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Phase-II: Community-Aware Charging Station Network Design for Electrified Vehicles in Urban Areas:
Reducing Congestion, Emissions, Improving Accessibility, and Promoting Walking, Bicycling, and use of Public Transportation

FINAL REPORT

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A major challenge for achieving large-scale adoption of EVs is an accessible infrastructure for the communities. The societal benefits of large-scale adoption of EVs cannot be realized without adequate deployment of publicly accessible charging stations due to mutual dependence of EV sales and public infrastructure deployment. Such infrastructure deployment also presents a number of unique opportunities for promoting livability while helping to reduce the negative side-effects of transportation (e.g., congestion, emissions, and noise pollution). In this phase, we develop a modeling framework (MF) to consider various factors and their associated uncertainties for an optimal network design for electrified vehicles. The factors considered in the study include: state of charge, dwell time, Origin-Destination (OD) pair.</td></tr>
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Phase-II: Community-Aware Charging Station Network Design for Electrified Vehicles in Urban Areas:

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EXECUTIVE SUMMARY

We developed a set of tools to support effective planning of network design for charging stations for EVs in urban areas. Such infrastructure deployment also presents a number of unique opportunities for promoting livability while helping to reduce the negative side-effects of transportation (e.g., congestion and emissions).

Mile-stone #1: Developed methods for efficient estimation of various factors important for network design and understand the uncertainties associated with these factors. Real time data from various publicly available resources are considered for the estimation of the factors.

Mile-stone #2: Given the factors contributing to livability aspects and robust network design for electrified vehicles, formulated a two-stage stochastic programming model to for the network design of EVs for a community.

Mile-stone #3: Applied the developed stochastic model and performed computational experiments, and analyzed the usefulness of the model in terms of improvements in livability factors and accessibility of the given network.

The goal of the project is to provide series of tools for the city and governmental planning agencies to evaluate the factors important for network design of EVs and improve livability aspects for the communities. Shared the findings with SEMCOG and planning to pilot the methods in collaboration with a SE-MI city under a project extension.

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Abstract

Advantages of electric vehicles (EVs) include diversification of the transportation energy feedstock, reduction of greenhouse gas and other emissions, energy security, fuel economy, reduced operating costs, and reduced emissions leading to lesser air pollution levels. In response to government's promotion of vehicle electrification objectives, the major automobile companies of the world are striving to produce affordable electrified vehicles for environmentally conscious consumers. Companies are introducing more models of EVs (hybrid vehicles, plug-in hybrid vehicles, pure battery electric vehicles) every year around the world. However, a major challenge for achieving large-scale adoption of EVs is an accessible charging infrastructure. The societal benefits of large-scale adoption of EVs cannot be realized without adequate deployment of accessible charging stations due to mutual dependence of EV sales and public infrastructure deployment. Such infrastructure deployment also presents several unique opportunities for promoting livability while helping to reduce the negative side-effects of transportation (e.g., congestion and emissions).

During this research, apart from solidifying our findings for the current EV charging station network design modeling framework (MF) developed during the previous phase of the project, we intend to develop additional modules that also account for human behavioral aspects to enrich the current MF. We believe that these extensions will greatly improve the practical usability of the MF and provide additional insights for the decision makers. The second phase will enhance the MF in following ways:

a) Explicitly account for accessibility range to EVs and drivers' behaviors within a community during charging station network design and support minimum coverage requirements, assess the impact of uncovered regions within a community, and facilitate effective tradeoffs between accessibility, utilization and budgets,

b) Inclusion of interaction between multi-modal transportation and EV charging stations network planning and develop a framework to study their synergy in improving overall transportation options in a community,

c) Design a pricing scheme template based on proposed network design, price/demand elasticity, utilization and demand pattern to incentivize the stakeholders involved in maintaining the infrastructure, and

d) Evaluation of the MF through a community case study in partnership with a regional planning agency such as SEMCOG.

This research relates and contributes to the attainment of strategic goals of the U.S. Department of Transportation and the U.S. Department of Energy. It contributes to the fostering of livable communities by increasing the access to transportation with EVs, improves adoption of EVs, promotes sustainable transportation and provides increased transportation choice. It further contributes to environmental sustainability through reduced carbon footprint of transport. Lastly, it contributes to the economic competitiveness through increased transportation productivity and more efficient utilization of existing system resources.

Introduction

One of the most promising approaches to alleviating emissions and satisfying the climate targets is the deployment of electric vehicles (EVs). Lower maintenance costs, better emissions profile, lower ownership cost, pollution-free driving, noise reduction, charge up at home, at work, and around the community are some of the advantages of up-taking the EVs. The electricity that powers an EV can be provided from many sources, which include low-emission sources like natural gas, and zero-emission sources like wind, solar, hydro, and nuclear power, which enable EVs to mitigate gaseous emissions drastically. In response to the government's promotion of vehicle electrification objectives, the major automobile companies of the world are striving to produce affordable EVs for environmentally conscious consumers. Companies are introducing more models of EVs (hybrid vehicles, plug-in hybrid vehicles, pure battery electric vehicles) every year around the world. However, a major challenge for achieving large-scale adoption of EVs is an accessible charging infrastructure. Such infrastructure deployment also presents some unique opportunities for promoting livability while helping to reduce the adverse side-effects of transportation (e.g., congestion and emissions). The presence of charging station networks is proven to be a significant factor in the adoption of EVs (Sierzchula et al. (2014)). Besides the accessibility to the network, the charging time is also essential for optimally locating the electric vehicle charging stations (EVCS). The research in Ito et al. (2013) indicated that EV users are less likely to pay for the fast charging at a retail location if the user has 'quick charge' option at home. In general, widespread adoption of

EVs is in alignment with sustainable transportation objectives in social, economic, and environmental perspectives for a community.
EVCS being outnumbered by the fuel stations in the worldwide markets. This gap could be reduced by designing effective networks of electric charging stations. In addition, an efficient network reduces the carbon footprint emission in the urban areas that are more densely populated during the business hours, and balances the energy demand increase due to EV charging more evenly. Investigating the impact of public charging station infrastructure on plug-in electric vehicle (PEV) charging stations deployment is a complex challenge. Lots of different users (residential, visitors, employee, the fleet users) have different charging needs and may require different infrastructure solutions. The users have different dwell time, frequency of charging (every day/unexpected) and state of charge (SOC). An EV could be recharged at home, public charging stations, and private working places. Wide range of consumers demand several power supply options. Broadly, the electric vehicle supply equipment (EVSE) can be classified into level 1, level 2 and level 3 based on the power supply. Level 1 is referred as home charging and has the electric power of 1.9kW and requires between 8-30 hours to fully charge an EV's battery depending on its size, and Level 2 is semi-rapid charging with 6.6 kW power, and takes between four and eight hours. Level 3 is the fast charging EVSE with a supply of 50kW power with charging time less than 30 minutes. While many of the existing studies on charging facility location problem are based on the assumption that charging service's demand is deterministic and revealed to the decision makers, however, various sources of uncertainties such as day of the week, time of the day, purpose of the trip, destination, affect the real demand. So, there might be a significant difference between the optimal solution of a deterministic model and a model involved by uncertainty. Stochastic programming is a method to model optimization problems which are affected by uncertain parameters. In this study, we use a two-stage stochastic programming model to optimally design a network for EVSEs for a community based on uncertainty in the demand. Also, there are many studies that have considered the electric vehicle charging station location problem, however, only a few of them investigate it in an urban area.

The study about the EV users' charging behaviors, especially their preference in charging levels and location, will help us to positively increase the EV adoption. Installing a public charging station costs at least $5,000 to $15,000 (Trigg et al. (2013)). So, an attempt to maximize the accessibility in the network by establishing more public charging stations without considering charging demand and EV drivers' behaviors can result in a low utilization for EV charging stations. Hence, considering uncertain demand, and analyzing EV users' travel patterns, charging behaviors and infrastructure utilization would help to design an effective charging station network (Xu et al. (2017)). Discrete choice analysis has proven to be a useful strategy to analyze and predict EV drivers' decisions regarding the location and level of charging. So, a choice modeling approach embedded within a two-stage stochastic programming model is proposed to determine an optimal network of charging stations including type, capacity, and location of electric charging stations based on EV drivers' preferences.

Specifically, the contributions of this study are: (1) embedding a choice model into a two-stage stochastic programming model to locate the charging facilities, determine the type of EVSE based on EV drivers' behaviors and select the optimal capacity for public EV charging stations in an urban area; (2) incorporating various uncertainties in the model such as EV demand flows, EV drivers' charging patterns, SOC, arrival and departure times, purpose of arrival to the community, and preferred walking distances; (3) investigating the effect of charging price on a driver's behavior toward choosing the charging facilities; (4) performing a case study representing public charging network design for Detroit's midtown area; and (5) providing some insight toward multi-modal transportation to improve the accessibility and transportation choices using the proposed framework.

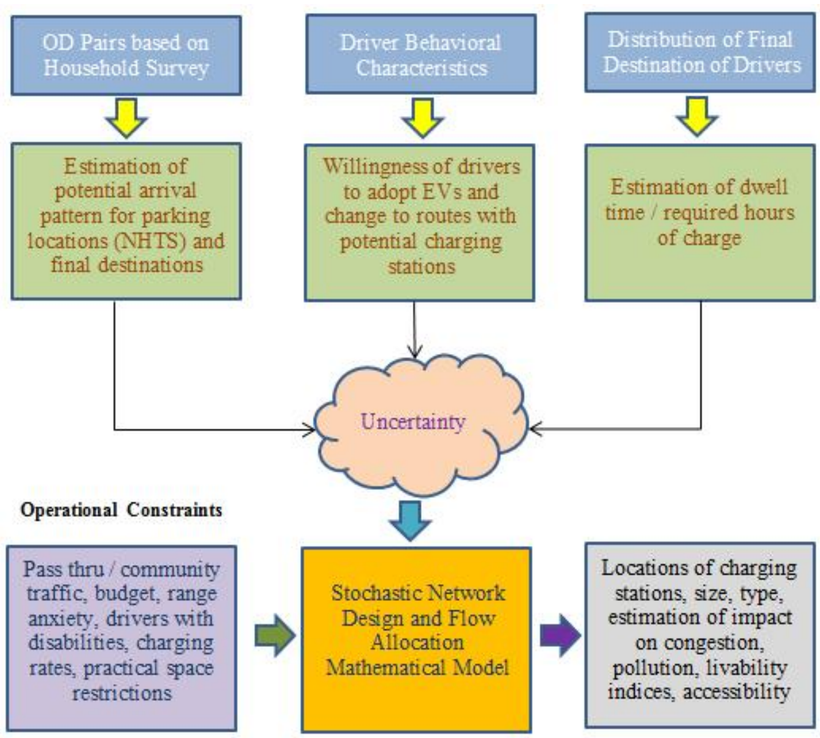


Figure 1: Overall modeling framework for improving community livability indices and adoption of EVs and charging stations. Phase - I

Literature Review

In this section, we first review the literature related to multi-modal transport network. Then we present the deterministic and stochastic approaches in literature for electric vehicle charging location problem. Finally, we provide the details for choice models regarding the behaviors of the EV drivers.

Multi-Modal Transport Network

With increases in traffic, the private transport system is collapsing especially in large urban areas of advanced countries when there is not enough capacity for private vehicles. Improving the share market of public transportation is one of the available solutions to this problem. Also, parking policies are developed to reduce the traffic congestion in down-towns by restricting the on-street and long-time parking. Additionally, proposals to use multiple mode of trips in the areas near the city centers to avoid congestion. 'Park-and-ride' (P&R) is an example for multiple trips, and well-studied in the literature. Developing multi-modal transportation design depends mainly on the development of transfer modes along with the parking facilities (Ricardo Garcia and Angel Marin, 2002). Numerous research studies have focused on users' behaviors while searching for parking locations, and reacting to new policies. The work in Chen et al. (2017) studies the impact of on-street parking on urban cities. They estimated vehicle delays for different traffic situations and parking occupations. Also, they suggested policies for bicycle lane design and parking permit. Using a survey, the research in Antolin et al. (2018) estimated the factors which affect the parking selection of users. They considered multiple scenarios in their estimations. For modeling and analysis of P&R facilities, the work in Fernandez et al. (1994) use choice models to estimate the demands for different travel modes. They proposed user equilibrium (UE) models to determine the traffic flow on each route. Considering auto mode, transit mode and P&R mode in multi-modal transportation, the authors in Liu and Meng (2014) modeled a network flow equilibrium problem. In order to integrate the P&R facilities into multi-modal transportation system, Song et al. (2017) developed a theoretical approach for designing P&R facilities and transit service frequency. They adopted an UE model in the multi-modal transportation network. The work in Litman (2017) summarizes factors affecting the principal planning, and the research in Geurs et al. (2016) investigates the impact of bicycle-train integration policies on ridership. A bi-objective programming model is proposed in Lu and Guo (2015) to determine the number and location of P&R facilities. The authors in Bovy and Hoogendoorn-Laser (2005) analyzed trips in a multi-modal network. They considered an entire trip from origin to destination to assess the effect of multi-modal trip features on the quality and competitiveness of inter-urban multi-modal train alternatives. Preferences of travelers toward different modes and station types were evaluated. There are very few studies which combined different mode choices for EV users within the context of locating and charging P&R facilities. The authors in Zhang et al. (2013) offered a combined travel choices network equilibrium model to consider the BEV drivers' preferences, and then the problem is formulated as a variational inequality model based on nested logit structure.

Deterministic Approach

A capacitated refueling location model with limited traffic flow was introduced by Upchurch et al. (2009) to maximize vehicle miles traveled by alternative-fuel vehicles. He et al. (2013) explored the allocation of public charging stations to increase the social welfare associated with transportation and power networks. Considering users' daily travel, Zhu et al. (2018) introduced a novel model for electric vehicle charging station (EVCS) aiming at minimizing the charging station installation and management cost. Xi et al. (2013) developed a simulation-optimization model for EVCS to maximize the service level to the EV drivers. Their results showed that the combination of level 1 and level 2 charger is more desirable than installing only charger level 1. Cavadas et al. (2015) addressed EVCS problem in an urban area. They proposed a mixed integer programming (MIP) model for locating the slow-charging stations. They considered travelers' parking locations as well as their daily activities in order to aggregate the demand on different places. Based on travel behavior, an optimization model was developed by Shahraki et al. (2015) to install charging stations optimally. Using a MIP model, the work in Wang and Lin (2013) locates multiple types of charging stations. Their results indicated that increase in EV ranges would lead to installing fewer charging stations. The authors in Lam et al. (2014) formulate a charging station location problem with the focus on human factors. It is shown that the problem is NP-hard. Based on computing multiple nomination models using reachability graph, Corcoran and Gagarin (2017) introduced a model for locating EVCS in the road networks. Reachability graph can deal with the drivers' range anxieties and improve the trip by making a detour to reach the charging station whenever the state of the charge falls below a certain threshold. In their model, capacity, type of the charger and demand for charging have not been considered.

Stochastic Approach

Although uncertainty is studied extensively in many fields, there are only a few research works considered uncertainty in EV infrastructure planning. Decisions made using deterministic parameters may under or overestimate the reality (Birge and Louveaux (2011)). Faridimehr et al. (2018) developed a decision support system consisting of a modeling framework using stochastic model and Monte Carlo sampling method to design an EV charging network optimally. They considered SOC, dwell time and demand distribution, driver preference to charge, market penetration for EVs and also drivers' willingness to walk. Sample average approximation (SAA) was used to tackle the computational intractability. Pan et al. (2010) developed a two-stage stochastic model for locating the charging stations to support both the transportation system and the power grid. Uncertainty is considered in demand for battery, loads, generation of renewable power sources. Hosseini and MirHassani (2015) incorporated the uncertainty in traffic flow into a two-stage stochastic model with both capacitated and uncapacitated versions to locate the charging station locations. With an objective to maximize the EV vehicle-miles-traveled and environmental benefits, Arslan and Karacsan (2016) present the EVCS problem as an extension of the flow refueling location problem (FRLP). They considered both hybrid and the single fueled vehicle and an effective Benders Decomposition approach was proposed to solve the problem. A multi-period optimization model was proposed by Li et al. (2016) to capture the dynamics in the topological structure of the network.

Charging Behavior Studies

Charging behaviors were studied by numerous authors with different outlooks. Scientifically-based research from charging behavior literature proves that charging behavior is multifarious amongst drivers Zoepf et al. (2013) Franke and Krems (2013). In order to develop models to evaluate the EV drivers' preferences to charging services, it is necessary to perceive individuals' behaviors (Daina et al. (2017)). Xu et al. (2017) developed a mixed logit model to explore the factors that affect the battery electric vehicle users (BEV) in Japan. They considered the fast and normal type of chargers and specific locations such as home, company and public station for installing the EVSEs. Battery capacity, midnight indicator, the initial state of charge (SOC) are identified as the main predictors for drivers' charging and location choice behaviors. Liu and Wang (2017) implemented tri-level programming to locate multiple levels of charging facility including wireless charging considering consumers' charging and routing choice. Hidrue et al. (2011) findings from a national survey showed that recharging time has considerable influence on consumers' preferences. Wolbertus et al. (2018) studied the policy effect on charging behavior and EV adoption at the same time. They used a large dataset to investigate the influences of daytime and free parking on EV drivers charging behavior. Sun et al. (2015) focused on charging time behavior using a mixed logit model. Their predictors to determine whether to charge or not are SOC, interval days and vehicle-kilometers of travel. The results state that experience of fast charging would affect the normal charging in a negative way. Also, the authors reported that nighttime charging is considerably correlated with other alternatives. Liu and Wang 2017 examined BEV drivers' charging and route choice behaviors using multinomial and nested logit models. He et al. (2015) suggested a tour-based BEV network equilibrium model to evaluate the driver's behavior facing a different type of public charging stations. More recently, Hardman et al. (2018) published a literature review on preferences for the consumers on EVCS for PEVs.

Using choice model within an optimization framework for locating new facilities in a competitive market was proposed by Benati and Hansen (2002). A random utility model was used to model customers' behaviors aiming to predict the market share of the locations. In Krohn et al. (2016), authors considered a client's utility function to incorporate waiting time for an appointment and quality of care as variables to maximize the involvement in healthcare facility locations. Similarly, a robust approach was applied by Garcia and Alfandari (2015) for selecting new housing program.

Data Collection and Preprocessing

In this project, we considered parking facilities as potential candidates for installing the EVSEs. Parking locations are selected by the drivers based on their walking distance preferences. We assume that if EVSEs are installed in any of the parking lots which are within a driver's walking distance preferences, then the driver will be attracted to one of them depending on the availability of that station at the time of arrival. If there are no charging stations within the drivers' walking distance, we do not consider that driver as demand in our model. In the two-stage stochastic model, demand uncertainty is captured via scenarios. The uncertainty in demand depends on many different sources such as time and purpose of arrival to the community, the duration of the drivers' activities, EV batteries' SOCs at the time of arrival, and their willingness to walk based on demographics, community size, and weather condition. More than five-gigabyte data has been gathered by SEMCOG between 9/10/2016 and 3/4/2017. The data contain Origin-Destination analysis and related metrics between different zones of the metro Detroit area. Figure 2 shows the structure of the data collected from SEMCOG. The data is used to build the multi-modal network. The following subsections describe the uncertainties that affect the demand for public EV charging stations.

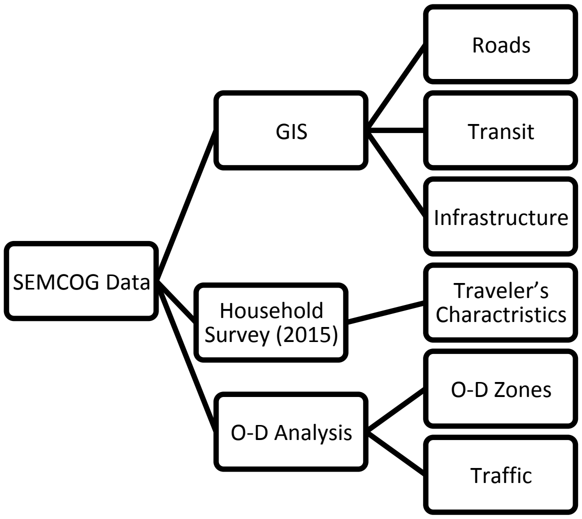


Figure 2 Data Taxonomy, Source: SEMCOG

Uncertainties

Dwell Time

Based on National Household Travel Survey (NHTS) data, work, study, social, family, shopping and meal are selected as six different destination categories in our analysis. Average dwell time for each category is shown in the Figure 3. Weibull distribution, suggested by Ming et al. (2008), is used to estimate the duration of EV drivers' activities considering average activity time for weekdays and weekends.

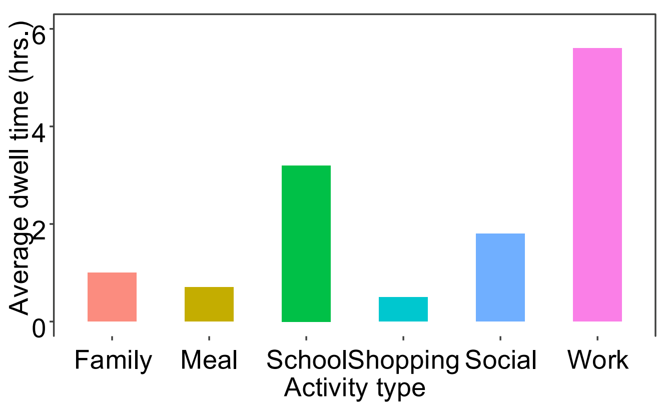


Figure 3 Average dwell time for activity types; Sources: [7] and [30].

Weekday vs. Weekend

During weekends, people are more tending to participate in social activities, go to shopping malls and visit their families than weekdays, in which demand mostly consists of people who are traveling for work or school, so it is expected that a different demand pattern occurs for charging stations compared to week days. Figure 4 indicates that the demand for charging stations is dependent on time and type of day. During weekdays, maximum demand happens during the morning when people are arriving at work or school; however maximum demand usually occurs around noon during weekends when people are going to shopping malls and social places. Aydogan et al. (2015) concluded that Weibull is the best-fitted distribution for arrival time at parking lots. So, two Weibull distributions are used to estimate the arrival time for weekends and weekdays.

State of Charge

While demand for EVs is increasing due to environment and economy related concerns, these vehicles have a limited capacity battery to charge and use. Many factors such as commuting distance, driver's behavior, traffic congestion and weather condition can affect the state of charge of an EV when it arrives at a final destination. Similar to Pingyi et al. (2017), we consider the normal distribution with mean 0.3 and standard variance of 0.1 for SOC of EVs when they arrive at charging locations. Figure 5 shows the initial SOC distribution of arriving EVs.

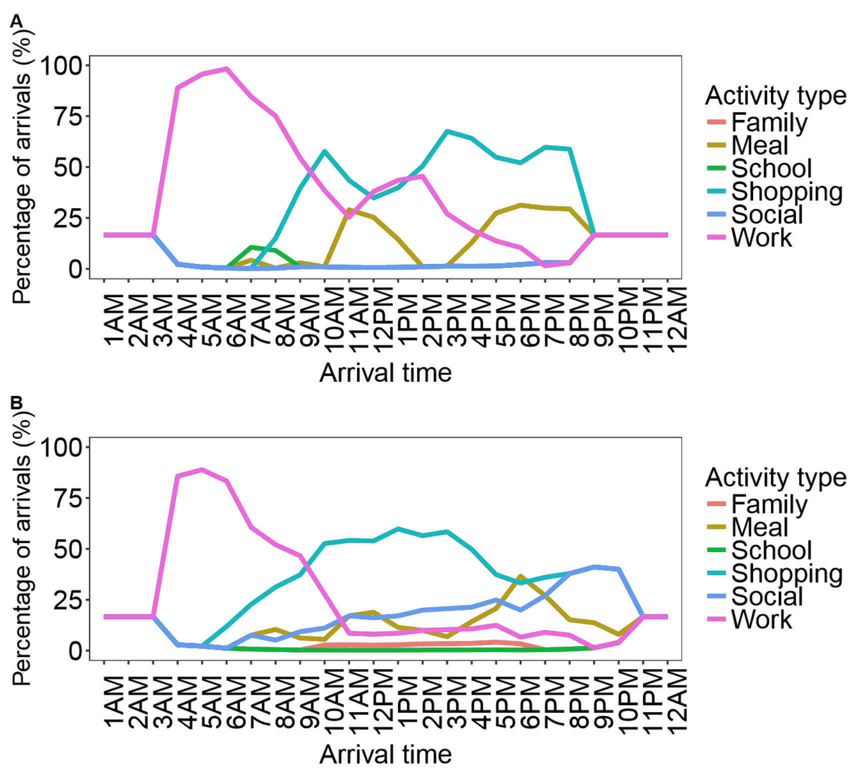


Figure 4 The expected percentage breakdown for various vehicle arrivals on: A) weekdays and B) weekends; .

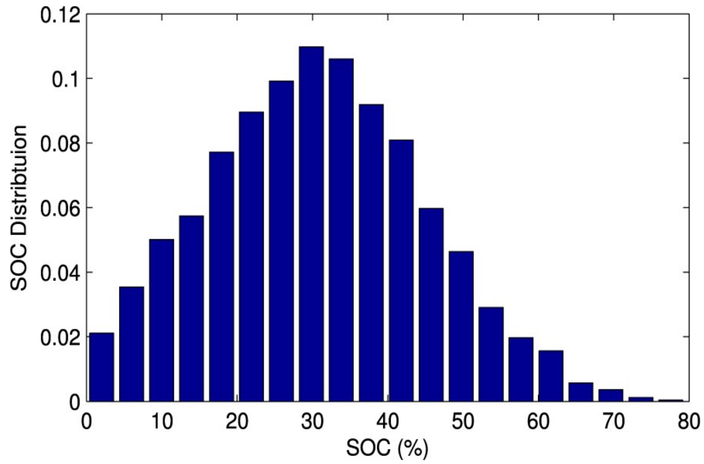


Figure 5 The initial SOC distribution of arriving EVs; Source: [13].

Willingness to Walk

The driver's willingness to walk can be influenced by their sociodemographic characteristics such as age, gender, occupation, and education level. Walking distances are shorter for children and elderly than young and middle-age groups. Past research studies also indicate that walking preferences are correlated with many design factors such as street connectivity, pedestrian infrastructure, and mixed land uses (Ann et al. (2008)). Many authors have implemented a distance decay function that illustrates the willingness to walk or bike a distance toward various types of destinations. The decay function's parameter depends on the type of the final destination. Research studies using distance decay function have revealed different behaviors for people that live in different areas. For example, Michael et al. (2008) found that people who live in Minnesota tend to walk and bike more for leisure and recreation purposes while Albert et al. (2014) found that people would walk and bike longer distances for work than for other purposes in Montreal. Estimation results of Yong and Ava (2012) show that negative exponential distribution can describe walking trips over short distances better than distributions such as Gaussian. They specify the distance decay function as:

$$P(d) = e^{-\beta \times d}$$

Which represents the proportion of people who are willing to walk or longer distances. They used 2009 NHTS data to estimate the decay parameter for different groups and trip purposes. The estimated distributions for walking preference for different activities are shown in Figure 6. In our study, we consider the effects of activity type, season, community size and U.S. region on the walking preference of drivers. The variation for each of these factors based on walking distance preferences, estimated by Yong and Ava (2012), is provided in the Table 1.

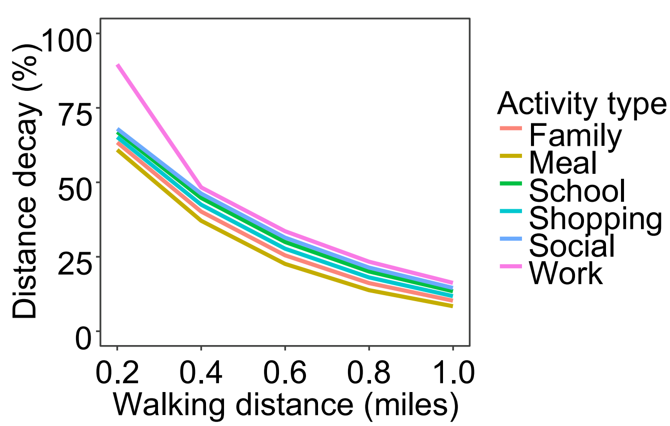


Figure 6 Distance decay function for walking trips to different destination types; Source: [53].

EV Market Penetration

Various social, environmental and economic factors can remarkably contribute to the increasing market share of different types of EVs.

Table 1: Estimated distance decay function parameters

Factor	Category	β
Season	Winter	1.88
	Spring	1.68
	Summer	1.64
	Autumn	1.7
Region	Northeast	1.85
	Midwest	1.65
	South	1.76
	West	1.65
Community	Town and country	1.68
	Suburban	1.63
	Urban and second city	1.78

Sydney and Belinda (2015) showed that the presence of charging infrastructure would contribute to the adoption of battery EVs but does not have any significant effect on the adoption of plug-in hybrid EVs. The data from the U.S. Department of Energy 2015 report clearly show that BEVs and PHEVs have different market share across the states between 2010 and 2014. In 2011, 'Energy Outlook' report of the U.S. Department of Energy estimated the market share of EVs is less than 1% in 2035 while it projected that EV annual sales would be around 13,800 cars at that time. Sanya et al. (2013) surveyed adult drivers in large U.S. cities in fall 2011 in order to find factors that can affect their interest in buying a plug-in electric vehicle. Besides demographic variables that can accurately predict the purpose of purchase. Results showed that availability of a charging station within the community has a significant effect on intent of purchase. From a policy point of view, one practical approach to leverage EV adoption is to construct more charging infrastructure. Using multiple linear regression, William et al. (2014) estimated the effect of consumer financial incentives and many socio-economic factors on national EV market shares of 30 countries for the year 2012. While their descriptive analysis shows that neither financial incentives nor charging infrastructure contribute to the adoption of EVs, statistical analysis confirms that installing one charging station (per 100,000 residents) could have twice the impact on a country's rate of new EV sales compared to$ 1,000 in financial incentives.

Discrete Choice Models

Discrete choice models are applied to help decision makers when they are trying to select the best choice among different options (choice set). These models are based on the assumption of maximizing the utility of the decision makers' behaviors (Kenneth, 2009). When an EV driver, labeled i, reaches to charging station, he/she could be faced by n different charging types, which are different in price and charging time. A choice among n charging types would give a certain level of utility to the EV driver. The utility that EV driver i achieves from charging type n is $U_{i,n}$,n = 1,...,N. Since this utility is known to an EV driver, then the behavioral model would choose charging type k if and only if $U_{i,k} \geq U_{i,n}$□k != n. So, a function, namely 'utility function,' can be defined based on those observed attributes as follow: $U_{i,n} = V_{i,n} + \varepsilon_{i,n}$
where $V_{i,n} = V(x_{i,n}, s_n)$ which captures the deterministic part of utility and in which is the random part and captures the non-observable variables V which are unknown to us, so we need to estimate them statistically.

Utility Construction

A study by Yuan (2016) analyzed the driver charging choices through web-based stated preference survey. The authors used mixed logit model including various predictor variables. The following predictor variables are considered in the utility function calculations.

- *Power(Pw):* 1.9, 6.6 and 50 KW are the powers that we consider for EVSE level 1, level 2, and level 3 respectively.
- *Dwell Time (DT):* Dwell Time is calculated based on arrival and departure of the EV drivers.
- *Energy Consumption (EC):* Based on the current BEVs in the market, we have considered 0.34 ($\frac{kW-h}{mi}$) for average energy consumption.
- *Max Range (MR):* We considered 75 mile as an average for BEV's maximum range.
- *Current Range (CR):* Current range will be calculated based on the SOC of BEVs when they arrive at charging stations.
- *Price(Pr):* Based on the current charging price at Michigan, 0.3($\frac{\$}{h}$),1.5($\frac{\$}{h}$) and 21($\frac{\$}{h}$) are considered as the charging prices for EVSE level 1, level 2, and level 3, respectively.

- *Electricity Price at Home (EPH):* 0.14($\frac{\$}{kW-h}$)is considered as an average for electricity price at home in Michigan.
- *Distance to Home (DH):* More than 50 cities and suburban within the 40-mile distance from midtown of Detroit are considered as origins of EV drivers. Collected from SEMCOG data, a distribution is obtained based on the origin population and traffic flow to estimate the distance to the home of EV drivers from parking locations. Also, we add a fixed distance for all the drivers which is varied from 0 to 40 miles in 10-mile increments. In this way, additional trips by the drivers are accounted before they head back to their original origin.

Also, to capture the interaction between dwell time, charging power and SOC and other predictor variables the following derived interaction variables are introduced:

Range Charged at Station (RCS)

This variable determines the amount of charge (miles) an EV can get during the charging period. RCS is calculated by taking the minimum of the amount of charge for an EV using a specific EVSE during driver's dwell time and the difference between the capacity and the current range of the battery.

$$\text{RCS} = \min\left(\frac{\Pr(kW) \times DT(h)}{EC(\frac{kW-h}{mi})}, (\text{MR (mi)} - \text{CR (mi)})\right)$$

Charging Cost (CC)

In order to calculate the charging cost at each station, we assume that an EV driver will only unplug the vehicle at the end of his/her activity. So, the charging cost can be calculated by the multiplying the charging cost by the dwell time:

$$\text{CC (\$)} = \Pr(\frac{\$}{h}) \times \text{DT(h)}$$

Cost at Home (CH)

The 'Cost at Home' variable is the product of amount of range to be charged at home (RCH), electricity price at home and the energy consumption.

$$\text{CH (\$)} = \text{RCH (mi)} \times \text{EC } (\frac{kW-h}{mi}) \times \text{ECH}(\frac{\$}{kW-h})$$

Also, RCH depends on whether the driver will charge EV at charging station and the amount of charge that is consumed during the trip to home. So, if the EV driver decides not to charge the vehicle at charging station then the range to be charged at home will be calculated as follow:

RCH (mi)= min{MR(mi),(MR(mi) - CR(mi) + DH(mi))}

However, if the EV driver decides to charge the vehicle at charging station then the amount of charge that it gets in the charging station will be considered in calculating the RCH:

RCH (mi)= min{MR(mi), (MR(mi) - CR(mi) + DH(mi) - RCS(mi))}

Remained Range (RR)

Remained Range represents the amount of charge (without charging) that remained at the end of the driver's trip. So, RR can be calculated as the difference between the current range and the distance to home.

RR (mi) = (CR (mi), (MR (mi) – CR (mi) + DH (mi) – RCS (mi))

Enough to Next Charging Opportunity (ENCO)

This variable indicates whether the current range is enough to the next charging opportunity. In our model, it is assumed that charging at home is the only next charging opportunity for the EV drivers. So, the ENCO is 1 if the current range is more than the distance to home. We considered $U_{n,j}$ as the utility of an EV driver who is willing to charge at station j using charging type n. Let us consider K as the set of predictor variables, then:

$$U_{n,j} = \sum_{k \in K} \beta_{n,j}^{k} X_{n,j}^{k} + \varepsilon_{n,j}^{k}$$

Table 2 shows the estimated fixed and random effect of variables provided by [49].

Table 2 Estimated Parameter using mixed logit model; Source: [49]

	Fixed Effects	Random Effects
Variable	Estimate	Standard Deviation
Intercept	4.756	0.022
Price	- 0.607	0.089
Charging Cost	-0.062	0.004
Cost at home	0.009	0.489
Dwell Time ≥ 30 min	4.756	0.188
EVSE power(Reference: Level 1)		
Level 2	1.229	0.253
Level 3	1.609	0.264
Ranged Charged	0.014	0.003
Remained Range	-0.130	0.006

ENCO	-4.401	0.078

Using the estimated parameters, we calculate the EV drivers' utility of charging at each using each type of EVSEs and also, the utility of not charging at that particular station. As mentioned earlier, when an EV driver arrives at the community to reach the final destination, a set of available parking stations is selected based on the driver's walking preference. Then the utility of the driver is calculated for each parking station from the selected set. This process is repeated for each driver. Finally, we aggregate the utility of the individual drivers to obtain the aggregated utility for each EVSE at each parking lot. The aggregated utilities are scaled between 0 and 5.

Model Formulation

Model Notations

The EVCS design problem is formulated as a scenario based, two-stage stochastic programming non-linear model to represent the randomness arising from dwell time, willingness to walk, EV market penetration, demand pattern in weekdays vs weekend and state of charge.

- Sets
  - J: Set of parking lots, indexed by $j \in J$.
  - T: Set of time slots $t \in T$.
  - N: Set of Electric Vehicle Supply Equipment (EVSE), indexed by $n \in N$.
  - B: Set of Buildings, indexed by $b \in B$.
  - $S(b)$: Set of possible parking lots based on drivers walking preference who are going to building b. indexed $s \in S(b)$.
  - Γ: Set of arrival and departure times indexed by $\gamma \in \Gamma$.
  - Ω: Set of scenarios, indexed by $\omega \in \Omega$.
- Model Parameters
  - c_n: Cost of installing EVSE of type n.
  - k_j: Capacity of parking j for installing EVSEs.
  - F: Total amount of budget for installing EVSEs.
  - $d_{\gamma,b}(\omega)$: Total Demand of building b within arrival and departure time set $\gamma \in \Gamma$ for a given $t \in T$, in scenario $\omega \in \Omega$.

- $u_{n,j}$ (ω): The aggregated utility of EV drivers who are willing to use EVSE type n at parking lot j in scenario ω □ Ω.
- $u_{nc,j}$ (ω): The aggregated utility of EV drivers who are not willing to charge their EVs at parking lot j in scenario ω □ Ω
- $d'_{\gamma,b,s}(\omega)$: The demand of building b who are willing to use parking from set s within arrival and departure time set for a given t in scenario ω.

- First-Stage Decision Variables
  - $x_{n,j}$: 1 if parking j is chosen for installing EVSE type n; 0 otherwise.
  - $z_{n,j}$: Number of EVSE type n in parking j
- Second-Stage Decision Variables
  - $y^{s}_{\gamma,b,j,n}$ (ω) : The proportion of the demand of building b from set $S(b)$ within arrival and departure time set $\gamma \in \Gamma$ for a given $t \in T$, which is satisfied by parking lot $j \in s$, where $s \in S(b)$,using EVSE n in a scenario $\omega \in \Omega$.

Non-linear Two-Stage Stochastic Model

The two-stage non-linear stochastic programming model is as follows:

First-Stage Model:

$$\text{Max } E_{\Omega}[\phi(x\ ,\ z\ ,\ \tilde{\omega})] \tag{1}$$

s.t.

$$\textstyle\sum_{n\ \in N} z_{n,j} \leq k_j \qquad \square\ j\ \square\ J \tag{2}$$

$$z_{n,j} \leq k_j x_{n,j} \qquad \square n\ \square\ N, j\ \square\ J \tag{3}$$

$$\sum_{n \in N} \sum_{j \in J} c_n z_{n,j} \leq F \tag{4}$$

$$x_{n,j}\ \square \{0,1\}, z_{n,j} \in Z_+ \qquad \square n\ \square\ N, j\ \square\ J \tag{5}$$

The second-stage recourse function based on the first-stage decisions x and z, and a scenario ω is given by the following non-linear programming sub problem:

$$\phi(x,\ z,\ \omega) = \text{Max} \textstyle\sum_{\gamma\ \in\ \Gamma} \sum_{b \in B} \sum_{s \in S(b)} \sum_{j \in s} \sum_{n \in N} d_{\gamma,b}(\omega)\ \ y^{s}_{\gamma,b,j,n}(\omega) \tag{6}$$

s.t.

$$\sum_{\substack{\gamma\in\Gamma:\\ \gamma(a)\le t\le\gamma(d)}}\sum_{b\in B}\sum_{\substack{s\in S(b):\\ j\in s}} d_{\gamma,b}(\omega)y^{s}_{\gamma,b,j,n}(\omega)\le z_{n,j} \tag{7}$$

$$\forall t\in T, j\in J, n\in N$$

$$\sum_{\substack{s\in S(b):\\ j\in s}} y^{s}_{\gamma,b,j,n}(\omega)\le \frac{e^{u_{n,j}(\omega)}x_{n,j}}{e^{u_{nc,j}(\omega)}+\sum_{l\in N}e^{u_{l,j}(\omega)}x_{l,j}} \tag{8}$$

$$\forall\gamma\in\Gamma, b\in B, j\in J, n\in N$$

$$\sum_{n\in N}\sum_{s\in S(b)}\sum_{j\in s} y^{s}_{\gamma,b,j,n}(\omega)\le 1 \qquad \forall\gamma\in\Gamma, b\in B \tag{9}$$

$$d_{\gamma,b}(\omega)\sum_{n\in N}\sum_{j\in s} y^{s}_{\gamma,b,j,n}(\omega)\le d'_{\gamma,b,s} \qquad \forall\gamma\in\Gamma, b\in B, s\in S(b$$

$$0\le y^{s}_{\gamma,b,j,n}(\omega)\le 1 \qquad \forall\gamma\in\Gamma, b\in B, s\in S(b), j\in s, n\in N \tag{11}$$

The first-stage objective function (1) maximizes the expected access to the charging stations. Constraints (2) and (3) determine charging capacity in the parking lots which are selected for providing EV charging service. Constraint (4) is the budgetary constraint. Constraints (5) define binary and integer restrictions. Constraints (6) maximize the coverage of potential EV traffic flows based on the decisions made in the first-stage and a realization of ω □ Ω. Constraints (7) describe the supply demand balance restrictions. Constraints (8) consider the EV preferences in choosing the different level of chargers based on the utility which is estimated by mixed logit model. Constraints (9) ensure that the allocation of flow to the charging station for each building does not exceed the building's demand in each time slot. Constraint (10) restricts the EV drivers be assigned to the stations that are in their walking distance. Constraints (11) define the variables restrictions.

The Linear Equivalent Model

The constraint (8) is given as follows:

$$\sum_{\substack{s\in S(b):\\ j\in s}} y^{s}_{\gamma,b,j,n}\le \frac{e^{u_{n,j}}x_{n,j}}{e^{u_{nc,j}}+\sum_{l\in N}e^{u_{l,j}}x_{l,j}}$$

As the denominator is positive this is equivalent to:

$$y^{s}_{\gamma,b,j,n}\left(e^{u_{nc,j}}+\sum_{j\in J}\sum_{l\in N} e^{u_{l,j}}x_{l,j}\right) \leq e^{u_{n,j}}x_{n,j}$$

For bounded continuous and binary variables y and x, respectively, a bi-linear variable will be defined as follow

$$o^{s}_{\gamma,b,j,n,l} = x_{l,j}y^{s}_{\gamma,b,j,n} \quad \forall\gamma \in \Gamma, n \in N, l \in N, b \in B, j \in J, s \in S(b)$$

A standard approach adopted for linearizing the bi-linear terms is to replace each term by its convex and concave envelopes, also called the McCormick envelopes.

$$o^{s}_{\gamma,b,j,n,l} \leq x_{n,j} \quad \forall\gamma \in \Gamma, n \in N, l \in N, b \in B, j \in J, s \in S(b)$$

$$o^{s}_{\gamma,b,j,n,l} \leq y^{s}_{\gamma,b,j,n} \quad \forall\gamma \in \Gamma, n \in N, l \in N, b \in B, j \in J, s \in S(b)$$

$$o^{s}_{\gamma,b,j,n,l} \geq x_{n,j} + y^{s}_{\gamma,b,j,n} - 1 \quad \forall\gamma \in \Gamma, n \in N, l \in N, b \in B, j \in J, s \in S(b)$$

By using the conversion, the model will be a two-stage linear stochastic model.

Case Study and Computational Experiments

To show the efficiency of the two-stage model, we conducted a variety of experiments using real data obtained through SEMCOG for the Midtown area of Wayne State University in Detroit, MI. Different types of destinations exist in this area which attracts lots of traffic. There are 67 offices, 44 school-related building, 12 social places, five family-related buildings, four restaurants and three shopping places in this area. Thirty-two parking lots are selected as potential locations for installing EVSEs as shown in Figure 7. We assume that parking lots are available from 6:00 A.M to 6:00 P.M and they have different capacities. The EV demand for the case study is estimated in a two-step process. The data from the SEMCOG shows that average annual daily traffic for the Detroit midtown area is approximately between 10,000 and 20,000. We assume that the total daily traffic for this area follows a uniform probability distribution. Furthermore, the EV demand for the final destination is calculated based on the different activity types during the time of the day and day of the week. Based on the activity types of drivers during the time of the day and day of the week, the EV demand is calculated. According to the Environmental Protection Agency (EPA) analysis, 3% and 5% of the light-duty vehicles fleet are constituted by electric vehicle. BEV market share can be affected by low-temperature weather condition negatively (John, 2012). Since our case study is in a cold area especially in winter, we considered 1% and 2% market share for BEVs in each case. Suggested by Yong and Ana (2012), we use negative exponential distribution functions to capture the willingness to walk pattern of EV drivers based on activity type, season, and community size. On average 13% of total demand is lost because there is no available parking within the drivers' walking distance preference.

Scenario Generation

Uncertainties are modeled using scenarios for the two-stage model. Each scenario indicates a single day which is affected by the total number of EV driver arriving at the community in a weekday or weekend in a specific season of the year. Following the uniform probability distribution, each Scenario occurs with the same probability in each season of the year. A random number from $U(0,1)$ is generated to determine the vehicle type in each scenario if the random number is less than the BEV market share, it is considered as BEV or demand in our problem. The arrival time of BEV drivers is estimated by Weibull distributions with parameters (8,3) and (13,4) for a weekend and a weekend respectively. Based on the driver's activity, the dwell time is calculated by using Weibull distribution. The scale and shape parameter for each type of activity and type of the day is provided in Table 3. When a driver arrives at the community, based on his/her activity type, a building/destination is assigned to him/her using a uniform distribution. As mentioned earlier, we use a normal distribution $N(0.3,0.1)$ to estimate SOCs of EV drivers when they arrive to a parking lot location. This process is repeated multiple times to generate a set of scenarios.

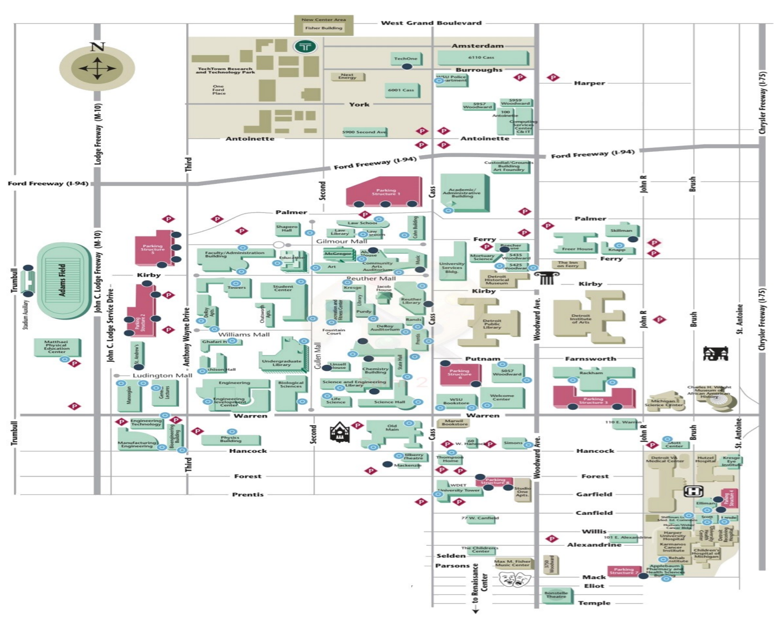


Figure 7 Part of the Detroit midtown area used in our analysis.

Table 3 Weibull distribution parameters for driver's dwell time

Type of day	Work	Social	Family	Meal	School	Shopping
Weekday	(5.89,10)	(1.89,10)	(1.05,10)	(0.79,2)	(3.61,2)	(0.56,2)
Weekend	(6.04,6)	(2.03,2)	(1.13,2)	(0.79,2)	(3.36,10)	(0.25,0.5)

Experiments and Result

In this subsection, we examine the robustness of the model parameters' for uncertainties and their impact on accessibility by experimenting different test cases. To reduce the computational complexity, we consider (6:00 A.M to 9:00 A.M), (9:00 A.M to 12:00 P.M), (12:00 P.M to 14:00 P.M) and (14:00 P.M to 18:00 P.M) as four time slots in a day. Also, \$900, \$3,450 and \$25,000 are considered as an average unit costs for level 1, level 2 and level 3 EVSEs respectively. In each Test Case, 10 scenarios were generated. As shown in Figure 8, ten parking locations are selected as available parking lots in the community.

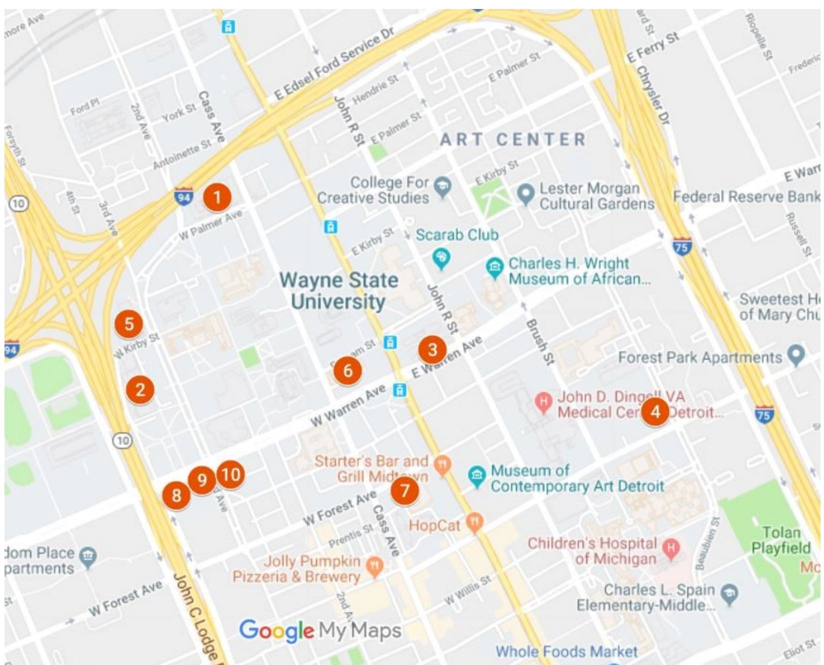


Figure 8 Parking lot locations used in Test Cases' analysis

Test Case 1

The average aggregated utility for each type of EVSE in 10 scenarios in each parking location is shown in Figure 9. Market share for BEV is considered as 1% and capacity of 5 is considered for each parking location to install EVSEs. Based on the driver's walking distance, a set of available parking lots is generated for each EV diver. Totally, 1,052 EV drivers arrive at the parking locations within the ten days. Figure 9 shows the heat map of demand flow toward each parking lot based on drivers' walking preference. Additional results are provided in Figure 10 and 11. In Figure 10, with the increase on the budget, for the fixed capacity, the accessibility is increasing until it saturates. Also, to increase the accessibility, there should always be a reasonable balance between budget and capacity. As shown in Figure 11, at the fixed capacity level, as the budget increases, more level 2 charge types are installed compared to level 1 which leads to higher accessibility. The results indicate that with a limited budget of $50,000, only three levels 2 EVSE's are installed at parking lots 3, 6 and 7, and the rest of the budget has been assigned to level 1. Figure 11 represents the distribution of EVSEs at each parking location. Blue and orange charging icons represent level 1, level 2 charge types, respectively.

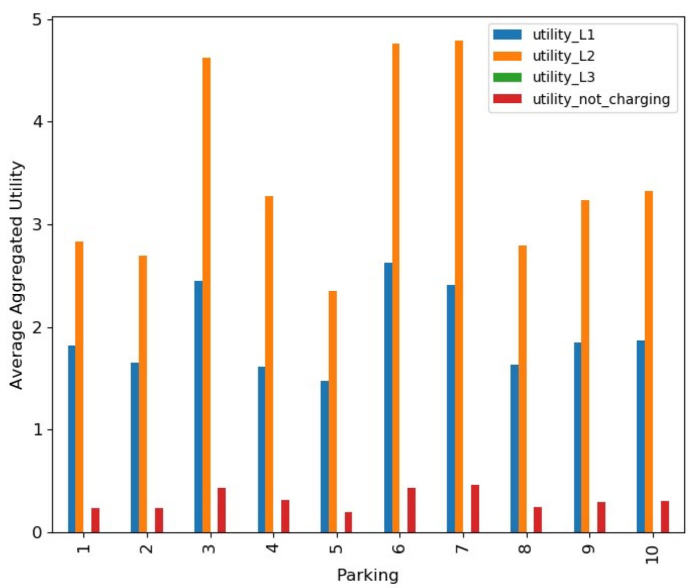


Figure 9 Average aggregated utility for each type of EVSE in each parking location

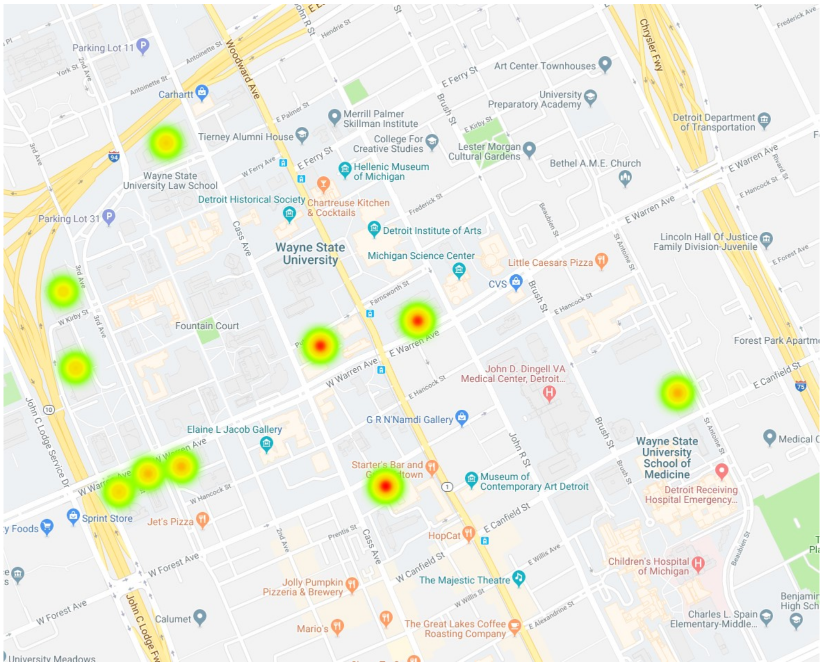


Figure 10 The heat map of demand flow toward each parking lot based on drivers' walking preference.

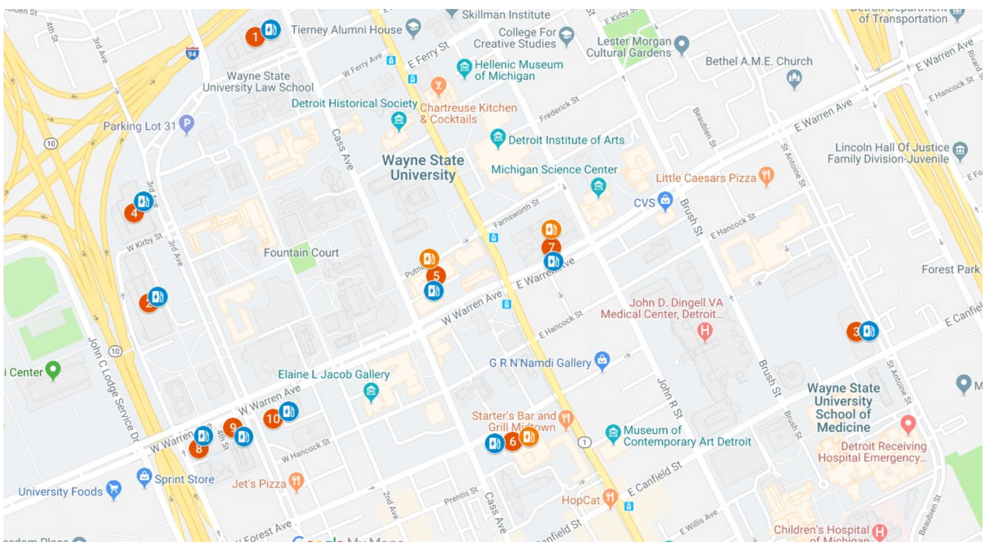


Figure 11 Distribution of EVSE Level 1 and level 2 based on limited budget of $50000

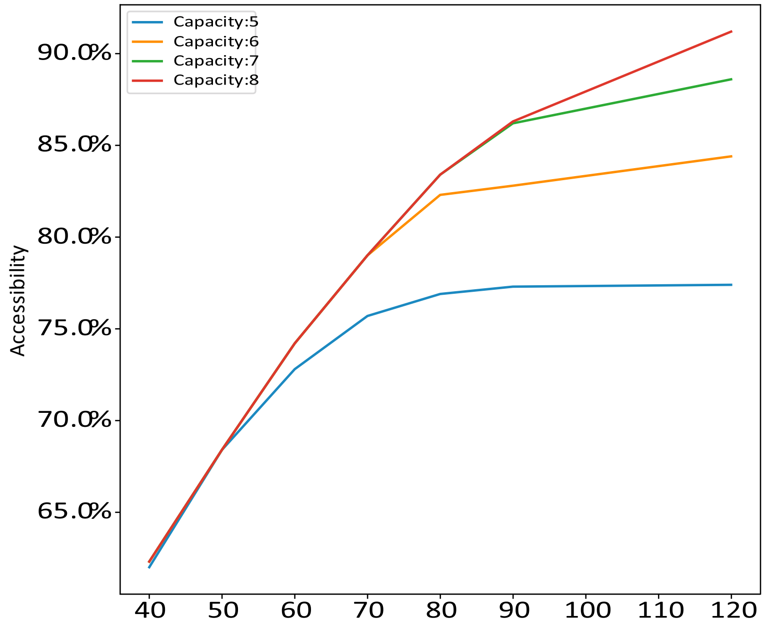


Figure 12 Accessibility percentage fluctuation in the presence of different capacity and budget

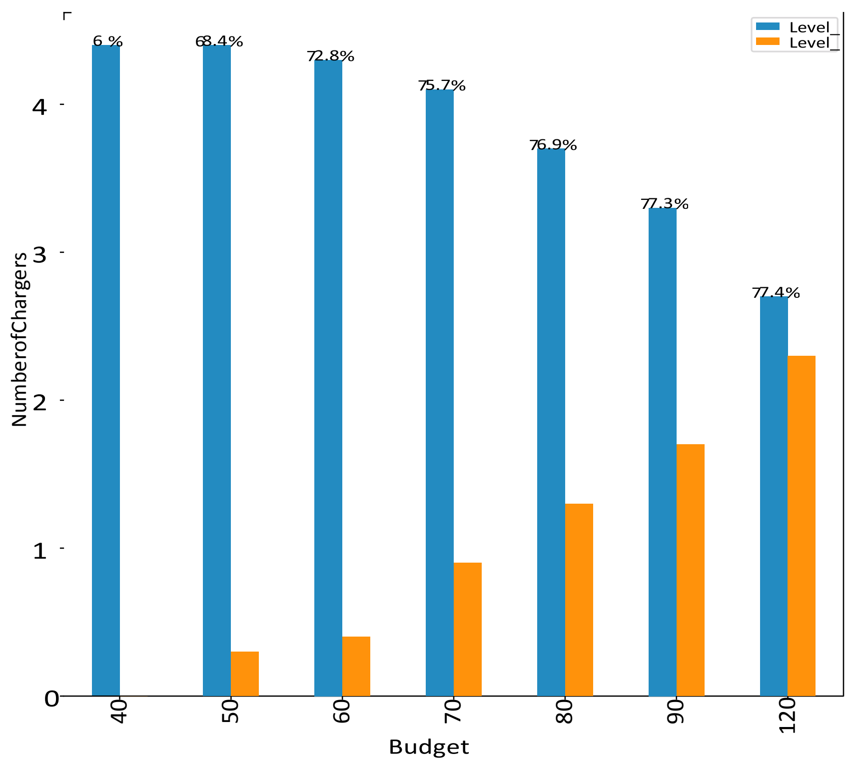


Figure 13 Number of installed Level 1 and level 2 chargers for different budgets at capacity 5, labeled by accessibility percentage.

Test Case 2

The rapid increase in availability and affordability of EVs brings the option of replacing the fossil fuel vehicle with EVs. According to Pingyi et al. (2017) worldwide EV sales increased by more than 40% between 2016 and 2017. In the U.S, 15,500 new EVs were introduced in 2016. Considering the increasing trend, stakeholders should always account for future demand for the charging stations. In this test case, we increase the current market share from 1% to 2 % to estimate the effect of market share on accessibility. The increase in market share leads to increase in number of drivers from 1,052 to 1,579. Results from Figure 14 show that with the increase in market share we have to install more charging stations to cease decrease in accessibility.

Test Case 3

In this test case, we examine the effect of price on the EV drivers charging choices by decreasing the level 3 charging price. For an EV driver, it costs about 35 cents per minutes to use level 3

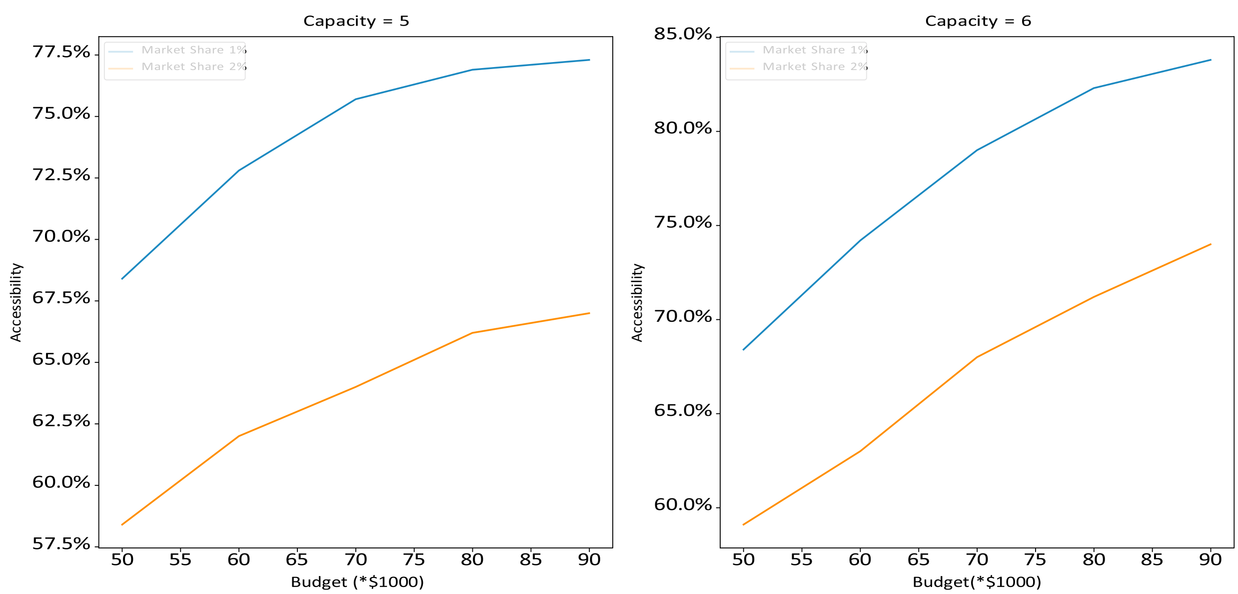


Figure 14 The effect of increase in Market share on accessibility

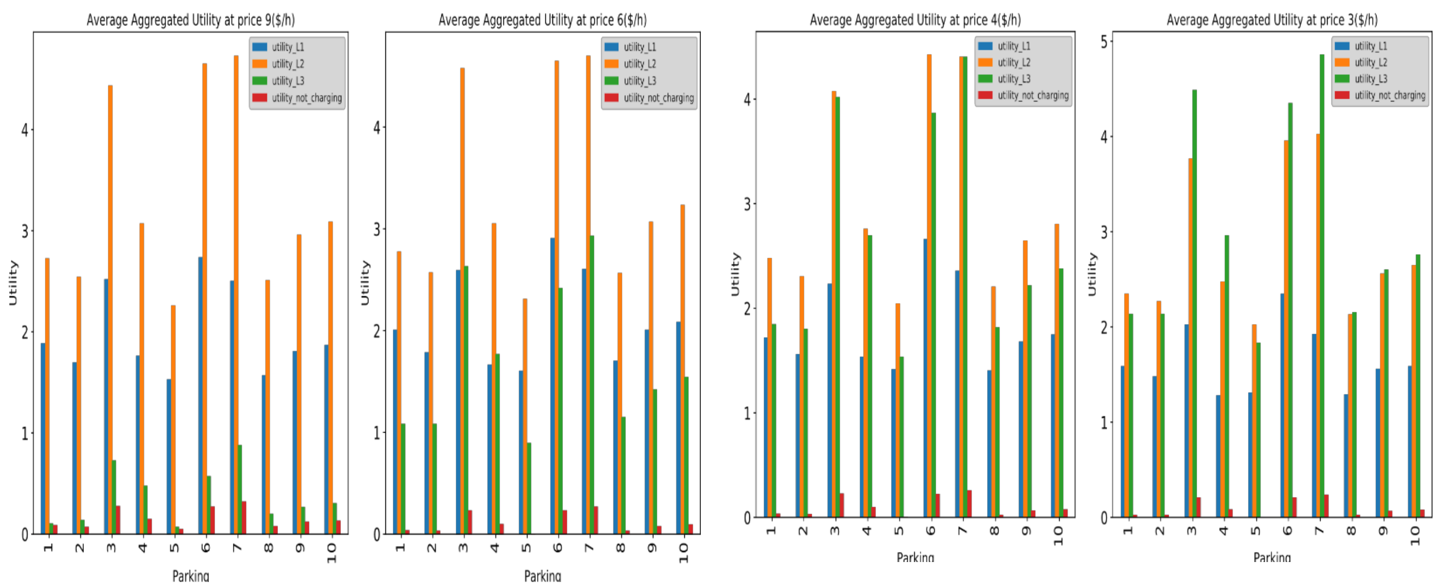
charger. The figure shows the EV driver's average aggregated utility for different charging price. Results indicate that, when charging price is lowered to $3/hr, people prefer to use fast charging over charging level 2 and charging level 1 with the price of $1.5/hr and 30 cents per hour, respectively.

Multi-modal Network

Big cities are affected by the adverse consequence of traffic congestions which lead to longer travel time, anxiety and an increase in pollution. These issues are not only the come from the moving vehicles; they also caused by parked vehicles and lack of enough public parking facilities. Reports shows that on average, cruising vehicles spend around 8 minutes to find a parking location which is 30% of traffic volume especially in downtown areas. Availability of public charging infrastructures which can be integrated with parking, locations would affect the EV drivers' travel route and parking choice behavior. Considering long-time charging requirement, the EV driver's choice of parking could change from parking at high traffic areas at the final destination to a parking-charging facility at the in-between destination and use other modes of transportation. So, installing new charging facilities at parking location within the concept of park-and-ride will attract EV drivers, with relatively high duration of stay, who are seeking to decrease travel delays and cost. Park-and-ride users are greatly associated with transferring between modes and walking distances. Locating parking charging facility closer to public transits and bike stations will reduce delays and keep the walking distances reasonable. So, locating parking charging facilities should be carefully integrated into the multi-modal network to consider the interactions of various transportation modes and EV drivers choice mode. Figure 16 shows a multi-modal network integrated with parking charging infrastructures. To build such a multi-modal network, a holistic algorithmic approach is needed to evaluate the journeys which reasonably integrate different modes of transportation. Each mode should be considered individually and in an integrated way to optimize the sequence of transportation modes. Multi-modal transportation requires diversity from schedule-based modes and unrestricted modes. Using the data gathered from SEMCOG, we incorporate the current modeling framework into the multi-modal network to optimally locate parking-charging facilities. This framework is useful to investigate the synergy between EV charging station and multi modal transportation to decrease the congestion and increase the social welfare and EV adoption. A multi-modal network consists of a set of nodes and directed links. The node set is defined by O-D pair data, building and infrastructure locations, transit stations. Links set are defined based on the road data, bus and metro routes and the physical walking path. In a model EV, drivers may use motorized vehicle (EV) and public transport as well as non-motorized (bicycle) or combination of them. A trip by

EV vehicle has the main stage of driving by EV and leaving the stage by parking the EV at parking-charging location and walking to the destination. In a multi-modal trip, we assume three stages: first driving by vehicle and parking/charging, then boarding to public transport and finally alighting the public transport and walking to the final destination. At the driving stage, traffic information is obtained by the traffic data.

Figure 15 EV driver's utility for different price of level 3 charging



At the public transportation, stage determining the feasible pattern requires the information of seat availability, available facilities at the station, delay data and working hours. To apply the choice modeling approach, estimations provided for transport mode, time, cost and service quality can be used. At the public transportation, stage determining the feasible pattern requires the information of seat availability, available facilities at the station, delay data and working hours. To apply the choice modeling approach, we estimations provided by Theo and Eric (2012) for the multi-modal travel choice model are useful. The estimation is useful to determine the EV drivers' utility for using each mode of transportation. Then the utility can be aggregated. Similar to previous section, the two-stage stochastic choice modeling approach can be used to locate parking-charging facilities in the Detroit metro area. This will in further help to reduce the congestion in downtown

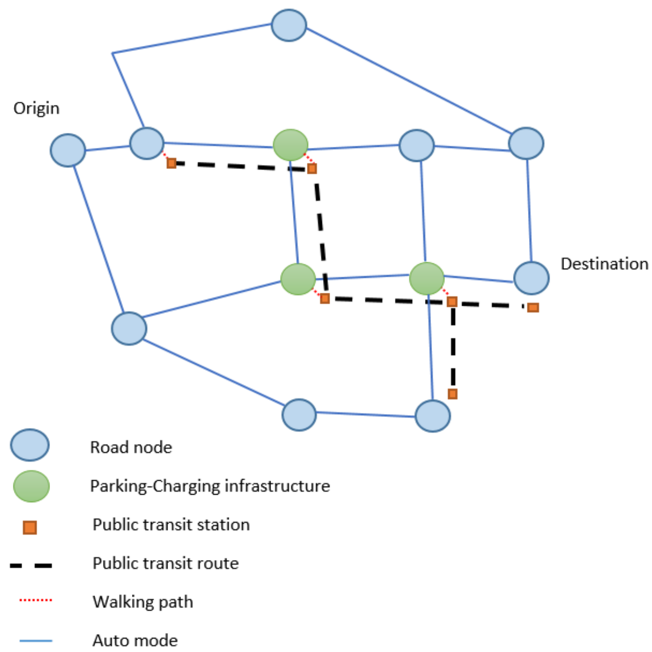


Figure 16 Parking Charging infrastructures integrated into Multi-modal network.

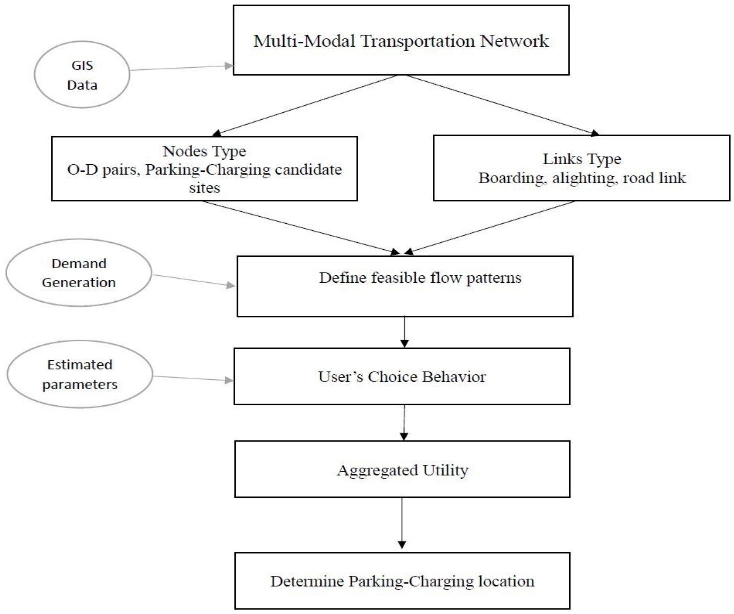


Figure 17 The framework of multi-Modal network to determine the location of parking-charging infrastructures

areas and increase accessibility, mobility, and livability. Figure 17 shows the framework for locating the parking-charging facility in a given community.

Conclusions

In this project, we propose a choice modeling approach embedded in a two-stage stochastic programming model for network design of EV in a given community. Various sources of uncertainties such as total EV flows, arrival and dwell times, batteries' SOCs at the time of arrival, and EV drivers' willingness to walk are considered. Additionally, using many factors such as charging price, cost at home, range charge, total trip distance, dwell time, we capture the BEV drivers' behaviors toward charging choices. The objective of the research is to enable the planning agencies with a matrix denoting the relation between budget and accessibility. Th results showed that with increasing the budget and capacity, we could increase the accessibility of EV owner to the charging stations. Also, based on the data and experiments, level 2 charger is most preferable charging type among EV owners. However, if stakeholders can decrease the charging price for level 3 to $3/hr, people would prefer to use charger level 3. The proposed model also demonstrates the robustness to any future changes in the community's pattern for willingness to walk. Also, using data collected from SEMCOG, we show how the current model is useful in the multi-modal setting to locate parking-charging infrastructures. The developed tools are expected to be used by planning agencies.

Results Dissemination

Following are the plans for knowledge dissemination from this phase of the project:

- Optimization codes are developed using Python language, and Gurobi was used as an optimization solver. The software codes will be packaged as modules and will be shared with planning agency (initially with SEMCOG) so they become part of their planning kit.
- The research was presented in the conferences (TRCLC meeting, INFORMS annual meeting).
- The study will be integrated in undergraduate and graduate courses (Courses - Introduction to Operations Research (UG) and Deterministic Optimization (PG)).

A manuscript has been prepared based on the current study and expected to be submitted in next couple of months. The first phase of the project was published (Sina, 2018). We are also preparing a white paper based on our case-study with SEMCOG and we intend to share the white-paper and possibly engage in training sessions with other national planning agencies.

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