PHASE-II: COMMUNITY-AWARE CHARGING STATION NETWORK DESIGN FOR PROMOTING LIVABILITY

REDUCING CONGESTION, EMISSIONS, IMPROVING ACCESSIBILITY, AND PROMOTING WALKING, BICYCLING, AND USE OF PUBLIC TRANSPORTATION

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PROJECT SPONSOR:
TRANSPORTATION RESEARCH CENTER FOR LIVABLE COMMUNITIES (TRCLC)
WESTERN MICHIGAN UNIVERSITY

Proposal - Problem Statement

Promoting Livability through Accessible EV Infrastructure

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- **Models for EV Charging Station Network Design**
  - Develop models and methods - "charging station network design"
    - Determine number, location, Capacity , and type of charging levels at stations
  - Assess impact on traffic flows (reduced congestion), improve livability metrics (reduced noise, greenhouse emission, increase walkability)
  - Consider user choices/behaviors (e.g., range anxiety, trip distributions, walking preference , charging price, charging cost at home) as well as preferences of charging station operators (cost of location, electricity, utilizations and revenues)
- **Target Adoption by SEMCOG & Other Planning Agencies**
  - Ensure models can work with routine and available datasets and planning requirements
  - Collaborate to pilot models in few communities
  - Account for potential integration into larger planning projects
  - Contribute to development of a practical tool kit for agencies

Current Literature & Studies …

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Multi Model Transport Network:

- **Fernandez et. al.(1994)** - Choice models to estimate the demands for different travel modes. User equilibrium (UE) models to determine the traffic flow on each route.

- Consideration of auto mode, transit mode and P&R mode in multi-modal transportation: **Liu et. al. (2014)** modeled a network flow equilibrium problem.

- **Chen et.al. (2017)** - Impact of on-street parking on urban cities.
  - Estimation of vehicle delays for different traffic situations and parking occupations.
  - Suggested policies for bicycle lane design and parking permit.

- **Antolin et.al.(2018) -** Estimate the factors which affect the parking selection of users. Using scenario for the estimations.

Current Literature & Studies …

Electric Vehicle Charging Stations (EVCS) Network Design:

Deterministic approach

- A capacitated refueling location model with limited traffic flow **Uupchurch et al.(2009):** Maximize the vehicle miles traveled by alternative-fuel vehicles

- **He et. al.(2013)** - Allocation of public charging stations to increase the social welfare associated with transportation and power networks

- **Xi et. al.(2013) -** Simulation-optimization model to maximize the service level to the EV drivers. Combination of level 1 and level 2 charger is more desirable than installing only charger level 1

- **Cavadas et. al (2015) -** EVCS in an urban area. A mixed integer programming (MIP) model for locating the slow-charging stations. Travelers' parking locations as well as their daily activities in order to aggregate the demand on different places

Current Literature & Studies …

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Electric Vehicle Charging Stations (EVCS) Network Design:

Stochastic approach

- **Pan et. Al.(2010)** - 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 et.al.(2015)** - 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 et.al.(2016)** present the EVCS problem as an extension of the flow refueling location problem (FRLP)

Current Literature & Studies …

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Charging behavior:

- Using choice model into optimization framework : Locating new facilities in a competitive market by **Benati et. al.(2002)**. A random utility model was used in order to model the customer's behavior aiming to predict the market share of the locations.

- **Xu et. al.(2017)**
  - A mixed logit model to explore the factors that affect the battery electric vehicle users (BEV) in Japan
  - 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

- **Wolbertus et. al.(2018)**
  - Study on policy effect on charging behavior and EV adoption at the same time
  - Large data set to investigate the daytime parking and free parking policies influence on EV drivers charging behavior

Problem Description

- **Research Gap:**
  - Focus on large-scale state-wide networks and not on urban areas
  - Deterministic charging demand
    - Demand is quite stochastic in reality (varying by hour of day, weekday/weekend patterns, commute purpose, destination, etc)

- **Research Goal:**
  - Develop a **stochastic programming** approach to determine **location, type of chargers and capacity** of charging stations
    - Assess **community livability metrics**
      - ☐ Accessibility to charging service
      - ☐ Charging station utilization rate
      - ☐ Walkability
    - Account for **behaviors of EV drivers**
      - ☐ Willingness to walk

Assumptions:

- Public parking facilities
- Vehicle parking location
- Vehicle charging time

Solution Approach

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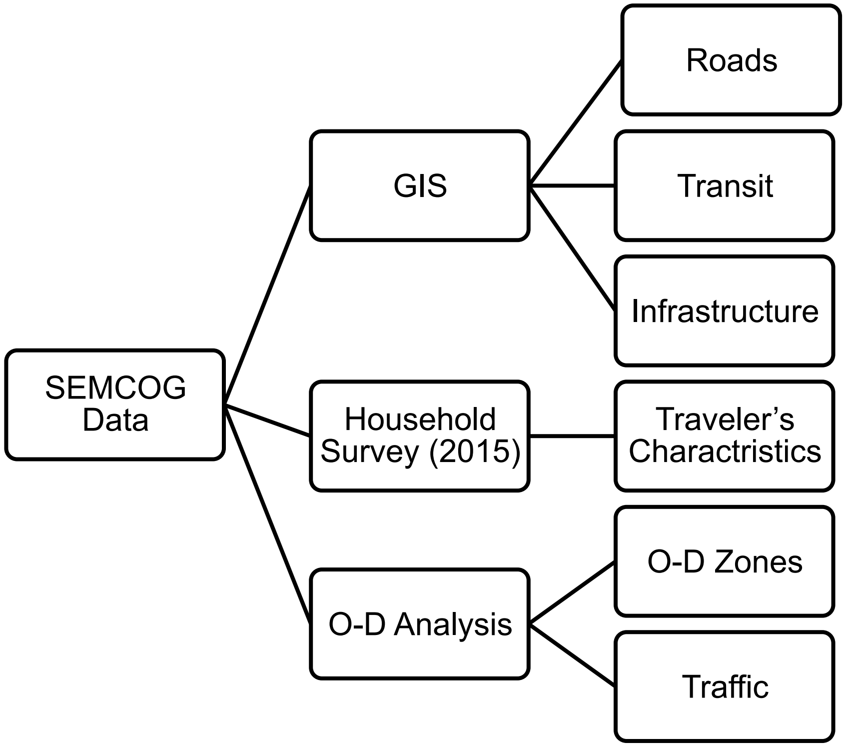
1. Collecting Data
2. Preprocessing
3. Constructing the utility function
4. Mathematical Model
5. Case Study
6. Sensitivity Analysis

Data Collection

- Data gathered from the literature and the other part is collected from SEMCOG
- SEMCOG supports coordinated, local planning with technical, data, and intergovernmental resources.



Preprocessing:
Generating Demand Using Uncertainties

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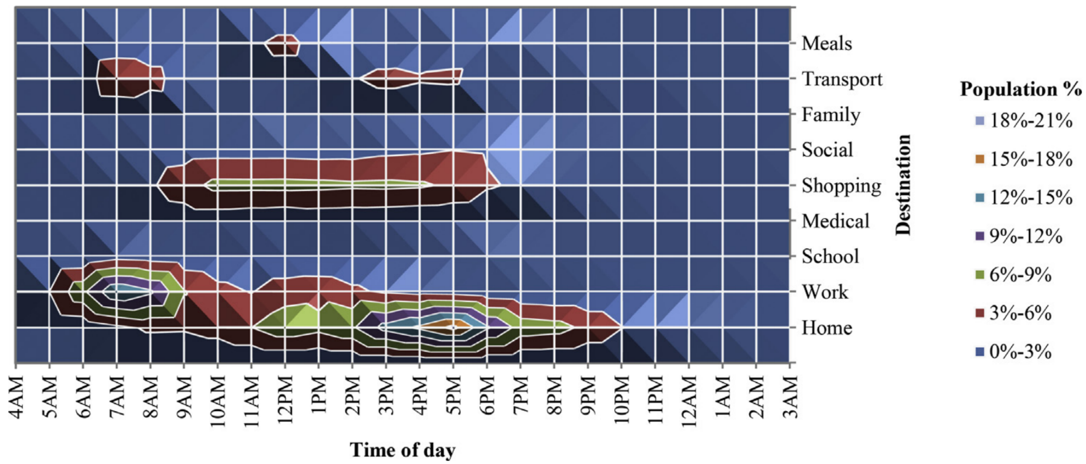
Traffic Demand Pattern (Arrival Times and Dwell Times; Weekdays)



Fraction of arrivals as a function of destination and time

EVSE power requirements, as determined from dwell times and next trip average distance.

Charging location	Dwell time (hours)	Next trip avg distance (miles)	Energy required (kWh)	Power required (kW)	EVSE type
Home	10.0	9.8	3.3	0.3	Level 1
Work	5.6	11.4	3.8	0.7	Level 1
School	3.2	8.5	2.8	0.9	Level 1
Medical	1.1	8.4	2.8	2.6	Level 2
Shopping	0.5	6.7	2.2	4.9	Level 2
Social	1.8	9.0	3.0	1.6	Level 1 or 2
Family	1.0	7.7	2.6	2.5	Level 2
Transport	0.3	7.0	2.3	8.3	Level 2
Meals	0.7	7.0	2.3	3.3	Level 2

EVSE power requirements, as determined from dwell times and next trip average distance

Source: Brooker, R. Paul, and Nan Qin. "Identification of potential locations of electric vehicle supply equipment." Journal of Power Sources 299 (2015): 76-84. – LINK (Data Source: NHTS - Trip distances, Destination types and Destination dwell times)

Preprocessing:
Generating Demand Using Uncertainties

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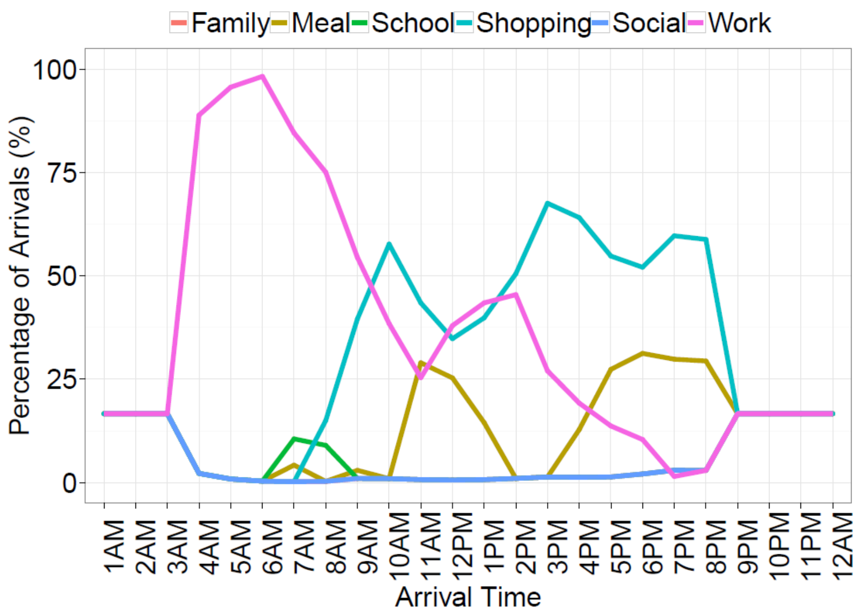
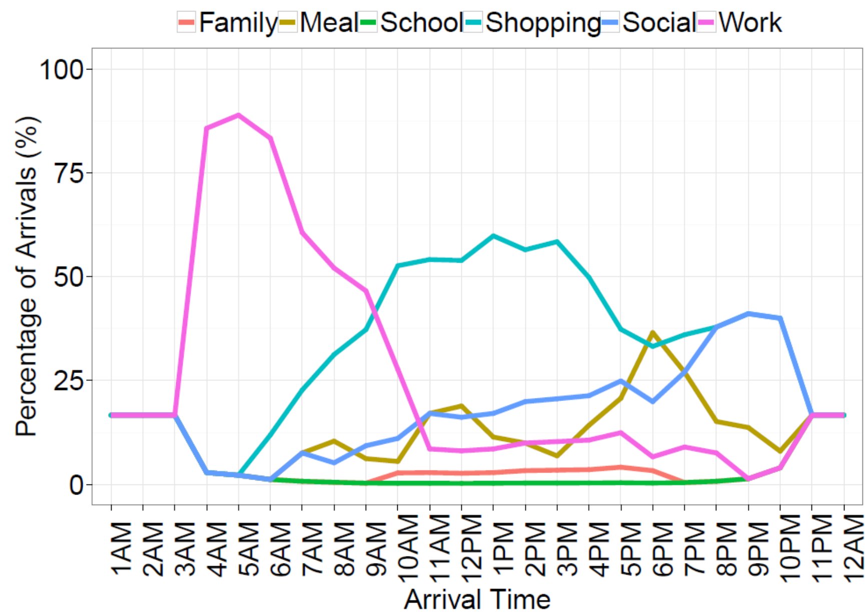
- **Arrival Pattern in Weekdays and Weekends**





The expected breakdown of vehicle arrival percentages for weekdays (left) and weekends (right)

Source: Brooker, R., Qin, N., 2015. Identification of potential locations of electric vehicle supply equipment.

Preprocessing:

Generating Demand Using Uncertainties

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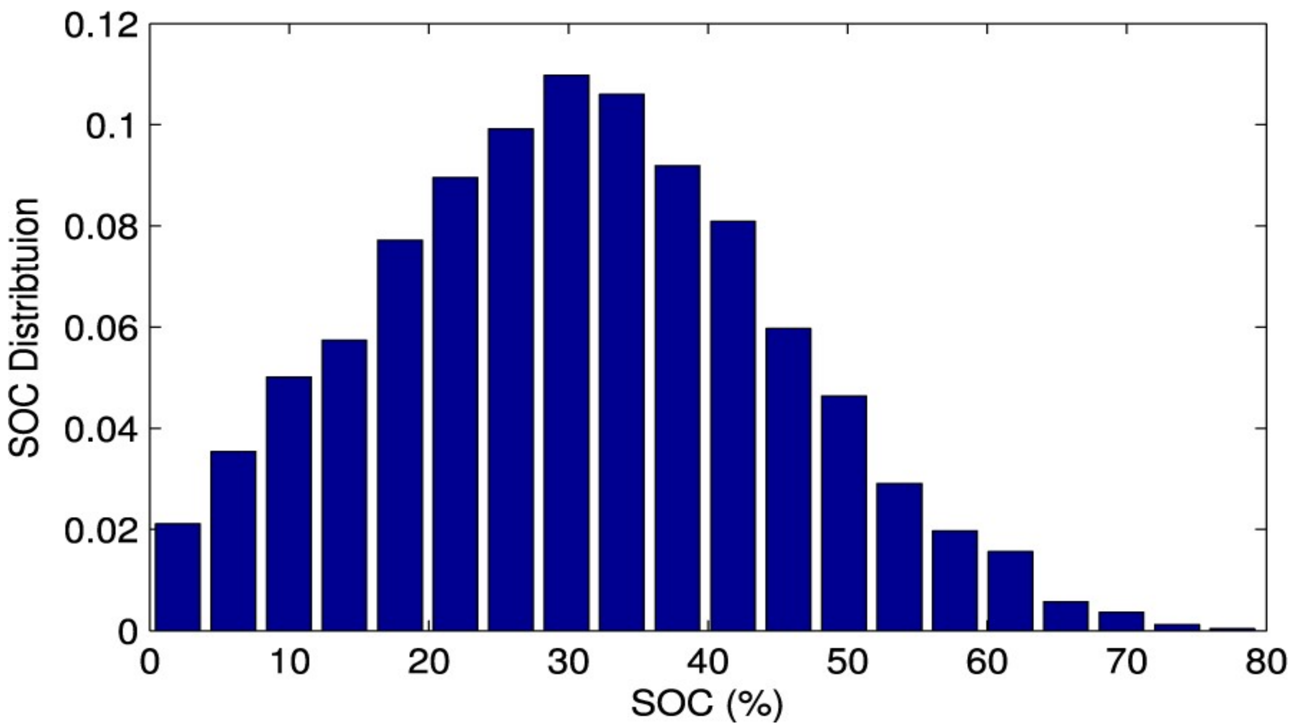
- **The initial distribution of State of Charge at the Time of Arrival**



Source: Brooker, R., Qin, N., 2015. Identification of potential locations of electric vehicle supply equipment.

Preprocessing:
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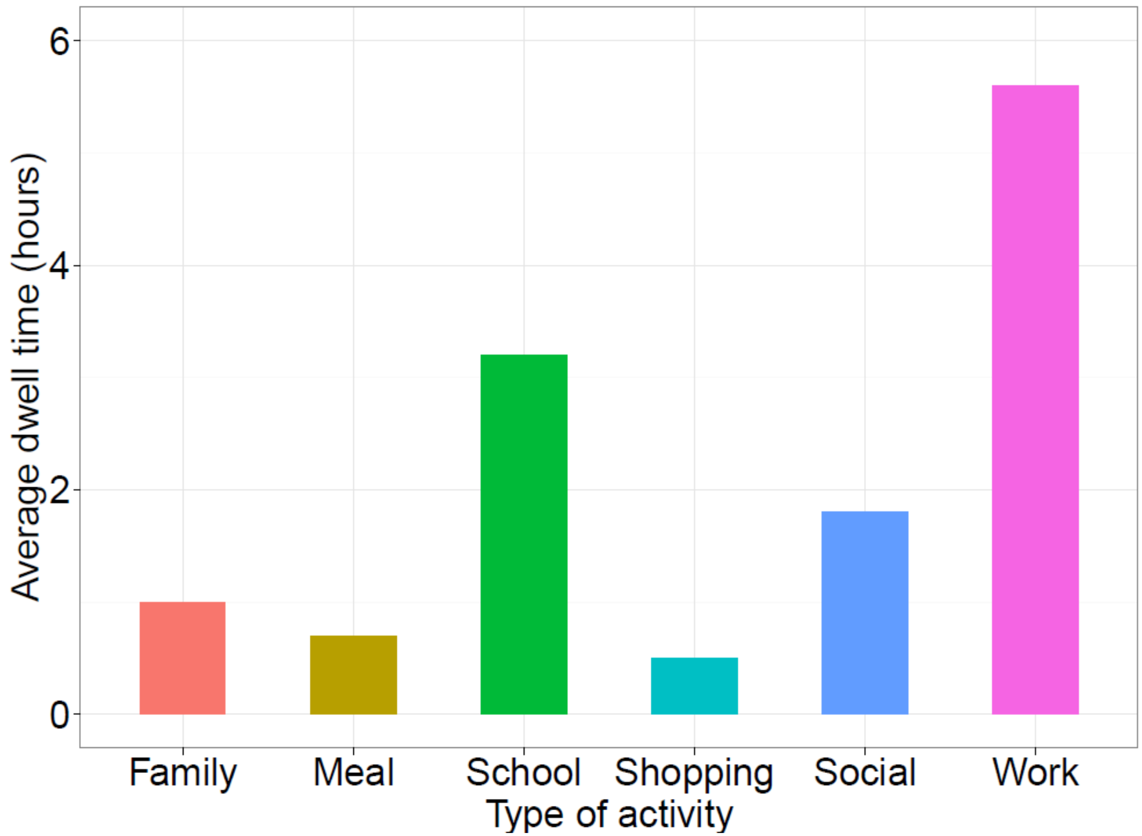
- **Average Dwell Time at Final Destination**

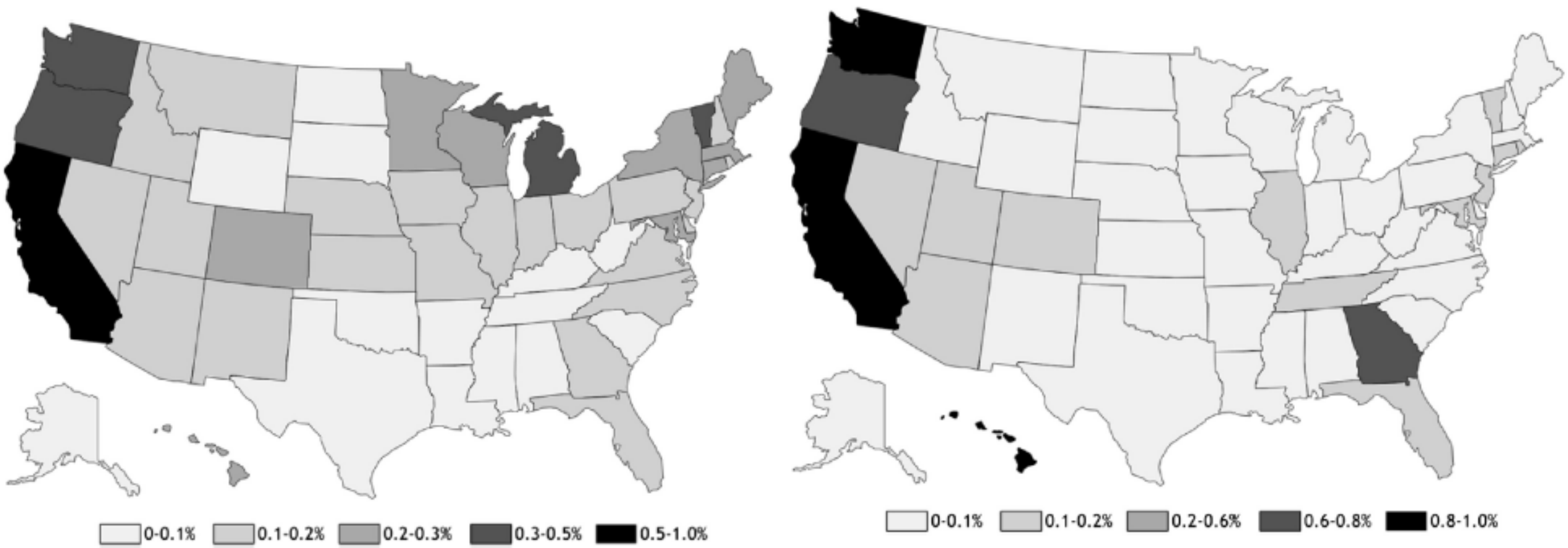


Average dwell time as a function of activity

Source: Brooker, R., Qin, N., 2015. Identification of potential locations of electric vehicle supply equipment.

Preprocessing:
Generating Demand Using Uncertainties

- **EV Market Penetration**

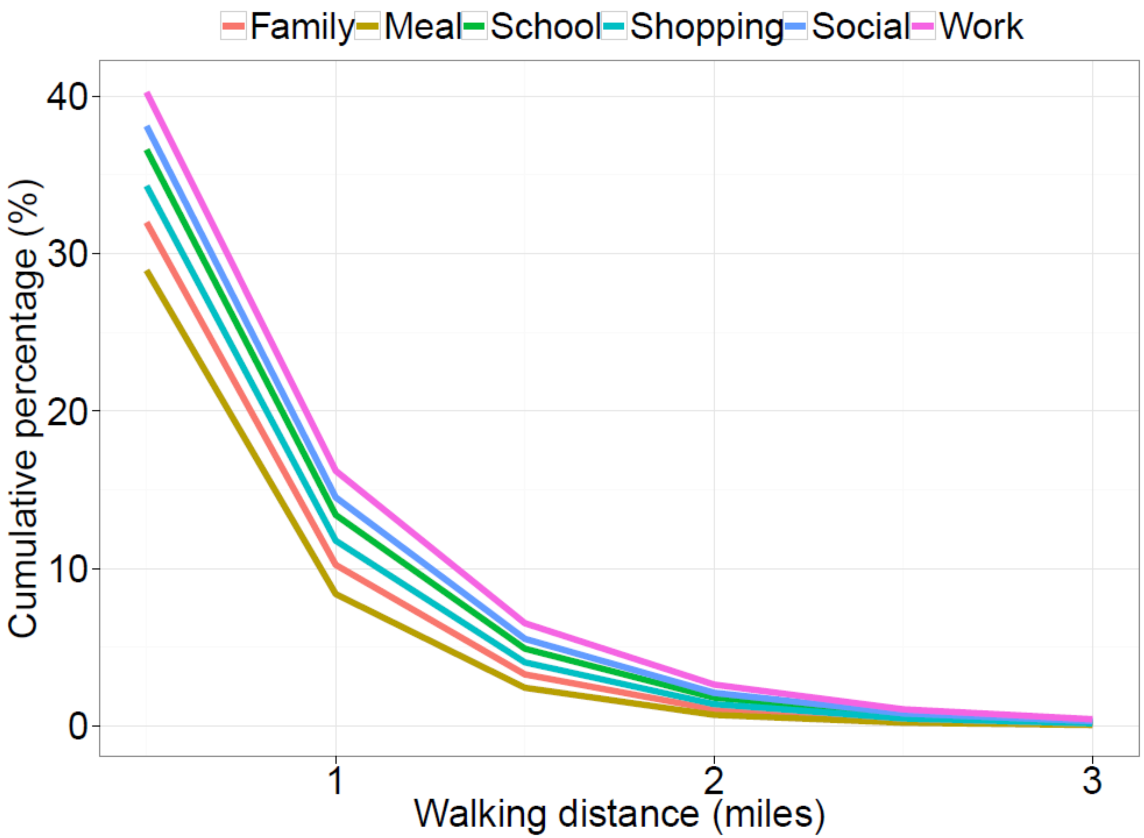


Cumulative 2010-2014 BEV market share (left) and PHEV market share (right) across the U.S.

Source: Vergis, S., Chen, B., 2015. Comparison of plug-in electric vehicle adoption in the United States: A state by state approach.

Preprocessing:
Generating Demand Using Uncertainties

- **Willingness of Walking Distance of Drivers (USA)**



Distance decay function for walking trips to different destination types

Source: Yang, Y., Diez-Roux, A., 2012. Walking distance by trip purpose and population subgroups.

Preprocessing:
Generating Demand Using Uncertainties

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- **Willingness of Walking Distance of Drivers (USA)**

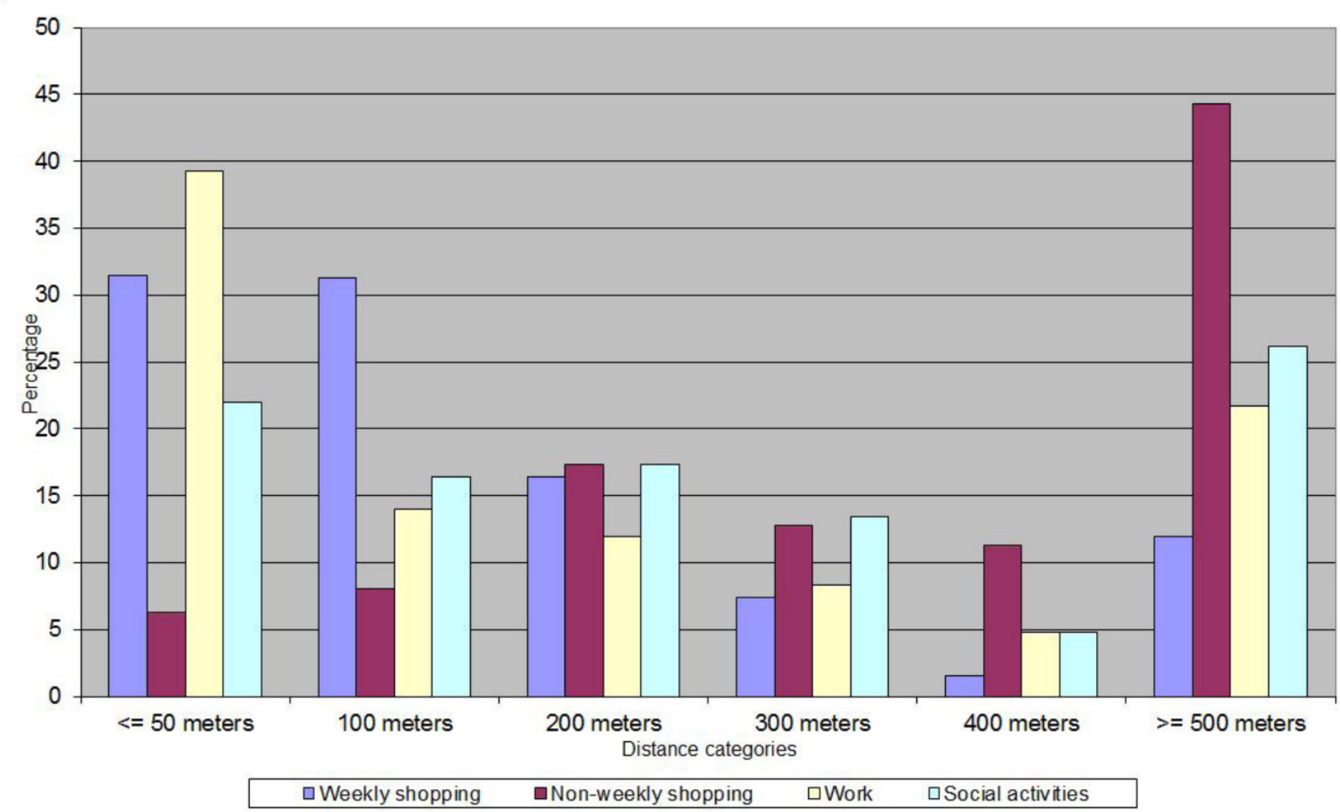
Factor	Category	β
Season	Winter (Dec-Feb)	1.88
	Spring (Mar-May)	1.68
	Summer (Jun-Aug)	1.64
	Autumn (Sep-Nov)	1.7
Region	Northeast	1.85
	Midwest	1.65
	South	1.76
	West	1.65
Community	Town and County	1.65
	Suburban	1.63
	Urban	1.78

Estimated parameter for distance decay function for different factors and their categories

Source: Yang, Y., Diez-Roux, A., 2012. Walking distance by trip purpose and population subgroups.

Preprocessing:
Generating Demand Using Uncertainties

- **Willingness of Walking Distance of Drivers (Netherlands)**



Maximum distance car drivers are willing to walk per trip purpose

Source: Timmermans, Harry, and Marloes de Bruin-Verhoeven. "Car drivers' characteristics and the maximum walking distance between parking facility and final destination." Journal of Transport and Land Use (2015). Eindhoven University of Technology, Netherlands - LINK

Choice Model

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Choice modeling approach captures the charging pattern for EV users and will lead to:

- Accelerating the *adoption* of EVs
- Better distribution of *budget* to charging infrastructures
- Increasing the *mobility, accessibility*

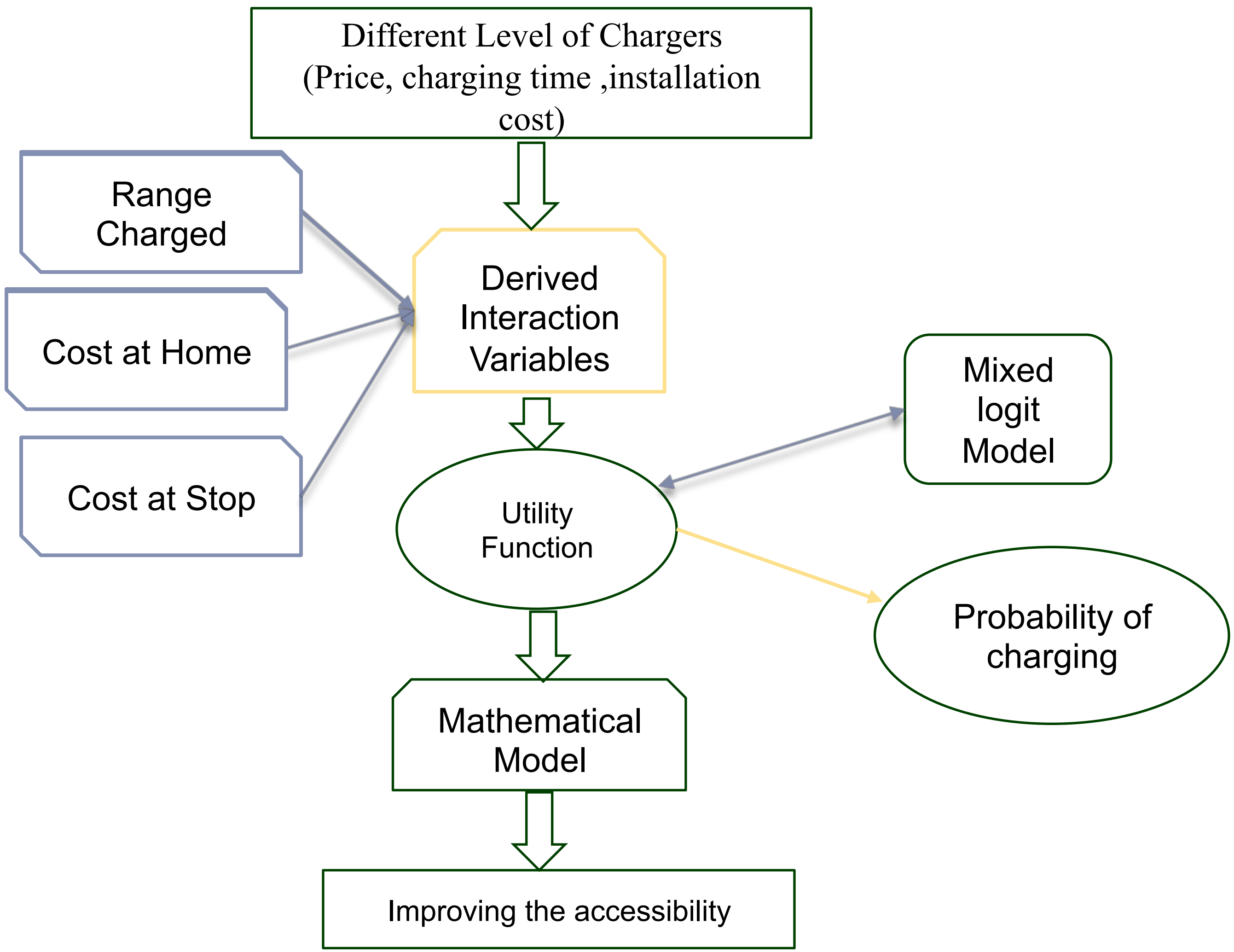
- ***Wen et al. (2015)*** analyzed the charging choices of BEV owners based on a web-based survey in different parts of U.S. (Journal of the Transportation Research Board)
- The choice model computes the volume flowing from demand sources to selected locations, requires to know EV driver preference data, namely the **utility** of drivers.

$$P(Charge)= e^{U_{it}} / \sum e^{U_{it}}$$

Where U_{it} is the utility of charging for respondent i under charging situation t

- The Choice decision was characterized by the following factors: *Charging price, maximum charging power, dwell time , distance to home, current electric range*.
- A **Mixed Logit Choice Model** was used to estimate those factors

Choice Modelling - Framework



Mathematical formulation – Two-stage Stochastic Programming Model

- **Notations**

J: Set of parking lots, indexed by j

B: Set of buildings

$S(b)$: Set of possible parking lots based on drivers walking preference who are going to building b

Γ: Set of arrival and departure times

T: Set of time periods

Ω: Set of scenarios

N: Set of charger types

- **Fixed Model Parameters**

F: Total amount of budget for installing EVSEs.

k_j: Capacity of parking j for installing EVSEs.

c_n: Cost of installing EVSE of type n.

Mathematical formulation – Two-stage Stochastic Programming Model

- Scenario Dependent Parameters

$d_{\gamma,b}(\omega)$: *Total Demand of building b within arrival and departure*

$u_{n,j}(\omega)$: *The aggregated utility of EV drivers who are willing to use EVSE type n at parking lot j in scenario ω*

$u_{ncj}(\omega)$: *The aggregated utility of EV drivers who are not willing to use EVSE type n at parking lot j in scenario ω*

$d_{\gamma,b,s}^{t}(\omega)$: *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

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

$y_{\gamma,b,j,n}^{s}(\omega)$: 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 $\omega \in \Omega$.

Mathematical formulation – Two-stage Stochastic Programming Model

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- **Non-linear Two-Stage Stochastic Model**

First-Stage Model:

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

s.t.

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

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

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

$$x_{n,j} \in \{0, 1\}, z_{n,j} \in \mathbb{Z}^+ \qquad \forall n \in N, j \in J \tag{5}$$

Mathematical formulation- Two-stage Stochastic Programming Model

- **Second-Stage Model:**

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

s.t.

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

$$\forall t\in T, j\in J, n\in N \tag{7}$$

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

$$\forall \gamma\in\Gamma, b\in B, j\in J, n\in N \tag{8}$$

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

$$d_{\gamma,b}(\omega)\sum_{n\in N}\sum_{j\in s} y^s_{\gamma,b,j,n}(\omega) \leq d'_{\gamma,b,s} \qquad \forall\gamma\in\Gamma, b\in B, s\in S(b) \tag{10}$$

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

Mathematical formulation- Two-stage Stochastic Programming Model

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- The Linear Equivalent Model

Consider constraint (8): $\sum_{s \in S(b): j \in s} y_{\gamma,b,j,n}^{s} \leq e^{u_{n,j}} x_{lj} / e^{u}$

As the denominator is positive this is equivalent to :

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

For bounded continuous and binary variables y and x, respectively, a bi-linear variable will be defined as follow: $o_{\gamma,b,j,n,l}^{s} = x_{n,j} \, y_{\gamma,b,j,n}^{s}$ $\forall \gamma \in \Gamma, n \in N, l \in N, b \in B, j \in J, s \in S(b)$

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.**

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

$$o_{\gamma,b,j,n,l}^{s} \leq y_{\gamma,b,j,n}^{s} \qquad \forall \gamma \in \Gamma, n \in N, l \in N, b \in B, j \in J, s \in S(b)$$

$$o_{\gamma,b,j,n,l}^{s} \geq x_{n,j} + y_{\gamma,b,j,n}^{s} - 1 \qquad \forall \gamma \in \Gamma, n \in N, l \in N, b \in B, j \in J, s \in S(b)$$

Computational Study: Case Study

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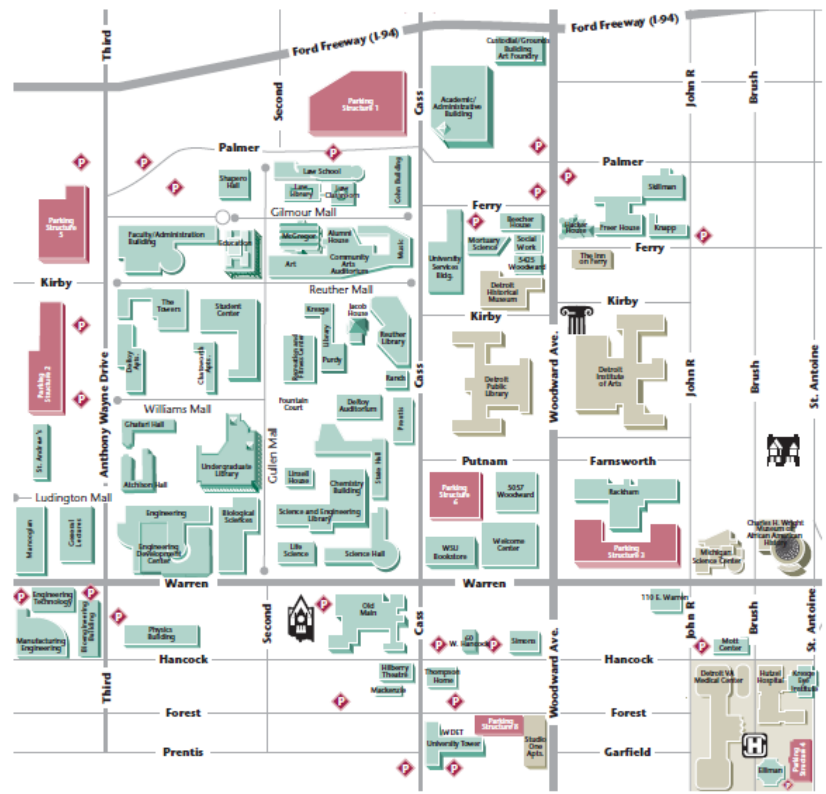
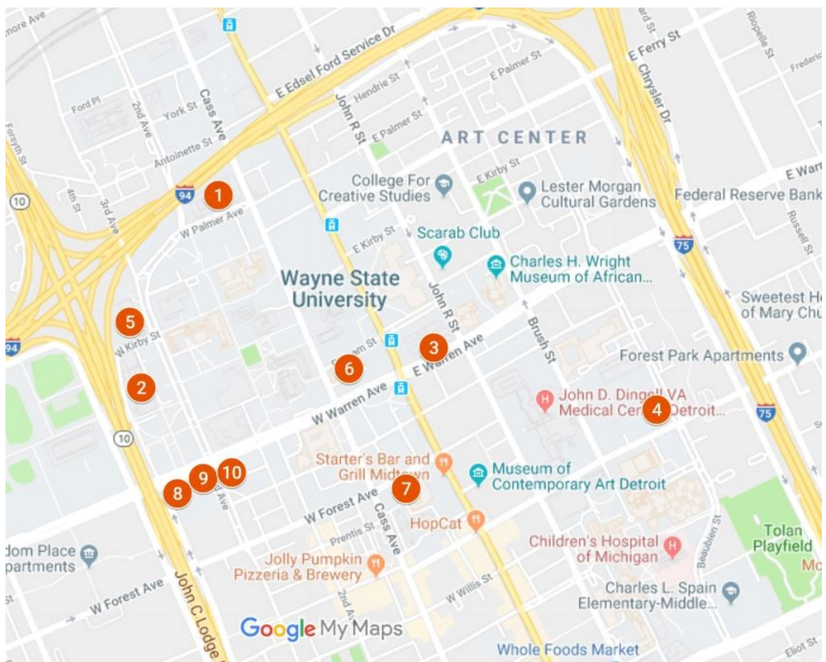
- **Setting**: Part of **Detroit Midtown**
  - Wide range of **employment types** (type of final destination) in this area
    - University faculties
    - Offices
    - Hospitals
    - Museums
  - Attracts a lot of traffic
  - 32 **parking lots** as potential locations for installing charging stations



- **EV Market Share:** Two Cases
  - **Conservative:** 1% for BEV
  - **Optimistic:** 2% for BEV

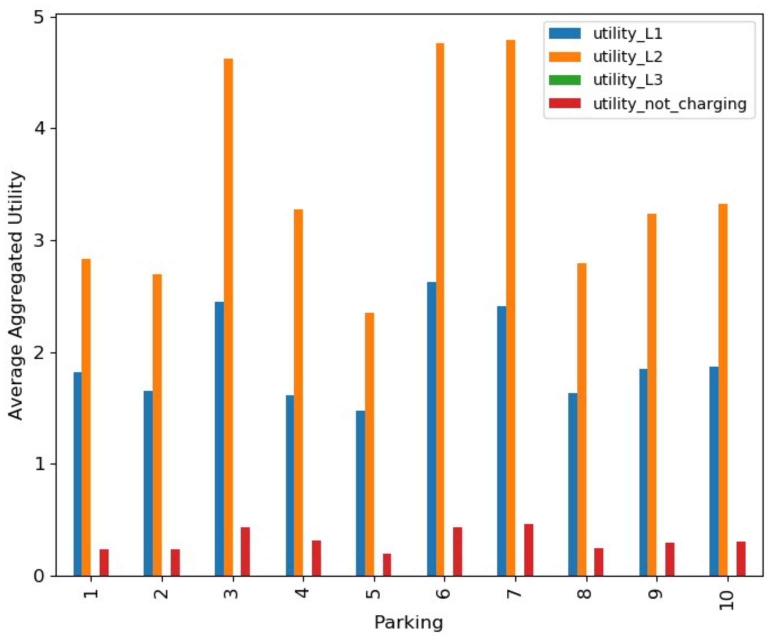
Experiments and Results

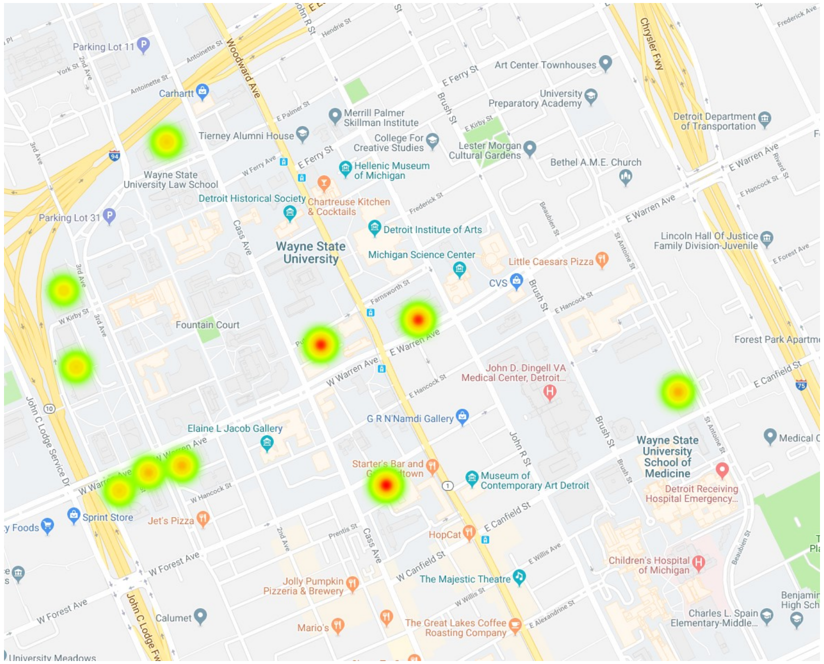
Daily Traffic = A random number between (10000,20000)
Number of Scenarios = 10
BEV Market Share = 1%
Number of Stations = 10
Types of EV Drivers Activities = Work , School , Family , Meal , Social , Shopping
Time Slots = (6:00 A.M - 9 A.M), (9:00 A.M - 12 P.M), (12:00 P.M - 14 P.M), (14:00 P.M - 18 P.M)
Installing Cost = Charger Level 1: $900, Charger Level 2: $3450, Charger Level 3: $25000



Experiments and Results

Test Case 1:
Capacity at each station = 5

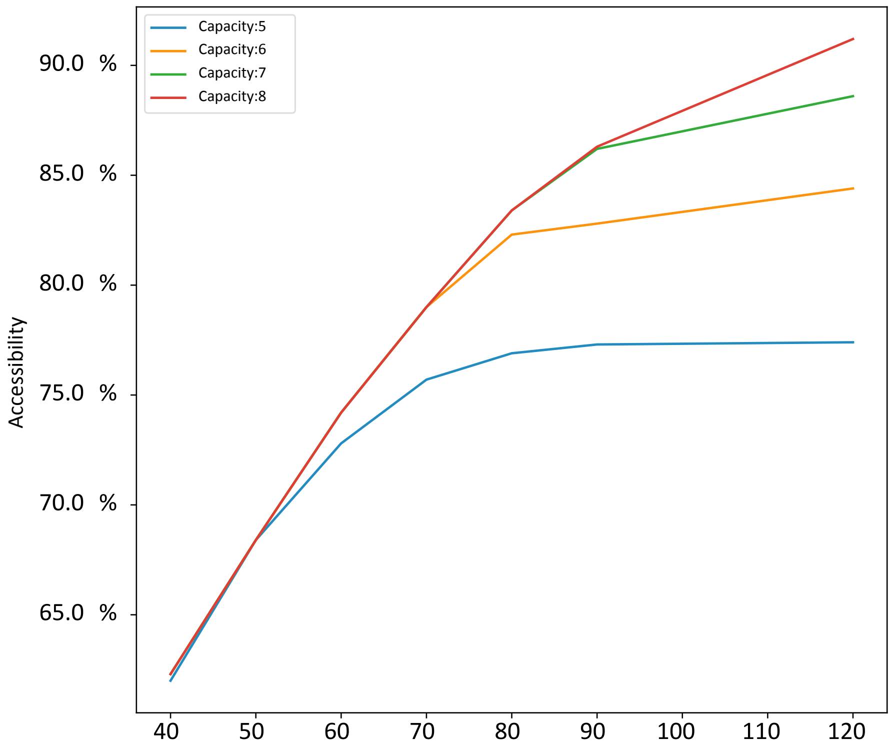




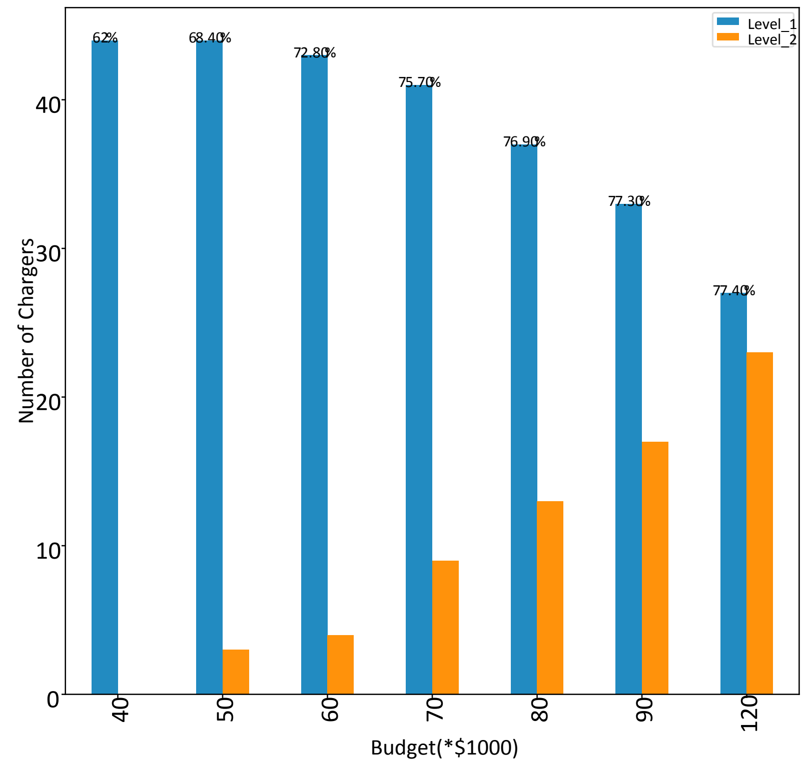
Heat map of demand flow

Experiments and Results

Test Case 1:



Budget (*$1000)



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

Experiments and Results

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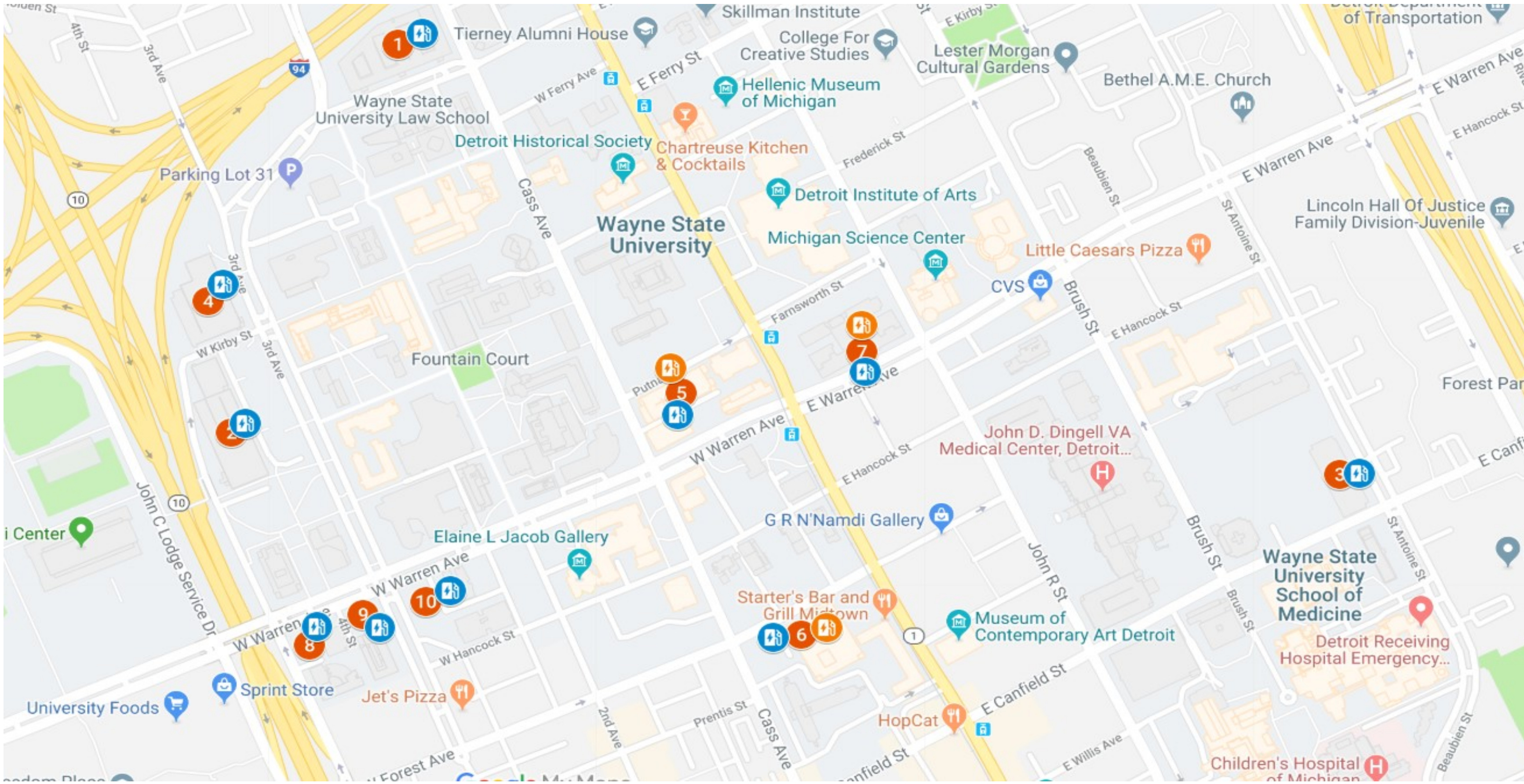
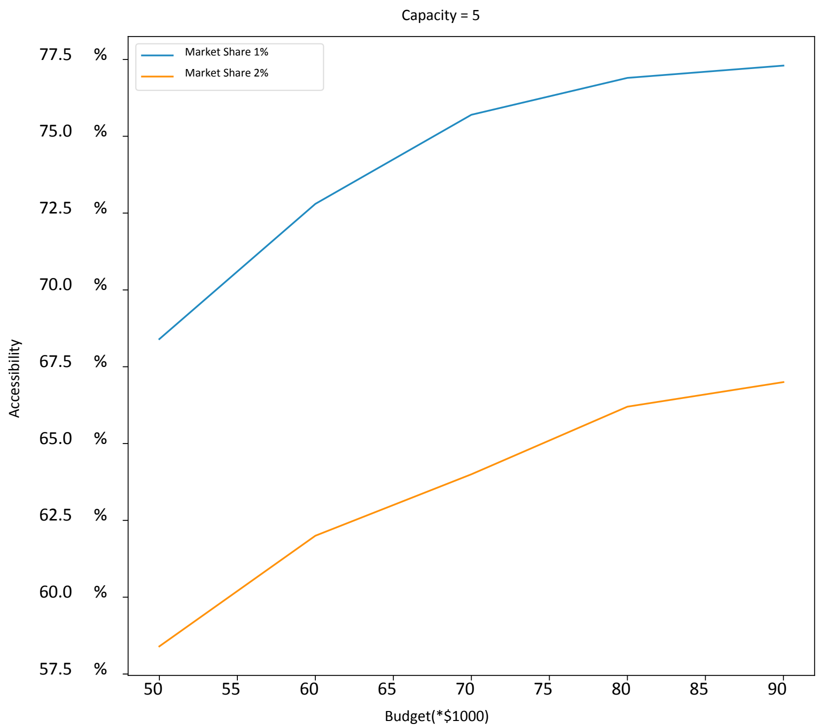
Test Case 1:

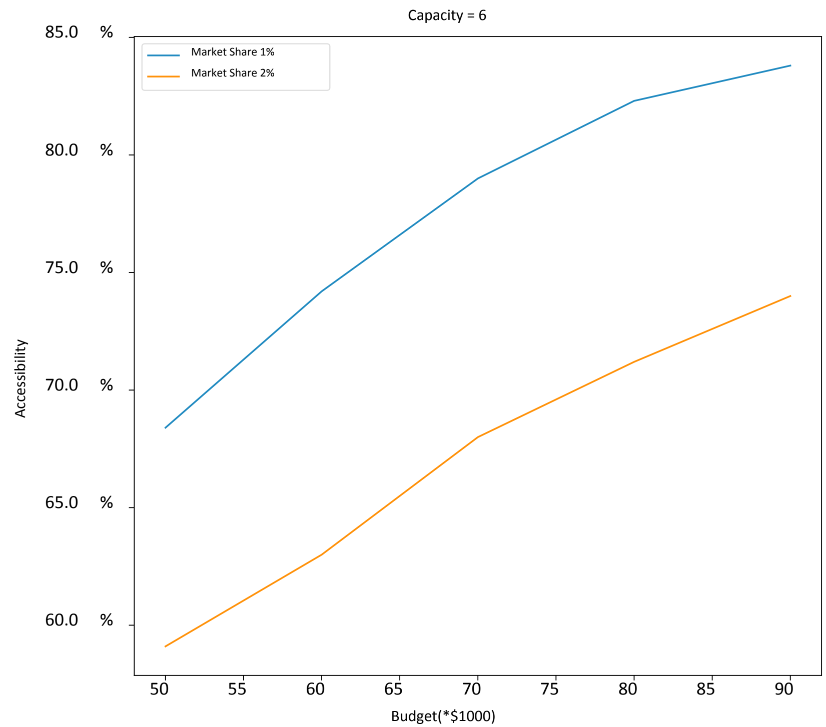


Distribution of EVSE Level 1 and level 2 based on limited budget of $50,000

Experiments and Results

Test Case 2: Market Share Effect on Accessibility

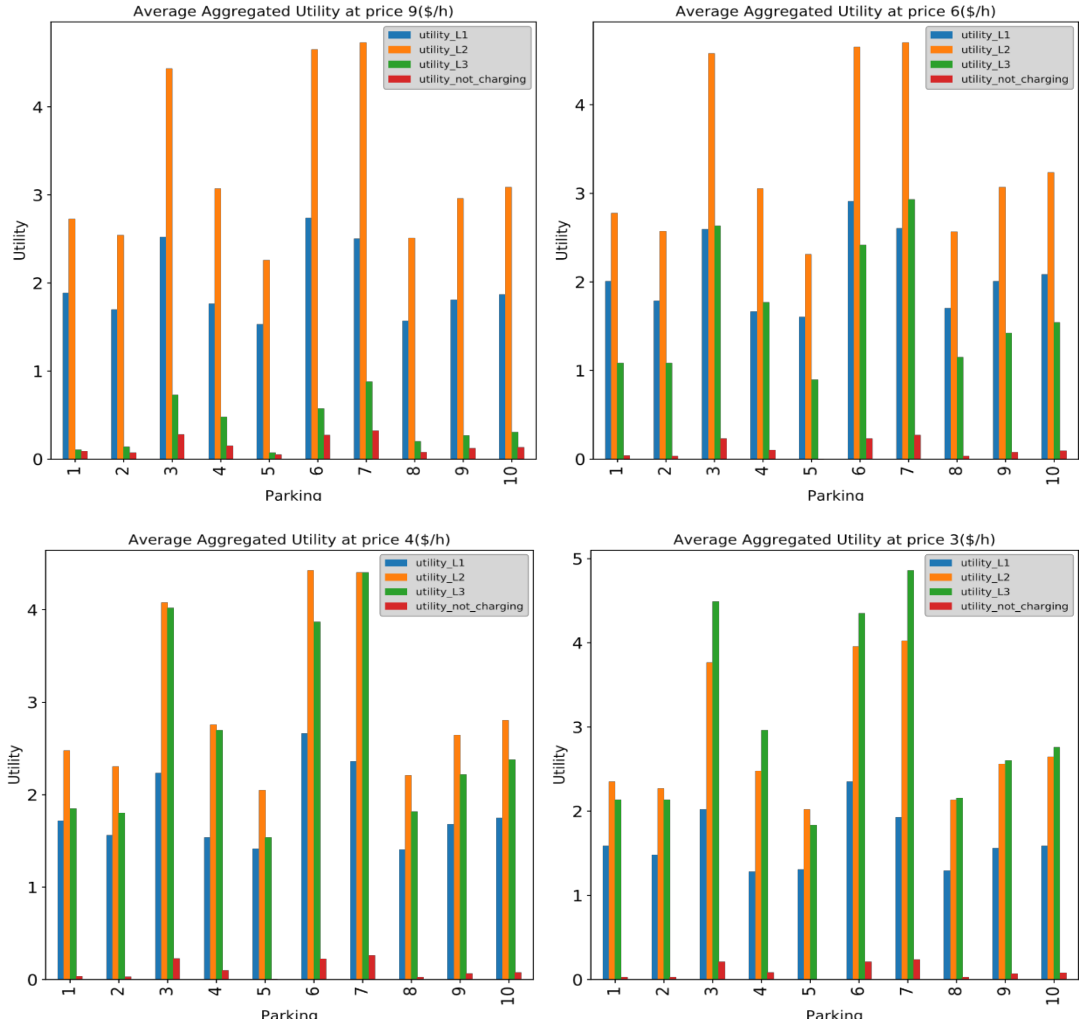




Effect of increase in market share on accessibility

Experiments and Results

Test Case 3: Pricing effect of Level 3 charger 3 on consumers Utility



Key observations:
- Utility is sensitive to $3/hr for Level 3
- Level 2 at $1.50/hr
- Level 3 at $0.50/hr

Multi-Modal Network

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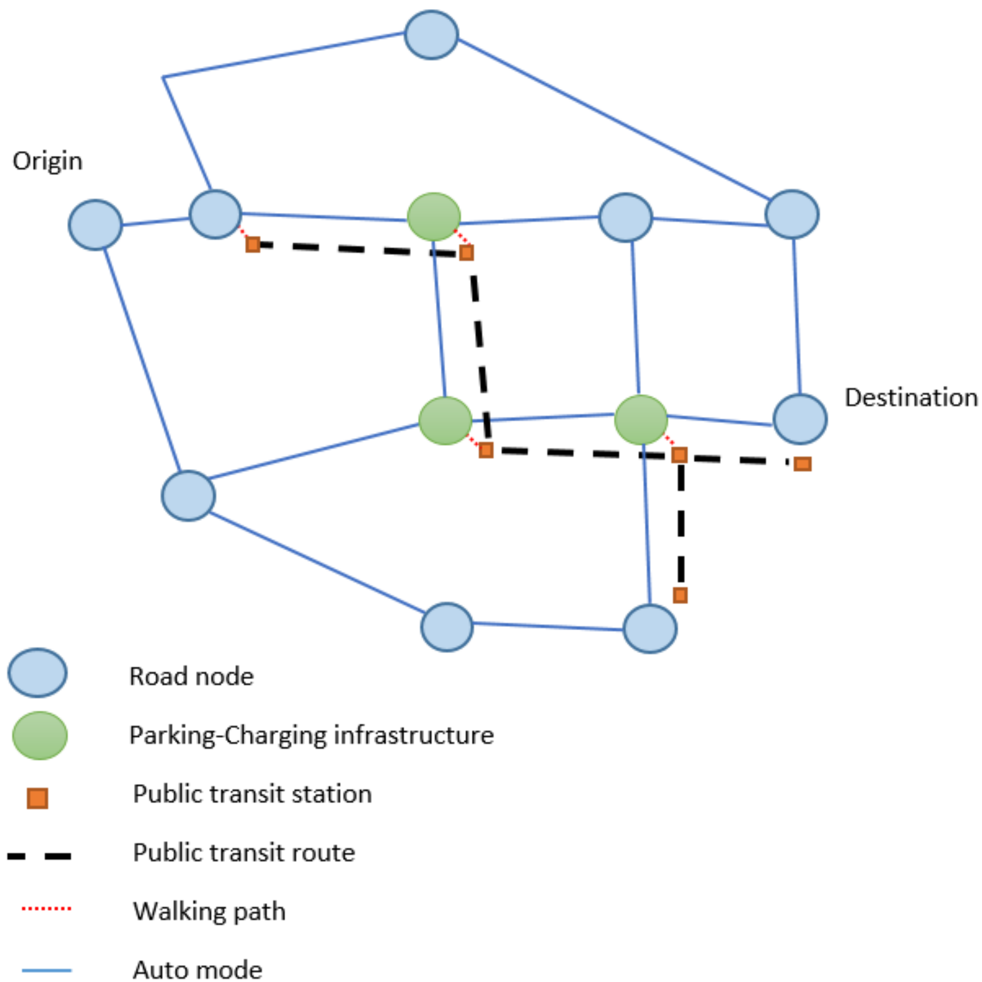

Multi-Modal Framework

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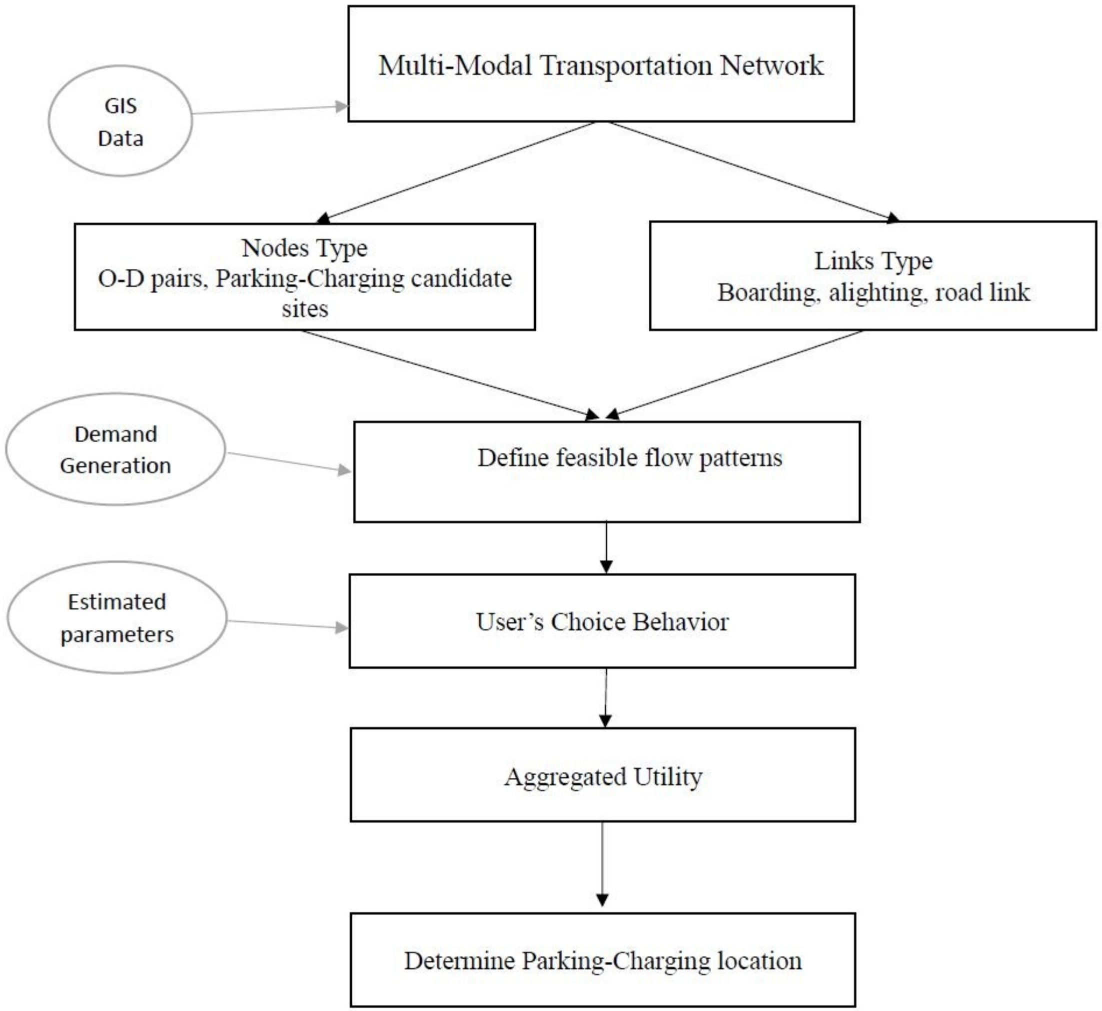

Conclusions

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- **A modeling framework** for planning agencies to design network for EV charging stations based on consideration of randomness in OD demand, walking range, arrival pattern, SOC, accessibility, multi-modal transportation.

- **Interdisciplinary behavioral study** on the drivers' willingness to walk and adoption of multi-modal transportation based on the quality, accessibility and proximity to EV charging station.

- **Case study for a community** with the guidance of a planning agency such as the SEMCOG. Documentation and reports on results of the study and details on the integration of the tool.

- **Pricing scheme for stockholders** was proposed toward different type of chargers.

Thank You!