# Electric Vehicle Charger Placement Optimization in Michigan: Phase I - Highways

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**Auto Companies**

- Ford Motor Company
- General Motors
- Toyota

**Transmission and Utility Companies**

- American Transmission Company
- Cherryland Electric Cooperative
- Consumers Energy
- DTE Energy
- Great Lakes Energy Cooperative
- Indiana Michigan Power
- ITC Transmission Company
- Lansing Board of Water and Light
- Michigan Electric Cooperative Association
- Michigan Municipal Electric Association
- Wolverine Power Cooperative

**Charging Station Companies**

- ChargePoint
- Greenlots

**Electric Vehicle Drivers & Owners**

**National Organizations**

- Electrify America
- National Association of State Energy Officials

**Other**

- 5 Lakes Energy
- Center for Automotive Research
- City of Ann Arbor
- Clean Fuels Michigan
- Corrigan Oil
- Ecology Center
- Meijer
- Michigan Agency for Energy
- Michigan Department of Environmental Quality
- Michigan Department of Natural Resources
- Michigan Department of Transportation
- Michigan Economic Development Corporation
- Michigan Energy Innovation Business Council
- Michigan Environmental Council
- Michigan Public Service Commission
- NextEnergy
- Sierra Club

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## EXECUTIVE SUMMARY

The Michigan Energy Office supports development of a DC fast charging network providing worry-free EV travel throughout Michigan by 2030. With no examples of network-wide EV charger placement ensuring EV travel continuity, the Michigan Energy Office initiated an analytical process, informed by stakeholders, to optimize EV charger placement in Michigan. Researchers at Michigan State University were engaged to optimize the location of DC fast charging stations while minimizing investment cost and user delay.

This report describes the results of optimized EV DC fast charger placement along Michigan highways to support light-duty vehicle traffic in the state by 2030. Placement is intended to support EV travel within Michigan and from Michigan to neighboring states and Canada. This report describes the first phase of the study. More in-depth placement in select Michigan communities will follow.

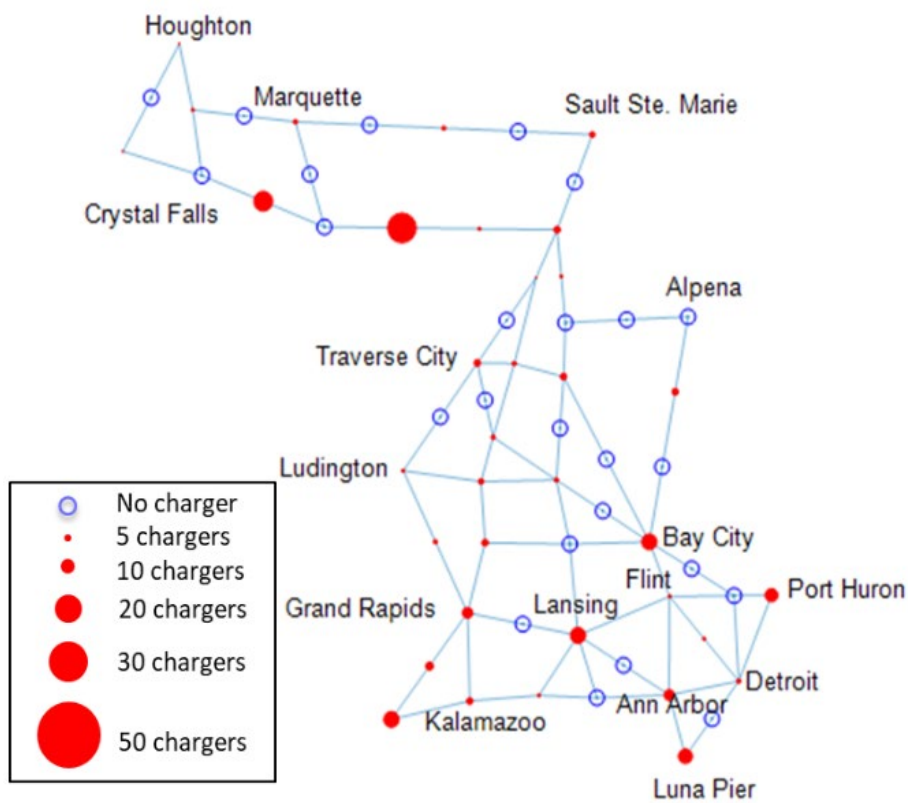
The optimization model was adapted for Michigan through vital stakeholder input and data sharing. Due to Michigan weather conditions, seasonal demand variation and technology performance were studied. Optimized charger placement for 2020, 2025, and 2030 were generated for low and high technology advancement scenarios (70kWh battery, 50kW charger; 100kWh battery, 150kW charger). A mixed technology scenario for 2030 (70 kWh battery, 150 kW charger) was generated to try to capture the variety of EVs on the road in 2030. The required number of charging stations varies from 15 to 43 and the required charging outlets vary from 32 to 600, depending on the scenario. For all modeled scenarios, an additional 10 percent of chargers are added to each location to improve the reliability of the system and to allow for redundancy.

The major findings are listed below:

1. Charging station placement in Michigan should be based on winter demand and battery performance. Optimized charging station placement for winter demand supports feasible EV travel year-round in Michigan, while optimized placement for summer demand does not allow feasible winter EV travel. To support year-round EV trips, optimized charging station placement is based on winter demand and battery performance for all scenarios in this study.

2. The network of 150kW charging outlets is the cheaper system to build. Though more expensive per unit, the 150kW chargers allow faster charging and higher throughput. Fewer charging outlets are required to serve demand, thus, reducing total system cost.
3. The cost to build an optimized bare-bones charging system supporting EV travel continuity in Michigan is likely within means. Total estimated investment costs vary from $7.1 to $28 million dollars, depending on the scenario. Cost estimation considers the required technology conversion for more advanced chargers, including the utility provision cost, and a modular system to simply increase the charging power. If multiple entities share the cost of implementation (i.e. 1/3 utilities, 1/3 state, 1/3 site host), the cost to build the system cost will be reasonable and likely within means.
4. Though a network of 150kW chargers support the shortest delay times, smaller range EVs on the road need to be considered when building the charging system state-wide. Across scenarios, average delay for EV drivers (refueling and queuing time together) range from 12 to 31 minutes. A network of 150kW chargers, which provides the shortest delays, will not necessarily ensure the expected short charging delays if many EVs are unable to accept more than 50kW of power or have shorter ranges than supported by the network. A DC fast charging network built without considering these vehicles will experience higher user delays than anticipated and EV trips for shorter range vehicles may still be infeasible.
5. Based on the optimization results, it is suggested that Michigan build out the mixed technology DC fast charging scenario (150kW chargers with 70kWh batteries) for 2030. As this scenario accounts for lower range vehicles, it ensures trip feasibility for more EVs on Michigan roadways. See the figure on the next page for the mixed scenario optimized placement map. Detailed placement by zip code can be found in Appendix A in Table 1A. During implementation, it is suggested to first focus on covering all station locations with at least two charging outlets. This supports feasible EV travel by ensuring station coverage and redundancy. Afterward, charging outlets can be increased incrementally, proportional to the optimized number of charging outlets, to reduce user delay. Regardless of the scenario selected by implementors, analysis of market growth, technology advancements, and technology projections are suggested when selecting the best scenario to adopt.

As the EV market share increases over time, more charging outlets are needed to support the larger demand. However, the optimized network is not incremental. There are cases where a station is needed in an earlier year but is no longer (optimally) required in later years. Instead, the charging outlets are distributed among other neighboring candidate points to reduce user delay. Although all proposed configurations (2020, 2025, and 2030) account for feasibility of EV trips, each configuration minimizes the detour and waiting delays for users, which vary based on the travel demand in each scenario. If the goal is to build a DC fast charging network to support EV travel in 2030, then implementers should focus on the 2030 placement maps.




**Mixed Scenario with 70 kWh Battery and 150 kW Charging Stations for 2030 Market Share, Including Partial Tourism Demand**

This study suggests that the 2030 scenarios should be the main focus of implementation to ensure future predicted demand is served. Even though stakeholders believe batteries and charging station technology advancements are expected by 2030, older vehicles with shorter EV ranges will likely also be on the roads. Thus, this study suggests placing DC fast charging stations to ensure coverage and trip feasibility for smaller battery EVs too. Given that the placement of EV charging stations in Michigan are optimized in this study, efforts should be made during EV DC fast charging implementation to place them at locations determined by the model for 2030.

# 1. INTRODUCTION

Electric vehicle sales have increased substantially in recent years and are projected to further increase in the future. In 2017, over one million new electric cars were sold globally, a 54% growth over 2016 sales [1]. In the U.S., total sales of plug-in electric vehicles grew 27% in 2017 from 2016 levels, and 81% in 2018 from 2017 levels. In Michigan, this increase was smaller, but still substantial, at over 11% [2]. The International Energy Agency projects global increase in electric vehicle sales to increase anywhere from 125 – 220 million light duty electric vehicles on roads by 2030 (IEA, 2018).

The electrification of transportation has emissions implications. Transportation is responsible for considerable fuel consumption and emission production in the US, with light-duty vehicles contributing 60 percent of the emissions produced in this sector [3]. High and volatile gasoline prices, in addition to emissions production, have caused alternative fuel vehicles (AFVs) to gain more attention during recent years. Electric vehicles (EVs), one type of AFV, have zero tailpipe emissions when running on battery power. Even though electricity is relatively cheap and ubiquitous, and the total cost of ownership of an EV today is often comparable to the total cost of ownership of a conventional gasoline vehicle, uptake of EVs has been low due to their higher upfront purchase cost compared to average conventional vehicles. Manufacturers are trying to close the price gap for new EVs entering the market. However, the limited range of all-battery EVs (BEVs), in particular, and a lack of supporting infrastructure make these vehicles less favorable for long distance trips.

Limited charging infrastructure for EVs has been one of the main barriers in adopting these vehicles. In conjunction with the limited battery range of BEVs, the lack of charging infrastructure leads to EV driver range anxiety. EV charging infrastructure is an issue in Michigan. It has less than 2% of total direct current (DC) fast charging ports in the U.S. and ranks 17$^{th}$ in the nation for DC fast charging ports. In Michigan, the number of EV sales per port is similar for BEVs and total EV sales (BEVs plus plug-in hybrid EVs, or PHEVs). For every DC fast charging port available, 15.2 BEVs are sold in Michigan, which is similar to the 15.4 EVs sold per L2 port [2]. This may suggest that BEV sales are low in Michigan due to low availability of DCFC ports. Though Michigan ranks 4$^{th}$ in the nation for PHEV sales, it ranks 25$^{th}$ in the nation for BEV sales. See Table 1 for a summary of Michigan EV sales and charging statistics.

**Table 1. Summary Statistics for Michigan and National Plug-in Electric Vehicles Sales and Charging Outlets Availability [2] (Last Updated: December 14, 2018)**

| | EV Sales | BEV Sales | PHEV Sales | DC Fast Charger Ports | Level 2 Ports |
|---|---|---|---|---|---|
| **Michigan** | 16,885 | 2,767 | 14,118 | 182 | 1,097 |
| **US** | 891,923 | 458,848 | 433,075 | 9,229 | 49,963 |
| ***% of US*** | ***1.89%*** | ***0.60%*** | ***3.26%*** | ***1.97%*** | ***2.20%*** |
| ***Rank*** | ***11*** | ***25*** | ***4*** | ***17*** | ***13*** |

The Michigan Energy Office supports development of an effective DC fast charging network ensuring worry-free EV travel throughout Michigan by 2030. However, it recognizes that though there is a need to improve EV charging infrastructure in Michigan, especially for DC fast charging, there is also limited funding available to implement it. Likewise, an ineffective charging network may lead to more recharging stops or make some EV trips impossible, resulting in significant delay and discouragement to EV travelers. The need to build a network to support the projected increase in light duty EVs on Michigan roads by 2030, despite current low EV usage, adds another layer of complexity. To this end, the Michigan Energy Office initiated an analytical process to optimize placement of DC fast charging stations along highways to support EV travel in Michigan by 2030.

This multi-phase project to optimize DC fast charging station placement in the state was initiated to uniquely consider Michigan's conditions, including travel demand and patterns, adverse weather profile, and electric grid infrastructure. The project seeks to minimize investment cost while ensuring the feasibility of statewide EV trips for light duty vehicles and an acceptable level of service for EV drivers.

In this first phase of the project focused on highways, the researchers reviewed the available literature and collected data to reshape an existing modeling framework for Michigan. A stakeholder engagement process facilitated by the Michigan Energy Office helped gather data and refine scenarios. Several stakeholder meetings occurred during the spring and summer of 2018 with a diverse stakeholder group including auto manufacturers, utilities, transmission companies, charging station companies, national organizations, non-profits, EV drivers, and State of Michigan departments, such as the Michigan Department of Transportation, Michigan Department of Environmental Quality, the Michigan Department of Natural Resources, and the Michigan Public Service Commission. Data and input gathered from stakeholders were key to creating a Michigan specific optimization model and determining its inputs.

We believe this effort to be unique and Michigan to be the first to develop optimized EV charging placement maps to support worry-free EV travel throughout the state. Though academic studies on optimizing EV charger placement have been conducted, none, to the knowledge of the research team, have been initiated by state or local governments to guide placement of EV charging infrastructure. This report relays pertinent literature, the problem statement, the modeling framework, the optimization algorithm, and the data collection process. Lastly, the findings will be detailed and discussed. The results will help inform the Michigan Energy Office in the development of its EV programs and EV charging funding opportunities. It is also hoped that project results will help inform other Michigan stakeholders as they implement DC fast charging infrastructure in the state.

## 2. PROBLEM STATEMENT

Though the overall project seeks to ensure worry-free EV travel throughout Michigan by 2030, this first phase seeks to determine optimal placement of DC fast charging stations along highways to make EV travel between Michigan cities, or inter-city travel, feasible. It seeks to also minimize total investment cost and travel delay (detour delay, queue waiting delay, and recharging delay). This phase of the project aims to answer the following questions:

- Where should charging stations be deployed along Michigan highways to support worry-free EV travel in Michigan by 2030?
- How many charging outlets must be built at each station?
- What is the approximate investment cost to build the determined infrastructure?

## 3. LITERATURE REVIEW

DC fast charging can help address issues hindering EV use. EV uptake is inhibited by range anxiety, particularly over long-distance travel between cities, and long EV “refueling” or charge times when compared to conventional internal combustion engine vehicles. This discourages potential EV users and prevents widespread adoption [4], [5]. DC fast charging stations can help overcome these issues by shortening charge times to support more realistic long-distance EV travel. However, DC fast charging stations are more expensive to implement and operate than slower chargers [6], [7]. Therefore, to address EV range anxiety and to facilitate long-distance travel, an efficient plan to locate DC fast charging stations is essential to support a future with more EVs.

Academic researchers have studied how to efficiently allocate EV charging stations while considering issues like total costs and level of service. The network of refueling stations for AFVs has been studied in the literature[8], [9]. Lee and Han [10] recognized EV charging infrastructure planning as a vital step for making longer trips feasible, which require multiple battery charges. They used a flow refueling location model (FRLM) to locate recharging stations in a road network, such that the travel flow between origin and destination pairs can be maximized through recharging at the available charging infrastructure. They extended the FLRM with a probabilistic travel range consideration, since different factors such as traffic, road conditions, weather, and temperature might cause EV ranges to vary. Though they did not directly account for charging station capabilities, which also affect charging time, they penalized waiting time in their proposed framework to indirectly consider this factor. Guo et al. [11] proposed a modelling framework for DC fast charging infrastructure development in a competitive environment when the decision-making process is not centrally controlled. They introduced a network-based optimization problem with multiple agents to understand the interactions of investors and users within a network. They recommend that their proposed framework can be used to study the future influence of a competitive market on public charging infrastructure layout. Lastly, Nie and Ghamami [12] presented an optimization model to explore EV travel along a long corridor that captures the tradeoff between investment in charging stations and larger batteries to provide a certain level of service for travelers. The results suggest that, for intercity travel, only DC fast charging stations can provide an acceptable level of service. This model is extended in Ghamami et al. [13] to minimize the total system cost, including infrastructure investment, battery cost, and user cost.

Several researchers have examined the optimization of EV charging infrastructure placement. Micari et al. [14] proposed a bi-level model in their methodology to determine both EV charging infrastructure sizing and siting. Their study considered three main topics: battery and engine specifications in EV technology, charging technologies, and EV demand. At the first level, the locations were identified. At the second level, the number of charging stations in each location (service area) was investigated. Zang et al. [15] also introduced a bi-level framework for EV charging station planning using queuing theory and a metaheuristic algorithm as a hybrid methodology. Their study examines slow public charging infrastructure affects EV users' travel patterns and demands for recharging, as well as increased EV ownership. They use Monte Carlo simulations (MCS) to first determine EV travel patterns. Next, their model optimized travel success by considering the impacts of charging station siting on travelers' routes. At this second level, social cost and satisfaction indices are considered.

In addition to finding optimal locations for charging stations, the limited range of EVs is another element of routing problems. The routing problems for EVs, despite different objectives, generally study route choice, i.e. the routes traveled by EVs considering their limited range [16]. More specifically, user equilibrium is widely used to model the travel behavior of EV users [5]. Due to the technological advancement and ubiquitous presence of internet and routing apps, users are aware of road traffic. They behave selfishly and non-cooperatively to minimize their own travel time and costs. Wardrop [17] defines this concept as the user equilibrium traffic assignment problem for intra-city transportation networks. This concept, more recently, has also been implemented in intercity networks [18]–[21].

In the literature, there are few studies attending to the role of technological advancements, namely battery capacities and charging rates, in EV infrastructure needs. In a recent study, travel data of over 750,000 conventional gasoline vehicles was collected in the state of Washington from 2004 through 2006. The researchers assumed EV users follow the travel patterns of conventional vehicles [22]. This data was then used to forecast future EV charger use and power requirements when all vehicles are electric and can drive up to 200 miles between recharging. It is assumed that these vehicles have uniform fuel efficiency of 3 miles/kWh. They found 5,000 charges per day per million EVs are needed, on average, with each charger offering about 400 kW of power. This enables 80 percent of EV travel. Another study examined long-term DC fast charging planning in the U.S., which considers a 15-year horizon starting in 2015 [23]. In this study, a multi-period framework was proposed and solved through genetic algorithm (GA) to determine location and timing of station openings, as well as the number of needed charging outlets at each location. In this study, battery and charger technologies are indirectly investigated through sensitivity analyses. Several range scenarios (from 75 mi to 300 mi) are proposed, which hinge upon the battery size and fuel efficiency. Regarding charging technologies and waiting times, multiple scenarios of charging time are proposed. This framework is applied to the California network as a case study. The results show that even though fast charging infrastructure are required for intercity trips, the number and location of these stations depends on the desired level of service and vehicles battery size (driving range).

As vehicle ranges increase, more long-distance EV trips are fulfilled and recharging events decrease. He et al. investigated the entire U.S. network for EV charger placement using 2010 long-distance travel data [24]. Study scenarios considered EV ranges of 60 to 250 miles. With ranges of 200 miles and higher, they found more than 93% of long-distance travels are fulfilled with no charging event. With ranges limited to 100 miles, 250 fast charging stations, with 150kW power, are required to enable equivalent trip completion results. In another recent study, the target analysis year is set at 2020, for which different anticipated scenarios are explored, namely charging powers of 50 kW, 100 kW, and 150 kW, and driving ranges of 62.5 mi, 125 mi, and 187.5 mi [6]. The current charging behavior of two pioneer countries in the EV market, Sweden and Norway, are deployed for analysis and calibration of queuing models to reflect the target year fast charging infrastructure requirements. Results show that, as the driving range of 62.5 miles is doubled to 125 miles, the charging events are cut in half, though dwell time at chargers increases. Increasing driving ranges beyond 125 miles does not significantly affect recharging events.

## 4. MODELING FRAMEWORK

The modeling framework proposed in this study is unique. It has the ability to capture travel time variation through link flows/nodes along the routes/stations and track the state of fuel for vehicle groups traveling between different origin-destination (OD) pairs. The model considers EVs with limited driving ranges and ensures the feasibility of long distance trips by providing the required infrastructure enroute, while minimizing investment cost and the total delay for all EVs. Various locations along major roads are differentiated by their land acquisition values and electric power availability.

This modeling framework is an extension of past research efforts. The general corridor model recently developed in Ghamami et al. [13] considers multiple OD pairs, a single EV type in terms of battery range, and one corridor of travel. However, there is a need to find the best allocation of EV charging stations throughout an intercity network, where parallel and intersecting corridors exist. This project extends the prior approach to consider travel between cities on an intercity network model. It considers the required detouring for refueling and a traffic assignment module is integrated with a facility location algorithm. This general modeling framework captures user preferences through a value of time parameter. It also allows multiple classes of electric vehicles in terms of the battery size and infrastructure investment cost.

The problem is formulated as a mixed integer mathematical programming with non-linear constraints. Thus, a heuristic bi-level solution algorithm is developed to solve this non-deterministic polynomial hard (NP-hard) optimization problem, where NP-hard represents the computational complexity of the problem. A Simulated Annealing (SA) algorithm is developed to solve this complex problem as a mixed integer program with non-linear constraints.

The mathematical model uses a decision-making framework to allocate an available budget for building charging stations that supports EV intercity trips. The proposed model considers limited EV range to find the optimal location of charging stations while minimizing the required delay from rerouting to access a charging station. The model provides the number of required charging outlets in each station that minimizes charging wait time. Each of these charging outlets includes space to park a car and to place a charger.

The model is unique for tracking the state of charge for all EVs by considering their spatial trajectories. Thus, stations are not located only in places with high traffic volume. They are also located in areas with higher need of recharging. The model considers EV user travel trajectories and their state of fuel so charging infrastructure will be located in areas where EV users need to recharge the battery. For example, even though city boundaries have a large amount of inbound and outbound traffic, they are not likely to be the best location for charging infrastructure to support intercity travel. The EV state of charge only drops to a critical level after a considerable distance is traveled, which takes them far away from city boundaries. The travel volume in a corridor is not the only metric to be considered when placing charging stations. It is important to know the proportion of the traffic volume consisting of short-range trips (no need for recharging) and the proportion consisting of long-range trips (need recharging due to the limited battery range).

In this project, the methodology and model described above is implemented for a real-world case study, where daily intercity trips for the state of Michigan are considered. The mathematical model is purely a research method. It requires calibration. The numbers used in previous studies were average estimates [6], [7]. To apply the model to Michigan, in addition to adaptions of model, several inputs required proper estimates. In this project, realistic parameters were set with stakeholder input. These parameters included the charger power, the charger cost, electricity provision cost, range of EVs, battery performance in adverse weather conditions, intercity traffic demand and seasonal variations, and the EV market share penetration. Data and input from project stakeholders were vital to adapting the methodology and model to Michigan.

### 4.1 Model Objective Function

In this problem, the objective is to minimize the total system cost, including the investment in DC fast charging stations and the travel delay due to recharging for all EV users. However, in the route choice problem, all users, including the EV users, are seeking to minimize their own travel time regardless of other travelers. Therefore, a user equilibrium problem needs to be embedded into a system optimal problem. This problem finds the optimal location of charging stations in a network, where users with various classes of vehicles try to minimize their own travel times (including recharging delays for EV users), subject to change by travel flows and also charger placement along the routes.

In this section, we formulate this problem as a mixed integer program with non-linear constraints and then solve it using a metaheuristic algorithm. The road network considered here includes a set of links ($e \in E$) and a set of nodes ($i \in I$), which have two main subsets: the set of current refueling stations ($N_1^m \subset I$) and the set of candidate points for building refueling stations ($N_2^m \subset I$). Notation $m \in M$ denotes different classes of vehicles in the network such as different AFVs, including EVs with certain battery sizes. This feature is available in the modeling framework to provide the State of Michigan with the ability to study other types of AFVs in the future, should the need arise.

Any node belonging to the set of current refueling stations or candidate refueling stations may be visited by users for either refueling or as a midpoint along their route. These reasons need to be differentiated due to their different impacts on the state of fuel. To this end, two sets of dummy nodes are introduced. The first dummy set is a duplicate of the current refueling stations set and represents the set of current refueling stations visited for refueling purpose $\left(N'^m_1\right)$. The second dummy set is a duplicate of the candidate refueling stations set and represents the set of candidate refueling stations that may be visited for the refueling purpose $\left(N'^m_2\right)$. If the dummy nodes ($N'^m_1$ $or$ $N'^m_2$) are visited, refueling happens. If only the regular nodes ($N_1^m$ $or$ $N_2^m$) are visited, the nodes are travel midpoints.

The objective function below minimizes the investment cost (charger, grid, construction, land, etc.) and user refueling, detour and waiting time costs. Table 2 details the model variables.

$$\min \sum_{m \in M} \sum_{i \in N'^m_2} (C_P^m x_i^m + z_i^m C_S^m) + \gamma_t \Big( \sum_{i \in N'^m_1 \cup N'^m_2} \pi_i + TT_d \Big)$$

**Table 2. Model Variable Descriptions and Definitions**

| Variable | Description | Unit/Value |
|---|---|---|
| $C_P^m$ | Charging Station Cost | dollars |
| $C_s^m$ | Charging Outlet Cost | dollars |
| $\gamma_t$ | Value of Time | dollars per 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 charging outlets |

The objective function consists of two main terms. The first term represents infrastructure investment cost, which includes the fixed cost of acquiring a charging station (i.e. electricity provision cost) at any location and the variable cost of charging outlets (i.e. cost of charger, construction cost, and land acquisition cost). For the charging station cost, the number of charging stations is multiplied by $C_P^m$ (measured in $ per station), which is the cost of a charging station. In order to calculate the charging outlet cost, the number of charging outlets is multiplied by $C_s^m$ (measured in $ per spot), which is the cost to provide one charging outlet. The second term represents the monetary value of total time spent for waiting, refueling in charging stations, and required detour to access a charging station. The total time is multiplied by $\gamma_t$, which is the value of time, assumed here to be $18/hr [25]. The decision variables are whether to locate a charging station at any of the candidate points and the number of charging outlets at each station, represented by $x_i^m$and $z_i^m$, respectively. The total delay includes waiting and refueling at charging stations ($\pi_i$) and total detour travel time required for refueling, defined as the additional time EV users spend on the road to reach a charging station ($TT_d$).

The main constraints of this model are (1) feasibility of EV trips for all OD-pairs considering their limited driving range, (2) traveler behavior in selecting routes and the charging stations along routes based on the user equilibrium concept (selfish preference of the users), and (3) differentiation between candidate locations based on their socioeconomic factors.

## 5. SOLUTION ALGORITHM

The optimization model proposed in this project is a mixed integer problem with non-linear constraints, which is known to be NP-hard. There are commercial solvers in the market that can solve such problems via branch-and-bound techniques. However, Michigan's road network is considered a large-scale network and solving such problems is computationally challenging for current commercial solvers in the market. A metaheuristic algorithm is required, which is designed to solve such problems.

The metaheuristic algorithm proposed in this project is developed based on the SA algorithm. A SA-based algorithm typically has two main steps. First, it searches over the feasible set of integer solutions, starting from a current feasible solution and then moves to a neighboring feasible solution. Second, it compares the objective functions of the current and the new solution. In cases where the objective function improves, the neighbor solution replaces the current solution with probability of one. In cases where the objective function is not improved (worse solution), the probability is a function of the relative difference between the neighbor and current solutions' objective function. The probability is gradually reduced as the solution process proceeds through the iterations of the algorithm. This probability is close to zero by the end of the iterations to avoid accepting worse solutions.

A neighbor solution can be generated based on the current solution by randomly changing only one of the decision variables (location or number of outlets at a given location). First, each location is associated with a weight factor (e.g., total flows, total delays). Then, the location is picked based on the weighted random selection. The following rules are used to guide the perturbation process.

- To add a new station, locations with higher traffic flow received priority.
- To remove an existing station, locations with lower traffic flow receive priority.
- To add new charging outlets to a station, stations with higher delay receive priority.
- To remove charging outlets from a station, stations with lower delay receive priority.

SA schemes allow larger objective function values (worse solutions) relative to the current solution to be accepted, which offers a mechanism to avoid getting trapped in local optimum solutions. This feature is useful when the problem is known to have multiple local optima in case of non-linear constraints. The SA algorithm is proven to be able to solve flow-capturing mixed integer programs efficiently. Instead of a continuous integer variable for the number of charging outlets in each candidate station, we define certain categories (levels) for the number of charging outlets. Each candidate station that is part of any solution might have one of these five defined levels for the number of charging outlets. These discrete sets are defined based on the scenario specifications, which means larger outlet numbers for higher demand and lower numbers for lower demand. The discrete sets are further refined as explained in section 5.1.

## 5.1 Algorithm Adjustment

### *5.1.1 Refinement of the Discrete Set of Charging Outlets*

This study adopts an approach to further improve the optimal solution based on the initial discrete set of charging outlets, which are defined as five levels of charging stations (5, 10, 20, 30, or 50 charging outlets). After solving the problem based on the initial search list, the problem is solved again using the optimal solution of the first step as an initial solution. A secondary discrete set of charging outlets for each node is redefined based on the current optimal solution, which supports smaller changes than the initial five levels. The secondary search list includes a discrete set with a range of $\pm 90\%$ of current optimal number of charging outlets for smaller charging stations with less charging outlets and $\pm 50\%$ of current optimal number of charging outlets for larger charging stations with more charging outlets. This method can further refine the number of charging outlets to get closer to a global optimal solution. Analysis of adjustment results shows that it reduces the final number of needed charging outlets by up to 20%.

### *5.1.2 Considering Seasonal Variation in Demand*

Modifications were made to the demand data from the Michigan Department of Transportation (MDOT) to consider seasonal variation. To find the location of charging facilities, the project initially analyzed the demand matrix provided by MDOT using the aggregate demand models. The MDOT demand only replicates the travel pattern for a typical weekday in fall. Changes were made to accommodate seasonal variation in the project. Due to the cold weather in winter and scenic views in spring, fall, and summer, the demand varies significantly in Michigan, which results in different traffic patterns throughout the year. This change in traffic patterns is accompanied by changes to battery efficiency, as Li-Ion batteries do not perform to full potential in cold temperatures. In order to capture the impact of these factors, the researchers used data from continuous counting stations throughout Michigan to derive solutions for each month considering both the effects of temperature and demand variations. Link performance functions were also modified to capture the scenic routes (such as US-31, which runs along Michigan's western lake shore before ending south at Mackinaw City).

### *5.1.3 System Safety Factor for Outlet Availability*

Based on stakeholder recommendations, the model is adjusted to increase the number of charging outlets by 10% from the minimum needed number of outlets. This is to address charging outlet availability under demand fluctuations or maintenance issues.

## 5.2 Battery Charge Assumptions

### *5.2.1 Interior Node Assumptions*

The network level problem assumes all EVs begin their trip fully charged. This is a logical assumption considering that inter-city trips are usually well-planned and, given the scarce available charging stations, all EV would likely begin their inter-city trips with full charge. Note that this is not the case for the intra-city trips which will be studied in a follow up study. The proposed model ensures EVs arrive at their destinations with at least 20 percent battery charge level [12]. To ensure this minimum battery charge at the destination, EVs may need to charge their battery enroute depending on the trip length. During any charging events enroute, the EV battery will be charged up to 80% of the battery capacity (due to exponential increase in recharging time in the last 20% of the battery capacity) except for the last required charging. For the last required charging along the EV trips, the model assumes the battery is charged only to the minimum needed charge to arrive at the destination. However, for EV trips with out-of-state origins or destinations, the model considers only the portion of these trips that occur in the state of Michigan in this way. Border nodes are treated differently and discussed in the following section.

### *5.2.2 Border Node Assumptions*

The modeling framework in this study is designed to support intercity trips within the state of Michigan. The model ensures all EVs can make it to their destinations within Michigan with at least 20% of their full charge by providing charging opportunities. However, supporting interstate and international travel from Michigan is also important. The boundary nodes, which connect Michigan to neighboring states and Canada, are also considered as origin or destination nodes by the model. The state of charge at boundary nodes is important when considering interstate and/or international trips.

For the portion of trips outside Michigan, the model ensures EVs can leave the state fully charged and have the ability to charge the battery at the closest candidate point as they enter or exit the state. We refer to these trips as external demand. As the model ensures feasibility of EV trips with a minimum available battery charge at the destination (border nodes in case of external demand), external demand EVs might not have enough charge available to continue their trip beyond the border nodes. Therefore, adjustments were made to support feasibility of EV trips for external demand.

In this study, based on the nationwide OD matrix, the external outgoing flows for each boundary node in the state of Michigan are estimated. The closest visited charging station to each boundary node is used to consider an estimate of the fuel state for the boundary node. Based on the state of fuel and the charging demand, the required number of charging spots at boundary nodes are assigned to allow EV drivers to leave Michigan fully charged.

# 6. DATA COLLECTION

This section details data collection. Input variables reflecting Michigan's situation is essential in finding a solution for charging station locations and the associated number of charging outlets for the state. This includes the cost associated with each station and its charging outlets depending on the station location, the electricity acquisition cost, types of chargers, EV specifications, EV market share, and travel demand information.

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

Michigan road network configuration and OD travel demand were provided by MDOT. The network was implemented in TransCAD transportation planning software and simplified for this study (Figure 1). The detailed statewide road network has details that are not necessary for intercity network evaluation, which is the focus of this phase. It is also computationally challenging, so a simplified Michigan network was developed. The OD demand values were obtained from state travel surveys and were transferred to an OD demand matrix using the MDOT's planning travel models. This demand table is estimated for about 3,000 traffic analysis zones (TAZs) for a weekday in the fall season with normal weather conditions.

To develop the simplified Michigan node network used in this study, the 3,000 TAZs are first aggregated to 24 nodes representing large cities throughout the state of Michigan with population higher than 50,000. Moreover, the aggregated demand table (base demand) is modified to capture seasonal variations in demand as a result of factors such as tourism or weather conditions. The seasonal variations are calculated based on the 122 continuous counting stations data provided by MDOT.

(a) Original Michigan road network from MDOT (b) Simplified intercity road network of the state of Michigan

**Figure 1. Original and Simplified Michigan Road Network**

*6.1.1 Seasonal Travel Variation and Monthly Demand Estimation*

Monthly traffic demand is estimated using counting station data provided by MDOT. Given the fluctuating traffic patterns each month, monthly demands for each OD pair is estimated, reflecting the existing traffic patterns in the network. The resulting monthly demands can be used as inputs to the charging location model to ascertain the sufficiency of estimated charging station locations and the number of outlets. Therefore, the observations from the continuous counting stations located on Michigan highways are used as a priori information. It is assumed that a proportional relationship exists between the traffic counts of the stations and the OD demands. Michigan Department of Transportation (MDOT) provided the counts of 122 continuous counting stations installed on Michigan highways from which 66 continuous counting stations are located on the current simplified network links. As a result of assigning detectors to their relevant links in the Michigan network, 90 out of 114 links have at least one count station. Note that the information of each individual continuous counting station is used for both directions of a link connecting two specific nodes. In addition, the network is simplified in Figure 2 by removing the intermediate nodes.

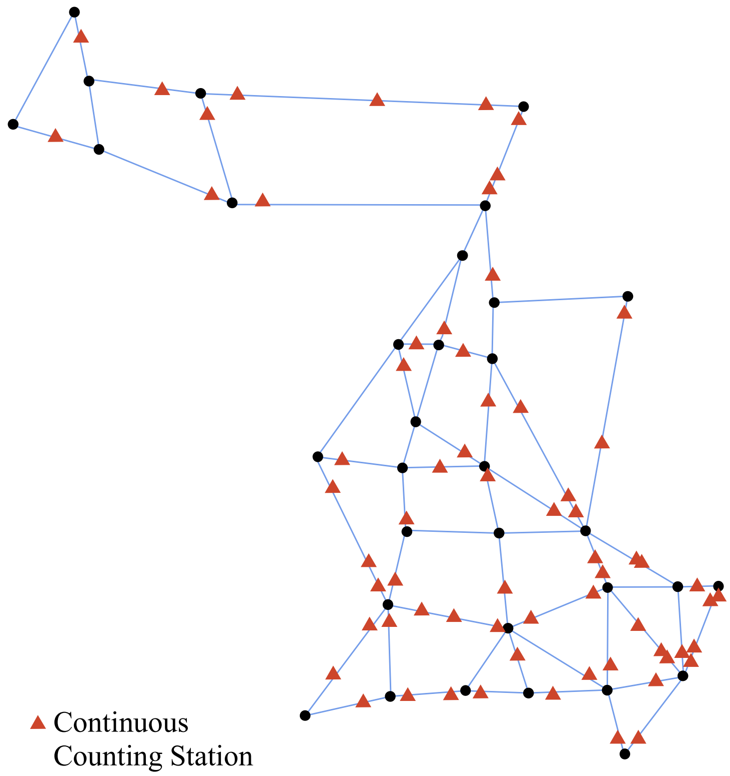



**Figure 2. Continuous Counting Station Locations on Simplified Michigan Network**

A heuristic method is developed and used to estimate the monthly demands incorporating the information of 66 continuous counting stations. Monthly factors for each count station, representing the share of annual demand for each month, are utilized as the main input of this method. OD base demands are also used as a reference value to be multiplied by the estimated monthly factors for the OD pair to result in monthly demands. The method developed to estimate monthly factors for each OD pair consists of multiple steps; finding an average factor for each month and each link with at least one detector, calculating shares of all OD pairs demand that are traveling on each link, finding the OD pairs without any assigned continuous counting station and assign adjacent count stations to them, and estimating monthly factors for each OD pair in the network.

As there might be multiple counting stations on each individual link in the network, an average value of the monthly factors ($f_i^m$) should be estimated to represent the traffic pattern of the link $i$, in each month $m$. Note that no factor is assumed for the links without any detector. Furthermore, the share of OD base demands is found for each link using a traffic assignment approach. To do so, OD base demands are given as the input of the traffic assignment and the proportion of each OD demand that uses each link are defined as $p_i^{OD}$, where $i$ is the link number and $OD$ is an origin and destination pair. Once the set of paths for each OD pair is defined, it should be checked whether all OD pairs have at least one count station in their paths set to be used as an estimation factor. The count stations of the links reaching to the origin or departing from the destination are used as an estimator for the OD pairs without any counting station. Finally, monthly factors are estimated using the share of each link from demand and the average factors of the links as below.

$$(Monthly\ Factor)_{OD}^{m} = \frac{\sum_{i \in k_{OD}} f_i^m P_i^{OD}}{\sum_{i \in k_{OD}} P_i^{OD}}$$

where $k_{OD}$ is the set of all links with a positive share of demand for the origin and destination pair, $OD$, coming from traffic assignment with the base demand input.

The multiplication of the estimated monthly factors by their equivalent OD base demand results in an estimation of monthly demand for each OD pair. The sum of all estimated OD demands for the state of Michigan is demonstrated in Figure 3 for different months as well as the average monthly demand over all months. The fluctuation of total travel demand in different months can be observed in this figure with the least total demand in January and the highest total demand in July.

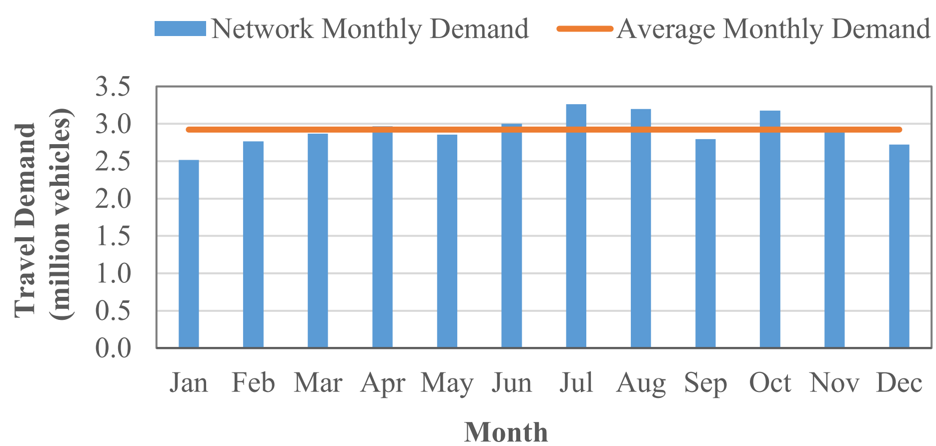



**Figure 3. Monthly Total and Average Travel Demand for Michigan**

In addition to seasonal variations, during the summer season there are many attractions that are visited by tourists from different places. The estimated demand for summer includes these trips. However, it is assumed that all trips begin with full charge. This calls for providing charging stations at these attraction sites for their return trips. The number of visitors is reported for major state parks by the Michigan Department of Natural Resources. National park visitor numbers were obtained from the National Park Service. The number of visitors divided by the average occupancy of vehicles results in the number of visiting vehicles. Since there is no data on the trip length distribution of these vehicles, it is assumed that all of the visiting vehicles need to be charged up to the 80% charge level from the minimum of 20% charge level. This is a logical and conservative assumption considering the remote location of these sites relative to the bare-bone highway network. Also, since there is no data on the utility provision costs to these sites, the nearest locations on the bare-bone highway system are used to estimate this cost at the attraction sites. Due to the remoteness of certain tourist attractions, costs estimated in this way are likely conservative. Actual implementation costs may be higher as remote locations may need additional electrical infrastructure, leading to increased implementation costs.

### 6.2. Charging Station and Outlet Costs

The modeling framework focuses on cost minimization, while satisfying a set of aforementioned constraints. Two categories of costs are considered in this framework: station cost and charger cost.

Station set up costs were requested from different charging station companies. The companies provided costs of site acquisition, project management, equipment, construction, utility upgrade, and maintenance. It must be noted that this project accounts for detailed site acquisition costs as well as utility costs for the candidate locations. Thus, for calculation purposes, these two components were excluded from the costs charging station companies presented and replaced by more realistic estimates derived from utility and transmission company sources. The details of these cost components are explained in the Section 6.2.1 Site Acquisition Costs and Section 6.2.2 Utility Provision Costs, respectively.

In this project, the following are considered station costs:

- site acquisition,
- utility upgrade,
- electrical panel and switch gear,
- engineering and design,
- permitting, and

- project management costs

Each charging outlet includes one DC fast charger, to charge one vehicle at a time with either a CHAdeMO or SAE combo connector, and a parking spot with the required access space for the vehicle. The cost of charging outlets consists of the DC fast charger cost, land cost, validation costs, and activation costs. Stations with a higher capacity, or more outlets, have a larger charging outlet cost, which includes land cost, the cost of each charger and the activation and validation costs.

The costs estimated by this methodology are conservative. It is assumed any selected station location is the only charging station located over a 5-mile radius, as the utility provision cost is estimated based on the average cost to provide a certain capacity in this area. All the charger outlets assigned by the model to the station are assumed to be at that one station. The estimated charging station cost is a lower-bound. It might not be desirable or possible to locate all assigned charger outlets in one station.

*6.2.1 Site Acquisition Costs*

Land acquisition for siting DC fast charging stations can take many forms from outright purchases to long-term lease agreements with and without site improvements. Sites may share space with other retail establishments, be coupled with other transportation fueling stations or be stand-alone establishments serving the needs of EV drivers. The value of a site rests with the revenue potential it poses for the best-use occupant and, hence, is directly correlated with the population density that makes up the potential customer base. Relatively low revenue establishments will find it difficult to justify high-value sites and low value sites may not generate optimal customer exposure. All this leads to many factors that make up the costs of siting an EV charging station, such that generalizations are difficult to assign. However, the existing literature on studies of commercial land values provides some basis for estimating the expected land values for commercial properties [26].

Commercial property can be purchased out-right or leased. The cost of purchasing property can be assessed based on property sale values, but the cost of siting commercial property through a lease agreement requires some assumptions. This project assumes a lease agreement represents a commitment for future stream of payments that cover the lease agreement. This commitment can be priced in a manner comparable to an out-right purchase by discounting future payment commitments. Hence, for a lease agreement, the purchase price equivalence can be calculated as:

$$PPE = \sum_{t=0}^{\infty} \frac{PMT}{(1+i)^t}$$

where PMT is the fixed payment per period (month or year); $i$ is the current discount rate for the payment period and is generally tied to the current interest rate for borrowing money; and $t$ is the time period. This is the standard equation for present value calculations. As the price and lease value of a property is tied to its revenue generating potential, the PPE should approximately equate with the property sale price at any given time.

In estimating the expected costs of commercial property for siting DC fast charging stations, the host location population density is the most visible and measurable basis for estimation. Other factors that contribute to commercial land values, like the presence of other shopping venues, foot and vehicle traffic, age of existing residential and non-residential structures and household income may vary substantially within neighborhoods. Hence, such granular factors are specific to the street-corner level of consideration for site location choices. Therefore, at this macro-level assessment, estimates of the commercial property valuations are based on population density. Seo et al. estimated that a one percent increase in the population density increases commercial land values by 3.5 percent when holding all else equal [27]. This is supported by an earlier study by Mc Donald, who found elasticity measures between 3.05 and 3.21 [28]. Using this elasticity measure then requires estimates of average Michigan commercial property values, average Michigan population density, and site-specific population densities.

Average undeveloped property values for commercial use were estimated at the national level in Larson (2015) [29]. As this is a national average and entails a significant share of western land parcels, basing estimates on this national average would severely under value commercial properties in Michigan's population centers. The Economic Research Service of the US Department of Agriculture provides land price differentials by region [30]. These differentials are primarily estimated for rural farmlands but should be reflective of regional differentials for all properties at the macro level. In this, the ratio of Great Lakes average price per acre to that of the lower 48 states suggests a 53 percent premium for land in Michigan, such that average undeveloped land for commercial use is priced at $168,000 per acre.

The U.S. Census provides estimates of population counts at the zip code level in the 2010 decennial census. These were mapped into a GIS map to calculate zip code area for estimating population densities. The resulting density estimates are shown in Figure 4. The modeling nodes for route placement of charging stations are overlaid with Figure 4 and land costs are calculated to develop comparative land costs (over different candidate points for building charging stations) that are combined with other costs in modeling optimal EV charger placement.

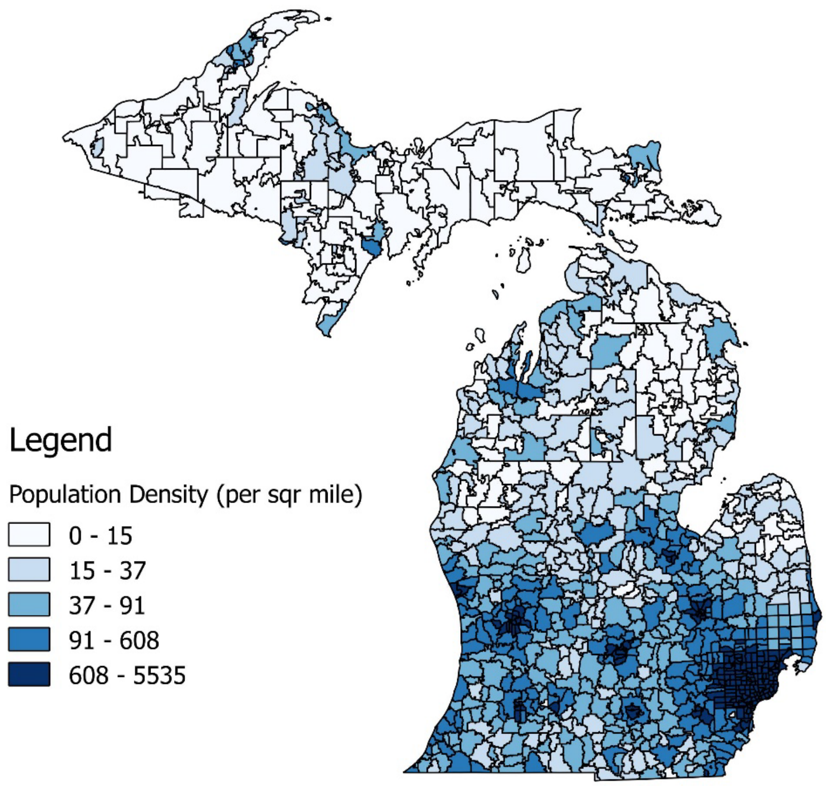



**Figure 4. Population Density (2010 Census)**

*6.2.2 Utility Provision Costs*

Another important factor in placing EV charging stations is the availability of electrical power. The Michigan Public Service Commission's website [31] was used to capture utility coverage throughout the state. The coverage map of the candidate locations is as shown in Figure 5. The coordinates of candidate locations in each utility company's service area were provided to it to inquire about the electricity costs at the applicable candidate locations. The costs are reported based on the average cost to provide a certain capacity in the 5-mile radius of each candidate location for charging stations.

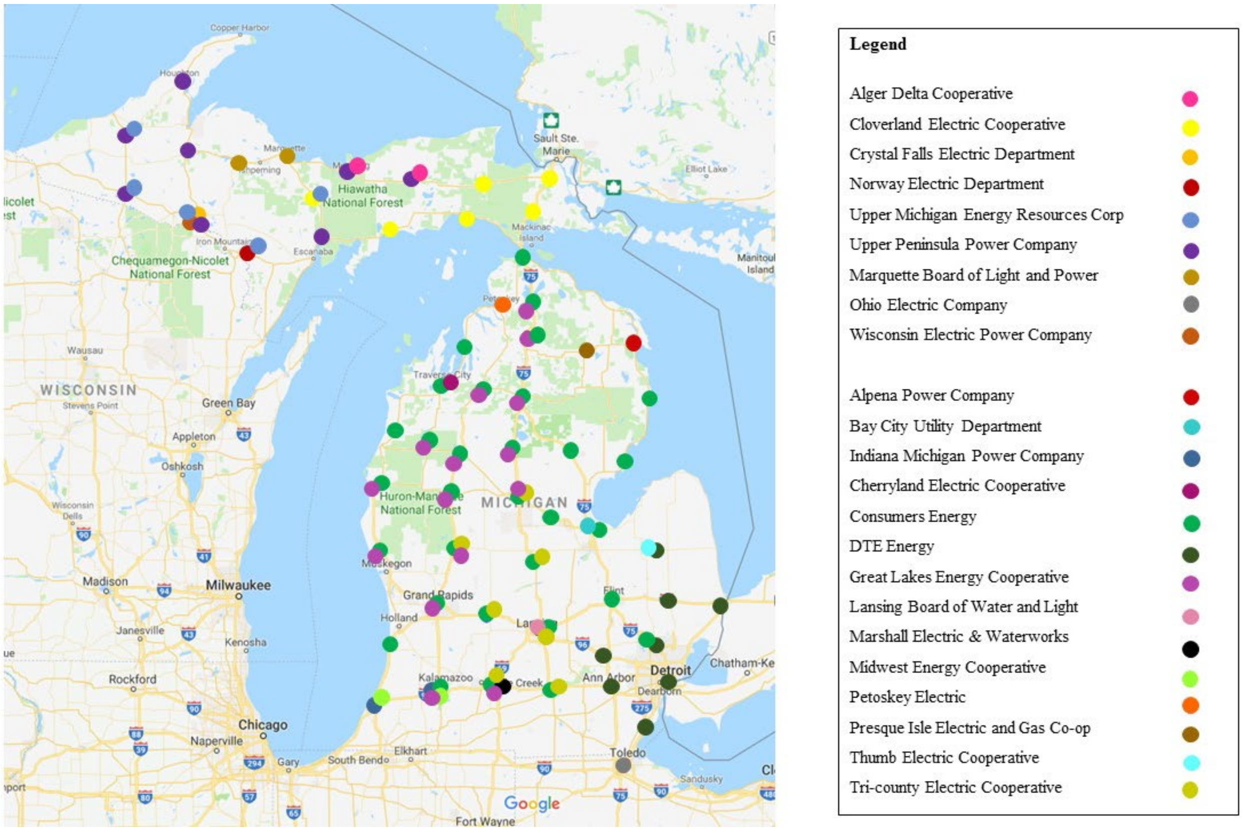



**Figure 5. Utility Companies Coverage Area**

*Consumers Energy*, *DTE Energy*, *Cherryland Electric Cooperative,* and *Great Lakes Energy Cooperative* provided electricity provision costs at nodes under their jurisdictions. For other candidate locations for which no data was reported, interpolation, extrapolation and averaging over the reported values are used to estimate the electricity provision cost. These costs include, but are not limited to:

- conduit from the transformer to the meter enclosure,
- meter enclosure,
- protective equipment, and
- conduit and conductor from the meter enclosure to the charging station.

Electricity provision costs were estimated and reported for four load levels: 100 kVA, 500 kVA, 1000 kVA and 2000 kVA. Interestingly, all utility companies reported the electricity provision cost remains constant within the aforementioned load ranges. However, as this project considers optimal charger placement within a 5-mile radius around the specified candidate locations (closer to the highway the better), and electricity provision costs can vary substantially within a short distance, the provided costs at each location are average values within the 5-mile radius. Also, for candidate locations under the jurisdiction of multiple utility companies, the average cost of the reported values by utility companies is used as an input to the proposed modeling framework. The maximum, minimum, average costs and standard deviations are reported in Table 3.

**Table 3. Electricity Provision Costs at Candidate Points Statewide**

| Minimum | Average | Maximum | Standard Deviation |
|---|---|---|---|
| $12,230 | $69,539 | $275,000 | $55,924 |

### 6.3 Vehicle and User Characteristics

In order to reflect the needs of the current and projected EV demand, this project considers battery range and performance in different weather conditions as well as the EV market share currently and in the future. These items are explained in the following subsections.

#### *6.3.1 Battery Range and Performance Variation*

Assumptions of current battery size were determined based on stakeholder feedback from several automobile manufacturers (Ford Motor Company, General Motors, Toyota). The stakeholders expressed belief that a broader variety of battery sizes will be available in the market in the foreseeable future. Stakeholders suggested battery ranges such as 50 kWh batteries for small cars, 70-80kWh for mid-size vehicles, and 100-120kWh for large vehicles. For this study, the current EV battery size is assumed to be 70kWh with an anticipated battery size of 100 kWh for future vehicles.

Batteries are also expected to be more efficient in the future. In terms of battery performance, stakeholders suggested assuming almost 4 miles/kWh battery performance in summer and an average of 2.75-3 miles/kWh across seasons in Michigan. However, temperature will likely still impact battery performance. Idaho National Laboratory data [32] indicates that temperature variations can influence EV ranges by more than 25%. Similarly, it is reported that the range of all-electric Nissan Leafs operated in Chicago in winter were 26% lower than those operated in Seattle in fall. Also, plug-in hybrid electric Chevrolet Volts had 29% lower ranges in Chicago winter compared to those in Chicago spring [32]. For this project, it is assumed that winter battery performance is 70% of summer performance. Thus, EVs with 100kWh battery can travel

147 miles in winter and up to 280 miles in summer on a single charge, while this range for EVs with 70kWh batteries is 103-196 miles. The aforementioned distances assume users will only use up to 80 percent of the battery energy before recharging and that they charge only up to 80 percent at public charging stations.

*6.3.2 Electric Vehicle Market Share*

This project focuses on developing an optimized EV DC fast charging station placement map for 2030. As such, projections for future EV market share in Michigan are required. A study conducted by M.J. Bradley & Associates [33] estimates the 2017 EV market share (proportion of EVs to all vehicles on the road) in Michigan to be 0.14%. Midcontinent Independent System Operator (MISO) and Bloomberg both have scenarios regarding EV market growth. Bloomberg projections are national forecasts (about 8% for 2025, 12% for 2030 and more than 50% for 2050) and may be overly optimistic for Michigan, considering the current trend in market growth of EVs. Thus, this study adopts MISO projections, which are more regionally focused. These projections are 1.49% for 2020, 3.74% for 2025, and 6% in 2030.

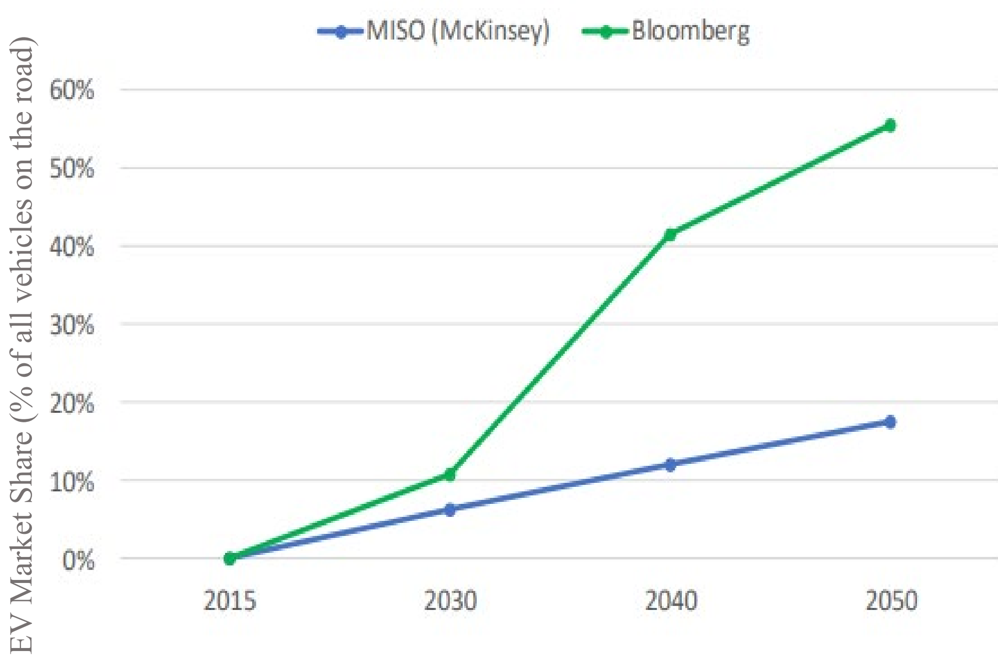



**Figure 6. Predicted EV Penetration**

## 7. RESULTS AND DISCUSSION

In this section, we first describe the scenarios and their assumptions on vehicle range, charging station power, and EV market share. For each scenario, the model provides charging station locations, the number of charging outlets, the associated costs, and recharging delay. Finally, the economic benefits of charger placement in each scenario are discussed.

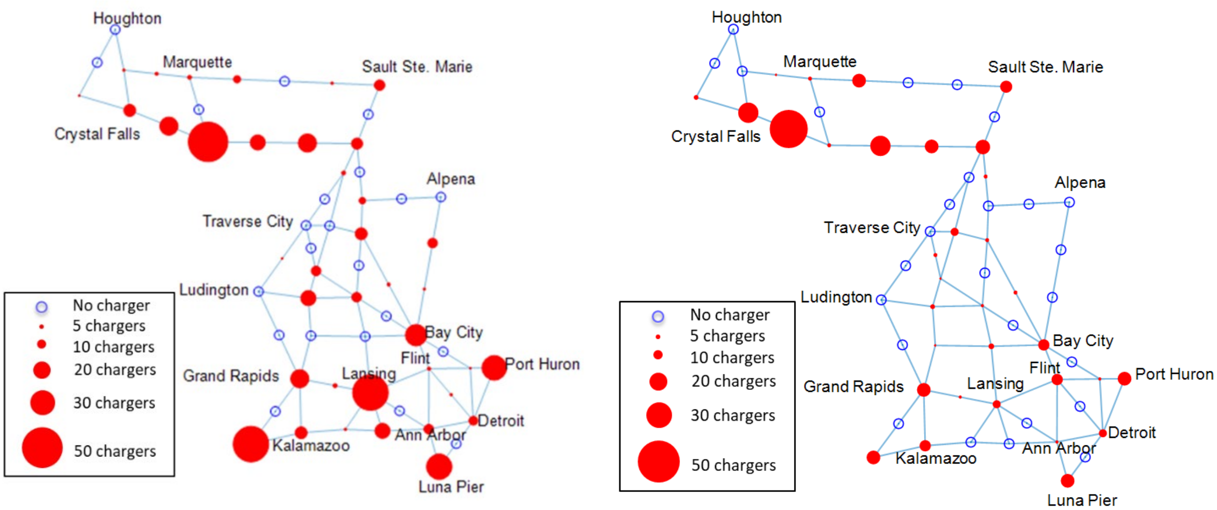
## 7.1 Model Scenarios

### *7.1.1 Selection of the Winter Scenario*

Initially, a large variety of scenarios were tested. The scenarios were divided based on technology advancement (batteries and charging stations), EV market penetration rates, and seasonal variation of travel demand.

The base model in terms of the vehicle range, station power, and EV market share was solved for two estimated demand tables for January (winter) and July (summer). The summer scenario has a higher total demand relative to the winter scenario due to additional trips in summer for tourism and other purposes. However, the battery efficiency is lower in the winter scenario due to the cold weather. This results in a higher available battery range in the summer scenario, despite a higher total demand. Due to the reduced battery performance in colder months, more charging stations and outlets are required to support travel demand during winter months (Figure 7).

As only one configuration of charging stations can be selected, the winter demand configuration with the larger number of charging stations and outlets was tested using summer demand. Travel feasibility and delay impacts were examined for the optimized winter network while supporting summer travel demand (Table 4). The comparison shows that the required charging infrastructure for winter covers charging needs for summer, even though charging station locations do not overlap at some locations. As the charging station locations are not optimized for summer demand, the average delay increases slightly when optimized charging infrastructure for winter supports summer EV travel. However, the winter charging infrastructure does not affect the feasibility of summer trips. In contrast, the solution for the summer scenario is not feasible for winter demand. Thus, the winter scenario solution is selected to keep EV trips feasible throughout the year, even though it slightly increases summer time delays, as shown in Table 4. All other scenarios in this study are tested only for the winter application.




(a) Charger placement to support winter demand and battery performance

(b) Charger placement to support summer demand and battery performance

**Figure 7. Charger Placement in 2030 with 70 kWh Battery and 50 kW DC Fast Charger**

**Table 4. Summer and Winter Analysis for Charging Infrastructure Optimization**

| Variable | Optimal Solution for Winter | Summer Demand with Optimal Solution for Winter | Optimal Solution for Summer |
|---|---|---|---|
| Number of Stations | 38 | 38 | 33 |
| Number of Charging Outlets | 552 | 552 | 315 |
| Total Delay (hours) | 3642 | 2314 | 2078 |
| Total investment cost (million $) | 25.6 | 25.6 | 16.2 |

*7.1.2 Technology Scenarios*

The scenarios in this project are divided into low-tech, high-tech, and mixed technology scenarios. In the low-tech scenarios, a smaller battery (70kWh) with current DC fast chargers (50kW) is used. In the high-tech scenario, an improved battery (100kWh) with a recently introduced DC fast charger (150kW) is used. These combinations are proposed, as the improvement and adoption of the battery and charging technology are expected to progress together during the upcoming years. Three demand scenarios (2020, 2025, and 2030) are tested for each technology scenario to examine the impact of projected EV market share increases over time. Lastly, a mixed technology scenario is also examined to evaluate the needs of smaller battery EVs (70kWh) on a 150kW DC fast charging network.

## 7.2 Optimized Results for Charging Station Placement and Charging Outlet Numbers

This section details the project findings. A total of thirteen scenarios were examined with three technology profiles: low-tech, high-tech, and mixed technology. Six scenarios were first examined using the optimization model without tourism data. In these scenarios, the original model results failed to place chargers in locations with known tourism demand, where EV tourists would require charging. Another six scenarios using the optimization model were examined using partial tourism data, which helped address this weakness. Finally, a mixed technology scenario was examined to see how a DC fast charging network can be developed to serve the needs of smaller battery EVs. The findings of these different scenarios are discussed below.

### *7.2.1 Low and High-Tech Results without Tourism Considerations*

A total of six scenarios were examined without tourism considerations. Three projection years (2020, 2025, and 2030) were examined for both low and high-tech scenarios. Figure 8 shows the optimized results for charging stations and the number of charging outlets in Michigan for the six scenarios. In Figure 8, each red dot represents a charging station. The size of the dot represents the optimized number of charging outlets at each station, with larger dots indicating more outlets. Table 5 summarizes the number of charging stations, charging outlets, the required investment for each scenario, and the provided level of service.

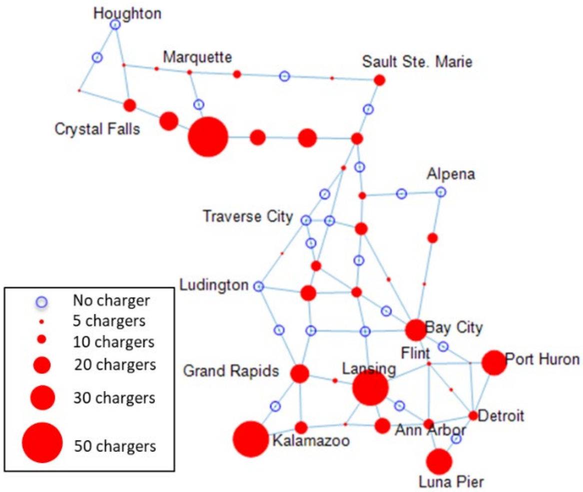
Unsurprisingly, as the market share of EVs increases over time, more charging outlets are needed to support the higher demand in both the low-tech and high-tech scenarios. However, the optimized network is not incremental. There are cases where a station might be needed in an early year, but is no longer (optimally) required in later years. Although all proposed configurations (2020, 2025, and 2030) account for feasibility of EV trips in terms of the range anxiety, different configurations are suggested to minimize the detour and waiting time delays for users, which varies depending on the travel demand in each scenario. This suggests that if the goal is to build a DC fast charging network to support EV travel in 2030, implementers should focus on the 2030 placement maps when considering inter-city travel.

In the high-tech scenarios, fewer charging stations are required since the battery size and vehicle range increases. As a result, longer distances can be traveled without the need for frequent battery recharging. Also, fewer charging outlets are required at each station due to higher throughput from the faster charging power. Lastly, though the per unit cost of 150 kW chargers is higher than the per unit cost of 50 kW chargers, the total system costs are lower for the high-tech scenarios due to the fewer charging stations and charging outlets required. It is worth noting that the reported costs are conservative. We assume only one station cost for each station location. Depending on the implementation and distribution of the proposed number of chargers, the costs might increase as the needed outlet numbers are split between multiple EV charging stations in an identified station location. See Table 5 and Figure 8 for scenario results.

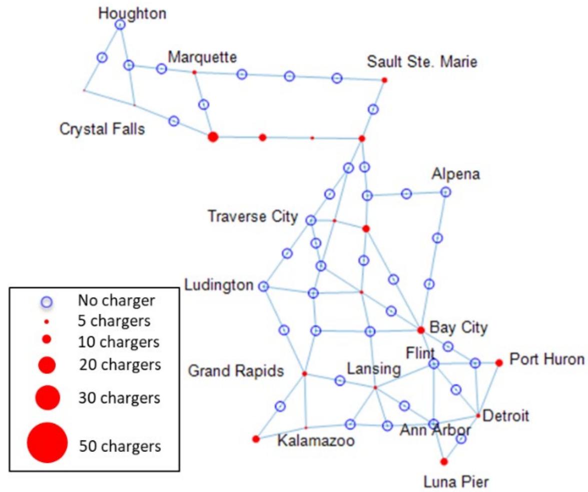
**Table 5. Scenario Results: Charging Stations, Outlets, Required Investment, and Charge Time**

| | **Scenarios** | | | | | |
|---|---|---|---|---|---|---|
| | ***Low-Tech:*** 70 kWh Battery & 50 kW Charger | | | ***High-Tech:*** 100 kWh Battery & 150 kW Charger | | |
| | **2030** | **2025** | **2020** | **2030** | **2025** | **2020** |
| **Scenario Specification** | | | | | | |
| EV Market Share (%) | 6 | 3.74 | 1.49 | 6 | 3.74 | 1.49 |
| **Optimum Charger Placement** | | | | | | |
| Number of charging stations | 38 | 38 | 32 | 20 | 18 | 15 |
| Number of charging outlets | 552 | 339 | 142 | 104 | 58 | 32 |
| **Investment Cost** | | | | | | |
| Charging station cost (Million dollar) | 5.93 | 6 | 5.27 | 3.68 | 3.28 | 2.83 |
| Land cost (Million dollar) | 1.04 | 0.64 | 0.27 | 0.20 | 0.11 | 0.06 |
| Charging outlet cost (Million dollar) | 18.6 | 11.4 | 4.79 | 8.01 | 4.42 | 2.44 |
| Total cost (Million dollar) | 25.6 | 18.1 | 10.3 | 11.9 | 7.81 | 5.33 |
| **Delay time** | | | | | | |
| Average Delay (min) | 30.7 | 31 | 31 | 12.4 | 13.4 | 13.3 |

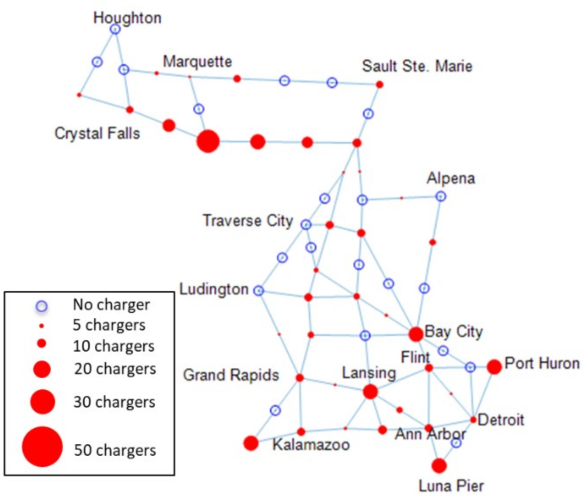
Tourism is not considered effectively by the model without supporting tourism travel data, which was not included in these scenarios. The model assumes that EV drivers depart fully charged in the morning. For tourists, this may be unrealizable, especially if they stay overnight at lodging where charging is not available. Given this issue and even though all EV travel is supported by the scenario results, EV tourists may need to detour to nearby sites that are not enroute to charge. The researchers recognized this weakness in the study and actively sought out Michigan tourism data so additional scenarios could examine tourism impacts. Results with partial tourism is discussed in the next section.



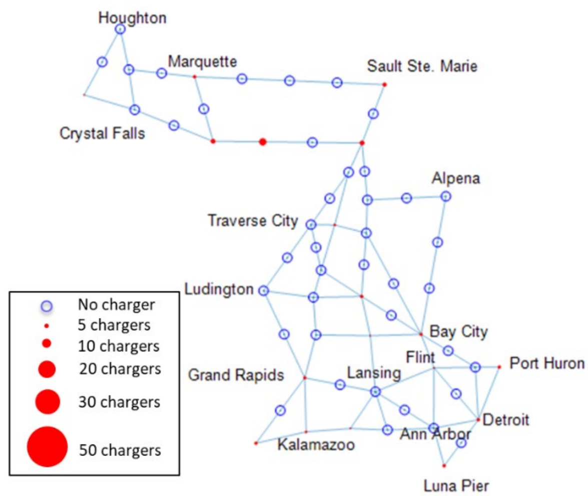

(a) 2030 Low-Tech: 70 kWh Battery & 50 kW Charger



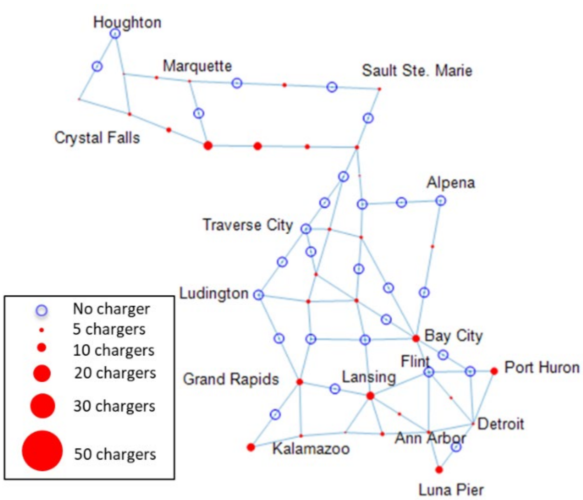

(d) 2030 High-Tech: 100 kWh Battery & 150 kW Charger



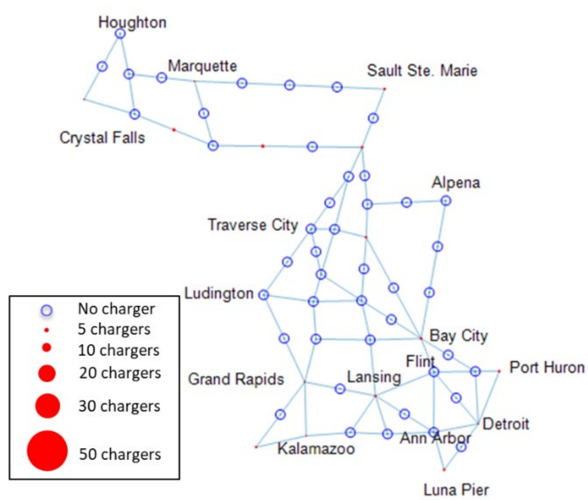

(b) 2025 Low-Tech: 70 kWh Battery & 50 kW Charger




(e) 2025 High-Tech: 100 kWh Battery & 150 kW Charger




(c) 2020 Low-Tech: 70 kWh Battery & 50 kW Charger




(f) 2020 High-Tech: 100 kWh Battery & 150 kW Charger

**Figure 8. Scenario Results (Charging Stations and Outlet Numbers) for 2020, 2025, and 2030**

*7.2.2 Low and High-Tech Results with Tourism Considerations*

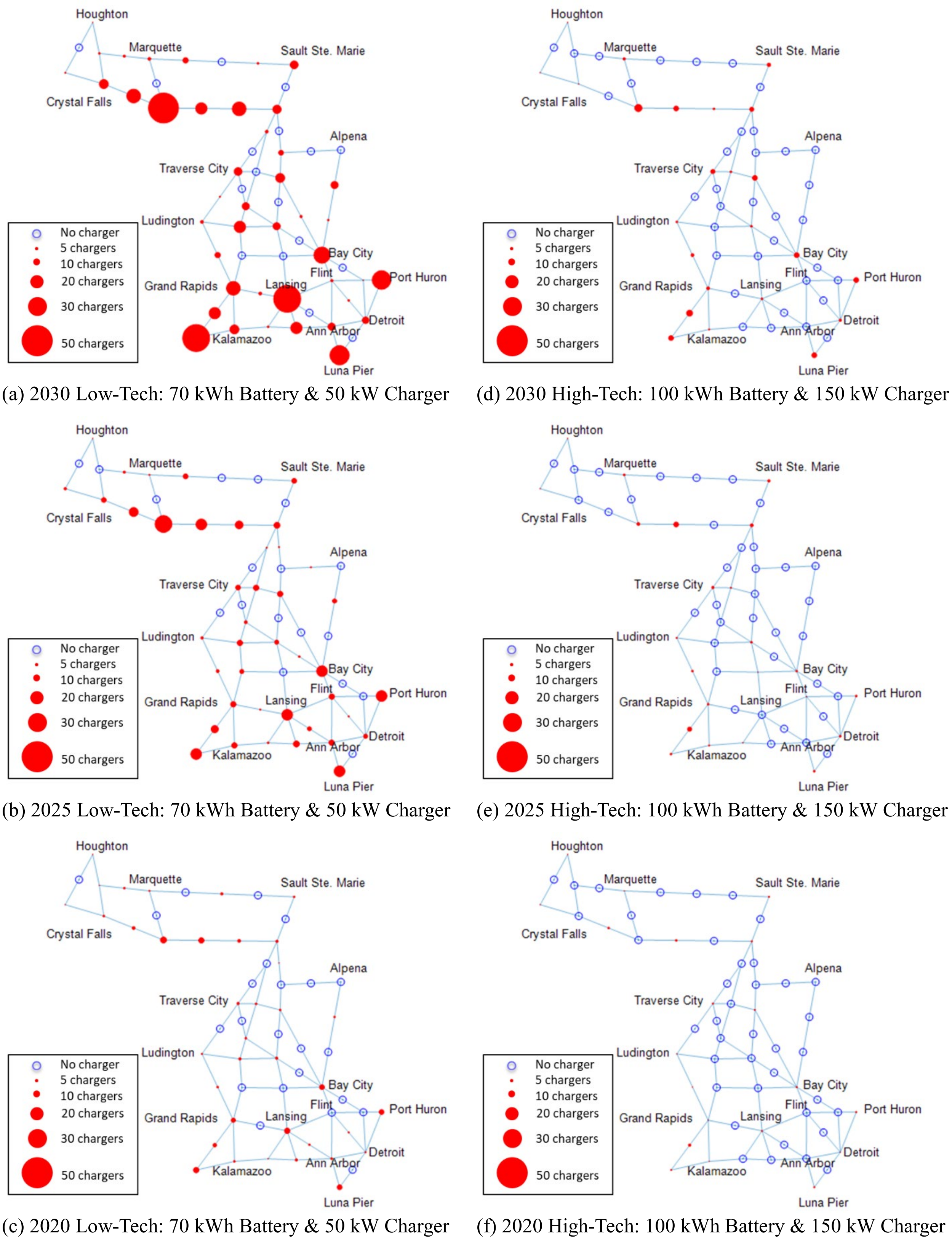
The main aim of this study is to support intercity EV trips to ensure feasibility and to reduce range anxiety. Due to the assumption that EV drivers begin fully charged at the beginning of each day, the model does not consider tourism trips well without tourism data. It is unlikely that tourists will be able to charge fully overnight. They will likely need to charge at charging stations even after arriving at a destination to continue their trip. Given the lack of initial tourism travel demand data, the model results failed to place stations in known Michigan tourism locations.

To address this issue, charging stations are added using partial tourism data to ensure that EV tourists will be able to start their intercity trip with a fully charged battery. EV tourists' charging needs are assumed to be distributed through 14 hours of the day, as visitors have more flexibility in choosing their departure time. The number of charging outlets required is a function of both the battery size and also the charging speed.

As tourism data was received late in the analysis, a full tourism analysis could not be included. A future supplemental analysis will be published to more fully examine tourism impacts on the developed infrastructure. Results considering partial tourism data are presented in Figure 9 and Table 6. Note that the delays cannot be reported for the tourism scenarios since the model structure is different from the modeling framework for the bare-bones highway system.

**Table 6. Partial Tourism Scenario Results: Charging Stations, Outlets, and Required Investment**

| | Scenarios | | | | | |
|---|---|---|---|---|---|---|
| | ***Low-Tech:*** 70 kWh Battery & 50 kW Charger | | | ***High-Tech:*** 100 kWh Battery & 150 kW Charger | | |
| | **2030** | **2025** | **2020** | **2030** | **2025** | **2020** |
| **Scenario Specification** | | | | | | |
| EV Market Share (%) | 6 | 3.74 | 1.49 | 6 | 3.74 | 1.49 |
| **Optimum Charger Placement** | | | | | | |
| Number of Charging Stations | 43 | 42 | 37 | 24 | 23 | 20 |
| Number of Charging Outlets | 600 | 368 | 159 | 131 | 76 | 44 |
| **Investment Cost** | | | | | | |
| Charging Station Cost (million dollars) | 6.64 | 6.59 | 5.97 | 4.37 | 4.14 | 3.70 |
| Land Cost (million dollars) | 1.13 | 0.69 | 0.30 | 0.25 | 0.14 | 0.08 |
| Charging Outlet Cost (million dollars) | 20.3 | 12.4 | 5.37 | 9.99 | 5.80 | 3.36 |
| Total Cost (million dollars) | 28.0 | 19.7 | 11.6 | 14.6 | 10.1 | 7.14 |




(a) 2030 Low-Tech: 70 kWh Battery & 50 kW Charger

(d) 2030 High-Tech: 100 kWh Battery & 150 kW Charger

(b) 2025 Low-Tech: 70 kWh Battery & 50 kW Charger

(e) 2025 High-Tech: 100 kWh Battery & 150 kW Charger

(c) 2020 Low-Tech: 70 kWh Battery & 50 kW Charger

(f) 2020 High-Tech: 100 kWh Battery & 150 kW Charger

**Figure 9. Partial Tourism Scenario Results (Charging Stations and Outlets) for 2020, 2025, and 2030**

Even though advancements in battery and charging station technologies are expected to happen by 2030, some older vehicles with smaller batteries or shorter EV range are still expected to be on the road. Thus, this study examines a mixed technology scenario with fast charging options (150kW) and smaller batteries (70kWh) to ensure coverage and feasibility for these EV trips. Figure 10 presents this scenario for 2030 demand.

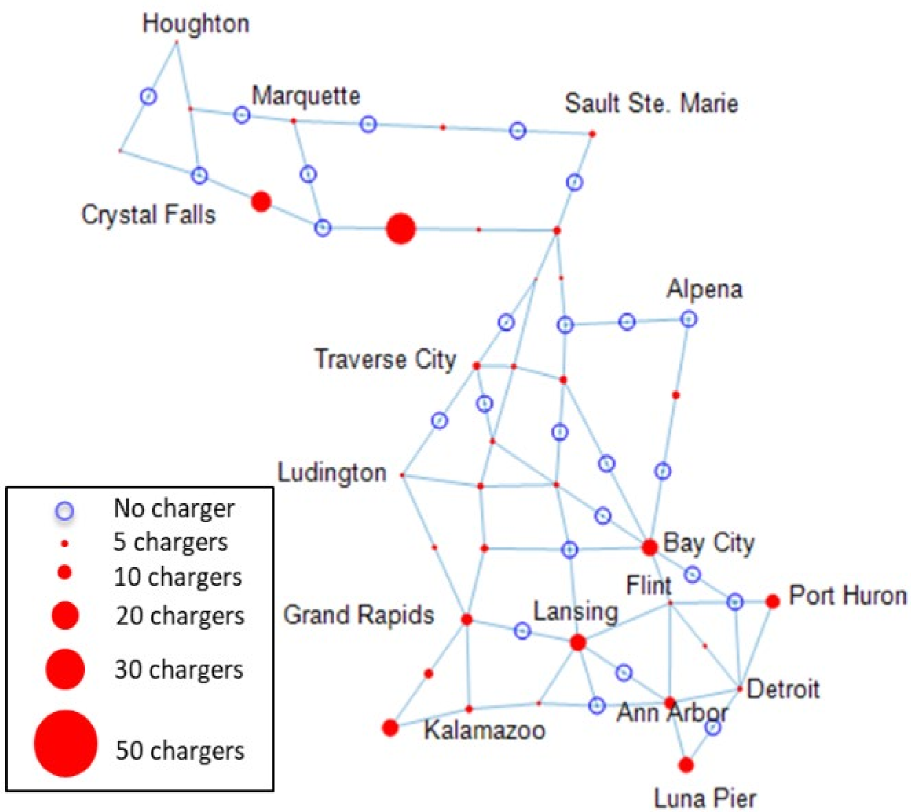



**Figure 10. Mixed Scenario with 70 kWh Battery and 150 kW Charging Stations for 2030 Market Share, Including Partial Tourism Demand**

In the mixed technology (150kW charger and 70kWh battery) scenario, the number of charging outlets and stations increases by about 50 percent compared to the high-tech (150kW charger and 100kWh battery) scenario to ensure trip feasibility given the smaller battery size (Table 7). Compared to the low-tech (50kW charger and 70kWh battery) scenario, the mixed technology scenario has about 19% less charging stations, with 68% fewer required outlets. Since the low-tech scenario has slower chargers (50kW compared to 150 kW in the mixed-tech scenario), it requires about three times more chargers to reduce the charging delay they cause. However, the number of stations does not change much. The same number of stations are required to ensure trip EV feasibility due to the same considered battery size (Table 7).

**Table 7. Comparison of Different Scenarios for 2030 Demand**

| | *Low-Tech* | *High-Tech* | *Mixed-Tech* |
|---|---|---|---|
| **Scenario Specification** | | | |
| EV market share (%) | 6 | 6 | 6 |
| Charging power (kW) | 50 | 150 | 150 |
| Battery energy (kWh) | 70 | 100 | 70 |
| **Optimum Charger Placement** | | | |
| Number of charging stations | 43 | 24 | 35 |
| Number of charging outlets | 600 | 131 | 196 |
| **Investment Cost** | | | |
| Charging station cost (million dollars) | 6.64 | 4.37 | 6.47 |
| Land cost (million dollars) | 1.13 | 0.25 | 0.37 |
| Charging outlet cost (million dollars) | 20.3 | 9.99 | 15.0 |
| Total cost (million dollars) | 28.0 | 14.6 | 21.8 |

The mixed technology scenario is the suggested scenario. Though it is more expensive to implement than the high-tech network ($21.8 vs. $14.6 million dollars), the mixed technology scenario results support smaller battery EVs in traveling throughout Michigan. However, it is cheaper than the low-technology scenario while also decreasing user delays from charging. With added stations and increased charging outlets, the mixed technology scenario decreases the likelihood that smaller battery EVs will become stranded on a 150 kW DC fast charging network in the state.

## 8. CONCLUSION

This project proposes the optimum configuration of DC fast charging stations to support intercity trips, or trips between cities, in Michigan and travel to neighboring states and Canada for light-duty vehicles. It identifies the charging station locations within a five-mile radius around the selected points, preferably with the station located near the highway, as well as the number of charger outlets required at each location.

The optimized EV DC fast charging station configuration is proposed for projected EV market growth in three scenario years (2020, 2025, or 2030) and for different technology advancements in EV battery size and DC fast charger power. Each optimal configuration of charging station placement and outlet numbers seeks to minimize user delay based on travel demand, while ensuring all inter-city EV trips are feasible. Unsurprisingly, the station placement and outlet number vary for different target years, depending on the projected EV travel demand. However, station placement is not necessarily incremental when moving from 2020, 2025, and 2030 scenarios. We suggest the 2030 scenarios be the main focus for implementation to optimally serve predicted 2030 EV demand.

EV battery performance during colder winter months must be considered when designing a DC fast charging system in Michigan. In design problems, planners typically consider the maximum demand. For EV infrastructure planning, the lower battery performance in cold seasons needs to be examined in addition to the maximum travel demand, which is in the summer for Michigan. Though travel demand is less in winter, the demand for EV charging may be high due to lower EV battery performance at cold temperatures. This study finds optimized charging station placement for winter travel demand can support feasible summer EV travel. However, the optimized summer charging station configuration cannot support feasible winter EV travel. Thus, all optimized EV charging station placements are based on winter demand in each scenario to support EV trips year-round.

This study finds a system with 150kW chargers, though more expensive individually, actually has lower total system cost when compared to a 50kW charging system when serving the same battery size EV. Though this study examines low and high technology scenarios (70kWh battery with 50kW charger and 100kWh battery with 150kW charger, respectively), it recognizes that some older vehicles with smaller batteries and shorter EV range will likely be on the roads in 2030. Even though advancements in batteries and charging station technologies are expected to occur by 2030, these lower range vehicles still need to be considered when planning EV charging infrastructure. Thus, this study also examines fast charging options with smaller batteries to ensure coverage and feasibility of trips for these vehicles (70kWh battery with 150kW charger).

It is suggested Michigan build the optimized charging network for the 2030 demand scenario using 150kW chargers with 70kWh batteries. This mixed technology scenario, which places 35 charging stations and 196 charging outlets, ensures trip feasibility for a wider range of EVs. Total system cost is $21.8 million dollars. When building the network, we suggest Michigan first focus on covering all the station locations with at least two charging outlets. This supports feasible EV travel by ensuring station coverage and redundancy in case of a station outage. Afterward, the number of charging outlets can be increased incrementally, proportional to the proposed number of charging outlets for 2030 demand, to reduce user delay as EV travel demand increases.

There are several caveats regarding study findings. First, the estimates for system implementation costs are conservative. For each identified EV charging station location, this project assumes one station is installed with the total number of demanded outlets. Thus, the estimates provided here can be considered a lower bound of possible implementation costs. It is conceivable that multiple stations may be located at the identified node, with the charging outlets across all stations at the node totaling to the needed number. Second, the optimization model cannot discern the charging needs of EV tourists at their destinations. A complimentary model is used to estimate the required number of charger outlets at selected attraction sites to support EV tourism trips. Tourism data was obtained late in this analysis, so only partial tourism data is considered here. A supplemental analysis will be published later this year with a more thorough analysis of the EV charging needs to support tourism in Michigan. Third, this study only focuses on inter-city trips for light-duty vehicles. It assumes that all EV trips begin with full battery charge. This is a reasonable assumption for inter-city trips that are well-planned, where users likely leave fully charged. However, this is not a valid assumption for the intra-city trips and their charging needs, which will be studied in Phase 2 of this project. Plans to support heavy duty EVs will also be governed by different assumptions and inputs, which should be explored in a separate study if needs arise. Fourth, traveler delay estimates are made assuming each scenario's battery size and charger power. However, actual delays after implementation may vary. Even though 150 kW chargers may be available, if vehicle batteries cannot accept more than 50 kW of power, the actual user delay may increase significantly.

Finally, we emphasize that this study is a technical analysis. It seeks to find the optimal configuration of DC fast charging station locations and the associated number of chargers at each location for the given target demands. The proposed framework ensures feasibility of light duty EV trips, while minimizing investment cost and user delays for EV travelers. The project findings are specific to the assumptions detailed here. We suggest implementers consider EV market growth and technology advancements when selecting which optimal scenario to adopt, especially if these results are used at a much later date, as these changes may impact the realized user delay, implementation costs, and EV travel feasibility. The study results provide no guidance on how the optimal EV DC fast charging stations can be implemented. The station configurations, programs, policies, payment schemes, and other implementation considerations are outside of this project scope. However, we hope that this technical analysis will be informative to EV DC fast charging system implementers as they select site locations and outlet numbers in Michigan.

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## APPENDIX A: CHARGING STATION LOCATION AND NUMBER BY ZIP CODE

Detailed location and number of charging outlets under different technology and demand scenarios are described in Table 1A – 3A. Table 1A focuses on the suggested scenario, which is a mixed technology scenario with a 70 kWh battery and a 150 kW charger.

**Table 1A- Distribution of Charging Outlets in Optimized Placement, Including Partial Tourism Demand in 2030**

| Node | Zip Code | City | ***Mixed Tech:*** 70 kWh Battery & 150 kW Charger |
|---|---|---|---|
| 1 | 49931 | Houghton | 2 |
| 2 | 49855 | Marquette | 3 |
| 3 | 49783 | Sault Saint Marie | 4 |
| 4 | 49912 | Bruce Crossing | 2 |
| 5 | 49920 | Crystal Falls | 0 |
| 6 | 49878 | Rapid River | 0 |
| 7 | 49701/49781 | Mackinaw City/St. Ignace | 5 |
| 8 | 49684 | Traverse City | 5 |
| 9 | 49738 | Grayling | 5 |
| 10 | 49707 | Alpena | 0 |
| 11 | 49431 | Ludington | 2 |
| 12 | 48617 | Clare | 3 |
| 13 | 48706 | Bay City | 12 |
| 14 | 49503 | Grand Rapids | 8 |
| 15 | 48906 | Lansing | 12 |
| 16 | 48504 | Flint | 2 |
| 17 | 48060 | Port Huron | 10 |
| 18 | 49022 | Benton Harbor | 12 |
| 19 | 49024 | Portage | 5 |
| 20 | 49068 | Marshall | 2 |
| 21 | 48104 | Ann Arbor | 8 |
| 22 | 48216 | Detroit | 3 |
| 23 | 48133 | Luna Pier | 11 |
| 24 | 49919 | Covington | 2 |
| 25 | 49770 | Petoskey | 2 |
| 26 | 49735 | Gaylord | 0 |
| 27 | 49646 | Kalkaska | 3 |
| 28 | 49601 | Cadillac | 3 |
| 29 | 49677 | Reed City | 4 |
| 30 | 49329 | Howard City | 5 |
| 31 | 48847 | Ithaca | 0 |

**Table 1A- Distribution of Charging Outlets in Optimized Placement, Including Partial Tourism Demand in 2030, Cont.**

| Node | Zip Code | City | ***Mixed Tech:*** 70 kWh Battery & 150 kW Charger |
|---|---|---|---|
| 32 | 48444 | Imlay City | 0 |
| 33 | 49201 | Jackson | 0 |
| 34 | 49948 | Mass City | 0 |
| 35 | 49862 | Munising | 0 |
| 36 | 49883 | Seney | 3 |
| 37 | 49728 | Eckerman | 0 |
| 38 | 49880 | Rock | 0 |
| 39 | 49814 | Champion | 0 |
| 40 | 49780 | Rudyard | 0 |
| 41 | 49892 | Vulcan | 15 |
| 42 | 49854 | Manistique | 23 |
| 43 | 49827 | Engadine | 2 |
| 44 | 49749 | Indian River | 2 |
| 45 | 49614 | Bear Lake | 0 |
| 46 | 49622 | Central Lake | 0 |
| 47 | 49668 | Mesick | 0 |
| 48 | 48629 | Houghton Lake | 0 |
| 49 | 48661 | West Branch | 0 |
| 50 | 48738 | Greenbush | 5 |
| 51 | 48703 | Au Gres | 0 |
| 52 | 49709 | Atlanta | 0 |
| 53 | 49445 | Muskegon | 3 |
| 54 | 48657 | Sanford | 0 |
| 55 | 48741 | Kingston | 0 |
| 56 | 48881 | Saranac | 0 |
| 57 | 49453 | Saugatuck | 6 |
| 58 | 48114 | Brighton | 0 |
| 59 | 48326 | Auburn Hills | 2 |
| 60 | 48166 | Newport | 0 |

**Table 2A- Distribution of Charging Outlets in Optimized Placement by Scenario with Partial Tourism Demand**

| | | | Tourism Scenarios | | | | | |
|---|---|---|---|---|---|---|---|---|
| Node | Zip Code | City | ***Low-Tech:*** 70kWh Battery & 50kW Charger | | | ***High-Tech:*** 100kWh Battery & 150kW Charger | | |
| | | | **2030** | **2025** | **2020** | **2030** | **2025** | **2020** |
| 1 | 49931 | Houghton | 2 | 2 | 2 | 2 | 2 | 2 |
| 2 | 49855 | Marquette | 5 | 2 | 2 | 4 | 3 | 2 |
| 3 | 49724 | Sault Saint Marie | 13 | 8 | 3 | 6 | 4 | 2 |
| 4 | 49912 | Bruce Crossing | 2 | 4 | 2 | 2 | 2 | 2 |
| 5 | 49920 | Crystal Falls | 15 | 8 | 3 | 2 | 0 | 0 |
| 6 | 49878 | Rapid River | 50 | 28 | 10 | 12 | 5 | 0 |
| 7 | 49701/49781 | Mackinaw City/St. Ignace | 14 | 10 | 4 | 7 | 5 | 2 |
| 8 | 49684 | Traverse City | 13 | 8 | 4 | 7 | 4 | 2 |
| 9 | 49738 | Grayling | 15 | 9 | 3 | 8 | 0 | 2 |
| 10 | 49707 | Alpena | 0 | 0 | 0 | 0 | 0 | 0 |
| 11 | 49431 | Ludington | 5 | 4 | 2 | 3 | 2 | 2 |
| 12 | 48617 | Clare | 12 | 7 | 4 | 3 | 3 | 0 |
| 13 | 48706 | Bay City | 27 | 18 | 8 | 8 | 3 | 2 |
| 14 | 49503 | Grand Rapids | 23 | 9 | 7 | 5 | 3 | 2 |
| 15 | 48906 | Lansing | 45 | 18 | 9 | 3 | 0 | 2 |
| 16 | 48504 | Flint | 4 | 9 | 0 | 0 | 2 | 0 |
| 17 | 48060 | Port Huron | 31 | 18 | 8 | 8 | 3 | 2 |
| 18 | 49022 | Benton Harbor | 45 | 18 | 9 | 8 | 3 | 2 |
| 19 | 49024 | Portage | 15 | 9 | 3 | 2 | 2 | 2 |
| 20 | 49068 | Marshall | 3 | 3 | 2 | 0 | 2 | 0 |
| 21 | 48104 | Ann Arbor | 12 | 9 | 3 | 0 | 0 | 0 |
| 22 | 48216 | Detroit | 11 | 7 | 2 | 4 | 3 | 2 |
| 23 | 48133 | Luna Pier | 32 | 18 | 8 | 8 | 3 | 2 |
| 24 | 49919 | Covington | 3 | 0 | 2 | 0 | 0 | 0 |
| 25 | 49770 | Petoskey | 5 | 2 | 0 | 0 | 0 | 0 |
| 26 | 49735 | Gaylord | 8 | 0 | 0 | 0 | 0 | 0 |
| 27 | 49646 | Kalkaska | 0 | 9 | 3 | 3 | 2 | 0 |
| 28 | 49601 | Cadillac | 12 | 5 | 3 | 0 | 0 | 0 |
| 29 | 49677 | Reed City | 19 | 9 | 4 | 0 | 0 | 0 |
| 30 | 49329 | Howard City | 0 | 7 | 0 | 0 | 0 | 0 |
| 31 | 48847 | Ithaca | 0 | 0 | 0 | 0 | 2 | 0 |
| 32 | 48444 | Imlay City | 2 | 0 | 0 | 0 | 0 | 0 |
| 33 | 49201 | Jackson | 19 | 10 | 4 | 0 | 0 | 0 |
| 34 | 49948 | Mass City | 0 | 0 | 0 | 0 | 0 | 0 |
| 35 | 49862 | Munising | 9 | 8 | 0 | 0 | 0 | 0 |
| 36 | 49883 | Seney | 0 | 0 | 4 | 0 | 0 | 0 |

**Table 2A- Distribution of Charging Outlets in Optimized Placement by Scenario with Partial Tourism Demand, Cont.**

| | | | Tourism Scenarios | | | | | |
|---|---|---|---|---|---|---|---|---|
| Node | Zip Code | City | ***Low-Tech:*** 70kWh Battery & 50kW Charger | | | ***High-Tech:*** 100kWh Battery & 150kW Charger | | |
| | | | **2030** | **2025** | **2020** | **2030** | **2025** | **2020** |
| 37 | 49728 | Eckerman | 3 | 0 | 0 | 0 | 0 | 0 |
| 38 | 49880 | Rock | 0 | 0 | 0 | 0 | 0 | 0 |
| 39 | 49814 | Champion | 4 | 4 | 3 | 0 | 0 | 0 |
| 40 | 49780 | Rudyard | 0 | 0 | 0 | 0 | 0 | 0 |
| 41 | 49892 | Vulcan | 23 | 15 | 5 | 0 | 0 | 3 |
| 42 | 49854 | Manistique | 19 | 18 | 9 | 8 | 8 | 3 |
| 43 | 49827 | Engadine | 23 | 13 | 5 | 3 | 0 | 0 |
| 44 | 49749 | Indian River | 0 | 2 | 2 | 0 | 0 | 0 |
| 45 | 49614 | Bear Lake | 2 | 0 | 0 | 0 | 0 | 0 |
| 46 | 49622 | Central Lake | 0 | 0 | 0 | 0 | 0 | 0 |
| 47 | 49668 | Mesick | 0 | 0 | 0 | 0 | 0 | 0 |
| 48 | 48629 | Houghton Lake | 0 | 0 | 0 | 0 | 0 | 0 |
| 49 | 48661 | West Branch | 4 | 0 | 0 | 0 | 0 | 0 |
| 50 | 48738 | Greenbush | 12 | 7 | 3 | 0 | 0 | 0 |
| 51 | 48703 | Au Gres | 3 | 0 | 0 | 0 | 0 | 0 |
| 52 | 49709 | Atlanta | 0 | 2 | 0 | 0 | 0 | 0 |
| 53 | 49445 | Muskegon | 9 | 5 | 3 | 5 | 3 | 2 |
| 54 | 48657 | Sanford | 0 | 3 | 0 | 0 | 0 | 0 |
| 55 | 48741 | Kingston | 0 | 0 | 0 | 0 | 0 | 0 |
| 56 | 48881 | Saranac | 5 | 2 | 0 | 0 | 0 | 0 |
| 57 | 49453 | Saugatuck | 19 | 12 | 6 | 10 | 7 | 4 |
| 58 | 48114 | Brighton | 0 | 7 | 3 | 0 | 0 | 0 |
| 59 | 48326 | Auburn Hills | 3 | 2 | 2 | 0 | 0 | 0 |
| 60 | 48166 | Newport | 0 | 0 | 0 | 0 | 0 | 0 |

**Table 3A- Distribution of Charging Outlets in Optimized Placement in Low-Tech and High-Tech Scenarios**

| | | | Scenarios | | | | | |
|---|---|---|---|---|---|---|---|---|
| Node | Zip Code | City | ***Low-Tech:*** 70 kWh Battery & 50 kW Charger | | | ***High-Tech:*** 100 kWh Battery & 150 kW Charger | | |
| | | | **2030** | **2025** | **2020** | **2030** | **2025** | **2020** |
| 1 | 49931 | Houghton | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 49855 | Marquette | 5 | 2 | 2 | 4 | 3 | 2 |
| 3 | 49724 | Sault Saint Marie | 13 | 8 | 3 | 6 | 4 | 2 |
| 4 | 49912 | Bruce Crossing | 2 | 4 | 2 | 2 | 2 | 2 |
| 5 | 49920 | Crystal Falls | 15 | 8 | 3 | 2 | 0 | 0 |
| 6 | 49878 | Rapid River | 50 | 28 | 10 | 12 | 5 | 0 |
| 7 | 49701/49781 | Mackinaw City/St. Ignace | 14 | 10 | 4 | 7 | 5 | 2 |
| 8 | 49684 | Traverse City | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 49738 | Grayling | 15 | 9 | 3 | 8 | 0 | 2 |
| 10 | 49707 | Alpena | 0 | 0 | 0 | 0 | 0 | 0 |
| 11 | 49431 | Ludington | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 48617 | Clare | 12 | 7 | 4 | 3 | 3 | 0 |
| 13 | 48706 | Bay City | 27 | 18 | 8 | 8 | 3 | 2 |
| 14 | 49503 | Grand Rapids | 23 | 9 | 7 | 5 | 3 | 2 |
| 15 | 48906 | Lansing | 45 | 18 | 9 | 3 | 0 | 2 |
| 16 | 48504 | Flint | 4 | 9 | 0 | 0 | 2 | 0 |
| 17 | 48060 | Port Huron | 31 | 18 | 8 | 8 | 3 | 2 |
| 18 | 49022 | Benton Harbor | 45 | 18 | 9 | 8 | 3 | 2 |
| 19 | 49024 | Portage | 15 | 9 | 3 | 2 | 2 | 2 |
| 20 | 49068 | Marshall | 3 | 3 | 2 | 0 | 2 | 0 |
| 21 | 48104 | Ann Arbor | 12 | 9 | 3 | 0 | 0 | 0 |
| 22 | 48216 | Detroit | 11 | 7 | 2 | 4 | 3 | 2 |
| 23 | 48133 | Luna Pier | 32 | 18 | 8 | 8 | 3 | 2 |
| 24 | 49919 | Covington | 3 | 0 | 2 | 0 | 0 | 0 |
| 25 | 49770 | Petoskey | 5 | 2 | 0 | 0 | 0 | 0 |
| 26 | 49735 | Gaylord | 8 | 0 | 0 | 0 | 0 | 0 |
| 27 | 49646 | Kalkaska | 0 | 9 | 3 | 3 | 2 | 0 |
| 28 | 49601 | Cadillac | 12 | 5 | 3 | 0 | 0 | 0 |
| 29 | 49677 | Reed City | 19 | 9 | 4 | 0 | 0 | 0 |
| 30 | 49329 | Howard City | 0 | 7 | 0 | 0 | 0 | 0 |
| 31 | 48847 | Ithaca | 0 | 0 | 0 | 0 | 2 | 0 |
| 32 | 48444 | Imlay City | 2 | 0 | 0 | 0 | 0 | 0 |
| 33 | 49201 | Jackson | 19 | 10 | 4 | 0 | 0 | 0 |
| 34 | 49948 | Mass City | 0 | 0 | 0 | 0 | 0 | 0 |
| 35 | 49862 | Munising | 9 | 8 | 0 | 0 | 0 | 0 |
| 36 | 49883 | Seney | 0 | 0 | 4 | 0 | 0 | 0 |

**Table 3A- Distribution of Charging Outlets in Optimized Placement in Low-Tech and High-Tech Scenarios, Cont.**

| | | | Scenarios | | | | | |
|---|---|---|---|---|---|---|---|---|
| Node | Zip Code | City | ***Low-Tech:*** 70 kWh Battery & 50 kW Charger | | | ***High-Tech:*** 100 kWh Battery & 150 kW Charger | | |
| | | | **2030** | **2025** | **2020** | **2030** | **2025** | **2020** |
| 37 | 49728 | Eckerman | 3 | 0 | 0 | 0 | 0 | 0 |
| 38 | 49880 | Rock | 0 | 0 | 0 | 0 | 0 | 0 |
| 39 | 49814 | Champion | 4 | 4 | 3 | 0 | 0 | 0 |
| 40 | 49780 | Rudyard | 0 | 0 | 0 | 0 | 0 | 0 |
| 41 | 49892 | Vulcan | 23 | 15 | 5 | 0 | 0 | 3 |
| 42 | 49854 | Manistique | 19 | 18 | 9 | 8 | 8 | 3 |
| 43 | 49827 | Engadine | 23 | 13 | 5 | 3 | 0 | 0 |
| 44 | 49749 | Indian River | 0 | 2 | 2 | 0 | 0 | 0 |
| 45 | 49614 | Bear Lake | 2 | 0 | 0 | 0 | 0 | 0 |
| 46 | 49622 | Central Lake | 0 | 0 | 0 | 0 | 0 | 0 |
| 47 | 49668 | Mesick | 0 | 0 | 0 | 0 | 0 | 0 |
| 48 | 48629 | Houghton Lake | 0 | 0 | 0 | 0 | 0 | 0 |
| 49 | 48661 | West Branch | 4 | 0 | 0 | 0 | 0 | 0 |
| 50 | 48738 | Greenbush | 12 | 7 | 3 | 0 | 0 | 0 |
| 51 | 48703 | Au Gres | 3 | 0 | 0 | 0 | 0 | 0 |
| 52 | 49709 | Atlanta | 0 | 2 | 0 | 0 | 0 | 0 |
| 53 | 49445 | Muskegon | 0 | 2 | 0 | 0 | 0 | 0 |
| 54 | 48657 | Sanford | 0 | 3 | 0 | 0 | 0 | 0 |
| 55 | 48741 | Kingston | 0 | 0 | 0 | 0 | 0 | 0 |
| 56 | 48881 | Saranac | 5 | 2 | 0 | 0 | 0 | 0 |
| 57 | 49453 | Saugatuck | 0 | 0 | 0 | 0 | 0 | 0 |
| 58 | 48114 | Brighton | 0 | 7 | 3 | 0 | 0 | 0 |
| 59 | 48326 | Auburn Hills | 3 | 2 | 2 | 0 | 0 | 0 |
| 60 | 48166 | Newport | 0 | 0 | 0 | 0 | 0 | 0 |