



## **EV Charging Infrastructure Study**

August 2025

Prepared for:

Michigan Office of Future Mobility & Electrification  
Michigan Department of Labor & Economic Opportunity

Prepared by:

Michigan State University  
Principal Investigator: Dr. Mehrnaz Ghamami  
Associate Professor Civil and Environmental Engineering  
428 S. Shaw Lane, East Lansing, MI 48824  
Phone: (517) 355-1288, Fax: (517) 432-1827  
Email: [ghamamim@msu.edu](mailto:ghamamim@msu.edu)

Authors:

Dr. Mehrnaz Ghamami  
Dr. Ali Zockaie  
Sajjad Vosoughinia  
Amirali Soltanpour



**MICHIGAN STATE**  

---

**U N I V E R S I T Y**

## Acknowledgement

The researchers at Michigan State University gratefully acknowledge the Michigan Office of Future Mobility & Electrification (OFME) and Michigan Department of Labor and Economic Opportunity (LEO) for sponsoring this research, recognizing the importance and timeliness of the topic, and supporting this innovative approach to electric vehicle charging infrastructure planning. We extend our sincere thanks to the OFME team, especially Shafiq Bari, for facilitating stakeholder meetings, which provided critical information for our analysis. Finally, we deeply appreciate the many stakeholders listed below for their active engagement, willingness to share data and insights, and their valued collaboration throughout this effort.

- Michigan Office of Future Mobility & Electrification (OFME)
- Michigan Department of Labor and Economic Opportunity (LEO)
- Michigan Department of Transportation (MDOT)
- Michigan Public Service Commission (MPSC)
- Utility Companies
  - Consumers Energy
  - DTE Energy
  - Indiana Michigan Power Company
- Cities and Communities
  - Southeast Michigan Council of Government (SEMCOG)
  - City of Detroit
- Auto Companies
- Charging Stations Companies

# Table of Contents

<b>ACKNOWLEDGEMENT.....</b>	<b>2</b>
<b>EXECUTIVE SUMMARY .....</b>	<b>5</b>
<b>INTRODUCTION.....</b>	<b>7</b>
<b>PROBLEM STATEMENT .....</b>	<b>7</b>
<b>LITERATURE REVIEW .....</b>	<b>8</b>
Charging Infrastructure Specifications .....	8
Charging Station Location .....	8
Electrification Efforts in Other States .....	10
<b>DATA COLLECTION .....</b>	<b>12</b>
Origin-Destination Travel Demand and Michigan Road Network .....	12
Seasonal Travel Variation and Monthly Demand Estimation.....	13
Charging Station and Charger Costs .....	14
Utility Provision Costs .....	14
Vehicle and User Characteristics .....	16
Battery Range and Performance Variation .....	16
Electric Vehicle Market Share .....	16
Land Use Information .....	17
Tourism Destinations .....	17
<b>INTERCITY CHARGING INFRASTRUCTURE .....</b>	<b>18</b>
Problem Statement .....	18
Analysis Framework .....	19
Model Objective Function .....	19
Solution Approach .....	21
Demand-Related Adjustments .....	21
<i>Seasonal Variation in Demand</i> .....	21
<i>Demand Fluctuations</i> .....	21
Battery Charge Assumptions .....	21
<i>Interior Node Assumptions</i> .....	21
<i>Border Node Assumptions</i> .....	22
Location and Number of Intercity Chargers .....	22
Seasonal Variations.....	22
Optimized Results for Charging Station Placement and Charger Numbers.....	22
<b>TOURISM CHARGING INFRASTRUCTURE.....</b>	<b>24</b>
Problem Statement.....	25
Solution Approach .....	25
Tourism Destination Trip Forecast .....	26
Origin-Destination Analysis .....	27
EV and Charging Demand Estimation .....	27
Charger Optimization.....	28
Location and Number of Tourism Destination Chargers .....	29
<b>URBAN AREA CHARGING INFRASTRUCTURE .....</b>	<b>31</b>
City Selection.....	31
Level 2 Chargers .....	32
Problem Statement.....	32

Analysis Framework .....	32
Location and Number of Level 2 Chargers in Urban Areas.....	33
DCFC Stations .....	34
Problem Statement.....	34
Analysis Framework .....	35
<i>Traffic Simulation</i> .....	36
<i>State of Charge Simulator</i> .....	38
<i>Optimization Model</i> .....	39
Solution Approach .....	40
Location and Number of DCFC in Urban Areas .....	41
Interconnection of Intercity and Destination Charging for Tourism.....	45
Interconnection of Level 2 and DCFC in Urban Areas.....	46
<b>CONCLUSION .....</b>	<b>47</b>
<b>REFERENCE .....</b>	<b>49</b>

## Executive Summary

The State of Michigan is committed to developing a robust charging infrastructure to enable seamless Electric Vehicle (EV<sup>1</sup>) travel across Michigan. This study analyzes intercity, urban, and tourism trips to assess energy demand at various locations for Direct Current Fast Chargers (DCFC) and Level 2 chargers. To identify the optimum EV charger needs across the state, the Michigan Office of Future Mobility and Electrification (OFME), launched this analytical study guided by stakeholder input. Researchers at Michigan State University (MSU) were engaged to determine the optimal number and locations for both DCFCs and Level 2 chargers while minimizing investment costs and user delays. This report presents the results of a strategic plan to expand EV charging infrastructure in Michigan to support light-duty vehicle travel under a 25% EV market share scenario<sup>2</sup>. The plan aims to support EV travel across a wide range of trip types, including daily urban travel, tourism-related trips, and long-distance journeys, both within Michigan and between Michigan, neighboring states, and Canada in both directions. Table 1 below summarizes the total EV chargers needed in the state.

Table 1: Estimated charger requirements and associated costs (based on a 25% EV market share scenario<sup>2</sup>)

	Number of new required chargers		
	DCFC	Level 2	Total
Intercity	1,724	-	1,724
Tourism	-	6,167	6,167
Urban	4,791	53,920	58,711
Total	6,515	60,087	66,602
Total estimated infrastructure cost	\$677 M	\$321 M	\$998 M

It is estimated that approximately 1,724 new DCFC chargers are required along major highways in Michigan to meet the projected demand. These chargers will support intercity travel, tourism-related trips, and the unserved charging demand from tourism destinations where users may detour to nearby DCFC stations. In addition, an estimated 6,167 Level 2 chargers are needed at tourism destinations where visitors typically stay for extended periods. The number of Level 2 chargers at these destinations is closely linked to the required number of intercity DCFC chargers; fewer Level 2 chargers result in a larger portion of charging demand being redirected to nearby DCFC stations, ultimately increasing the need for additional DCFC infrastructure.

Urban Level 2 charging at residential locations plays a critical role in reducing the overall energy demand for DC fast charging by enabling routine, overnight charging. However, DCFC remains essential in cases where residential chargers are unavailable, charging time at home is insufficient, or users neglect to plug in their vehicles. In Michigan, approximately 80% of residents live in single-family homes (1), suggesting that the majority of residential charging will likely occur at these single-family residences. It is estimated that 90% of single-family homes and 50% of multi-family residences will need access to home charging. Additionally, a winter scenario is considered, as urban travel patterns remain relatively stable across seasons. However, colder temperatures reduce battery efficiency, increasing the energy demand for chargers. For urban trips, it is estimated that 4,791 DCFC chargers will be needed in major urban areas across Michigan to support daily travel, along with 53,920 Level 2 chargers at multi-family housing units. Additionally, approximately 855,243 new Level 2 chargers are projected to be required at single-family

<sup>1</sup> In this study, the term 'EV' specifically refers to Battery Electric Vehicles (BEVs).

<sup>2</sup> The 25% market share represents the share of electric vehicles in all vehicles in operation.

homes. However, since home charging is generally considered private property, these chargers are excluded in the summary tables and associated infrastructure investment costs. It's important to note that the required number of DCFC and Level 2 chargers are closely interconnected. Greater availability of Level 2 chargers at trip origins and destinations increases the likelihood that users will begin their trips with a higher state of charge or finish with a lower one, knowing they can charge at their destination. This reduces the need for en-route DCFC use and subsequently lowers the number of DCFC chargers required.

The total infrastructure cost to support all EV trips based on 25% market share in Michigan is estimated at \$998 million, including \$677 million for DC fast chargers and \$321 million for Level 2 chargers. These costs include the cost of chargers as well as associated expenses such as grid infrastructure, construction, and land.

Figure 1 present maps of the charging infrastructure needed to support intercity and tourism travel, as well as urban trips across Michigan, under a 25% EV market share.

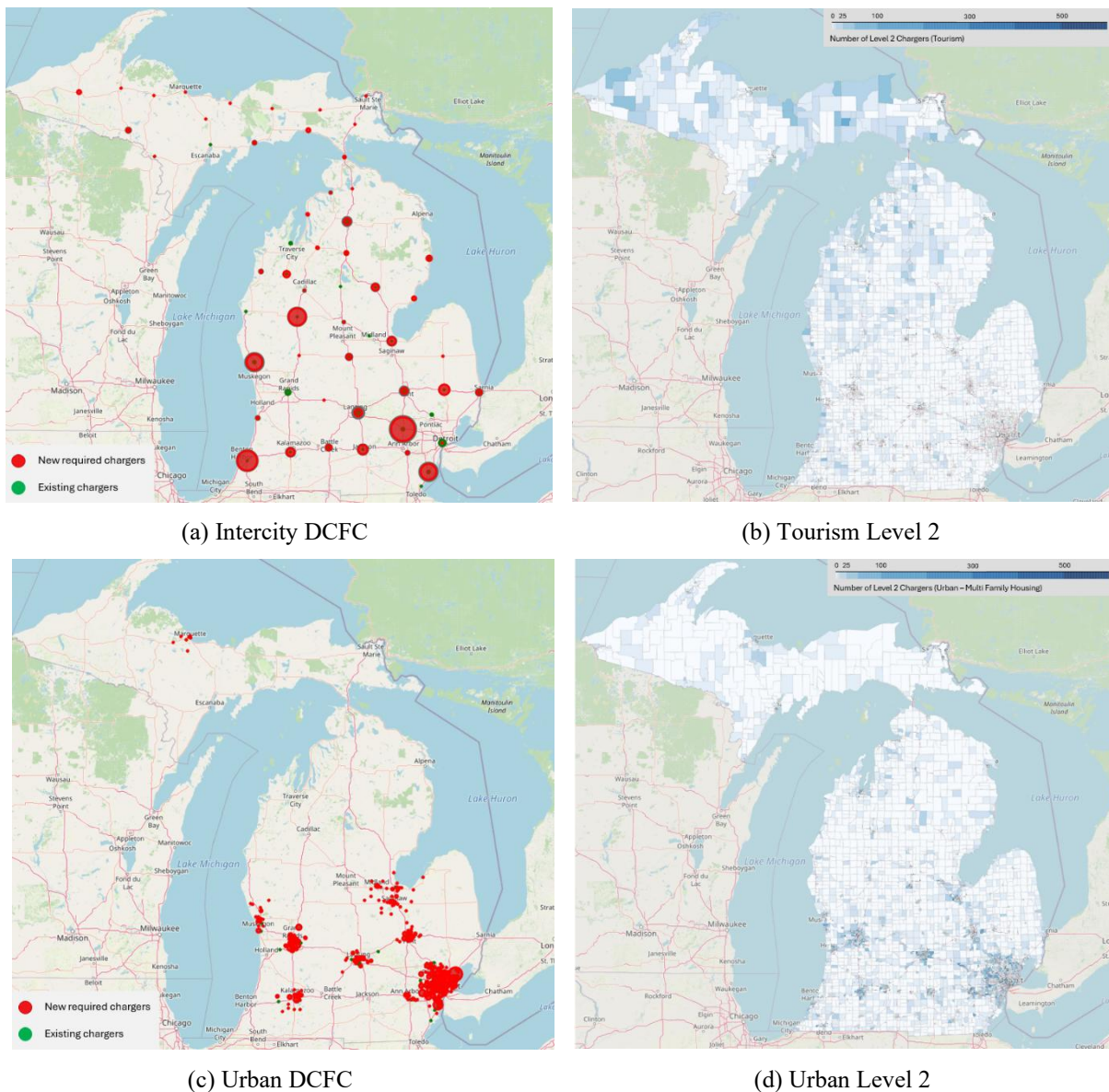


Figure 1: Map of charging infrastructure in Michigan

## Introduction

EV technology offers a critical means of addressing traffic-related air pollution and broader environmental concerns by eliminating on-road emissions. In recent years, EV adoption has grown substantially, largely driven by improved energy efficiency and zero tailpipe emissions. Factors such as fuel costs, purchase prices, and demographic characteristics play a significant role in shaping the market share of alternative fuel vehicles (2, 3). By the end of 2023, EVs and PHEVs<sup>1</sup> made up 0.76% of vehicles in Michigan, compared to 4.85% in California and 1.52% nationwide. Meanwhile, Michigan had 3,133 public chargers, California 42,769, and the United States 159,842 in total, equating to 21, 35, and 27 EVs per charger, respectively (4). The Michigan Future Mobility Plan aspires to accommodate 2 million EVs by 2030, supported by the installation of 100,000 chargers (5). Nonetheless, concerns such as range anxiety, long charging times, and limited charging infrastructure continue to impede widespread EV acceptance (6). Building an extensive EV charging network is essential to overcome these barriers and boost market share, requiring strategic integration of both slow and fast chargers to guarantee trip feasibility, reduce range anxiety, and provide acceptable service levels for EV users (7).

In recent years, EV adoption has become an effective means of advancing sustainability and fostering economic development. Despite these potential gains, many consumers remain hesitant to purchase EVs due to perceived limitations (8). Consequently, it is crucial to examine these constraints from both supplier and user perspectives and develop strategies to overcome them (9). A comprehensive EV charging infrastructure—encompassing residential setups, urban public stations, and facilities for intercity travels plays a pivotal role in supporting sustainable transportation by ensuring convenient, low-impact options. In this report, an EV charging station refers to a specific location where one or more individual chargers or charging ports are installed to replenish an electric vehicle's battery (Figure 2). As EVs continue to gain popularity among users, the strategic placement of charging stations along travel corridors, at tourism hotspots, and in everyday community settings becomes increasingly important for ensuring accessibility and promoting environmental-friendly practices.

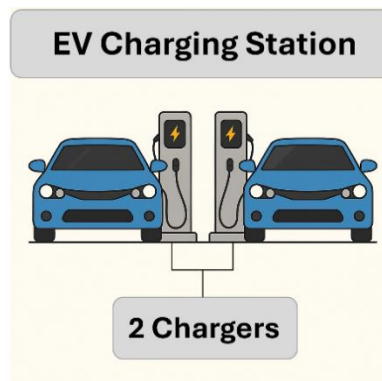


Figure 2: Example of an EV charging station with two chargers.

## Problem Statement

Despite the growing adoption of EVs in Michigan, the state's charging infrastructure remains inadequate to support the ambitious goals set forth in the Michigan Future Mobility Plan, which aims for 2 million EVs and 100,000 chargers by 2030. Limited charging availability, range anxiety, and concerns over charging time continue to hinder widespread EV adoption, requiring a strategic approach to infrastructure deployment. To address these challenges, this study aims to:

- Estimate the number and types of chargers required in the state, considering the projected 25% EV market share on the road and other relevant assumptions.

---

<sup>1</sup> Plug-in Hybrid Electric Vehicles (PHEVs)

- Categorize the charging stations by various accessibility and use case types to ensure efficient and equitable deployment.
- Map the estimated charging station locations by dividing the state into appropriate regions of interest.
- Conduct a comparative analysis of EV infrastructure deployment strategies in other states to identify best practices.
- Assess electric grid capacity and identify gaps that could impact the scalability of EV charging infrastructure.

By integrating data-driven analysis and industry best practices, this study will offer actionable recommendations to enhance Michigan’s EV charging network, supporting a seamless transition to sustainable transportation.

## Literature Review

This section reviews the literature on charging infrastructure specifications, charging station location, and other states’ efforts on electrification to provide context for the current study.

### Charging Infrastructure Specifications

EV charging infrastructure worldwide is generally categorized into three levels, each defined by its voltage and charging duration. Level 1, the slowest option, adds roughly 40 miles of range in about eight hours. By contrast, Level 2—commonly found in both residential and public settings—can deliver around 100 miles in the same timeframe. Level 3, also referred to as DCFC, can restore up to 80% of a battery’s capacity in 30 minutes or less, making it especially suitable for extended trips (10, 11). Although DCFC significantly cuts charging time, it involves higher installation costs and can accelerate battery degradation through increased currents and temperatures. Level 2, on the other hand, is more affordable and places less strain on the battery (12, 13). By combining Level 2 chargers with DCFC stations, a more adaptable and well-rounded charging network can be established to address the diverse needs of EV drivers. Figure 3 illustrates the details of different charger types.

Charger Type	Primary Use	Charging Power	Charger Cost	Charging Time	Charging Price
Level-1	Residential	1.2 – 1.9 kW	\$0.2K - \$1.5K	8 – 16 hours	0.02 – 0.06 \$/mile
Level-2	Residential & Public	2.6 – 19.2 kW	\$0.5K – \$5K	4 – 8 hours	0.02 – 0.06 \$/mile
Level-3 DCFC	Public	50 – 350 kW	\$28K - \$140K	20 – 30 minutes (80%charge)	0.12 – 0.25 \$/mile

Figure 3: Summary of charging infrastructure specifications<sup>1</sup>

### Charging Station Location

The increasing adoption of EVs is essential for reducing vehicle emissions and mitigating air pollution (14, 15). However, EV adoption faces significant challenges due to limited range, insufficient charging infrastructure, and long charging times compared to conventional vehicles (14, 16). Range anxiety, particularly during long-distance travel, further hinders widespread EV use (17, 18). DCFC stations offer a solution by substantially shortening charging times, facilitating longer trips and encouraging broader EV

<sup>1</sup> The charger costs shown in the table represent average estimated values based on data from various companies across the U.S.



adoption. Nevertheless, these fast charging stations have higher implementation and operational costs than slower chargers (19, 20), making efficient infrastructure planning critical.

Many studies have focused on optimizing the allocation of EV charging stations while balancing total costs and level of service. Lee and Han (21) employed a flow refueling location model (FRLM) that considered probabilistic EV travel ranges due to variable traffic and weather conditions, indirectly factoring in station waiting times. Guo et al. (22) proposed a network-based optimization framework for competitive environments, highlighting investor and user interactions and recommending it for future market impact studies on public charging infrastructure. Nie and Ghamami (16) presented an optimization model exploring EV travel along corridors, emphasizing the trade-off between investments in charging stations and larger battery sizes for intercity travel, concluding that DC fast charging stations are essential. Ghamami et al. (23) further extended this model to minimize the total system costs, including infrastructure, battery, and user costs.

Micari et al. (24) developed a bi-level optimization model addressing EV charging infrastructure sizing and siting, incorporating EV demand, battery, and charging technology considerations. Similarly, Zang et al. (25) proposed another bi-level framework using queuing theory and metaheuristic algorithms, considering slow public charging infrastructure's impact on EV user travel patterns, social costs, and satisfaction.

Routing problems due to limited EV ranges have also been investigated, focusing on route selection considering EV constraints (26). User equilibrium models, reflecting realistic selfish travel behavior and leveraging modern routing technologies, have been applied extensively to intercity networks (27–30), building upon Wardrop's (31) foundational concepts.

Technological advancements in battery capacities and charging rates significantly influence EV infrastructure needs. A Washington State study using data from conventional gasoline vehicles forecasted future EV charger demand and power requirements (32). Another U.S.-wide study utilized genetic algorithms for long-term DC fast charging station planning over a 15-year horizon, examining sensitivity to battery sizes and charging times (33). He et al. (34) investigated the entire U.S. network for EV charger placement, noting significant impacts of vehicle ranges on required charging infrastructure. Another study calibrated queuing models based on Swedish and Norwegian charging behaviors, finding substantial reductions in charging events as vehicle ranges increased from 62.5 miles to 125 miles, beyond which additional increases had minimal impact (20).

For urban charging infrastructure, data-driven studies leveraged various datasets to optimize charging station locations. Andrews et al. (35) utilized metropolitan travel survey data, while Dong et al. (15) applied activity-based models to household travel data. Taxi trajectory data has been extensively employed to identify hotspots for charging stations, maximizing electric vehicle miles traveled (36–38) and minimizing infrastructure investment costs (39). Workplace EV charging demands were also considered in optimization models minimizing infrastructure costs (40).

Origin-Destination (OD) models have been instrumental in capturing travel behaviors for charging infrastructure allocation. Several studies modeled travel patterns independently of infrastructure presence (41–47), while others considered infrastructure impacts explicitly (14, 29, 48–50). Large-scale urban networks pose computational challenges, leading many researchers to adopt fixed travel patterns for practicality.

While traditionally urban EV trips have received less attention due to shorter travel distances, recent studies have increasingly recognized their importance (51, 52). Baouche et al. (52) used travel surveys, and Kang and Recker (53), alongside Nie et al. (54), adopted activity-based approaches for charging station locations.

Tourism often involves long-distance travel and extended stays, requiring tailored EV charging infrastructure planning. Proper planning can reduce costs for both providers and users, and influences EV users' itinerary (55). An effective approach to planning chargers for EV tourism combines DCFCs for intermediate charging during long-distance trips with Level 2 chargers at tourist destinations, where visitors stay longer. Thus, an integrated framework is needed to optimize the placement and capacity of both Level 2 chargers and DCFCs within tourist regions.

Research on EV tourism is still emerging. Wang and Lin (56) used set- and maximum-coverage models with mixed integer programming to locate chargers based on vehicle refueling patterns, applying their approach to Penghu Island and considering tourist sites for Level 2 chargers. Wang et al. (57) addressed tourist trip design for EVs, factoring in time windows and range constraints. Suanpang et al. (58) employed reinforcement learning for EV-charging recommendations, using Chiang Mai, Thailand, as a smart tourism city case study. Xu et al. (59) developed a model for selecting EV charging station sites using kernel density analysis of urban populations, including tourist areas, to maximize EV user satisfaction. Knowles et al. (60) created an EV readiness index assessing 94 road trip itineraries related to Canada's national parks.

Optimizing charging infrastructure requires balancing different objectives, such as minimizing investment costs (39, 61–63), access times (64), or urban travel times (65). Studies aiming to minimize total system costs, considering infrastructure investments and user delays, provide a balanced approach (29, 66–69).

## Electrification Efforts in Other States

A key component of this research is examining how other states have approached similar initiatives. Our focus includes neighboring states such as Illinois, Indiana, Ohio, and Wisconsin, as well as states recognized for their proactive or well-funded efforts in EV planning, including California, Washington, Massachusetts, Texas, and Florida. Table 2 provides a summary of these states and their approaches.

Table 2: EV charging station regulations by state

State	NEVI <sup>1</sup> /Intercity	Residential	Workplace	Tourism	Utility Involvement
Illinois	One at minimum, every 50 miles along designated EV corridors in Illinois.	One EV capable parking spot for each residential unit that has a designated parking space.	Nothing specific statewide.	Lake Michigan Electric Vehicle creates an EV charging corridor along Lake Michigan coastline.	ComEd installs new charging stations on Chicago's south side, Ameren Illinois is working to grow EV charging by modernizing the electric grid to accommodate for new chargers.
Indiana	---	There are no ordinances for the state, some utility companies have incentives for installing EV chargers in your homes.	There are no ordinances for the state, some utility companies have incentives for installing EV chargers for the workplace.	Lake Michigan Electric Vehicle creates an EV charging corridor along Lake Michigan coastline.	Duke Energy, Northern Indiana Public Service Company, and other large Indiana utility companies are engaged in NEVI.
Ohio	At least one station every 50 miles along 1,854 miles of Ohio's Alternative Fuel Corridors.	There are no statewide ordinances, City of Columbus, Tallmadge, and Painesville have ordinances based on the number of dwelling units.	There are no statewide ordinances, City of Columbus, Tallmadge, and Painesville have ordinances for the workplace.	The installation of chargers every 50 miles will support tourist journey through Ohio.	AEP Ohio has an electric vehicle charging station rebate program, and other smaller utility companies have incentives for installing EV chargers.

<sup>1</sup> National Electric Vehicle Infrastructure (NEVI)

State	NEVI <sup>1</sup> /Intercity	Residential	Workplace	Tourism	Utility Involvement
Wisconsin	At least one station every 50 miles along Wisconsin's Alternative Fuel Corridors.	Local government cannot require a private developer to install EV chargers.	A uniform statewide commercial building code and prohibits municipalities from adopting or enforcing their own standards.	Lake Michigan Electric Vehicle creates an EV charging corridor along Lake Michigan coastline.	Wisconsin Public Service helps residents with the cost of installing their own EV chargers.
Massachusetts	The completeness of major highway corridors with EV chargers, financially self-sustaining charging stations, stations will be readily available to travelers for long distances.	Requires at least 1 space per home or a minimum of 10% of spaces in a new multi-family parking lot be provided with electric wiring to allow for future EV charging.	At least one parking space in any new commercial construction with over 15 parking spaces must be made-ready for EV chargers.	The Massachusetts Electric Vehicle Incentive Program (MassEVIP) provides grants for 60% of the cost of Level 1 or Level 2 EV chargers, up to \$50,000 per street address.	Eversource, National Grid, and Unitil each offer programs that support EV charger deployment by providing make-ready distribution infrastructure and customer rebates.
Washington	At least one station every 50 miles along Washington's Alternative Fuel Corridors.	10% of new build parking spaces reserved for EV charging, and 20% need to be charger station ready.	10% of new build parking spaces reserved for EV charging, and 20% need to be charger station ready.	A percentage of total parking spaces need EV charging stations, EV ready parking spaces, and EV capable parking spaces based on occupancy of new construction buildings.	Tri-City Development brings public EV charging stations to under served corridors. Utility Electrification requirements, by January 1, 2027, large combination utilities will be required to file an integrated system plan with the Utilities and Transportation Commission that details the utility's plans for reaching required targets for gas decarbonization and electrification.
California	Establish standards for charger operators to inform customers about the availability and accessibility of public EV charging infrastructure.	40% of parking spaces must be capable of supporting a low-power Level 2 EV charger.	For public parking facilities, minimum EV charger pre-wiring installation requirements are based on the number of parking spaces, per parking facility.	Assembly Bill 1236 and Assembly Bill 970 (2021) mandate that cities and counties adopt ordinances to expedite the permitting process for EV charging stations.	Southern California Edison is committed to expanding access to public charging through various programs over the next several years. San Diego Gas & Electric along with other investor-owned utilities, received approval from the California Public Utilities Commission for a total of \$54.5 million to install up to 800 charging ports at parks, beaches, and schools.

State	NEVI <sup>1</sup> /Intercity	Residential	Workplace	Tourism	Utility Involvement
Florida	NEVI funds will aim to close network gaps by improving connection to DCFC sites.	Local governments may not enact or enforce ordinances or regulations relating to EV chargers.	There are no ordinances in place for EV chargers for workplace buildings, additionally local governments may not enact or enforce ordinances or regulations relating to EV chargers.	Florida Department of Transportation (FDOT) developed the Electric Vehicle Infrastructure Master Plan to establish a comprehensive network of EV charging stations along the State Highway System.	Florida Power & Light is building an 800+ mile stretch of fast charging stations. Duke Energy Florida offers programs for residential charging to receive credits for charging during off-peak hours. Tampa Electric Company Drive Smart Program is a pilot initiative aimed at expanding EV charging infrastructure for business customers.
Texas	NEVI's expansion plan focuses on providing charging stations in both urban and rural locations, with an emphasis on making travel easier for EV drivers traveling between cities.	City of Dallas found EV charging at multi-family residences a challenge and initiated a campaign to educate owners.	EV charging stations in workplace buildings is primarily governed by local building codes and regulations, which can vary by city or county.	Texas has been working to install charging stations at state parks. This initiative allows tourists to enjoy outdoor activities without concerns about vehicle charging.	Austin Energy offers home rebates up to \$1,200 (Home EV Charger Rebate) and \$5,000 for businesses (Charging, Incentives and Resources) to install EV chargers. CPS Energy provides the FlexEV Rewards programs, offering rebates to EV owners who charge their vehicles at home.

## Data Collection

Data is one of the vital components of any research project, serving as the foundation for analysis and decision-making. This section explains the different data used in this study and their sources.

### Origin-Destination Travel Demand and Michigan Road Network

The Michigan road network was provided to the research team by the Michigan Department of transportation (MDOT) in TransCAD format and includes 37,125 links and 16,976 nodes. The links comprise 11,516 freeways or highways, 20,742 arterials, and 4,867 ramps, while the nodes include 4,237 signalized intersections.

Additionally, MDOT supplied OD travel demand data, which is derived from periodic travel surveys. These survey results serve as inputs for MDOT's travel planning models, generating a travel demand table for approximately 3,000 traffic analysis zones (TAZs) for a typical weekday in the fall. Figure 4 illustrates the Michigan road network and TAZ.

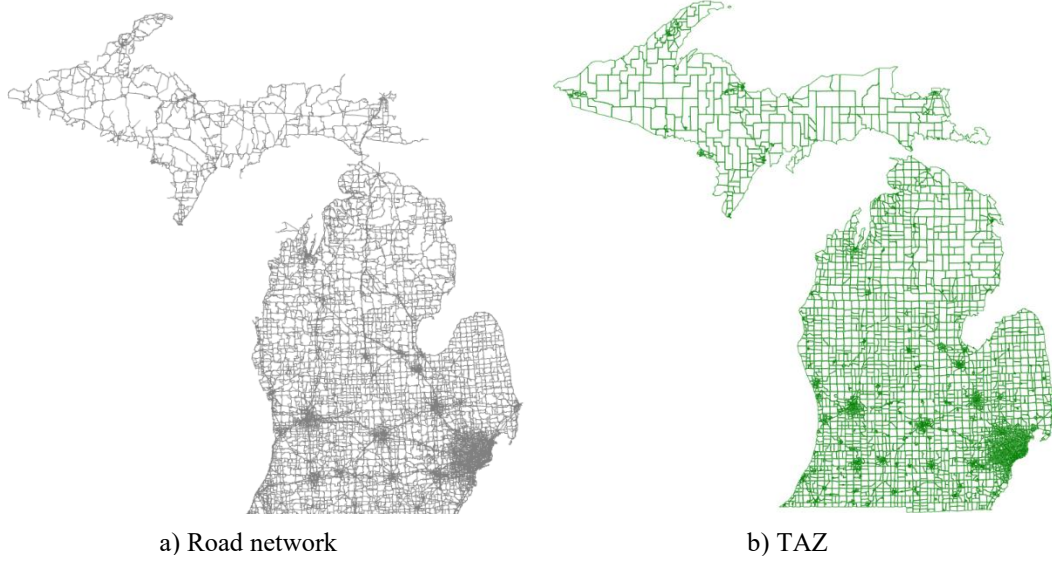


Figure 4: State-wide Michigan network

### Seasonal Travel Variation and Monthly Demand Estimation

Continuous vehicle counts (24/7) are available from 122 counting stations provided by MDOT. These counts help estimate travel demand while accounting for fluctuations in traffic patterns throughout the year. The travel demand for each OD pair is derived based on these variations, ensuring it accurately represents existing travel demand conditions. These estimates serve as inputs for the charging location model, helping evaluate the adequacy of proposed charging station placements and the number of chargers. To achieve this, Continuous Counting Station (CCS) data from Michigan roads is utilized as a priori information, under the assumption that a proportional relationship exists between traffic counts and OD demands.

A heuristic method is developed to estimate monthly travel demands by incorporating data from CCSs. This approach relies on monthly factors derived from each counting station, representing the proportion of annual travel demand allocated to each month. These factors serve as the primary input for the estimation process. OD base demands are used as reference values, which are multiplied by the corresponding monthly factors to determine the monthly travel demand for each OD pair. The estimation process consists of multiple steps: calculating an average monthly factor for each link with at least one detector, determining the share of OD pair travel demand traveling on each link, identifying OD pairs without assigned CCSs and allocating adjacent count stations to them, and finally, estimating monthly factors for all OD pairs in the network.

Since multiple counting stations may be present on a single link in the network, an average value of the monthly factors ( $f_i^m$ ) is calculated to represent the traffic pattern of link  $i$  for each month  $m$ . No factor is assigned to links without any detectors. Additionally, the share of OD base travel demands for each link is determined using a traffic assignment approach. In this process, OD base travel demands serve as input to the traffic assignment model, and the proportion of each OD travel demand that utilizes a specific link is denoted as  $p_i^{OD}$ , where  $i$  represents the link number and  $OD$  represents an origin-destination pair. Once the set of paths for each OD pair is established, it must be verified that all OD pairs have at least one counting station along their route to serve as an estimation factor. If an OD pair lacks a direct counting station, detectors located on links leading to the origin or departing from the destination are used as an alternative estimation factor. Finally, monthly factors are estimated by incorporating the demand share of each link and the average factors of the links, as described in the equation below.

$$\text{Monthly Factor}_{OD}^m = \frac{\sum_{i \in k_{OD}} f_i^m p_i^{OD}}{\sum_{i \in k_{OD}} p_i^{OD}} \quad (1)$$

where  $k_{OD}$  represents the set of all links that carry a positive share of travel demand for the origin-destination pair,  $OD$ , as determined by the traffic assignment model using the base travel demand as an input.

## Charging Station and Charger Costs

The costs associated with charging stations and chargers were sourced from various charging infrastructure providers, including Greenlots, ChargePoint, Ford Pro, RED-E, and Consumers Energy. Charger cost refers to the expense associated with purchasing each individual EV charging unit. This cost varies depending on the charger type (e.g., Level 2 or DCFC), power capacity, and manufacturer specifications. Charging station costs encompass a broader range of expenditures, including electrical panel and switchgear installation, engineering and design, permitting, and project management. Utility provision costs for each candidate location<sup>1</sup>, which are further detailed in the following subsection, were obtained from utility providers. Additional details regarding the necessary grid upgrades are provided in the following section. Table 3 presents the details of charging station and charger costs for each charger level.

Table 3: Estimated charging station installation and charger costs used in this study

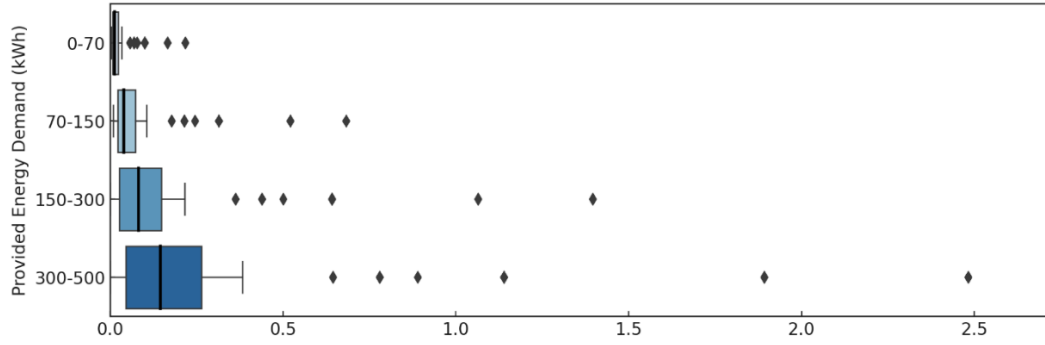
	DCFC		Level 2	
	Installation	Charger	Installation	Charger
<b>Min</b>	\$55,881.00	\$58,131.50	\$3,158.61	\$2,668.33
<b>Max</b>	\$80,125.00	\$76,249.50	\$5,465.00	\$4,443.23
<b>Ave.</b>	\$69,032.74	\$71,407.63	\$4,311.80	\$3,555.78
<b>Std. Dev.</b>	\$11,187.44	\$7,681.93	\$1,153.19	\$887.45

## Utility Provision Costs

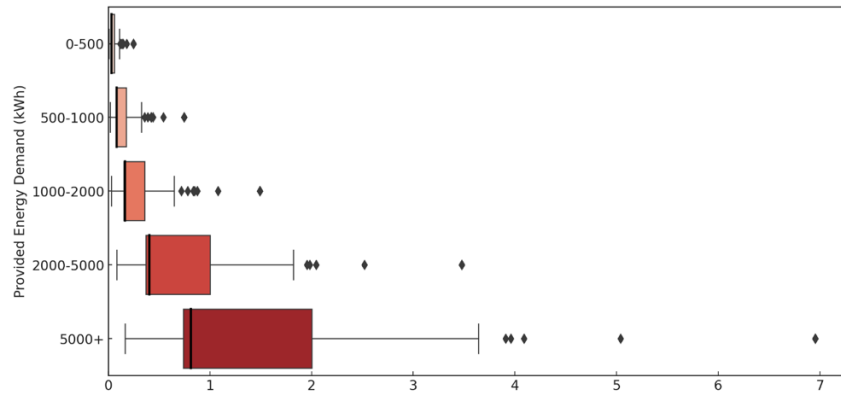
The state of Michigan is divided into multiple regions, each managed by different utility providers, including Investor-Owned, Cooperative, and Municipal Utilities, that have supplied cost estimates for delivering electricity at specific power levels to designated charging locations. Five distinct energy levels were evaluated separately for Level 2 and DCFC stations. These utility costs account for expenses related to acquiring, installing, and maintaining the necessary power grid infrastructure to meet different levels of energy demand at charging stations.

Utility costs exhibited significant variation due to differences in grid conditions and land development, ranging from rural landscapes to densely populated urban centers. While some locations maintained stable costs across all energy levels, others experienced sharp cost increases as the energy demand grew, often due to required grid capacity expansions or technological upgrades. To capture this variability, the study developed a step function that models utility costs across different hourly energy demand ranges. Figure 5 illustrates the distribution of these costs for each energy level.

<sup>1</sup> Candidate locations refer to potential sites for installing charging stations.



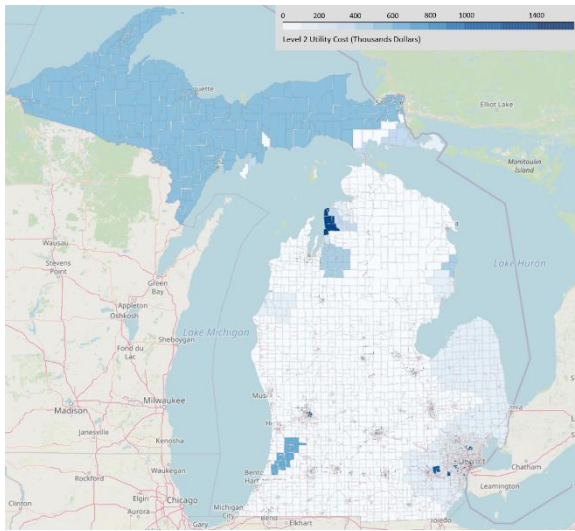
(a) Utility cost for Level 2 (million \$)



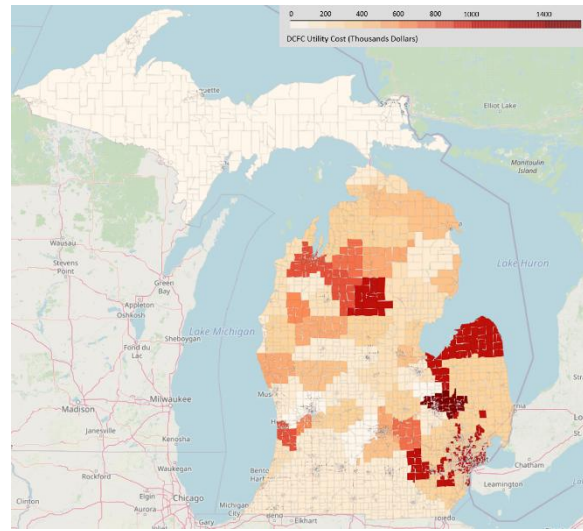
(b) Utility cost for DCFC (million \$)

Figure 5: Utility cost distribution across various energy demand levels

Figure 6 illustrates the average utility upgrade costs for Level 2 chargers and DCFCs across TAZs. In cases where utility provision cost data is unavailable for a specific TAZ, the estimated cost from the nearest available TAZ is assigned to ensure a comprehensive cost assessment. Figure 7 shows the hosting capacity maps of Consumers Energy and DTE Energy, two major utility providers in Michigan.

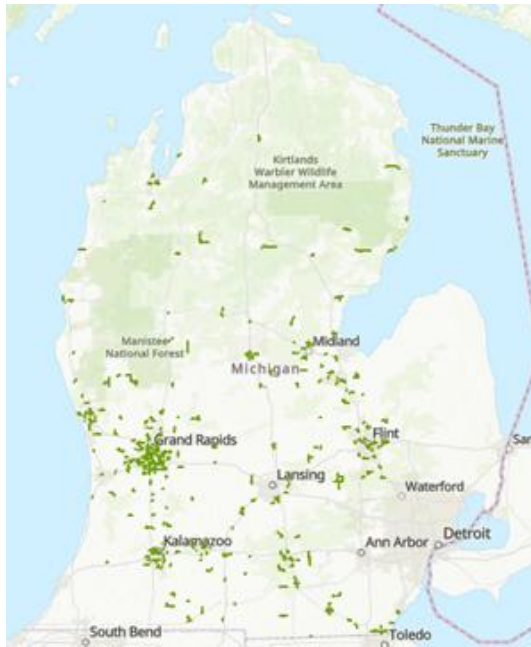


(a) Level 2



(b) DCFC

Figure 6: Average utility cost distribution across Michigan



a) Consumers Energy (2025 update)



b) DTE (2023 update)

Figure 7: Hosting capacity maps

## Vehicle and User Characteristics

To effectively meet the projected growth in EV travel demand, this study considers a range of key factors, including vehicle battery range, performance variations under different weather conditions, and the anticipated evolving EV market share. Designing a robust and efficient charging infrastructure requires a thorough understanding of both vehicle capabilities and user characteristics. Since the primary goal of the system is to support drivers in operating their EVs reliably and conveniently, careful consideration of these factors is essential. The following subsections provide a detailed breakdown of each of these elements and their implications for charging system design.

### Battery Range and Performance Variation

The battery size assumption in this study is set at 70 kWh, based on stakeholder feedback from major automobile manufacturers. While a variety of battery capacities exist in the market and are expected to expand in the future, the average recommended battery size by auto manufacturers is 70 kWh.

Battery efficiency is also expected to improve over time. Stakeholders suggested an average battery performance of 3.5 miles/kWh in summer. However, temperature fluctuations will continue to impact battery efficiency. For this study, winter battery performance is assumed to be 70% of summer performance (70). Consequently, an EV with a 70 kWh battery is expected to have a range of 137–196 miles, depending on the season. These estimates assume that users utilize only up to 80% of battery capacity before recharging and that they charge up to 80% at public charging stations.

### Electric Vehicle Market Share

The adoption rate of EVs has steadily increased over the past decade. Based on stakeholder feedback and market projections, Michigan's EV market share is expected to reach 25% by 2030 (71). Stakeholders, including automobile manufacturers and transportation agencies, anticipate continued growth in EV adoption, influenced by advancements in technology, policy incentives, and infrastructure development.

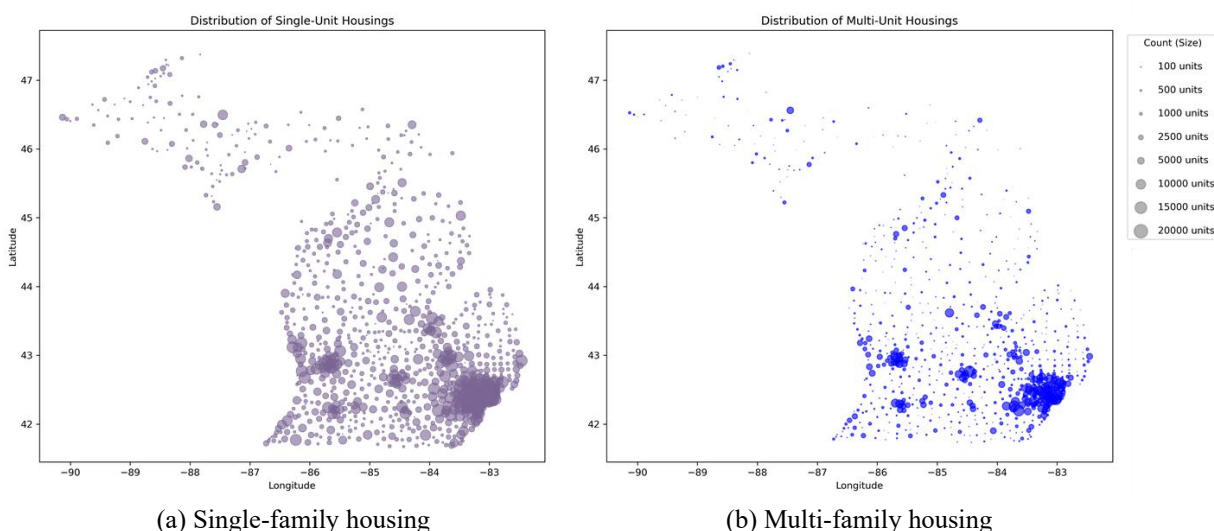


## Land Use Information

Land use data has played a crucial role in various aspects of this project, including estimating the initial State of Charge (SoC) and planning for residential charging infrastructure.

The initial SoC is influenced by users' access to available chargers, which is strongly tied to land-use. To assess this relationship, land-use data was collected from both MDOT and various cities and communities. In cases of discrepancies between sources, local city or community data was prioritized over MDOT data to ensure higher accuracy. The land-use categories considered in this study include residential (single- and multi-family), industrial, and commercial.

For urban residential charging infrastructure planning, information on the distribution of single-family housing (SFH) and multi-family housing (MFH) units was gathered from the American Community Survey (ACS) database (1). Figure 8 illustrates the SFH and MFH distribution across Michigan, where more than 3 million SFH units and over 800,000 MFH units are recorded. Both housing types exhibit higher densities in the Lower Peninsula, particularly in major urban areas, highlighting key locations for residential charging infrastructure deployment.



(a) Single-family housing

(b) Multi-family housing

Figure 8: Distribution of single-family and multi-family housing units across Michigan

## Tourism Destinations

One objective of this study is to develop a charging network that supports tourism trips by prioritizing long-term stay locations as potential sites for slower (level 2) EV chargers. These locations, where visitors typically stay for more than six hours, include hotels, motels, and rental cabins. As shown in Figure 9, 5,055 candidate points fall into this category. Destination charging, typically provided through Level 2 chargers, offers several important advantages that make it a valuable component of a comprehensive EV charging strategy. First, it is generally more cost-effective to install and operate compared to high-powered DC fast chargers, making it a practical option for widespread deployment at tourist destinations. Second, by allowing drivers to charge their vehicles while engaged in other activities, it helps alleviate range anxiety by providing convenient access to energy without requiring dedicated charging stops. Finally, slower charging rates are known to reduce the rate of battery degradation, helping to extend battery lifespan and maintain long-term vehicle performance. These benefits make destination charging a strategic complement to fast-charging infrastructure, particularly in urban and tourist destinations.

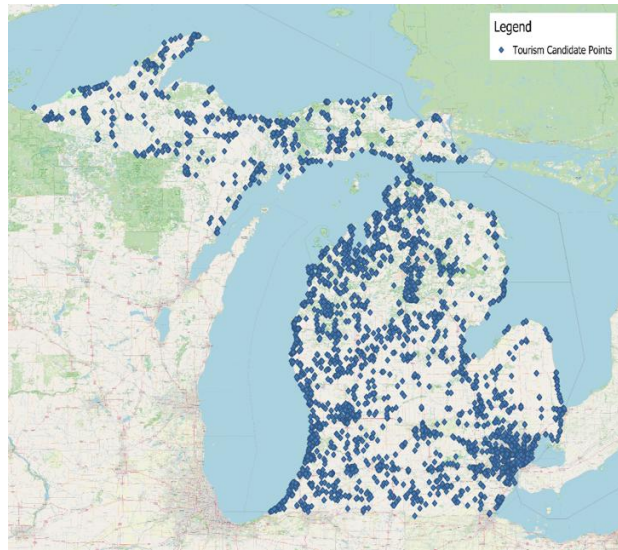


Figure 9: Candidate points for EV chargers supporting tourism

## Intercity Charging Infrastructure

This section outlines the required locations and quantities of DCFCs<sup>1</sup> needed to support intercity travel in Michigan. It begins with the problem statement, followed by the modeling framework, and concludes with results and discussion.

### Problem Statement

With the growing adoption of EVs, ensuring reliable intercity travel remains a challenge due to limited battery range and the uneven distribution of charging infrastructure along major highways. While advancements in battery technology have extended driving ranges, many EVs still require recharging on long trips. Michigan's DCFC network is not uniformly distributed, creating critical gaps that deter long-distance EV travel and contribute to range anxiety, detours, and delays. Without a well-planned charging network, these issues will continue to hinder widespread EV adoption. To address these challenges, a strategic, cost-effective, and timely approach to placing charging stations is essential. Given the involvement of various stakeholders, including transportation agencies and utility companies, and limited resources, an optimization model is necessary to ensure efficient infrastructure deployment. This model must balance investment costs and user convenience, ensuring chargers are placed at optimal locations to minimize travel detours and congestion at charging stations.

This section focuses on identifying the best locations for DC fast charging stations along Michigan highways to enable feasible intercity EV travel. The analyzed trips include both tourism and nondiscretionary intercity travel, such as commuting between home and work or school, essential trips for medical care or family obligations, business-related travel, and everyday utilitarian trips like shopping, errands, or attending appointments. It aims to reduce both total investment costs and various travel delays including detour, queue waiting, and recharging delays. Specifically, it addresses these key questions:

- Where should charging stations be located along Michigan highways to support tourism and intercity EV travel?
- How many chargers should be installed at each station?
- What is the estimated investment cost for developing the proposed infrastructure?

---

<sup>1</sup> This study assumes that DCFCs are available for 14 hours per day.

## Analysis Framework

This study adopts a unique modeling framework that captures travel time variations, while also tracking the state of charge for vehicle groups between different OD pairs. It specifically addresses the limited driving ranges of EVs, ensuring that long-distance trips are feasible through strategically placed en-route infrastructure. At the same time, it minimizes both investment costs and overall travel delays. The framework also differentiates potential locations along major roads based on factors such as land acquisition costs and electric power availability.

Optimizing EV charging station placement across a broader intercity network where multiple corridors intersect and run parallel is a key challenge. A traffic assignment module is integrated with a facility location algorithm to enhance station placement efficiency. The framework also accounts for user preferences such as detour and waiting time through a value of time parameter.

The problem is formulated as a mixed-integer nonlinear programming model. Due to its NP-hard nature, a heuristic bi-level solution algorithm is developed to address computational complexity. Specifically, a Simulated Annealing (SA) algorithm is employed to solve the problem efficiently despite its non-linear constraints.

The mathematical model employs a decision-making framework to strategically allocate a budget for constructing charging stations that support intercity EV travel. It accounts for EVs' limited range by identifying optimal station locations that minimize rerouting delays. Additionally, the model determines the required number of chargers at each station to reduce wait times, ensuring that each charger provides adequate space for both vehicle parking and charger installation.

The model uniquely tracks the state of charge for all EVs by incorporating their spatial trajectories. This approach ensures that charging stations are not placed solely based on high traffic volumes but are also located in areas with a greater need for recharging. Considering both travel trajectories and battery levels, the model identifies optimal sites where EV users actually require battery replenishment. For instance, even though city boundaries experience significant inbound and outbound traffic, they may not be ideal for intercity charging because EVs typically reach a critical charge level only after traveling considerable distances away from these boundaries. Thus, when planning charging station locations, it is essential to consider not only the overall travel volume but also the mix of short-range trips that do not require recharging and long-range trips that do.

To adapt the model for Michigan, several key input parameters needed accurate estimation. Realistic parameters were established with stakeholder input, including charger power and cost, electricity provision cost, EV range, battery performance under adverse weather conditions, intercity travel demand and seasonal variations, and EV market share penetration. Stakeholder data was essential in tailoring the methodology and model to the specific context of Michigan.

## Model Objective Function

The goal is to minimize the overall system cost, comprising both the investment in DC fast charging stations and the travel delays experienced by EV users during recharging. However, because every traveler, including EV drivers, chooses routes solely based on minimizing their own travel time, a user equilibrium must be integrated into the system optimization. In other words, the problem seeks to determine the optimal locations for charging stations within a network where vehicles are trying to minimize their individual travel time (including recharging delays for EVs) and are affected by traffic flows and the placement of chargers.

In this section, we formulate the problem as a mixed-integer program with nonlinear constraints and solve it using a metaheuristic algorithm. The road network consists of a set of links ( $e \in E$ ) and nodes ( $i \in I$ ), which are divided into two main subsets: existing refueling stations ( $N_1^m \subset I$ ) and candidate locations for new refueling stations ( $N_2^m \subset I$ ). The notation ( $m \in M$ ) represents different vehicle classes in the network, including various alternative fuel vehicles (AFVs) such as EVs with specific battery capacities. This modeling framework allows the State of Michigan to analyze other AFV types in the future if needed.

Any node within the set of existing or candidate refueling stations may be visited by users either for refueling or simply as a midpoint along their route. These two scenarios must be distinguished, as they have different effects on the vehicle's fuel state. To address this, two sets of dummy nodes are introduced.

The first set ( $N_1^m$ ) is a duplicate of the existing refueling stations and represents those stations when visited specifically for refueling. The second set ( $N_2^m$ ) is a duplicate of the candidate refueling stations and denotes those stations when used for refueling. If a dummy node ( $N_1^m$  or  $N_2^m$ ) is visited, refueling occurs. Conversely, if only the regular nodes ( $N_1^m$  or  $N_2^m$ ) are visited, they serve solely as travel midpoints.

The objective function below aims to minimize both the investment costs, including chargers, grid infrastructure, construction, and land, and the costs associated with user refueling, detours, and waiting times. Table 4 provides a detailed overview of the model variables.

$$\text{Min} \sum_{m \in M} \sum_{i \in N_2^m} C_p^m x_i^m + U_i^m x_i^m + z_i^m C_s^m + \gamma_t \left( \sum_{i \in N_1^m \cup N_2^m} \pi_i + TT_d \right) \quad (2)$$

Table 4: Intercity model variable description and definitions

Variable	Description	Unit/Value
$C_p^m$	Charging Station Cost	\$/day <sup>1</sup>
$C_s^m$	Charger Cost	\$/day
$U_i^m$	Utility Cost	\$/day
$\gamma_t$	Value of Time	\$/hour
$\pi_i$	Delay time for waiting and refueling at charging stations	hour
$TT_d$	Total Detour Travel Time Required for Refueling	hour
$x_i^m$	Charging Stations Decision Variable	build or not $\in \{0,1\}$
$z_i^m$	Size of a charging station	number of chargers

The objective function comprises two main components. The first component accounts for infrastructure investment costs, including the fixed cost of establishing a charging station at a location, the variable utility cost determined by the number of chargers and power capacity at each site, and the variable cost of chargers (which includes the charger price, construction expenses, and land acquisition costs). The cost of installing charging stations is calculated by multiplying the number of stations by  $C_p^m$  (measured in dollars per station). Similarly, the cost of chargers is determined by multiplying the number of chargers by  $C_s^m$  (measured in dollars per charger). The second component represents the monetary value of the total time spent by users on waiting, refueling at charging stations, and detouring to access a station. The total time is multiplied by  $\gamma_t$ , the value of time, which is assumed to be \$18 per hour (72). The decision variables include whether to establish a charging station at a candidate location and the number of chargers at each station, represented by  $x_i^m$  and  $z_i^m$ , respectively. The total delay consists of two parts: the waiting and refueling time at charging stations  $\pi_i$  and the additional travel time required for detours to reach a charging station  $TT_d$ , which represents the extra time EV users spend on the road to access a charging facility.

The key constraints of this model include:

- **EV Trip Feasibility:** Ensuring that all OD pairs are reachable for EVs while accounting for their limited driving range.
- **Traveler Route and Charging Station Selection:** Capturing user behavior based on the user equilibrium principle, where each traveler chooses routes and charging stations to minimize their own travel time. Given that users' route choices influence the optimal placement of charging infrastructure, and that the location of charging infrastructure, in turn, affects future route decisions.
- **Site Differentiation:** Distinguishing candidate charging station locations based on socioeconomic factors (i.e., utility make ready cost) that may influence feasibility and placement decisions.

<sup>1</sup> In this study, the infrastructure lifetime is assumed to be 10 years, and the associated costs are divided by the total number of days in that period to enable comparison with other variables in the objective functions.

## **Solution Approach**

The optimization model developed in this project is a mixed-integer problem with nonlinear constraints. Michigan's road network is large-scale, making it computationally demanding for existing solvers. To address this challenge, a metaheuristic algorithm is implemented, specifically designed to efficiently handle complex optimization problems of this nature.

The metaheuristic algorithm proposed in this project is based on the SA algorithm, which follows a two-step process. First, it explores the feasible set of integer solutions by starting from an initial feasible solution and transitioning to a neighboring feasible solution. Second, it evaluates and compares the objective function values of the current and new solutions. If the new solution improves the objective function, it is accepted with a probability of one. If the new solution is worse, acceptance is determined by a probability function based on the relative difference between the objective values of the current and neighboring solutions. This probability decreases gradually as the algorithm progresses through iterations, approaching zero by the end to prevent the acceptance of inferior solutions. When modifying the solution, several decision rules guide the changes: locations with higher traffic flow are more likely to be selected for the addition of new stations, while those with lower traffic volumes are considered first for removal. Similarly, when increasing the number of chargers at a station, preference is given to sites with higher delay levels, whereas stations with minimal delays are more likely to undergo reductions in charger count. SA allows the acceptance of solutions with higher objective function values (worse solutions) compared to the current solution, helping to prevent the algorithm from getting stuck in local optima. This feature is particularly beneficial for problems with multiple local optima due to nonlinear constraints. SA has been shown to efficiently solve flow-capturing mixed-integer programs.

### **Demand-Related Adjustments**

#### *Seasonal Variation in Demand*

The project initially analyzed the MDOT travel demand matrix using aggregate demand models. This travel demand represents typical travel patterns on a fall weekday. However, to reflect seasonal changes, adjustments were made. Michigan experiences significant travel demand fluctuations due to factors like cold weather in winter and scenic views during the spring, fall, and summer, which alter traffic patterns throughout the year. Additionally, colder temperatures impact the performance of Li-Ion batteries, reducing their efficiency and leading to changes in EV user charging behavior (70). To capture these effects, the researchers used data from CCS across Michigan. The CCS collect traffic data 24 hours a day, thus reflecting any seasonal variation at different locations around the state. Using this data solutions are developed for each month based on temperature and travel demand variations.

#### *Demand Fluctuations*

Following stakeholder recommendations, the model was adjusted to increase the number of chargers by 10% above the minimum required. This adjustment accounts for fluctuations in travel demand and potential maintenance issues, ensuring sufficient charger availability.

### **Battery Charge Assumptions**

#### *Interior Node Assumptions*

The network-level model sets the initial SoC at 60%, based on stakeholder feedback, to reflect real-world EV user behavior. This value strikes a balance between drivers pre-planning for longer trips and the common practice of starting shorter trips with approximately 60% SoC. This assumption does not apply to urban (within the city) trips, which will be addressed in a subsequent section. The model ensures that EVs reach their destinations with at least a 20% battery charge, accounting for users' range anxiety (16). To achieve this, EVs may need to charge en-route, depending on the trip length. During charging events, the battery is typically charged up to 80% of its capacity, as recharging time increases exponentially in the last 20% of battery capacity. For the last charging stop in each trip, the model assumes the battery is only charged to the minimum level needed to reach the destination. For trips with out-of-state origins or

destinations, the model only applies this charging strategy to the portion of the trip that occurs within Michigan. Border nodes are treated separately and are discussed below.

#### *Border Node Assumptions*

This study's modeling framework is designed to support intercity trips within Michigan, ensuring that all EVs can reach their destinations within the state with at least 20% battery charge by providing sufficient charging opportunities. Additionally, the model recognizes the importance of supporting interstate and international travel to and from Michigan. Boundary nodes, which connect Michigan to neighboring states and Canada, are treated as the potential origin or destination points. The state of charge at these boundary nodes is crucial for considering the feasibility of interstate and international trips.

For trips outside Michigan, the model ensures that EVs leave the state fully charged and can recharge at the nearest available charging point when entering or exiting the state. These trips are classified as external travel demand. While the model ensures that EVs arrive at their destinations with a minimum charge (including border nodes for external demand), there may not be enough charge to continue the journey beyond the border nodes. To address this, adjustments were made to ensure the feasibility of EV trips for external travel demand.

In this study, the external outgoing traffic flows for each boundary node in Michigan are estimated using the nationwide OD matrix. The closest charging station to each boundary node is identified to estimate the fuel state at these nodes. Based on the fuel state and charging demand, the model determines the required number of charging spots at each boundary node to ensure that EV drivers can leave Michigan with a full charge.

## **Location and Number of Intercity Chargers**

### **Seasonal Variations**

During summer Michigan highways experience higher travel demand compared to winter due to increased number of trips for tourism and other activities. However, battery efficiency decreases in winter due to colder temperatures, leading to a shorter available battery range despite lower overall travel demand. As a result, additional charging stations and chargers are necessary during winter months to accommodate travel demand.

Since only one charging station configuration can be implemented, it is essential to test the performance of charging stations and charger configurations under different seasonal travel demands. It was observed that during winter a greater number of charging stations and chargers are required due to reduced battery efficiency in colder temperatures, while during summer despite having higher travel demand, EV travel benefits from longer battery range (70). To evaluate the feasibility of the winter configuration under summer conditions, the optimized charging station configuration for winter is tested to accommodate summer travel demand. The results indicate that the winter charging infrastructure sufficiently supports summer charging needs, even though some charging station locations do not perfectly align with summer travel demand patterns (70). While this configuration slightly increases average delays for summer EV travel, it does not impact trip feasibility. In contrast, if the charging infrastructure are designed to support summer travel and battery performance, the designed charging infrastructure will be inadequate for winter travel demand, making it an impractical choice for year-round use. Therefore, the charging station configuration will be designed to support winter travel, ensuring EV trips remain feasible throughout the year, despite the minor increase in summer delays.

### **Optimized Results for Charging Station Placement and Charger Numbers**

This section details the project findings. Table 5 summarizes the number of charging stations, chargers, and the required charging infrastructure investment, considering EVs with 70kWh batteries and 150kW DCFC stations under 25% adoption scenario. It is important to note that the reported cost is conservative because the model assumes only one charging station per location. Under this assumption, \$14.85 million are allocated for station construction, and \$134.80 million are allocated for chargers, resulting in a total of \$149.64 million. In practice, chargers may be installed at multiple stations within a

five-mile radius along the corridor, potentially raising both infrastructure and installation expenses. As a result, the final, real-world distribution of chargers could lead to slightly higher overall costs depending on the availability of site-hosts.

Table 5: Summary of the currently available, planned and required intercity chargers

	Total required	Existing chargers		New required
		Tesla	Non-Tesla	
Number of charging stations <sup>1</sup>	55	38		17
Number of chargers	2136	124	288	1724

Figure 10-12 show the total required chargers, existing chargers, and newly required chargers for each location, respectively. The size of the circles in the figures represents the number of chargers needed at each location. Figure 11 specifically highlights the current 150kW DC fast chargers in Michigan, which are available for intercity travel. To qualify as an existing intercity charging station, a charger must be located within 1 mile of an Interstate exit or a highway intersection along designated corridors. Charging stations that do not meet this criterion are excluded from the intercity study.

As shown in Figure 12, Brighton, located near Detroit, has the highest charger requirement, with 200 chargers. This is due to the high travel demand entering and exiting Detroit. Since Detroit serves as either the origin or destination for these trips, there is less need to install a large number of chargers within the city itself to support intercity travel. Instead, ensuring adequate charging infrastructure along highways connecting Detroit to neighboring cities is crucial for supporting the high intercity travel demand. The next highest charger requirements are in Benton Harbor, Reed City, Newport, and Muskegon. This is primarily due to the significant travel demand toward Chicago, around Lake Michigan and to Upper Peninsula destinations.

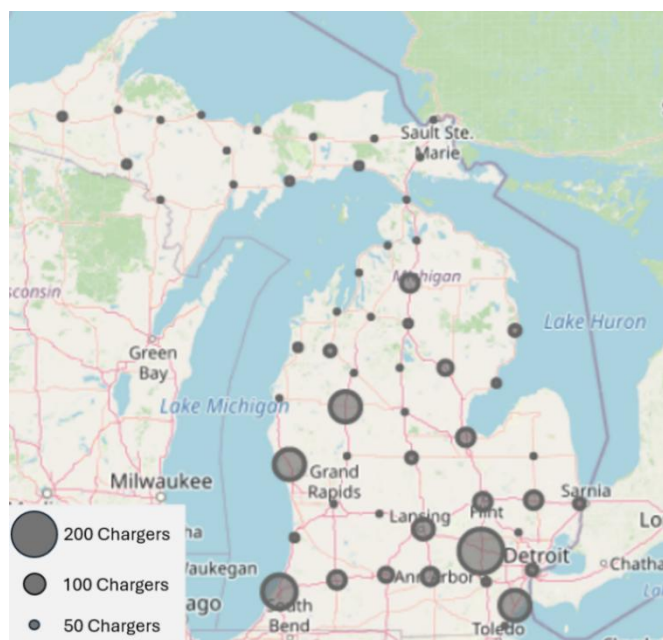


Figure 10: Total required chargers to support intercity trips in Michigan

<sup>1</sup> The total number of existing charging stations (sites) is 38. Out of the 38 existing charging stations, one station includes only Tesla chargers, 25 stations have only non-Tesla chargers, and 12 stations are equipped with both.



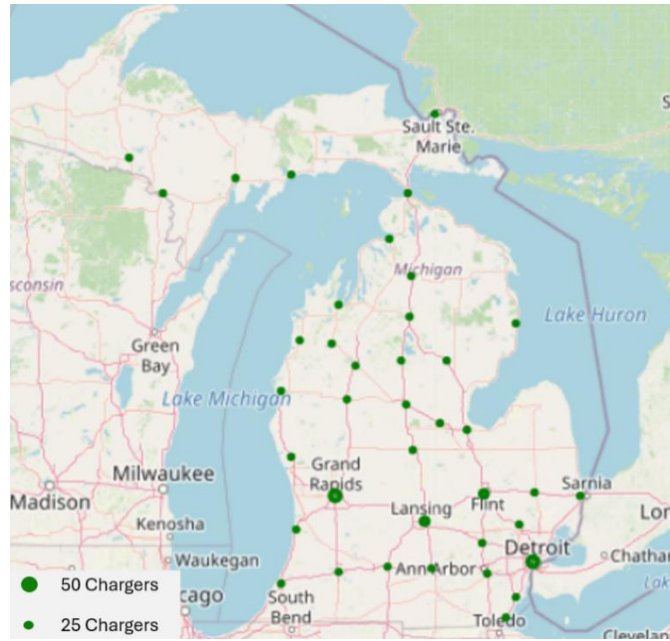


Figure 11: Existing chargers to support intercity trips in Michigan

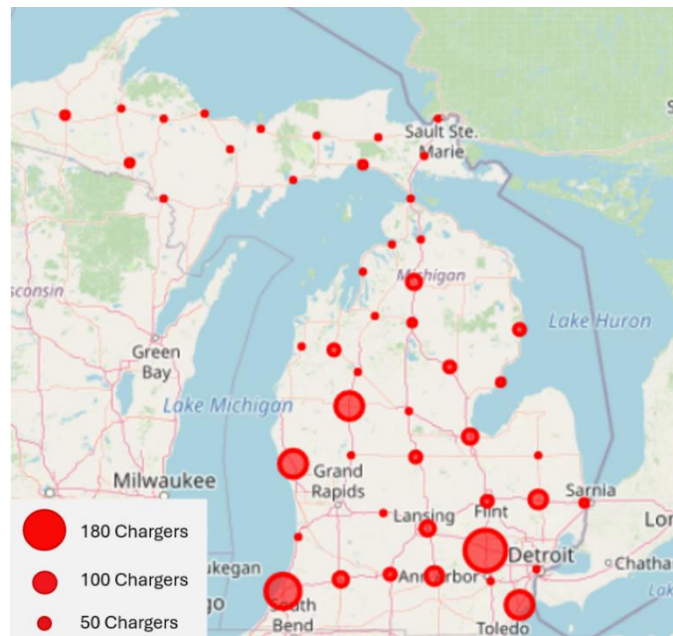


Figure 12: New required chargers to support intercity trips in Michigan

## Tourism Charging Infrastructure

This section outlines the required locations and quantities of Level 2<sup>1</sup> chargers needed to support tourism travel in Michigan. It begins with the problem statement, followed by the solution approach, and concludes with results and discussion.

<sup>1</sup> This study assumes that Level 2 chargers are available for 24 hours per day.



## Problem Statement

This section aims to propose a framework for identifying both the optimal sites and required number of slow (Level 2) chargers at tourism destinations in Michigan. The framework has two main goals: (i) pinpointing the best placement and quantity of Level 2 chargers at candidate destinations, and (ii) ensuring that unserved projected charging demand of Level 2 network, if any, can be satisfied by available DCFCs, while minimizing detours for users.

The study formulates an optimization problem, structured as a mixed-integer linear program (MILP), and offers a heuristic solution approach. A node-based approach is adopted to model charging demand for the Level 2 charging infrastructure. A queuing model is deemed unsuitable, as level 2 charging can require several hours per session. Trip feasibility remains a key constraint. This framework evaluates charging infrastructure from three perspectives:

- **Transportation network:** Reducing unserved charging demand and detours.
- **Grid network:** Controlling costs linked to necessary grid expansions triggered by the additional EV charging load.
- **Charging infrastructure cost:** Minimizing investment outlays for both charging stations and chargers.

## Solution Approach

As illustrated in Figure 13, the proposed modeling framework is divided into four principal sections, each covering a sequence of steps: (i) Tourism Destination Trip Forecast, (ii) Origin-Destination Analysis, (iii) EV and Charging Demand Estimation, and (iv) Charger Optimization. Each of these steps addresses a specific part of the modeling process, ultimately enhancing the framework's accuracy and effectiveness, including the selection of optimal Level 2 charger locations and quantities.

The first two components quantify tourism travel within the study region, an essential step given the lack of dedicated tourism travel demand data, such as origin-destination matrices specific to tourism trips. The EV and charging demand estimation section outlines the assumptions used for evaluating charging needs, while the charger optimization section introduces the mathematical formulation of the problem and its respective solution techniques.

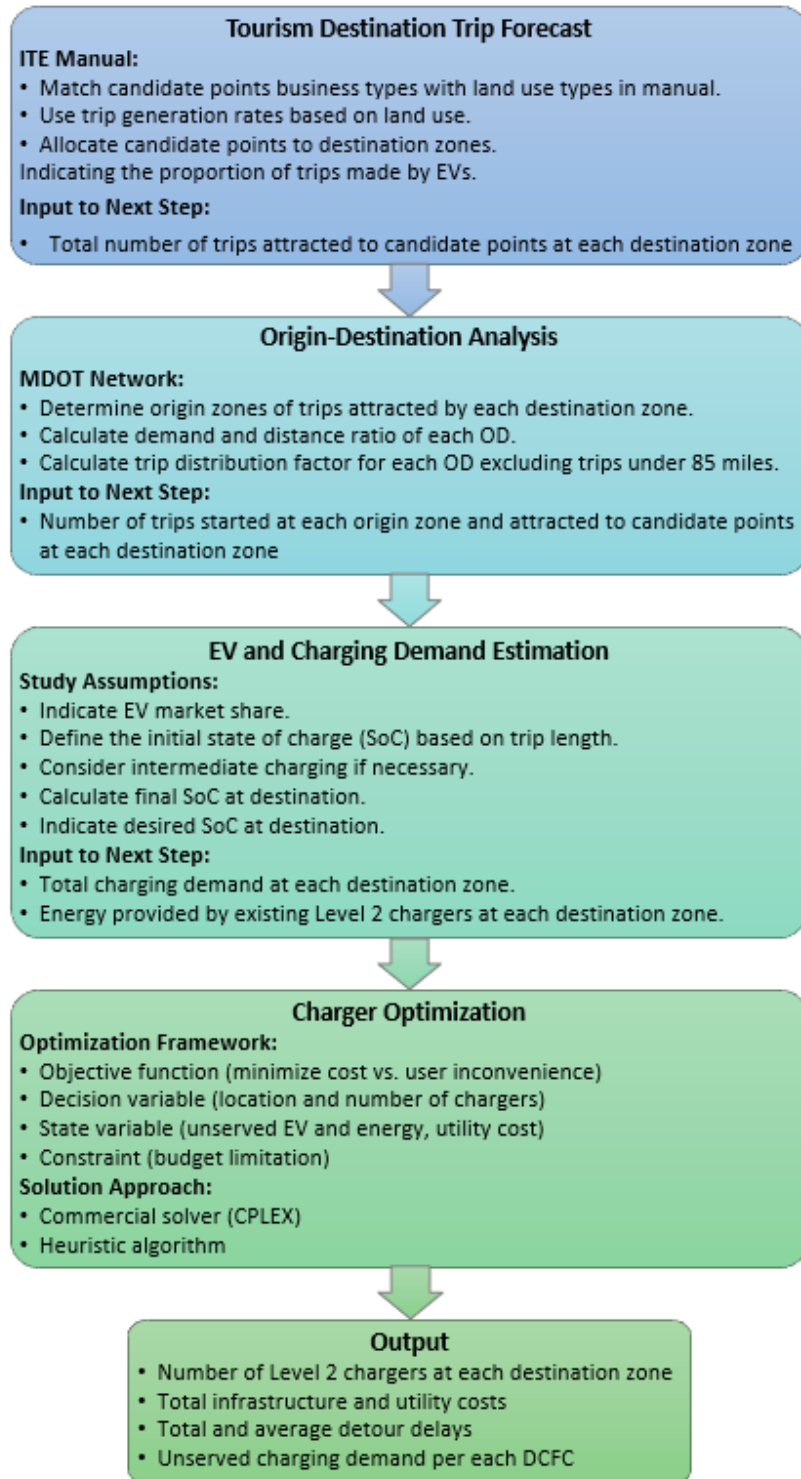


Figure 13: Modeling framework for tourism destination charging

### Tourism Destination Trip Forecast

To begin, candidate sites for destination chargers are grouped according to their respective zones. By matching each site's business type with the land use categories defined in the *Trip Generation Manual* by the Institute of Transportation Engineers (ITE) (73), it becomes possible to estimate the number of trips

attracted to each location. The manual presents trip generation rates for various land uses, typically based on a facility's total floor area or number of employees. This makes it feasible to calculate the number of trips drawn to each destination zone.

For the purposes of this study, long-term stay locations such as hotels and motels serve as candidate sites. According to the manual, hotels generate an average of 14.34 trips per employee per day, while motels account for 12.81. Given a 50% split between arriving and departing trips, these figures convert to 7.17 daily trips per employee for hotels and 6.40 for motels.

### Origin-Destination Analysis

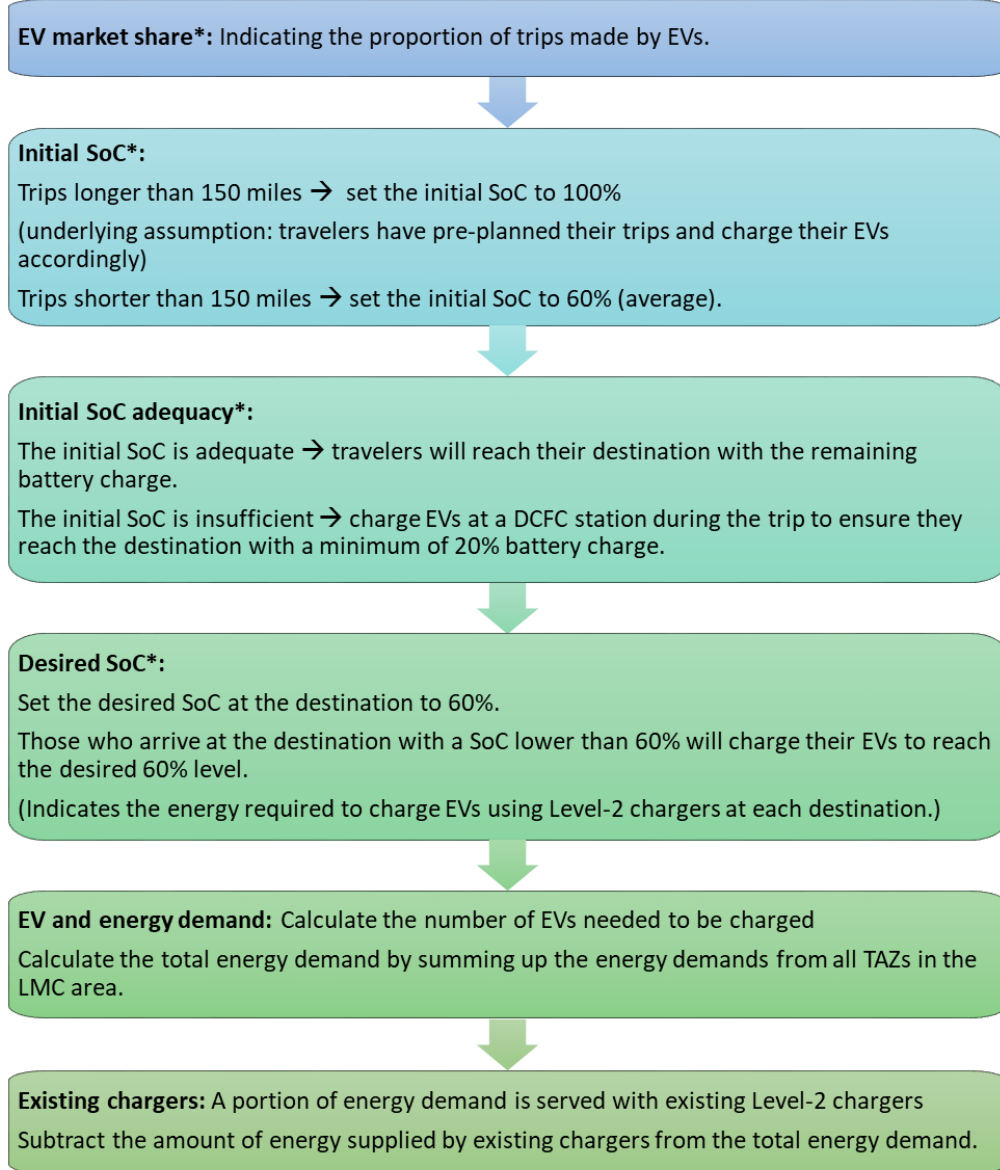
After determining the number of trips drawn to each destination zone, the next step is to identify their points of origin. The distance traveled plays a crucial role in an EV's SoC: longer journeys lower the SoC upon arrival and can necessitate intermediate charging. Additionally, trips originating from more distant locations are more likely to terminate at long-term stay establishments (e.g., hotels). As such, the trip distribution factor should incorporate these aspects. On the other hand, fewer long-distance OD trips occur compared to shorter ones, so the distribution factors must strike a balance between OD demand and travel distance.

$$P_{ij}(i \in I, j \in J | d_{ij} \geq 85 \text{ mi}) = \frac{\frac{q_{ij}}{\sum_j q_{ij}} * \frac{d_{ij}}{\sum_j d_{ij}}}{\sum_i (\frac{q_{ij}}{\sum_j q_{ij}} * \frac{d_{ij}}{\sum_j d_{ij}})} \quad (3)$$

Equation (1) presents the method for calculating the trip distribution factor for each destination zone, excluding trips shorter than 85 miles, as these are less likely to end at long-term stay accommodations. In this equation, the probability that zone  $i$  is the origin for trips directed to zone  $j$  ( $P_{ij}$ ) depends on two ratios: (1) the travel demand between zones  $i$  and  $j$  ( $q_{ij}$ ) relative to the total demand attracted by zone  $j$  ( $\sum_j q_{ij}$ ), and (2) the distance between zones  $i$  and  $j$  ( $d_{ij}$ ) relative to the total distance from any zone to  $j$  ( $\sum_j d_{ij}$ ). This combined ratio captures the joint effect of travel demand and trip distance on the distribution process.

### EV and Charging Demand Estimation

This step follows the processes outlined in Figure 14. Key assumptions regarding EV market share, initial SoC, and desired SoC are established to assess the need for intermediate fast charging and determine the final charging demand at the destination. Using travel patterns and accounting for the energy supplied by existing Level 2 chargers, the total EV charging demand is estimated.



\* Levels are set based on stakeholders feedback

Figure 14: EV and charging demand estimation process

### Charger Optimization

This step presents the tourism charger optimization framework, which determines the optimal placement and number of Level 2 chargers, at tourism destinations, to minimize overall system costs. The objective function, as presented in the following equation, accounts for both capital expenditures, including station and charger installation costs ( $C_s$  and  $C_c$ ), land acquisition ( $C_{l_j}$ ), and utility upgrades ( $C_{u_j}$ ), as well as user-related costs, such as detour delays ( $TT_j^d$ ) and additional expenses incurred when charging at a DCFC station due to insufficient Level 2 chargers at the destination ( $\lambda \sum_{j \in J} E_j^{unserved}$ ).

$$\min \frac{1}{k} \sum_{j \in J} (C_s x_j + P C_c z_j + C_{l_j} x_j + C_{u_j}) + \gamma \sum_{j \in J} (TT_j^d EV_j^{unserved}) + \lambda \sum_{j \in J} E_j^{unserved} \quad (4)$$

To ensure feasibility, the framework incorporates key infrastructure and operational considerations. It accounts for budgetary limitations, preventing charger allocation to locations beyond the available investment capacity. The model also determines the necessary utility upgrades based on the number of chargers installed at each site while ensuring that when existing chargers meet local energy demand, additional installations are not required. Furthermore, the framework evaluates unserved charging demand, estimating the number of EVs that would need alternative charging solutions if Level 2 availability is insufficient ( $EV_j^{unserved}$ ).

To solve this problem efficiently, multiple solution approaches were developed and assessed based on computational time and accuracy. An exact optimization method was initially implemented using a commercial solver capable of handling mixed-integer programming problems. However, due to computational challenges in large-scale networks, a heuristic approach was introduced to generate near-optimal solutions within a practical timeframe.

The heuristic method prioritizes charger placement by evaluating detour times, charging demand, and available infrastructure. Charger allocation follows an incremental process, adding chargers to locations where they provide the greatest benefit.

Ultimately, the framework balances cost-effectiveness and service coverage, ensuring that unserved charging demand is either met through strategically placed Level 2 chargers or redirected to the nearest available DCFC station. The selected optimization method provides a scalable and adaptable solution for expanding charging infrastructure while considering both financial constraints and user convenience.

## Location and Number of Tourism Destination Chargers

This section presents the location and number of level 2 chargers needed at tourism destinations to support eco-tourism. The default parameter values for the base case are provided in Table 6, while location-specific variables, such as land acquisition and utility upgrade costs, are excluded due to their extensive variability. The total tourism charging demand across Michigan amounts to 1,313.98 MWh, of which 177.26 MWh is already supplied by existing Level 2 chargers. This leaves 1,136.72 MWh requiring additional charger installations. To quantify user inconvenience, the value of time and charging cost differential are incorporated into the analysis, ensuring a balanced assessment of cost-effectiveness and service efficiency.

Table 6: Tourism destination charging parameters

Description	Value
EV market share	25%
Battery efficiency	3.5 Mile/kWh
Battery Capacity	70 kWh
Charger efficiency	1.18
Study period	24 hours
Value of time	\$18.00/hour
Total number of EV trips ending at tourism destinations	50,063 vehicles
Total charging demand	1,313.98 MWh
Total energy provided by existing Level 2 chargers	177.26 MWh
DCFC to Level 2 charging cost differential	\$ 0.25/kWh
Infrastructure Lifetime	10 years
Level 2 station cost per station	\$5,465.00
Level 2 charger cost per charger per power	403.93 (\$/kW)

The results in Table 7 compare various technology advancement scenarios each featuring different Level 2 charging powers (ranging from 7 kW to 19 kW) and evaluates their impact on infrastructure costs, charging performance, and user experience. While the 7 kW chargers yield the lowest objective function value, they may not provide sufficient energy to charge an EV battery up to the desired SoC within the typical duration of stays at tourism destinations. This limitation affects the practicality of 7 kW chargers in ensuring reliable charging for EV travelers. Consequently, while the 7 kW charger is included for comparison, it is not considered a viable option for the final network design.

Among the remaining scenarios, a trade-off exists between infrastructure costs, energy supply, and user delays. As charging power decreases, the number of chargers required increases, rising from 4,084 chargers at 19 kW to 7,412 chargers at 9 kW. This increase in charger installations allows the network to better accommodate charging demand, reducing the number of unserved EVs and ensuring energy availability remains stable across all power levels.

Although higher-powered chargers (19 kW) reduce user delays, they come with a higher infrastructure cost (\$73.05 million). Conversely, 11 kW chargers strike a balance between cost efficiency and charging feasibility, providing a more scalable solution while keeping user delays at an acceptable level. Considering these factors, 11 kW is selected as the preferred option for the final comprehensive charging network.

Table 7: Tourism destination charging results for different Level 2 charging powers

Level 2 Charging Power (kW):	19 kW	<b>11 kW</b>	9 kW	7 kW
Number of Stations	1,502	<b>1,503</b>	1,503	1,503
Number of Chargers	4,084	<b>6,167</b>	7,412	9,205
Total Infrastructure Cost	\$73.05 M	<b>\$66.71 M</b>	\$66.60 M	\$65.26 M
Stations Cost	\$8.21 M	<b>\$8.21 M</b>	\$8.21 M	\$8.21 M
Charger Cost	\$31.34 M	<b>\$27.40 M</b>	\$26.95 M	\$26.03 M
Land Cost	\$3.17 M	<b>\$3.18 M</b>	\$3.18 M	\$3.18 M
Utility Cost	\$30.33 M	<b>\$27.92 M</b>	\$28.26 M	\$27.85 M
Total Delay <sup>1</sup>	9.79 hour	<b>10.02 hour</b>	6.85 hour	6.46 hour
Average Delay per unserved EV <sup>2</sup>	11.32 min	<b>19.39 min</b>	14.92 min	20.73 min
Objective Function Value	20,537 (\$/day)	<b>18,662 (\$/day)</b>	18,551 (\$/day)	18,121 (\$/day)
Energy Demand	1,313.98 MWh	<b>1,313.98 MWh</b>	1,313.98 MWh	1,313.98 MWh
Existing Energy	177.26 MWh	<b>177.26 MWh</b>	177.26 MWh	177.26 MWh
Supplied Energy	1,135.33 MWh	<b>1,135.89 MWh</b>	1,135.99 MWh	1,136.22 MWh
Unserved Energy	1.39 MWh	<b>0.82 MWh</b>	0.73 MWh	0.50 MWh
Unserved EV <sup>3</sup>	52 vehicles	<b>31 vehicles</b>	28 vehicles	19 vehicles

<sup>1</sup> The total detour time incurred by users to reach the nearest DCFC station due to insufficient Level 2 chargers at the destination.

<sup>2</sup> Average detour time per user to reach the nearest DCFC station due to a lack of Level 2 chargers at the destination.

<sup>3</sup> Total number of users required to make a detour to reach the nearest DCFC station due to a lack of Level 2 chargers at the destination.

This analysis highlights the importance of aligning infrastructure planning with practical charging needs, ensuring that EV travelers have access to sufficient charging without excessive costs or delays. Figure 15 shows the number of tourism destination Level 2 chargers within each TAZ in Michigan.

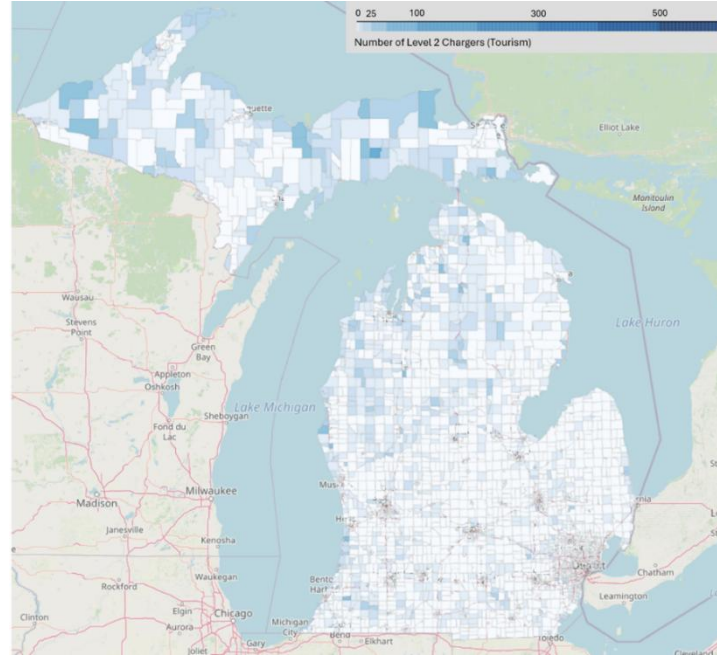


Figure 15: Distribution of Level 2 chargers (11 kW) at tourism destinations in Michigan

## Urban Area Charging Infrastructure

This section presents the required locations and quantities of Level 2<sup>1</sup> chargers and DCFCs<sup>2</sup> to support urban travel in Michigan. It begins with the selection of major urban areas for EV charger placement analysis. For both Level 2 and DCFC infrastructure, the discussion starts with the problem statement, followed by the modeling framework, and concludes with the results and discussion.

### City Selection

Using the statewide Michigan network, various data points, including the number of zones, generated travel demand, lane lengths, and estimated miles traveled, are extracted for each candidate city. Major cities with sufficient network details and trip generation are selected for EV charger placement analysis. Additionally, Marquette, the city with the highest generated travel demand in Michigan's Upper Peninsula, is included in the analysis. A summary of the candidate cities can be found in (74), while Table 8 presents the selected cities for the detailed EV charger placement study.

Table 8: Selected cities for urban study

City	Number of nodes	Number of zones	Generated travel demand (vehicles)
Marquette	62	21	65,585
Muskegon	387	52	369,790
Ann Arbor	413	36	400,781
Kalamazoo	369	55	480,641
Saginaw	783	116	622,718
Flint	694	84	656,694
Lansing	896	92	682,634
Grand Rapids	1031	82	1,229,411
Detroit	5461	301	5,130,782

<sup>1</sup> This study assumes that Level 2 chargers are available for 24 hours per day.

<sup>2</sup> This study assumes that DCFCs are available for 14 hours per day.

## Level 2 Chargers

### Problem Statement

Charging at home is the most convenient option for EV users, allowing them to recharge their vehicles overnight without disruption. Currently, the majority of EV owners reside in SFHs, where access to home chargers is more common. However, as EV adoption grows, this trend may shift, with more users living in MFH, where access to dedicated home charging is severely limited. Given the budget constraints in infrastructure development, investments must be strategically allocated to maximize impact. This study determines the required number of chargers at both SFHs and MFHs based on the distribution of each dwelling type across Michigan and within each major urban area, ensuring an equitable expansion of residential charging options. While DCFC is essential for long-distance travel, investing in Level 2 chargers remains crucial for residential charging since they mitigate battery degradation by providing a slower, more battery-friendly charging rate, extending battery life and reducing long-term replacement costs.

### Analysis Framework

Figure 16 illustrates the urban residential analysis framework, which begins by incorporating housing type distribution and future EV adoption projections, assuming a 25% EV market share across Michigan. The framework then determines the optimal allocation of residential chargers between SFHs and MFHs using two approaches:

- **Proportional Allocation:** Assumes that charger distribution follows the same proportions as housing types.
- **Weighted Allocation:** Recognizes that SFH residents have a higher likelihood of EV ownership, leading to a slight preference for charger placement in SFH units.

Once the total number of chargers needed to meet statewide EV demand is established, the next step is to evaluate access levels to home charging. A 100% access rate implies that every housing unit with an EV has a dedicated residential charger. For MFHs, a sharing rate can also be introduced, allowing multiple EV owners to share access to a single charger, improving efficiency and optimizing infrastructure investments.

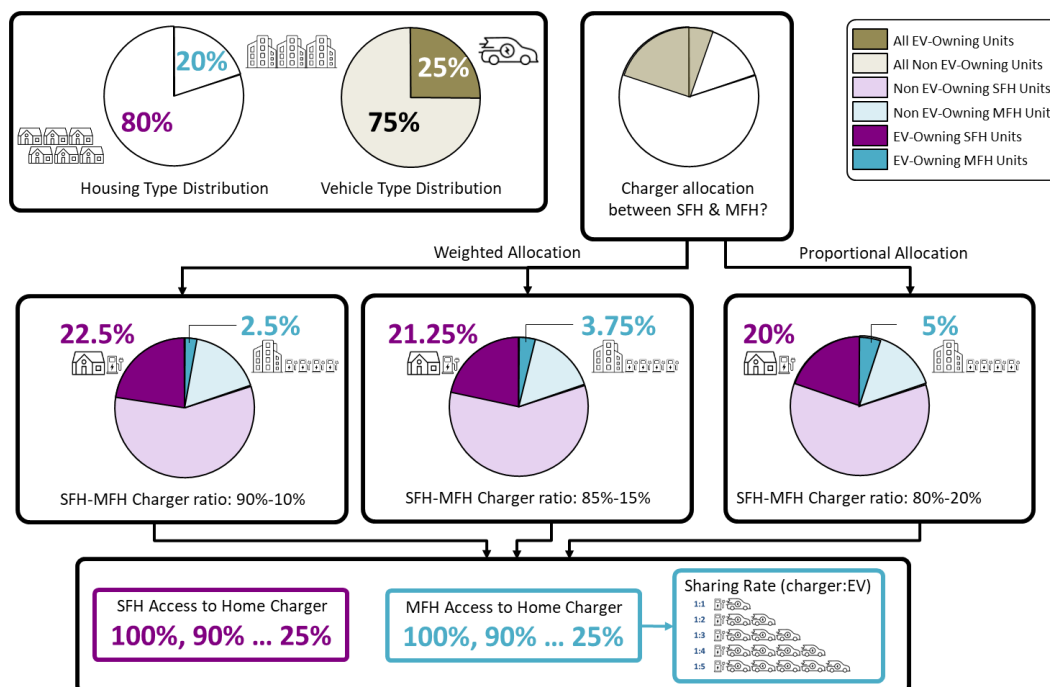


Figure 16: Urban residential charging infrastructure analysis framework



## Location and Number of Level 2 Chargers in Urban Areas

Table 9 and Figure 17 illustrate the required number of chargers for residential units under both proportional and weighted allocation approaches. In the weighted allocation, chargers are distributed following a 90%-10% ratio between SFH and MFH, respectively. The analysis assumes a 90% home charger access rate for SFH residents, while 50% access is considered for MFH residents. This means that the allocated chargers ensure 90% of EV-owning SFH units and 50% of EV-owning MFH units have home charging access. As expected, the weighted allocation results in more chargers being assigned to SFH units and fewer to MFH units compared to the proportional allocation, reflecting the higher likelihood of EV ownership among SFH residents.

Table 9: Urban residential Level 2 charging results for urban residential units

Allocation approach:	Proportional		Weighted	
Housing type:	SFH	MFH	SFH	MFH
Number of Zones	3,704	2,862	3,704	2,677
Number of Chargers	784,238	103,509	855,243	53,920
Total Infrastructure Cost	\$3,504.79 M	\$475.55 M	\$3,820.28 M	\$254.21 M
Charging Station Cost <sup>1</sup>	\$20.24 M	\$15.64 M	\$20.24 M	\$14.63 M
Charger Cost <sup>2</sup>	\$3,484.55 M	\$459.91 M	\$3,800.04 M	\$239.58 M

<sup>1</sup> Charging station cost refers to the electrical panel and switchgear installation, engineering and design, permitting, and project management, and may encompass multiple chargers within a single station.

<sup>2</sup> Charger cost refers to the expense associated with purchasing each individual EV charging unit.



Figure 17: Number of required Level 2 chargers at urban residential units

Figure 18 presents maps illustrating the distribution of Level 2 residential chargers for MFH units across TAZs under both allocation approaches, assuming a 50% access rate to home chargers at MFHs. The results confirm that higher charger demand is concentrated in major urban areas, particularly in the southern Lower Peninsula (LP), where population density is higher, as well as Marquette in the Upper Peninsula (UP).

By comparing the two maps, it is evident that the proportional allocation approach assigns a greater number of chargers to MFH units compared to the 10% weighted allocation approach. This highlights the impact of allocation strategy choices on residential charger distribution, emphasizing how prioritizing SFH units in the weighted approach results in fewer chargers being allocated to MFH units despite their limited home charging accessibility.

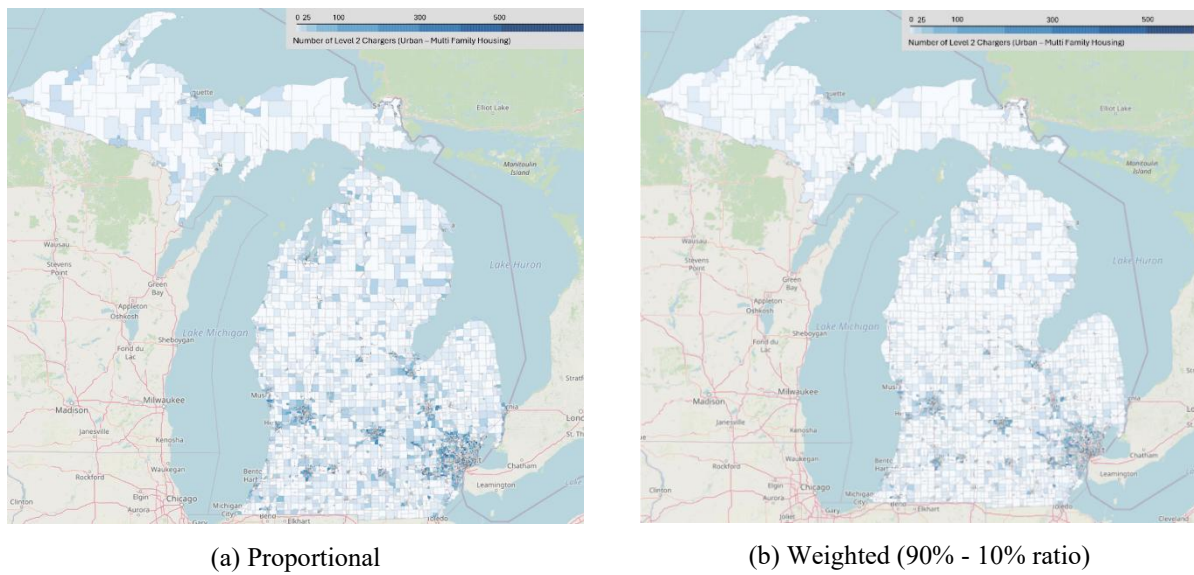


Figure 18: Distribution of Level 2 residential chargers for MFH units across TAZs under allocation approaches

Table 10 presents the number of Level 2 residential chargers required in nine major urban areas in Michigan under the weighted allocation approach. The results indicate that 495,941 out of 855,243 chargers (58%) for SFHs and 41,515 out of 53,920 chargers (77%) for MFHs should be deployed in these major urban areas, highlighting their critical role in residential charging infrastructure expansion.

Table 10: Urban residential Level 2 charging results for major urban areas under weighted allocation approach

Major urban areas	Single-family housing chargers (90% access)	Multi-family housing chargers (50% access)
Ann Arbor	17,848	3,582
Detroit	282,458	22,442
Flint	31,952	1,694
Grand Rapids	51,788	4,717
Kalamazoo	21,801	2,342
Lansing	33,574	3,625
Marquette	5,003	445
Muskegon	17,991	910
Saginaw	33,527	1,759
Total	495,941	41,515

## DCFC Stations

### Problem Statement

As EV adoption grows, urban charging infrastructure must be strategically expanded to meet demand. Unlike intercity trips, urban EV trips are more spontaneous, and users may start with varying states of charge. While the length of daily urban trips is usually smaller than the average driving range of an EV on a full charge, many users do not always begin their trips with a fully charged battery. Limited access to home or workplace chargers, failure to regularly plugin in vehicles, and inadequate overnight charging time

can leave users with lower-than-expected battery levels, creating range anxiety and uncertainty in urban EV travel.

To address these challenges, there is an immediate need for strategically placed DCFC in urban areas. These chargers will alleviate range anxiety, reduce uncertainty in EV trips, and ensure seamless urban mobility. Given the limited resources and involvement of multiple stakeholders, including city planners, transportation agencies, and utility providers, an optimization model is necessary to determine the best locations and capacities for DCFC stations. This study incorporates a dynamic traffic simulation model to track user trips and estimate charging behavior and state of charge. The influence of Level 2 chargers, located at residential areas, shopping centers, and workplaces, is also considered in the state of charge estimator function to better reflect real-world charging patterns.

This section focuses on identifying the optimal locations for DC fast charging stations in urban areas to ensure reliable and accessible charging infrastructure for daily EV travel. It aims to reduce both total investment costs and various travel delays including detour, queue waiting, and recharging delays. Specifically, it addresses these key questions:

- Where are the traffic analysis zones that require charging stations to effectively support daily EV travel?
- How many chargers should be installed at each station?
- What is the estimated investment cost for developing the proposed infrastructure?

### **Analysis Framework**

The first step in the proposed modeling and solution framework is data collection. This study requires various datasets, including OD travel demand, road network information, land use data, land and electricity provision costs, as well as charging station and charger costs and specifications. Users' trips are then simulated using a dynamic traffic simulation tool, with OD demand and road network data as key inputs. The simulation outputs trip trajectories and dynamic skims, such as travel times and distances for each OD pair across different departure time intervals.

Unlike intercity trips, which are typically well-planned with fully charged batteries at departure, urban trips are more spontaneous, and users may start with varying states of charge. To account for this, a state of charge simulator is developed, considering trip purpose and land use at the trip origin to estimate the initial battery charge for each trip trajectory. Finally, all the collected and simulated data serve as inputs for the optimization model.

The modeling framework in this study accounts for the limited range of EVs, ensuring that every EV trip remains feasible by strategically providing charging infrastructure. Simultaneously, it aims to minimize both the total infrastructure cost and the monetary value of delays experienced by EV users. The model evaluates candidate locations for charging stations based on factors such as land acquisition and electricity provision costs. Key constraints incorporated in the model include flow conservation equations, charging station allocation, SoC tracking, trip feasibility, and charging and queuing delays at stations. The problem is formulated as a mixed-integer programming model with nonlinear constraints. Figure 19 presents the overall framework and the sequential steps of this study.

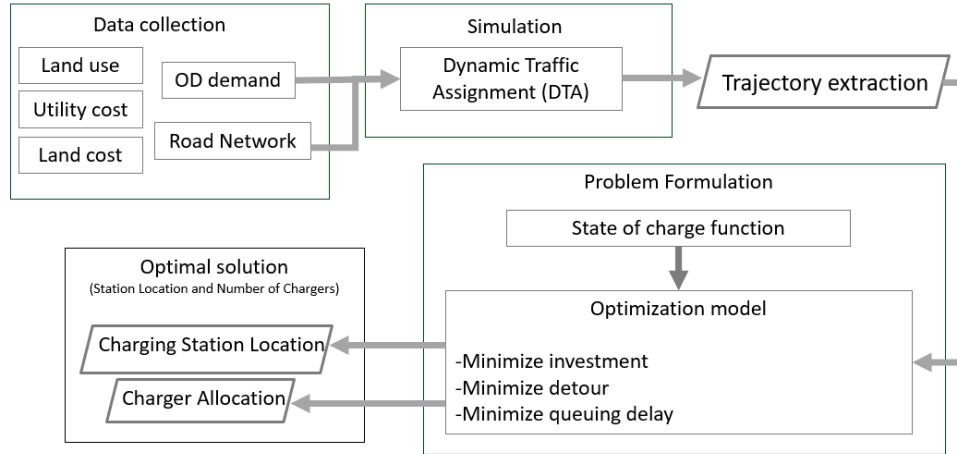


Figure 19: Urban DCFC general research framework

### Traffic Simulation

Traffic state and congestion levels influence the route choices of both EV users and non-EV drivers. Additionally, the trip chains of EV users must be considered when determining charger placement. In this project, road traffic across the Michigan state-wide network is simulated, and the trajectories of EV trips, representing vehicle travel paths over time, are extracted for different cities on a daily basis.

Traffic simulation is a computational tool used for planning, operational analysis, and design in transportation systems. One of its key applications is the visual representation of current or future scenarios to support decision-making. To estimate time-dependent charging demand at different locations, EV trip trajectories are analyzed, with 25% of all trips in selected city sub-networks randomly assigned to EVs. A state-wide Michigan traffic simulation is conducted using a traffic simulator to facilitate this analysis.

Transportation models are generally categorized into three levels based on detail: microscopic, mesoscopic, and macroscopic. For this study, the mesoscopic simulation tool DYNASMART-P (75) is used due to its fast execution and ease of calibration. In mesoscopic simulations, traffic flow is represented at an intermediate level of detail, where individual vehicles are moved according to macroscopic speed-density relationships, balancing computational efficiency with realistic traffic flow propagation.

DYNASMART-P, utilizing dynamic traffic assignment, supports a wide range of transportation planning and operational decision-making. This tool integrates dynamic traffic assignment models with traffic simulation, allowing for a more comprehensive analysis of network conditions. One of its key advantages is the ability to model traffic flows based on the decisions of adaptive users who adjust their routes in real time to optimize their travel paths throughout the planning horizon. This capability addresses many of the limitations present in conventional planning tools.

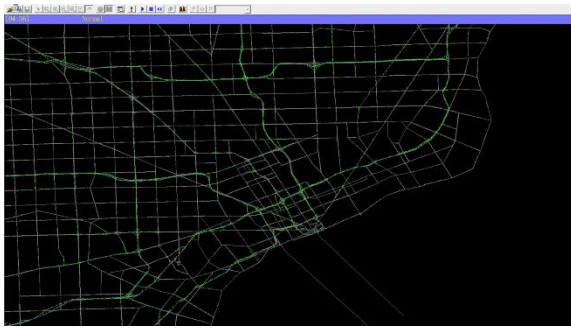
DYNASMART-P processes road network data and system configurations as inputs, generating individual vehicle trips based on time-dependent OD demands. Once vehicles are introduced into the network, they are assigned routes that minimize generalized travel costs, and the system proceeds to a user equilibrium state. The software outputs detailed vehicle trajectories, including those of electric vehicles, as well as the optimal paths from origins to destinations. EV trajectories are extracted from the simulation results and integrated into an optimization framework to determine the optimal charging infrastructure configuration, minimizing overall system costs. A portion of vehicles, both electric and non-electric, are considered adaptive, meaning they can switch routes in response to congestion or gridlock. These vehicles have access to real-time traffic information, allowing them to make informed routing decisions. DYNASMART-P requires five key categories of data, outlined below.

- **Network Data:** The primary input in this category is a file containing statewide network nodes and link information. The Michigan road network was supplied by MDOT in the form of a TransCAD file, which is converted into a format compatible with DYNASMART-P. Figure 4 illustrates Michigan's statewide road network.

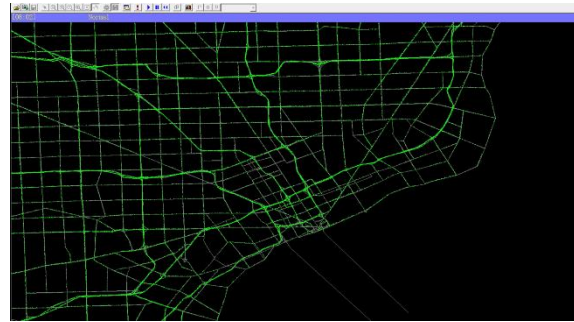
- **Control Data:** This file specifies the control types for all network nodes (intersections) and includes phasing details for signalized intersections.
- **Demand Data:** MDOT provides a static travel demand matrix on a daily basis. Hourly factors are applied to these static demands to generate a time-dependent OD demand matrix for dynamic simulation.
- **Traffic Flow Relations:** Speed-density curves, specific to the Michigan network, are calibrated using data collected from MDOT's CCSs along Michigan freeways.
- **Scenario and System Data:** These inputs define the simulation settings and are essential for scenario analysis, enabling the evaluation of different traffic conditions and network configurations.

Using the statewide Michigan road network, illustrated in Figure 4, and the prepared input files, the simulation is executed in DYNASMART-P, where vehicles are assigned to routes that minimize generalized travel costs. Based on the traffic assignment results, the trajectories of trips originating from selected cities are extracted for each city. It is assumed that 25% of all trips within each city are taken by EVs. These EV trip trajectories serve as inputs to the charging simulator, which estimates charging needs and identifies vehicles that require recharging.

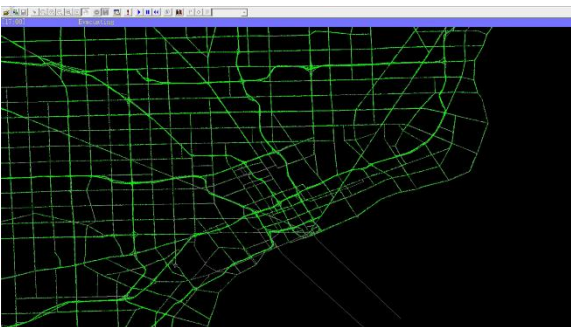
To illustrate the traffic simulation results, Figure 20 presents snapshots of simulated vehicle movements within Detroit at four different times: early morning, morning peak period, afternoon peak period, and off-peak night period. The lightness or darkness of the green color on each route represents the level of congestion, the darker the green, the more congested the route.



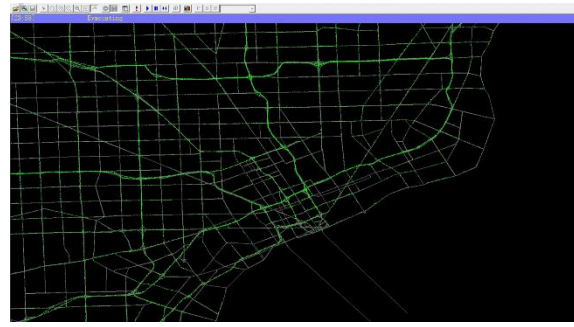
(a) Morning off-peak hours



(b) Morning peak hours



(c) Evening peak hours



(d) Night off-peak hours

Figure 20: Simulation results for the Detroit metropolitan area



### State of Charge Simulator

Unlike intercity trips, which are typically considered standalone journeys, urban trips are often part of a chain and are less preplanned. As a result, EV users may begin their urban trips with varying states of charge, whereas intercity trips are more likely to start with a fully charged battery. The initial state of charge for EVs depends on the trip origin and departure time, while the desired SoC (state of charge EVs aim to have at the end of their trips) is influenced by the trip destination and arrival time.

To estimate EV charging behavior, this study develops a simulation tool based on a 2016 Michigan Department of Transportation survey (76). This survey provides insights into time-dependent trip purposes across Michigan, as illustrated in Figure 21. The survey categorizes trip activities into seven groups: home-based work (HBWork), non-home-based work (NHBWork), home-based school (HBSchool), home-based shop (HBShop), home-based social (HBSocial), home-based other (HBOther), and non-home-based other (NHBOther).

However, for EV applications, distinguishing trips based on whether they originate from home or work is crucial, as these locations generally offer higher availability of Level 2 chargers. To simplify the classification, the survey's original categories are reorganized into four groups:

- HBWork (Home-Based Work)
- NHBWork (Non-Home-Based Work)
- NHBOther (Non-Home-Based Other)
- HBNWork (Home-Based Non-Work), which consolidates HBSchool, HBShop, HBSocial, and HBOther due to their similar charging opportunities.

Using the time-dependent trip purposes and land-use information, the simulation probabilistically estimates the origin, destination, and purpose of each trajectory, helping to determine the charging behavior of EV users.

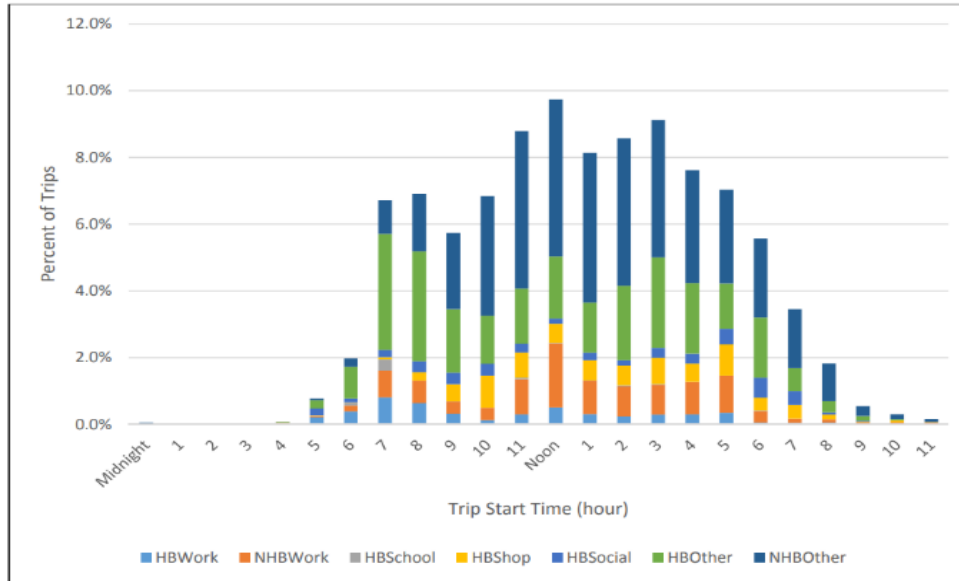


Figure 21: Person trips by start time (hour) and general purpose

This study differentiates trips originating from home based on whether the EV has access to a home charger. Both single- and multi-family units with home charging access are assumed to have a similar initial state of charge. Additionally, since some workplaces offer charging facilities for employees, EVs departing from workplaces are more likely to start their trips with a higher initial state of charge compared to those from residential areas without home charging access. This study employs a normal distribution in the charging simulation to account for the stochastic nature of users' charging behavior, considering both their initial and desired state of charge. The total charge required for each trajectory is determined by the

difference between the desired state of charge and the initial charge, plus the energy consumed en-route to the destination. If this value is positive, the EV requires recharging; otherwise, the vehicle does not need charging and is excluded from the optimization modeling framework.

Table 11 presents the mean and standard deviation of the initial state of charge for vehicles departing from different land uses before 12 PM, as well as the desired state of charge for vehicles arriving at various land uses after 5 PM, based on a normal distribution. It is assumed that EVs experience a reduction in state of charge throughout the day due to multiple trips. To account for this, the initial state of charge is decreased by 0.1 for trips starting between 12 PM and 5 PM and by 0.2 for trips starting after 5 PM. Additionally, since urban trips are often part of a trip chain, trips arriving before 5 PM are unlikely to be the final destination, as they are more likely to be followed by additional trips. To reflect this, the desired state of charge is adjusted by increasing it by 0.1 for trips arriving between 6 AM and 12 PM and by 0.05 for trips arriving between 12 PM and 5 PM. Additionally, it is assumed that 90% of single-family units have access to home chargers, while 50% of multi-family units have home charging availability.

Table 11: Initial and desired state of charge of vehicles

	Initial state of charge		Desired state of charge	
	Mean	SD	Mean	SD
Home- single family				
With home charger	0.75	0.05	0.15	0.1
Without home charger	0.5	0.2	0.4	0.1
Home- multi family				
With home charger	0.75	0.05	0.15	0.1
Without home charger	0.5	0.2	0.4	0.1
Work	0.6	0.2	0.25	0.1
Other	0.55	0.3	0.25	0.1

### Optimization Model

The proposed optimization model aims to minimize the total system cost, which encompasses infrastructure investment costs for charging stations and chargers, as well as the total delay incurred by EV users. Due to the high nonlinearity of this objective function, the problem is decomposed into two sub-problems. The first sub-problem focuses on minimizing the investment in charging stations, charging delay, and detour delay. The second sub-problem then minimizes the cost of chargers and the delay experienced by EV drivers at charging stations.

This section formulates the main objective function, which is decomposed into two sub-objective functions corresponding to each sub-problem. The road network comprises a set of zones ( $i \in I$ ), and each electric vehicle ( $j \in J$ ) follows a trajectory derived from dynamic traffic simulation. This trajectory includes details such as OD pairs, route choices, departure times, trip lengths, and travel times. Additionally, a discrete set of time periods ( $\tau \in T$ ) represents the arrival times of vehicles at charging stations, enabling the model to capture the visiting flow at different times.

The objective function aims to minimize the total investment cost, including chargers, grid infrastructure, construction, and land, as well as user-related costs such as charging, detour, and waiting time. Table 12 provides definitions for each model parameter.

$$\text{Min} \sum_{i \in I} (C_i^s x_i + U_i x_i + C_i^p z_i) + \gamma \left( \sum_{i \in I} \sum_{\tau \in T} \pi_i^\tau + \sum_{j \in J} TTD_j \right) \quad (5)$$

Table 12: Model variable descriptions and definitions

Variable	Description	Unit/Value
$C_i^s$	Charging station cost	\$/day <sup>1</sup>
$C_i^p$	Charger cost	\$/day
$U_i$	Utility cost	\$/day
$\gamma$	Value of time	\$/hour
$\pi_i^\tau$	Delay time for waiting and refueling at charging stations	hour
$TTD_j$	Detour travel time required for charging	hour
$x_i$	Charging station decision variable	Build or not $\in \{0,1\}$
$z_i$	Number of chargers	Integer Number

The objective function comprises two primary components. The first component, the infrastructure investment cost, includes the fixed cost of establishing charging stations, the variable electricity provision cost, determined by the number of chargers and power capacity at each site, and the variable cost of procuring chargers. The cost of charging stations encompasses the necessary facilities for charger installation, while the cost of chargers includes equipment expenses, activation fees, construction costs, and land acquisition costs. The second component represents the monetary value of delays incurred by EV users. This includes the charging and queuing delays, captured by  $\pi_i^\tau$ , as well as the detour time required for EV users to reach a charging station, represented by  $TTD_j$ . These delays are converted into monetary terms using the value of time, represented by  $\gamma$ . The decision variables in the model include the zones where charging stations should be installed and the number of chargers at each station.

The objective function is accompanied by a set of constraints that ensure feasibility. These constraints govern SoC tracking, flow conservation, detour time, and queuing conditions. To account for SoC, EVs cannot charge beyond their battery capacity, meaning they cannot recharge at stations where the required charge exceeds their available capacity. Additionally, it is assumed that EVs charge only once to reach their destination and can only access charging stations within their current driving range. Detour time for each trip is determined by the difference between the initial trip duration and the adjusted duration when a vehicle stops at a charging station. These constraints collectively ensure a realistic and efficient charging network design.

### Solution Approach

As previously discussed, the optimization model is a mixed-integer problem with non-linear constraints. Due to its computational complexity, commercial solvers struggle to efficiently find solutions, particularly for large-scale networks. To address this challenge, a decomposition technique is employed to break the problem into two sub-problems. The first sub-problem focuses on locating charging stations within the network while minimizing the costs associated with station installation, detours, and charging delays. The second sub-problem determines the required number of chargers at each station, aiming to minimize both charger costs and queuing delays for EV users. A dedicated solution framework is developed for each sub-problem to enhance computational efficiency and solution quality.

The first sub-problem focuses on determining the optimal locations for charging stations. Its objective function is defined as follows:

$$\text{Min} \sum_{i \in I} (C_i^s + U_i)x_i + \gamma \left( \sum_{\tau \in T} \sum_{\theta \in T} \sum_{i \in I} \sum_{j \in J} Q_{ij}^{\tau\theta} R_{ij}^\theta + \sum_{j \in J} TTD_j \right) \quad (6)$$

<sup>1</sup> In this study, the infrastructure lifetime is assumed to be 10 years, and the associated costs are divided by the total number of days in that period to enable comparison with other variables in the objective functions.



The decision variable in the objective function,  $x_i$ , is a binary variable that equals 1 if a charging station is established at location  $i$  and 0 otherwise. This objective function, combined with its constraints, forms a mixed-integer program with linear constraints. Commercial solvers such as CPLEX can be used to solve these problems efficiently for small to moderate-sized instances. However, as the problem size increases, computational complexity grows exponentially, making exact solutions impractical for large-scale networks. To address this challenge, a metaheuristic approach based on SA is implemented for large case studies. The SA-based algorithm follows two key steps. First, it explores the feasible set of integer solutions to identify a neighboring solution to the current one. Next, the algorithm compares the objective values of the current and neighboring solutions. If the neighboring solution improves the objective function, it replaces the current solution. If the new solution is worse, it may still be accepted with a probability that depends on the relative difference between the objective function values. This probability gradually decreases as iterations progress, approaching zero by the end of the algorithm, ensuring that worse solutions are no longer accepted. This mechanism helps prevent the solution from getting trapped in local optima. Once the charging station locations are determined, vehicle trajectories are assigned to available stations in a way that minimizes total detour time.

The second sub-problem determines the optimal number of chargers at each charging station. Based on the solution from the first sub-problem, the trajectories assigned to each charging station are known. These trajectories arrive at charging stations following a temporal distribution, typically exhibiting AM and PM peak travel demand periods. Upon arrival, EV users either begin charging immediately if a charger is available or wait in a queue until one becomes free. This sub-problem balances the trade-off between installing additional chargers and allowing users to experience queuing delays. The objective function for this sub-problem aims to minimize both the cost of chargers and the queuing delay experienced by EV users at charging stations, formulated as follows:

$$\text{Min } C_i^p z_i + \gamma \sum_{\tau \in T} y_i^\tau \bar{W}_i^\tau \quad (7)$$

The decision variable in this sub-problem is the number of chargers at each station. The variable  $y_i^\tau$  represents the number of EVs arriving at a charging station, while the queuing delay is captured by  $\bar{W}_i^\tau$ . The objective function value is estimated based on assumptions regarding arrival and service rates.

Assuming uniform arrival and service rates, queuing behavior can be modeled using a deterministic queueing approach (77). Under this assumption, the objective function and constraints form a mixed-integer problem with nonlinear constraints. Since the objective function is strictly convex, and the constraints are convex, the problem can be effectively solved using the Golden-section search technique, which identifies the extreme value of a function within a predefined interval (78). The deterministic queueing assumption provides the minimum number of chargers required to accommodate EV charging demand. However, if the vehicle arrival rate at a charging station is lower than the service rate, the arrival process can be better represented using a Poisson distribution with an exponential service rate distribution. In this case, the M/M/k queueing model should be applied to capture users' queuing behavior (77). The average queue size in an M/M/k system is convex with respect to traffic flow (79), allowing the optimal objective function value to be determined using the Golden-section search technique. It is important to note that the M/M/k model is applicable only when the service rate exceeds the arrival rate. If the arrival rate surpasses the service rate, only the deterministic queueing approach remains valid.

### Location and Number of DCFC in Urban Areas

This section presents the project results, detailing the optimized parameters for each urban area, as shown in Table 13. The urban areas are sorted based on total energy required. For each city, the table includes the number of zones, which corresponds to the traffic analysis zones defined by MDOT. It also presents the total number of required charging stations and chargers, as well as the number of new required charging stations and chargers, excluding existing infrastructure. In the proposed model, each charging station represents a traffic analysis zone, meaning that the total number of chargers required at each zone

are reported for the station representing that zone. However, the required chargers can be implemented across multiple stations within that zone meaning that the station cost estimated can be conservative for zones with large number of chargers. The results also include the average detour time, queuing time, and charging time for each city. Detour time refers to the extra time users spend deviating from their main route to access a charging station. Since there are no budget constraints in the model, the average queuing time remains close to zero. Additionally, the number of EV trips made between 6 AM and 10 PM is recorded. The total energy required and total costs for each city are also reported. Figure 22 illustrates the newly required chargers in each urban area. The circle radius in the figures represents the number of chargers needed at each location.

Table 13: Results of the optimization model for charging station placement and charger counts for major urban areas

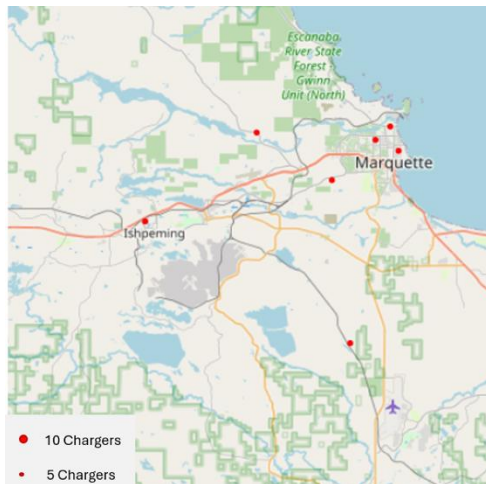
Parameter/City	Marquette	Ann Arbor	Muskegon	Kalamazoo	Flint	Saginaw	Lansing	Grand Rapids	Detroit
Battery size (kWh)	70	70	70	70	70	70	70	70	70
Charging station (kW)	150	150	150	150	150	150	150	150	150
Number of zones	21	36	52	55	84	116	92	82	301
Total required stations	7	14	20	23	22	42	36	37	141
Total required chargers	41	122	174	219	278	342	356	616	2766
New required stations	6	12	17	21	20	40	31	31	127
New required chargers	33	119	166	215	269	337	333	603	2716
Average detour delay (min)	2.3	1.5	1.7	2.1	1.7	2.2	1.8	2.3	2.4
Average queuing delay (min)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0
Average charging delay (min)	7.3	6.6	6.7	6.7	6.7	6.9	6.7	6.7	6.9
EV urban trips	12,626	54,816	71,571	88,921	117,668	124,843	131,351	232,903	961,697
Total energy required (MWh)	38.6	133.51	172.83	232.56	291.17	339.86	342.11	617.23	2758.71
Total station cost <sup>1</sup> (M\$)	0.49	0.99	1.40	1.73	1.66	3.30	2.56	2.53	10.58
Total utility cost <sup>2</sup> (M\$)	0.19	2.13	5.11	3.90	26.52	10.56	17.37	19.66	40.82
Total charger cost <sup>3</sup> (M\$)	2.58	9.31	12.99	16.85	21.12	26.38	26.08	46.99	213.83
Total infrastructure cost <sup>4</sup> (M\$)	3.26	12.43	19.50	22.48	49.30	40.23	46.01	69.18	265.23

<sup>1</sup> Charging station cost refers to the electrical panel and switchgear installation, engineering and design, permitting, and project management, and may encompass multiple chargers within a single station.

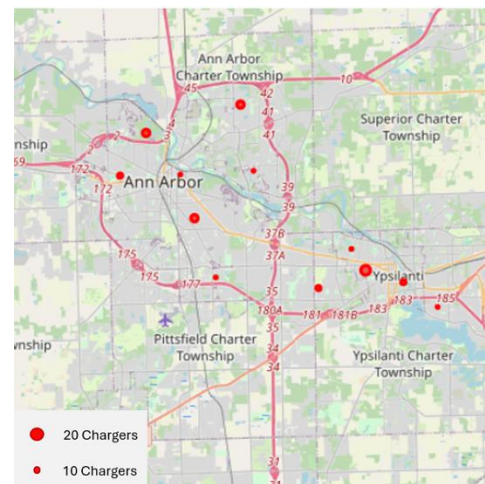
<sup>2</sup> Utility cost refers to the expenses associated with acquiring, installing, and maintaining the necessary power grid infrastructure to support varying levels of energy demand at charging stations.

<sup>3</sup> Charger cost refers to the expense associated with purchasing each individual EV charging unit.

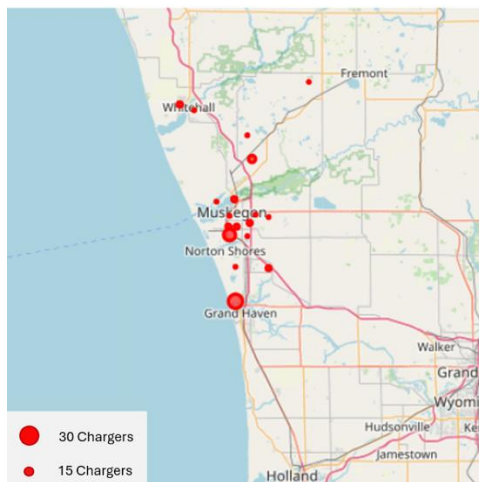
<sup>4</sup> Total infrastructure cost is the sum of charging station, charger, and utility costs.



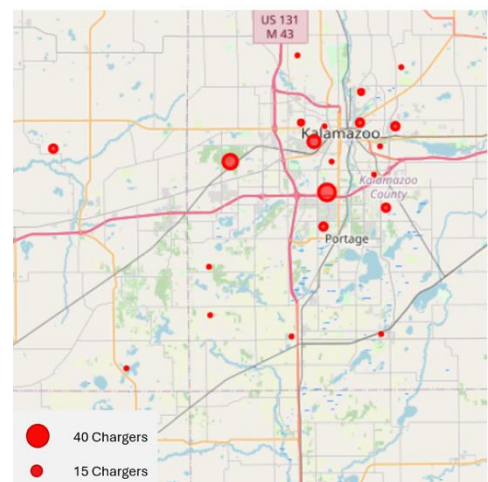
(a) Marquette



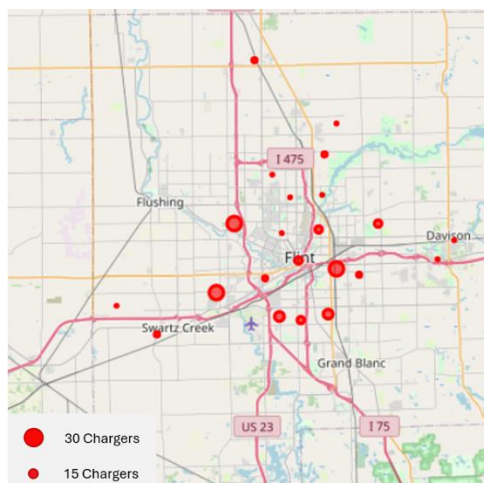
(b) Ann Arbor



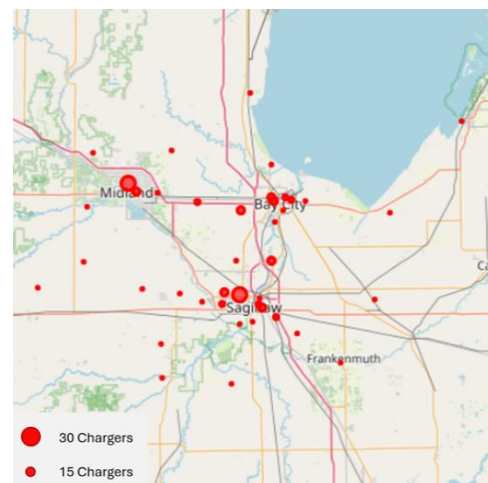
(c) Muskegon



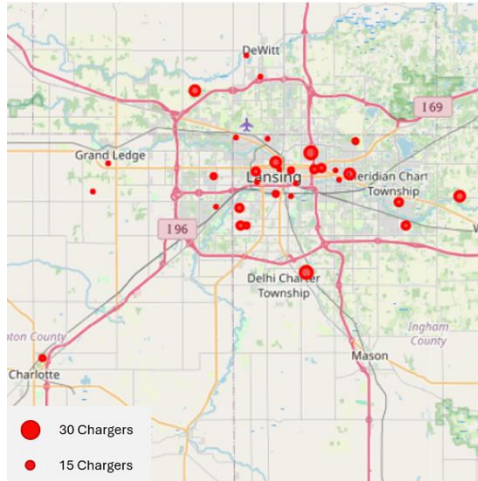
(d) Kalamazoo



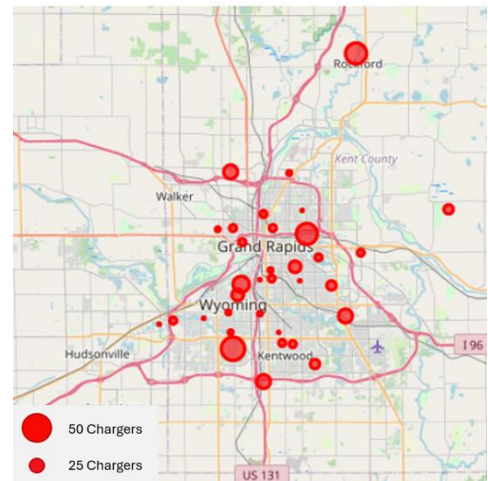
(e) Flint



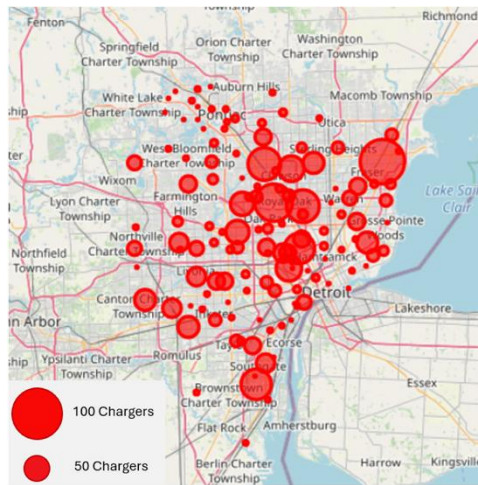
(f) Saginaw



(g) Lansing



(h) Grand Rapids



(i) Detroit

Figure 22: Optimized DCFC locations for urban trips

## Framework for Cross-Sector EV Charging

To develop an efficient and well-balanced EV charging infrastructure, it is crucial to integrate both intercity DCFC with destination Level 2 charging at hotels for tourism trips and Level 2 and DCFC charging in urban areas. Proper coordination of these charging networks ensures optimal charger utilization, prevents redundancy, and enhances accessibility for EV users.

Integrating intercity DCFC with Level 2 charging at tourism destinations is crucial for creating a well-balanced and efficient EV charging network. A key challenge arises when hotels and motels either lack Level 2 chargers or have them, but they are fully occupied, leaving EV users without an immediate charging option. In such situations, EV users may need to detour to nearby DCFC stations rather than wait for an available charger, increasing energy demand at these fast-charging locations. This additional strain on DCFC stations can lead to congestion, longer waiting times, and reduced charging availability for both tourists and intercity travelers. By integrating these networks, we can better anticipate energy demand, strategically allocate chargers, and minimize unnecessary detours, ultimately improving the overall efficiency and convenience of the charging infrastructure.

Similarly, coordinating Level 2 and DCFC charging in urban areas helps balance energy demand and prevent congestion. The availability of Level 2 chargers at homes, workplaces, and public locations



directly influences the need for DCFC stations. In areas where Level 2 charging is insufficient, a higher number of users will rely on DCFC stations, leading to increased energy demand and longer waiting times. Integrating these charging types allows for a strategic placement of urban fast chargers, ensuring they complement the existing Level 2 infrastructure while maintaining an efficient and accessible network.

The entire integration framework is illustrated in Figure 23, and the following sections detail how these charging networks interact and present the study's findings.

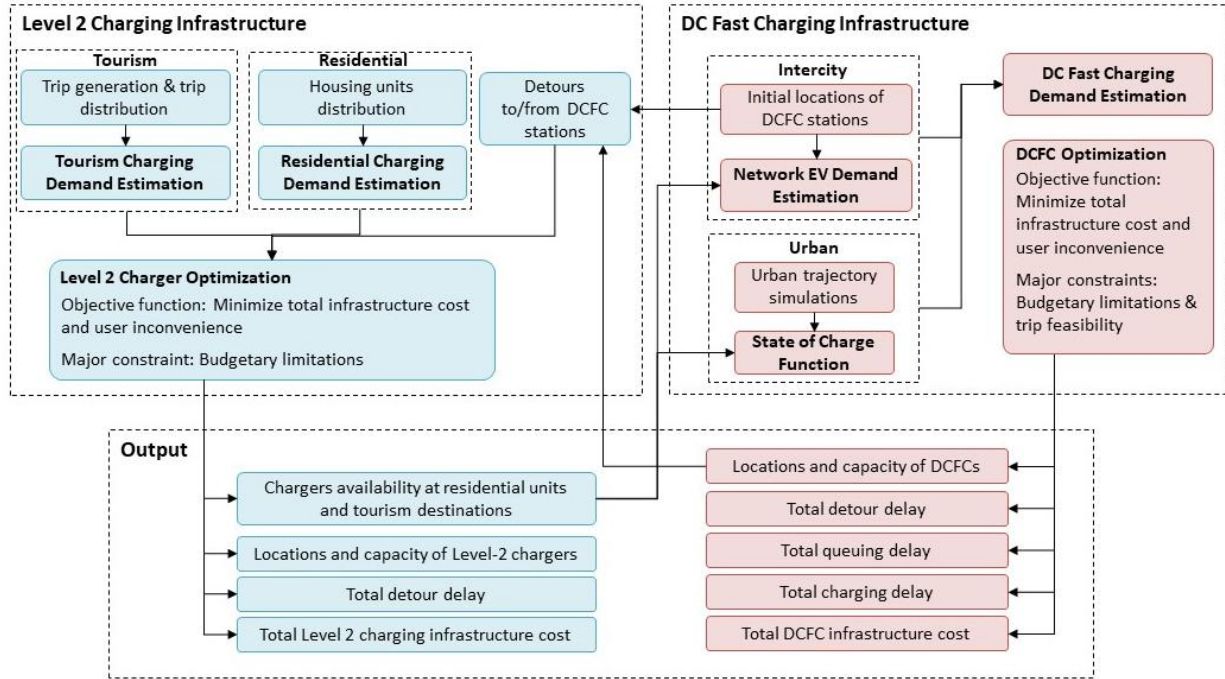


Figure 23: Comprehensive EV charging integration framework

## Interconnection of Intercity and Destination Charging for Tourism

Tourism trips often involve long-distance travel and extended stays, requiring a tailored approach to EV charging infrastructure planning. An effective strategy combines DCFCs for intermediate charging along travel corridors with Level 2 chargers at tourist destinations where visitors remain for longer periods. Therefore, in addition to intercity trips, tourism travel must also be accounted for when estimating DCFC energy demand along highways. A further challenge arises when hotels and motels either lack Level 2 chargers or have chargers that are fully occupied, leaving EV users without immediate access to charging. In such cases, users may detour to nearby DCFC stations, increasing energy demand and potential congestion at those locations.

To address this, the process begins by identifying DCFC station locations along major highways based on budget constraints and trip feasibility. Next, the detour distance between each Level 2 charging location at tourism destinations and its nearest DCFC station is calculated. Using this information, the location and capacity of Level 2 charging stations are determined according to the available budget and charging demand at each destination. Any unserved energy demand at these Level 2 locations is then redirected to their nearest DCFC stations. The combined total of redirected and original DCFC energy demand is used to re-evaluate the location and capacity of DCFC stations. These updates, in turn, affect detour distances and unserved energy demand at Level 2 stations. The process continues iteratively until a stable solution is reached. Figure 24 displays a map illustrating the locations and capacities of the charging infrastructure. Figure 24(a) highlights the locations and number of DCFC with a power rating of 150 kW needed to support intercity travel, as well as any tourism-related travel demand that can be accommodated by these chargers. A total of \$14.85 million is allocated for station construction, and

\$134.80 million is allocated for chargers—supporting the installation of 1,724 DCFC chargers for both intercity and tourism-related trips along the highways in Michigan. The total cost of this infrastructure is \$149.64 million. It is important to note that these chargers may be installed at multiple stations within a five-mile radius along the corridor. Figure 24(b) shows the locations and number of Level 2 chargers with a power rating of 11 kW required at various tourism destinations to support long-duration tourism visits. A total of \$66.71 million is allocated to install 6,167 Level 2 chargers. These chargers may be installed across multiple stations within the designated zone.

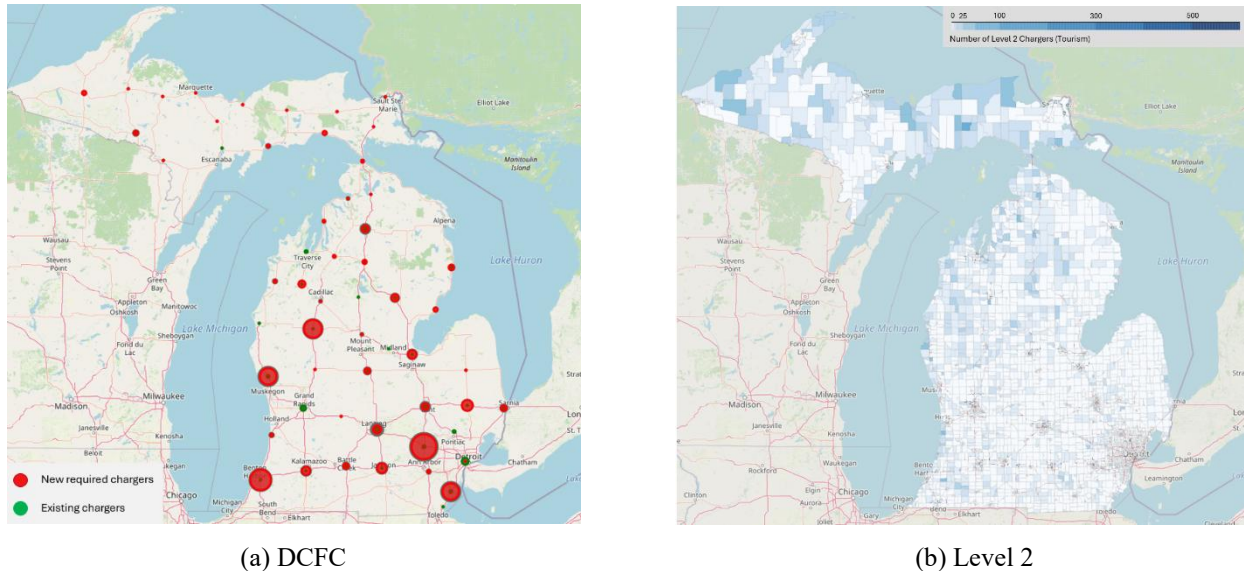


Figure 24: Map of charging infrastructure to support intercity and tourism trips in Michigan

## Interconnection of Level 2 and DCFC in Urban Areas

Urban trips rely on a balanced mix of Level 2 chargers, commonly found at homes, workplaces, and public destinations like shopping centers, and DCFCs to address the varying charging needs of EV users. The accessibility and availability of Level 2 chargers at home and work significantly influence how often users depend on DCFCs during the day. For instance, EV users who can charge at home or at their workplace may start trips with a higher initial SoC, reducing or even eliminating their need for fast charging. Conversely, users without access to residential or workplace charging are more likely to rely on public DCFCs to complete their daily travel, especially during longer or unexpected trips.

To accurately estimate charging demand and energy needs, it is crucial to assess the distribution of Level 2 chargers across different land use types. This involves identifying the origin and destination of each EV trip, whether it begins or ends at a single-family residence, multi-family unit, workplace, or other location. Depending on these factors, both the initial and desired SoC can vary significantly. For example, a trip starting from a home with access to Level 2 charging will likely have a higher initial SoC, while trips ending at such locations may have lower desired SoC since users can recharge upon arrival. On the other hand, trips without access to Level 2 chargers at either end will have greater energy demand, increasing the likelihood of using DCFCs along the way. By incorporating these relationships into planning, we can better understand where and when DCFCs are truly needed, avoid overbuilding infrastructure, and create a more efficient and user-friendly urban charging network.

Figure 25 displays a map showing the locations and capacities of the planned charging infrastructure. Figure 25(a) and Figure 25(b) highlight the locations and number of DCFC and Level 2 chargers, with power ratings of 150 kW and 11 kW respectively, needed to support urban travel.

A total of \$151.49 million is allocated for DCFC station construction, and \$376.13 million for DCFC chargers, supporting the installation of 4,791 DCFC chargers across major urban areas. The total cost for DCFC infrastructure is \$527.62 million. Additionally, \$14.63 million is allocated for Level 2 station

construction, and \$239.58 million for Level 2 chargers at multi-family housing locations, enabling the installation of 53,920 Level 2 chargers. The total cost for Level 2 infrastructure is \$254.21 million. Additionally, approximately 855,243 new Level 2 chargers are projected to be required at single-family homes. However, since home charging is generally considered the responsibility of individual property owners, these costs are not included in the total infrastructure investment. It is worth mentioning that these chargers may be installed across multiple stations within the designated zone.

These estimates are based on the assumption that 90% of single-family homes and 50% of multi-family housing units have access to home charging. This assumption was made based on feedback from stakeholders to better reflect real-world conditions. Any variation in this assumption regarding home charger access may affect the results for both Level 2 and DCFC requirements due to the integrated nature of the two charging types.

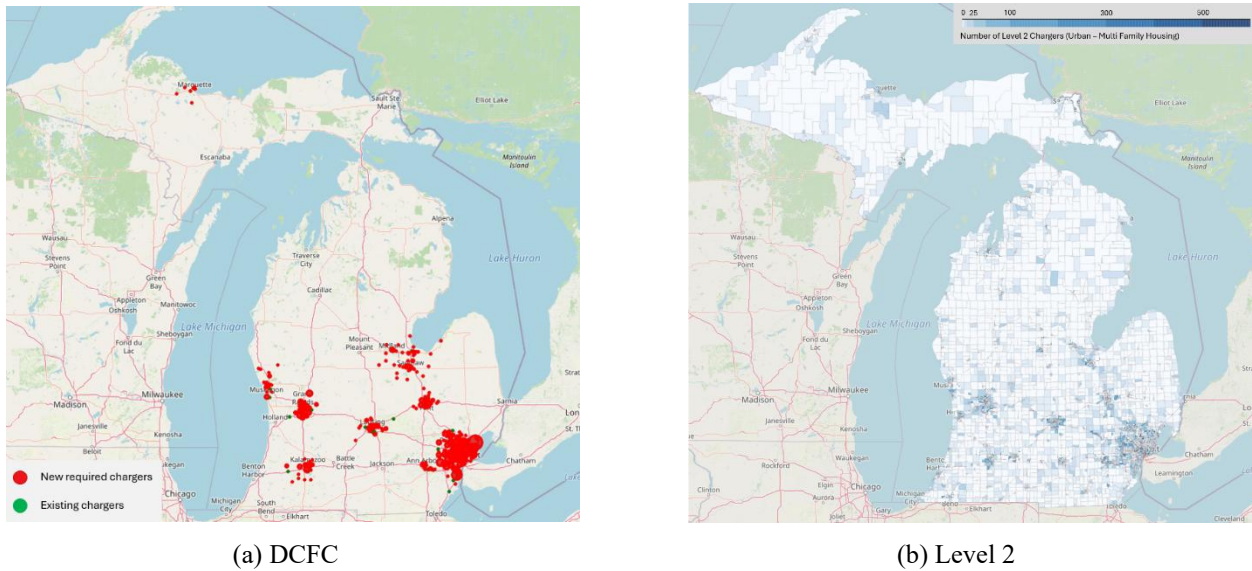


Figure 25: Map of charging infrastructure to support urban trips in Michigan

## Conclusion

This project aimed to develop a data-driven, cost-effective deployment strategy for EV charging infrastructure across Michigan to support a 25% EV market share. The strategy focused on meeting the charging needs of intercity travelers, urban commuters, and visitors to tourism destinations. Led by the Michigan Office of Future Mobility & Electrification in partnership with Michigan State University researchers, the initiative sought to identify optimal locations for both Direct Current Fast Charging (DCFC) and Level 2 chargers, balancing infrastructure investment with the need to reduce user inconvenience and travel delays.

The study employed a comprehensive analytical framework that integrated stakeholder feedback, detailed travel demand forecasting, statewide traffic simulations, and advanced optimization modeling. The core of the modeling approach combined mixed-integer programming techniques with heuristic methods, most notably, the Simulated Annealing algorithm, to solve complex, large-scale optimization problems involving nonlinearity and multiple constraints.

The model incorporated a wide range of critical inputs. It accounted for diverse travel behavior patterns, including urban, intercity, and tourism-related travel. It incorporated seasonal variability in EV performance to ensure that the infrastructure would be resilient throughout the year, especially during Michigan's harsh winters. The modeling also factored in battery characteristics, such as range and charging needs, and user preferences related to charging frequency, location, and duration of stay.

For a projected 25% EV market share, the analysis recommended a multifaceted deployment strategy. For intercity and tourism travel, 1,724 new DCFC chargers were proposed along major highways and corridors to support long-distance mobility. These would be complemented by 6,167 Level 2 chargers located at tourism destinations where vehicles are typically parked for longer durations. In urban residential areas, especially where multi-family housing is prevalent, 4,791 DCFC chargers and 53,920 Level 2 chargers were recommended to accommodate the charging needs of residents.

The total investment required to realize this infrastructure vision is estimated at approximately \$998 million. Of this, \$677 million would be allocated to DCFC installations, while \$321 million would be directed toward the deployment of Level 2 chargers. These results are summarized in Table 14 of the report.

Table 14: Summary of the findings (based on a 25% EV adoption rate)

	Number of new required chargers			Cost of new required chargers		
	DCFC	Level 2	Total	DCFC	Level 2	Total
Intercity trips in Michigan	1,724	-	1,724	\$149.64 M	-	\$149.64 M
Tourism trips in Michigan	-	6,167	6,167	-	\$66.71 M	\$66.71 M
Urban trips in Michigan	4,791	53,920	58,711	\$527.62 M	\$254.21 M	\$781.83 M
Total	6,515	60,087	66,602	\$677.26 M	\$320.92 M	\$998 M

The study emphasized the interdependent relationship between DCFC and Level 2 charging infrastructure. By increasing the availability of Level 2 chargers, particularly in residential settings and at tourism destinations, the overall reliance on DCFC infrastructure can be reduced. This not only leads to more efficient use of resources but also helps avoid overburdening the electric grid. Furthermore, the analysis revealed that seasonal impacts on EV performance necessitate the design of a robust charging network capable of meeting peak winter travel demand, thereby ensuring consistent service year-round.

This study provides clear and actionable guidance for policymakers, transportation agencies, and urban planners. It advocates for a phased and adaptive implementation strategy, whereby the charging network is developed incrementally in response to real-world data and utilization trends. By continuously monitoring infrastructure performance and aligning future investments with actual EV adoption rates, Michigan can build a scalable, cost-effective, and reliable EV charging network that supports its long-term mobility and sustainability goals.



## Reference

1. American Community Survey. <https://data.census.gov/table?q=DP04>. Accessed May 11, 2025.
2. Zhang, X., D. Rey, and S. T. Waller. Multitype Recharge Facility Location for Electric Vehicles. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 33, No. 11, 2018, pp. 943–965. <https://doi.org/10.1111/mice.12379>.
3. Nie, Y., M. Ghamami, A. Zockaie, and F. Xiao. Optimization of Incentive Policies for Plug-in Electric Vehicles. *Transportation Research Part B: Methodological*, Vol. 84, 2016, pp. 103–123. <https://doi.org/10.1016/j.trb.2015.12.011>.
4. Get Connected EV Quarterly Report 2023 Q4. 2024.
5. MI Future Mobility Plan Pillar 2 \_ OFME \_ Michigan Business. 2024.
6. Mao, H., J. Shi, Y. Zhou, and G. Zhang. The Electric Vehicle Routing Problem with Time Windows and Multiple Recharging Options. *IEEE Access*, Vol. 8, 2020, pp. 114864–114875. <https://doi.org/10.1109/ACCESS.2020.3003000>.
7. Wang, H., D. Zhao, Q. Meng, G. P. Ong, and D. H. Lee. A Four-Step Method for Electric-Vehicle Charging Facility Deployment in a Dense City: An Empirical Study in Singapore. *Transportation Research Part A: Policy and Practice*, Vol. 119, 2019, pp. 224–237. <https://doi.org/10.1016/j.tra.2018.11.012>.
8. McKercher, B., and A. Tkaczynski. Will Electric Vehicles Decarbonise Drive Tourism? *Annals of Tourism Research Empirical Insights*, Vol. 5, No. 2, 2024. <https://doi.org/10.1016/j.annale.2024.100133>.
9. Eijelaar, E., and P. Peeters. *Zero-Emission Tourism Mobility A Research and Policy Agenda PIB Connecting Success Formulas: Sustainable Mobility and Energy in Austria and the Netherlands-K2K Consortium Development Zero-Emission Tourism Mobility*. 2018.
10. Mastoi, M. S., S. Zhuang, H. M. Munir, M. Haris, M. Hassan, M. Usman, S. S. H. Bukhari, and J. S. Ro. An In-Depth Analysis of Electric Vehicle Charging Station Infrastructure, Policy Implications, and Future Trends. *Energy Reports*. Volume 8, 11504–11529.
11. Khan, W., A. Ahmad, F. Ahmad, and M. Saad Alam. A Comprehensive Review of Fast Charging Infrastructure for Electric Vehicles. *Smart Science*. 3. Volume 6, 256–270.
12. Ou, S. Estimate Long-Term Impact on Battery Degradation by Considering Electric Vehicle Real-World End-Use Factors. *Journal of Power Sources*, Vol. 573, 2023. <https://doi.org/10.1016/j.jpowsour.2023.233133>.
13. Stroe, D.-I., M. Swierczynski, S. K. Kær, E. M. Laserna, and E. S. Zabala. *ECCE 2017 : IEEE Energy Conversion Congress & Expo : Cincinnati, Ohio, October 1-5*. 2017.
14. He, F., D. Wu, Y. Yin, and Y. Guan. Optimal Deployment of Public Charging Stations for Plug-in Hybrid Electric Vehicles. *Transportation Research Part B: Methodological*, Vol. 47, 2013, pp. 87–101. <https://doi.org/10.1016/J.TRB.2012.09.007>.
15. Dong, J., C. Liu, and Z. Lin. Charging Infrastructure Planning for Promoting Battery Electric Vehicles: An Activity-Based Approach Using Multiday Travel Data. *Transportation Research Part C: Emerging Technologies*, Vol. 38, 2014, pp. 44–55. <https://doi.org/10.1016/J.TRC.2013.11.001>.
16. Nie, Y., and M. Ghamami. A Corridor-Centric Approach to Planning Electric Vehicle Charging Infrastructure. *Transportation Research Part B: Methodological*, Vol. 57, 2013, pp. 172–190. <https://doi.org/10.1016/J.TRB.2013.08.010>.
17. Pistoia, G. *ELECTRIC AND HYBRID VEHICLES POWER SOURCES, MODELS, SUSTAINABILITY, INFRASTRUCTURE AND THE MARKET*. 2010.
18. Jing, W., I. Kim, M. Ramezani, and Z. Liu. Stochastic Traffic Assignment of Mixed Electric Vehicle and Gasoline Vehicle Flow with Path Distance Constraints. *Transportation Research Procedia*, Vol. 21, 2017, pp. 65–78. <https://doi.org/10.1016/J.TRPRO.2017.03.078>.
19. Botsford, C., and A. Szczepanek. *Fast Charging vs. Slow Charging: Pros and Cons for the New Age of Electric Vehicles*. 2009.

20. Gnann, T., S. Funke, N. Jakobsson, P. Plötz, F. Sprei, and A. Bennehag. Fast Charging Infrastructure for Electric Vehicles: Today's Situation and Future Needs. *Transportation Research Part D: Transport and Environment*, Vol. 62, 2018, pp. 314–329. <https://doi.org/10.1016/J.TRD.2018.03.004>.
21. Lee, C., and J. Han. Benders-and-Price Approach for Electric Vehicle Charging Station Location Problem under Probabilistic Travel Range. *Transportation Research Part B: Methodological*, Vol. 106, 2017, pp. 130–152. <https://doi.org/10.1016/J.TRB.2017.10.011>.
22. Guo, Z., J. Deride, and Y. Fan. Infrastructure Planning for Fast Charging Stations in a Competitive Market. *Transportation Research Part C: Emerging Technologies*, Vol. 68, 2016, pp. 215–227. <https://doi.org/10.1016/J.TRC.2016.04.010>.
23. Ghamami, M., A. Zockaie, and Y. M. Nie. A General Corridor Model for Designing Plug-in Electric Vehicle Charging Infrastructure to Support Intercity Travel. *Transportation Research Part C: Emerging Technologies*, Vol. 68, 2016, pp. 389–402. <https://doi.org/10.1016/J.TRC.2016.04.016>.
24. Micari, S., A. Polimeni, G. Napoli, L. Andaloro, and V. Antonucci. Electric Vehicle Charging Infrastructure Planning in a Road Network. *Renewable and Sustainable Energy Reviews*, Vol. 80, 2017, pp. 98–108. <https://doi.org/10.1016/J.RSER.2017.05.022>.
25. Zang, H., Y. Fu, M. Chen, H. Shen, L. Miao, S. Zhang, Z. Wei, and G. Sun. Bi-Level Planning Model of Charging Stations Considering the Coupling Relationship between Charging Stations and Travel Route. *Applied Sciences (Switzerland)*, Vol. 8, No. 7, 2018. <https://doi.org/10.3390/app8071130>.
26. Lin, C., K. L. Choy, G. T. S. Ho, S. H. Chung, and H. Y. Lam. Survey of Green Vehicle Routing Problem: Past and Future Trends. *Expert Systems with Applications*, Vol. 41, No. 4, 2014, pp. 1118–1138. <https://doi.org/10.1016/J.ESWA.2013.07.107>.
27. Ouyang, Y., Z. Wang, and H. Yang. Facility Location Design under Continuous Traffic Equilibrium. *Transportation Research Part B: Methodological*, Vol. 81, No. P1, 2015, pp. 18–33. <https://doi.org/10.1016/J.TRB.2015.05.018>.
28. An, S., N. Cui, Y. Bai, W. Xie, M. Chen, and Y. Ouyang. Reliable Emergency Service Facility Location under Facility Disruption, En-Route Congestion and in-Facility Queuing. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 82, 2015, pp. 199–216. <https://doi.org/10.1016/J.TRE.2015.07.006>.
29. Hajibabai, L., Y. Bai, and Y. Ouyang. Joint Optimization of Freight Facility Location and Pavement Infrastructure Rehabilitation under Network Traffic Equilibrium. *Transportation Research Part B: Methodological*, Vol. 63, 2014, pp. 38–52. <https://doi.org/10.1016/J.TRB.2014.02.003>.
30. Bai, Y., T. Hwang, S. Kang, and Y. Ouyang. Biofuel Refinery Location and Supply Chain Planning under Traffic Congestion. *Transportation Research Part B: Methodological*, Vol. 45, No. 1, 2011, pp. 162–175. <https://doi.org/10.1016/J.TRB.2010.04.006>.
31. Wardrop, J. G. *Some Theoretical Aspects of Road Traffic Research*. 1952.
32. Bryden, T. S., G. Hilton, A. Cruden, and T. Holton. Electric Vehicle Fast Charging Station Usage and Power Requirements. *Energy*, Vol. 152, 2018, pp. 322–332. <https://doi.org/10.1016/J.ENERGY.2018.03.149>.
33. Xie, F., C. Liu, S. Li, Z. Lin, and Y. Huang. Long-Term Strategic Planning of Inter-City Fast Charging Infrastructure for Battery Electric Vehicles. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 109, 2018, pp. 261–276. <https://doi.org/10.1016/J.TRE.2017.11.014>.
34. He Graduate Research Assistant, Y., K. M. Kockelman, P. Corresponding Author Professor, E. Schoch Professor in Engineering, and K. A. Perrine. *OPTIMAL LOCATIONS OF U.S. FAST CHARGING STATIONS FOR LONG-DISTANCE TRIPS BY BATTERY ELECTRIC VEHICLES*. 2018.

35. Andrews, M., M. K. Do, J. D. Hobby, G. H. Tucci, and Y. Jin. *Modeling and Optimization for Electric Vehicle Charging Infrastructure*.
36. Tu, W., Q. Li, Z. Fang, S. lung Shaw, B. Zhou, and X. Chang. Optimizing the Locations of Electric Taxi Charging Stations: A Spatial–Temporal Demand Coverage Approach. *Transportation Research Part C: Emerging Technologies*, Vol. 65, 2016, pp. 172–189. <https://doi.org/10.1016/J.TRC.2015.10.004>.
37. Shahraki, N., H. Cai, M. Turkay, and M. Xu. Optimal Locations of Electric Public Charging Stations Using Real World Vehicle Travel Patterns. *Transportation Research Part D: Transport and Environment*, Vol. 41, 2015, pp. 165–176. <https://doi.org/10.1016/J.TRD.2015.09.011>.
38. Cai, H., X. Jia, A. S. F. Chiu, X. Hu, and M. Xu. Siting Public Electric Vehicle Charging Stations in Beijing Using Big-Data Informed Travel Patterns of the Taxi Fleet. *Transportation Research Part D: Transport and Environment*, Vol. 33, 2014, pp. 39–46. <https://doi.org/10.1016/J.TRD.2014.09.003>.
39. Yang, J., J. Dong, and L. Hu. A Data-Driven Optimization-Based Approach for Siting and Sizing of Electric Taxi Charging Stations. *Transportation Research Part C: Emerging Technologies*, Vol. 77, 2017, pp. 462–477. <https://doi.org/10.1016/J.TRC.2017.02.014>.
40. Huang, Y., and Y. Zhou. An Optimization Framework for Workplace Charging Strategies. *Transportation Research Part C: Emerging Technologies*, Vol. 52, 2015, pp. 144–155. <https://doi.org/10.1016/J.TRC.2015.01.022>.
41. Zockaie, A., H. Z. Aashtiani, M. Ghamami, and Y. Marco Nie. Solving Detour-Based Fuel Stations Location Problems. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 31, No. 2, 2016, pp. 132–144. <https://doi.org/10.1111/mice.12170>.
42. Upchurch, C., M. Kuby, and S. Lim. A Model for Location of Capacitated Alternative-Fuel Stations. *Geographical Analysis*, Vol. 41, No. 1, 2009, pp. 85–106. <https://doi.org/10.1111/j.1538-4632.2009.00744.x>.
43. Lim, S., and M. Kuby. Heuristic Algorithms for Siting Alternative-Fuel Stations Using the Flow-Refueling Location Model. *European Journal of Operational Research*, Vol. 204, No. 1, 2010, pp. 51–61. <https://doi.org/10.1016/J.EJOR.2009.09.032>.
44. Kuby, M., and S. Lim. Location of Alternative-Fuel Stations Using the Flow-Refueling Location Model and Dispersion of Candidate Sites on Arcs. *Networks and Spatial Economics*, Vol. 7, No. 2, 2007, pp. 129–152. <https://doi.org/10.1007/s11067-006-9003-6>.
45. Kuby, M., and S. Lim. The Flow-Refueling Location Problem for Alternative-Fuel Vehicles. *Socio-Economic Planning Sciences*, Vol. 39, No. 2, 2005, pp. 125–145. <https://doi.org/10.1016/J.SEPS.2004.03.001>.
46. Hodgson, M. J. A Flow-Capturing Location-Allocation Model. *Geographical Analysis*, Vol. 22, No. 3, 1990, pp. 270–279. <https://doi.org/10.1111/j.1538-4632.1990.tb00210.x>.
47. Berman, O., R. C. Larson, and N. Fouska. *Optimal Location of Discretionary Service Facilities*. 1992.
48. Riemann, R., D. Z. W. Wang, and F. Busch. Optimal Location of Wireless Charging Facilities for Electric Vehicles: Flow-Capturing Location Model with Stochastic User Equilibrium. *Transportation Research Part C: Emerging Technologies*, Vol. 58, No. Part A, 2015, pp. 1–12. <https://doi.org/10.1016/J.TRC.2015.06.022>.
49. He, J., H. Yang, T. Q. Tang, and H. J. Huang. An Optimal Charging Station Location Model with the Consideration of Electric Vehicle's Driving Range. *Transportation Research Part C: Emerging Technologies*, Vol. 86, 2018, pp. 641–654. <https://doi.org/10.1016/J.TRC.2017.11.026>.
50. Bai, Y., T. Hwang, S. Kang, and Y. Ouyang. Biofuel Refinery Location and Supply Chain Planning under Traffic Congestion. *Transportation Research Part B: Methodological*, Vol. 45, No. 1, 2011, pp. 162–175. <https://doi.org/10.1016/J.TRB.2010.04.006>.
51. Cavadas, J., G. H. de Almeida Correia, and J. Gouveia. A MIP Model for Locating Slow-Charging Stations for Electric Vehicles in Urban Areas Accounting for Driver Tours. *Transportation*

- Research Part E: Logistics and Transportation Review*, Vol. 75, 2015, pp. 188–201.  
<https://doi.org/10.1016/J.TRE.2014.11.005>.
52. Baouche, F., R. Billot, R. Trigui, and N. E. El Faouzi. Efficient Allocation of Electric Vehicles Charging Stations: Optimization Model and Application to a Dense Urban Network. *IEEE Intelligent Transportation Systems Magazine*, Vol. 6, No. 3, 2014, pp. 33–43.  
<https://doi.org/10.1109/MITS.2014.2324023>.
  53. Kang, J. E., and W. W. Recker. An Activity-Based Assessment of the Potential Impacts of Plug-in Hybrid Electric Vehicles on Energy and Emissions Using 1-Day Travel Data. *Transportation Research Part D: Transport and Environment*, Vol. 14, No. 8, 2009, pp. 541–556.  
<https://doi.org/10.1016/J.TRD.2009.07.012>.
  54. Nie, Y., M. Ghamami, A. Zockaie, and F. Xiao. Optimization of Incentive Policies for Plug-in Electric Vehicles. *Transportation Research Part B: Methodological*, Vol. 84, 2016, pp. 103–123.  
<https://doi.org/10.1016/J.TRB.2015.12.011>.
  55. Csiszár, C., B. Csonka, D. Földes, E. Wirth, and T. Lovas. Urban Public Charging Station Locating Method for Electric Vehicles Based on Land Use Approach. *Journal of Transport Geography*, Vol. 74, 2019, pp. 173–180. <https://doi.org/10.1016/J.JTRANGE.2018.11.016>.
  56. Wang, Y. W., and C. C. Lin. Locating Multiple Types of Recharging Stations for Battery-Powered Electric Vehicle Transport. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 58, 2013, pp. 76–87. <https://doi.org/10.1016/J.TRE.2013.07.003>.
  57. Wang, Y. W., C. C. Lin, and T. J. Lee. Electric Vehicle Tour Planning. *Transportation Research Part D: Transport and Environment*, Vol. 63, 2018, pp. 121–136.  
<https://doi.org/10.1016/J.TRD.2018.04.016>.
  58. Suanpang, P., P. Jamjuntr, P. Kaewyong, C. Niamsorn, and K. Jermstiparsert. An Intelligent Recommendation for Intelligently Accessible Charging Stations: Electronic Vehicle Charging to Support a Sustainable Smart Tourism City. *Sustainability (Switzerland)*, Vol. 15, No. 1, 2023.  
<https://doi.org/10.3390/su15010455>.
  59. Xu, D., W. Pei, and Q. Zhang. Optimal Planning of Electric Vehicle Charging Stations Considering User Satisfaction and Charging Convenience. *Energies*, Vol. 15, No. 14, 2022.  
<https://doi.org/10.3390/en15145027>.
  60. Knowles, N. L. B., D. Scott, and S. Mitchell. The Great Canadian (Electric) Road Trip: Evaluating EV Use in National Park Tourism. *Tourism and Hospitality*, Vol. 5, No. 2, 2024, pp. 314–332.  
<https://doi.org/10.3390/tourhosp5020021>.
  61. MirHassani, S. A., and R. Ebrazi. A Flexible Reformulation of the Refueling Station Location Problem. *Transportation Science*, Vol. 47, No. 4, 2013, pp. 617–628.  
<https://doi.org/10.1287/trsc.1120.0430>.
  62. Mak, H. Y., Y. Rong, and Z. J. M. Shen. Infrastructure Planning for Electric Vehicles with Battery Swapping. *Management Science*, Vol. 59, No. 7, 2013, pp. 1557–1575.  
<https://doi.org/10.1287/mnsc.1120.1672>.
  63. Li, S., Y. Huang, and S. J. Mason. A Multi-Period Optimization Model for the Deployment of Public Electric Vehicle Charging Stations on Network. *Transportation Research Part C: Emerging Technologies*, Vol. 65, 2016, pp. 128–143. <https://doi.org/10.1016/J.TRC.2016.01.008>.
  64. Nicholas, M. A., S. L. Handy, and D. Sperling. *Using Geographic Information Systems to Evaluate Siting and Networks of Hydrogen Stations*. 2004.
  65. He, F., Y. Yin, and J. Zhou. Deploying Public Charging Stations for Electric Vehicles on Urban Road Networks. *Transportation Research Part C: Emerging Technologies*, Vol. 60, 2015, pp. 227–240. <https://doi.org/10.1016/J.TRC.2015.08.018>.
  66. Zhu, Z., Z. Gao, J. Zheng, and H. Du. Charging Station Planning for Plug-In Electric Vehicles. *Journal of Systems Science and Systems Engineering*, Vol. 27, No. 1, 2018, pp. 24–45.  
<https://doi.org/10.1007/s11518-017-5352-6>.

67. Nourbakhsh, S. M., and Y. Ouyang. Optimal Fueling Strategies for Locomotive Fleets in Railroad Networks. *Transportation Research Part B: Methodological*, Vol. 44, No. 8–9, 2010, pp. 1104–1114. <https://doi.org/10.1016/J.TRB.2010.03.003>.
68. Ghamami, M., M. Kavianipour, A. Zockaie, L. R. Hohnstadt, and Y. Ouyang. Refueling Infrastructure Planning in Intercity Networks Considering Route Choice and Travel Time Delay for Mixed Fleet of Electric and Conventional Vehicles. *Transportation Research Part C: Emerging Technologies*, Vol. 120, 2020, p. 102802. <https://doi.org/10.1016/J.TRC.2020.102802>.
69. Chen, Z., W. Liu, and Y. Yin. Deployment of Stationary and Dynamic Charging Infrastructure for Electric Vehicles along Traffic Corridors. *Transportation Research Part C: Emerging Technologies*, Vol. 77, 2017, pp. 185–206. <https://doi.org/10.1016/J.TRC.2017.01.021>.
70. Ghamami, M., A. Zockaie, J. Wang, S. Miller, M. Kavianipour, M. (Sam) Shojaei, F. Fakhrmoosavi, L. Hohnstadt, and H. Singh. *Electric Vehicle Charger Placement Optimization in Michigan: Phase I – Highways*. 2019.
71. HNTB, Michigan State University, EVNoire, Atlas Public Policy, and CALSTART. *MI-Plan-for-EV-Infrastructure-Deployment*.
72. van den Berg, V. A. C., and E. T. Verhoef. Autonomous Cars and Dynamic Bottleneck Congestion: The Effects on Capacity, Value of Time and Preference Heterogeneity. *Transportation Research Part B: Methodological*, Vol. 94, 2016, pp. 43–60. <https://doi.org/10.1016/J.TRB.2016.08.018>.
73. Institute of Transportation Engineers. *Trip Generation Manual*. ITE, 2012.
74. Ghamami, M., A. Zockaie, S. Miller, M. Kavianipour, F. Fakhrmoosavi, H. Singh, F. Jazlan, and M. Shojaei. *Electric Vehicle Charger Placement Optimization in Michigan: Phase II-Urban*. 2020.
75. Jayakrishnan, R., H. S. Mahmassani, and T. Y. Hu. An Evaluation Tool for Advanced Traffic Information and Management Systems in Urban Networks. *Transportation Research Part C: Emerging Technologies*, Vol. 2, No. 3, 1994, pp. 129–147. [https://doi.org/10.1016/0968-090X\(94\)90005-1](https://doi.org/10.1016/0968-090X(94)90005-1).
76. Wilaby, M., and J. Casas. *MI Travel Counts III Household Travel Survey Final Methodology Report*. 2016.
77. Zukerman, M. *Introduction to Queueing Theory and Stochastic Teletraffic Models*. 2000.
78. Kavianipour, M., F. Fakhrmoosavi, H. Singh, M. Ghamami, A. Zockaie, Y. Ouyang, and R. Jackson. Electric Vehicle Fast Charging Infrastructure Planning in Urban Networks Considering Daily Travel and Charging Behavior. *Transportation Research Part D: Transport and Environment*, Vol. 93, 2021, p. 102769. <https://doi.org/10.1016/J.TRD.2021.102769>.
79. Grassmann, W. The Convexity of the Mean Queue Size of the M/M/c Queue with Respect to the Traffic Intensity. *Journal of Applied Probability*, Vol. 20, No. 4, 1983, pp. 916–919. <https://doi.org/10.2307/3213605>.