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Simulating Current and Future EV Growth Scenarios in Indiana



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16. Abstract As Indiana transitions toward electric mobility, data-driven planning is essential to guide electric vehicle (EV) charging infrastructure investment and deployment. This study evaluates the current and future performance of Indiana's EV charging infrastructure using Multimodal Energy-Efficient Trip Simulation in Real Time (METS-R), a high-resolution simulation platform. Five EV adoption scenarios, ranging from pessimistic to optimistic, are modeled for the years 2024 through 2031, to assess spatial and temporal variations in public charging demand. Results reveal increasing public charging demand under high adoption scenarios, with significant disparities between urban and non-urban areas. Accessibility to public charging is found to be uneven across Indiana, with access to Direct Current Fast Charging (DCFC) more limited than to Level 2 (L2) chargers. Demand-to-supply analysis identifies Zip Code Tabulation Areas (ZCTAs) with high EV demand relative to accessible charging supply, highlighting priority areas for targeted deployment. Temporal variations in charging demand underscore the importance of time-of-day planning, while vehicle miles traveled (VMT) analysis highlights the dominant role of local roads usage in EV travel. Revenue projections indicate substantial market potential but also underscore the importance of strategic siting and accurate forecasting, with a median return on investment (ROI) of approximately 0.90 over an 8-year period. The estimated economic development impacts include approximately 2,000 jobs, \$130 million in earnings, and \$400 million in gross output. The study concludes with actionable recommendations for the Indiana Department of Transportation (INDOT) and stakeholders to guide EV infrastructure investment and deployment, including scenario-based planning, accessibility-informed location prioritization, and targeted deployment in areas with high demand-to-supply ratio.			
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EXECUTIVE SUMMARY

Introduction

Indiana is experiencing increased electric vehicle (EV) adoption, highlighting the need for continued public investment in EV charging infrastructure. With EV registrations increasing nearly fivefold between 2018 and 2024, Indiana Department of Transportation (INDOT) seeks data-driven strategies to plan, evaluate, and deploy charging stations that meet current and future mobility needs.

This study is motivated by the need to know when, where, and what type of charging infrastructure should be developed to meet current and future demand. To support this goal, this study uses the high-resolution Multimodal Energy-Efficient Trip Simulation in Real Time (METS-R) simulation platform developed at Purdue University to assess EV demand and charging infrastructure performance under five growth scenarios (from most pessimistic to most optimistic) spanning the years 2024 to 2031. This makes the simulation robust and provides the opportunity to examine a range of scenarios reflecting potential policy shifts aligned with projected future EV adoption trajectories. The simulation integrates large-scale GPS-based location data, survey responses, charging station inventories, and real-world charging data to evaluate system-wide impacts on EV travel behavior, charging station usage, infrastructure reliability, vehicle miles traveled, revenue, return on investment (ROI), economic development impact (EDI), charging accessibility, and demand-to-supply alignment for both current and future EV growth scenarios.

Findings

The simulation and empirical analysis reveal several important trends in EV travel demand, charging behavior, and infrastructure use. EV travel is concentrated on four road types: tertiary, residential, primary, and secondary. A notable distinction exists between urban and nonurban areas where urban EV miles traveled (EVMT) are dominated by residential roads, implying short, home-based trip patterns, while nonurban EVMT is concentrated on tertiary roads, reflecting longer inter-community travel. Direct Current Fast Charging (DCFC) stations are utilized more frequently but for shorter durations, whereas Level 2 (L2) stations accommodate longer average sessions, especially in suburban and rural areas. Usage patterns vary considerably by time of day, with clear distinctions between daytime and nighttime activity. Spatially, high-demand areas cluster within specific Zip Code Tabulation Areas (ZCTAs), which either remain consistent, or shift based on EV adoption scenarios. Despite recent infrastructure growth, reliability remains a concern since over 40% of charging trips exceeded 50 mi in 2024, suggesting insufficient network coverage. We note that charging trip lengths increase further in later years as EV charging infrastructure expansion fails to keep pace with increasing demand. Accessibility analysis further shows that

charging access is uneven across Indiana. Impedance-weighted accessibility is higher around major urban centers, while many rural and peripheral areas have lower access. Access to DCFCs remains more spatially constrained than access to L2 chargers, indicating a persistent fast-charging gap. The demand-to-supply analysis also identifies several ZCTAs where EV demand is high relative to accessible charging supply, for example in the northern Indianapolis metropolitan area, southeastern Indiana, and West Lafayette. These results indicate that infrastructure planning should account not only for where EV demand is highest, but also for where demand exceeds accessible charging supply. Revenue analysis indicates that L2-only stations yield the lowest returns, DCFC-only stations perform moderately, while mixed stations, offering both L2 and DCFC, generate the highest revenue. Additionally, the median ROI is approximately 0.90, indicating that 50% or more of the charging stations recover at least 90% of their total investment cost within an 8-year period. Moreover, the estimated EDI includes approximately 2,000 jobs, \$130 million in earnings, and \$400 million in gross output generated from the development of the EV charging stations (EVCSs).

Implementation

Based on data-driven analysis in this study, we provide a strategic implementation plan for INDOT and its stakeholders.

1. Suburban areas should be prioritized for both L2 and DCFC installations, with rural areas receiving greater emphasis in L2 and towns (population of 2,500 to 50,000) on DCFC stations.
2. Future planning should place stronger emphasis on appropriately placing DCFC stations given their projected faster growth in demand compared to L2.
3. Scenario-based planning should be adopted to ensure infrastructure remains flexible and resilient to uncertain EV adoption trajectories, avoiding both overbuilding and underbuilding.
4. Planners should prioritize deployment in high-demand ZCTAs based on metrics such as total charging time, number of visits, accessibility, and demand-to-supply ratio, while scaling back investments in areas with projected decline.
5. Temporal dynamics in charging demand should inform operational strategies, including adjusting business hours and enhancing nighttime capacity where necessary.
6. Accessibility gaps must be addressed so that users are not required to travel long distances to reach an EVCS, with particular attention to improving DCFC access in underserved areas.
7. Mixed charging stations should be considered in locations where both fast-charging demand and longer-duration charging needs are present, given their stronger revenue performance.
8. The ROI analysis found that the lowest ROI is approximately 55%, indicating that a small proportion of charging stations are underutilized. This may relate to the accessibility findings, highlighting the need for further attention to improve accessibility.
9. Road maintenance strategies should be re-evaluated to reflect EVs' heavy reliance on tertiary, residential, secondary, and primary roads, ensuring infrastructure longevity and service quality.

This report offers a replicable, simulation-based framework for Indiana to scale reliable and accessible EV infrastructure in alignment with long-term mobility and economic objectives.

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1. INTRODUCTION

1.1 Background and Motivation

Indiana is experiencing a pivotal transformation in its transportation landscape, marked by advances in vehicle electrification, highlighting the need for continued public investment. The state has been allocated nearly \$100 million in federal funds through the National Electric Vehicle Infrastructure (NEVI) program to establish a comprehensive network of electric vehicle (EV) charging stations at strategically selected locations across both urban and rural areas¹. This initiative reflects a proactive commitment to sustainable transportation and acknowledges the essential role of data-driven infrastructure planning in addressing the evolving mobility needs of Indiana's residents. The transition to electric mobility, while promising, introduces a set of complex and multidimensional challenges for transportation systems. EVs differ fundamentally from conventional vehicles in terms of energy replenishment requirements, charging duration, and spatial dependence on fixed infrastructure. Without strategic foresight, these differences can result in congestion at EV charging stations (EVCS), underutilization of assets, and regional inaccessibility. For instance, rural areas may face slower deployment of charging infrastructure, potentially hindering EV adoption in these regions.

As shown in Figure 1.1, while the total number of registered vehicles in Indiana has remained relatively stable over the past 6 years (2018–2024), the number of registered EVs has grown rapidly—from 3,441 in 2018 to 33,373 in 2024, indicating a nearly tenfold increase. This trend demonstrates the accelerating pace of EV adoption and underscores the urgent need for responsive infrastructure planning. To support this growth, Indiana has significantly expanded its charging infrastructure. As depicted in Figure 1.2, the spatial distribution of Level 2 (L2) and Direct Current Fast Charging (DCFC) stations shows a concentration in urban centers, with sparser coverage in rural regions. Meanwhile, Figure 1.3 illustrates the sharp increase in cumulative EV charging ports, particularly since 2020, with L2 ports surpassing 1,100 by 2024 and DCFC exceeding 776. This expansion trend demonstrates Indiana Department of Transportation's (INDOT) continued commitment to scaling EV infrastructure in alignment with national electrification targets. However, disparities in access between charger types and geographic locations remain evident.

Understanding current and projected EV travel and charging behaviors is foundational to the strategic planning and long-term sustainability of EV infrastructure (Chen, Hamim, Moras, et al., 2025). Unlike internal combustion engine vehicles (ICEV), EVs are constrained by shorter driving ranges, longer refueling times, and limited public charging availability, making user behavior a critical factor in infrastructure effectiveness. Key behavioral metrics, such as trip frequency, average distance traveled, time-of-day activity patterns, and location-specific charging preferences, exhibit high variability across population, land use typologies, and regional contexts (Chen, Hamim, & Ukkusuri, 2025). Failing to account for these variations can lead to spatial

¹ In early 2026, federal reallocations reduced this total to approximately \$75 million.

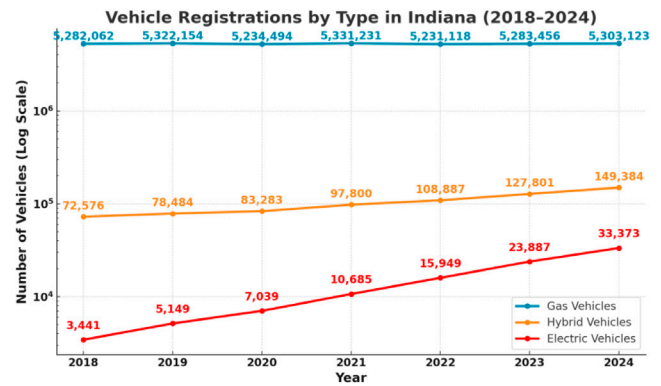


Figure 1.1 Vehicle Registrations by Type in Indiana.

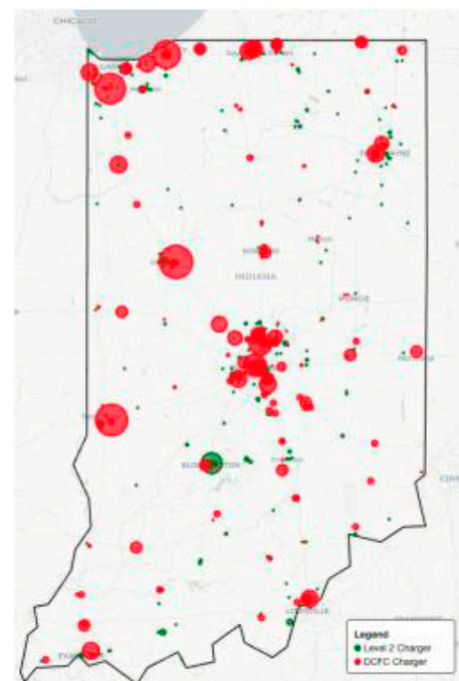


Figure 1.2 Spatial Distribution of L2 and DCFC Chargers.

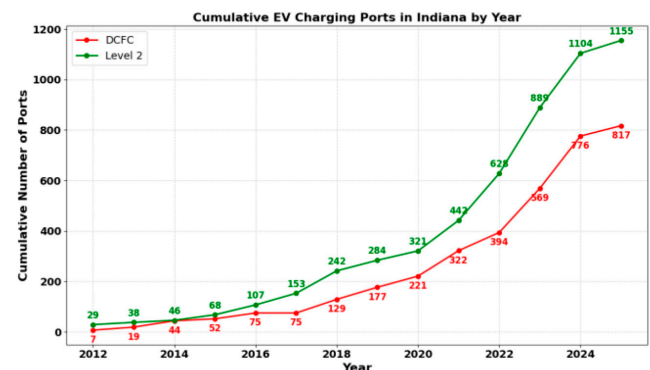


Figure 1.3 Cumulative Number of L2 and DCFC Chargers Over the Years.

mismatches between charging supply and demand, burden EV adoption, reducing utilization rates, and undermining user satisfaction. Therefore, accurate EV operation modeling, grounded in empirical, high-resolution data, is essential to ensure that EV infrastructure is responsive to evolving mobility needs, supports charging access, and maximizes public investment efficiency.

Deploying public L2 and DCFC stations entails substantial capital and operating costs. As a result, stakeholders increasingly rely on performance indicators to assess economic viability, resilience and prioritize investments (Hamim et al., 2025a; Vaishali & Prabha, 2024a, 2024b). In the United States, federal programs such as the NEVI Formula Program are allocating hundreds of millions of dollars per state to support EV charging deployment (Chu et al., 2023). While much of the early effort has focused on network expansion, there is now an urgent need to rigorously evaluate the economic performance of EV infrastructure to ensure long-term viability. Merely deploying chargers is insufficient. A comprehensive understanding of economic return, including return on investment (ROI), economic development impact (EDI), and user accessibility, is essential to guide smart and sustainable infrastructure investments. Without such analyses, underutilized or poorly located charging stations may become financial liabilities, resulting in wasted public investment and diminished public trust. Moreover, the costs associated with installing, operating, and maintaining EV chargers are substantial and can vary widely based on charger capacity, site-specific installation complexity, and required grid connection upgrades (Gamage et al., 2023; Singh et al., 2024). For example, DCFC stations typically involve higher capital and utility upgrade costs compared to L2 chargers. These significant upfront investments highlight the need for a strategic, data-driven approach to determine where and when EV charging infrastructure should be deployed to maximize both economic returns and public benefits. To enable transparency and accountability in public infrastructure planning, economic performance metrics provide decision makers at INDOT, Metropolitan Planning Organizations, utilities, and the private sector with evidence-based tools for optimizing EV charging infrastructure siting, phasing, and scaling. Additionally, integrating monetized accessibility metrics such as population coverage within a 5- to 15-mi radius of a charger enhances the ability to evaluate investments through both a financial and accessibility lens, ensuring that underserved areas are not overlooked.

To translate empirical demand insights into actionable operational strategies, simulation has emerged as a critical tool in modern transportation planning. Advanced, high-fidelity simulation platforms allow researchers and decision makers to evaluate the complex interplay between travel behavior, infrastructure design, traffic conditions, and energy systems in a virtual environment prior to real-world implementation. These models integrate temporal and spatial dimensions of travel demand with vehicle-specific characteristics, enabling the estimation of key performance metrics such as charger utilization rates, station-level electricity demand, congestion impacts and charging reliability. In contrast to static analysis, simulation offers a dynamic, systems-level perspective that supports scenario-based evaluation under varying levels of EV adoption and

spatial configurations. This capability is vital for identifying high-priority investment areas, anticipating operational bottlenecks, and informing adaptive infrastructure deployment strategies that are robust to future uncertainties.

Building upon the travel demand analysis conducted by Purdue University in partnership with INDOT, our research team leverages future EV demand projections for the next few years. These projections incorporate evolving vehicle ownership rates, socio-demographic profiles, trip characteristics, and detailed charging behaviors across Indiana's diverse geographic landscape. By integrating these inputs into a calibrated, high-resolution simulation framework, we can assess the performance of alternative infrastructure configurations under multiple growth scenarios. The simulation outputs produce a comprehensive set of planning-relevant metrics, including vehicle miles traveled (VMT) by EVs, station-level charging reliability, spatial-temporal electricity loads, and regional demand distributions. These insights provide INDOT and related stakeholders with an evidence-based foundation for making informed, cost-effective, and accessible investment decisions that are aligned with Indiana's long-term mobility and sustainability objectives. Furthermore, we introduce the EV Charging Infrastructure Economic Assessment Framework (EV-EAF), a simulation-integrated framework that quantifies ROI, EDI and accessibility in both spatial and economic terms. By converting charging access and usage patterns into monetized indicators, the framework enables the prioritization of infrastructure investments based on measurable, actionable, and context-specific performance metrics. Ultimately, the EV-EAF equips INDOT with a rigorous, transparent, and data-driven methodology to support strategic, cost-effective, and accessibility-informed decision making that advances Indiana's long-term goals for mobility, sustainability, and economic development.

1.2 Research Objectives and Deliverables

The current project is a parallel expansion of SPR-4706 (Moras et al., 2024) where the research team will use the demand data collected from the project to simulate the network-level impacts of the EV demand and quantify metrics of interest for EV planning and operations. Figure 1.4 shows the research workflow used in this project. Using a high-fidelity simulation model developed at Purdue University (Lei et al., 2024), the research team will integrate the current and future demand scenarios for passenger EV cars developed from SPR-4706 and will provide an understanding of (i) the forecast of EV travel patterns, (ii) which corridors are likely to see significant EV usage, (iii) guidance on using the trip data to understand charging station locations based on current and future trips, (iv) potential demand at the charging stations, (v) ROI on charging stations based on visits, (vi) the VMT by EVs on various roadways categorized by urban and rural trips for various future scenarios, and (vii) the impacts of EV miles traveled (EVMT) on gas tax reduction. The team will also project the EV travel patterns that describe the daily trip distance and charging frequencies of EV users. The EV users' charging preferences using different EV charger types (L2 and DCFC) and their preferred locations for this charging will be investigated.

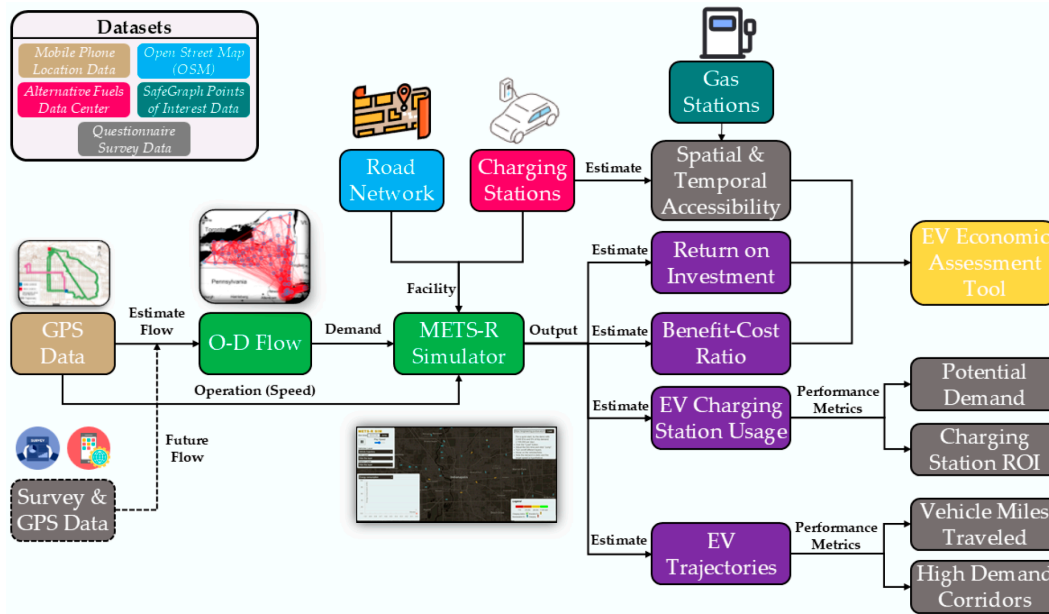


Figure 1.4 Workflow of the Project Illustrating the Various Datasets Used in the METS-R Simulator to Simulate Current and Future EV Demand Scenarios in Indiana.

With the information provided in the INDOT EV deployment plan and planning tools, including the existing and the planned charging station locations, and estimated numbers of various types of chargers, the research team will evaluate the impact of different adoption scenarios for the future years and will provide charging station and Zip Code Tabulation Area (ZCTA) level analysis and guidance for INDOT on their EV infrastructure deployment strategy.

In addition, this project enhances the economic planning and decision-making framework for EV charging infrastructure development in Indiana by introducing a rigorous, data-driven evaluation methodology. Building on the foundational work, the study proposes the EV-EAF to quantify the cost-effectiveness, accessibility, and return on public investment of existing and future charging station deployments. The framework incorporates key economic metrics such as ROI based on capital, operational, and maintenance costs versus estimated revenues and utilization rates; EDI quantified through employment generation, earnings, and gross output estimated via an Input-Output modeling approach to capture the broader regional economic multiplier effects of infrastructure investment; and accessibility metrics capturing the spatial coverage of chargers and the population served, including multifamily and underserved communities. The study further quantifies economic performance and cost efficiency of charging stations at both site and system levels using standardized economic formulations and geospatial analysis, and integrates these results into an enhanced Indiana Visualization Dashboard to support stakeholder decision making and scenario comparisons. Based on these analyses, the project provides policy and planning recommendations to guide INDOT and its partners on infrastructure phasing, scaling, and

public-private investment strategies that maximize returns and promote accessibility.

The deliverable of this project consists of five parts:

1. List of studies related to EV adoption and demand generation, draft survey design materials.
2. Datasets for simulation calibration. This refers to the processed high-quality vehicle trajectories based on the raw Global Positioning System (GPS) points collected from connected vehicle vendors.
3. EV demand scenarios for current and future years. This refers to the EV demand and infrastructure data of various simulation scenarios for reproducing the numerical results.
4. An EV simulation toolkit calibrated for Indiana. This refers to the executable simulation program with necessary user guidance.
5. A report summarizing the simulation metrics, insights, accessibility analysis, economic evaluation results, and policy suggestions corresponding to different EV growth scenarios.

1.3 Report Organization

The rest of the report is organized as follows. Chapter 2 presents a review of the literature related to EV infrastructure modeling, covering both supply- and demand-side approaches, and outlines the relevant data sources and prior findings that inform this study. It also summarizes the advantages and limitations of existing economic performance indicators for EV charging infrastructure, including ROI, benefit-cost ratio, and accessibility, providing foundational insights to guide framework design. Chapter 3 describes the Multimodal Energy-Efficient Trip Simulation in Real Time (METS-R SIM) framework, including the simulator's architecture, input datasets, calibration methodology, and its role in evaluating EV infrastructure usage under

various future demand scenarios. In addition, it introduces the EV-EAF, including its components, evaluation logic, and methodologies for accessibility analysis, ROI calculation, and benefit–cost ratio estimation. Chapter 4 provides detailed results and discussion, including synthesized EV demand and supply patterns, real-world charging behavior, background traffic conditions, and system performance metrics. It also presents the assessment results derived from the EV-EAF and simulation outputs, highlighting regional variations in economic performance and demonstrating the functionality of the visualization tool developed for stakeholder engagement and decision support. Subsections explore EV infrastructure usage, density of charging needs at the ZCTA level, reliability of the charging network, vehicle miles traveled by EVs, and the projected ROI and broader economic performance of charging infrastructure. Chapter 5 summarizes the key findings, provides actionable recommendations for INDOT and related stakeholders, and outlines the study’s limitations along with directions for future research and tool enhancements.

2. LITERATURE REVIEW

2.1 EV Infrastructure Supply-Side Modeling

This section provides an overview of the EV infrastructure supply-side modeling related literature including network models and simulation models.

2.1.1 Existing EV Infrastructure Simulators

Several EV infrastructure simulators have been developed to model EV travel patterns and charging behaviors. Among the most prominent are EVI-Pro, REVISE 2.0, E-Drive, and ATEAM. Each tool differs in its modeling approach, data input, and application focus.

EVI-Pro: Developed by the National Renewable Energy Laboratory (NREL)², EVI-Pro has been used in multiple detailed planning studies over the last few years (Davis, 2024; Moniot et al., 2019; Muratori, Wood, et al., 2018). The simulator relies on travel survey data and EV sales projections to estimate daily EV charging demand. It has been used in planning efforts for locations such as Columbus, Ohio, and the state of Massachusetts. EVI-Pro models daily activities based on projected EV adoption but does not perform trip assignments or incorporate network-level analysis. It assumes that only multiunit dwelling (MUD) residents require public or workplace charging and that consumers select charging scenarios that support their current travel needs while minimizing operating costs. Due to the limited availability of EV user data at the time of development, EVI-Pro uses travel diaries from gasoline vehicle (GV) users as a proxy.

REVISE 2.0: Developed by Oak Ridge National Laboratory (ORNL) was last updated in 2021(Xie et al., 2018). It utilizes origin-destination (O-D) travel demand data, EV adoption projections, and discounted infrastructure cost estimates to support

strategic planning for inter-city EV fast-charging infrastructure. The tool has been applied to nationwide corridor planning efforts in the U.S. It employs a mixed-integer programming model to determine optimal locations and timing for charging station deployment. REVISE 2.0 accounts for EV growth rates over time and partitions the long-term planning horizon into multiple stages.

E-Drive: Developed by M.J. Bradley & Associates, E-Drive was last updated in 2022 (ERM, 2021). The simulator integrates data from the American Community Survey (ACS), National Household Travel Survey (NHTS), the Alternative Fuels Data Center (AFDC), and accessibility metrics to assess infrastructure needs. It has been applied in several states, including Maine, New York, Pennsylvania, Virginia, and North Carolina. E-Drive ranks census tracts using a weighted scoring approach, providing a suitability score (0–100) to guide siting decisions. It is particularly useful for gap analyses and identifying future infrastructure needs.

ATEAM: The ATEAM model, developed by Argonne National Laboratory (ANL) and last updated in 2022, simulates EV travel and charging behaviors using data from NHTS, EV adoption forecasts, and ChargePoint session records (Mintz et al., 2019). Implemented in Java with Repast Symphony 2.5, ATEAM models driver agent activity schedules at the census tract level. Unlike other models, it focuses exclusively on EVs and simulates both charging behavior and infrastructure investments. The model uses a simplified “sketch” road network, rather than a full real-world network, to reduce computational demands. ATEAM has been applied to cities including Chicago, Washington, D.C., and Baltimore.

A brief comparison of the existing EV infrastructure simulators with the proposed METS-R simulator is presented in Table 2.1. While existing tools such as EVI-Pro, REVISE 2.0, E-Drive, and ATEAM primarily focus on EV-only modeling and operate at limited scalability, METS-R introduces several enhancements. It uniquely incorporates both EV and GV travel data, utilizes high-resolution GPS trajectories and survey responses, and supports network-level traffic routing. Unlike others that rely on static growth-rate assumptions for adoption modeling, METS-R integrates dynamic behavioral insights from mobile-phone location and questionnaire data. Additionally, its use of an agent-based modeling (ABM) framework coupled with high-performance computing (HPC) allows for scalable simulations, and it is the only platform among the compared tools offering an online visualization interface.

2.1.2 Metrics Used for Evaluating EVCSs

To evaluate the operational performance and utilization efficiency of EVCS, several quantitative metrics have been adopted in the literature (Borlaug et al., 2023; Ruseruka et al., 2024; Siddique et al., 2022; Weekx et al., 2025; Zhao et al., 2024). Among the most widely used are:

- (i) Proportion of Time In-Use which measures the ratio of the time a charging station is actively used for charging relative to the total time it is available for public use. This metric reflects station occupancy and helps identify underutilized or overburdened locations.

² NREL has been renamed National Laboratory of the Rockies (NLR)

TABLE 2.1
Comparison of EV Infrastructure Simulators.

Topic	EVI Pro by NREL	REVISE 2.0 by Oak Ridge	E-Drive by MJB&A	ATEAM by Argonne	METS-R by Purdue Team
Method & Scalability	Optimization (not scalable)	Optimization (not scalable)	Weighting (not scalable)	ABM (not scalable)	ABM with HPC Module (scalable)
Mix of Vehicles	Only EVs	Only EVs	Only EVs	Only EVs	Both EVs and GVs
Datasets Used	Travel Survey, PEV Sales	O-D Demand, Infrastructure Cost, BEV Sales	ACS, NHTS, AFDC Stations, Accessibility Metrics	NHTS, BEV Adoption Forecast, Charging Station Data	GPS Data of EV & GV, OpenStreetMap (OSM) Road Network, Charging Station, Questionnaire Survey
Traffic Routing With Network Modeling	No	No	No	No	Yes
EV Charging Model	Scenario Based	Queueing Model	None	Rule Based	Queueing Model
EV Adoption Model	Growth Rate	Growth Rate of Population	Growth Rate of Population	Growth Rate of Population	Generated from Survey & Mobile-Phone Location Data Combination
Visualization	No	No	No	No	Online Visualization

TABLE 2.2
EV Infrastructure Demand.

Data Source	Description	Use Case Example
EV Registration	Official records that provide information about EVs legally registered in an area.	EV registration data from each first-level administrative division in Italy was used to generate OD inter-city trip pairs, enabling an assessment of the interaction between EVs and charging infrastructure (Micari et al., 2017).
Travel Diary	Data collection methods are used to understand individual and group travel behavior. Travel diary records the details of a person's trip, including destination, mode of transportation, departure and arrival times, and purpose of the trip.	- Travel diary data was used to simulate home-based weekday travel patterns in California, optimizing charging station placement (Nicholas et al., 2013). - American Travel Survey (ATS) data helped generate spatial demand for intercity travel (Chicago-Madison-Minneapolis corridor), enabling optimal charging station configuration (Ghamami et al., 2016).
Synthetic EV Traffic	Artificially generated traffic loads that mimic real-world patterns by considering temporal and spatial locality, often used in computer systems to simulate various workloads and evaluate network performance.	- Zhang et al. (2018) simulated one-day urban trips in Cologne, Germany, using 700,000 synthetic car trajectories derived from real traffic data to estimate dynamic pricing strategies for charging stations. - Luo et al. (2016) generated 32,640 synthetic EV traffic profiles based on rush-hour Google Maps traffic flow data to optimize charging scheduling algorithms.

- (ii) Mean Session Time which captures the average duration of individual charging events at a station. It provides insights into charging behavior and infrastructure load, distinguishing between short-duration top-ups and longer full charges.
- (iii) Mean Number of Visits which denotes the average number of charging sessions per day at a given station. This metric is a proxy for station popularity and demand intensity.

Collectively, these metrics offer a comprehensive picture of station-level usage patterns, facilitating planning for capacity upgrades, pricing strategies, and optimal siting of future charging infrastructure.

2.2 EV Infrastructure Demand-Side Modeling

This section provides an overview of the EV infrastructure demand-side modeling related literature.

2.2.1 Data Sources Used for EV Simulation

Charging stations are built to meet the demand for EV charging. Therefore, when simulating EV infrastructure, it is essential to incorporate demand-side modeling. Table 2.2 summarizes data sources to generate demand for EV infrastructure.

2.3 EV Infrastructure Economic Assessment

This literature review synthesizes key economic and financial performance indicators relevant to the evaluation of EV charging infrastructure, drawing from academic research, government reports, and industry analyses. We compare how these metrics are defined and applied, highlight their roles in decision-making frameworks, particularly for public sector planning in places like Indiana, and discuss the advantages and limitations

of each. Finally, we recommend a set of indicators most applicable for evaluating EV charging investments in Indiana's context.

Utilization rate and efficiency are fundamental performance indicators that link the infrastructure capacity of EVCSs to their actual usage (Borlaug et al., 2023; Gellrich et al., 2022; Hamim et al., 2025b). Utilization is commonly defined as either the percentage of time a charger is in use, calculated as the number of hours in use divided by total available hours, or as the average number of sessions per day relative to the station's capacity. High utilization is critical for improving the economics of charging infrastructure, as fixed costs are distributed across a larger number of charging sessions, thereby increasing cost effectiveness. Industry analysts frequently cite utilization as a decisive factor in charger profitability. However, real-world utilization rates are often much lower. Average public DCFC station utilization in many regions hovers between 5–10% (Pritchard et al., 2023), reflecting the classic “chicken-or-egg” problem of EV adoption: low EV traffic results in underused chargers, which in turn impairs station profitability and dampens future infrastructure investment. Utilization metrics are also essential for planning and optimization. Academic studies often use models that maximize station efficiency or seek to serve the maximum number of EVs given resource constraints. Public agencies employ utilization rates to assess performance and prevent overbuilding infrastructure that may sit idle. It is important, however, to interpret utilization data carefully. Extremely high utilization, typically above 80%, may signal congestion and increased wait times for drivers, which can reduce user satisfaction. The goal is not to maximize utilization blindly, but to strike a balance between economic efficiency and service quality. Furthermore, during the early phases of network deployment, policymakers may tolerate low utilization in strategically valuable locations (e.g., rural corridors or underserved areas) to ensure geographic accessibility and long-term network viability.

Cost per user or per session is a straightforward yet informative indicator that measures the unit cost of providing charging services. It is typically calculated by dividing the total costs of a charger or charging network, including capital expenditures, operations, and maintenance, by the number of charging sessions or unique users over a specific period. This metric provides a practical gauge of cost-effectiveness and infrastructure efficiency. A high cost per session implies that the station is underutilized and costly to operate relative to its use, while a low cost per session reflects more efficient utilization of the infrastructure. In basic terms, as station usage increases, the cost per user decreases. Planners and analysts can apply this metric when comparing technology options or communicating the implications of low utilization. For instance, a recent analysis noted that low customer volumes lead to “high cost per session,” which can deter private-sector investment (Knupfer et al., 2018). The cost per user/session metric is frequently cited in feasibility studies, municipal reports, and economic justifications for charging projects, sometimes labeled as “cost per charge delivered” or “cost per EV served.” A related and more granular metric is cost per kilowatt-hour (kWh) delivered, which calculates the effective cost of delivering energy, inclusive of fixed and variable costs. This figure can be directly compared to the tariff charged to EV drivers. For example, if it costs \$0.50/kWh to deliver electricity,

and the charging price is \$0.30/kWh, there is a shortfall that must be offset by public subsidies or alternative revenue streams. While this indicator does not account for benefits, such as emissions reductions or economic development, it combines cost and utilization into a single, intuitive measure of operational efficiency. However, it can penalize early-stage or rural deployments where stations are intentionally underutilized to ensure network coverage or accessibility. Despite this limitation, cost per session is a useful benchmark in mature networks for informing pricing strategies, as sustainable operations typically require that charging fees eventually exceed the cost per session.

Capital and operating cost metrics form the foundational inputs to all economic performance indicators related to EV charging infrastructure (Danial et al., 2021; Sheng et al., 2021). While these cost metrics are not performance indicators in themselves, they are frequently tracked and analyzed across projects because they have a substantial influence on key economic outcomes such as ROI, payback period, and cost per session. Capital costs include charger hardware and installation expenses. For example, the upfront cost to install a DC fast charger can vary significantly, typically ranging from \$80,000 to over \$250,000 for the equipment, with installation costs often matching or exceeding hardware costs (AFDC, n.d.-b; Ruedig, 2026). High capital expenditures increase the initial investment burden, lengthening payback periods and reducing ROI, which is why cost containment strategies, such as volume procurement or streamlined permitting, are critically important. On the operating and maintenance (O&M) side, major ongoing costs include electricity (including demand charges), networking fees, repair and maintenance contracts, and warranty coverage. According to the AFDC (n.d.-a), routine maintenance costs are estimated at \$400 per charger per year, while extended warranties for DC fast chargers can add up to \$800 annually. When utilization is low, these fixed operating costs represent a significant burden on a per-session basis, directly reducing financial performance. As a result, these costs are carefully tracked in both planning and postdeployment monitoring. Infrastructure planners sometimes express costs in terms of cost per charger installed or cost per mile of corridor covered, particularly when evaluating network efficiency and spatial coverage. For states like Indiana, maintaining visibility into capital and O&M cost trends is essential for budget forecasting, funding allocation, and identifying opportunities for cost reduction. In summary, while cost metrics do not directly measure outcomes or impacts, they are critical inputs to all economic assessments and often serve as threshold criteria, projects with excessively high costs may be deemed infeasible even if they provide societal benefits.

ROI is a classic profitability metric that compares net returns to investment costs (Baik et al., 2018; Schroeder & Traber, 2012). It is generally calculated as the net benefit divided by total cost, often expressed as a percentage. In the EV charging context, ROI accounts for revenues, such as charging fees and ancillary income, against all incurred costs including equipment, installation, electricity, and maintenance. A positive ROI indicates that the station generates profit relative to its cost. ROI is widely used by private charge point operators and investors to assess the financial viability of a charging site. For example, a

recent study modeled ROI for fast-charging stations under various utilization and pricing scenarios to determine profitability thresholds. However, achieving high ROI remains difficult in the short term. A McKinsey report argues that profitability is currently a challenge for public fast chargers due to low utilization rates, averaging only about 7.5% in 2022, which falls well below the level required for strong ROI (Fröde et al., 2023). A related indicator, Internal Rate of Return (IRR), represents the discount rate at which the net present value (NPV) of future cash flows is zero (Vagropoulos et al., 2014; Yang et al., 2021). It is commonly used in EV infrastructure investment analyses to compare the return against a hurdle rate or cost of capital. While both ROI and IRR are intuitive and commonly used in private-sector decision making, they focus narrowly on direct financial returns and often overlook broader societal benefits. In public-sector contexts, relying solely on ROI may undervalue projects that yield significant externalities, such as emission reductions or local economic development. Therefore, these financial metrics are frequently paired with social benefit indicators in policy evaluations. NPV represents the dollar value of net benefits, defined as revenues minus costs, over a project's lifetime, discounted to present value.

$$NPV = \sum_{t=0}^T \frac{C_t}{(1+r)^t} = 0 \quad (\text{Equation 2.1})$$

where, C_t = net cash flow at time t .
 r = RR (the unknown to solve for)
 T = project lifetime in years
 C_0 is typically negative (initial investment)

A positive NPV suggests that a project is expected to yield a return exceeding its costs after accounting for the time value of money. NPV allows for the integration of comprehensive cash

flow projections, including upfront capital costs, ongoing operational expenses, and revenues from user fees or subsidies, to determine whether an investment will break even or generate a surplus over time. Financial planning tools such as the Atlas EV Charging Financial Analysis Tool, use discounted cash flow models to simulate NPV under a range of assumptions and site-specific scenarios (Nigro, 2019).

EDI is a measurable change in a region's economic, social, and environmental well-being resulting from projects, policies, or investments. One of the EDI approaches is Economic Multiplier/ Input–Output (I–O) Model, the I–O approach is a quantitative impact assessment method that is most applicable to investment driven transportation projects that impact business attraction, expansion, retention, or tourism directly. Typical multipliers are expressed in terms of regional economic output, employment, or income. Their magnitudes vary depending on the type of transportation investment and its relationship to other investments in the regional economy, the economic multiplier approach is based largely on *input–output modeling*. Input–output models are essentially accounting frameworks that track interindustry transactions such as the number of units of purchases (inputs) that each industry requires from all industries to produce one unit of sales (output). These models provide a means for calculating the indirect and induced effects on business sales and spending, given a set of direct project effects on business sales, employment, or wages.

Table 2.3 shows the advantages and limitations of different indicators used in EV infrastructure economic assessment.

2.3.1 Justification for Selected Indicators

Selecting appropriate metrics is critical to ensure that EV charging infrastructure investments are economically sound and financially sustainable. Each offers unique but complementary

TABLE 2.3
Advantages and Limitations of EV Infrastructure Economic Assessment.

Indicator	Advantages	Limitations
Utilization Rate	- Strong predictor of financial viability - Easy to monitor and interpret - Informs site planning and scaling decisions	- May be low in early deployment stages - Overemphasis could penalize essential low-demand sites - Does not reflect revenue or cost directly
Cost per User/Session	- Simple efficiency metric - Helps track cost-effectiveness - Useful for benchmarking and communication	- Does not reflect benefits or revenue - Penalizes low-use but high-need stations - Definitions can vary (per user, session, or kWh)
Capital and O&M Costs	- Critical inputs for all other metrics - Tracks deployment efficiency - Identify cost-reduction opportunities	- Does not measure performance or benefits - Cost alone does not determine value - Highly site-specific and variable
ROI/IRR	- Simple and widely understood - Quantifies profitability for investors - Useful for screening private investments	- Ignores societal/external benefits - Highly sensitive to utilization and pricing assumptions - May undervalue strategic/rural sites
NPV	- Accounts for time value of money - Captures full life-cycle cash flows - NPV offers an absolute measure of value - Payback period highlights risk horizon	- Depends on long-term forecasts and discount rate - May overlook intangible benefits - Payback period ignores post-recovery gains
EDI	- Helps policymakers to measure projects' local employment, wage growth, and tax revenue generation - Uses data-driven techniques like input-output modeling to predict impacts on specific sectors	- Fails to capture non-financial impacts like overall quality of life, health, and happiness - The employment estimation cannot distinguish between full-time or part-time workers

insights that align with the priorities of state-level planning, NEVI program guidelines, and INDOT's public service mandate. For Indiana, we propose Accessibility, ROI and EDI as the three core indicators:

- Accessibility measures the proximity and ease of access to charging infrastructure for EV users. As a state agency, INDOT has a responsibility to promote infrastructure that serves statewide connectivity, not just high-demand corridors. Accessibility improvements, such as increased population coverage within 5 or 15 mi of a station.
- ROI analysis answers the practical question: *Can this site sustain operations without ongoing subsidies?* When partnering with private entities or site hosts, Indiana should require basic pro forma financial analyses to assess whether projects are structured for sustainable operation without the need for ongoing subsidies. Additionally, Indiana might consider integrating an investment risk score into its evaluation framework. Projects with very long payback periods or those relying heavily on optimistic utilization assumptions could be flagged for greater scrutiny or scored lower. By embedding ROI within a multicriteria decision-making framework, the state can prioritize projects that are both economically efficient and financially sustainable over the long term.
- EDI captures the broader regional and local economic benefits generated by the development of EV charging infrastructure beyond direct operational revenues. Investments in charging stations can stimulate local economies by attracting new businesses, increasing foot traffic to host sites such as retail centers, restaurants, and hotels, and creating construction and maintenance employment opportunities. For INDOT, quantifying EDI involves assessing metrics such as job creation, increases in local tax revenue, property value appreciation near charging corridors, and induced business activity at or near station locations. Furthermore, EDI considerations can help justify investments in corridors that may not demonstrate strong near-term financial returns but hold significant long-term potential for regional economic growth. By embedding EDI within its project evaluation criteria, Indiana can ensure that charging infrastructure investments align with broader statewide economic development goals.

3. METS-R SIMULATOR AND ECONOMIC ASSESSMENT FRAMEWORK (EV-EAF): DATA AND METHODS

3.1 Data Description

To simulate current and future EV growth scenarios, multiple data sources are integrated. EV demand data are obtained through questionnaire surveys from SPR-4706 (Moras et al., 2024) and GPS-based location data are obtained from mobile devices to capture current EV ownership, purchase behavior, and anticipated charging needs over the next 1, 2, 3, 5, and 8 years. Baseline EVCS data are sourced from the U.S. Department of Energy's AFDC. For future years, charging infrastructure expansion is informed by potential station locations identified in prior planning efforts led by INDOT, incorporating spatial suitability and projected demand growth. These inputs provide critical insights into EV market penetration across both urban and rural areas of Indiana and support the development of various realistic future demand scenarios. Additionally, traffic speed information is retrieved via Google Maps API, and Indiana's road network data is obtained from OSM.

In the EV-EAF, the Extreme Optimistic and Extreme Pessimistic scenarios, projected across future time horizons of 1, 2, 3, 5, and 8 years starting from 2023, are applied to evaluate both accessibility and economic performance of EV charging infrastructure over time. These two scenarios were selected as representative bounds of uncertainty, capturing the upper and lower limits of potential EV adoption and infrastructure deployment. This approach enables a focused yet comprehensive assessment of system performance under best- and worst-case conditions without the added computational and interpretive complexity of analyzing all five intermediate scenarios developed in this study.

3.2 METS-R Simulation Framework

This research utilizes the METS-R SIM platform, developed at Purdue University (Lei et al., 2024). METS-R SIM integrates a high-fidelity microscopic traffic simulation model with an EV energy consumption model, enabling the large-scale simulation of EV operations across diverse network conditions. The framework of METS-R Simulator is presented in Figure 3.1 which is composed of three core components:

1. **Traffic Simulation Engine:** Generates detailed vehicle trajectories and energy consumption profiles based on input travel demand and road network configurations.
2. **High-Performance Computing Module:** Supports the integration of customized vehicle behaviors, including operational patterns and charging strategies, allowing for scalable and efficient simulations.
3. **Online Visualization Interface:** Provides a shareable and transparent platform for accessing, reviewing, and communicating simulation outputs in real time.

METS-R is particularly valuable for this research project as it enables the estimation of EV travel patterns, charging demand, and infrastructure utilization under various adoption and policy scenarios. By incorporating realistic traffic dynamics, energy consumption characteristics, and spatially explicit charging behaviors, METS-R supports data-driven planning and investment decisions. The platform's scalability and scenario-based flexibility make it well-suited for evaluating both current infrastructure performance and future system needs across Indiana's roadway network. Additional information on the capabilities and implementation of METS-R SIM is available online (Lei & Ukkusuri, 2025).

3.3 Performance Metrics

The following performance metrics are estimated:

1. EV charging infrastructure usage measured by the load (visits/capacity) and electricity demand at every charging station
2. Density of EV charging needs at the ZCTA level in current and future demand scenarios separated by road class and urban-rural locations
3. EV charging infrastructure reliability measured by the percentage of time that at least one charging port is available within 50 mi for each EV
4. ROI on implementing various charging infrastructure designs, this is calculated by the revenue generated by EV chargers, build and maintenance cost of EV charger deployment

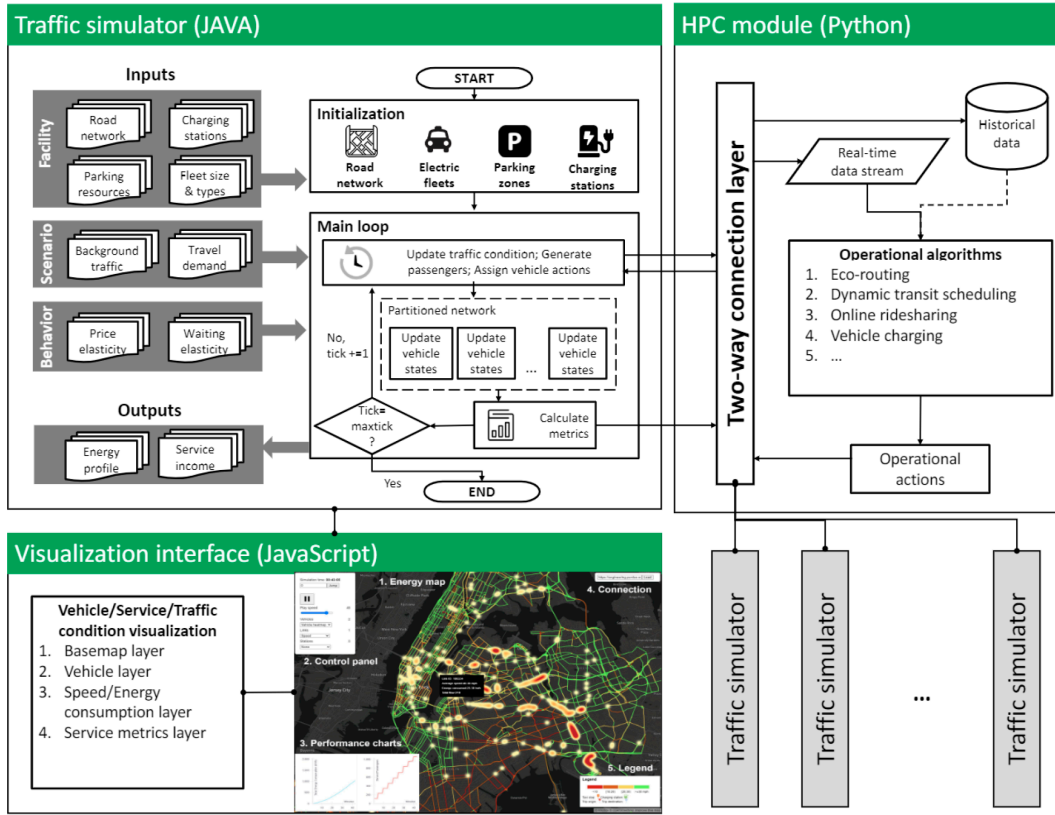


Figure 3.1 Framework of METS-R SIM.

5. VMT of EVs and GVVs based on current and future scenarios and their impact on gas tax revenue categorized by road classes and land-use types

3.4 Measurement Indicators for EV-EAF

3.4.1 Indicators

The designed EV-EAF provides a comprehensive, data-driven methodology for evaluating and prioritizing EV charging investments across Indiana. Building on scenario-based modeling and economic performance indicators, this framework is designed to help INDOT, and its partners make informed decisions that balance financial feasibility, public benefit, and service accessibility. The core of the EV-EAF framework is the use of standardized economic performance indicators that quantify the financial, societal, and accessibility implications of EV charging infrastructure investments. These indicators enable INDOT and its partners to prioritize projects based on cost-efficiency, public value, and long-term sustainability. This section presents the detailed definitions and formulations of the three selected indicators: accessibility, ROI, and EDI.

3.4.1.1 Accessibility. Accessibility to EV charging infrastructure was measured using an impedance-weighted opportunity approach. In this study, EV charging opportunities refer to the number of available chargers at each charging station location,

measured separately for all chargers, DCFC, and L2 chargers. Rather than treating all stations within a fixed travel-time threshold as equally accessible, this method assigns a gradually decreasing weight to each charging opportunity as travel impedance increases. This approach reflects the principle of impedance decay, where the likelihood or attractiveness of reaching a destination decreases with increasing travel time or distance.

For each spatial unit i , accessibility to EV charging infrastructure was calculated as:

$$A_i = \sum_j O_j f(c_{ij}) \quad (\text{Equation 3.1})$$

where A_i represents the accessibility score for origin i , O_j is the number of charging opportunities at station location j , and C_{ij} is the travel impedance between origin i and charging station j . The impedance term may be measured using either travel time or travel distance. The function $f(c_{ij})$ is an impedance decay function that converts travel impedance into an accessibility weight ranging from 0 to 1. This formulation is consistent with the general accessibility framework in which accessibility depends on both the spatial distribution of opportunities and the transportation cost required to reach them. The referenced paper defines accessibility similarly as the weighted sum of opportunities, where the impedance function should decrease monotonically, equal to 1 when impedance is zero, and approach 0 as impedance becomes very large.

The impedance decay function was specified using a power-exponential form:

$$f(x) = \exp(-\alpha x^\beta) \quad (\text{Equation 3.2})$$

where x denotes travel impedance, and α and β are decay parameters. The parameter α controls the overall rate of decay, while β controls the shape or curvature of the decay function. A larger decay rate implies that accessibility declines more rapidly as travel impedance increases. Following the impedance decay parameters shown in the referenced figure, the travel-time-based accessibility measure used:

$$f(t) = \exp(-0.019t^{1.340}) \quad (\text{Equation 3.3})$$

where t is travel time in minutes. For distance-based accessibility, the function was defined as:

$$f(d) = \exp(-0.146d^{0.827}) \quad (\text{Equation 3.4})$$

where d is travel distance in miles. These functional forms are appropriate because the referenced paper shows that impedance curves are well represented by exponential-family functions, particularly power-exponential forms.

Accordingly, the travel-time-based accessibility to EV charging infrastructure was calculated as:

$$A_i^{time} = \sum_j O_j \exp(-0.019t_{ij}^{1.340}) \quad (\text{Equation 3.5})$$

Similarly, the distance-based accessibility was calculated as:

$$A_i^{dist} = \sum_j O_j \exp(-0.146d_{ij}^{0.827}) \quad (\text{Equation 3.6})$$

Separate accessibility measures were estimated for three charging infrastructure categories: total EVCS access, DCFC access, and L2 access. For total EVCS accessibility, O_j represents the total number of chargers at station O_j . For DCFC and L2 accessibility, O_j represents the number of DCFC and L2 chargers, respectively. This allows the analysis to compare general EV charging access with access to specific charger types, recognizing that DCFC and L2 chargers serve different charging needs.

To facilitate comparison across space and years, the resulting accessibility values were normalized as:

$$A_i^{norm} = \frac{A_i - A_{min}}{A_{max} - A_{min}} \quad (\text{Equation 3.7})$$

where A_i^{norm} ranges from 0 to 1. Higher values indicate greater access to EV charging infrastructure, either because more chargers are nearby or because charging opportunities can be reached with lower travel impedance. Lower values indicate limited access due to fewer nearby charging opportunities, longer travel times, or both. This normalized accessibility measure was then used to evaluate spatial disparities in EV charging access and to compare temporal changes in access across years.

3.4.1.2 ROI. ROI measures the net financial return of an EV charging station relative to its capital and operating expenditures. It is used to evaluate financial sustainability and attractiveness for public-private investment.

$$ROI = \frac{(\text{Total Revenue} - \text{Total Cost})}{\text{Total Cost}} \quad (\text{Equation 3.8})$$

The total cost of deploying EV charging infrastructure is influenced by a range of factors, including the upfront cost of the charging equipment, installation-related expenses, ongoing maintenance requirements, and associated business or operational overheads (Morrissey et al., 2016; Muratori et al., 2019). The *Total Cost* in ROI calculations comprises two main components: the capital cost of the charging infrastructure $C_{capital}$ and the operation and maintenance cost $C_{O\&M}$. The capital cost is defined as the sum of the equipment cost and the installation cost, expressed as:

$$C_{capital} = C_{equipment} + C_{installation} \quad (\text{Equation 3.9})$$

The operation and maintenance cost accounts for recurring expenses over the lifespan of the equipment. It is calculated as the present value of annual O&M expenses, discounted over the expected life of the charger:

$$C_{O\&M} = \sum_{i=1}^{life} \frac{C_{O\&M,i}}{(1+dr)^i} \quad (\text{Equation 3.10})$$

In this analysis, the annual O&M cost is assumed to be an average of \$400 annually (AFDC, n.d.-a), applied consistently throughout the charger's operational life. A discount rate dr of 3.5% is used, reflecting the social rate of time preference—an approach that incorporates intertemporal welfare trade-offs and aligns with standard practices in public infrastructure evaluation, as discussed in Moore and Vining (2018). The parameter *life* represents the expected operational lifespan of the equipment, which is assumed to be 15 years, matching the typical service life of EVs used in the analysis.

3.4.1.3 EDI. EDI measures the total economic impact of EV charging infrastructure investment on a regional economy by capturing both direct and indirect effects across interconnected industries. It is used to evaluate the economic multiplier effect and broader regional development benefits of public infrastructure spending.

$$EDI = \sum_i (L_{ij} \Delta D_j) \quad (\text{Equation 3.11})$$

Where L_{ij} is the Leontief multiplier coefficient derived from the I-O model, representing the total output generated in sector i per unit of final demand change in sector j , and ΔD_j is the initial change in final demand (i.e., capital investment in charging infrastructure).

The Leontief Inverse Matrix is defined as:

$$L = (I - A)^{-1} \quad (\text{Equation 3.12})$$

where I represents the identity matrix and A is the direct requirements matrix representing inter-industry transactions. Finally, the output I–O model includes: (1) employment, (2) earnings: include wages, salaries, and employer contributions for health insurance, and (3) gross output: total value of sales by producing enterprises including value of intermediate goods used in production.

EDI analysis measured by employing JOBS model developed by NREL. the I–O data incorporated in JOBS model direct, indirect, and induced refer to Regional Input-Output Modeling System (RIMS II) that published by U.S. Department of Commerce’s Bureau of Economic Analysis (BEA). RIMS II provides an economic snapshot of an economy at one point in time and allows for analyses of various shocks both to the economy as a whole and to specific affected industries.

3.4.2 Cost and Benefit Value Settings

The capital cost values used in this study are sourced from JOBS model developed by the NLR. The equipment and non-equipment cost data were gathered from a variety of sources, including existing industry and academic literature, stakeholder consultations, and Department of Energy publications (Ke et al., 2022). Where multiple data points were available, the analysis relies on average values. Charger costs, for example, fluctuate significantly over time as large-scale manufacturing becomes more efficient and other productivity factors evolve. An NREL dataset on electricity generation component costs served as the basis for estimating average conduit and cable costs, as well as for developing a formula to project transformer costs. Remaining station development costs were calculated in a comparable way and are expressed as a proportion of pre-installation equipment costs. Table A.3 and Table A.4 present the detailed equipment expense and station development cost employed in this analysis.

In this report, we adopt these values as default parameter settings for evaluating EV charging investments using the EV-EAF framework. These baseline inputs allow for a consistent, scalable assessment of financial and societal returns across different project types and scenarios. However, it is important to note that these values are intended to be flexible. Stakeholders and planners, especially within INDOT and partnering agencies, are encouraged to replace default assumptions with real-world station-specific costs, localized utility rates, or state-specific engineering and permitting estimates where available. This approach ensures that the EV-EAF framework remains adaptable and capable of reflecting the true cost environment and economic conditions unique to Indiana.

4. RESULTS AND DISCUSSIONS

4.1 EV Demand and Infrastructure Supply Scenarios

Scenarios are generated from a synthetic dataset that integrates survey data on EV adoption, charging preferences, and daily travel activities (Moras et al., 2024). The construction of scenarios is based on respondents’ stated likelihood of EV adoption and the chronological order of their preferred adoption years.

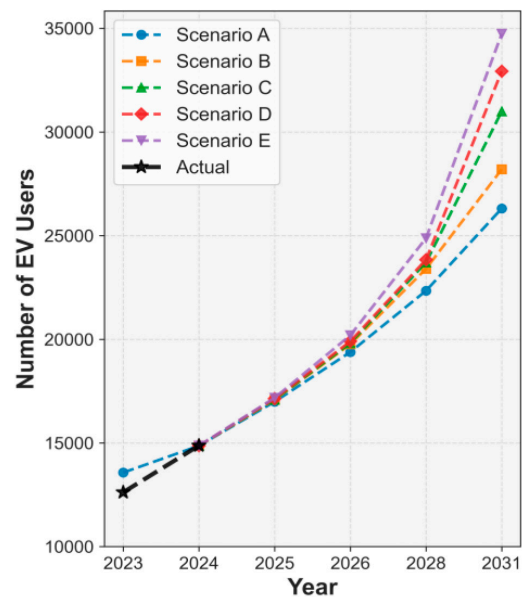


Figure 4.1 EV User Demand Scenarios.

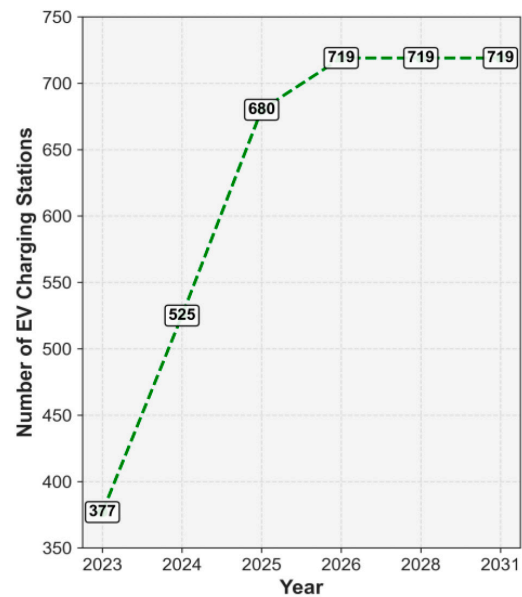


Figure 4.2 EVCS Infrastructure Scenarios.

Using scale numbers assigned to different levels of likelihood, five scenarios are developed annually, ranging from the most pessimistic (Scenario A) to the most optimistic (Scenario E). The corresponding EV charging infrastructure is constructed using data from the AFDC and projections from future EV planning efforts. Figure 4.1 presents the simulated number of EV users for the base year 2023, as well as for each scenario in the years 2024, 2025, 2026, 2028, and 2031. Figure 4.2 shows the total number of EVCSs available in each year, which serve as the basis for simulating EV user charging behavior across the scenarios.

4.2 Real-World Charging Findings From ChargePoint

To validate the simulated EV charging events, a representative sample of EVCS usage data were collected from ChargePoint stations across Indiana, covering the period from February 21, 2024, to June 27, 2024. ChargePoint infrastructure is widely distributed throughout the state, as illustrated in the spatial distribution shown in Figure 4.3. Therefore, analyzing usage data from these stations provides valuable insights into representative EV user charging behavior in Indiana.

Figure 4.4, Figure 4.5, and Figure 4.6, present variations in three key station performance metrics: average usage time, utilization rate, and visits per day where, usage time refers to the average duration of charging sessions (in minutes), utilization rate is calculated as the ratio of time the charger is in use to the total available time, and visits per day represents the average number of charging sessions per day.

Significant weekday–weekend variations are observed, particularly for L2 chargers. L2 stations show higher variability in both usage time and utilization rate compared to DCFC. While

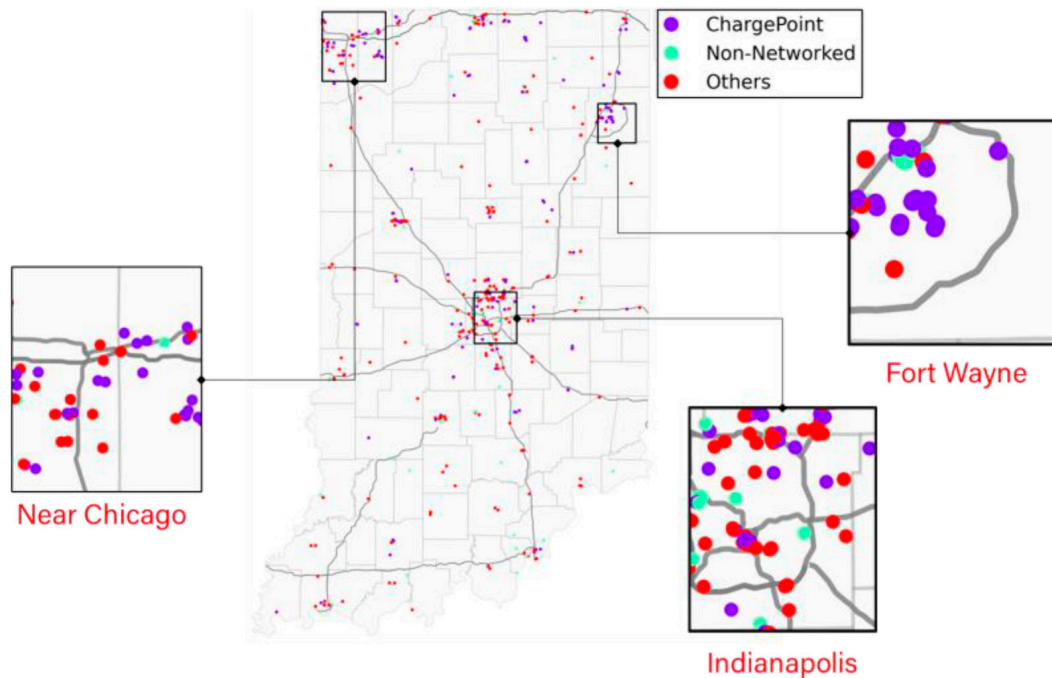


Figure 4.3 Spatial Distribution of EVCSs Across Indiana.

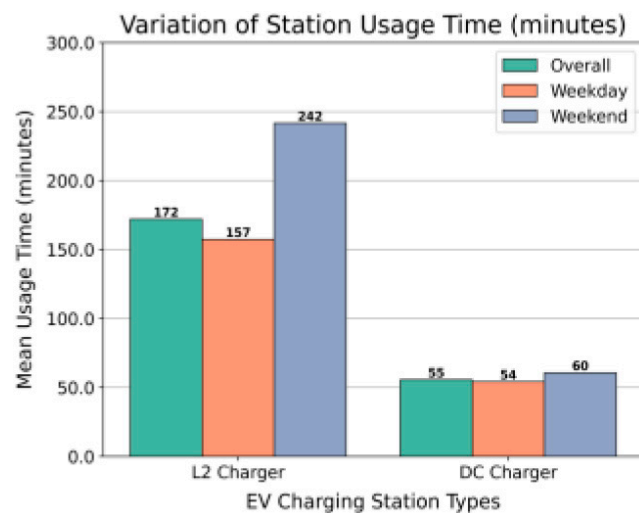


Figure 4.4 Variation of Station Usage Time (Minutes).

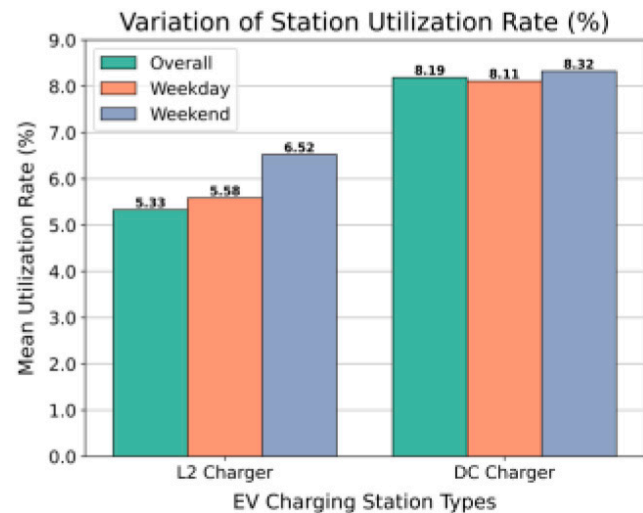


Figure 4.5 Variation of Station Utilization Rate (%).

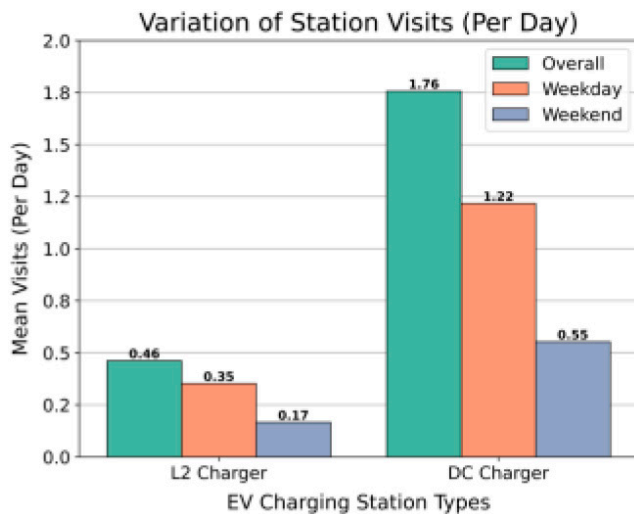


Figure 4.6 Variation of Station Visits (Per Day).

usage time tends to increase on weekends, the number of visits per day generally decreases, possibly indicating that users combine charging with other trip purposes during weekends. These findings suggest that co-locating charging stations with activity centers or mixed land-use areas may encourage greater utilization of public charging infrastructure. Detailed spatial distributions of EVCS performance metrics are provided in Appendix B, Section B.1.

4.3 Background Traffic Speed Estimates

Background traffic speed estimates are collected from Google API. Google Maps displays information about traffic conditions across an area. Google Maps API provides functions to produce georeferenced rasters from real-time Google Maps traffic information. Having Google traffic information in a geo-referenced data format facilitates analysis of traffic information (e.g., spatially merging traffic information with other data sources).

Pixel values in rasters are derived from Google traffic colors and can be one of four values, as shown in Table 4.1.

To create a raster around a point, we set the centroid coordinate, the zoom level, and the height/width around the centroid coordinate (height/width are in terms of pixels, and kilometer distance of a pixel is determined primarily by the zoom level). Furthermore, for each road we use the closest raster to represent the traffic conditions.

Figure 4.7 displays the traffic conditions in the State of Indiana's road network.

TABLE 4.1
Google Traffic's Legend.

Google Traffic Color	Description	Raster Value
Green	No traffic delays	1
Orange	Medium traffic	2
Red	High traffic	3
Dark Red	Heavy traffic	4

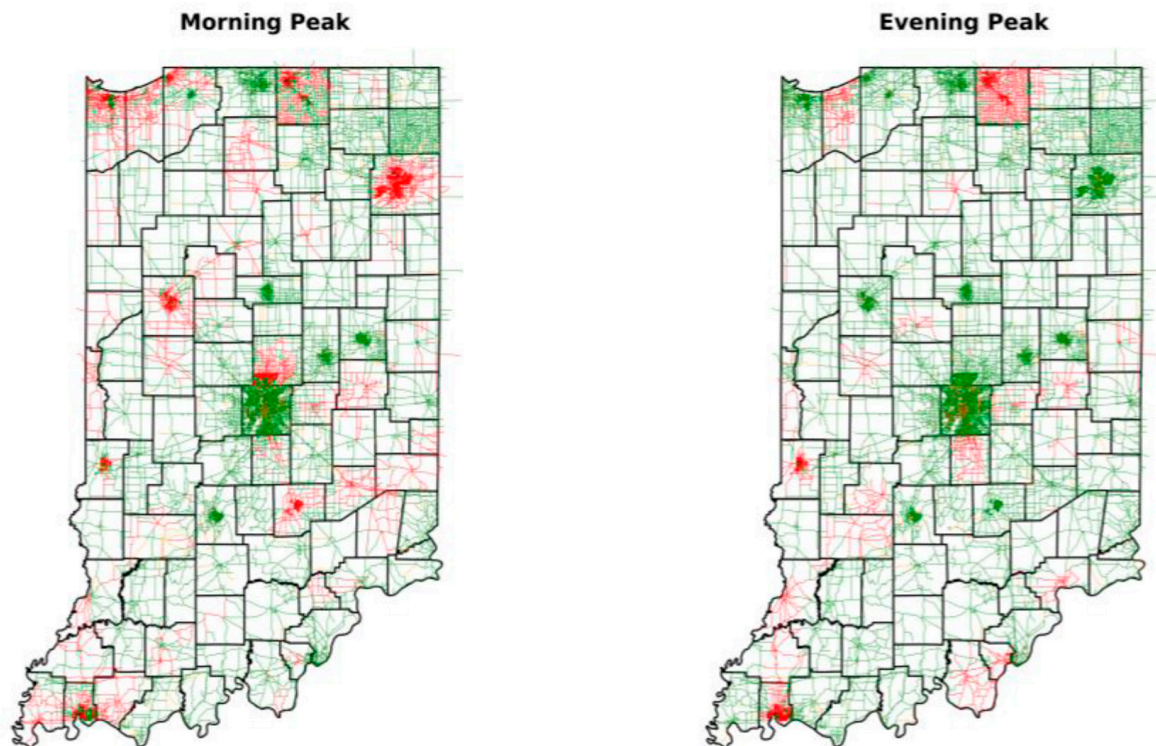


Figure 4.7 Google Traffic Speed Estimates in the State of Indiana.

4.4 Performance Metrics and Analytics

4.4.1 EV Charging Infrastructure Usage

EVCS usage is analyzed based on total charging time per day and the number of daily visits per station, categorized by charger type and surrounding community type (i.e., city, suburban, town, and rural). According to the National Center for Education Statistics' locale framework (Geverdt, 2015), areas with populations over 50,000 are classified as Urbanized Areas (UAs), while those with 2,500–50,000 are Urban Clusters (UCs). Together, UAs and UCs constitute “urban areas,” while all remaining population, housing, and territory are considered “rural.” Within this framework, territory in a UA and a Principal City is a city, territory in a UA but outside a Principal City is suburban, territory in a UC is a town, and all else is rural. Figure 4.8 presents the total charging time (in hours) across different scenarios, differentiated by charger type over the years. Overall, DCFC stations exhibit lower charging times compared to L2 stations, which is intuitive

since the former has greater power output requiring less time to charge an EV. An increasing trend in charging time is observed from pessimistic to optimistic scenarios (A to E) for both charger types, primarily driven by the growing number of EV users. While this general pattern holds, some minor variations and exceptions are present. For L2 stations, total charging time gradually increases over the years. In contrast, DCFC stations show a decline in average charging time until 2026, followed by an upward trend, likely due to the static number of available stations despite increasing demand. As expected, the aggregated charging time across all stations increases over time, reflecting the overall growth in EV adoption.

Figure 4.9 illustrates the distribution of charging time (in hours) at EVCSs by community type, aggregated across different scenarios in Indiana. For L2 stations, suburban and rural areas exhibit higher charging times compared to urban areas, with the lowest values observed in towns. In contrast, for DCFC stations, suburban and towns generally show higher charging

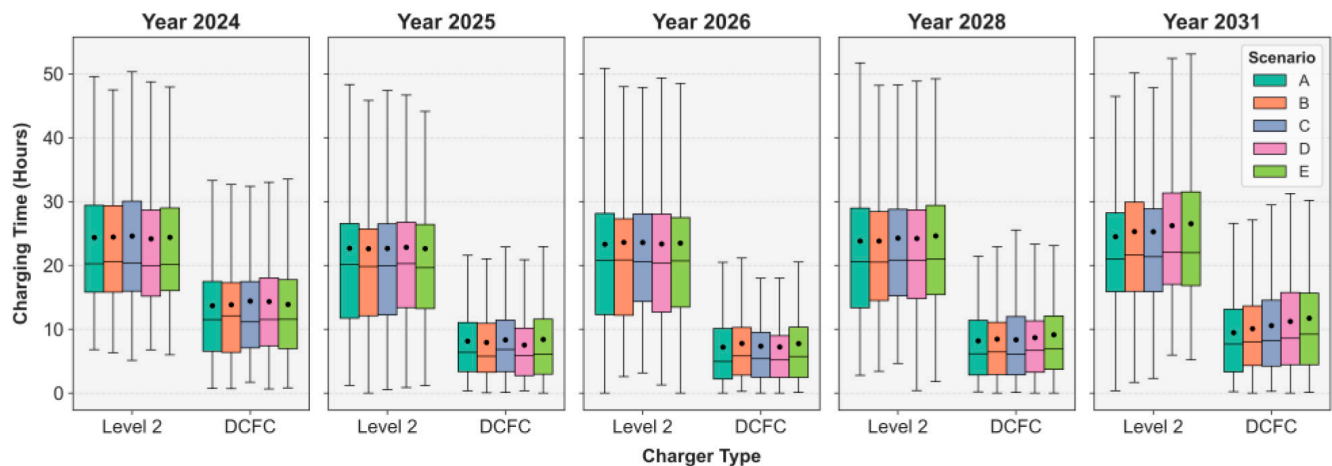


Figure 4.8 Distribution of Charging Time in Hours at EVCSs by Charger Types Across Indiana. The Boxplots Show the 25th, 50th (Median), and 75th Percentiles of Total Charging Time. Black Dots Represent the Mean Values for Each Group.

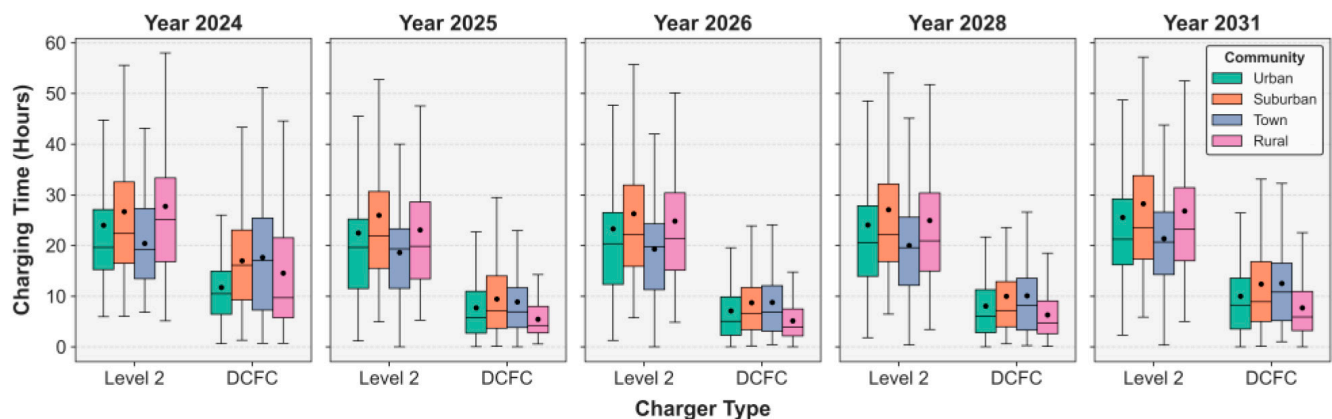


Figure 4.9 Distribution of Charging Time in Hours at EVCSs by Community Types, Aggregated Across Different Scenarios in Indiana. The Boxplots Show the 25th, 50th (Median), and 75th Percentiles of Total Charging Time. Black Dots Represent the Mean Values for Each Group.

times than urban areas, while rural areas experience the lowest charging times, except in the year 2024, where this pattern slightly deviates.

These results suggest spatial disparities in charging infrastructure performance across community types. Higher charging times in suburban and rural areas, particularly at L2 stations, may indicate insufficient station capacity or greater reliance on slower charging modes. For DCFCs, the relatively low usage in rural areas (after 2024) may reflect limited EV adoption or more efficient station availability relative to demand. These insights highlight the need for tailored infrastructure planning that accounts for community-specific travel patterns, station availability, and projected EV growth to ensure balanced access and minimize wait or charging durations across all regions.

Figure 4.10 presents the number of visits to EVCSs across different scenarios, differentiated by charger type over the years. Overall, DCFC stations experience a higher number of visits compared to L2 stations. From pessimistic to optimistic scenarios (A to E), an increasing trend in visits is observed for DCFC stations, primarily driven by the rise in EV adoption.

In contrast, the number of visits to L2 stations remains relatively stable across scenarios and years. While this overall pattern is consistent, some minor variations are evident. Specifically, visits to DCFC stations decline slightly until 2026 and then increase, likely due to a static number of DCFC stations that struggle to meet growing demand. As anticipated, the total number of visits across all stations increases over time, reflecting the expanding EV user base and greater reliance on public charging infrastructure.

Figure 4.11 illustrates the distribution of number of visits to EVCSs by community type, aggregated across different scenarios in Indiana. For L2 stations, suburban and rural areas experience higher visits compared to urban areas, with the lowest value observed in towns. In contrast, for DCFC stations, suburban and towns generally show higher number of visits than urban areas, while rural areas experience the lowest visits, except in the year 2024, where this pattern slightly deviates.

To examine the temporal variation in EVCS usage across a day, the top 10% of stations by total charging time are identified for the entire day, daytime (6 a.m. to 6 p.m.), and nighttime (6 p.m. to 6 a.m.) under Scenario A of Year 2024, the most

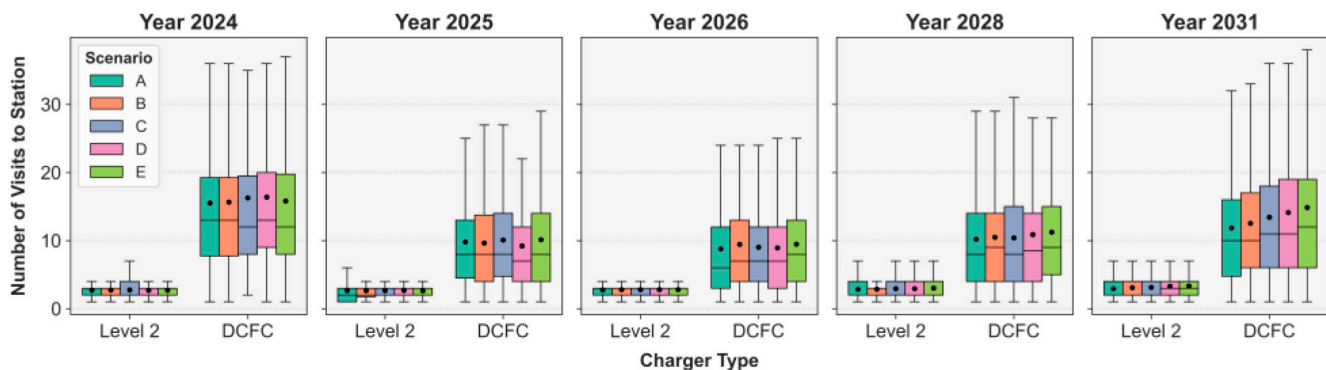


Figure 4.10 Distribution of Number of Visits to EVCSs by Charger Types Across Indiana. The Boxplots Show the 25th, 50th (Median), and 75th Percentiles of Total Charging Time. Black Dots Represent the Mean Values for Each Group.

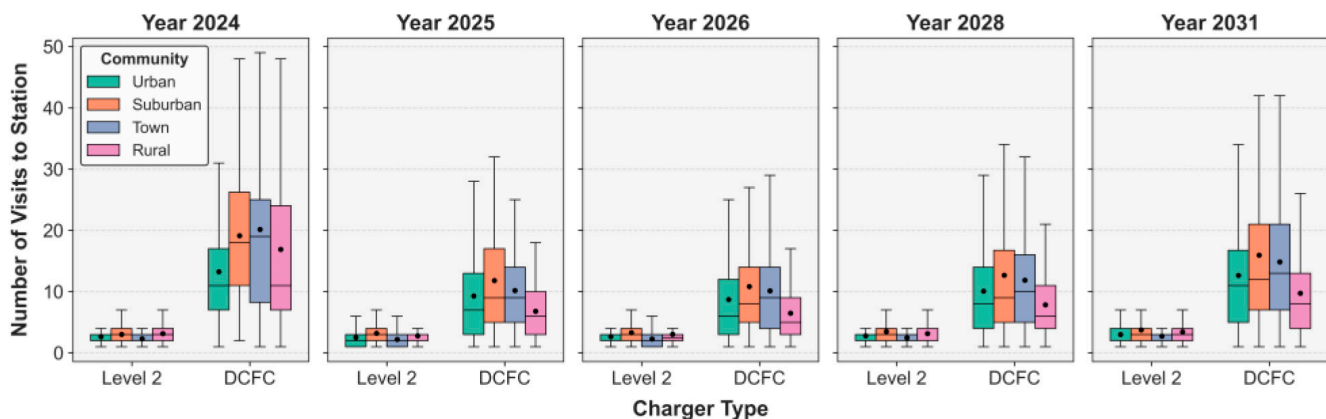


Figure 4.11 Distribution of Number of Visits to EVCSs by Community Types, Aggregated Across Different Scenarios in Indiana. The Boxplots Show the 25th, 50th (Median), and 75th Percentiles of Total Charging Time. Black Dots Represent the Mean Values for Each Group.

pessimistic EV adoption case, and presented in Figure 4.12. The zoomed inset reveals that certain stations near Evansville exhibit high usage when considering the full day but are not among the most used during the daytime. Conversely, some stations show high usage only during nighttime hours, highlighting distinct temporal usage patterns. By examining Figure 4.13,

which represents Scenario E for Year 2024, the most optimistic case for EV adoption, it can be observed that while the usage pattern remains consistent across day and night, the number of highly utilized stations and their locations have shifted. This underscores the need to analyze various scenarios to better understand the variation in demand.

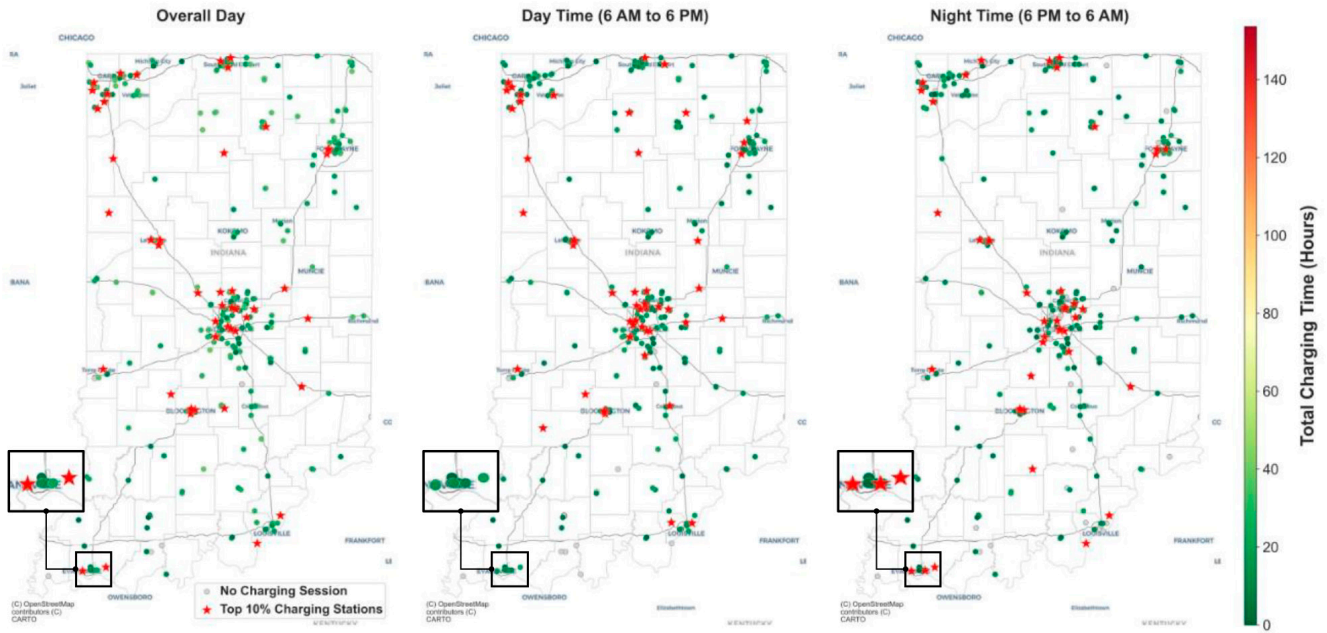


Figure 4.12 Hourly Variation of Charging Time at EVCSs (Scenario A of Year 2024).

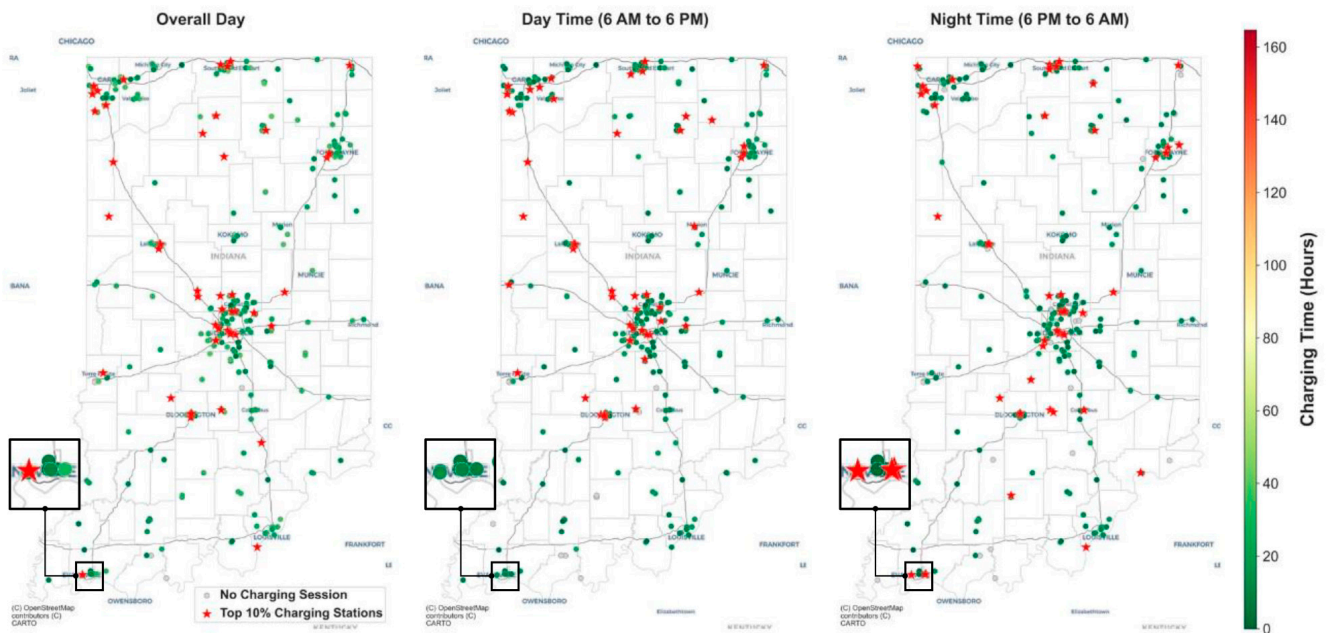


Figure 4.13 Hourly Variation of Charging Time at EVCSs (Scenario E of Year 2024).

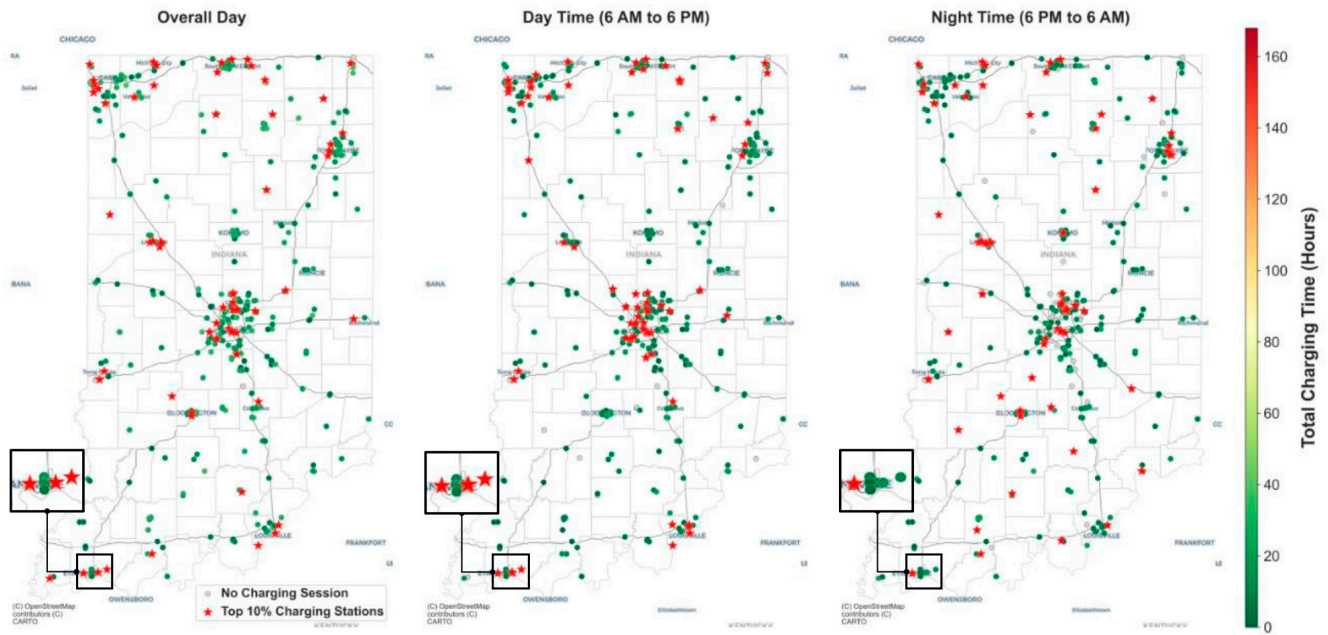


Figure 4.14 Hourly Variation of Charging Time at EVCSs (Scenario A of Year 2031).

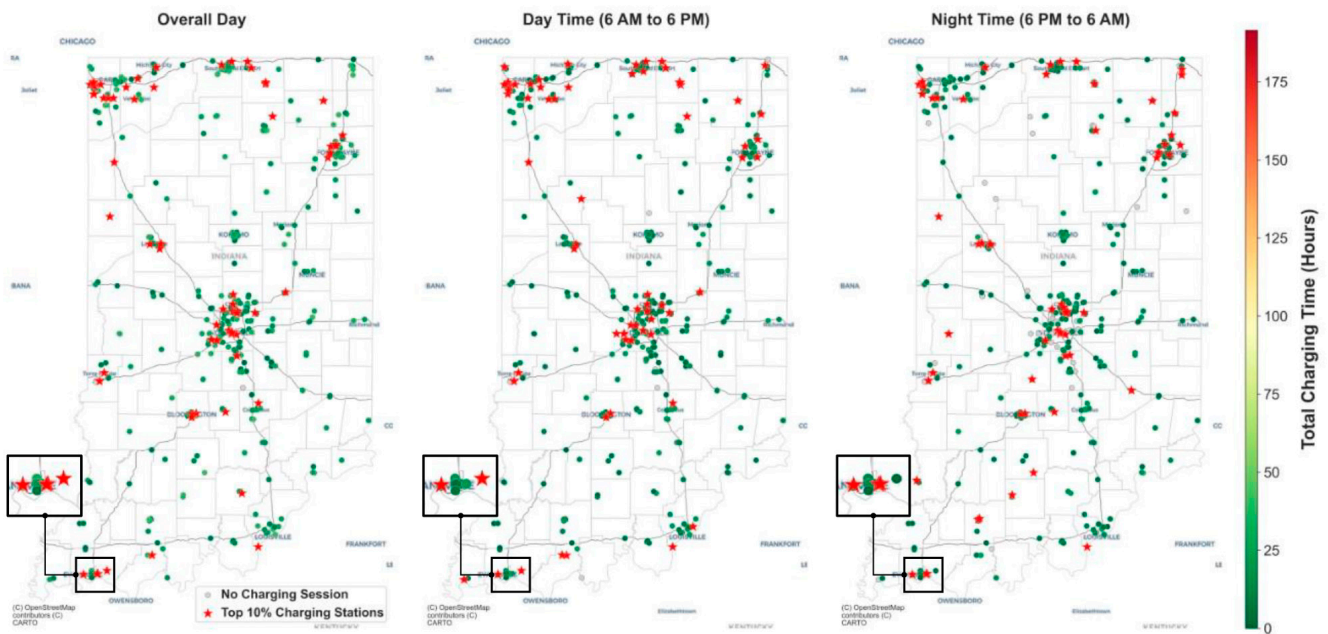


Figure 4.15 Hourly Variation of Charging Time at EVCSs (Scenario E of Year 2031).

Figure 4.14 and Figure 4.15 present the most pessimistic (Scenario A) and most optimistic (Scenario E) scenarios for Year 2031, respectively. These figures also highlight within-day variations in EVCS usage. With the increase in EV users, all three zoomed insets show at least one EVCS among the top 10% of the most used stations. However, notable differences between

Scenario A and Scenario E are evident. Specifically, in Scenario E, three stations remain in the top 10% for the entire day, while only two stations make the list during both daytime and nighttime, with different stations appearing in each period. This result further reinforces the need of accounting for varying demand scenarios to accurately predict the future usage of EVCSs.

4.4.2 Density of EV Charging Needs at the ZCTA Level

The density of EV charging demand at the ZCTA level is analyzed using two key metrics: the total daily charging time and the number of daily visits per ZCTA. By aggregating station-level charging time within each ZCTA, localized patterns of EV charging demand are estimated. This approach captures spatial variation in charging needs and enables the identification of ZCTAs with elevated current or projected future demand. Figure 4.16 illustrates the total daily charging time (in hours) for all EVCSs at the ZCTA level, with the top 10% high-demand ZCTAs highlighted using blue outlines. These maps help distinguish ZCTAs that are currently experiencing high demand, expected to see rising demand in the near or distant future, and projected to decline in demand, even if they are currently active. Such insights support targeted infrastructure planning by identifying priority areas for EVCS deployment or

expansion. The high-demand ZCTAs are concentrated around major metropolitan areas including Indianapolis, Evansville, South Bend, Northwest Indiana, Lafayette, and Fort Wayne. The socio-demographic characteristics typical of these Metropolitan Statistical Areas (MSAs) likely explain the higher concentration of EV users utilizing public charging infrastructure. Understanding these ZCTA characteristics can help identify the driving factors behind increased public charging demand and guide targeted infrastructure development in these priority regions.

Figure 4.17 illustrates the daily number of visits to all EVCSs at the ZCTA level, with the top 10% high-demand ZCTAs highlighted using blue outlines. Unlike total charging time, this metric emphasizes areas that serve a high volume of users, making it particularly useful for identifying ZCTAs with concentrated user activity. When the objective is to determine which locations experience the highest number of charging

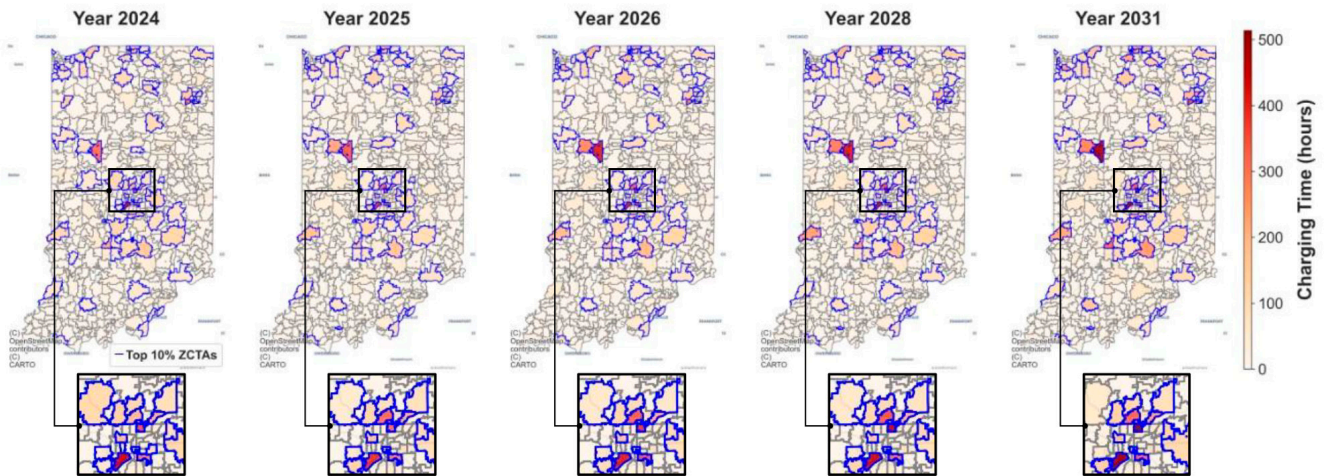


Figure 4.16 Density of Charging Needs in Terms of Hours at the ZCTA Level Across Years for Scenario E.

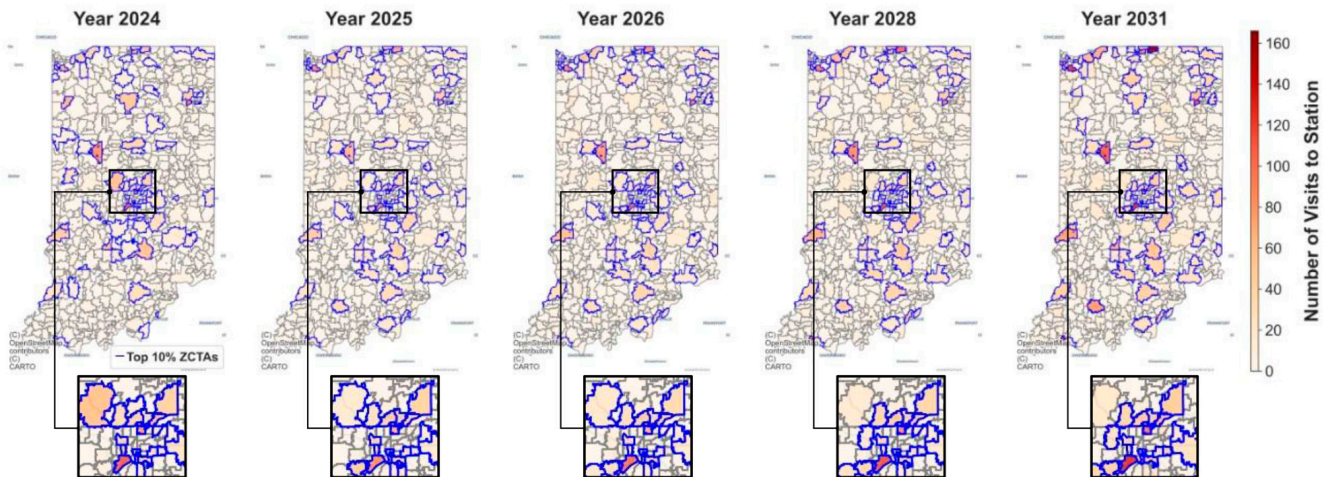


Figure 4.17 Density of Charging Needs in Terms of Visits at the ZCTA Level Across Years for Scenario E.

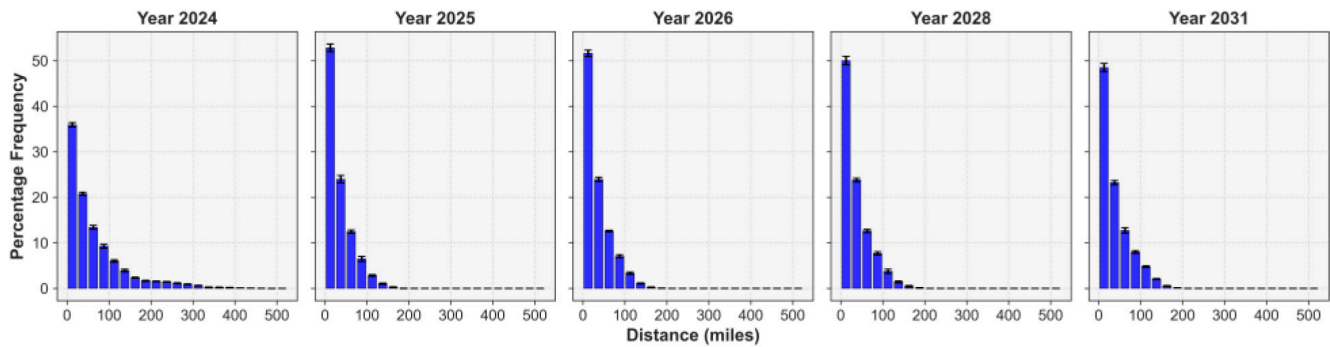


Figure 4.18 Percentage Frequency Distribution of Charging Trip Distances Across Different Years. Error Bars Represent the Standard Deviation Across Different Adoption Scenarios.

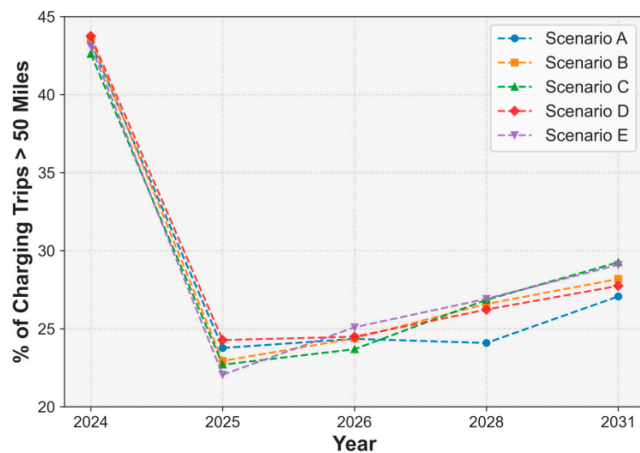


Figure 4.19 Percentage of Charging Trips Longer Than 50 Miles Over the Years Across Different Scenarios.

events, this approach provides clearer insights. The maps help distinguish ZCTAs that are currently experiencing high visit volumes, those expected to see increased user activity in the near or distant future, and those projected to decline in usage over time, even if they are currently active. These insights support targeted infrastructure planning by identifying priority areas for the deployment or expansion of public EVCSs. Consistent with the charging time patterns, ZCTAs with high visit volumes are predominantly located around major metropolitan areas including Indianapolis, Evansville, South Bend, Northwest Indiana, Lafayette, and Fort Wayne. Charging needs of EVCS for other scenarios are provided in Appendix B, Section B.2.

4.4.3 EV Charging Infrastructure Reliability

Reliability, in the context of EV charging infrastructure, is defined as the availability of a charging station within 50 mi of the location where an EV user decides to charge. To evaluate this reliability, Figure 4.18 presents the percentage distribution of charging trip distances across different years, along with

the standard deviation across scenarios. In Year 2024, shorter trips for charging are observed to be less frequent. However, as the years progress, the frequency of shorter charging trips increases, indicating improved accessibility of the charging network over time.

In many planning models, a 50-mi threshold is commonly used to evaluate the reliability of EV charging infrastructure (Hanig et al., 2025). Figure 4.19 presents the percentage of charging trips exceeding 50 mi across different years and scenarios. In 2024, more than 40% of charging trips are longer than 50 mi. This share drops to below 25% in 2025, but gradually increases in subsequent years, reaching nearly 30% by 2031. These trends suggest that, for a significant portion of charging events, charging infrastructure remains insufficiently accessible, compelling EV users to travel longer distances to reach public charging stations.

The EVCS infrastructure in 2026, 2028, and 2031 is projected to remain unchanged, as shown in Figure 4.2. However, the number of EV users is projected to increase over the years, as observed in Figure 4.1. Compared to 2025, the percentage of charging trips exceeding 50 mi increases in 2026, despite the growth in the number of EVCSs. This indicates that the expansion of charging infrastructure has not kept pace with the growing number of EV users. Conversely, the scenarios for 2028 and 2031 can be viewed as “do-nothing” scenarios for 2026, where EV user numbers increase but the charging infrastructure remains stagnant. The simulation results suggest that the gap between supply and demand will continue to widen under these conditions. Therefore, future planning for EV charging infrastructure must be reassessed to accommodate the increasing demand from EV users.

4.4.4 Vehicle Miles Traveled by EVs

Table 4.2 provides a classification of highway types along with their descriptions, based on the OSM standard. This analysis aims to identify which highway types are most frequently used by EVs.

The simulation for all years consistently shows that tertiary, residential, secondary, and primary highways are dominantly

TABLE 4.2
Highway Classification Legends.

Class	Description
Motorway	A high-speed, controlled-access highway (e.g., freeway or interstate) with grade-separated interchanges, no at-grade crossings, and restrictions for slow traffic (e.g., pedestrians, bicycles).
Trunk	Nonmotorway roads that connect major regions or cities (e.g., national highways).
Primary	Major roads linking large towns or serving as urban arterial routes.
Secondary	Highways which are not part of major routes, but nevertheless form a link in the national route network..
Tertiary	Roads connecting smaller settlements, and within large settlements for roads connecting local centres.
Unclassified	Minor public roads, typically at the lowest level of administrative hierarchy in that jurisdiction.
Residential	Roads in housing areas.
Motorway_link	Ramps or slip roads connecting motorways to other roads (e.g., exit/entrance ramps).
Trunk_link	Connectors between trunk roads and lower-class roads (similar to motorway links but for trunk routes).
Primary_link	Short ramps or slip roads linking primary roads to others.
Secondary_link	Short ramps or slip roads linking secondary roads to others.
Tertiary_link	Short ramps or slip roads linking tertiary roads to others.
Service	Access roads for parking, deliveries, or utilities (e.g., alleys, campground roads).
Living_street	Pedestrian-priority streets with very low speed limits.

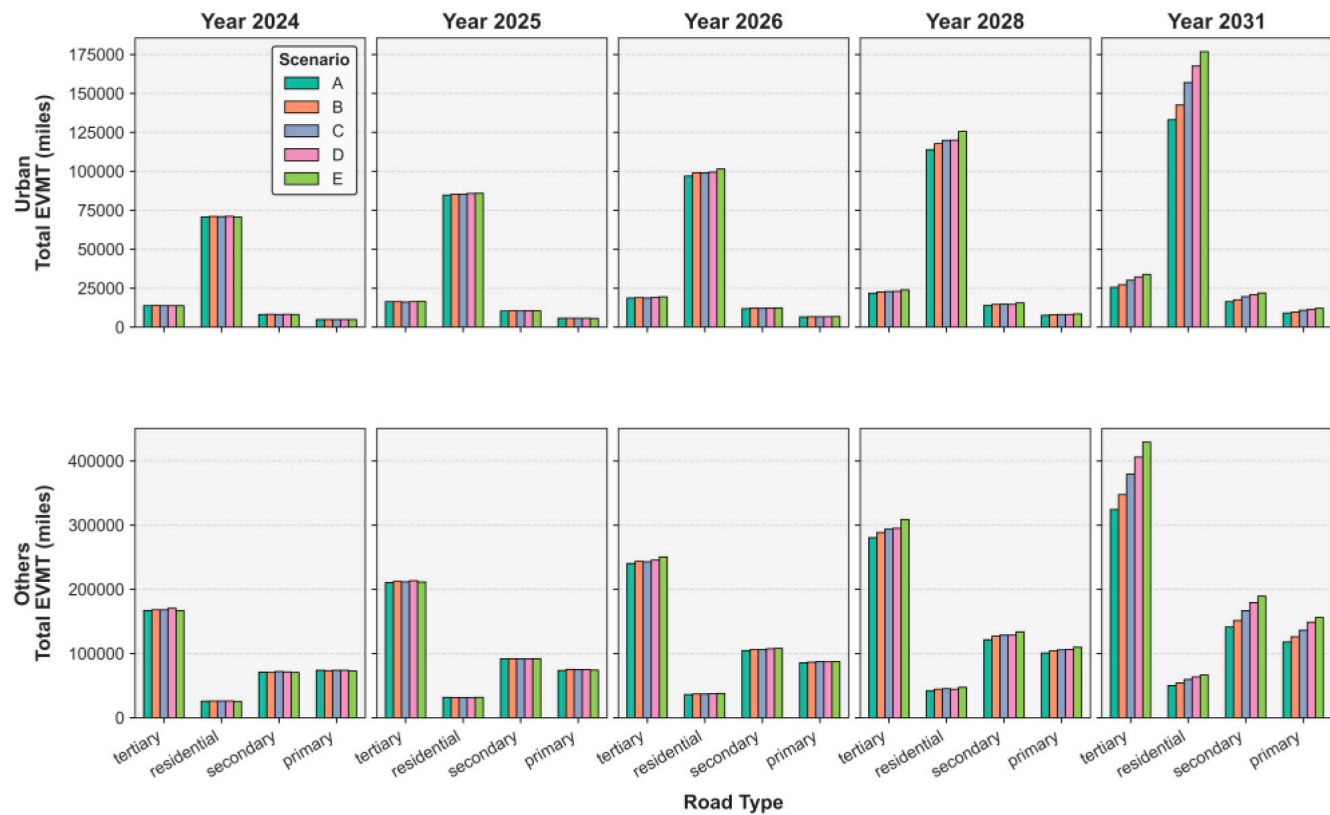


Figure 4.20 EVMT Across Simulation Scenarios by Road Types.

used by EVs across all scenarios. Across all road types, there is a clear upward trend in EV miles traveled (EVMT) from 2024 to 2031, driven by increasing EV adoption (see Table 2.2).

Figure 4.20 presents the total EVMT disaggregated by road type, area type, policy scenario, and projection year. Among all road classifications summarized in Table 4.2, the four road

types with the highest EVMT are tertiary, residential, secondary, and primary roads, respectively. Across scenarios, EVMT remains grow relatively stable during the early projection years (2024–2026), which reflecting moderate growth of EV fleet penetration during this period. However, a notable differentiation emerges by 2028 and becomes most pronounced in 2031 where

the EV penetration exponentially increase. Moreover, EVMT gaps for each scenario begin to be noticeable, this attributing a significance EV adoption gape across scenarios (see Figure 4.1).

Regarding area type, urban areas exhibit substantially lower total EVMT compared to nonurban areas. This disparity reflects the spatial composition of Indiana, where the majority of the land area is concentrated in nonurban contexts, including suburban, small town, and rural areas. Of particular interest is the differential road-type utilization across area types: urban EVMT is disproportionately concentrated on residential roads, whereas nonurban EVMT is dominated by tertiary roads. This finding imply that urban trips tend to be shorter and home-based, accumulating miles on local residential-class links, while nonurban trips are typically longer and intercommunity in nature, utilizing tertiary roads as the primary connective infrastructure. This finding suggests an opportunity to expand charging infrastructure on often-overlooked road types, such as tertiary and residential roads. Additional potential implication of these findings is the need to reassess road maintenance strategies in response to shifting EV travel patterns.

4.4.5 Revenue From Charging Stations

Table 4.3 summarizes the power output and charging cost assumptions for each charger type. We assume that L2 chargers have an average power output of 12 kWh with a charging fee of \$0.25 per kWh. In contrast, Level 3 (L3) or DCFC provide a higher power output of 50 kWh at a rate of \$0.35 per kWh. For mixed charging stations (those equipped with both L2 and L3 chargers), the average power output and charging fee are calculated proportionally based on the number of each charger type present.

Figure 4.21 shows that L2 chargers consistently generate the lowest revenue, followed by L3 chargers. In contrast, mixed stations—those offering mixed chargers (having both L2 and L3 charging)—show the highest median revenue. This finding is somewhat unexpected, as mixed stations generally have lower charging costs than L3-only stations. This suggests that EV users may prefer the flexibility offered by mixed charging options, possibly favoring cost-effectiveness and convenience over speed alone.

TABLE 4.3
Charger Type's Power Output and Charging Cost Assumptions.

	L2	L3	Mixed (L2 and L3)
Power Output	12 kWh	50 kWh	$12 \text{ kWh} \times \frac{\sum \text{L2 station}}{\sum \text{L2 and L3 station}}$ $+ 50 \text{ kWh} \times \frac{\sum \text{L3 station}}{\sum \text{L2 and L3 station}}$
Charging Cost	\$0.25/kWh	\$0.35/kWh	$\$0.25/\text{kWh} \times \frac{\sum \text{L2 station}}{\sum \text{charging station}}$ $+ \$0.35/\text{kWh} \times \frac{\sum \text{L3 station}}{\sum \text{L2 and L3 station}}$

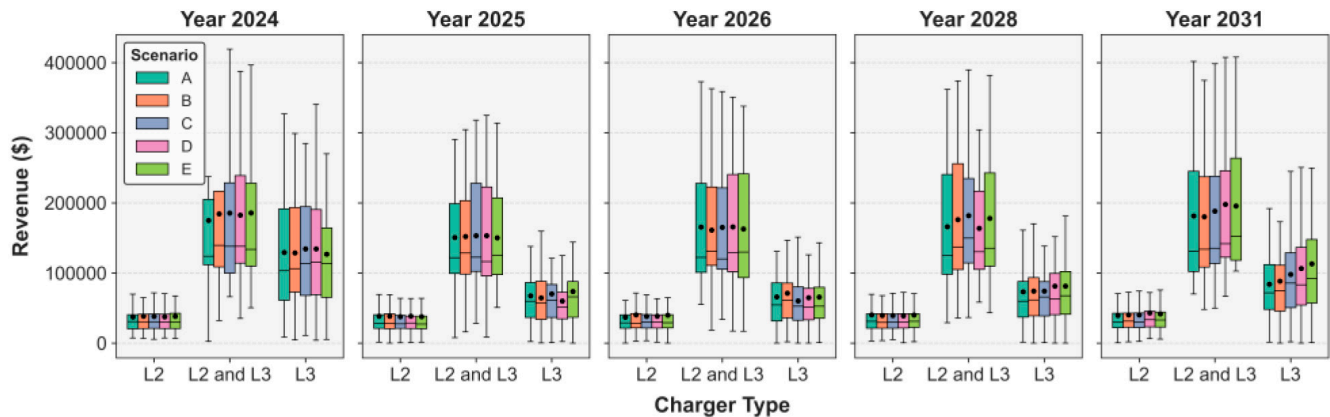


Figure 4.21 Revenue Projection Across Simulation Scenarios by Charger Types.

A noticeable decline in L3 revenue occurs after 2024. A hypothesis is that the expansion of the charging network has led to greater availability, thereby distributing usage more evenly across stations and reducing utilization—and revenue—at individual L3 stations. This argument is supported by the trend observed from 2026 to 2031: Revenue increases steadily from the pessimistic scenario (Scenario A) to the optimistic scenario (Scenario E), despite no increase in the number of EVCS. This indicates that higher EV adoption, rather than infrastructure expansion alone, is driving revenue growth.

Based on these findings, we recommend prioritizing the installation of mixed public charging stations. The analysis also highlights that EVCS revenue, especially for L3 chargers, is highly dependent on EV adoption. An oversupply of charging stations relative to demand can lead to declining revenues and eventual stagnation. However, predicting EV adoption remains challenging. Many consumers may be reluctant to switch to EVs unless they are confident that adequate charging infrastructure is already in place—creating a classic chicken-and-egg dilemma. To address this, government intervention is essential. Policymakers should consider simultaneously incentivizing both EV adoption and EVCS deployment to ensure balanced growth and break the cycle. One approach is to reduce the costs of establishing EVCSs, which would encourage their widespread deployment. By making infrastructure more accessible, range anxiety—a major barrier to EV adoption—could be alleviated, indirectly boosting demand for EVs. Additionally, implementing targeted policies, such as subsidies or tax incentives for EV purchases, could directly stimulate consumer demand. This, in turn, would increase charging station utilization, creating a positive feedback loop that supports the growth of the EV ecosystem.

4.5 Economic Assessment

This section presents a comprehensive evaluation of Indiana's EV charging infrastructure using three core indicators: accessibility, ROI, and EDI. These metrics form the foundation of the EV-EAF, which integrates spatial analysis and economic modeling to assess charger deployment across varying future scenarios. Building on the simulation outputs developed in previous tasks, Subsections 4.5.1 through 4.5.3 detail the evaluation procedures and results for each indicator, highlighting spatial disparities, economic feasibility, and the overall value proposition of the infrastructure investments.

4.5.1 EV Charging Infrastructure Accessibility

Accessibility to EV charging infrastructure is essential for sustained EV adoption, particularly because home charging is not feasible for all households. To evaluate spatial disparities in charging availability, we measured EV charging infrastructure accessibility using a weighted access metric based on travel time to nearby charging facilities. Accessibility was calculated for all EVCSs, DCFCs, and L2 chargers separately. Figure 4.22 shows the spatial distribution of weighted access to all EVCSs, DCFCs, and L2 chargers in 2024. Overall, accessibility is higher in and around major urban centers, including Indianapolis, Fort Wayne, and South Bend, reflecting the greater concentration of charging infrastructure in these areas. In contrast, many rural and peripheral areas exhibit lower accessibility. The comparison across charger types also indicates that access to DCFCs is more limited and spatially concentrated than access to L2 chargers, suggesting that fast-charging availability remains uneven across the state.

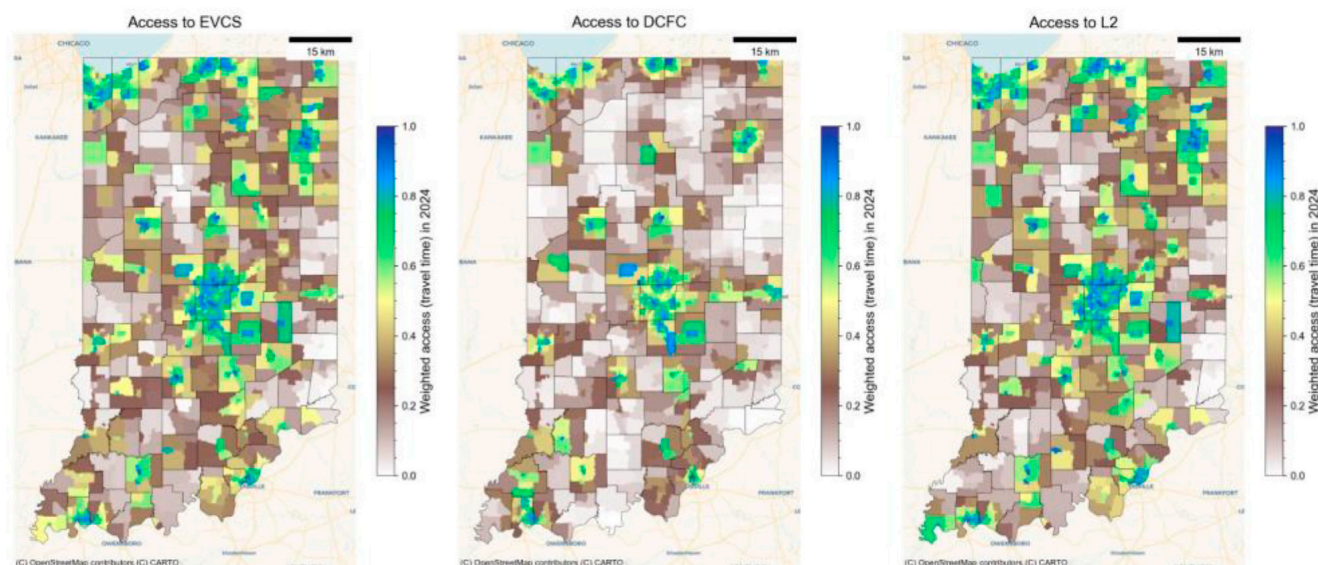


Figure 4.22 Spatial Distribution of Accessibility to EV Charging Infrastructure by Total Chargers, DCFCs, and L2 Chargers.

To understand temporal changes in accessibility to EV charging infrastructure in Indiana, Figure 4.23 and Figure 4.24 present changes in travel time, travel distance, and accessibility from 2023 to 2031 for all EVCSs, DCFCs, and L2 chargers. Figure 4.23 shows that both travel time and travel distance to charging infrastructure generally decrease over time, indicating improved spatial coverage as the charging network expands. The reduction is particularly noticeable for DCFCs, which have the highest travel burden in 2023 but show substantial improvement in later years. However, DCFC access remains more constrained than access to L2 chargers and all EVCSs, as reflected by its higher median and wider distribution of travel time and distance.

Figure 4.24 further confirms this improvement by showing an increase in accessibility scores over time. Accessibility based on travel time and distance increases for all charger categories, with the most notable improvement observed for DCFCs. This suggests that planned infrastructure expansion can meaningfully reduce spatial barriers to fast charging. In contrast, accessibility to L2 chargers and all EVCSs is already relatively high in 2023 and improves more gradually over time. Overall, these results indicate that Indiana's EV charging accessibility is expected to improve through 2031, although disparities by charger type remain, particularly for DCFCs.

Figure 4.25 presents the spatial distribution of EV charging demand, charging infrastructure supply, and the resulting

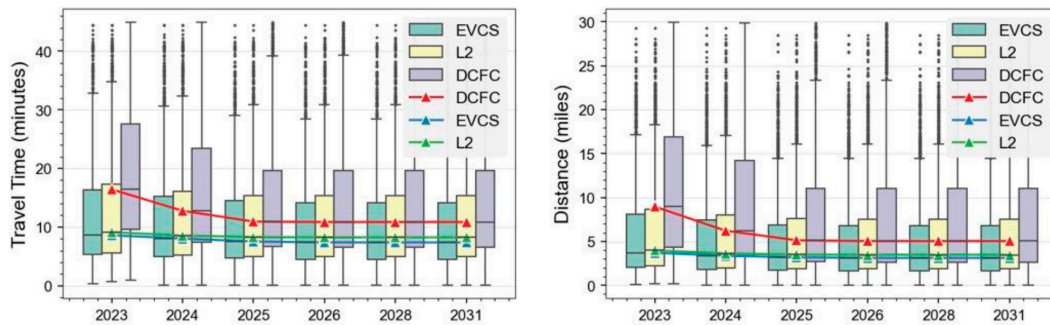


Figure 4.23 Boxplots Showing the Temporal Changes in Travel Time and Travel Distance Required to Access EV Charging Infrastructure in Indiana by Charger Type.

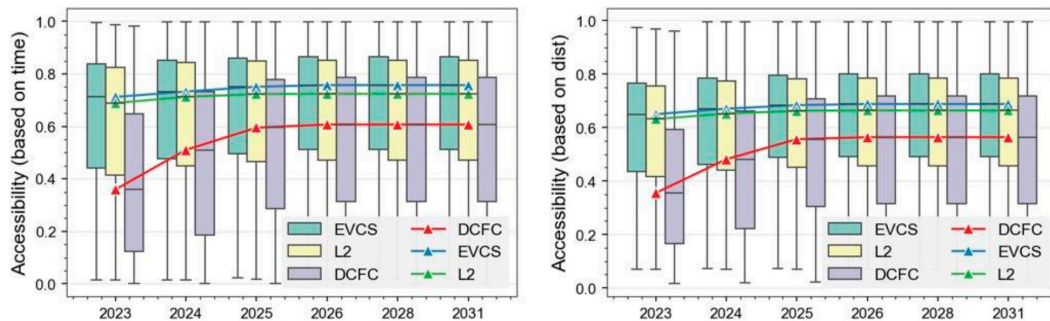


Figure 4.24 Boxplots Showing the Temporal Changes in EV Charging Infrastructure Accessibility in Indiana Based on Travel Time and Travel Distance by Charger Type.

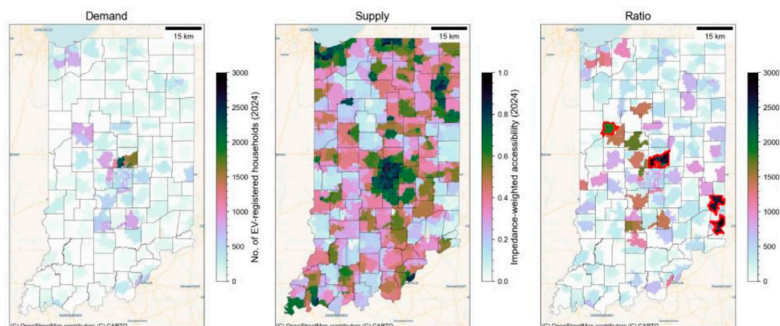


Figure 4.25 Demand-to-Supply Assessment of EV Charging Infrastructure in Indiana in 2024, Showing EV-Registered Households, Impedance-Weighted Charging Accessibility, and Areas With High Demand Relative to Available Charging Supply.

demand-to-supply ratio across Indiana in 2024. Demand is represented by the number of EV-registered households, while supply is measured using impedance-weighted accessibility to EV charging infrastructure. The demand-to-supply ratio combines these two measures to identify areas where EV charging demand is high relative to available infrastructure access. The results show that high EV demand is concentrated primarily in urban and suburban areas, particularly around the Indianapolis metropolitan region and other population centers. However, the supply map indicates that charging infrastructure accessibility does not always align with these demand concentrations. As a result, several ZCTAs exhibit high demand-to-supply ratios, indicating potential gaps between local charging needs and current EV infrastructure access. These high-ratio areas are highlighted in the ratio panel and represent locations where charging demand substantially exceeds the available supply.

The most critical areas include ZCTAs in the northern Indianapolis metropolitan area, particularly around Carmel and Fishers, including 46032, 46037, 46038, 46060, 46062, and 46074. Additional high-priority areas are observed in southeastern Indiana near the Indiana–Ohio border, including 47001, 47012, and 47025, with 47025 showing the highest demand-to-supply ratio among the identified locations. West Lafayette, a college town, represented by ZCTA 47906, also appears as a critical area with high demand relative to available charging access. These same ZCTAs are also expected to experience increasing charging needs in future years, suggesting that the current infrastructure gap may become more pronounced without targeted investment.

Overall, the results indicate that EV charging infrastructure planning should not rely solely on the spatial distribution of chargers or EV households independently. Instead, the demand-to-supply ratio provides a more policy-relevant measure by identifying areas where EV adoption and charging access are

misaligned. The highlighted ZCTAs may serve as priority locations for future EVCS deployment to better align infrastructure expansion with current and projected charging needs.

4.5.2 Return on Investment (ROI) Analysis

The ROI analysis was conducted over an 8-year horizon spanning 2024 to 2031, with capital costs beginning in 2024 representing the accumulated equipment procurement and site development expenditures for each EVCS (see Table A.3 and Table A.4). Figure 4.26 presents a cashflow snapshot for a representative EVCS, where negative values on the y-axis indicate expenditures and positive values indicate revenue. This particular example illustrates a DCFC station, in which transformer installation, equipment installation, electrical infrastructure and site readiness, and engineering design constitute the major capital cost components for station establishment. In addition to upfront capital costs, each EVCS incurs annual operation and maintenance (O&M) expenditures throughout the analysis period. Revenue, on the other hand, varies across stations as it is a function of individual station utilization rates, as discussed in Section 4.4.5. Applying the ROI formula defined in Section 3.4.1, the EVCS represented in Figure 4.26 yields an ROI of approximately 0.7895, indicating that the station recovers 78.95% of its total investment cost by the end of the 8-year analysis period.

Since each EVCS in the simulation carries a unique utilization profile, every station produces a distinct cashflow trajectory and, consequently, a unique ROI estimate. Figure 4.27 presents a boxplot summarizing the descriptive statistics of ROI estimates across all stations and scenarios. The results demonstrate a notably consistent distribution across scenarios, with a mean ROI of approximately 0.85 and a median of approximately 0.90. The interquartile range is relatively narrow, with the 25th percentile at approximately 0.80 and the 75th percentile at approximately

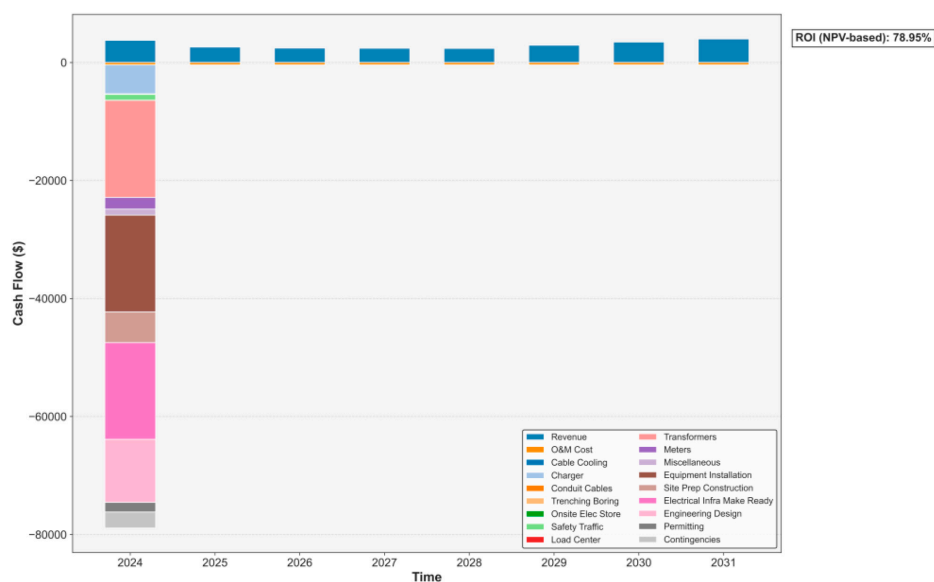


Figure 4.26 EVCS's Cashflow Example.

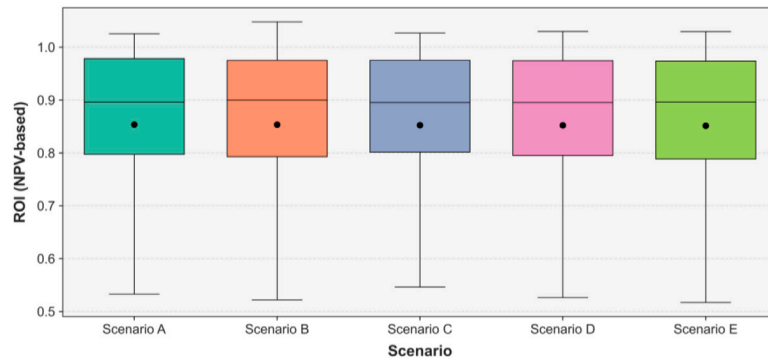


Figure 4.27 ROI Boxplots Across Different Simulation Scenarios.

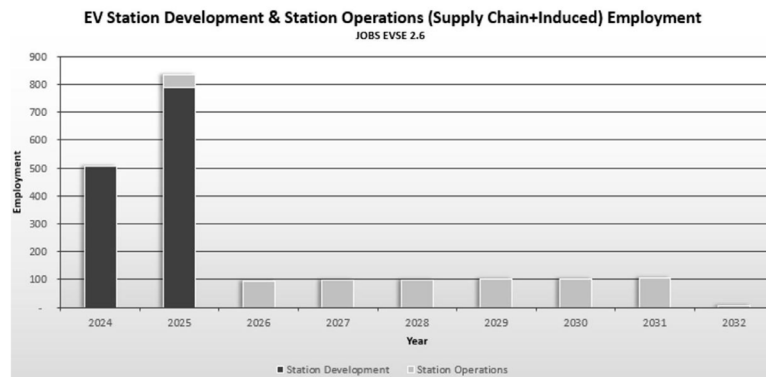


Figure 4.28 EVCS Development Employment.

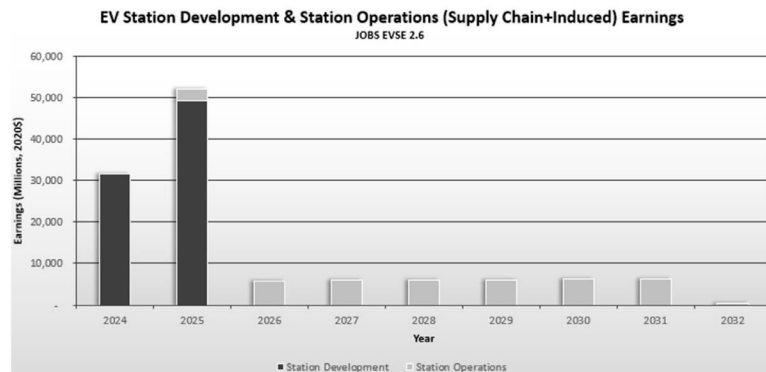


Figure 4.29 EVCS Development Earnings.

0.97, indicating limited variability and suggesting that the majority of simulated stations are projected to recover a substantial portion of their investment within the analysis period.

4.5.3 Economic Development Impact (EDI)

The EDI outcomes attributable to EVCS development, as estimated using the JOBS model, are reported across three indicators: (1) employment, (2) earnings, and (3) gross output. As shown in Figure 4.28, cumulative employment over the 8-year analysis period amounts to approximately 2,000 jobs,

encompassing both full- and part-time workers. The majority of this employment, approximately 1,300 jobs, is attributable to station development expenditures, with the remainder generated by ongoing EVCS operations. Employment activity is most concentrated in the 2024–2025 period, which corresponds directly to the peak period of station establishment, particularly in 2025 when a substantial number of DCFC stations were deployed.

Figure 4.29 presents the earnings output associated with EVCS development. Total cumulative earnings over the analysis period amount to approximately \$130 million, encompassing wages, salaries, and employer contributions to benefits such as

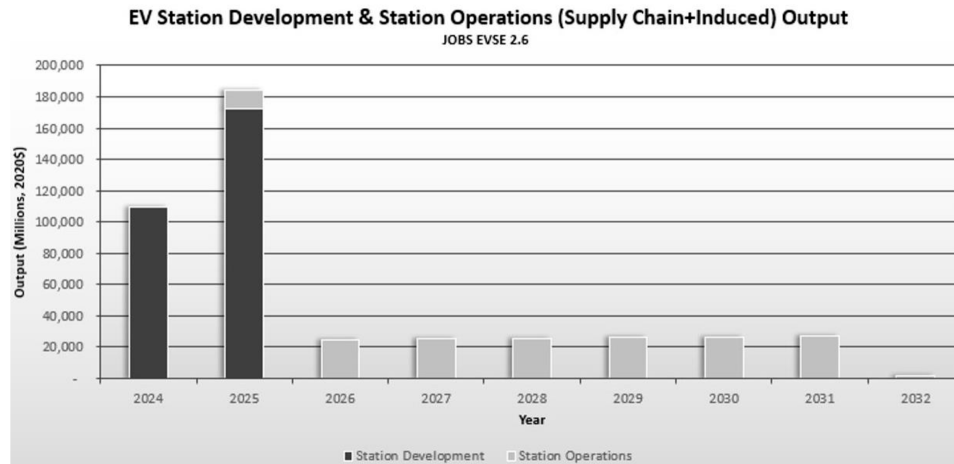


Figure 4.30 EVCS Development Gross Output.

health insurance. Finally, Figure 4.30 illustrates the gross output result, which totals approximately \$400 million over the same period. It should be noted that gross output represents the sum of intermediate inputs and value added across all affected sectors; as such, it inherently reflects double-counting when goods or services produced in one sector serve as inputs to another. Consequently, gross output should be interpreted as a measure of total economic activity stimulated by the investment rather than a net contribution to regional wealth, for which value-added metrics provide a more precise representation.

5. CONCLUSIONS

This project advances the understanding of EV infrastructure needs in Indiana by leveraging a simulation-based planning approach that integrates empirical EV demand data with real-world charging infrastructure records. Using the high-resolution METS-R simulation platform, the study offers a forward-looking assessment of EV charging patterns under five distinct adoption scenarios spanning the years 2024 to 2031. In addition to simulating charging usage, revenue, EVMT, and infrastructure reliability, this study evaluates spatial accessibility, demand-to-supply alignment for EV charging infrastructure, ROI, and EDI. The results show that although accessibility improves over time, DCFC access remains more constrained than L2 access, and several ZCTAs exhibit high EV demand relative to available charging supply. Additionally, the estimated ROI seems promising with average and median close to 1.0. By simulating user behaviors, spatial demand distribution, and temporal usage trends, this research provides data-driven insights for infrastructure planning. The resulting analyses highlight critical gaps in current infrastructure, underscore the need for scenario-sensitive deployment strategies, and identify high-demand zones and times for targeted intervention. In doing so, this work offers a practical decision-support framework for INDOT and other stakeholders to inform sustainable, and economically sound investments in EV charging infrastructure across Indiana.

5.1 Summary of Findings

The key findings based on the analyses presented in Chapter 4 are summarized below:

- **EV Infrastructure Usage Patterns:** Across all scenarios, DCFC stations exhibited higher utilization in terms of visit counts, reflecting their attractiveness for quick charging. However, L2 stations were used for longer durations, consistent with their slower charging speeds. Importantly, suburban and rural areas showed disproportionately higher charging times at L2 stations, highlighting disparities in infrastructure provision and greater reliance on slower charging modes outside of urban cores. These spatial differences suggest that infrastructure growth has not been evenly distributed and that charging capacity in lower-density communities is already stretched.
- **Temporal and Spatial Dynamics:** Station usage varied not only by charger type and community type but also across the day. Several stations that were among the top 10% in overall daily usage were not in the top 10% during daytime or nighttime alone, indicating distinct temporal usage patterns. Nighttime peaks at certain locations underscore the need to incorporate time-of-day granularity in planning models. At the ZCTA level, high-demand zones consistently clustered around major metropolitan areas such as Indianapolis, Fort Wayne, South Bend, and Lafayette, but results also highlighted future demand growth in specific suburban and semiurban ZCTAs. This underlines the importance of anticipating emerging hot spots and not only reinforcing already high-demand regions.
- **Infrastructure Reliability:** Reliability, measured by the share of charging trips requiring more than 50 mi of travel, revealed persistent accessibility gaps. In 2024, over 40% of charging trips exceeded 50 mi, indicating insufficient coverage. While this share dropped to below 25% in 2025 due to expansion, it climbed back toward 30% by 2031 under scenarios where infrastructure growth stagnated despite rising EV adoption. This trend highlights a mismatch between infrastructure expansion and adoption growth, suggesting that current investment trajectories may fall short of ensuring efficient and reliable access. The results emphasize that long-term planning must go beyond incremental growth, as static deployment scenarios will widen the supply-demand gap and exacerbate spatial inaccessibility.

- **Revenue:** Mixed chargers (combining L2 and DCFC) consistently generate the highest revenue across all scenarios and simulation years, followed by standalone DCFC and L2 chargers. This ranking reflects EV drivers' charging preferences, indicating a higher demand for versatile charging options.
- **EVMT:** The most frequently traveled road types by EVs, across all scenarios and years, are tertiary, residential, secondary, and primary highways. This finding suggests an opportunity to expand charging infrastructure on often-overlooked road types, such as tertiary and residential roads in response to EV travel patterns.
- **Accessibility to EV Charging Infrastructure:** The accessibility analysis shows uneven EV charging access across Indiana, with higher impedance-weighted accessibility around major urban centers such as Indianapolis, Fort Wayne, South Bend, and Lafayette, and lower access in many rural and peripheral areas. Access to DCFCs remains more spatially limited than access to L2 chargers. Although travel time and distance to charging infrastructure generally decline from 2023 to 2031 and accessibility improves across all charger categories, DCFCs continue to have higher travel burdens and wider accessibility variation, indicating a persistent fast-charging gap.
- **Demand-to-Supply Mismatch:** The demand-to-supply analysis identifies ZCTAs where EV charging demand is high relative to impedance-weighted charging access. While EV demand is concentrated in urban and suburban areas, charging supply does not always align with these patterns. High-priority ZCTAs include 46032, 46037, 46038, 46060, 46062, and 46074 in the northern Indianapolis metropolitan area; 47001, 47012, and 47025 in southeastern Indiana, with 47025 showing the highest ratio; and 47906 in West Lafayette. These results suggest that planning should prioritize areas where EV demand exceeds accessible charging supply.
- **ROI:** The mean ROI of approximately 0.85 and a median of approximately 0.90. The interquartile range is relatively narrow, with the 25th percentile at approximately 0.80 and the 75th percentile at approximately 0.97, indicating limited variability and suggesting that the majority of simulated stations are projected to recover a substantial portion of their investment within the analysis period.
- **EDI:** Over an 8-year period, the development and operation of EVCS are estimated to generate approximately 2,000 jobs, \$130 million in earnings, and \$400 million in gross output. Most of the employment and economic activity is concentrated during the 2024–2025 peak station development phase, with the majority of jobs tied to construction and deployment rather than ongoing operations.

5.2 Implementation Plans

Based on simulation results and empirical validations, several implementation plans are proposed for INDOT and other stakeholders to guide EV infrastructure planning in Indiana. First, both L2 and DCFC stations in suburban areas have been found to be highly utilized; for example, stations of both types located in suburban Terre Haute ranked among the top ten most utilized sites. In contrast, utilization patterns differ across other contexts such as rural areas in Lafayette show higher usage of L2 stations, whereas towns in Jasper exhibit greater demand for DCFC stations. These findings highlight potential priority zones for guiding station buildout strategies. Therefore, suburban areas should be prioritized for both L2 and DCFC installations,

while rural areas warrant greater emphasis on L2 deployment and towns on DCFC deployment.

Second, the usage of L2 stations has remained relatively stable over the years, whereas DCFC stations show a pronounced upward trend in future usage as can be seen from Figure 4.10. This reflects both EV users' growing preference for faster charging technologies and the increasing deployment of DCFC stations for public charging. A key barrier to EV adoption is the longer charging time compared to refueling, which can be mitigated through fast charging options. Therefore, given the stronger projected growth in DCFC demand relative to L2, future planning should place greater emphasis on the strategic placement of DCFC stations.

Third, infrastructure planning should adopt scenario-based strategies to address uncertainties in EV adoption, thereby avoiding both overbuilding and underbuilding. Temporal variations in station usage are also evident. For instance, stations near Evansville rank among the most utilized when considering the full day but not during daytime hours, while other stations show peak demand only at night. Charging demand is closely tied to user travel behavior, as reflected in these temporal usage variations. Such temporal patterns (see Figure 4.12, Figure 4.13, Figure 4.14, and Figure 4.15) underscore the need for operational adjustments, including enhancing nighttime capacity in certain regions and aligning business hours with local demand.

Fourth, high-demand ZCTAs are concentrated around metropolitan areas such as Indianapolis, Evansville, South Bend, Lafayette, Fort Wayne, and Northwest Indiana, where both charging hours and visit volumes are projected to increase. Proactive investment in these areas can help prevent future bottlenecks and improve network reliability. The maps shown in Figure 4.16, Figure 4.17, and Figures A.4 to A.7 provide insights into spatial shifts in EV charging demand derived from realistic simulations of projected data. Thus, planners should prioritize deployment in such high-demand ZCTAs. In contrast, ZCTAs with stable or declining demand should receive lower priority, enabling resources to be redirected toward emerging hot spots and ensuring infrastructure expansion aligns with needs.

Fifth, accessibility gaps remain a concern, as many users must travel long distances to reach public charging stations (see Figure 4.18). The 2028 and 2031 scenarios effectively represent 'do-nothing' cases relative to 2026, in which EV adoption continues to rise while charging infrastructure remains unchanged. Under such conditions, the gap between supply and demand is projected to widen further. This highlights the need to pace infrastructure development in line with the growth of EV demand. Therefore, identifying and addressing locations where users face longer travel distances to access charging can help mitigate these accessibility challenges.

Sixth, from Figure 4.20 we found that primary, secondary, residential and tertiary roads are heavily used for EV daily travel. This finding suggests an opportunity to expand charging infrastructure on often-overlooked road types, such as tertiary and residential roads. Additionally, the potential implication of these findings is the need to reassess road maintenance strategies in response to EV travel patterns.

Seventh, from Figure 4.21 we found that mixed charging stations (having both L2 and DCFC) constantly generate higher revenue compared to L2 and DCFC across years and scenarios. We recommend prioritizing the installation of mixed public charging stations. Additionally, the analysis reveals that DCFC station's revenue is highly sensitive to EV adoption scenarios, that highly emphasized particularly in 2031. We consequently advise that any financial assessment must be grounded in robust and accurate adoption projections to reliably determine revenue potential.

Eighth, infrastructure deployment should explicitly account for accessibility gaps across charger types. Although accessibility to EV charging infrastructure is projected to improve through 2031, the results show that access to DCFC stations remains more constrained and spatially concentrated than access to L2 chargers. Therefore, DCFC deployment should be prioritized in areas where fast-charging access is currently limited, especially in locations with high travel time or distance to existing DCFC stations. At the same time, L2 deployment should continue to support residential, workplace, and community-based charging needs, particularly in areas where users rely on longer-duration charging.

Ninth, planners should use the demand-to-supply ratio as a prioritization metric for future EVCS deployment. The ratio provides a more policy-relevant measure than demand or supply alone because it identifies areas where EV adoption and charging infrastructure access are misaligned. Based on the results, ZCTAs in the northern Indianapolis metropolitan area, southeastern Indiana, and West Lafayette should be considered priority candidates for future investment. These areas exhibit high EV demand relative to current charging accessibility and are also expected to experience increasing charging needs in future years. Targeting these locations can help reduce localized infrastructure gaps and improve the accessibility and efficiency of future EV charging investments.

Tenth, since some stations fall to the lower end of the ROI distribution (e.g., 25th percentile at ~80%, minimum ROI is 55%), policymakers should consider targeted operational subsidies or utilization-based support for underperforming stations to ensure financial viability across all sites. Additionally, given that revenue is tied directly to station utilization rates, policies promoting EV adoption and driver awareness of charging locations would further improve ROI consistency

5.3 Limitations

While this study presents a robust analysis of EV charging infrastructure in Indiana, it has certain limitations. EV user demands are estimated only for passenger cars, so future research can include all vehicle types. The simulation assumes static infrastructure development in later years (2026–2031) for most scenarios, which may not reflect future investments or policy-driven expansions. Moreover, although the model integrates behavioral data from surveys and GPS traces, it assumes relatively fixed charging preferences over time. This may underrepresent adaptive behavior as users respond to new technologies, pricing, or experiences.

The accessibility and demand-to-supply analyses also have limitations. The impedance-weighted accessibility measure depends on the selected impedance decay parameters and assumes that travel time or travel distance adequately captures users' willingness to access charging stations. However, charging decisions may also be influenced by charging price, station reliability, waiting time, connector compatibility, parking availability, and perceived safety. In addition, the demand-to-supply ratio uses EV-registered households as a proxy for charging demand, which may not fully capture workplace charging needs, through-travel demand, tourism-related charging, or charging demand from non-household fleets. Future work can improve this analysis by incorporating observed charging sessions, real-time station availability, queuing delays, charger uptime, electricity pricing, and grid hosting capacity.

The ROI analysis was conducted only for charging stations that existed in 2023, since stations built in 2024 or later would have ROI estimates covering less than an eight-year period due to the simulation ending in 2031. Additionally, the revenue estimation assumed that charging prices remained constant over time. Regarding the EDI estimation, the model does not distinguish between full-time and part-time jobs in its employment generation figures.

Forecasting EV adoption also remains inherently uncertain, as future trajectories could be significantly altered by shifts in technology, policy, or market conditions. Addressing these limitations in future work will require modeling adaptive charging behavior, incorporating dynamic pricing, simulating infrastructure under active policy intervention, and expanding the analysis to include additional performance indicators, such as wait times and user satisfaction. Additional data collection on real-world charging events and testing under grid constraints and emergency situations would further enhance the framework's practical utility and resilience to both natural disasters and cyberattacks.

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APPENDICES

Appendix A. List of Acronyms

Appendix B. Performance Analytics of EV Charging Stations

Appendix A. List of Abbreviations

ABM	Agent-Based Modeling
ACS	American Community Survey
AFDC	Alternative Fuels Data Center
ANL	Argonne National Laboratory
ATS	American Travel Survey
BEA	Bureau of Economic Analysis
DCFC	Direct Current Fast Charging
EDI	Economic Development Impact
EV	Electric Vehicle
EVCS	EV Charging Stations
EV-EAF	EV Charging Infrastructure Economic Assessment Framework
EVMT	EV Miles Traveled
GPS	Global Positioning System
GV	Gasoline Vehicle
HPC	High-Performance Computing
ICEV	Internal Combustion Engine Vehicles
INDOT	Indiana Department of Transportation
I-O	Input-Output
IRR	Internal Rate of Return
kWh	Kilowatt-Hour
L2	Level 2
L3	Level 3
METS-R SIM	Multimodal Energy-Efficient Trip Simulation in Real Time simulator
MSAs	Metropolitan Statistical Areas
NEVI	National Electric Vehicle Infrastructure
NHTS	National Household Travel Survey
NLR	National Laboratory of the Rockies
NPV	Net Present Value
NREL	National Renewable Energy Laboratory
O&M	Operating and Maintenance
O-D	Origin-Destination
ORNL	Oak Ridge National Laboratory
OSM	OpenStreetMap
RIMS II	Regional Input-Output Modeling System
ROI	Return on Investment
Uas	Urbanized Areas
Ucs	Urban Clusters
VTM	Vehicle Miles Traveled
ZCTA	Zip Code Tabulation Area

Appendix B. Performance Analytics of EV Charging Stations

B.1. Real-World Charging Findings From ChargePoint

B.1.1. Spatial Variation of EVCS Performance Metrics

Figure B.1 through Figure B.3 present the distributions of three key EVCS performance metrics: average usage time, average utilization rate, and average visits per day, respectively.

From Figure B.1, it can be observed that the average usage time across stations ranges from 0 to 1,930 minutes. A substantial proportion of EV chargers are not being used at all, as indicated by a notable spike at zero. The histogram reveals that approximately 29.6% of the stations recorded zero mean usage time, highlighting underutilization in many locations.

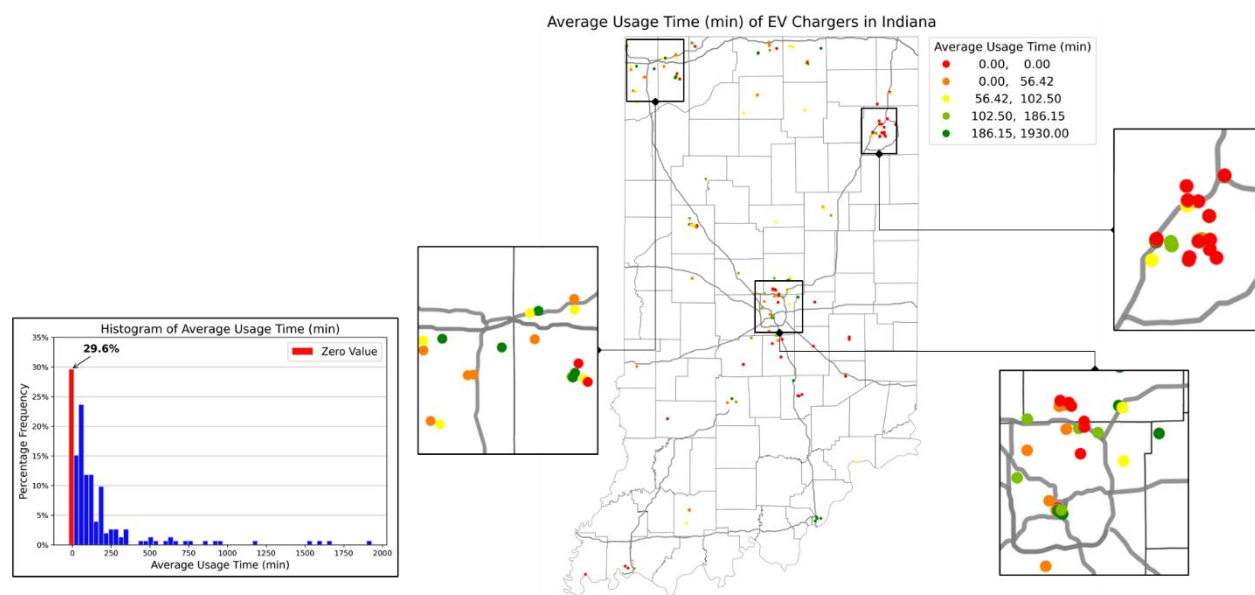


Figure B.1 Spatial Variation of Usage Time (Minutes).

Figure B.2 illustrates the distribution of average utilization rates, which range from 0% to 67.19%. Similar to usage time, a significant number of EV chargers exhibit no utilization. Specifically, the histogram shows that around 27.6% of stations had a zero utilization rate, indicating that these chargers were not used during the observation period.

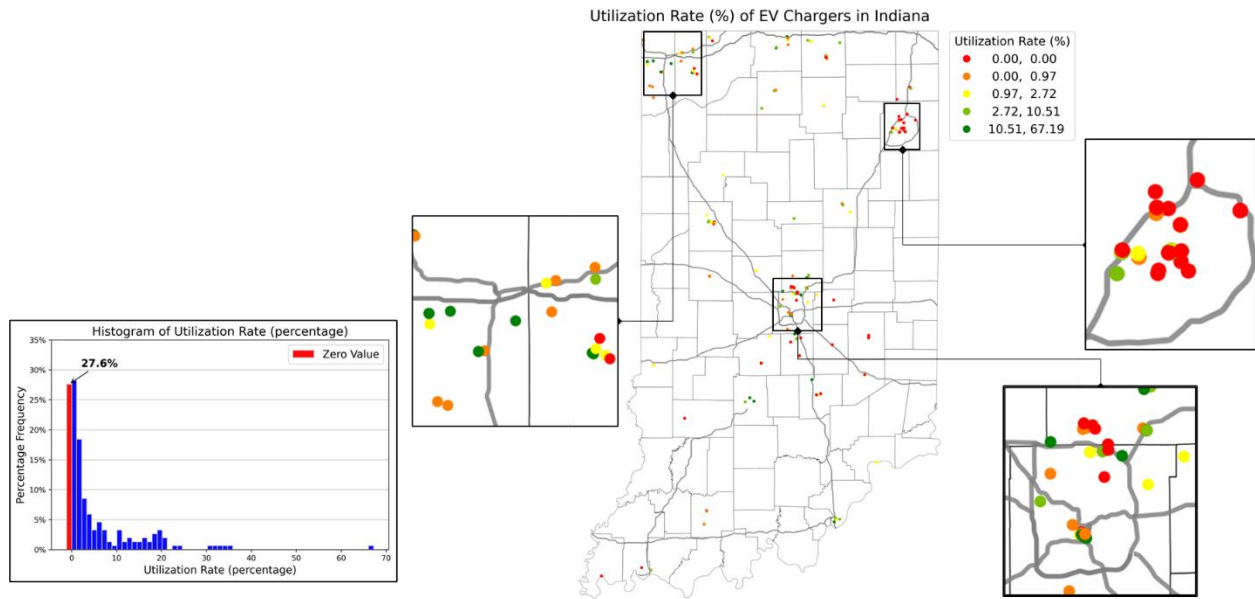


Figure B.2 Spatial Variation of Utilization Rate (%).

Figure B.3 shows the variation in average visits per day, which ranges from 0 to 2.52. A considerable number of stations received no regular visits. The histogram indicates that approximately 29.6% of stations recorded zero daily visits, suggesting that nearly one-third of chargers had no consistent user activity.

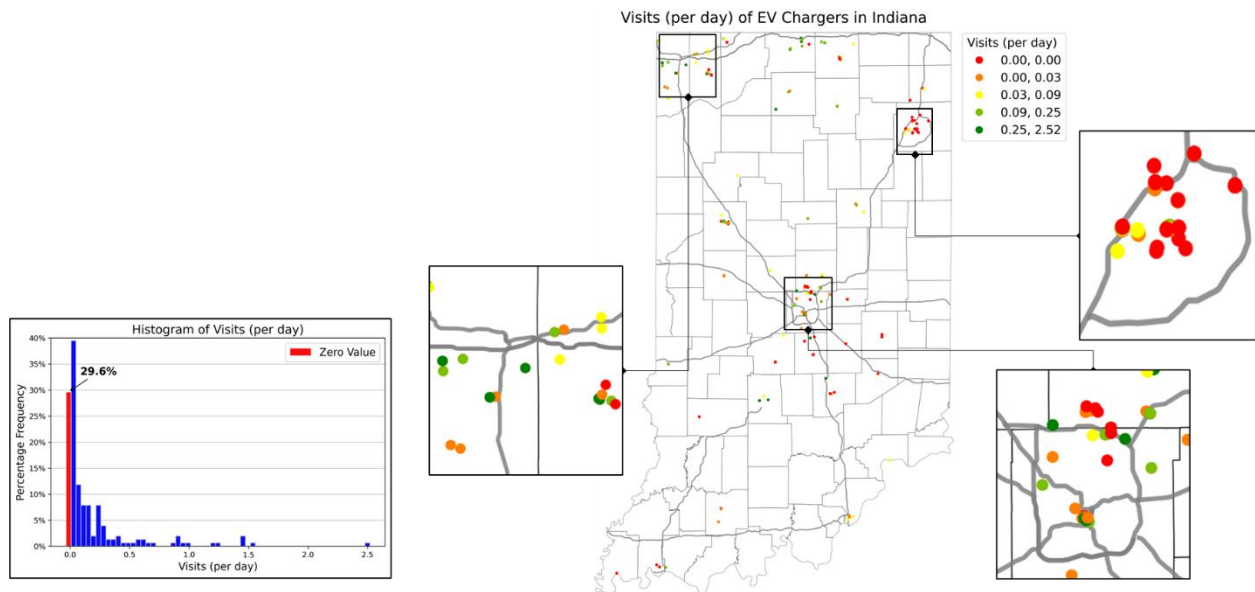


Figure B.3 Spatial Variation of Visits (Per Day).

These results underscore the existence of spatial heterogeneity in public EVCS usage and point to opportunities for optimizing station placement and improving accessibility and visibility, particularly in low-demand areas.

B.2. Performance Metrics and Analysis

B.2.1. Density of EV Charging Needs at the ZCTA Level

Figure B.4 through Figure B.7 present the density charging needs in terms of hours at the ZCTA level across years for Scenario A through D.

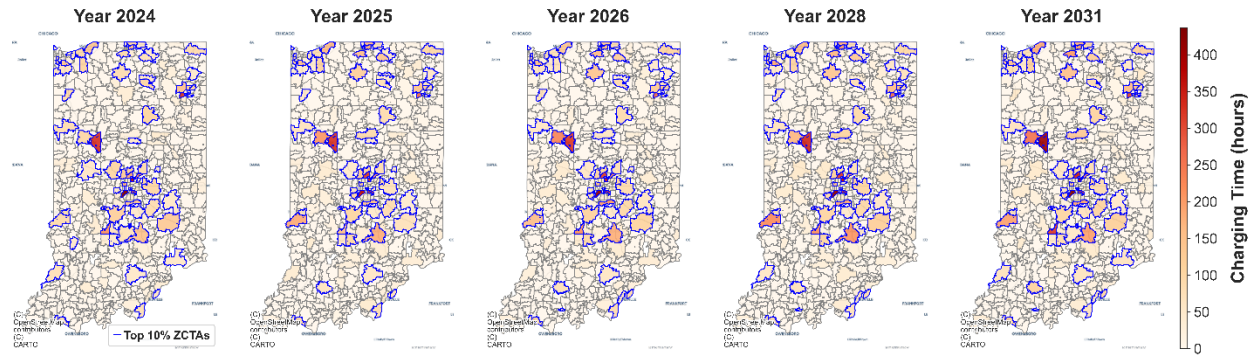


Figure B.4 Density of Charging Needs in Terms of Hours at the ZCTA Level Across Years for Scenario A.

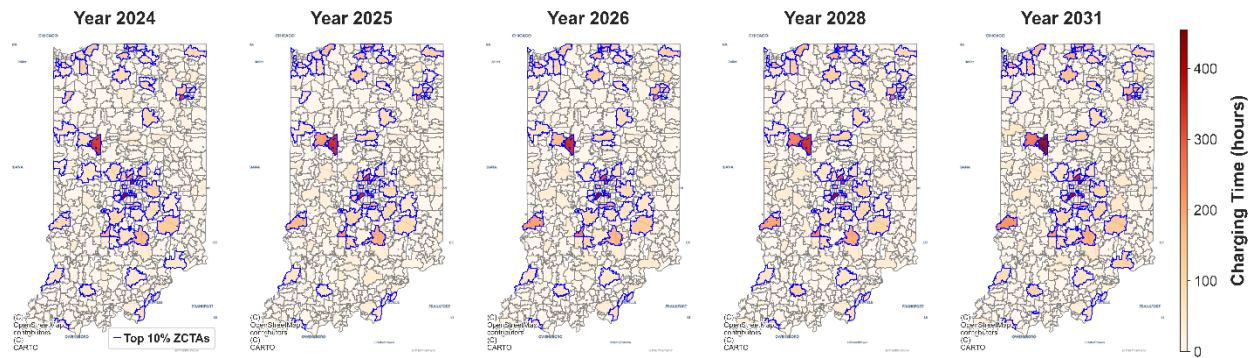


Figure B.5 Density of Charging Needs in Terms of Hours at the ZCTA Level Across Years for Scenario B.

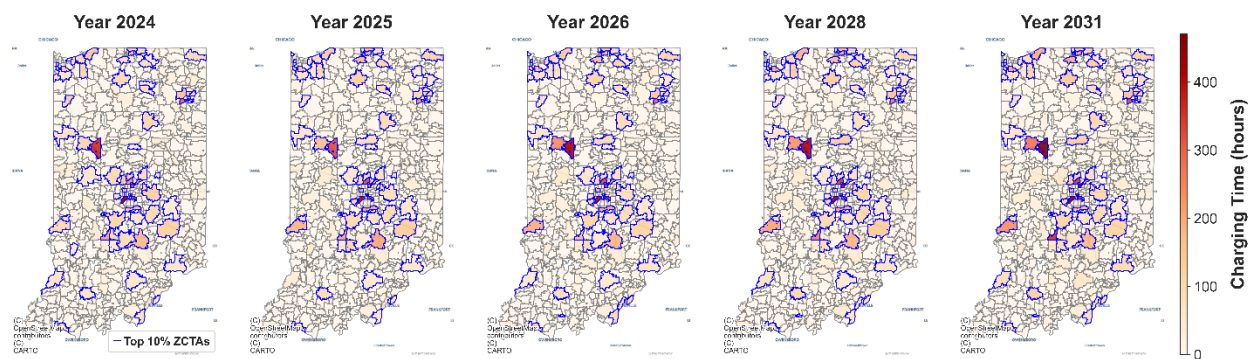


Figure B.6 Density of Charging Needs in Terms of Hours at the ZCTA Level Across Years for Scenario C.

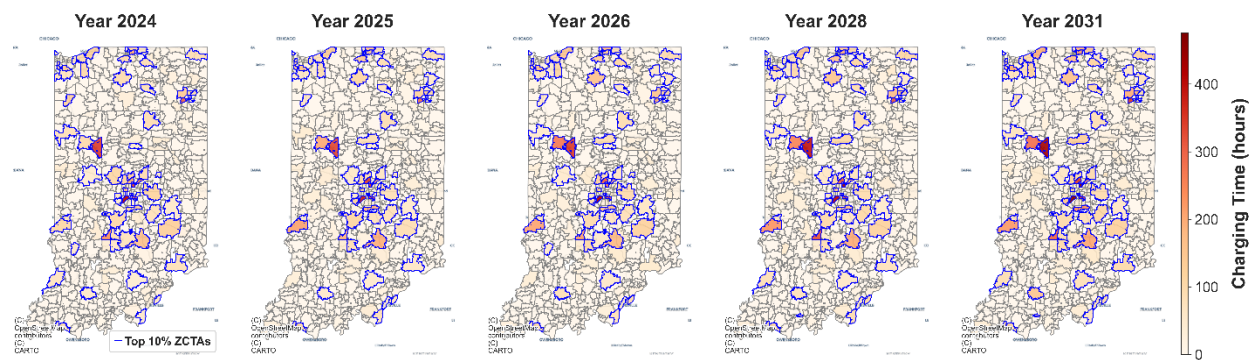


Figure B.7 Density of Charging Needs in Terms of Hours at the ZCTA Level Across Years for Scenario D.

Figure B.8 through Figure B.11 presents the density charging needs in terms of visits at the ZCTA level across years for Scenario A through D.

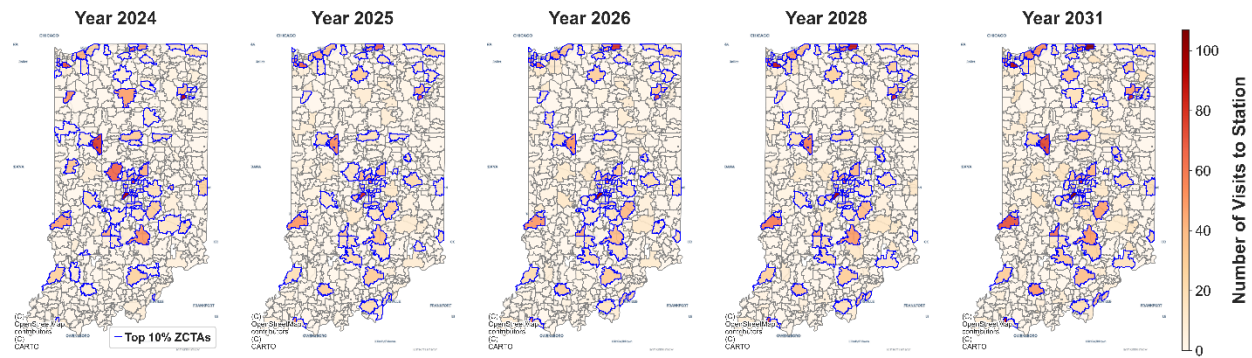


Figure B.8 Density of Charging Needs in Terms of Hours at the ZCTA Level Across Years for Scenario A.

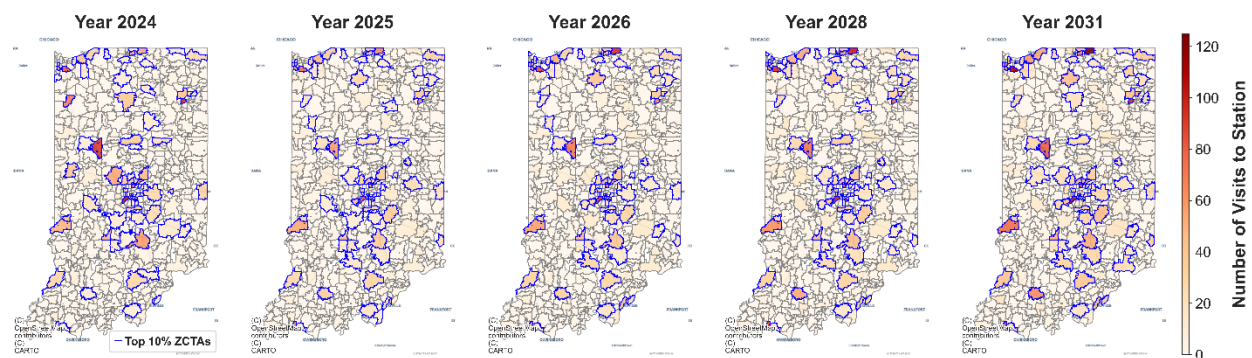


Figure B.9 Density of Charging Needs in Terms of Hours at the ZCTA Level Across Years for Scenario B.

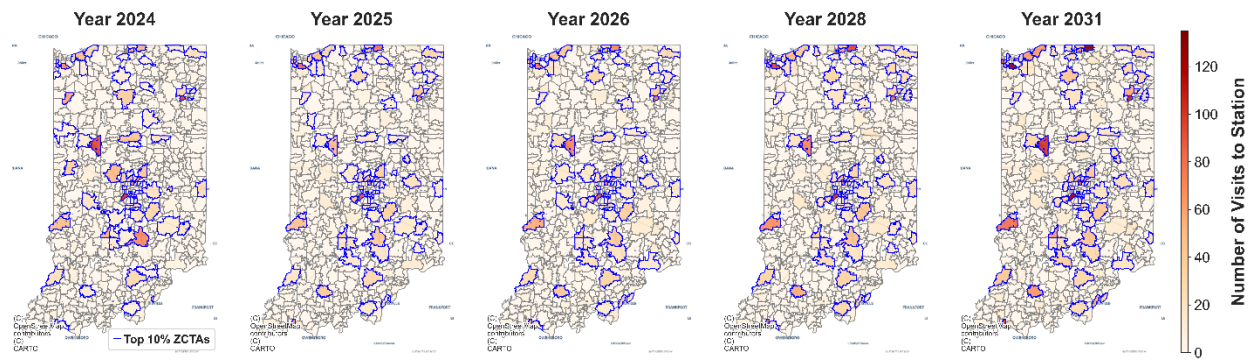


Figure B.10 Density of Charging Needs in Terms of Hours at the ZCTA Level Across Years for Scenario C.

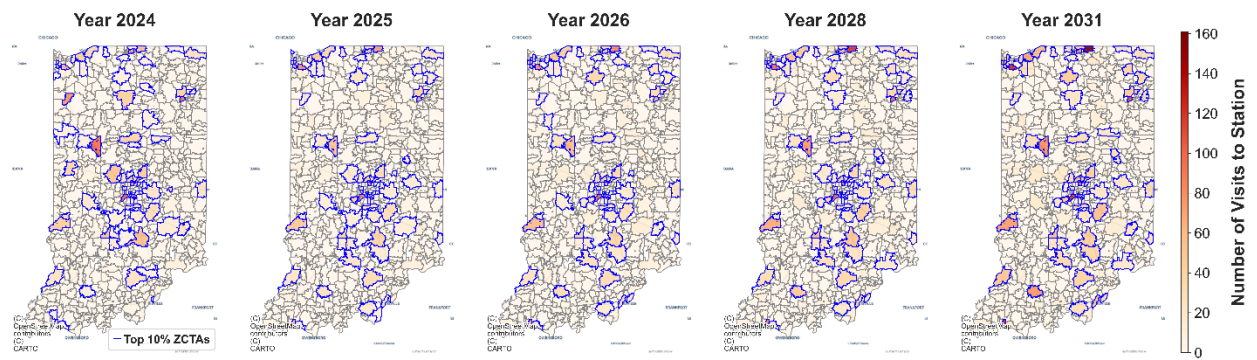


Figure B.11 Density of Charging Needs in Terms of Hours at the ZCTA Level Across Years for Scenario D.

Table B.1 and Table B.2 present the top 10 public charging stations for Year 2031, Scenario E, with L2 and DCFC chargers, respectively.

Table B.1**List of Top 10 Public Charging Stations L2 Chargers for Year 2031 Scenario E.**

Station Name	Station Address	City	State	Zip Code	Charger Type	Community Type
Beacon Health System	3245 Health Dr	Granger	IN	46530	L2	Suburban
Professional Office Building	630 Professional Bldg Dr	Indianapolis	IN	46203	L2	Urban
City of Evansville - Sycamore Street Public Garage	500 Sycamore St	Evansville	IN	47708	L2	Urban
Indianapolis International Airport - Terminal	7800 Col H. Weir Cook Memorial Dr.	Indianapolis	IN	46241	L2	Urban
Parking Garage	13111 Old Meridian St	Carmel	IN	46032	L2	Urban
Merchants Garage - Tesla Destination	31 S Meridian St	Indianapolis	IN	46204	L2	Urban
Culver's - Tesla Destination	4141 S US Hwy 41	Terre Haute	IN	47802	L2	Suburban
Judicial Center	3205 Justice Dr	Indianapolis	IN	46203	L2	Urban
Caesars Southern Indiana	11999 Casino Center Dr	Elizabeth	IN	47117	L2	Rural
Inn at Saint Mary's - Tesla Destination	53993 US 933	South Bend	IN	46637	L2	Suburban

Table B.2**List of Top 10 Public Charging Stations L3 Chargers for Year 2031 Scenario E.**

Station Name	Station Address	City	State	Zip Code	Charger Type	Community Type
Indianapolis International Airport - Terminal	7800 Col H. Weir Cook Memorial Dr.	Indianapolis	IN	46241	DCFC	Urban
I&M Eastbound – George N Craig Travel Plaza	2971 Moose Trl Dr	Elkhart	IN	46514	DCFC	Urban
Target – Tesla Supercharger	8005 Calumet Ave	Munster	IN	46321	DCFC	Suburban
Dorsett Hyundai Mitsubishi	74 W Springhill Dr	Terre Haute	IN	47802	DCFC	Suburban
Napleton Nissan – Schererville	1301 Indianapolis Blvd	Schererville	IN	46375	DCFC	Suburban
John Jones Cadillac of Salem	1450 S ST RD 60	Salem	IN	47167	DCFC	Town
Hard Rock Casino	5400 W 29th Ave	Gary	IN	46406	DCFC	Suburban
Ford Charge – Ruxer Ford	123 Place Rd	Jasper	IN	47546	DCFC	Town
Meijer 131 (Indianapolis, IN)	11351 E Washington St	Indianapolis	IN	46229	DCFC	Suburban
Chase Bank – Thatcher Lane	14801 Thatcher Ln	Carmel	IN	46032	DCFC	Suburban

B.3. Vehicle Miles Traveled by EVs

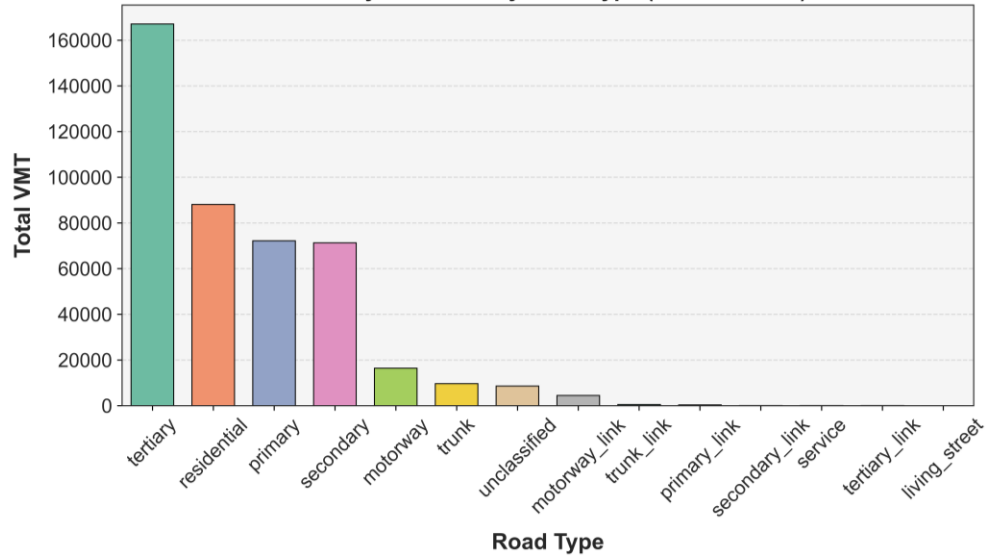


Figure B.12 One-Day Total VMT by Road Types (Baseline Data).

B.4. Revenue From Charging Stations

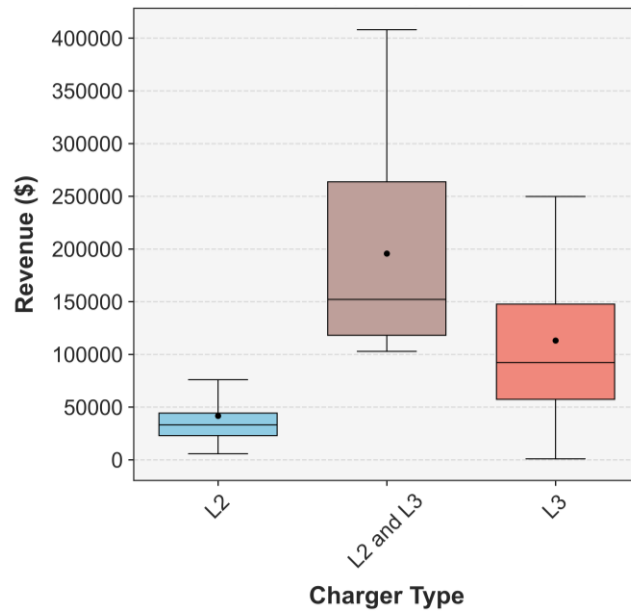


Figure B.13 Revenue's Boxplot Across Charger Types (Baseline Data).

B.5. Economic Development Impact

Table B.3
EVCS Equipment Expenses.

	L2: Public	DCFC 50 kW: Public
Cable cooling	\$0	\$0
Charger	\$4,900	\$27,900
Conduit and Cables	\$20	\$25
Trenching and Boring	\$80	\$80
On-site Electrical Storage	\$0	\$332,800
Safety and Traffic Control	\$1,000	\$3,000
Load Center/Panels	\$10	\$40
Transformers	\$16,447	\$37,865
Meters	\$2000	\$2,000
Miscellaneous (mounting hardware, etc.)	\$1000	\$2,000

Table B.4
EVCS Development Cost.

	L2: Public	DCFC 50 kW: Public
Equipment Installation	\$16,412	\$145,044
Site Preparation and Construction	\$5,197	\$45,931
Electrical Infrastructure and Make Ready	\$16,412	\$145,044
Engineering and Design	\$10,668	\$94,279
Permitting	\$1,641	\$14,504
Contingencies	\$2,735	\$24,174

About the Joint Transportation Research Program (JTRP)

On March 11, 1937, the Indiana Legislature passed an act which authorized the Indiana State Highway Commission to cooperate with and assist Purdue University in developing the best methods of improving and maintaining the highways of the state and the respective counties thereof. That collaborative effort was called the Joint Highway Research Project (JHRP). In 1997 the collaborative venture was renamed as the Joint Transportation Research Program (JTRP) to reflect the state and national efforts to integrate the management and operation of various transportation modes.

The first studies of JHRP were concerned with Test Road No. 1 — evaluation of the weathering characteristics of stabilized materials. After World War II, the JHRP program grew substantially and was regularly producing technical reports. Over 1,600 technical reports are now available, published as part of the JHRP and subsequently JTRP collaborative venture between Purdue University and what is now the Indiana Department of Transportation.

Free online access to all reports is provided through a unique collaboration between JTRP and Purdue Libraries. These are available at docs.lib.purdue.edu/jtrp/.

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