^a$ | SoC at arrival for EV $m$ | Parameter |
| $B_m$ | Battery capacity of EV $m$ | Parameter |
| $\eta$ | Charging efficiency factor | Parameter |
| $d_{im}$ | Distance from demand location $m$ to station $i$ | Parameter |
| $S_{min}$ | Minimum required service coverage | Parameter |
| $D_{max}$ | Maximum allowable travel distance | Parameter |
| $\beta$ | Proportionality factor | Parameter |
| $Pop_i$ | Population in block $i$ | Parameter |

**Table 31 Notations for Queuing Theory Framework**

| Notation | Description | Type |
|---|---|---|
| $\lambda_s$ | Arrival rate at station $s$ | Parameter |

| | | |
|---|---|---|
| $\mu$ | Service rate per charger | Parameter |
| $c_s$ | Number of chargers at station $s$ | Parameter |
| $K_s$ | Maximum capacity of station $s$ | Parameter |
| $\rho_s$ | Utilization ratio at station $s$ | Parameter |
| $\Phi_n$ | Probability of exactly $n$ vehicles in the system | Parameter |
| $\xi_{loss}$ | Probability of system being full | Parameter |
| $w_s$ | Average waiting time at station $s$ | Parameter |
| $q_s$ | Average queue length at station $s$ | Parameter |

*Source Code*

Monte Carlo Simulation

```
import pandas as pd
from geopy.distance import geodesic
import numpy as np
import matplotlib.pyplot as plt
import math
import random

random.seed(10)
np.random.seed(10)
```

```
# Load the Excel spreadsheet into a pandas DataFrame
df = pd.read_excel('C:/Users/sayan/Downloads/EVCS/Data/Howard_Baltimore/BaltimoreMSA/TAZODNew2.xlsx')

# Calculate distance for each row and store it in a new column
distances = []
for index, row in df.iterrows():
    origin = (row['Origin_Lat'], row['Origin_Lon'])
    destination = (row['Destination_Lat'], row['Destination_Lon'])
    distance = geodesic(origin, destination).miles
    distance = round(distance, 1)  # Round distance to one decimal place
    distances.append(distance)

df['Distance (miles)'] = distances

# Drop rows with Distance (miles) equal to 0
df = df[df['Distance (miles)'] != 0]

# Categorize the trips based on trip length
df['Trip Category'] = pd.cut(df['Distance (miles)'], bins=[0, 15, 30, float('inf')], labels=['HBW', 'HBNW', 'HBO'])

# Count the number of trips in each category
trip_counts = df[['Trip Category', 'Trips']].groupby('Trip Category').sum()
```

```
# Define dictionaries for mean speeds and standard deviations
mean_speeds = {'HBW': 30.2, 'HBNW': 38, 'HBO': 50.4}
std_devs = {'HBW': 4, 'HBNW': 5.08, 'HBO': 6.78}

# Function to generate random speeds based on normal distribution
def generate_random_speed(row):
    category = row['Trip Category']
    mean = mean_speeds[category]
    std = std_devs[category]
    return np.random.normal(mean, std)

# Generate random speeds based on normal distribution
df['Random Speed'] = df.apply(generate_random_speed, axis=1)

# Calculate travel time in minutes for each trip using the random speeds
df['Travel Time (minutes)'] = df['Distance (miles)'] / df['Random Speed'] * 60

# Group the DataFrame by 'Trip Category' and calculate the mean and standard deviation of travel time for each group
mean_travel_time = df.groupby('Trip Category')['Travel Time (minutes)'].mean()
std_travel_time = df.groupby('Trip Category')['Travel Time (minutes)'].std()

# Save the mean and standard deviation of travel time for each trip category to separate variables
mean_hbw = round(mean_travel_time['HBW'], 1)
std_hbw = round(std_travel_time['HBW'], 1)
mean_hbnw = round(mean_travel_time['HBNW'], 1)
std_hbnw = round(std_travel_time['HBNW'], 1)
```

```
mean_hbo = round(mean_travel_time['HBO'], 1)
std_hbo = round(std_travel_time['HBO'], 1)

# Calculate the percentage of different trips
p_hbw = trip_counts.iloc[0, 0] / trip_counts.sum()
p_hbnw = trip_counts.iloc[1, 0] / trip_counts.sum()
p_hbo = trip_counts.iloc[2, 0] / trip_counts.sum()

# Group the DataFrame by unique 'Origin_Lat' and 'Origin_Lon' and calculate the mean of 'HHs20' for each group
grouped_df = df.groupby(['Origin_Lat', 'Origin_Lon'])['HHs20'].mean().reset_index()

# Calculate the total number of unique households by summing 'HHs20'
total_households = grouped_df['HHs20'].sum()

# Create a list of percentage distributions for households with different numbers of cars
percentage_distribution = [0.10057, 0.346925, 0.357646, 0.19486]

# Calculate the number of cars for each household based on the percentage distribution
num_cars_distribution = np.random.choice(range(4), int(total_households), p=percentage_distribution)

# Sum the total number of cars
total_cars = sum(num_cars_distribution)

# Calculate total_ev as a percentage of the number of cars
total_ev = math.ceil((total_cars * 0.1))  # Assuming 10% of cars are EVs
```

```
print("Total Number of Cars:", total_cars)
print("Total Number of EVs:", total_ev)

# ---------Trips, Departures, and Arrivals
# Step 1: Probability of HBNW and HBO trips after completion of HBW trips
hbnw_prob = p_hbnw.item() / p_hbw.item()
hbo_prob = p_hbo.item() / p_hbw.item()

# Step 2: Distance traveled for all three trip categories
hbw_distances = df[df['Trip Category'] == 'HBW']['Distance (miles)']
hbnw_distances = df[df['Trip Category'] == 'HBNW']['Distance (miles)']
hbo_distances = df[df['Trip Category'] == 'HBO']['Distance (miles)']

# Step 3: EV utilization and SoC after each trip
initial_soc = 1  # Initial state of charge (SoC)
T = 24 * 60  # Total minutes in a day

# Define charging powers and range added per hour for different charger levels (in kW and miles/hour)
level1_power_range = (1.3, 2.4)  # Level 1 charger power range (kW)
level1_range_added_per_hour = (3, 5)  # Range added per hour for Level 1 charger (miles/hour)

level2_power_range = (3, 19)  # Level 2 charger power range (kW)
level2_range_added_per_hour = (18, 28)  # Range added per hour for Level 2 charger (miles/hour)

level3_power = (150, 200)  # Level 3 charger power (kW)
```

```
level3_range_added_per_hour = (100, 200)  # Range added per hour for Level 3 charger (miles/hour)


# Function to estimate departure, arrival, and travel time for an individual EV
def estimate_departure_arrival_travel_time_with_trip_count(congestion_factor=1.07):
    departure_times = []
    arrival_times = []
    travel_times = []
    current_time = 0  # Start at the beginning of the day

    # Function to generate trip times for a given category
    def generate_trip_times(mean, std):
        travel_time = np.random.normal(mean, std)
        departure_time = np.random.randint(current_time, T)
        arrival_time = (departure_time + travel_time) % T
        return departure_time, arrival_time, travel_time

    # First HBW trip
    dep, arr, trav = generate_trip_times(mean_hbw, std_hbw)
    departure_times.append(dep)
    arrival_times.append(arr)
    travel_times.append(trav)
    current_time = arr  # Update current time to arrival time of the first trip

    # Probability for additional HBNW and HBO trips
    prob = np.random.random()
    if prob < hbnw_prob:
```

```
        dep, arr, trav = generate_trip_times(mean_hbnw, std_hbnw)
        departure_times.append(dep)
        arrival_times.append(arr)
        travel_times.append(trav)
        current_time = arr

    if prob < hbo_prob:
        dep, arr, trav = generate_trip_times(mean_hbo, std_hbo)
        departure_times.append(dep)
        arrival_times.append(arr)
        travel_times.append(trav)
        current_time = arr

    # Apply congestion factor to travel times between 8-9 AM and 5-6 PM
    for i in range(len(departure_times)):
        if (8*60) <= departure_times[i] < (9*60) or (17*60) <= departure_times[i] < (18*60):
            travel_times[i] *= congestion_factor

    return departure_times, arrival_times, travel_times

# Total number of trips in the dataset
total_trips = df['Trips'].sum()

# Number of EV trips (10% of the total trips)
num_ev_trips = int(total_trips * 0.1)
```

```
# Monte Carlo simulation for EV trips
results_home_charge = []
results_away_charge = []
for _ in range(num_ev_trips):  # Limit the number of simulations to the number of EV trips
    dep_times, arr_times, trav_times = estimate_departure_arrival_travel_time_with_trip_count()
    results_home_charge.append((dep_times, arr_times, trav_times))
    results_away_charge.append((dep_times, arr_times, trav_times))

# Print results for verification
print(f"Simulated {num_ev_trips} EV trips out of {total_trips} total trips.")
print("Home Charging Results:", results_home_charge[:5])  # Print first 5 results for brevity
print("Away Charging Results:", results_away_charge[:5])  # Print first 5 results for brevity

# ---------Stations NEW
# Step 1: # Number of households with EVs
total_home_chargers = math.ceil(total_ev / 2.02)
print("Total Number of Households with EVs:", total_home_chargers)

# Calculate the minimum SoC required for one EV trip (50%)
required_soc_for_trip = 0.5
charge_threshold = 0.3

# Calculate the average range added per hour for Level 2 and Level 3 chargers
avg_level2_range_added_per_hour = np.mean(level2_range_added_per_hour)
avg_level3_range_added_per_hour = np.mean(level3_range_added_per_hour)
```

```
# Define parameters for comparison
home_charger_percentages = [0, 0.5, 0.6, 0.7, 0.8, 0.9]
# Initialize lists to store results
total_public_chargers_list = []
total_home_chargers_list = []

for home_charger_percentage in home_charger_percentages:
    # Set the probability based on home_charger_percentage
    p_home = home_charger_percentage
    p_public = 1 - p_home
    # Initialize SoC for each EV randomly to either 1 or 0.5
    initial_socs = np.random.choice([0.8, required_soc_for_trip], size=len(results_home_charge),
p=[p_home, p_public])

    home_charging_count = 0
    public_charging_count_raw = 0
    for index, result in enumerate(results_home_charge):
        departure_times, arrival_times, travel_times = result
        initial_soc = initial_socs[index]
        for i in range(len(travel_times)):
            soc_after_trip = initial_soc - travel_times[i] * 0.004545
            if soc_after_trip >= charge_threshold:
                home_charging_count += 1
                initial_soc = soc_after_trip
            else:
                public_charging_count_raw += 1
                # Charging at public charging stations
```

```
            # Randomly select the charger level (82% Level 2, 18% Level 3)
            charger_level = np.random.choice([2, 3], p=[0.82, 0.18])

            if charger_level == 2:
                range_added_per_hour = np.mean(level2_range_added_per_hour)
            else:
                range_added_per_hour = np.mean(level3_range_added_per_hour)

            charging_time_to_full = (1 - soc_after_trip) / range_added_per_hour
            charging_time_to_trip = (required_soc_for_trip - soc_after_trip) / range_added_per_hour

            try:
                next_departure_time = departure_times[i + 1]
                gap_between_departures = next_departure_time - arrival_times[i]

                if gap_between_departures >= charging_time_to_full:
                    initial_soc = 1
                elif gap_between_departures >= charging_time_to_trip:
                    initial_soc = required_soc_for_trip
                else:
                    initial_soc = soc_after_trip + ((gap_between_departures/60) * range_added_per_hour)

                if (8 * 60) <= next_departure_time < (9 * 60) or (17 * 60) <= next_departure_time < (18 * 60):
                    if (9 * 60) <= departure_times[i + 1] < (17 * 60) or (18 * 60) <= departure_times[i + 1] or departure_times[i + 1] < (8 * 60):
```

```
                travel_times[i] /= 1.07
            if (9 * 60) <= next_departure_time < (17 * 60) or (18 * 60) <= next_departure_time
or next_departure_time < (8 * 60):
                if (8 * 60) <= departure_times[i + 1] < (9 * 60) or (17 * 60) <= departure_times[i
+ 1] < (
                        18 * 60):
                    travel_times[i] *= 1.07


        except:
            continue




    avg_range_added_per_hour = (avg_level2_range_added_per_hour * 0.82) +
(avg_level3_range_added_per_hour * 0.18)
    max_charging_time = (205 * (1 / avg_range_added_per_hour)) * (required_soc_for_trip -
charge_threshold)  # average time to charge from empty to full
    max_charges_per_station_per_day = 16 / max_charging_time * 4  # 16 hours a day and 4
vehicles at a time


    proportion_households_with_evs = math.ceil((total_ev / total_cars) * total_households)
    total_home_chargers = math.ceil(proportion_households_with_evs *
home_charger_percentage)
    public_charging_count = public_charging_count_raw + home_charging_count * (1 -
home_charger_percentage)
    total_public_chargers = math.ceil(public_charging_count / max_charges_per_station_per_day)
    total_home_chargers_list.append(total_home_chargers)
    total_public_chargers_list.append(total_public_chargers)


    # Print total number of public and home chargers
```

```
    print(f"For Home Charger Percentage: {home_charger_percentage * 100}%")
    print(f"Total Number of Public Charging Stations: {total_public_chargers}")
    print(f"Total Number of Home Charging Stations: {total_home_chargers}")
    print()

# Plotting
plt.figure(figsize=(12, 8))
# Plotting columns with custom colors and styles
bar_width = 0.4
index = np.arange(len(home_charger_percentages))
plt.bar(index, total_home_chargers_list, bar_width, label='Home Chargers', color='#b30000', edgecolor='#b30000', alpha=0.7)
plt.bar(index + bar_width, total_public_chargers_list, bar_width, label='Public Chargers', color='#6699ff', edgecolor='#6699ff', alpha=0.7)
# Adding text labels with custom fonts and sizes
for i in range(len(home_charger_percentages)):
    plt.text(index[i], total_home_chargers_list[i] + 10, str(total_home_chargers_list[i]), ha='center', fontsize=14, fontweight='bold')
    plt.text(index[i] + bar_width, total_public_chargers_list[i] + 10, str(total_public_chargers_list[i]), ha='center', fontsize=14, fontweight='bold')

plt.xlabel('Home Charger Percentage', fontsize=14, fontweight='bold')
plt.ylabel('Number of Chargers', fontsize=14, fontweight='bold')
plt.title('Comparative Analysis of Home and Public Chargers', fontsize=16, fontweight='bold')
# Customize x-axis labels to display percentages without decimal points and trailing zeros
plt.xticks(index + bar_width / 2, [f"{int(p*100)}%" for p in home_charger_percentages], fontsize=12)
plt.yticks(fontsize=12)
```

```
plt.legend(fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```

Bi-Level Optimization

```
import numpy as np
import random
import pandas as pd
from deap import base, creator, tools, algorithms
import geopandas as gpd
from shapely.geometry import Point
import matplotlib.pyplot as plt


# Load your data files
away_charge_results = pd.read_csv('C:/Users/sayan/Downloads/EVCS/Data/Howard_Baltimore/Phase2_FinalCode/away_charge_results_currenthighest.csv')
taz_data = pd.read_excel('C:/Users/sayan/Downloads/EVCS/Data/Howard_Baltimore/Phase2_FinalCode/TAZODNew2.xlsx')
# Step 1: Extract unique TAZs based on Origin_Lat and Origin_Lon, and sum trips
taz_data_unique = taz_data.groupby(['Origin_Lat', 'Origin_Lon'], as_index=False).agg({'Trips': 'sum'})


# Check how many unique TAZs we have (should be 1397)
print(f"Total Unique TAZs: {len(taz_data_unique)}")
print(taz_data_unique.head())
```

```
# Step 2: Compute proportion of trips for each TAZ
total_trips_all_taz = taz_data_unique['Trips'].sum()
taz_data_unique['Proportion'] = taz_data_unique['Trips'] / total_trips_all_taz

# Print to verify Proportion
print(taz_data_unique[['Origin_Lat', 'Origin_Lon', 'Trips', 'Proportion']].head())

# Step 3: Calculate the total number of EV trips (from the away_charge_results file)
total_ev_trips = len(away_charge_results)

# Step 4: Distribute EV trips proportionally across TAZs
taz_data_unique['EV_Trips'] = np.round(taz_data_unique['Proportion'] * total_ev_trips).astype(int)

# Print to verify EV Trips
print(taz_data_unique[['Origin_Lat', 'Origin_Lon', 'Trips', 'Proportion', 'EV_Trips']].head())



taz_data_unique.to_csv('C:/Users/sayan/Downloads/EVCS/Data/Howard_Baltimore/Phase2_FinalCode/taz_data_unique_ev_trips.csv', index=False)
from scipy.spatial import cKDTree

# Use the unique TAZ data with Origin_Lat, Origin_Lon, and EV_Trips
num_stations = 2113  # Example, change as needed
num_taz = len(taz_data_unique)  # Number of unique TAZs (1397)
```

```
# Decision variables for each station
creator.create("FitnessMulti", base.Fitness, weights=(-1.0, -1.0))
creator.create("Individual", list, fitness=creator.FitnessMulti)

toolbox = base.Toolbox()
toolbox.register("attr_int", random.randint, 0, 1)  # Binary decision for station placement
toolbox.register("individual", tools.initRepeat, creator.Individual, toolbox.attr_int, num_taz)
toolbox.register("population", tools.initRepeat, list, toolbox.individual)

# Parameters and Costs
construction_cost = 21000
operation_cost = 3000
pile_cost = 6500
land_use_cost = 5000
ce_on_peak = 0.33
pe_on_peak = 0.35

# Power Network Parameters
V_min, V_max = 0.95, 1.05
I_max = 200
base_voltage = 11  # Base voltage in kV
line_resistance = 0.1  # Line resistance (Ohms)
line_reactance = 0.2  # Line reactance (Ohms)

# Lower-Level Objective: Minimize Charging Cost
def lower_level_cost(x, y):
```

```
    # Iterate over the number of TAZs, since we place stations in TAZs
    charging_cost = sum([x[i] * taz_data_unique['EV_Trips'].iloc[i] for i in range(min(len(x), len(taz_data_unique)))]) * 100
    return charging_cost


# Upper-Level Objective: Maximize Profit with a geographic spread penalty
def upper_level_profit(individual):
    x = individual[:num_taz]  # Decision variables are based on the number of TAZs
    y = [4] * num_stations  # Fixed number of chargers per station (4)

    # Use the number of EV trips in each TAZ (taz_data_unique['EV_Trips'])
    # Ensure the number of stations and TAZs do not exceed each other
    total_ev_trips = sum([x[i] * taz_data_unique['EV_Trips'].iloc[i] for i in range(min(len(x), len(taz_data_unique)))])

    # Calculate revenue based on EV trips
    Rcharging = total_ev_trips * (pe_on_peak - ce_on_peak)

    # Costs
    Cop = sum(x) * operation_cost
    Ccon = sum(x) * construction_cost
    Cp = sum(station * pile * pile_cost for station, pile in zip(x, y))
    Cl = sum(x) * land_use_cost

    # Optimize the Geographic spread penalty using KDTree
    station_coords = np.array([[taz_data_unique['Origin_Lat'].iloc[i], taz_data_unique['Origin_Lon'].iloc[i]] for i in range(len(taz_data_unique)) if x[i] == 1])
```

```
    if len(station_coords) > 1:
        tree = cKDTree(station_coords)
        distances, _ = tree.query(station_coords, k=2)  # Find the nearest station for each station
        # distances[:, 1] is the distance to the nearest neighbor (k=2 gives self-distance and neighbor)
        nearest_distances = distances[:, 1]
        geographic_penalty = sum([1 / (dist ** 2) if dist > 0 else 10000 for dist in nearest_distances])
# Apply penalty based on nearest distances
    else:
        geographic_penalty = 0  # No penalty if there's only one station

    # Profit calculation with geographic spread penalty
    profit = Rcharging - (Cop + Ccon + Cp + Cl) - geographic_penalty
    return -profit  # NSGA-II minimizes objectives

# Power Network Constraints
def power_network_constraints(V, I, P, x, y):
    # Voltage Constraints
    voltage_constraint = all(V_min <= V_i <= V_max for V_i in V)

    # Power Balance Constraints (P[i][i] - sum of P[i][j] over all j = 0)
    power_balance_constraint = all((P[i, i] - sum(P[i, j] for j in range(len(V)))) == 0 for i in
range(len(V)))

    # Current Constraints
    current_constraint = all(I_ij <= I_max for I_ij in I)
```

```
    return voltage_constraint and power_balance_constraint and current_constraint


# # Facility Constraints: Charging demand must not exceed charging pile capacity
# def facility_constraints(x, y):
#     facility_constraint = all(sum(zimt for zimt in range(len(away_charge_results))) <= xi * yi for xi, yi in zip(x, y))
#     return facility_constraint


# Maximum Stations per TAZ Constraint: Ensure no more than one station per TAZ
def max_stations_constraints(x):
    return all(xi <= 2 for xi in x)


# SoC Constraints: Ensuring State of Charge stays within bounds
def soc_constraints(Soc_min=0.25, Soc_max=0.90):
    soc_constraint = all(Soc_min <= soc <= Soc_max for soc in np.random.uniform(Soc_min, Soc_max, size=len(away_charge_results)))
    return soc_constraint


# Function to place stations in TAZs (ensuring proper station placement logic)
def place_stations(x, num_stations):
    placed_stations = []
    total_stations = 0


    # Case 1: If the number of stations is less than or equal to the number of TAZs
    if num_stations <= num_taz:
        for i in range(num_taz):
            if x[i] == 1 and total_stations < num_stations:
```

```
                placed_stations.append(i)
                total_stations += 1

    # Case 2: If the number of stations is greater than the number of TAZs
    else:
        # First, place one station in each TAZ
        for i in range(num_taz):
            placed_stations.append(i)
            total_stations += 1
            if total_stations >= num_stations:
                break

        # Then, place additional stations in TAZs with the highest demand
        while total_stations < num_stations:
            for i in range(num_taz):
                if total_stations < num_stations:
                    placed_stations.append(i)  # Add additional stations in the same TAZ
                    total_stations += 1

    return placed_stations

# Evaluate the individual solutions with the adjusted logic
def evaluate(individual):
    x = individual[:num_taz]
    y = [4] * num_stations  # Fixed number of chargers per station (4)
```

```
    # Upper-Level Objective: Profit Maximization
    upper_obj = upper_level_profit(individual)

    # Lower-Level Objective: Cost Minimization
    lower_obj = lower_level_cost(x, y)

    # Power Network Constraint Placeholder Values
    V = [1.0] * len(x)  # Placeholder for voltage at each node
    I = [50] * len(x)  # Placeholder for current at each line
    P = np.zeros((len(x), len(x)))  # Placeholder for power flow

    # Constraints
    #facility_constraint = facility_constraints(x, y)
    soc_constraint = soc_constraints()
    max_stations_constraint = max_stations_constraints(x)
    power_constraints = power_network_constraints(V, I, P, x, y)

#     # Log constraint status
#     print(f"Facility constraint: {facility_constraint}")
#     print(f"SoC constraint: {soc_constraint}")
#     print(f"Max stations constraint: {max_stations_constraint}")
#     print(f"Power constraints: {power_constraints}")

    # Ensure all constraints are satisfied
    if not (soc_constraint and max_stations_constraint and power_constraints):
        return float('inf'), float('inf')  # Penalty if constraints are violated
```

```
    return upper_obj, lower_obj

# Register Genetic Algorithm Operations
toolbox.register("evaluate", evaluate)
toolbox.register("mate", tools.cxTwoPoint)
toolbox.register("mutate", tools.mutFlipBit, indpb=0.05)
toolbox.register("select", tools.selNSGA2)

# Genetic Algorithm Parameters
population_size = 100
generations = 50

# Create the initial population
population = toolbox.population(n=population_size)

# Run the NSGA-II Algorithm
algorithms.eaMuPlusLambda(population, toolbox, mu=population_size,
lambda_=population_size, cxpb=0.9, mutpb=0.1, ngen=generations,
                          stats=None, halloffame=None, verbose=True)

# Extracting Results
fronts = tools.sortNondominated(population, len(population), first_front_only=True)
pareto_front = fronts[0]

# Output Results for Charging Stations
charging_stations = []
```

```
# Function to place stations
def place_stations(x, num_stations):
    stations_placed = []
    stations_count = 0
    for i in range(len(x)):
        if stations_count >= num_stations:
            break
        if x[i] == 1:
            stations_placed.append(i)
            stations_count += 1
    # If there are more stations than TAZs, place additional stations with offsets
    while stations_count < num_stations:
        for i in range(len(x)):
            if stations_count >= num_stations:
                break
            stations_placed.append(i)  # Reuse TAZs
            stations_count += 1
    return stations_placed

# Extracting Results
fronts = tools.sortNondominated(population, len(population), first_front_only=True)
pareto_front = fronts[0]

# Output Results for Charging Stations
charging_stations = []
```

```
# Loop through the pareto_front to extract results for each individual
for ind in pareto_front:
    stations_placed = place_stations(ind[:num_taz], num_stations)

    # Create DataFrame for all charging stations, ensuring correct station-to-TAZ mapping
    charging_stations = [
        {
            'Station': i,
            'TAZ': station,
            'Latitude': taz_data_unique.loc[station, 'Origin_Lat'],
            'Longitude': taz_data_unique.loc[station, 'Origin_Lon'],
            'Piles': 4,
            'Cost': lower_level_cost(ind[:num_taz], [4] * num_stations),
            'Profit': -upper_level_profit(ind)
        }
        for i, station in enumerate(stations_placed)
    ]


df_charging_stations = pd.DataFrame(charging_stations)

# Save the results to a CSV file
df_charging_stations.to_csv('C:/Users/sayan/Downloads/EVCS/Data/Howard_Baltimore/Phase2
_FinalCode/charging_stations_locations.csv', index=False)
# Check the fitness values before plotting
for ind in pareto_front:
```

```
    print(ind.fitness.values)

# If the fitness values look fine, proceed with the plot
plt.figure(figsize=(10, 6))
profits = [-ind.fitness.values[0] for ind in pareto_front if ind.fitness.valid]
stations = [ind.fitness.values[1] for ind in pareto_front if ind.fitness.valid]
plt.scatter(stations, profits)
plt.xlabel('Number of Stations')
plt.ylabel('Profit')
plt.title('Pareto Front: Profit vs. Number of Stations')
plt.show()



# Visualization: Map of Charging Stations
# Load the Baltimore MSA shapefile
baltimore_msa = gpd.read_file('C:/Users/sayan/Downloads/EVCS/Data/Howard_Baltimore/Phase2_FinalCode/MD_Metro_Counties/MD_Metro_Counties.shp')

# Convert charging stations DataFrame to a GeoDataFrame
df_charging_stations['geometry'] = df_charging_stations.apply(lambda row: Point(row['Longitude'], row['Latitude']), axis=1)
gdf_charging_stations = gpd.GeoDataFrame(df_charging_stations, geometry='geometry')

# Plot the map with charging station locations
fig, ax = plt.subplots(figsize=(10, 8))
baltimore_msa.plot(ax=ax, color='lightgrey', edgecolor='black')
```

```
gdf_charging_stations.plot(ax=ax, color='blue', markersize=10, marker='o', label='Charging Stations')

plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Map of Charging Stations in Baltimore MSA')
plt.legend()
plt.show()
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.cluster import KMeans

# Assuming df_charging_stations and taz_data_unique are the dataframes created earlier

# --------------------------------------------------
# 1. Heatmap of Charging Demand by TAZ (Density Plot)
# --------------------------------------------------
plt.figure(figsize=(10, 8))
plt.hexbin(taz_data_unique['Origin_Lon'], taz_data_unique['Origin_Lat'], gridsize=50, C=taz_data_unique['EV_Trips'], cmap='Reds')
plt.colorbar(label='Number of EV Trips')
plt.title('Heatmap of Charging Demand Across TAZs')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```

```
# --------------------------------------------------
# 2. Histogram of EV Trips per Charging Station
# --------------------------------------------------
plt.figure(figsize=(10, 6))
plt.hist(taz_data_unique['EV_Trips'], bins=30, color='blue', edgecolor='black')
plt.title('Distribution of EV Trips per Charging Station')
plt.xlabel('EV Trips per Charging Station')
plt.ylabel('Frequency')
plt.show()

# --------------------------------------------------
# 3. Charging Station Utilization Plot (Bar Chart)
# --------------------------------------------------
plt.figure(figsize=(12, 6))
plt.bar(df_charging_stations['Station'], df_charging_stations['Piles'], color='green')
plt.title('Utilization of Charging Stations')
plt.xlabel('Charging Station')
plt.ylabel('Number of Charging Piles')
plt.show()



# --------------------------------------------------
# 6. Geographic Cluster Analysis of Charging Stations
# --------------------------------------------------
coords = taz_data_unique[['Origin_Lat', 'Origin_Lon']].values
```

```
kmeans = KMeans(n_clusters=5, random_state=0).fit(coords)
taz_data_unique['Cluster'] = kmeans.labels_

plt.figure(figsize=(10, 8))
plt.scatter(taz_data_unique['Origin_Lon'], taz_data_unique['Origin_Lat'], c=taz_data_unique['Cluster'], cmap='viridis')
plt.colorbar(label='Cluster ID')
plt.title('Geographic Clustering of Charging Stations')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```

Queuing Framework

```
import os
import simpy
import random
import math
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

##############################
# 1. Charging Time Calculation Using Only Level 2 and Level 3
##############################

# Level 2 and Level 3 parameters (for commercial stations)
level2_range_added_per_hour = (18, 28)   # in miles/hour
```

```
avg_level2 = np.mean(level2_range_added_per_hour)  # ≈ 23 mph

level3_range_added_per_hour = (100, 200)   # in miles/hour
avg_level3 = np.mean(level3_range_added_per_hour)   # ≈ 150 mph

# Parameters from Phase 1:
distance_equivalent = 205  # miles (representative full-charge range)
required_soc_for_trip = 0.5
charge_threshold = 0.3
required_increment = required_soc_for_trip - charge_threshold  # e.g., 0.2

# Calculate charging times (in hours) for the required increment
charging_time_level2_hours = (distance_equivalent / avg_level2) * required_increment
charging_time_level3_hours = (distance_equivalent / avg_level3) * required_increment

# Convert to minutes
charging_time_level2 = charging_time_level2_hours * 60
charging_time_level3 = charging_time_level3_hours * 60

print("Level 2 charging time (minutes):", charging_time_level2)
print("Level 3 charging time (minutes):", charging_time_level3)

# Effective charging time (weighted: 82% Level 2, 18% Level 3)
T_charge_eff = 0.82 * charging_time_level2 + 0.18 * charging_time_level3
print("Effective charging time (minutes):", T_charge_eff)
```

```
# Compute service rate (mu) in vehicles per minute
mu = 1.0 / T_charge_eff
print("Service rate (mu) [vehicles per minute]:", mu)

##############################
# 2. Queuing Simulation Functions (M/M/c/K)
##############################

class ChargingStationModel:
    def __init__(self, env, c, K, mu):
        """
        SimPy-based model of a charging station as an M/M/c/K queue.

        Parameters:
          env: SimPy environment.
          c: Number of chargers (servers).
          K: Total capacity (servers + waiting spaces).
          mu: Service rate (vehicles per minute).
        """
        self.env = env
        self.c = c
        self.K = K
        self.mu = mu
        self.servers = simpy.Resource(env, capacity=c)
        self.num_in_system = 0   # current number in system (service + waiting)
        self.blocked = 0         # count of arrivals rejected
```

```
        self.total_arrivals = 0
        self.waiting_times = []  # times from arrival until service begins
        self.system_times = []   # times from arrival until departure

        # For time-series recording:
        self.state_time = {n: 0 for n in range(K+1)}
        self.last_event_time = 0.0
        self.time_series = []  # list of (time, num_in_system)

    def update_state(self, new_state):
        now = self.env.now
        dt = now - self.last_event_time
        prev_state = self.num_in_system
        if prev_state <= self.K:
            self.state_time[prev_state] += dt
        self.last_event_time = now
        self.num_in_system = new_state

    def record_state(self):
        self.time_series.append((self.env.now, self.num_in_system))


def customer(env, station: ChargingStationModel):
    arrival_time = env.now
    station.total_arrivals += 1
    if station.num_in_system >= station.K:
```

```
            station.blocked += 1
            return
        station.update_state(station.num_in_system + 1)
        with station.servers.request() as req:
            yield req
            service_start = env.now
            waiting_time = service_start - arrival_time
            station.waiting_times.append(waiting_time)
            service_time = random.expovariate(station.mu)
            yield env.timeout(service_time)
            departure = env.now
            station.system_times.append(departure - arrival_time)
            station.update_state(station.num_in_system - 1)

def arrival_generator(env, station: ChargingStationModel, lam):
    while True:
        interarrival = random.expovariate(lam)
        yield env.timeout(interarrival)
        env.process(customer(env, station))

def state_recorder(env, station: ChargingStationModel, sample_interval=1):
    while True:
        station.record_state()
        yield env.timeout(sample_interval)

def run_simulation(lam, mu, c, K, sim_time, sample_interval=1, record_ts=False):
```

```
"""
Run simulation for one station.

Parameters:
  lam: Arrival rate (vehicles/min)
  mu: Service rate (vehicles/min)
  c: Number of chargers
  K: Capacity (servers + waiting)
  sim_time: Total simulation time (minutes)
  sample_interval: Interval for recording state (minutes)
  record_ts: If True, record time-series data

Returns:
  (metrics, time_series) tuple. If record_ts is False, time_series is None.
"""
random.seed(42)
np.random.seed(42)
env = simpy.Environment()
station = ChargingStationModel(env, c, K, mu)
env.process(arrival_generator(env, station, lam))
if record_ts:
    env.process(state_recorder(env, station, sample_interval))
env.run(until=sim_time)
station.update_state(station.num_in_system)
total_arrivals = station.total_arrivals
blocked = station.blocked
```

```
    blocking_probability = blocked / total_arrivals if total_arrivals > 0 else 0
    avg_waiting_time = np.mean(station.waiting_times) if station.waiting_times else 0
    avg_system_time = np.mean(station.system_times) if station.system_times else 0
    total_time = sim_time
    avg_queue_length = sum(n * station.state_time[n] for n in station.state_time) / total_time
    total_service_time = sum([sys_time - wait for sys_time, wait in zip(station.system_times, station.waiting_times)])
    utilization = total_service_time / (c * sim_time) if sim_time > 0 else 0

    metrics = {
        'blocking_probability': blocking_probability,
        'avg_waiting_time': avg_waiting_time,
        'avg_system_time': avg_system_time,
        'avg_queue_length': avg_queue_length,
        'utilization': utilization,
        'total_arrivals': total_arrivals,
        'blocked': blocked
    }
    return metrics, station.time_series if record_ts else None

def mmck_theoretical(lam, mu, c, K):
    """
    Compute theoretical metrics for an M/M/c/K queue.

    Returns a dict with keys:
      'P': steady-state probabilities list,
      'P_loss': blocking probability,
```

```
    'q': mean queue length,
    'w': mean waiting time,
    'rho': utilization per server.
  """
  c_int = int(c)
  K_int = int(K)
  sum1 = sum((lam/mu)**n / math.factorial(n) for n in range(c_int))
  sum2 = ((lam/mu)**c_int / math.factorial(c_int)) * sum((lam/(c_int*mu))**(n - c_int) for n in
range(c_int, K_int+1))
  C = sum1 + sum2
  P = []
  for n in range(K_int+1):
    if n < c_int:
      Pn = ((lam/mu)**n / math.factorial(n)) / C
    else:
      Pn = ((lam/mu)**n / (math.factorial(c_int) * (c_int**(n-c_int)))) / C
    P.append(Pn)
  P_loss = P[K_int]
  q = sum((n - c_int) * P[n] for n in range(c_int, K_int+1))
  w = q / (lam * (1 - P_loss)) if lam * (1 - P_loss) > 0 else float('inf')
  rho = lam / (mu * c_int)
  return {
    'rho': rho,
    'P_loss': P_loss,
    'q': q,
    'w': w,
    'P': P
```

```
    }

##############################
# 3. Load Data from Phases 1 & 2
##############################

# File paths (update as needed)
station_file = r'C:\Users\sayan\Downloads\EVCS\Data\Howard_Baltimore\Phase2_FinalCode\NSGAII\BMSA_0.09\0.8_SoC\0.5\charging_stations_locations.csv'
taz_file = r'C:\Users\sayan\Downloads\EVCS\Data\Howard_Baltimore\Phase2_FinalCode\NSGAII\BMSA_0.09\taz_data_unique_ev_trips.csv'

df_stations = pd.read_csv(station_file)
df_taz = pd.read_csv(taz_file)

# Operating period: From 7 AM to 10 PM = 15 hours = 900 minutes.
T_operating = 15 * 60  # 900 minutes

def compute_capacity(c):
    return 2 * c

##############################
# 4. Run Integrated Analysis for Each Station
##############################

results_list = []
```

```
all_time_series = []  # To collect time series from all stations

for idx, station in df_stations.iterrows():
    taz_id = station['TAZ']
    try:
        taz_info = df_taz.iloc[int(taz_id)]
    except Exception as e:
        print(f"Error finding TAZ {taz_id}: {e}")
        continue
    EV_trips = taz_info['EV_Trips']
    lam = EV_trips / T_operating  # vehicles per minute based on 900 minutes
    c = int(station['Piles'])
    K = compute_capacity(c)
    theo_metrics = mmck_theoretical(lam, mu, c, K)
    # Run simulation with time series recording for each station.
    sim_metrics, ts = run_simulation(lam, mu, c, K, sim_time=T_operating, sample_interval=1,
record_ts=True)
    results_list.append({
        'Station': station['Station'],
        'TAZ': taz_id,
        'Num_Chargers': c,
        'EV_Trips': EV_trips,
        'Arrival_Rate_lam': lam,
        'Capacity_K': K,
        'Service_Rate_mu': mu,
        'Theoretical_Blocking_Prob': theo_metrics['P_loss'],
        'Theoretical_Avg_Waiting_Time': theo_metrics['w'],
```

```
        'Theoretical_Mean_Queue_Length': theo_metrics['q'],
        'Theoretical_Utilization': theo_metrics['rho'],
        'Sim_Blocking_Prob': sim_metrics['blocking_probability'],
        'Sim_Avg_Waiting_Time': sim_metrics['avg_waiting_time'],
        'Sim_Mean_Queue_Length': sim_metrics['avg_queue_length'],
        'Sim_Utilization': sim_metrics['utilization']
    })
    if ts is not None:
        # Convert time series to numpy array and store
        ts_array = np.array(ts)  # each is (time, num_in_system)
        all_time_series.append(ts_array)

df_results = pd.DataFrame(results_list)
print("Integrated Queuing Metrics for Each Station:")
print(df_results.head())

##############################
# 5. Plotting Snapshot Metrics and Saving Outputs
##############################

# Define output folder structure
base_output_folder                                                                    =
r'C:\Users\sayan\Downloads\EVCS\Data\Howard_Baltimore\Phase3_FinalCode'
market_penetration = "0.09"
soc_scenario = "0.8"
household_percentage = "0.5"
```

```
output_folder = os.path.join(base_output_folder, market_penetration, soc_scenario, household_percentage)

os.makedirs(output_folder, exist_ok=True)


# Save results table

table_filepath = os.path.join(output_folder, "results_table.csv")

df_results.to_csv(table_filepath, index=False)

print(f"Results table saved to: {table_filepath}")


# Save units information

units = {

    "Station": "ID (unitless)",

    "TAZ": "ID (unitless)",

    "Num_Chargers": "Number (unitless)",

    "EV_Trips": "Trips per day",

    "Arrival_Rate_lam": "vehicles/min",

    "Capacity_K": "Vehicles",

    "Service_Rate_mu": "vehicles/min",

    "Theoretical_Blocking_Prob": "Probability (unitless)",

    "Theoretical_Avg_Waiting_Time": "minutes",

    "Theoretical_Mean_Queue_Length": "Vehicles",

    "Theoretical_Utilization": "Fraction (unitless)",

    "Sim_Blocking_Prob": "Probability (unitless)",

    "Sim_Avg_Waiting_Time": "minutes",

    "Sim_Mean_Queue_Length": "Vehicles",

    "Sim_Utilization": "Fraction (unitless)"

}
```

```
units_filepath = os.path.join(output_folder, "results_units.txt")
with open(units_filepath, "w") as f:
    for col, unit in units.items():
        f.write(f"{col}: {unit}\n")
print(f"Units information saved to: {units_filepath}")

# Snapshot Plots
# Plot 1: Blocking Probability
plt.figure(figsize=(10,6))
plt.scatter(df_results['Station'], df_results['Sim_Blocking_Prob'], color='red', label='Simulated Blocking Prob')
#plt.scatter(df_results['Station'], df_results['Theoretical_Blocking_Prob'], color='blue', label='Theoretical Blocking Prob')
plt.xlabel('Station ID')
plt.ylabel('Blocking Probability')
plt.title('Blocking Probability per Charging Station')
plt.legend()
plt.grid(True)
plot1_path = os.path.join(output_folder, "blocking_probability.png")
plt.savefig(plot1_path)
plt.close()
print(f"Plot saved to: {plot1_path}")

# Plot 2: Average Waiting Time
plt.figure(figsize=(10,6))
plt.scatter(df_results['Station'], df_results['Sim_Avg_Waiting_Time'], color='red', label='Simulated Avg Waiting Time')
```

```
#plt.scatter(df_results['Station'], df_results['Theoretical_Avg_Waiting_Time'], color='blue', label='Theoretical Avg Waiting Time')

plt.xlabel('Station ID')

plt.ylabel('Average Waiting Time (min)')

plt.title('Average Waiting Time per Charging Station')

plt.legend()

plt.grid(True)

plot2_path = os.path.join(output_folder, "average_waiting_time.png")

plt.savefig(plot2_path)

plt.close()

print(f"Plot saved to: {plot2_path}")


# Plot 3: Simulated Mean Queue Length

plt.figure(figsize=(10,6))

plt.scatter(df_results['Station'], df_results['Sim_Mean_Queue_Length'], color='green', label='Simulated Mean Queue Length')

plt.xlabel('Station ID')

plt.ylabel('Mean Queue Length (vehicles)')

plt.title('Simulated Mean Queue Length per Charging Station')

plt.legend()

plt.grid(True)

plot3_path = os.path.join(output_folder, "sim_mean_queue_length.png")

plt.savefig(plot3_path)

plt.close()

print(f"Plot saved to: {plot3_path}")


# Plot 4: Utilization
```

```
plt.figure(figsize=(10,6))
plt.scatter(df_results['Station'], df_results['Sim_Utilization'], color='purple', label='Simulated Utilization')
#plt.scatter(df_results['Station'], df_results['Theoretical_Utilization'], color='orange', label='Theoretical Utilization')
plt.xlabel('Station ID')
plt.ylabel('Utilization')
plt.title('Utilization per Charging Station')
plt.legend()
plt.grid(True)
plot4_path = os.path.join(output_folder, "utilization.png")
plt.savefig(plot4_path)
plt.close()
print(f"Plot saved to: {plot4_path}")

# Additional Plots with Rounded-Up "Vehicles" Values
# For "Sim_Mean_Queue_Length"
plt.figure(figsize=(10,6))
sim_mql_rounded = np.ceil(df_results['Sim_Mean_Queue_Length'])
plt.scatter(df_results['Station'], sim_mql_rounded, color='green', label='Simulated Mean Queue Length')
plt.xlabel('Station ID')
plt.ylabel('Mean Queue Length (vehicles)')
plt.title('Simulated Mean Queue Length')
plt.legend()
plt.grid(True)
sim_mql_rounded_path = os.path.join(output_folder, "sim_mean_queue_length_rounded.png")
```

```
plt.savefig(sim_mql_rounded_path)
plt.close()
print(f"Plot saved to: {sim_mql_rounded_path}")

# For "Theoretical_Mean_Queue_Length" (original vs. rounded)
plt.figure(figsize=(10,6))
theo_mql_original = df_results['Theoretical_Mean_Queue_Length']
theo_mql_rounded = np.ceil(theo_mql_original)
plt.scatter(df_results['Station'], theo_mql_original, color='blue', label='Theoretical Mean Queue Length')
plt.scatter(df_results['Station'], theo_mql_rounded, color='orange', label='Theoretical Mean Queue Length (Rounded Up)', marker='x')
plt.xlabel('Station ID')
plt.ylabel('Mean Queue Length (vehicles)')
plt.title('Theoretical Mean Queue Length (Original vs. Rounded Up)')
plt.legend()
plt.grid(True)
theo_mql_path = os.path.join(output_folder, "theoretical_mean_queue_length_combined.png")
plt.savefig(theo_mql_path)
plt.close()
print(f"Plot saved to: {theo_mql_path}")

##############################
# 6. Time-Series Plots for All Stations
##############################

# If we recorded time series for each station, we now combine them.
```

```
if all_time_series:
    # Assume all time series have the same time stamps.
    # First, find the common time stamps from the first station.
    common_times = all_time_series[0][:,0]  # first column is time
    # Sum and average the number in system across all stations for each time stamp.
    total_queue = np.zeros_like(common_times)
    for ts in all_time_series:
        total_queue += ts[:,1]  # second column is num_in_system
    avg_queue = total_queue / len(all_time_series)

    # Plot aggregate (sum) time series
    plt.figure(figsize=(12,6))
    plt.plot(common_times, total_queue, label="Total Number in System (All Stations)")
    plt.xlabel("Time (minutes)")
    plt.ylabel("Total Number of Vehicles")
    plt.title("Aggregate Time-Series of Queue Length Across All Stations")
    plt.legend()
    plt.grid(True)
    agg_ts_path = os.path.join(output_folder, "aggregate_time_series_queue_length.png")
    plt.savefig(agg_ts_path)
    plt.close()
    print(f"Aggregate time-series plot saved to: {agg_ts_path}")

    # Plot average time series
    plt.figure(figsize=(12,6))
    plt.plot(common_times, avg_queue, label="Average Number in System per Station",
color="magenta")
```

```
    plt.xlabel("Time (minutes)")
    plt.ylabel("Average Number of Vehicles")
    plt.title("Average Time-Series of Queue Length per Station")
    plt.legend()
    plt.grid(True)
    avg_ts_path = os.path.join(output_folder, "average_time_series_queue_length.png")
    plt.savefig(avg_ts_path)
    plt.close()
    print(f"Average time-series plot saved to: {avg_ts_path}")
else:
    print("No time series data available for all stations.")

##############################
# 7. Time-Series Plot for One Random Station
##############################

# For comparison, plot time series for one randomly selected station.
if len(all_time_series) > 0:
    random_station_ts = all_time_series[0]  # using the first station as an example
    times = random_station_ts[:,0]
    queue_lengths = random_station_ts[:,1]

    plt.figure(figsize=(12,6))
    plt.plot(times, queue_lengths, label="Queue Length")
    plt.xlabel("Time (minutes)")
    plt.ylabel("Number of Vehicles in System")
```

```
    plt.title("Time-Series of Queue Length for Station ID " + str(df_stations.iloc[0]['Station']))
    plt.legend()
    plt.grid(True)
    ts_plot_path = os.path.join(output_folder, "time_series_queue_length_station_" + str(df_stations.iloc[0]['Station']) + ".png")
    plt.savefig(ts_plot_path)
    plt.close()
    print(f"Time-series plot for one station saved to: {ts_plot_path}")
else:
    print("No time series data available for individual station plotting.")
# Compute the rounded simulated mean queue length for each station
sim_mql_rounded = np.ceil(df_results['Sim_Mean_Queue_Length'])

# Count the number of stations for each unique rounded queue length
queue_counts = sim_mql_rounded.value_counts().sort_index()

# Create a bar plot with a muted color
plt.figure(figsize=(10,6))
bars = plt.bar(queue_counts.index.astype(int), queue_counts.values, color='darkorange', edgecolor='black')
plt.xlabel('Rounded Mean Queue Length (vehicles)')
plt.ylabel('Number of Stations')
plt.title('Count of Stations by Rounded Mean Queue Length')

# Annotate each bar with the count of stations
for bar in bars:
    height = bar.get_height()
```

```
    plt.text(bar.get_x() + bar.get_width()/2.0, height, f'{int(height)}', ha='center', va='bottom')


plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
rounded_queue_bar_path = os.path.join(output_folder, "simulated_rounded_queue_length_barplot.png")
plt.savefig(rounded_queue_bar_path)
plt.close()
print(f"Rounded queue length bar plot saved to: {rounded_queue_bar_path}")



# Compute the rounded simulated average waiting time for each station
sim_waiting_time_rounded = np.ceil(df_results['Sim_Avg_Waiting_Time'])


# Count the number of stations for each unique rounded waiting time
waiting_time_counts = sim_waiting_time_rounded.value_counts().sort_index()


# Create a bar plot with a muted color (using "steelblue")
plt.figure(figsize=(10,6))
bars = plt.bar(waiting_time_counts.index.astype(int), waiting_time_counts.values, color='steelblue', edgecolor='black')
plt.xlabel('Rounded Average Waiting Time (min)')
plt.ylabel('Number of Stations')
plt.title('Count of Stations by Rounded Average Waiting Time')


# Annotate each bar with the count of stations
for bar in bars:
```

```
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2.0, height, f'{int(height)}', ha='center', va='bottom')

plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
waiting_time_bar_path = os.path.join(output_folder, "simulated_rounded_average_waiting_time_barplot.png")
plt.savefig(waiting_time_bar_path)
plt.close()
print(f"Rounded average waiting time bar plot saved to: {waiting_time_bar_path}")



# Convert simulated utilization rate to percentages and round to the nearest integer
sim_utilization_pct = (df_results['Sim_Utilization'] * 100).round().astype(int)

# Count the number of stations for each unique utilization percentage
utilization_counts = sim_utilization_pct.value_counts().sort_index()

# Create a bar plot with a muted color (using "teal")
plt.figure(figsize=(10,6))
bars = plt.bar(utilization_counts.index, utilization_counts.values, color='teal', edgecolor='black')
plt.xlabel('Simulated Utilization (%)')
plt.ylabel('Number of Stations')
plt.title('Count of Stations by Simulated Utilization')

# Annotate each bar with the count of stations
for bar in bars:
```

```
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2.0, height, f'{int(height)}', ha='center', va='bottom')

plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
utilization_bar_path = os.path.join(output_folder, "simulated_utilization_barplot.png")
plt.savefig(utilization_bar_path)
plt.close()
print(f"Simulated utilization bar plot saved to: {utilization_bar_path}")


# Convert simulated blocking probability to percentages and round to the nearest integer
sim_blocking_pct = (df_results['Sim_Blocking_Prob'] * 100).round().astype(int)

# Count the number of stations for each unique blocking probability percentage
blocking_counts = sim_blocking_pct.value_counts().sort_index()

# Create a bar plot with a muted color (using "maroon")
plt.figure(figsize=(10,6))
bars = plt.bar(blocking_counts.index, blocking_counts.values, color='maroon', edgecolor='black')
plt.xlabel('Simulated Blocking Probability (%)')
plt.ylabel('Number of Stations')
plt.title('Count of Stations by Simulated Blocking Probability')

# Annotate each bar with the count of stations
for bar in bars:
```

```
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2.0, height, f'{int(height)}', ha='center', va='bottom')

plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
blocking_bar_path = os.path.join(output_folder, "simulated_blocking_probability_barplot.png")
plt.savefig(blocking_bar_path)
plt.close()
print(f"Simulated blocking probability bar plot saved to: {blocking_bar_path}")
```

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