Designing Community-Aware Charging Networks for Electric Vehicles

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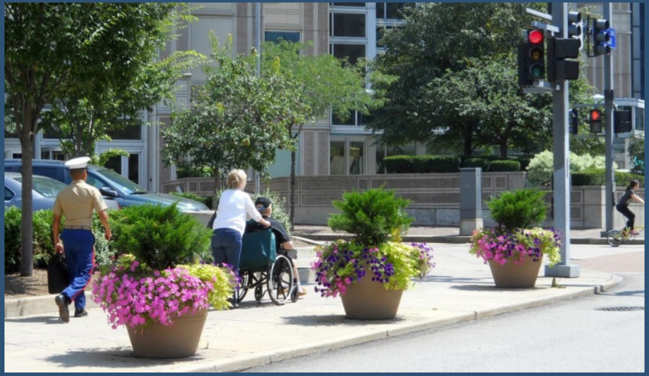

Outline

- Motivation
- Key Literature
- Problem Description
- Uncertainties and Data Analysis
- Solution Approach
- Computational Study
- Future Research

Motivation

- **Promise** of Electric Vehicles (EV):
  - **Diversification** of the transportation **energy feedstock**
  - **Reduction of greenhouse gas** and other emissions
  - Improving public health by improving **local air quality**

- **Direct and indirect policy incentives** for EV market share growth:
  - **Public charger availability** is an indirect policy incentive
    - **The most strongly related variable** among several socio-economic ones **to EV adoption** (Sierzchula et al., 2014)

- **Key decisions** for EV charging network infrastructure:
  - Number and location of charging service stations
  - Type of charging stations

Key Literature: Deterministic

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- **Capar, I. et al., 2013. Arc cover-path-cover formulation and strategic analysis of alternative-fuel station locations**
  - Presented a **computationally efficient** model for **flow-refueling location model**
  - Provided insights for managerial concerns such as **OD demand forecasting uncertainty**, robustness of optimal locations in regard to **vehicle driving ranges**

- **Cavadas, J. et al. 2015. MIP model for locating slow-charging stations for EVs in urban areas accounting for driver tours**
  - Locate **slow-charging stations** for EVs in an **urban** environment
  - Possibility of **several stops** by each driver during the day and the driver can only charge the vehicle at one of these locations
  - Impact of considering **demand transference** can be rather high in networks where demand is relatively low

Key Literature: Stochastic

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- **Tan, J. & Lin, W., 2014. Stochastic flow capturing location and allocation model for siting EV charging stations**
  - Compared a **deterministic** case where charging demand is fixed over time to a **stochastic** one where consumer demand for charging service is random
  - **Stochastic programming** (SP) provides more realistic results

- **Hosseini, M. & MirHassani, S.A., 2015. Refueling-station location problem under uncertainty**
  - **Two-stage SP** to locate **permanent and portable charging stations** with and without considering capacities to maximize the served traffic flows
  - Stochastic models firstly try to cover **trips between large cities**
  - Permanent stations get located in and around **heavily populated nodes**

Problem Description

Model for EV Charging Station Network Design

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- **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 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
      - Willingness to use public charging stations

Assumptions:

- Public parking facilities
- Semi-rapid chargers
- Vehicle parking location
- Vehicle charging time

Uncertainties and Data Analysis

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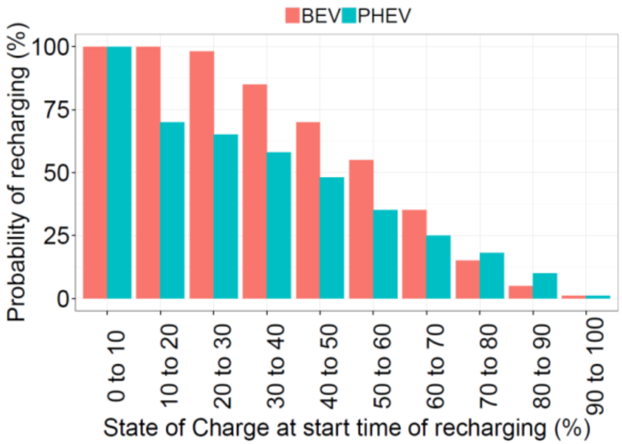
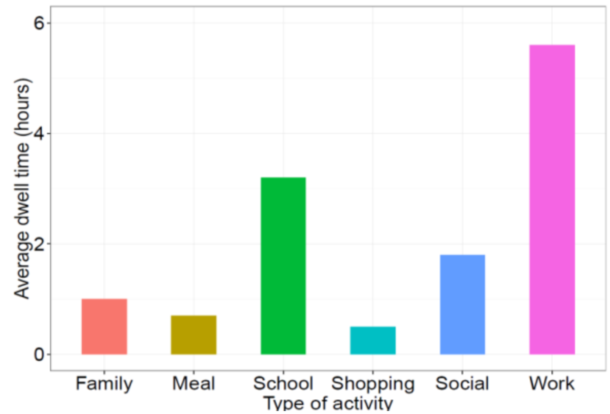
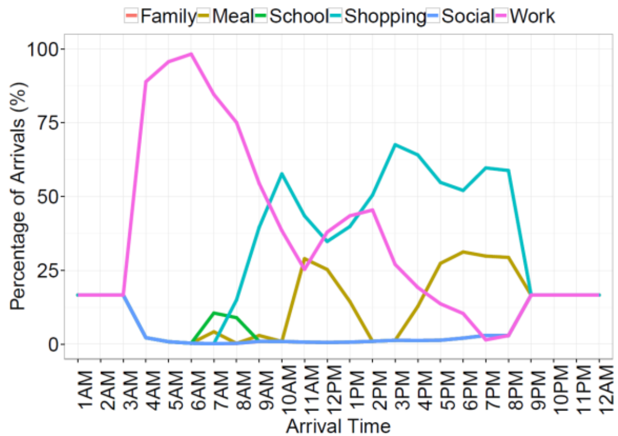
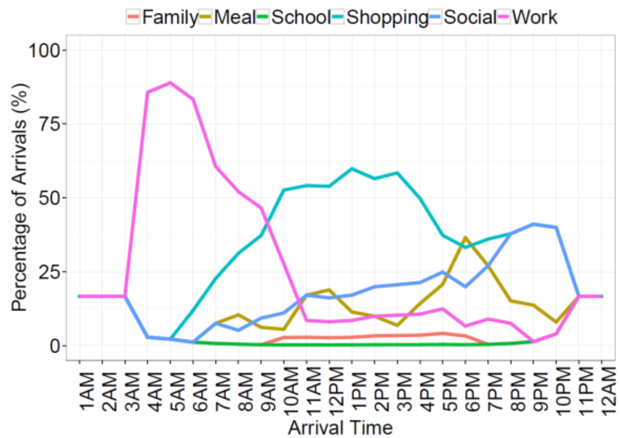








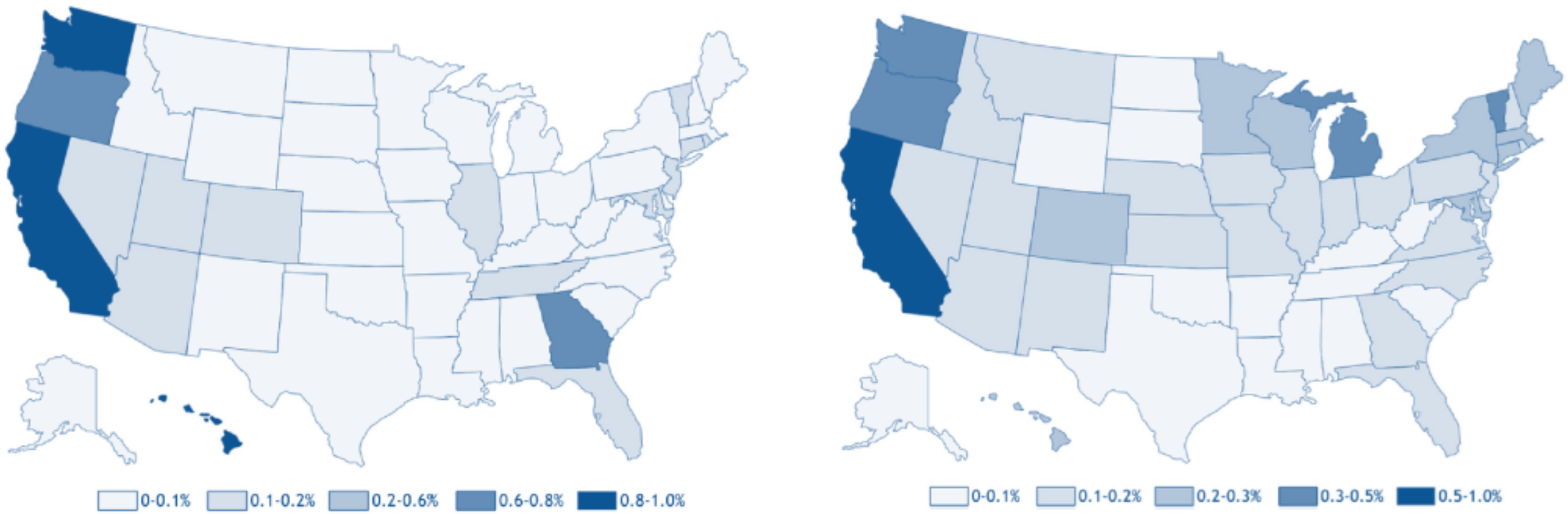
The expected breakdown of vehicle arrival percentages for weekdays (left) and weekends (right).

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 parameters for distance decay function

Data Sources:
Brooker, R., Qin, N., 2015. Identification of potential locations of electric vehicle supply equipment.
Yang, Y., Diez-Roux, A., 2012. Walking distance by trip purpose and population subgroups.

Uncertainties and Data Analysis …

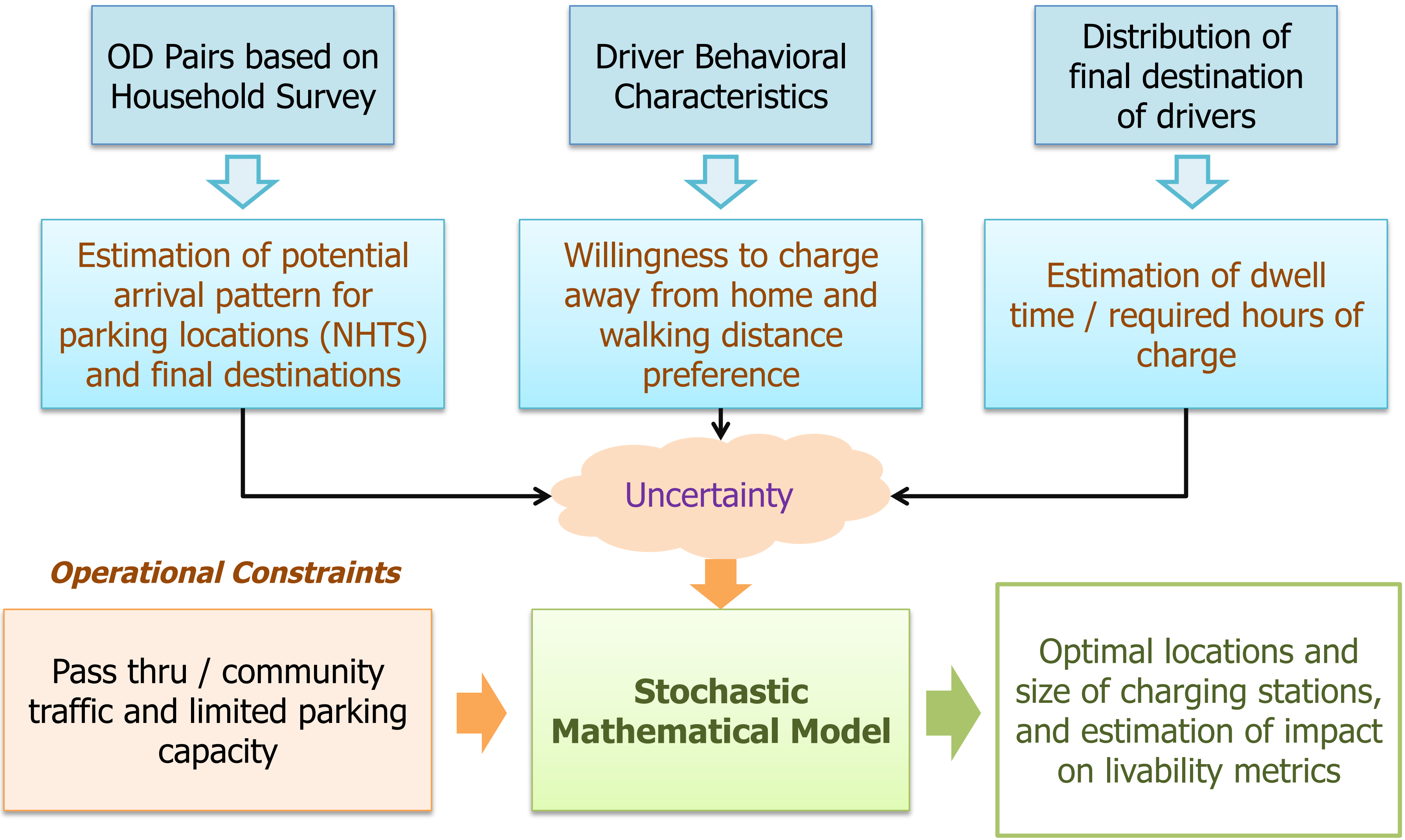


Cumulative 2010-2014 BEV market share (left) and PHEV market share (right) across the U.S.

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

- US DoT:
  - **Share of vehicles** needing charging can reach **5%**
    - PHEV share would be ~ 2% and BEV ~ 3%
  - **3.5% of fleet** projected to be **full EV or PHEV** by 2022-2025
    - California Zero Emission Vehicles (ZEV) program considered in reference case
    - Adoption of ZEV program by nine additional states

Solution Approach



Maximizes accessibility to public EV charging service!

Solution Approach: Notation

- **Sets**

S:Set of parking lots, indexed by $s \in S$

L_s:Set of number of charging stations in location s, indexed by $l \in L_s$

T:Set of time slots, indexed by $t \in T$

B:Set of buildings, indexed by $b \in B$

Γ:Set of arrival and departure times, indexed by $\gamma(t) \in \Gamma$ containing time slot $t \in T$

Ω:Set of scenarios

- **Fixed Model Parameters**

p:Number of **candidate locations** for installing charging stations

m_l:Number of **charging stations**, $l \in L_s$

- **Scenario Dependent Parameters**

$d_{\gamma(t),b,s}(\omega)$:**Demand** with arrival and departure time of $\gamma(t) \in \Gamma$ for a given $t \in T$ for **building** b that are **willing to park** their vehicle in **location** $s \in S'$, $S' \subset S$ in scenario $\omega \in \Omega$.

- **First-Stage Decision Variables**

x_s:1 if **location** $s \in S$ is selected for installing charging stations.

$z_{l,s}$:1 if $l \in L_s$ **charging capacity** is installed in location $s \in S$.

- **Second-Stage Decision Variables**

$y_{\gamma(t),p,s}(\omega)$:Proportion of demand with arrival and departure time of $\gamma(t) \in \Gamma$ for a given $t \in T$ for building b that are willing to charge their vehicle in location $s \in S'$, $S' \subset S$ in scenario $\omega \in \Omega$

Solution Approach: Model

- **First-Stage Model**

$$Max\ f(x,z)=E[\varphi(x,z,\omega)]$$

p locations for installing charging stations:

$$\sum_{s\in S} x_s = p$$

Charging capacity in each location:

$$\sum_{l\in L_s} z_{l,s} \le 1 \quad \forall s\in S$$

$$z_{l,s} \le x_s \quad \forall l\in L_s, s\in S$$

Feasible set for the binary first-stage variables:

$$x_s, z_{l,s} \in \{0,1\} \quad \forall l\in L_s, s\in S$$

- **Second-Stage Model**

$$\varphi(x,z,\omega)=Max \sum_{t\in T,\gamma(t)\in\Gamma,b\in B,s\in S} y_{\gamma(t),b,s}(\omega) * d_{\gamma(t),b\ldots}$$

Supply-demand balance:

$$\sum_{\gamma(t)\in\Gamma,b\in B} y_{\gamma(t),b,s}(\omega) * d_{\gamma(t),b,s}(\omega) \le \sum_{l\in L_s} m_l * z\ldots$$

Demand assignment to parking lots:

$$\sum_{s\in S} y_{\gamma(t),b,s}(\omega) \le 1 \quad t\in T, \gamma(t)\in\Gamma, b\in B$$

$$y_{\gamma(t),b,s}(\omega) \ge 0 \quad \forall \gamma(t)\in\Gamma, b\in B, s\in S, t\in T$$

Solution Approach: SAA

Sample Average Approximation

- **Optimal SP solution** ≅ solution for **sample scenario set** (Mak et al., 1999)
- **Estimating required number of scenarios**:
  - Estimate **upper bound** for optimal solution:
    - Generate M sample scenario sets of size N, $i.e.$ $(\omega_j^1, \omega_j^2, \dots, \omega_j^N)$ for $j=1,\dots,M$ and compute:

      $\vartheta_N^j = 1/N \sum_{i=1}^{N} \varphi(x,z,\omega_j^i)$ $\quad \vartheta_{N,M} = 1/M \sum_{j=1}^{M} \vartheta_N^j$ $\quad \sigma_{\vartheta_{N,M}}^2 = 1/M(M-1) \sum_{j=1}^{M} (\dots$
  - Estimate **lower bound** for optimal solution:
    - Any feasible solution of first-stage problem: lower statistical bound for optimal value
    - Choose a sample of size N', $i.e.$ $(\omega^1, \omega^2, \dots, \omega^{N'})$ for lower bound and compute:

      $f(x,z) = 1/N' \sum_{j=1}^{N'} \varphi(x,z,\omega^j)$ $\quad \sigma_{N'}^2 = 1/N'(N'-1) \sum_{j=1}^{N'} (\varphi(x, \dots$
    - Estimating UB is not easy as it needs decomposition algorithms but getting LB is easier even though it needs high number of scenarios.
  - Estimating **optimality gap** and its **quality**:

    $gap = \vartheta_{N,M} - f(x,z)$ $\quad \sigma_{gap}^2 = \sigma_{\vartheta_{N,M}}^2 + \sigma_{N'}^2$

Solution Approach: Heuristic

- SAA requires high computational resources

Algorithm 1 Pseudo-code of the heuristic

$bestsolution \leftarrow \emptyset$.
for $s \leftarrow 1$ to $NumberofParkingLots$ **do**:
    Compute score measure r_s.
end for
Construction phase:
$initialsolution \leftarrow \emptyset$
Compute attractiveness ratio ρ_s for all parking lots.
Add parking lots to the initial solution in decreasing order of the attractiveness ratio until p parking lots are selected.
Improvement phase:
$currentsolution \leftarrow initialsolution$
while $f(currentsolution)$ can be improved **do**
    remove-insert($currentsolution$)
end while
Store best solution found so far.

$$r_s = \sum_{s,s' \in S, s \neq s'} c_s e^{-\beta d_{ss'}}$$

$$\rho_s = r_s q_s$$

c_s : Charging capacity of parking lot s.

$d_{ss'}$: Distance between parking lot s and parking lot s'.

q_s : Proportion of scenarios in which parking lot

Computational Study: Case Study

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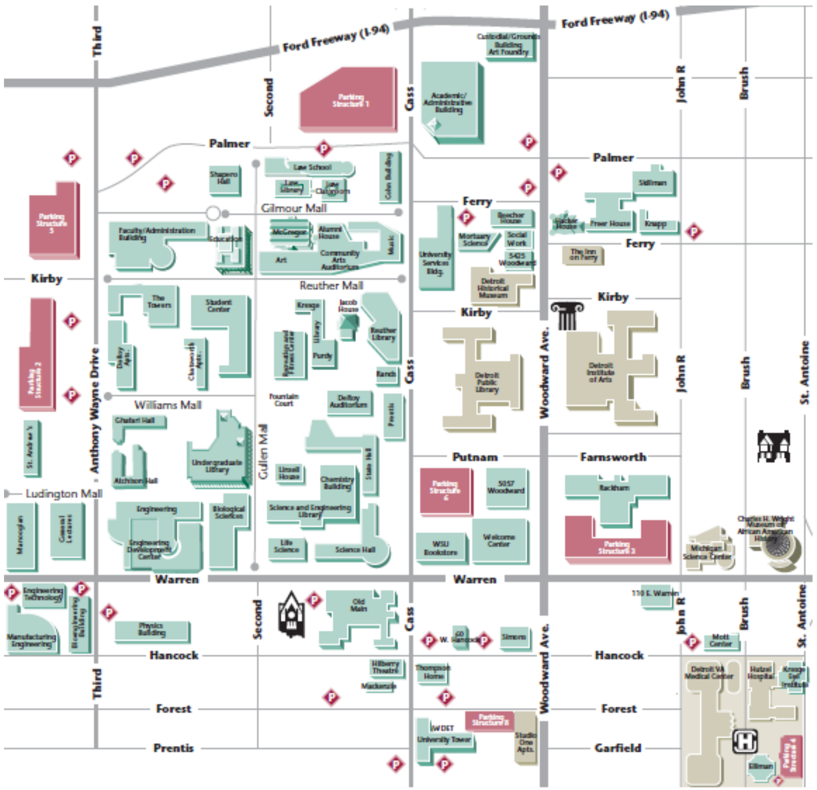
- **Setting**: Part of **Detroit Midtown**
  - Wide range of **employment types** (type of final destination) in this area
    - University faculties
    - Offices
    - Hospitals
    - Museums
  - Attracts a lot of traffic
  - 32 **parking lots** as potential locations for installing charging stations



- **EV Market Share:** Two Cases
  - **Conservative:** (1%,2%) for (BEV,PHEV)
  - **Optimistic:** (2%,3%) for (BEV,PHEV)

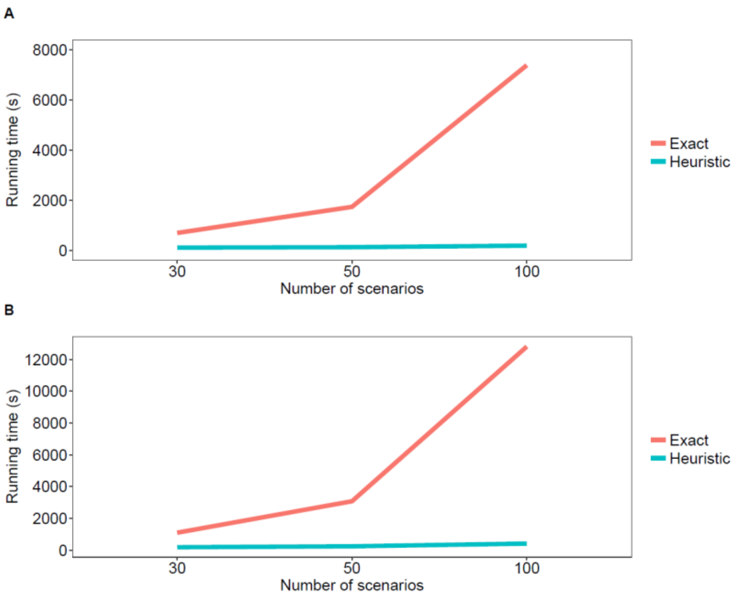
Computational Study: SAA and Heuristic

SAA perf. when (M,N’) = (20,1,000) and (BEV,PHEV) = (1%,2%)

p	N	UB (%)	LB (%)	gap (%)	gap SD	Opt (s)	Heuristic (%)	Heuristic (s)
2	30	57.98	56.59	2.39	0.0064	397	57.98	68
	50	58.70	58.25	0.77	0.0062	1,226	58.70	74
	100	58.56	58.54	0.02	0.0055	4,564	58.56	93
4	30	73.89	73.42	0.63	0.0056	720	73.88	114
	50	74.61	73.85	1.02	0.0041	1,759	74.61	131
	100	74.59	73.74	1.14	0.0040	7,406	74.59	193
6	30	83.97	83.62	0.35	0.0039	1,071	83.21	160
	50	84.11	83.80	0.31	0.0034	2,173	83.17	186
	100	83.40	83.30	0.10	0.0031	9,572	82.86	303
8	30	91.16	90.61	0.61	0.0026	1,124	90.28	185
	50	91.13	90.78	0.38	0.0021	3,099	90.18	245
	100	90.87	90.86	0.02	0.0018	12,832	90.11	414

SAA perf. when (M,N’) = (20,1,000) and (BEV,PHEV) = (2%,3%)

p	N	UB (%)	LB (%)	gap (%)	gap SD	Opt (s)	Heuristic (%)	Heuristic (s)
2	30	50.42	50.00	0.85	0.0056	462	50.42	82
	50	50.91	50.10	1.58	0.0054	1,141	50.91	87
	100	50.91	50.31	1.17	0.0048	4,761	50.91	106
4	30	63.35	63.16	0.30	0.0064	1,595	63.33	169
	50	63.19	63.11	0.13	0.0063	3,644	63.19	211
	100	63.46	63.42	0.07	0.0057	16,656	63.41	317
6	30	72.56	71.55	1.39	0.0071	1,663	72.34	208
	50	72.04	71.46	0.81	0.0059	3,246	71.84	273
	100	71.82	71.40	0.58	0.0050	12,165	71.73	474
8	30	78.91	78.49	0.52	0.0048	1,494	78.53	273
	50	79.44	78.92	0.66	0.0045	2,908	79.01	374
	100	79.12	78.69	0.54	0.0044	12,248	78.70	667



Comparison of exact running time vs. heuristic running time for *a*) *p*=4 & *b*) *p*=8 cases when (BEV,PHEV) = (1%,2%).

Computational Study: Settings

- **Willingness to walk** patterns in community:
  - **Optimistic**: High willingness to walk
  - **Pessimistic**: Low willingness to walk

- **Performance measures** of public EV charging placement:
  - Accessibility
  - Lost demand
  - Charging utilization rate
  - Total walking distance
  - Walking distance per capita

Computational Study: Insights

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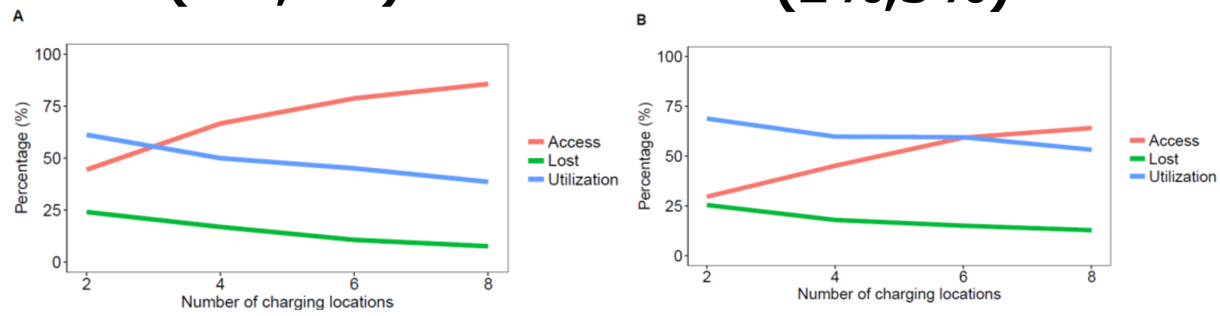
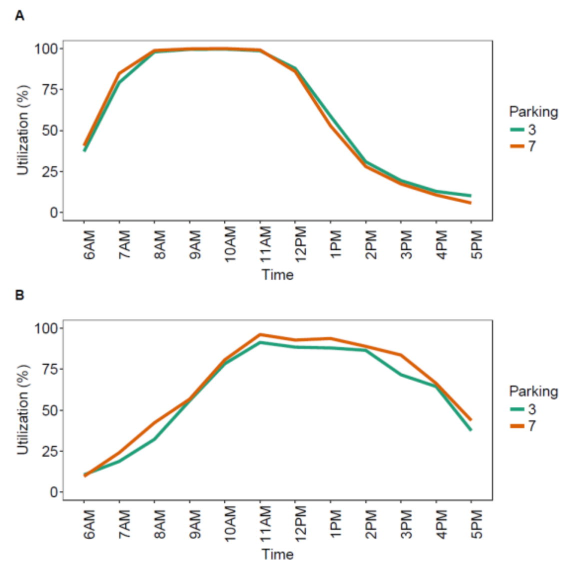
Percentage of accessibility, lost demand and charging utilization in A) (1%, 2%) and B) (2%,3%) market shares.

(1%,2%) (2%,3%)

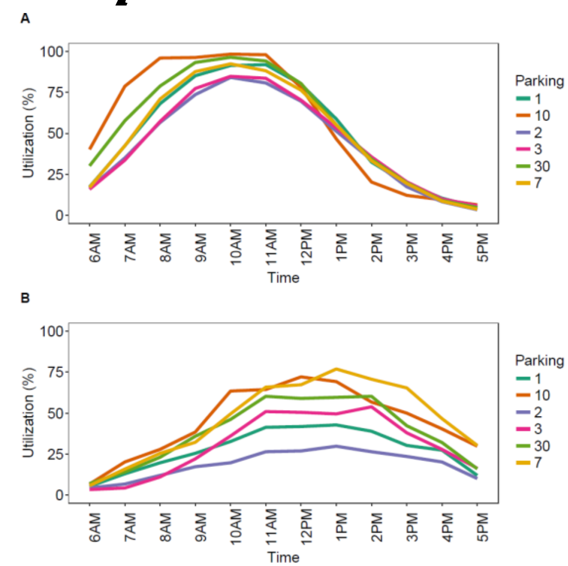


Average hourly utilization in A) weekdays and B) weekends in an optimistic case when p=2, left, and p=6, right.

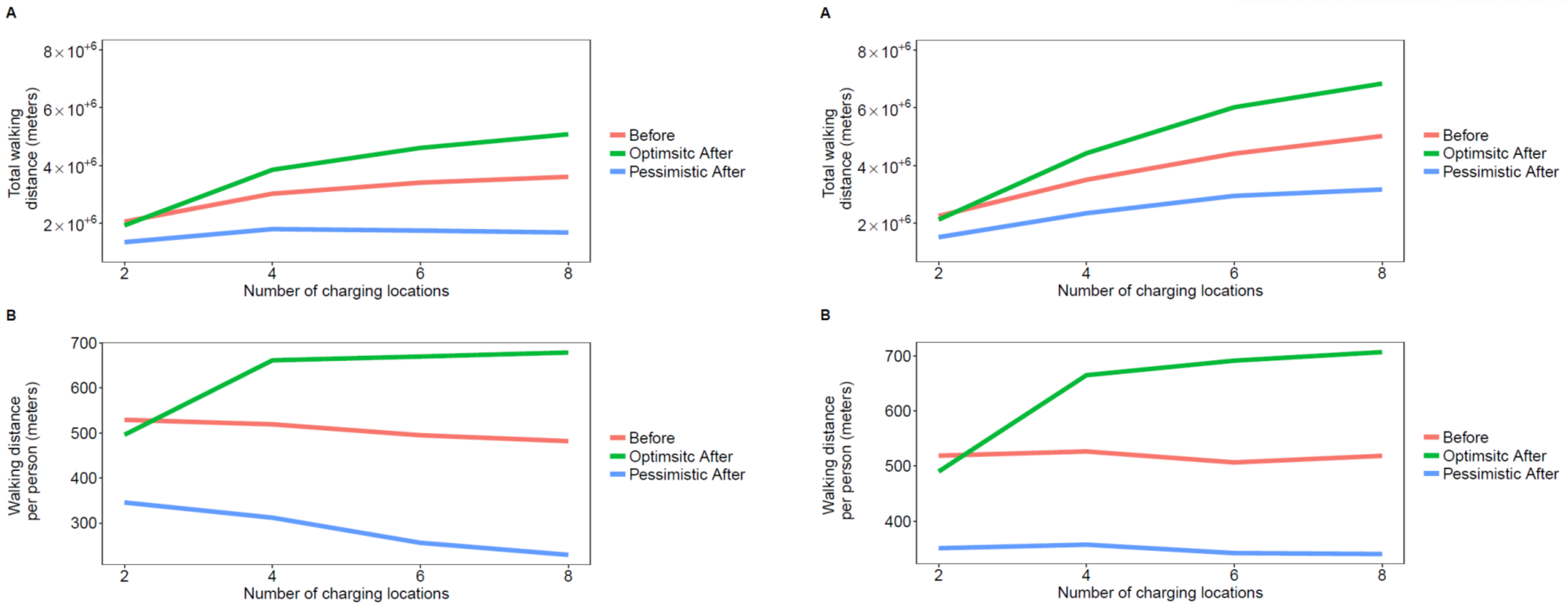
p =2 locations



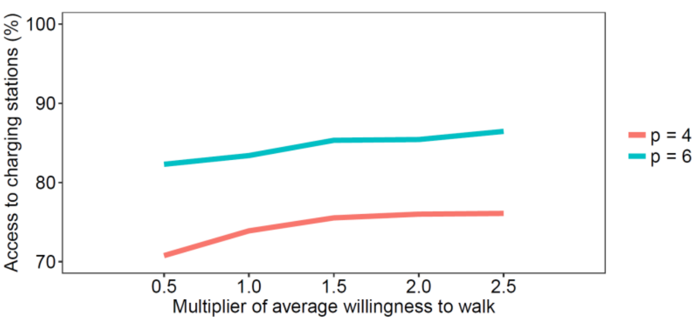
p =6 locations



Computational Study: Insights …



A) Total walking distance and B) walking distance per capita for people with access to EV charging service B) (BEV,PHEV) market shares are (1%,2%) , left, and (2%,3%), right.



Accessibility for different average of willingness to walk distribution when (BEV,PHEV) market shares are (1%,2%).

Assess Usefulness of SP Approach

- Recourse problem:

$$RP=E\downarrow\Omega\ [\varphi(x,z,\omega)]$$

- Expected value problem:

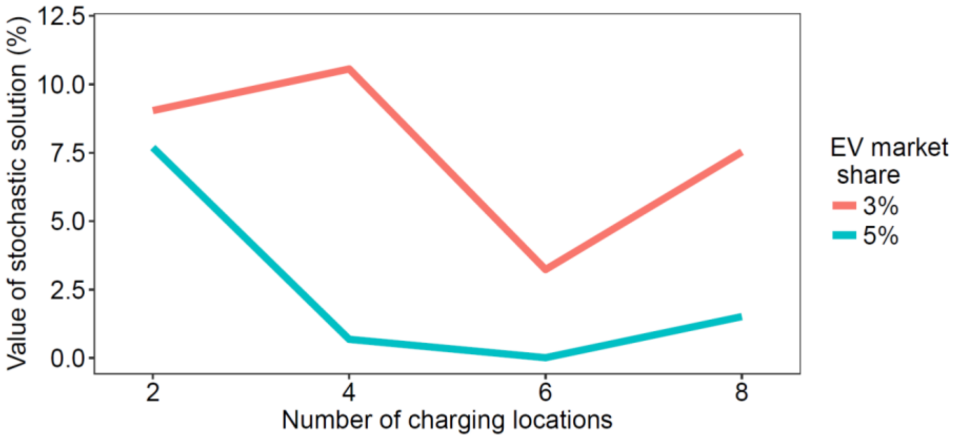
$$EV=\varphi(x,z,\omega\ )$$

- $(x\ ,z\ )$ is the result of EV, the expected result of using expected value solution:

$$EEV=E\downarrow\Omega\ [\varphi(x\ ,z\ ,\omega)]$$

$$VSS=RP-EEV$$

Median of value of stochastic solution for five different runs and different values of p and EV market share.



Future Research

- Our model could be used to **design incentive mechanism** for charging station operators to finalize location decisions
  - We will develop an **incentive allocation** model which will optimize the allocation of incentive resources across multiple charging stations to influence their optimal locations
- Assess the impact of behavioral uncertainties by a social scientist
- We used **expected value (risk-neutral)** function for two-stage model.
  - What is the impact of including **risk-measures** in the objective function on optimal location and capacity of EV charging stations in the community?
- Inclusion of **multi-modal transportation** in the model.
  - Study of impact of multi-modal transportation on EV network design

Contribution

- **Designing Community-Aware Charging Networks for EVs**
  - **Two-stage SP** model to determine **location** and **capacity** of public EV charging stations for communities to maximize access
  - Incorporation of **uncertainties** (EV demand flows, EV drivers' charging patterns, arrival and departure time, purpose of arrival to a community, walking preferences)
  - Adoption of **SAA** to solve two-stage model
  - Effective **heuristic** for **large-scale instances**
  - **Case study** (Detroit midtown area) and post-analysis framework
- **Designing Community-Aware Charging Networks for EVs**
  - **Exploration and Integration:** Called for data from several different sources to generate meaningful formulation and scenarios
  - Model presented to **SEMCOG**
  - **Computational Complexity:** Several hours for large scenario set
- **Presentations**
  - Manuscript submitted to **IEEE Transactions on Intelligent Transportation Systems** (Jan 2017)
  - Presented:
    - INFORMS National Meeting, 2016

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Thank You!