Final Report

A Comprehensive Analysis of EV Charging Demand Prediction, Infrastructure Planning, and Power Network Resilience in the Era of Electric Mobility

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Date
August 2024

Prepared for the Sustainable Mobility and Accessibility Regional Transportation Equity Research Center, Morgan State University, CBEIS 327, 1700 E. Coldspring Lane, Baltimore, MD 21251

ACKNOWLEDGMENT

This research was supported by the Sustainable Mobility and Accessibility Regional Transportation Equity Research Center at Morgan State University and the University Transportation Center(s) Program of the U.S. Department of Transportation.

Disclaimer

1. Report No. SM12	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Integrating Residential and Commercial Electric Vehicle Charging Infrastructure: A Bi-Level Optimization Approach		**5. Report Date** 08/31/2024
		6. Performing Organization Code
7. Author(s) *Include ORCID #* Sayantan Tarafdar (ORCID ID: *0000-0002-9376-9905*) Yi Zhang Dr. Yaobang Gong Dr. Xianfeng Yang		**8. Performing Organization Report No.**
9. Performing Organization Name and Address 1173 Glenn Martin Hall, College Park, MD 20742 University of Maryland, College Park		**10. Work Unit No.**
		11. Contract or Grant No. 69A3552348303
12. Sponsoring Agency Name and Address US Department of Transportation Office of the Secretary-Research UTC Program, RDT-30 1200 New Jersey Ave., SE Washington, DC 20590		**13. Type of Report and Period Covered** Final, September 2023 - September 2024
		14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

Electric vehicles (EVs) have gained significant popularity, becoming an attractive option for cleaner transportation systems, with market adoption in the USA growing substantially over the years. However, a key challenge for this expanding market is the limited charging infrastructure in both residential and commercial spaces. This project studies the optimal number and placement of charging stations needed to accommodate EVs at residential and commercial locations based on market penetration rates and the adoption of charging infrastructure in households. Focusing on the Baltimore Metropolitan Statistical Area (MSA), the study integrates real-world Origin-Destination (OD) trip data with census data to examine the relationship between residential and commercial EV charging infrastructures. Scenario analyses for market penetration rates of 0.09%, 0.75%, 1.61%, 5%, 7.5%, and 10% illustrate the shifting landscape of charging infrastructure demands, revealing an inverse relationship between the availability of residential charging facilities and the need for commercial chargers. Additionally, the study investigates the optimal placement and distribution of commercial EV charging stations within the Baltimore MSA, specifically for a market penetration rate of 0.7%, representing 15,350 EVs and 7,600 households with EVs. Using a bi-level optimization model with power load constraints, the research aims to balance the interests of charging station investors with EV user satisfaction by maximizing profits and minimizing charging costs. The analysis shows significant reductions in the need for commercial charging stations as household adoption of residential chargers increases, particularly at higher States of Charge (SoC). These findings underscore the importance of balancing residential and commercial charging infrastructure to meet the evolving needs of EV users, providing a framework for policymakers and utility providers to develop sustainable EV charging strategies that support greater EV adoption and contribute to environmental sustainability.

17. Key Words: Electric vehicles, charging station planning, residential and commercial charging, power load			**18. Distribution Statement**
19. Security Classif. (of this report): Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 46	**22. Price**

Abstract

Electric vehicles (EVs) have rapidly gained popularity, emerging as a key component of cleaner transportation systems. In the USA, the adoption of various EV types has grown substantially in recent years. However, the expansion of this market faces the significant challenge of limited charging infrastructure in both residential and commercial areas. This project aims to determine the optimal number and placement of charging stations needed to support EVs at residential and commercial locations, considering market penetration rates and the adoption of household charging infrastructure. The developed model is applied to the Baltimore Metropolitan Statistical Area (MSA) to assess the required number of charging stations. By integrating real-world Origin-Destination (OD) trip data with census data, the study explores the relationship between residential and commercial EV charging infrastructure. Through scenario analysis for market penetration rates of 0.09%, 0.75%, 1.61%, 5%, 7.5%, and 10%, the study reveals a clear inverse relationship between the availability of residential charging facilities and the demand for commercial chargers.

Additionally, the study focuses on the optimal placement and distribution of commercial EV charging stations within the Baltimore MSA, specifically examining a market penetration rate of 0.7%, which represents 15,350 EVs and 7,600 EV-equipped households. Utilizing a bi-level optimization model, the study seeks to balance the interests of charging station investors with EV user satisfaction by maximizing profits and minimizing charging costs. The model also considers the constraints imposed by the capacity and additional load placed on the power network. The analysis indicates a significant reduction in the need for commercial charging stations as household adoption of residential chargers increases, particularly at higher States of Charge (SoC). These findings emphasize the importance of a balanced approach to residential and commercial charging infrastructure, offering valuable insights for policymakers and utility providers in developing sustainable EV charging strategies. By considering market penetration rates, household adoption of charging facilities, and optimal SoC management, this approach provides a robust framework for fostering greater EV adoption and advancing environmental sustainability.

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Chapter 1. Introduction

1.1. Research Background

Electric vehicles (EVs) have gained significant popularity and become an attractive option for cleaner transportation systems. The market adoption of different types of EVs in the USA has grown considerably in recent years. One of the challenges for such a growing market is the limited charging infrastructure in both residential and commercial spaces. This project 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, as EVs offer greater energy efficiency (1, 2) and lower emissions (3) compared to conventional fossil fuel vehicles. The market offers several types of EVs (4), 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 (5). Moreover, drivers' anxiety about driving range significantly influences the adoption of EVs (6, 7). Therefore, expanding the existing charging infrastructure and establishing additional charging facilities is crucial to meet the growing demand (8). As the number of EVs continues to grow, there is an urgent need to enhance the charging infrastructure to accommodate the increasing charging requirements (9, 10).

EV charging infrastructure is typically categorized into residential and commercial types. Residential charging has proven to be a practical, efficient, and cost-effective solution, especially for early EV adopters when commercial charging infrastructure was less prevalent. Conversely, commercial charging facilities offer significant benefits to EV users by providing fast charging options and enabling extended driving ranges. While previous studies have explored the impact of EV Charging Stations (EVCS) in both commercial and residential contexts separately, the interplay between residential charging availability and the demand for commercial charging stations remains under-researched. Despite recognizing that the availability of residential charging can influence the need for commercial infrastructure, a significant gap persists in both qualifying and quantifying this impact. This paper seeks to address this critical gap by analyzing how the presence or absence of residential charging facilities affects the demand for commercial charging infrastructure, taking into account various charging patterns. Using traffic networks and EV profiles from Baltimore, Maryland, as a case study, the research aims to derive insights into the dynamics of EV charging demand. Additionally, the results will provide a preliminary understanding of how different market penetration rates of EVs impact this relationship.

1.2. EV Charging Planning

In the first phase of this project, the planning of EV charging stations typically involves three key steps: forecasting EV charging demand, modeling the location and size of charging stations, and solving the planning model. Existing methods for forecasting EV charging demand include the Monte Carlo load forecasting model based on the charging period (11), forecasting models based on trip chains considering temporal and spatial distribution (12), and statistical load forecasting models based on charging probability (13). Additionally, some studies have examined the search behavior, navigation patterns, and usage habits of EV users, leading to the development of a charging demand evaluation method grounded in Bayesian reasoning (14).

In the context of charging station location and sizing models, this research takes into account the interests of key stakeholders, including charging station investors, EV owners, and the distribution network. Various models are designed to achieve different objectives, such as maximizing the annual traffic flow captured by fast charging stations while minimizing total investment costs and energy losses (15). Some models focus on multi-objective bi-level planning (16), optimizing both economic factors and the security and power quality constraints of the distribution network (17). To solve these models, a range of methods are employed, including grid-based and Voronoi diagram algorithms (18), particle swarm optimization algorithms (19), and genetic algorithms (20).

However, practical challenges extend beyond merely ensuring returns for investors. The overall economic benefits and service satisfaction are significantly influenced by factors such as the cost of charging, which is affected by EV user preferences, charging queue times, travel distance, power availability, and pricing. To address these complexities, this study proposes a bi-level optimization model that integrates the interests of both charging station investors and EV users. The upper level of the model focuses on maximizing the profitability of charging stations, while the lower level is dedicated to enhancing user satisfaction by minimizing charging costs and optimizing charging schedules.

1.3. EV Charging Location Optimization

In the first phase of this research, the required number of commercial charging stations was determined based on the percentage of the population with access to residential charging facilities and their charging behavior (21). The second phase focuses on optimally locating these charging stations using a bi-level optimization approach. The bi-level programming model developed in this phase ensures the efficient utilization of charging infrastructure by balancing the needs of EV users with the operational constraints of the charging stations. This approach integrates the interests of both charging station investors and EV users, aiming to optimize overall economic costs while enhancing 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 needed. This study integrates real-world Origin-

Destination (OD) trip data with census data to explore the relationship between residential and commercial EV charging infrastructure. By conducting scenario analyses for market penetration rates of 0.09%, 0.75%, 1.61%, 5%, 7.5%, and 10%, the study illustrates how the demand for charging infrastructure shifts with varying levels of EV adoption. The findings reveal a clear inverse relationship between the availability of residential charging facilities and the demand for commercial chargers.

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

These insights underscore the importance of balancing residential and commercial charging infrastructure to meet the evolving needs of EV users. Policymakers and utility providers can leverage these findings to formulate sustainable EV charging strategies, taking into account market penetration rates, household adoption of charging facilities, and optimal SoC management to reduce reliance on commercial infrastructure. This comprehensive approach offers a robust framework for developing sustainable EV charging networks, thereby fostering greater EV adoption and contributing to environmental sustainability.

Chapter 2. Literature Review

2.1. Residential and Commercial Charging Stations

EV charging infrastructure is typically categorized as residential or 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. Studies indicate that between 50% to 80% of all PIEV charging events occur at home, underscoring its predominance in the EV charging landscape (22). Residential charging infrastructure primarily consists of Level 1 and Level 2 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 (23). The preference for residential charging is primarily driven by its convenience and cost-effectiveness, further supported by installation subsidies (24) and time-of-use electricity tariffs, which make overnight charging more economical (25, 26). 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 (27), 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 other challenges as well. Charging patterns could concentrate during peak hours, potentially straining the power grid (28–31). Furthermore, difficulty accessing charging facilities may arise due to traffic constraints (32), power constraints (33), or both (34, 35). 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 (36–38).

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 (39). Additionally, fast commercial chargers are commonly found along highway corridors (40, 41). 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 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 (42–46). These studies underscore the importance of strategic site selection in metropolitan areas to enhance service coverage and operational efficiency (47–49). Moreover, real-world driving data has been used to simulate recharging demands, aiming to minimize missed trips and optimize the commercial charging network (36, 50). 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 (51–53). This understanding aids in developing a charging infrastructure that aligns with current demand and anticipatory growth patterns.

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 (54). 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 (55). However, the limited availability of commercial charging facilities remains a significant obstacle to widespread EV adoption (56).

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 (57). 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 (58–61). Therefore, analyzing driver profiles and behaviors is crucial to making informed decisions regarding charging investments.

2.2. Charging Location Optimization

The impact of EV owners on the charging system has led to the development of incentive programs (62–64). 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 (65). 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.

Site selection for EV commercial charging stations 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 (66) introduced an LRP for battery swap stations, while Li-ying and Yuan-Bin (67) explored multiple charging station LRPs with time windows. Goeke et al. (68) improved solutions for battery swap station LRPs using adaptive variable neighborhood search algorithms. Government approaches tend to focus on deploying commercial recharging infrastructure to boost EV market penetration. Mak et al. (69) developed robust optimization models for battery-swapping infrastructures, and Xi et al. (70) applied a simulation-optimization model to locate EV chargers in central Ohio. Other studies (36, 71, 72) utilized large-scale trajectory data and geospatial modeling to evaluate and develop commercial charging infrastructure. Li et al. (73) 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 (74, 75).

Different optimization techniques have been employed to tackle the charging station siting problem. Meng et al. (76) utilized geographic area theory to analyze regional layout characteristics for planning charging station locations , providing insights into spatial distribution patterns. Wu et al. (77) proposed a Triangular Intuitionistic Fuzzy Number (TIFN)-based structure considering economic, social, environmental, and planning factors. Ademulegun et al. (78) developed a strategy incorporating technical-physical-socio-economic factors, which demonstrated the importance of a holistic approach to planning. He et al. (79) 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. (80) created a siting model to maximize EV drivers' current activities, and Cao et al. (81) used a probability calculating model to forecast charging load and minimize user travel costs. Bai et al. (82) 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 (83) 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. (84) developed a modified geographic PageRank (MGPR) model to estimate charging demand based on trip OD and social parameters. Wang et al. (85) 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. (86) used a p-median approach with hierarchical analysis to optimize construction cost, charging station distance, parking, and distribution network. Hodgson (44) and Kuby and Lim (47) 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. (76) proposed an asymptotic coverage model and a multi-objective NSGA-II was used to maximize system benefits and coverage level. Multiple studies (35, 87–90) 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 (91–99) 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. (100) 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 (101). As proposed by Zeng et al. (102), 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. (103) further extends 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.

Chapter 3. Model Development

3.1. Study Site Selection

To model the impacts of residential charging facilities on the demands of commercial charging infrastructure, the Baltimore-Columbia-Towson Metropolitan Statistical Area (MSA), commonly referred to as the Baltimore MSA, was 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 (104). **Figure 1 Error! Reference source not found.**illustrates the study area.

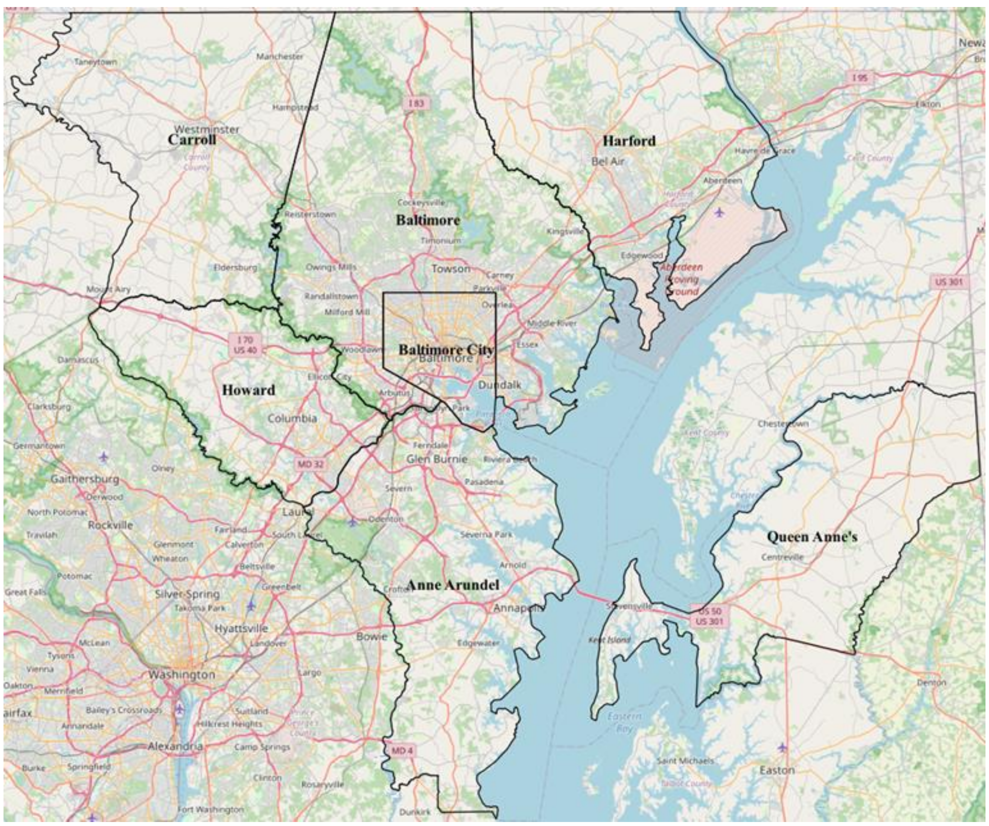

Figure 1. Study Area

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.

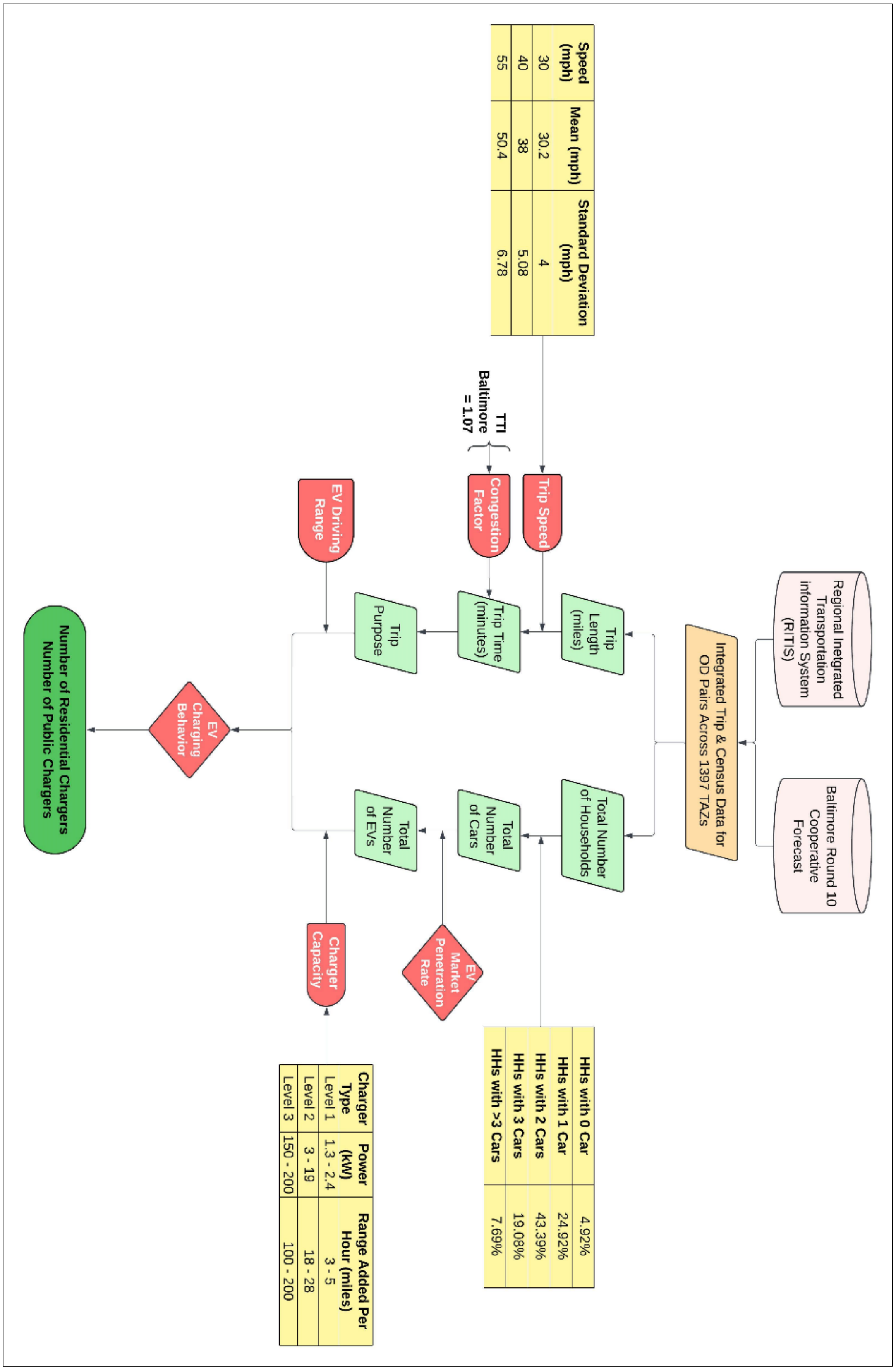

Figure 2 below provides an overview of the modeling, along with the datasets employed in this study.

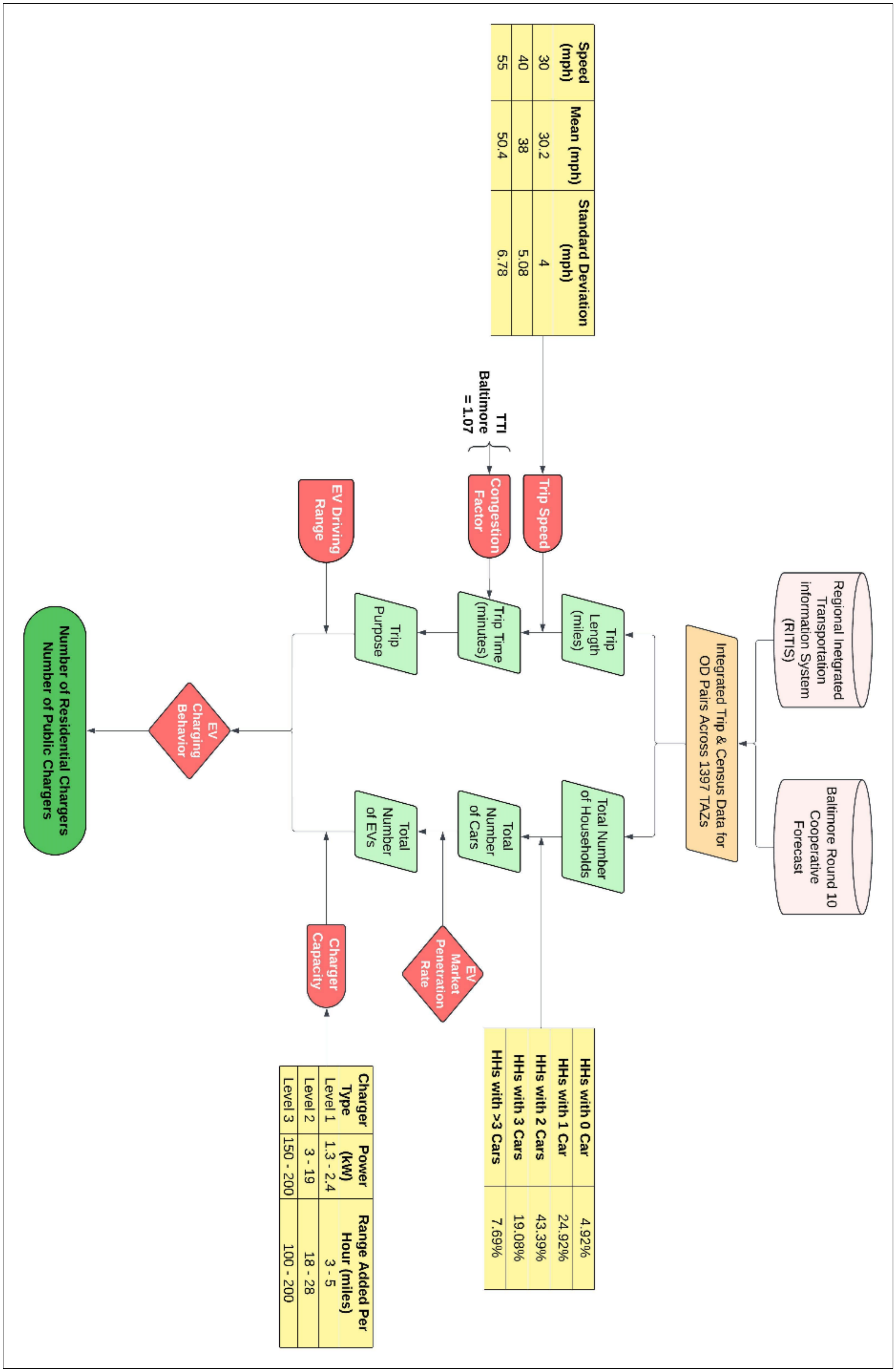

Figure 2. Model Overview

3.2. Travel Demand

The OD trip data from the Regional Integrated Transportation Information System (RITIS) (105) 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 (106) 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 (106)

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 (107), which calculates the vehicle ownership percentages in the State of Maryland using the data from the 2009 National Household Travel Survey (NHTS) (108). **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) (107)

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 (109) 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 3**), respectively, with 0.75% representing the average EV adoption rate in the state.

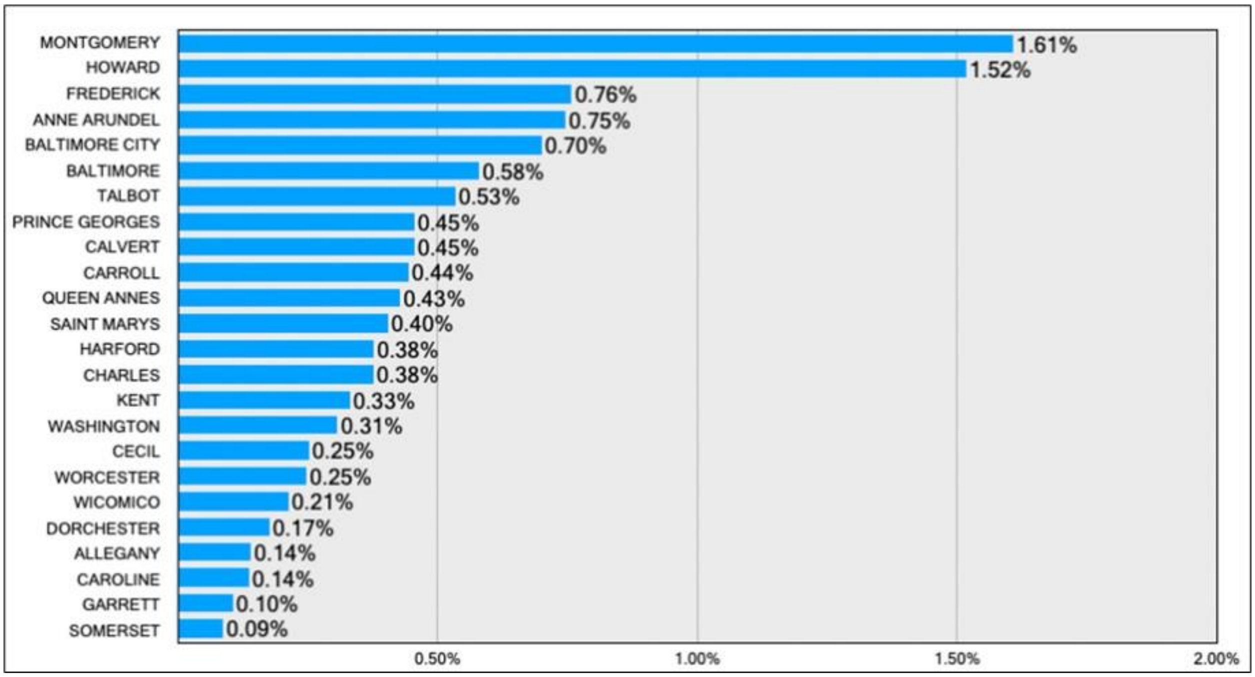

Figure 3. PIEVs as a Percentage of All Vehicles Registered in Each Maryland County as of August 2021 (109)

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

3.4. 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) (110). Level 1 chargers, utilizing a standard residential 120-volt AC outlet, typically require around 40 to more than 50 hours to 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 (111).

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 (112). 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 (113).

3.5. Monte Carlo Simulation

Recent studies have employed probabilistic models to explore EV charging patterns (114, 115). 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 4** 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 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.

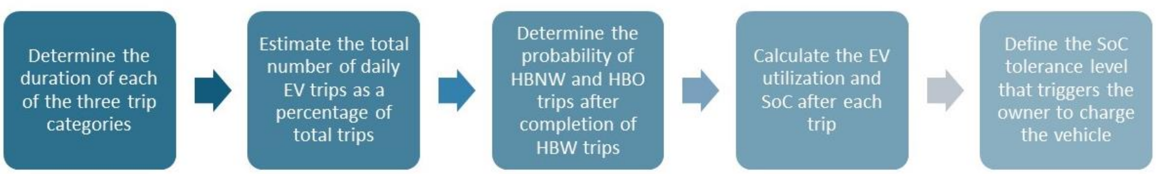

Figure 4. Flowchart Depicting EV Load Estimation in the Daily Routine Estimation Process

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 the daily trips based on their purpose (116). For this study, three broad categories of trips originating from residential locations are considered:

1. HBW: This category includes trips to work or school; i.e., 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 (117) 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 daily EV trips (114). 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).

$$N_{(u)} = EV_{tot} * N_{avg} * y(u), \text{ where } \forall_u = 1, 2, \dots, U_p \tag{1}$$

$$y(x) = \prod_{r=1}^{U_p} \rho_{(r)}^{[x=r]} \tag{2}$$

where $\rho_{(r)}$ is the probability of a trip occurring with the purpose r; x is an integer variable satisfying $[x = r]$; U_p, $N_{(u)}$, 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 (118), while 50% SoC represents a typical threshold for ensuring sufficient charge for immediate trips without causing range anxiety (28). 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% (28) 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.

3.6. Bi-level Optimization

This section focuses on deriving an optimal construction plan for 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.

Sets and Parameters

Block Set N, the entire area is divided into n blocks: N = {1, 2, ….,n}

Position of Each Alternative Charging Station $l_{station}$:

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

Charging Demand Set M: M = {1,2, … ,m}

Charging Amount Set Q: Q = $\{q_1, q_2, \dots, q_m\}$

Charging Time Window Set T_m: $T_m = \{[t_{1\_start}, t_{1\_end}], [t_{2\_start}, t_{2\_end}], \dots, [t_{m\_start}, t_{m\_end}]\}$

Charging Demand Position p_m: $p_m = \{\left[p_{1_{longi}}, p_{1_{lati}}\right], \left[p_{2_{longi}}, p_{2_{lati}}\right], \dots, \left[p_{m\_longi}, p_{m\_lati}\right]\}$

Decision variables

x_i: Binary variable indicating if a charging station is selected in block i ($x_i = 1$); otherwise, ($x_i = 0$).

y_i: Integer variable representing the number of charging piles at charging station i.

z_{imt}: Binary variable indicating if EV m will be charged in the charging station i at time t, if yes, $z_{imt} = 1$; otherwise $z_{imt} = 0$

Upper-level model

The objective of the upper-level model is to maximize the profit for the EV charging system infrastructure.

$$\text{maximize } F = P - C_{op} - C_{con} - C_p - C_l \tag{3}$$

P, the charging profit, is the difference between the charging revenue and cost:

$$P = R_{charging} - C_{charging} \tag{4}$$

$R_{charging}$ is the charging revenue representing the income from the charging station:

$$R_{charging} = \sum_{i=1}^{N} \sum_{t}^{T} \sum_{m}^{M} z_{imt} * p_e(t) \tag{5}$$

where $p_e(t)$ is the charging price for users at the time t, and $C_{charging}$ is the charging cost, which is calculated at the lower level:

$$C_{charging} = \sum_{i=1}^{N} \sum_{t}^{T} \sum_{m}^{M} z_{imt} * c_e(t) \tag{6}$$

$$p_e(t) = \begin{cases} c_e(t) * (1 + Low\ Markup\ Percentage)\ if\ t \in off - peak\ hours \\ c_e(t) * (1 + High\ Markup\ Percentage) if\ t \in peak\ hours \end{cases} \tag{7}$$

where the unit electricity price at the time t is $c_e(t)$ which is the time-of-use price.

C_{op} represents the ongoing costs of operating the charging stations:

$$C_{op} = \sum_{i=1}^{N} x_i * c_{op\_i} \tag{8}$$

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:

$$C_{con} = \sum_{i=1}^{N} x_i * c_{con} \tag{9}$$

where 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:

$$C_p = \sum_{i=1}^{N} x_i * y_i * c_p \tag{10}$$

where c_p is the cost to buy one charger (level 2 and level 3). C_l is the land use cost, representing the expenses associated with using the land for charging stations.

$$C_l = \sum_{i=1}^{N} x_i * c_{l\_i} \tag{11}$$

where c_{l_i} is the land-use cost for the charging station selected in the block i.

Lower Level

The lower-level model focuses on minimizing the total charging cost ($C_{charging}$), providing an optimal charging schedule as output.

$$minimize\ C_{charging} \tag{12}$$

The total charging cost is the summary of the charging cost of all vehicles in the time period.

$$C_{charging} = \sum_{i=1}^{N} \sum_{t}^{T} \sum_{m}^{M} z_{imt} * c_e(t) \tag{13}$$

Constraints

1. *Power Load Constraint:*

Define the total power demand at time t as the sum of the power demands of all charging activities occurring at that time. This can be represented as:

$$W(t) = \sum_{i=1}^{N} \sum_{t}^{T} \sum_{m}^{M} z_{imt} * p_{imt} \tag{14}$$

where p_{imt} is the power demand of vehicle m at station i at time t. The power load on the electricity grid should be smaller than the threshold w_{max}.

$$W(t) \leq\ w_{max} \text{ for all t} \tag{15}$$

This constraint ensures that the total power demand at any given time does not exceed the maximum allowable power load on the grid, thus preventing overloading and ensuring a stable power supply.

2. *Time Window Constraint:*

All vehicles should be charged with their demanded power within the preferred time window $[t_{m\_start}, t_{m\_end}]$.

$$t(z_{imt}) \in [t_{m_{start}}, t_{m_{end}}] \text{ for all m} \tag{16}$$

This constraint ensures that each vehicle receives the required amount of charge within its specified time window, respecting user preferences and availability.

3. *Facility Constraint:*

The number of chargers should satisfy the charging demand at each charging station.

$$\sum_{m}^{M} z_{imt} \leq x_i y_i \tag{17}$$

for all charging stations at the time t.

This constraint ensures that the number of charging piles available at each station is sufficient to meet the demand at any given time.

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 (119). 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 (120). 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 (121). Transaction fees for commercial EVSE units using credit card payment systems range from 5% to 7.5% (122). 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 (122). Demand charges for electricity can increase monthly utility bills by up to $2,000 (122). 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 (122). Suitable EV charging sites can be as small as half an acre (123), with an acre of land in Baltimore County, Maryland, costing between $50,000 and $190,000 in 2024 (124). 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 4. Results Discussions

4.1 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.

0.09% Market Penetration

Figure 5 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.

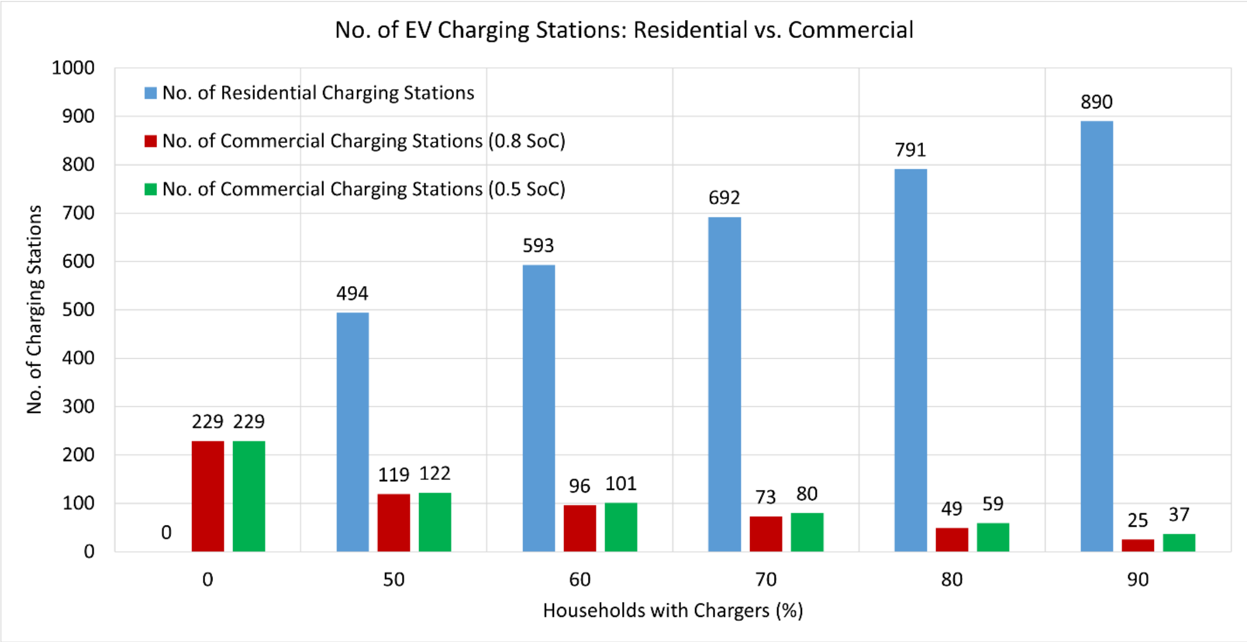

Figure 5. Comparison of the Number of EV Chargers (Residential vs. Commercial) for EV Market Penetration Rate = 0.09%

0.75% Market Penetration

Figure 6 depicts an increase of the market penetration rate 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 in reducing the strain on commercial charging infrastructure as market penetration grows.

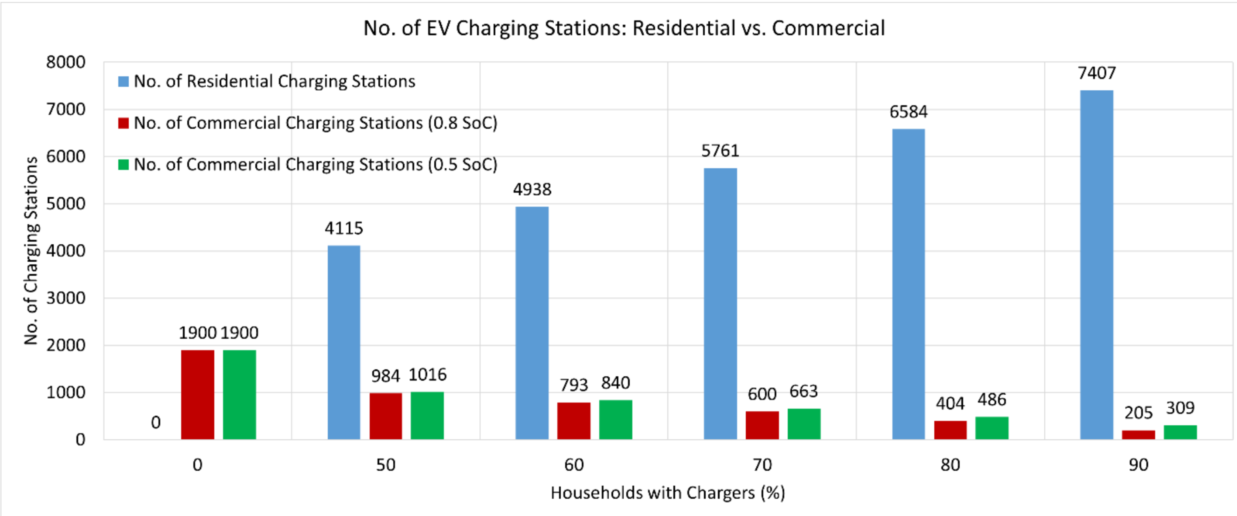

Figure 6. Comparison of the Number of EV Chargers (Residential vs. Commercial) for EV Market Penetration Rate = 0.75%

1.61% Market Penetration

At 1.61% market penetration, illustrated in **Figure 7**, 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 at 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.

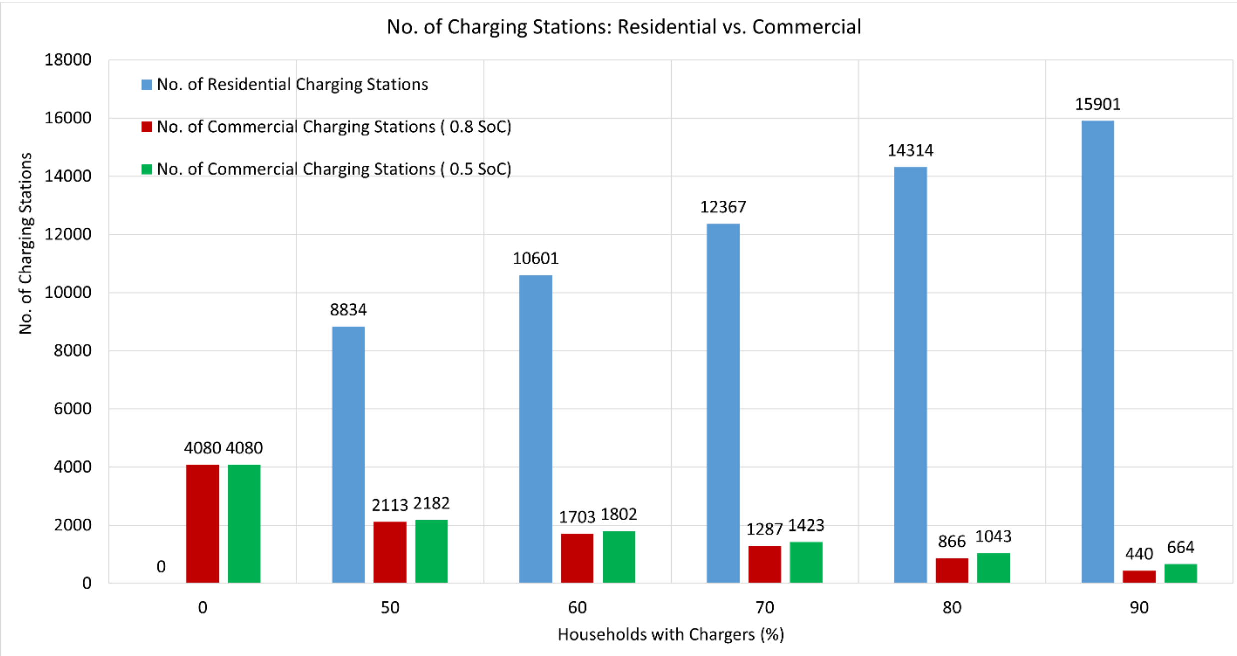

Figure 7. Comparison of the Number of EV Chargers (Residential vs. Commercial) for EV Market Penetration Rate = 1.61%

4.2. 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.

5% Market Penetration

At a 5% market penetration rate, EV adoption has reached a significant level, requiring substantial charging infrastructure (**Figure 8**). 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.

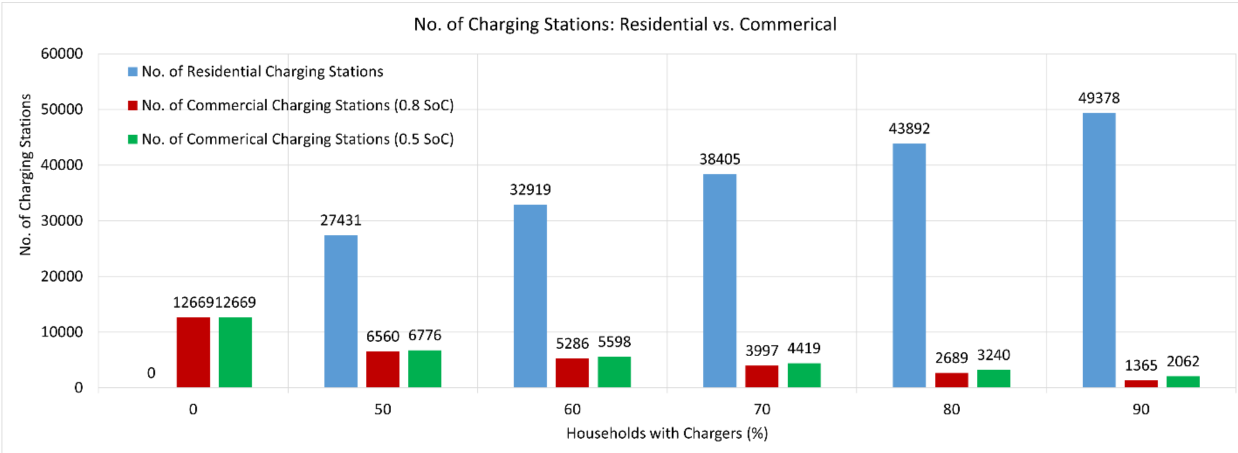

Figure 8. Comparison of the Number of EV Chargers (Residential vs. Commercial) for EV Market Penetration Rate = 5%

7.5% Market Penetration

At a 7.5% market penetration rate (**Figure 9**), 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 requires 6,634 stations, while 80% of SoC needs 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.

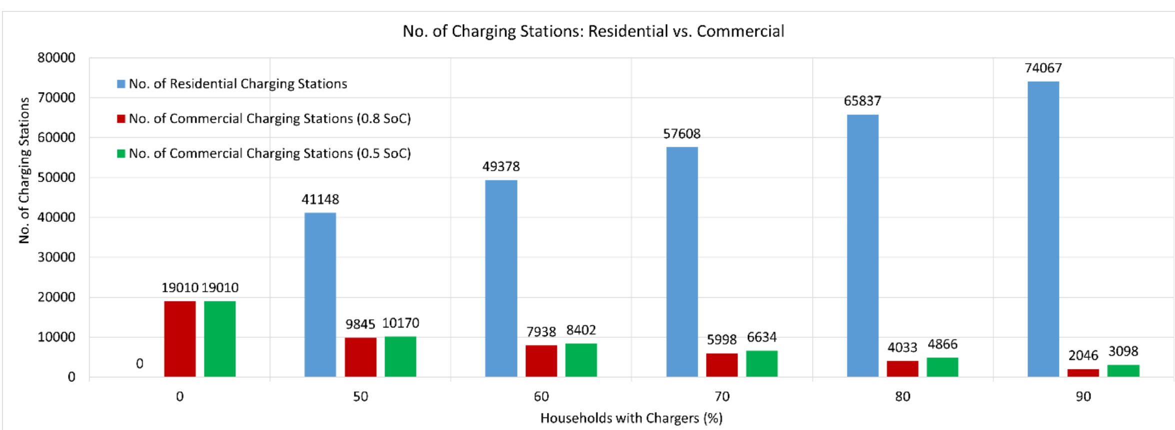

Figure 9. Comparison of the Number of EV Chargers (Residential vs. Commercial) for EV Market Penetration Rate = 7.5%

10% Market Penetration

Figure 10 depicts the scenario at a 10% market penetration rate, where the extensive adoption of EVs necessitates a robust charging infrastructure network. 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.

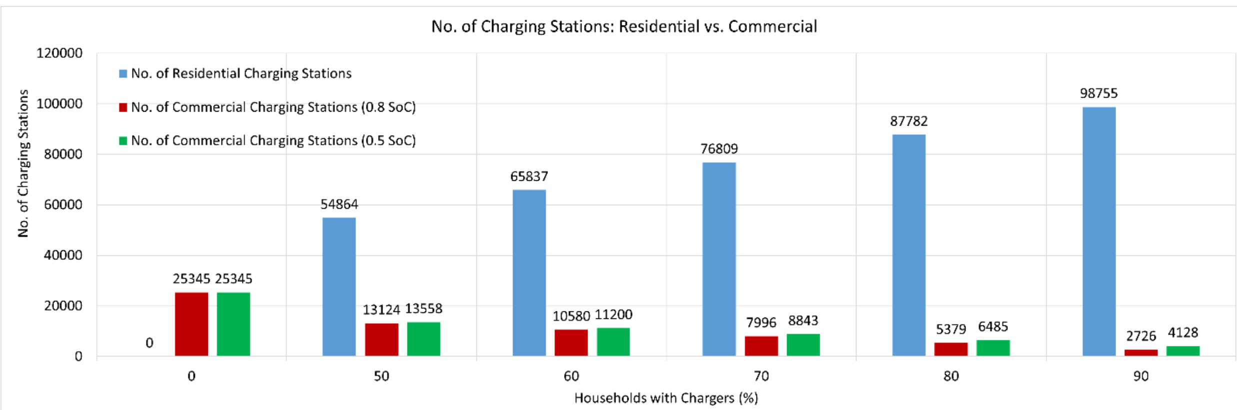

Figure 10. Comparison of the Number of EV Chargers (Residential vs. Commercial) for EV Market Penetration Rate = 10%

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 11** 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.

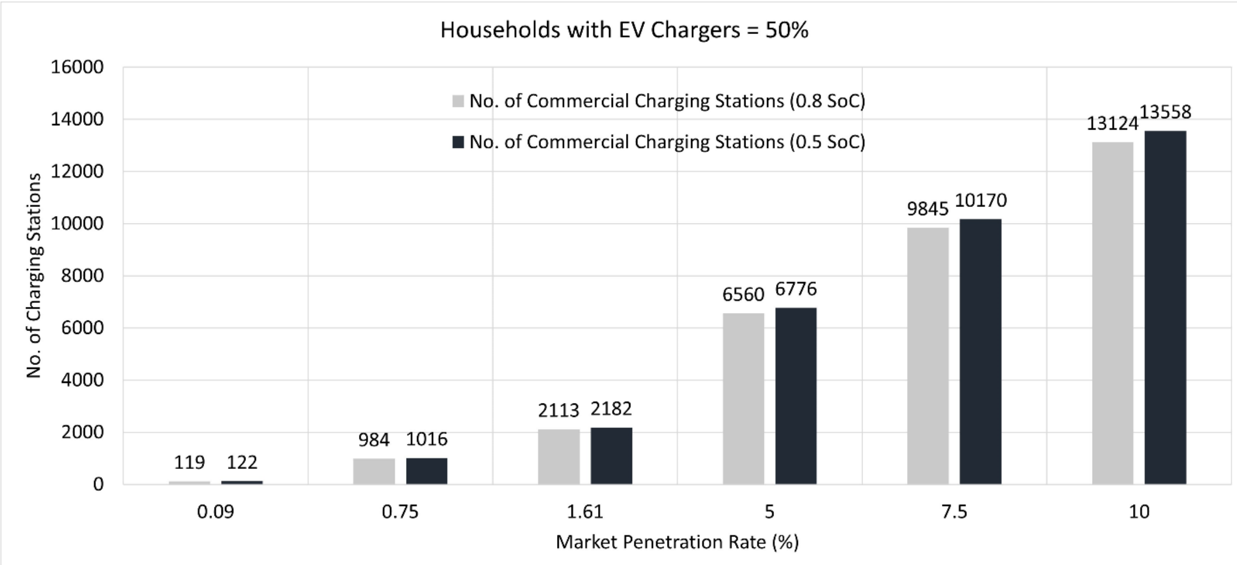

Figure 11. Number of Commercial Charging Stations for Different Market Penetration Rates, Households with Chargers = 50%

Figure 11 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.

4.3. Bi-Level Optimization: 0.70% Market Penetration Rate

The second phase of this study has chosen a market penetration rate of 0.7% as it represents the EV market penetration rate for Baltimore City and is used as a representative figure for the

Baltimore MSA. At a 0.7% market penetration rate, there are 15,350 EVs in the Baltimore MSA, with 7,600 households having EVs. The number of commercial charging stations required varies significantly based on the percentage of households with residential chargers and the SoC (**Figure 12**). Without residential charging facilities (0% adoption rate), 1774 commercial charging stations are necessary. As household adoption of residential chargers increases, the need for commercial stations declines. With 50% of households having residential chargers, the required number of commercial charging stations reduces to 919 for an 80% SoC and 949 for a 50% SoC, representing a decrease of 48.2% and 46.5%, respectively. When 60% of households adopt residential chargers, the demand drops to 741 for an 80% SoC and 784 for a 50% SoC, a reduction of 58.2% and 55.8%, respectively. At 70% household adoption, the requirement decreases to 561 for an 80% SoC and 619 for a 50% SoC, reflecting a 68.4% and 65.1% decrease, respectively. With 80% household adoption, the need for commercial stations reduces to 377 for an 80% SoC and 454 for a 50% SoC, showing reductions of 78.8% and 74.4%, respectively. Finally, with 90% household adoption, only 192 commercial charging stations are needed for an 80% SoC and 289 for a 50% SoC, an 89.2% and 83.7% decrease, respectively.

These numbers provide critical insights into how residential charging infrastructure impacts the demand for commercial charging stations. Higher household adoption rates and higher SoC levels consistently result in fewer required commercial charging stations. For example, the transition from 50% to 90% household adoption at 80% SoC reduces by 79.1%, while at 50% SoC, the reduction is 69.5%. Additionally, comparing 50% SoC to 80% SoC within the same household adoption rate, the reductions range from 1.6% to 33.6%, highlighting the impact of higher SoC levels on reducing the need for commercial charging stations.

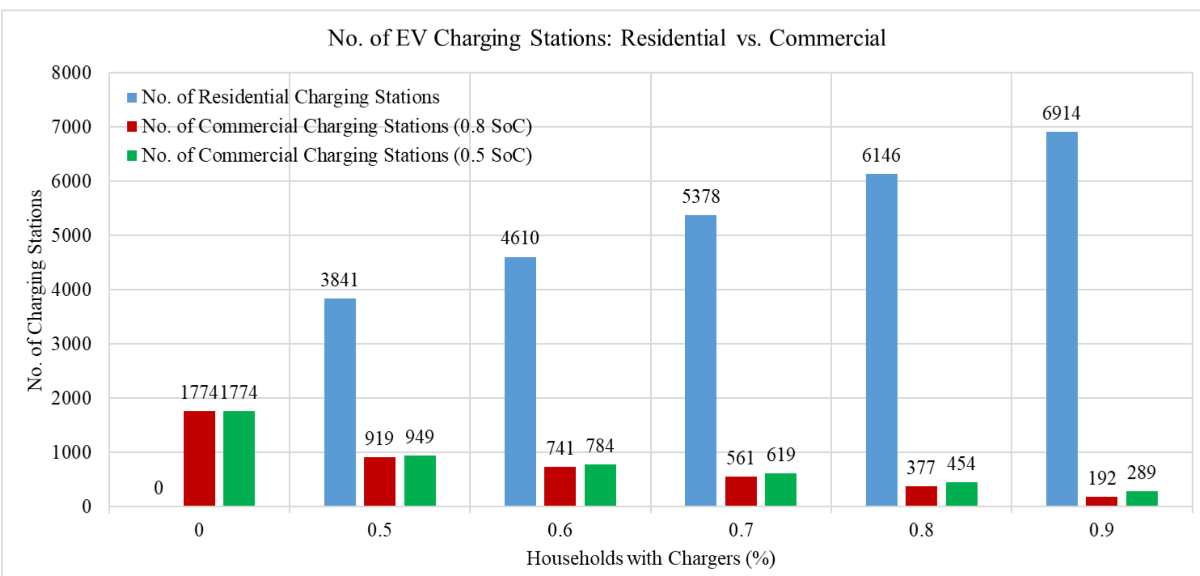

Figure 12 Comparison of the Number of EV Chargers (Residential vs. Commercial) for EV Market Penetration Rate = 0.70%

To dive deeper into the previous analysis, **Figure 13** below illustrates the distribution of commercial EV charging stations across the Baltimore MSA where 90% of households have residential chargers. The concentration of charging stations is significantly higher in densely populated and high-traffic areas such as Baltimore City. This pattern indicates the increased demand for charging infrastructure to support the daily commuting needs of EV users in urban centers. The necessity for more stations at a 50% SoC compared to an 80% SoC highlights how lower SoC levels lead to more frequent charging requirements, necessitating a higher number of stations to meet the demand effectively.

The map also reveals that areas like Annapolis and other surrounding regions exhibit a similar trend but on a smaller scale. Even here, the high adoption rate of residential chargers significantly reduces the number of required commercial stations, underscoring the impact of residential charging availability on overall infrastructure needs.

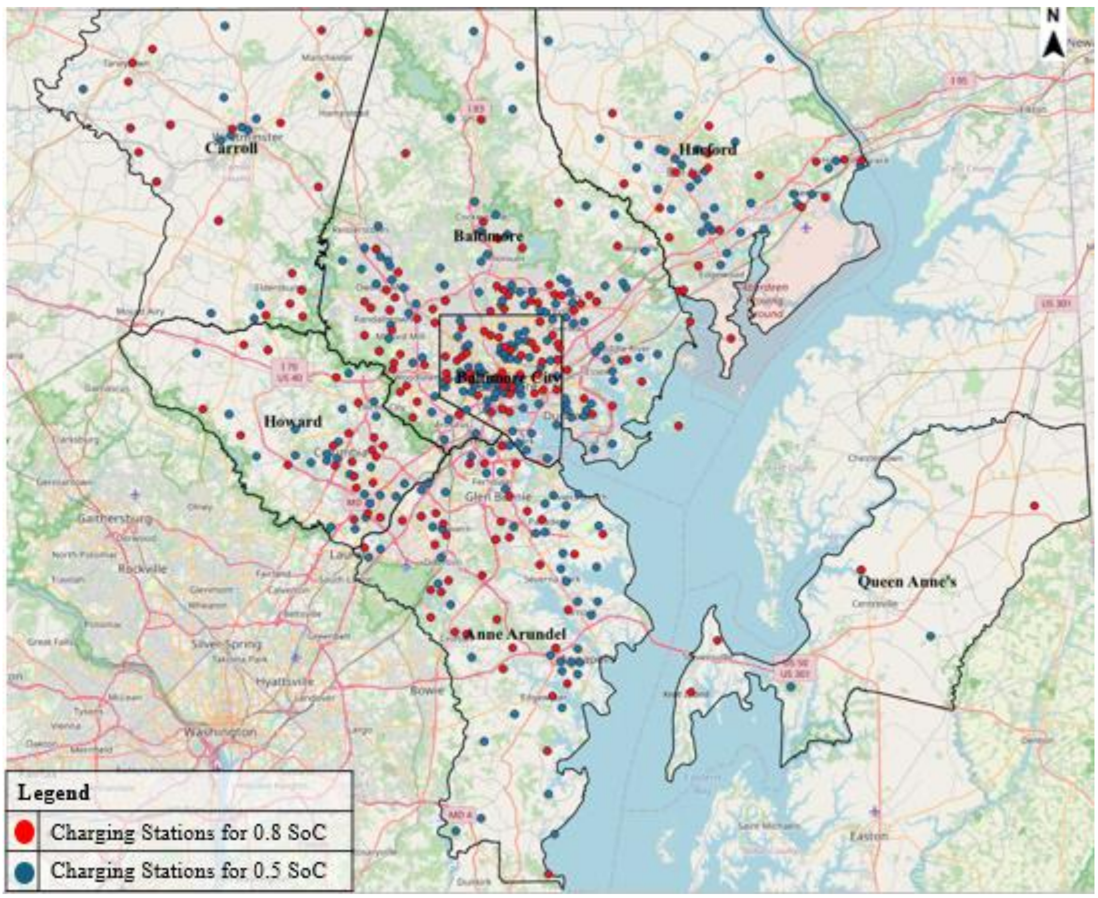

Figure 13 Distribution of Commercial EV Charging Stations in the Baltimore MSA for 90% Residential Charging Facilities

Concurrently, if 60% of households have residential chargers, urban centers like Downtown Baltimore City (**Figure 14**), Annapolis (Anne Arundel County) (**Figure 15**), and Columbia (Howard County) (**Figure 16**) show the separation and overlap of red and blue dots, indicating the varying demand based on different SoC levels. For instance, red dots (80% SoC) are fewer and more spaced out than blue dots (50% SoC), reflecting that higher SoC reduces the frequency of required charges and, consequently, the number of stations needed. Conversely, the higher number of blue dots (50% SoC) shows that lower SoC levels necessitate more frequent charging, requiring more stations.

The red and blue dots overlap, suggesting strategic placement of charging stations to accommodate varying SoC requirements, ensuring that infrastructure can effectively meet diverse charging needs. This also implies that while some locations are critical for all SoC levels, others might be specifically necessary only for lower SoC levels due to increased charging frequency.

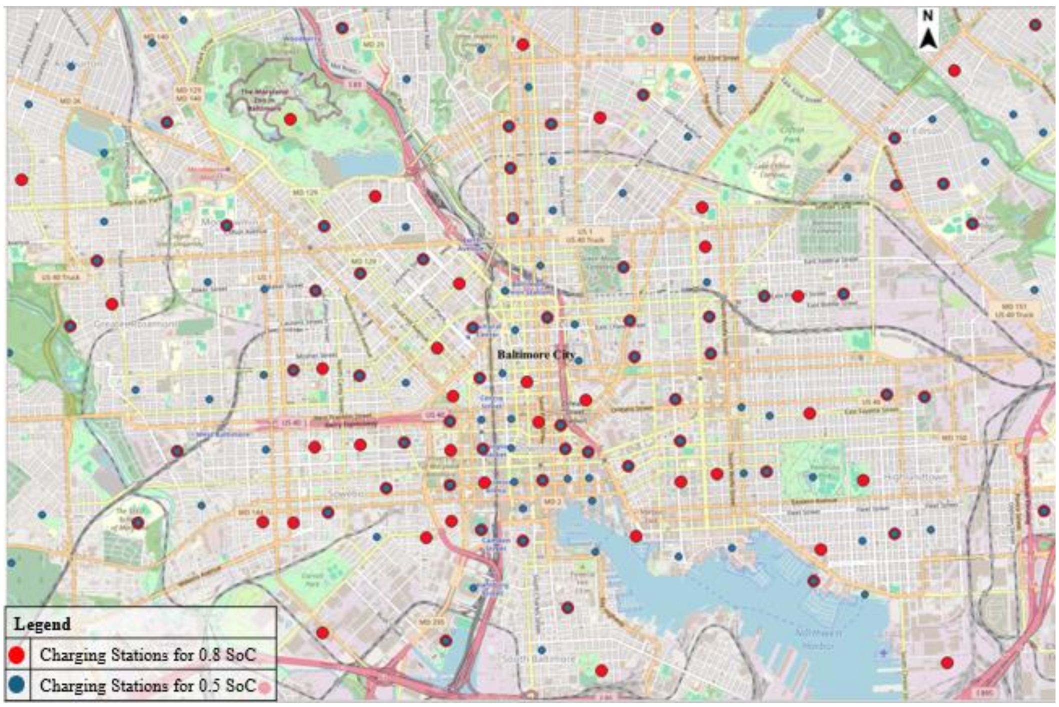

Figure 14 Distribution of Commercial EV Charging Stations in Downtown Baltimore City for 60% Residential Charging Facilities

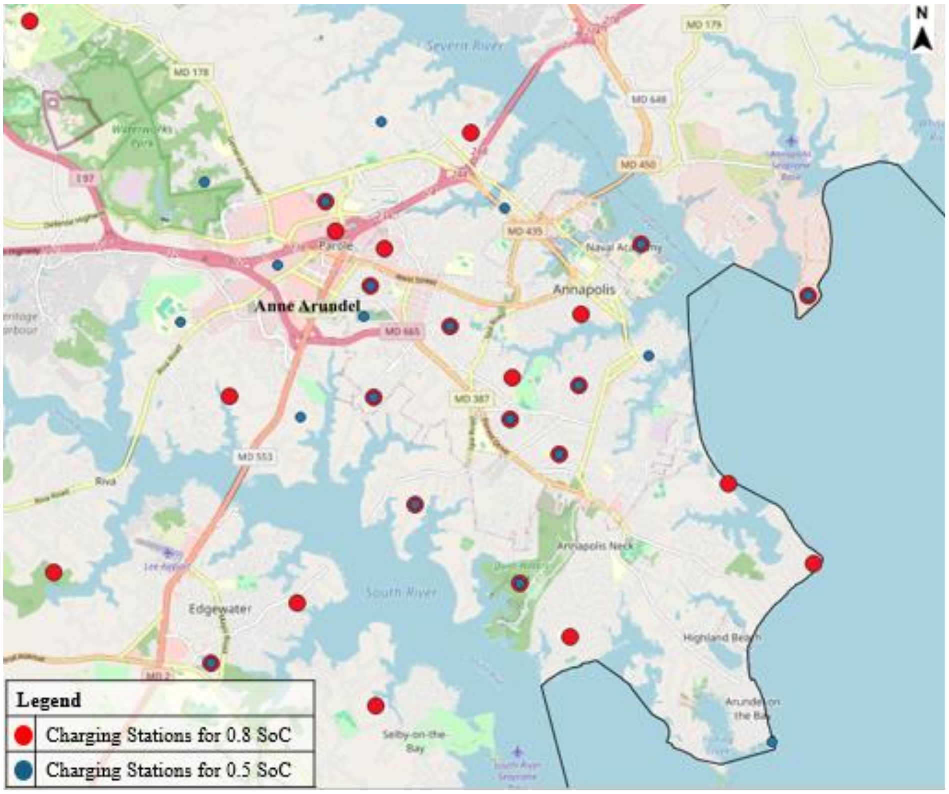

Figure 15 Distribution of Commercial EV Charging Stations in Annapolis for 60% Residential Charging Facilities

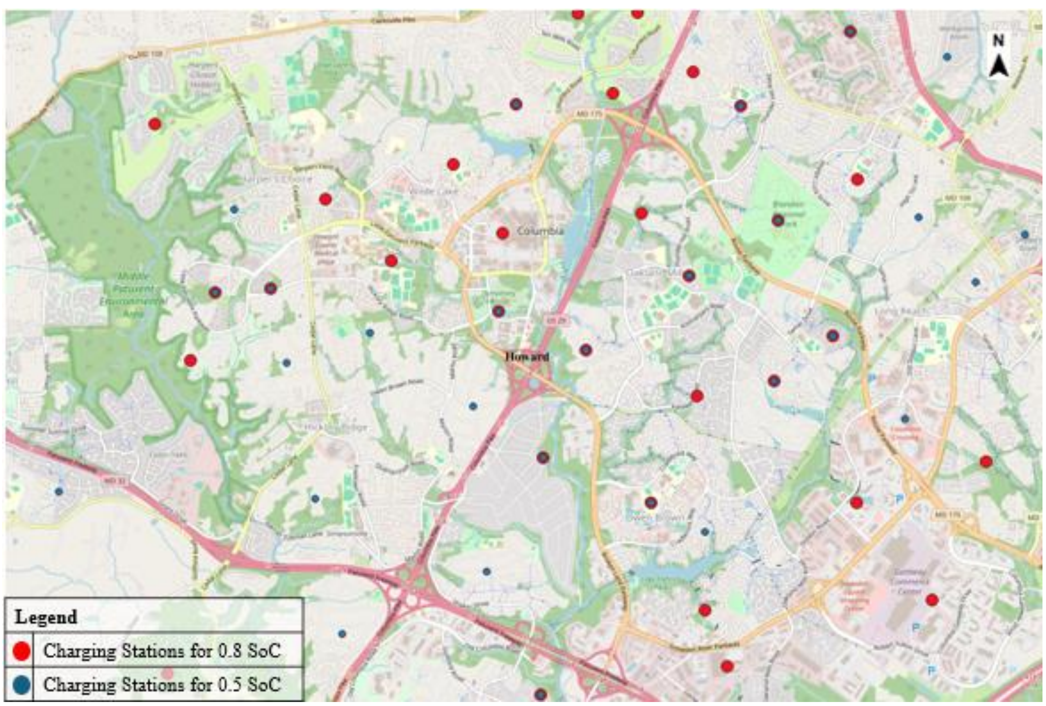

Figure 16 Distribution of Commercial EV Charging Stations in Columbia for 60% Residential Charging Facilities

Additionally, the study aims to calculate the annual profit generated by each scenario. This involves assessing the operational costs, installation expenses, and revenues from charging services. The insights gained will help understand the financial viability and optimal deployment of commercial charging infrastructure, ensuring that the charging needs of EV users are met efficiently while maximizing the profitability for charging station operators. This comprehensive approach aids in making informed decisions regarding the costs and charges associated with EV charging stations, including construction, land purchase, land use, and operational expenses. The weekly profit margin for different commercial charging station scenarios is shown in **Table 5**.

Table 5 Weekly Profit Margin for Commercial Charging Stations for 0.70% EV Market Penetration Rate

Households with Chargers (%)	No. of Commercial Charging Stations (0.8 SoC)	Profit ($)	No. of Commercial Charging Stations (0.8 SoC)	Profit ($)
0	1774	244817.72	1774	244817.72
50	919	238759.19	949	238971.77
60	741	237497.88	784	237802.58
70	561	236222.4	619	236633.39
80	377	234918.57	454	235464.2
90	192	233607.66	289	234295.01

Insights from industry analysis indicate that Level 2 charging stations can generate annual revenues ranging from approximately $8,395 to $75,600 per charger, depending on location and utilization rates (125). Applying standard profit margins of 15% to 35% translates to an annual profit per charger between $1,259.25 and $26,460. For example, the calculated weekly profit of $233,607.66 equates to an annual profit of $15,817.04 per charger. This is consistent with the higher end of industry expectations, supported by the profit margin numbers described above. These observations underscore the necessity of considering both SoC levels and the presence of residential chargers in the planning process. Strategic placement based on these factors can effectively balance the infrastructure needs with actual demand, preventing redundancy and enhancing overall network efficiency. This approach not only supports the economic viability of the proposed charging station network but also lays a robust foundation for further investment and expansion in EV infrastructure, ensuring comprehensive coverage in urban settings.

Chapter 5. Conclusions and Future Research

5.1. Summary and Conclusions

This study investigates the relationship between residential and commercial EV charging infrastructure 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. **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.

5.2. Limitations and Future Research Directions

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.

Future research could expand on this work by incorporating more granular data on user behavior and preferences, leveraging machine learning algorithms for better demand forecasting. Additionally, integrating renewable energy sources and considering their impact on the grid could provide a more sustainable approach to EV infrastructure planning. Exploring the effects of dynamic pricing models and real-time data on charging behavior and station utilization could further refine the optimization model.

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.

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