This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

A Stochastic Programming Approach for Electric Vehicle Charging Network Design

Sina Faridimehr, Saravanan Venkatachalam, and Ratna Babu Chinnam

***Abstract*— The advantages of electric vehicles (EVs) include reduction of greenhouse gas and other emissions, energy security, and fuel economy. The societal benefits of large-scale adoption of EVs cannot be realized without adequate deployment of publicly accessible charging stations. We propose a two-stage stochastic programming model to determine the optimal network of charging stations for a community, considering uncertainties in the arrival and dwell times of vehicles, the state of charge of arriving vehicles' batteries, drivers' walking ranges and charging preferences, demand during weekdays and weekends, and the community's rate of EV adoption. We conducted studies using the sample average approximation method, which asymptotically converges to an optimal solution for a two-stage stochastic problem. However, this method is computationally expensive for large-scale instances. Therefore, we also developed a heuristic to produce nearly optimal solutions quickly for our data instances. We conducted computational experiments using various publicly available data sources and evaluated the benefits of the solutions for a given community, both quantitatively and qualitatively.**

***Index Terms*— Two-stage stochastic programming, electric vehicle, charging network, sample average approximation.**

I. Introduction

ELECTRIC vehicles (EVs) hold much promise, including diversification of the transportation energy feedstock, reduction of greenhouse gas and other emissions, and improved public health through improving local air quality. In general, widespread adoption of EVs is in alignment with sustainable transportation objectives based on social, economic, and environmental perspectives. It is estimated that EVs that draw their power from the U.S. electrical grid emit at least 30% less CO_2 than comparable gasoline or diesel-fueled vehicles [1]. As EV usage for daily commutes increases, consideration of the ability to recharge these vehicles away from home becomes even more important. The ever-growing need to recharge EVs away from home necessitates designing effective charging station networks. Using multiple linear regression, Sierzchula *et al.* [2] examined the effect of consumer financial incentives and several socioeconomic factors on the national EV market shares of 30 countries for the year 2012. The analysis shows that installing one charging station per 100,000 residents could have double the impact of a $1,000 financial incentive on the EV adoption rate.

Many studies have addressed how to locate charging stations for EVs. However, the majority of these have concentrated on large-scale state-wide networks, and only a few articles have investigated the design of a public charging station network for an urban area. Moreover, existing papers on the charging station location problem often assume that demands for charging service are deterministic and known to the decision makers, while in reality, the traffic flows are stochastic in nature (varying by the hour of the day, weekday/weekend, purpose of the commute, destination, etc.) and are thus characterized by significant uncertainty. The optimal solution for a deterministic model might be infeasible and/or significantly suboptimal in the presence of these uncertainties. This paper adds to the growing field of EV charging station network design by proposing a two-stage stochastic programming model to determine the locations and capacities of charging stations for an urban community. By considering uncertainties in charging patterns, demand, and drivers' behavior, the proposed stochastic model provides robust charging network designs, improving access to charging services. However, two-stage stochastic programming models often require a large number of scenarios for good representation of uncertainties. We use the sample average approximation (SAA) method, a Monte Carlo simulation-based sampling technique, in which the expected value of the objective function is approximated using a finite sample of scenarios. Since SAA can generally only solve small-size problems within a reasonable amount of time, we also propose an effective heuristic for large-scale instances. The proposed two-stage model and solution approach are evaluated with a case study that is based on data representing the midtown area of Detroit, Michigan, U.S.

In summary, the major contributions of this paper are: (1) formulation of a two-stage stochastic programming model to determine the location and capacity of public EV charging stations in an urban area in order to maximize access; (2) incorporation of uncertainties in EV demand flows, EV drivers' charging patterns, arrival and departure times, purpose of arrival to the community, and preferred walking distances; (3) adoption of SAA to solve the two-stage model; (4) an effective heuristic that provides near-optimal solutions for large-scale instances; and (5) a case study representing public charging network planning for Detroit's midtown area

Manuscript received January 9, 2017; revised November 5, 2017 and February 15, 2018; accepted May 18, 2018. This work was supported by the U.S. Department of Transportation through the Transportation Research Center for Livable Communities at Western Michigan University. The Associate Editor for this paper was E. Kosmatopoulos. *(Corresponding author: Saravanan Venkatachalam.)*

The authors are with the Department of Industrial and Systems Engineering, Wayne State University, Detroit, MI 48202 USA (e-mail: sina.faridimehr@wayne.edu; saravanan.v@wayne.edu; ratna.chinnam@wayne.edu).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TITS.2018.2841391

and a post-analysis framework to analyze the outputs of the two-stage model regarding the charging service's accessibility and utilization. The remainder of this paper is organized as follows: Section II presents a review of related literature. Section III describes the problem and the uncertainties considered in our model. Section IV formulates the model and describes the solution methodology. Section V presents the case study, scenario construction, computational experiments, and evaluations of the results. Finally, Section VI concludes the paper and provides directions for future studies.

II. Literature Review

During the past decade, many researchers have focused on optimally locating refueling stations for alternative-fuel vehicles. However, most of them have focused on EV charging in large state-wide networks to cover demands from EV drivers commuting between cities and metropolitan areas, while only a few articles have examined the design of charging networks for communities or urban areas. Much of the extant literature also considers deterministic approaches where all the parameters are assumed to be known, and there is a shortage of stochastic approaches that consider uncertainties regarding the available budget for constructing the charging network, type of charging stations, short-term and long-term charging demands, and charging behaviors of EV drivers.

A capacitated flow refueling location model that considers a limit on the traffic flow that any location can refuel in order to maximize the miles that alternative-fuel vehicles can travel is introduced in [3]. The work in [4] proposes a maximal covering model to find the optimal locations for EV charging stations in an urban area by maximizing the covered demand within a given distance. Model to obtain optimal locations capable of serving the round trip on each route is presented in [5], and another similar research work that guarantees an EV's access to a charging station within its driving range is addressed in [6]. Furthermore, the research is extended in [7] to answer some strategic questions, such as what is the minimum number of charging stations for refueling a certain percentage of the traffic flow, and how the refueling demand forecast impacts the location of fuel stations, using a computationally efficient model for flow-refueling locations. A capacitated multiple recharging-station location problem is considered in [8] with budget constraints and vehicle routing behaviors. A cost minimization model for EV charging stations in an urban area considering travel and investment costs is proposed in [9].

Other deterministic approaches include models to locate charging stations for EVs in an urban environment while considering several stops made by the driver [10], recharging behavior of drivers [11], environmental factors and service radius [12], lifetime cost of equipment, installation, and operation of charging stations for plug-in EVs [13], and vehicle travel patterns [14]. A major limitation of all these studies is that they assume a deterministic problem setting. As we confirm through our experiments and in [15], employing a stochastic formulation can lead to a significant improvement with respect to planners' objectives.

While planning under uncertainty has been addressed in many settings, such as transportation, energy, disaster planning, supply chain management, and production planning, the literature that considers uncertainties in planning for EV charging networks is limited. Based on transportation system and power grid, a two-stage stochastic programming model to find the optimal locations for battery exchange stations for plug-in hybrid electric vehicles (PHEVs), accounting for uncertainties in the demand for batteries, loads, and the generation capacities of renewable power sources is developed in [16]. Another study [17] proposes a two-stage stochastic program for locating permanent and portable charging stations to maximize the served traffic flows, and in [18] a stochastic flow-capturing location model is developed to locate a predetermined number of fast EV charging stations within a given region, with uncertainties in EV flows.

To efficiently assist city planners and policy makers in planning for a public EV charging network within a community, we need to adequately capture the uncertainties that exist in the demand for the public charging service. To the best of our knowledge, this is the first study to address the problem of locating public EV charging stations within a community using a two-stage stochastic programming approach while accounting for uncertainties in the customers' demand for the public charging service, arrival and dwell times, batteries' SOCs at the time of arrival, preferences for charging away from home, and EV drivers' willingness to walk.

III. Problem Description and Uncertainties

Unlike a conventional vehicle, an EV must frequently be parked for several hours to recharge its battery due to range constraints. Hence, we consider public parking facilities as potential locations for installing charging stations, which can in turn improve access for EVs as well as their adoption. The maximum number of installable charging stations depends on the total capacity of a parking lot. Without loss of generality, we assume that all charging-point terminal types are semi-rapid charging stations (level-2 type charging stations), which are typically recommended for public and private parking lots, and that they provide a 10- to 20-mile range per hour of charging. Also, a driver's walking distance to the final destination is considered as the decisive contributing factor for choosing a parking lot [19]. Based on a driver's walking distance preference, we determine a set of possible parking lots where the driver can park the EV, and then the driver is randomly assigned to one of these. If charging stations are installed in any of the parking lots that are within a driver's walking distance preference, the driver will be attracted to one of those parking lots depending on the availability of a charging station at the time of arrival. If there is no parking lot within the maximum distance that a driver is willing to walk, we assume that the driver will park the car on the street, and since it is difficult to track the walking distance to the final destination in this case, we do not consider this driver's demand in our analysis. We also assume that once a driver starts charging at a station, the vehicle will not

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

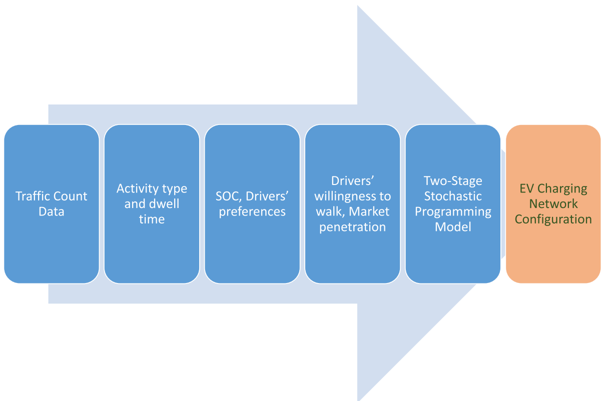

Fig. 1. Flow-diagram representing overall approach

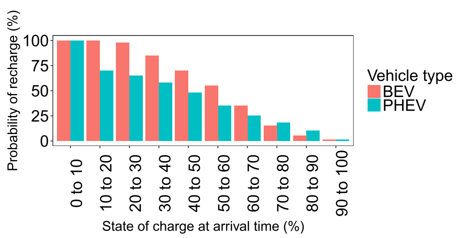

Fig. 2. Probability of recharging as a function of the batteries' SOCs at arrival time; Source: [20].

be unplugged until the driver's activity in the community is finished.

Designing a public EV charging network entails estimating the demand for the charging service. Like facility location models, we assume that demand occurs at fixed points in a network. Demand will be focused on the different parking lots based on drivers' willingness to walk in order to use the charging stations. Scenarios representing demand uncertainty in the two-stage model will indicate the time and purpose of arrival to the community, EV batteries' SOCs at the time of arrival, the duration of the drivers' activities, drivers' preferences for charging away from home, and their willingness to walk based on demographics, community size, and seasonal factors. The overall approach is depicted in Fig. 1. The following subsections present the uncertainties that are considered to affect demand for public EV charging stations.

A. State of Charge

A recent study analyzing two years of data of charging events that occurred away from home between January 2011 and December 2013 concluded that drivers of the Nissan Leaf (a pure battery electric vehicle, BEV) prefer to charge their vehicles before their batteries' SOCs drop to lower levels, while drivers of the Chevrolet Volt (a PHEV) tend to begin recharging only when there is little charge left in the battery since PHEVs rely on both an electric motor and an internal combustion engine for propulsion [20]. Fig. 2 compares the observed probabilities of recharging for the Nissan Leaf and the Chevrolet Volt for different values of the batteries' SOCs at the time of arrival.

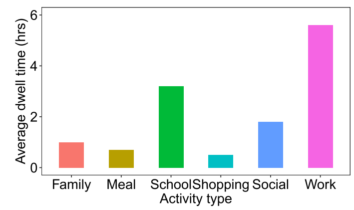

Fig. 3. Average dwell time for activity types; Sources: [20] and [21].

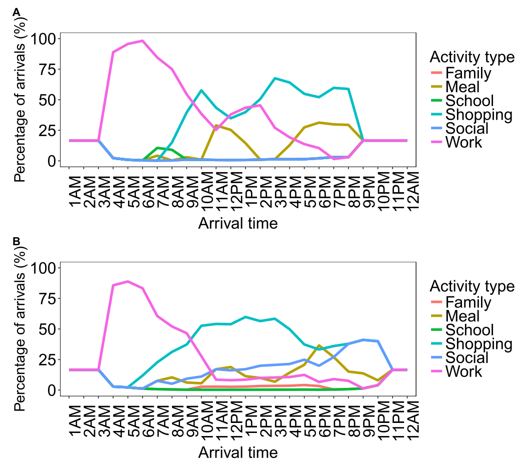

Fig. 4. The expected percentage breakdown for various vehicle arrivals on: A) weekdays and B) weekends; Sources: [20] and [21].

B. Dwell Time

We define six different destination categories based on National Household Travel Survey (NHTS) data: work, social, family, meal, study, and shopping. Fig. 3 shows the average time that people tend to park their vehicles based on their activity types [21]. Zhong *et al.* [22] concluded that Weibull, log-normal, and log-logistic distributions are the best distributions for modeling the duration of weekday and weekend activities. While their analysis shows that the model type and/or parameters or both might be different for an activity on a weekday versus a weekend, they found the Weibull distribution to be most applicable. In addition, they found that certain activities such as socializing and shopping tend to last longer on the weekend. We accordingly use the Weibull distribution in our analysis to estimate parking durations for EV drivers using the average activity time, and the durations of all weekday and weekend activities except meal activity are differentiated.

C. Weekday Vs. Weekend

The demand pattern for a public EV charging service can vary from day to day since people tend to attend social events, visit their families and go to shopping centers during the weekend more than on weekdays. For weekdays, most of the demand is due to people traveling to work or school. Fig. 4 confirms that the demand for charging stations depends on the time and type of day. On weekdays, the maximum demand occurs in the morning, when people are arriving at work or school, while the maximum demand usually occurs

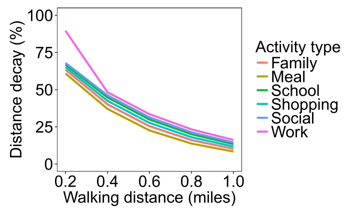

Fig. 5. Distance decay function for walking trips to different destination types; Source: [26].

around noon on weekends, when people are going to shopping malls and social places. According to [23], the best fitted distribution for arrival time at parking lots is a Weibull distribution. Hence, without loss of generality, we use two Weibull distributions to estimate the arrival time of EVs at parking lots on weekdays and on weekends.

D. Preference for Charging Away From Home

An Idaho National Laboratory analysis of data from 2012 and 2013 on over 4,000 Leafs and 1,800 Volts across the U.S. shows that 13% of Leaf drivers and 5% of Volt drivers charge their vehicles only at home. This indicates that the vast majority of drivers tend to use publicly accessible charging stations. This analysis also shows that although many people who drive more daily miles tend to charge their vehicles in places other than their home, the effect of daily miles traveled on the probability of charging away from home is small. Hence, without loss of generality, we do not consider the effect of driving distance to the community as a factor that will affect the chances of using EV charging stations.

E. EV Market Penetration

Many social, environmental, and economic factors contribute to an increasing market share for different types of EVs. A survey in [24] regarding adult drivers in large U.S. cities in Fall, 2011 sought to comprehend factors affecting the purchase of a plug-in EV. Besides demographic variables that can strongly predict the intent to purchase, the results show that the presence of a charging station within the community is the only awareness variable that has a significant effect on the intent to purchase. The Environmental Protection Agency (EPA) has estimated that 3.5% of the U.S. vehicle fleet will be BEVs or PHEVs during 2022-2025 time frame [25].

F. Willingness to Walk

Drivers' willingness to walk can be affected by sociodemographic characteristics such as age, gender, education level, and occupation. Many researchers have used a distance decay function to represent the willingness to walk or bike to different types of destinations as shown in Fig. 5. The parameter of this decay function depends on the activity type. Estimation results in [26] confirm that a negative exponential distribution can describe walking trips over short distances better than other distributions, such as a Gaussian distribution. The authors specified the distance decay function as:

$$P(d) = e^{-\beta d}, \tag{1}$$

TABLE I
ESTIMATED PARAMETER FOR THE DISTANCE DECAY FUNCTION

Factor	Category	β
Season	Winter (Dec to Feb)	1.88
	Spring (Mar to May)	1.68
	Summer (Jun to Aug)	1.64
	Autumn (Sep to Nov)	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

which shows the percentage of people who are willing to walk d or longer distances. They used 2009 NHTS data to estimate the decay parameter β for different groups and trip purposes. Their analysis shows that people are more willing to walk for recreation, social events, and work activities than for studying, shopping, or eating meals. Table I shows the parameters of the distance decay function influenced by variations in the factors like season, region, and community size.

IV. MODEL FORMULATION AND SOLUTION APPROACH

A. Model Formulation

Two-stage stochastic programming is a common approach for modeling decision making problems that involve uncertainty. First-stage decision variables represent 'here-and-now' decisions that are determined before the realization of randomness, and second-stage decisions are determined after scenarios representing the uncertainties are presented. In our model, binary variables in the first-stage determine the parking lots and the number of charging station installations for selected parking lots. In the second-stage, a recourse decision is made to assign EV drivers to one of their preferred parking lots based on their willingness to walk in such a way that the expected access of EV drivers to the public charging network is maximized.

We consider a set of S potential parking lots for placement of charging stations in a community. Given a parking lot $s \in S$, the number of charging stations that can be built in s is restricted to the set $L(s)$, and let $l \in L(s)$ denotes a charging capacity for a given $s \in S$. A demarcation for potential number of EV charging stations that can be installed for each parking lot s is made as each $s \in S$ varies in size. The set T represents the hours within the planning horizon, and indexed by $t \in T$. The set Γ denotes arrival and departure times for EV drivers and a combination of arrival and departure times is defined by $\gamma \in \Gamma$ with $\gamma(a)$ and $\gamma(d)$ denoting the arrival and departure times for γ, respectively. The final destinations of the EV drivers is denoted by I, a set of buildings. Also, the set $S'(i)$ denotes the subset of parking lots for potential use by the EV drivers whose final destination is building i. Let $\tilde{\omega}$ represents a random variable for the demand and each scenario ω is a realization of $\tilde{\omega}$.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Given the demand for different combinations of dwell time, final destinations and parking lots for each scenario, the mathematical model maximizes the expected access for the community by choosing parking lots and the number of EV charging stations installations for the chosen parking lots.

We define the following sets, parameters, and variables for the model:

- Sets
  - S: Set of parking lots, indexed by $s \in S$.
  - $L(s)$: Set of possible numbers of charging stations in a parking lot s, indexed by $l \in L(s)$.
  - I: Set of buildings, indexed by $i \in I$.
  - T: Set of time slots, indexed by $t \in T$.
  - Γ: Set of arrival and departure times, indexed by $\gamma \in \Gamma$.
  - Ω: Set of scenarios, indexed by $\omega \in \Omega$.
- Model Parameters
  - p: Number of parking lots that have charging stations installed.
  - m_l: Number of charging stations, $l \in L(s)$.
  - $d_{\gamma,i,s}(\omega)$: Demand with arrival and departure times set $\gamma \in \Gamma$ for a given $t \in T$ for a building $i \in I$ from drivers who are willing to park their vehicle in parking lot $s \in S'(i)$, where $S'(i) \subset S$ depending on i, in a scenario $\omega \in \Omega$.
  - $c_{l,s}$: Cost for installing l EV charging stations at location s.
  - B: Total available budget.
- First-Stage Decision Variables
  - x_s: 1, if parking lot $s \in S$ is used for installing charging stations; 0, otherwise.
  - $z_{l,s}$: 1, if $l \in L(s)$ charging stations are installed in parking lot $s \in S$; 0, otherwise.
- Second-Stage Decision Variables
  - $y_{\gamma,i,s}(\omega)$: Proportion of demand with arrival and departure times set $\gamma \in \Gamma$ for a building i from drivers who are willing to charge their vehicle in parking lot $s \in S'(i)$, where $S'(i) \subset S$ depending on i, in a scenario $\omega \in \Omega$.

The two-stage stochastic programming model is as follows:

First-Stage Model:

$$\text{Max } E_\Omega[\varphi(x, z, \tilde{\omega})] \tag{2}$$

$$\text{s.t. } \sum_{s \in S} x_s = p, \tag{3}$$

$$z_{l,s} \le x_s \quad \forall s \in S, l \in L(s), \tag{4}$$

$$\sum_{l \in L(s)} z_{l,s} \le 1 \quad \forall s \in S, \tag{5}$$

$$x_s, z_{l,s} \in \{0, 1\} \quad \forall s \in S, l \in L(s). \tag{6}$$

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

$$\varphi(x, z, \omega) = \text{Max} \sum_{\gamma \in \Gamma} \sum_{i \in I} \sum_{s \in S} y_{\gamma,i,s}(\omega) d_{\gamma,i,s}(\omega) \tag{7}$$

$$\text{s.t.} \sum_{\substack{\gamma \in \Gamma: \\ \gamma(a) \le t \le \gamma(d)}} \sum_{i \in I} y_{\gamma,i,s}(\omega) d_{\gamma,i,s}(\omega) \le \sum_{l \in L_s} m_l z_{l,s} \quad \forall s \in S, \ t \in T, \tag{8}$$

$$\sum_{s \in S} y_{\gamma,i,s}(\omega) \le 1 \quad \forall \gamma \in \Gamma, \ i \in I, \tag{9}$$

$$0 \le y_{\gamma,i,s}(\omega) \le 1 \quad \forall \gamma \in \Gamma, \ i \in I, \ s \in S. \tag{10}$$

In this model, first-stage decisions are made regarding the locations of charging stations and the charging capacity in each location. The objective function (2) maximizes the expected access representing the proportions of drivers using the EV network configuration prescribed by the first-stage decisions, and E_Ω is an expectation operator, with $E_\Omega[\varphi(x, z, \omega)]$ representing $\sum_{\omega \in \Omega} p_\omega \varphi(x, z, \omega)$, where p_ω is the probability of scenario ω's occurrence and $\sum_{\omega \in \Omega} p_\omega = 1$. Constraint (3) ensures that p parking lots are selected for installing EV charging stations. Constraints (4) and (5) determine charging capacity in any parking lot that is selected for providing EV charging service. Constraint (6) defines the feasible set for the binary first-stage variables. In the second-stage, for a realization $\omega \in \Omega$, recourse decisions are made to maximize the coverage of potential EV traffic flows based on the decisions made in the first-stage. Constraint (8) describes the supply–demand balance restrictions. It ensures that demand for any time period 't' assigned to a parking lot 's' for EV charging does not exceed its charging capacity. Constraint (9) ensures that proportions of allocation with an arrival and departure time 'γ' and building 'i' does not exceed its demand. Constraint (10) defines the bounds for the variables. The binary variables $z_{l,s}$ are useful in constructing budgetary constraints for the model. A budgetary constraint for the first-stage model is given as:

$$\sum_{s \in S, l \in L(s)} c_{l,s} z_{l,s} \le B. \tag{11}$$

The budgetary constraint is used in the computational experiments for sensitivity analysis in the later section.

B. Solution Approach

1) Sample Average Approximation: According to [27], unless there are only a small number of scenarios that can represent uncertainties in a problem, it is usually impossible to solve that stochastic programming problem. The authors showed that the optimal solution to a stochastic programming problem can be approximated by a much smaller sample of scenarios than the actual number of scenarios and that this approximation monotonically improves as we increase the number of scenarios. SAA, which was proposed by Mak *et al.* [27], is also an effective approach when a sufficient number of scenarios for estimating an optimal solution is unknown. For the sake of completeness, we provide the procedure for the SAA method:

1) Estimate an upper bound for the optimal solution:

- Generate M independent sample sets of scenarios, each of size N, i.e., $(\omega_j^1, \omega_j^2, \ldots, \omega_j^N)$ for $j = 1, 2, \ldots, M$.
- For each sample set $j = 1, 2, \ldots, M$, find the optimal solution:

$$\upsilon_N^j = \frac{1}{N}\sum_{i=1}^{N} \varphi(x, z, \omega_j^i). \tag{12}$$

- Compute the following:

$$\overline{\upsilon}_{N,M} = \frac{1}{M}\sum_{j=1}^{M} \upsilon_N^j, \tag{13}$$

$$\sigma^2_{\overline{\upsilon}_{N,M}} = \frac{1}{M(M-1)}\sum_{j=1}^{M}(\upsilon_N^j - \overline{\upsilon}_{N,M})^2. \tag{14}$$

The expected value of υ_N is greater than or equal to the optimal value υ^*. Since the sample average $\overline{\upsilon}_{N,M}$ is an unbiased estimation of the expected value of υ_N, $\overline{\upsilon}_{N,M}$ provides an upper statistical bound for the optimal solution.

2) Estimate a lower bound for the optimal solution:

- Let f be the objective function in (2), and if $(\overline{x}, \overline{z})$ is a feasible solution for the first-stage problem, then $f(\overline{x}, \overline{z}) \leq \upsilon^*$. Hence, choosing any feasible solution for the first-stage problem will provide a lower statistical bound for the optimal value.
- Choose a sample of scenarios of a size N' that is much larger than N and independent of samples, i.e., $(\omega^1, \omega^2, \ldots, \omega^{N'})$, to find the upper limit and estimate the objective function f:

$$f(\overline{x}, \overline{z}) = \frac{1}{N'}\sum_{i=1}^{N'} \varphi(x, z, \omega^i). \tag{15}$$

- Compute the variance for this estimation:

$$\sigma^2_{N'}(\overline{x}, \overline{z}) = \frac{1}{N'(N'-1)}\sum_{i=1}^{N'}(\varphi(x, z, \omega^i) - f(\overline{x}, \overline{z}))^2. \tag{16}$$

3) Estimate the optimality gap:

- Use the upper bound and the lower bound that are computed in the previous steps to estimate the optimality gap:

$$gap_{M,N,N'}(\overline{x}, \overline{z}) = \overline{\upsilon}_{N,M} - f(\overline{x}, \overline{z}). \tag{17}$$

4) Check the quality of the estimated optimality gap:

- The variance of the estimated optimality gap can be found by

$$\sigma^2_{gap} = \sigma^2_{\overline{\upsilon}_{N,M}} + \sigma^2_{N'}(\overline{x}, \overline{z}). \tag{18}$$

2) Heuristic: Because SAA requires relatively high computational resources, we developed a heuristic to solve large-scale problems efficiently. This heuristic is inspired by a score measure introduced in [28]. The score incorporates the charging capacity of each parking lot as well as its distance to other parking lots. The heuristic consists of a construction phase during which we build an initial solution and an improvement phase where we employ local search moves to find a better solution. The pseudocode for the heuristic is as follows:

Algorithm 1 Pseudocode for the heuristic

$bestsolution \leftarrow \emptyset$.
for $s \leftarrow 1$ to $Number of ParkingLots$ **do**:
  Compute score 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 have been added.
Improvement phase:
$currentsolution \leftarrow initialsolution$.
while $f(currentsolution)$ can be improved **do**
  remove-insert($currentsolution$).
end while
Store best solution found so far.

In the construction phase, the score for each parking lot as a potential location for installing charging stations is calculated as:

$$r_s = \sum_{s,s' \in S, s' \neq s} c_s e^{-\beta d_{s,s'}}, \tag{19}$$

where β is a user defined parameter. The score is measured as an incentive for the charging capacity (c_s) of each parking lot, using the distance ($d_{s,s'}$) to other parking lots as a cost. A parking lot that has greater capacity for installing charging stations and is nearer to other parking lots will have a higher score.

To consider the effect of the random parameters in constructing the initial solution, we use a set of sample scenarios to obtain the probability of parking lot s being chosen as one of the optimal locations for installing charging stations. The estimated probability for parking lot s, q_s, is computed based on the fraction of scenarios in which parking lot s is among the optimal locations. The attractiveness measure for parking lot s, ρ_s, is computed by multiplying this probability by the corresponding score:

$$\rho_s = r_s q_s. \tag{20}$$

Parking lots will be added to the initial solution in decreasing order of the attractiveness measure until p parking lots have been selected. In the improvement step, we use a local search method, the remove-insert procedure. Each parking lot that is in the initial solution is repeatedly replaced with one of the parking lots that has not been selected, namely, the parking lot that has the highest attractiveness measure, until there is no improvement in the objective function. This procedure is repeated for all parking lots that are selected in the initial solution, and finally, the best value found for the objective function is stored.

V. Case Study and Computational Experiments

To demonstrate the efficacy of the proposed approach, our case study investigates the community data for the midtown area of Detroit, Michigan, U.S. There is a wide range of employments with different types of final destinations in this area, it attracts a lot of traffic, and it is characterized by an urban university, commercial offices, hospitals, and museums. This area includes 135 buildings ($|I| = 135$), of which 67 are office buildings, 12 are social places, 5 are family-related buildings, 4 are restaurants, 44 are school buildings, and 3 are shopping places. There are 32 parking lots ($|S| = 32$) that can be considered as potential locations for installing EV charging stations. We assume that the parking lots are open between 6am and 6pm ($|T| = 12$) and have different capacities for installing charging stations. The center of each parking lot is considered as our candidate for installing a charging station, and Euclidean distances are used to measure the distance between any two points in the community. The EV demand for the case study is estimated in a two step process. The data from the Southeast Michigan Council of Governments [29] shows that average annual daily traffic for the Detroit midtown area is approximately between 10,000 and 20,000, and like [7], we assume that the total daily traffic for this community follows a uniform probability distribution. Furthermore, the EV demand for final destination is calculated based on the different activity types during the time of the day and day of the week as suggested in [20] and [21].

Based on an EPA analysis, we examine cases in which EVs constitute 3% and 5% of the light-duty vehicle fleet. According to [30], weather/climate is positively correlated with the BEV market share. Since our case study is in an area with low winter temperatures, the BEV market share is considered lower than the PHEV market share. We construct two cases for our computational experiments. In the first case, we assume that the market shares are 1% and 2% for BEVs and PHEVs, respectively. In the second case, these market shares are assumed to be 2% and 3%, respectively.

In this study, we use negative exponential distribution functions estimated by Yang and Diez-Roux [26] to describe the patterns of willingness to walk for various activity types, considering the effects of season and community size in the U.S. Each driver is randomly assigned to a parking lot that is within his/her walking distance preference. For both cases of the EV market share, 13% of the total demand is not considered in our model since there is no parking lot within these drivers' walking distance preferences, and it is also difficult to track their walking distance to their final destination if they use other EV-charging sources placed on streets or at other non-parking-lot locations. We considered four different values (2, 4, 6, and 8) for the number of parking lots (p) to install charging stations in. The optimization models for

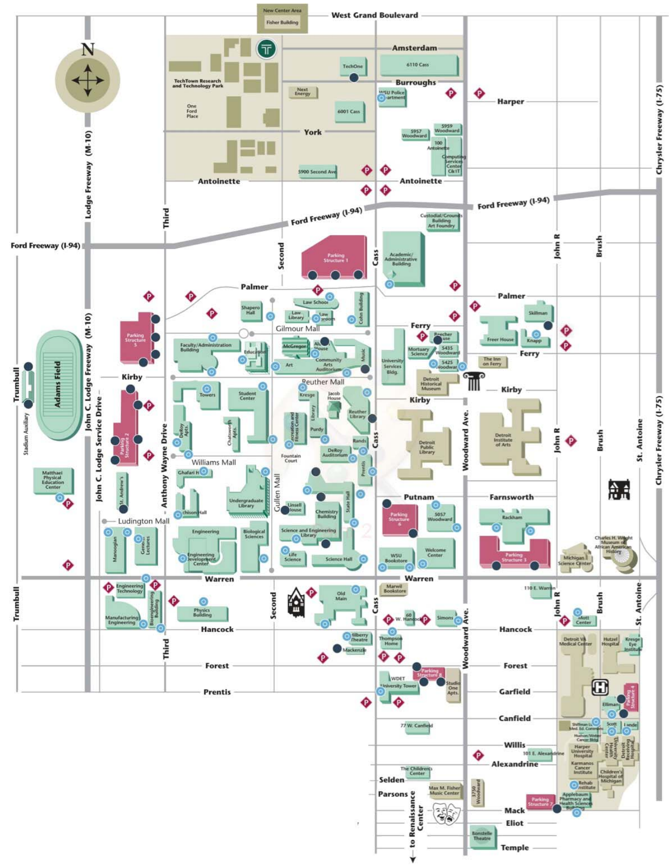

Fig. 6. Part of the Detroit midtown area used for our analysis.

SAA and the heuristic were implemented in Python 2.7, using Gurobi 6.5.1 software for solving optimization problems. All of the computations were performed on a system with an Intel ® Xeon ® CPU, 3.10 GHz, and 24GB RAM.

A. Scenario Construction

For the two-stage model, uncertainties are modeled by use case scenarios. A scenario represents a single day of public EV charging service and is influenced by short-term (weekday vs. weekend) and long-term (seasonal) variations and the total number of EVs arriving in the community. The probability of a scenario's occurrence is based on a uniform probability distribution. Without loss of generality, we assume that any given scenario day in winter, spring, summer, or autumn has equal probability.

In each scenario, a random number from $U(0, 1)$ determines the type of each vehicle in the community. When the random number is less than the BEV market share, between the BEV market share and the sum of the BEV and PHEV market shares, or greater than the sum of the BEV and PHEV market shares, the vehicle is assumed to be a BEV, a PHEV, or an ICE (internal combustion engine), respectively. If the vehicle is an EV, Weibull distributions with shape and scale parameters (8, 3) and (13, 4) are used to determine the EV drivers' arrival time in the community on a weekday and a weekend day, respectively. As explained in Section III-B, the purpose of a

TABLE II
WEIBULL DISTRIBUTION PARAMETERS FOR ACTIVITY DURATION

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)

TABLE III
SAA PERFORMANCE WHEN $(M, N') = (20, 1{,}000)$ AND $(\text{BEV}, \text{PHEV}) = (1\%, 2\%)$

p	N	UB (%)	LB (%)	gap (%)	gap SD	Opt (s)	Heuristic (%)	Heuristic (s)
	30	57.98	56.59	2.39	0.0064	397	57.98	68
2	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
	30	73.89	73.42	0.63	0.0056	720	73.88	114
4	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
	30	83.97	83.62	0.35	0.0039	1,071	83.21	160
6	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
	30	91.16	90.61	0.61	0.0026	1,124	90.28	185
8	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

TABLE IV
SAA PERFORMANCE WHEN $(M, N') = (20, 1{,}000)$ AND $(\text{BEV}, \text{PHEV}) = (2\%, 3\%)$

p	N	UB (%)	LB (%)	gap (%)	gap SD	Opt (s)	Heuristic (%)	Heuristic (s)
	30	50.42	50.00	0.85	0.0056	462	50.42	82
2	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
	30	63.35	63.16	0.30	0.0064	1,595	63.33	169
4	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
	30	72.56	71.55	1.39	0.0071	1,663	72.34	208
6	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
	30	78.91	78.49	0.52	0.0048	1,494	78.53	273
8	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

driver's arrival is determined, and a Weibull distribution is used to estimate the duration of various types of weekday and weekend activities. Table II represents the parameters for this distribution based on the type of activity. In this table, the first and second numbers represent the shape and scale parameters, respectively.

For a final destination, each EV driver is randomly assigned to a target destination/building using a uniform distribution based on the driver's purpose of arrival to the community. A random number is generated from the exponential distribution as shown in Fig. 5 to determine the distance each EV driver is willing to walk based on the purpose of his/her arrival. Community size and type of region are also considered in the distributions to estimate the distances drivers are willing to walk. If there is no parking lot within the distance a driver is willing to walk, then our model does not consider this driver's demand. The uniform distribution $U(0, 1)$ is used to assign charging preferences to the EV drivers. A random number that is greater than 13% for a BEV or 5% for a PHEV determines that the driver is willing to charge away from home. Consistent with recommendations from [31] and [32], we assume without loss of generality that the batteries' SOCs for vehicles arriving at the charging stations follow a normal distribution $N(0.30, 0.10)$, with a mean of 0.30 and a standard deviation of 0.10. Based on the batteries' SOCs at the arrival time, uniform distribution $U(0, 1)$ is used to determine each EV driver's willingness to charge their EV at public charging stations. This is further compared with the associated probability of recharging based on the type of EV, as discussed earlier in the Section IIIA. If the random number is less than or equal to the probability of recharging then that EV is considered as a demand for the EV charging network in the community. Similarly, multiple scenarios are constructed for the two-stage stochastic programming model to simulate the arrival patterns, batteries' SOCs, dwell durations, charging preferences, and willingness to walk in the community.

B. SAA Settings

To estimate an upper bound for the expected accessibility of public EV charging stations, $N = 30$, 50, and 100 scenarios are used, and this is repeated $M = 20$ replications. The average of these 20 runs is an estimate of the upper bound on the accessibility. A sample of $N' = 1,000$ scenarios that are separate from those that were used to get the upper bound is used to estimate a lower bound for the optimal solution. The computational performances of heuristic and exact method are summarized in Tables III and IV. The computation run times

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

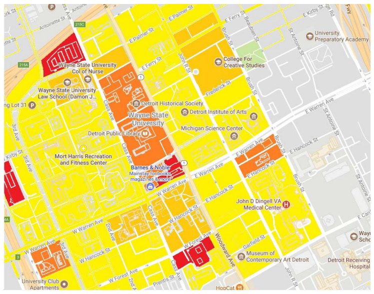

Fig. 7. Demand map used for the case study.

show that the optimization model using SAA is able to solve problems with eight optimal locations in less than five hours. In these tables, UB (%) and LB (%) indicate the upper and lower bounds for the expected accessibility of the public EV charging service using SAA. Gap (%) and gap SD indicate the differences between the upper and lower bounds and the standard deviation, respectively. Opt(s) is the running time for the SAA in seconds. The best solution found by our heuristic for the upper bound of the objective function and its running time are indicated as Heuristic (%) and Heuristic (s).

C. Performance Measures

The number of public chargers per capita could have a significant effect on both the BEV market share and the PHEV market share. The average of the total monetary benefits for EV consumers across 25 major metropolitan areas is around \$2,800 per BEV and \$1,600 per PHEV [33]. To deal with uncertainties in the demand for the public EV charging service and to simulate the expected output measures with different numbers of chargers in the community, we generate a set of 50 scenarios for our analysis. We study two different cases for the willingness to walk pattern in the community in order to generate optimistic and pessimistic bounds for the level of walking of people who have access to the public EV charging network. In the optimistic case, we assume that people are willing to walk long distances and will always choose the farthest available charging station from their final destination, whereas in the pessimistic case, people are only willing to walk short distances and always choose the nearest available station to their building. Five different indicators are used to measure the performance of the public EV charging placement: accessibility, lost demand, charging station utilization, total walking distance, and walking distance per capita. Accessibility is defined as the percentage of EV drivers who could charge their vehicles in public charging stations in the community, and lost demand is the percentage of EV drivers who could not use the public EV network due to insufficient capacity. Charging station utilization is the percentage of time that a charging station is used by an EV on the average. To assess walking patterns among people before and after the public EV charging stations are installed, we use the total walking distance and the walking distance per capita.

Fig. 7 represents the demand distribution for the Fig. 6, and Fig. 8 represents the locations selected by the heuristic based on the two-stage stochastic formulation. The color

Fig. 8. Network configuration for different p's a) $p = 2$, b) $p = 4$, c) $p = 6$, and d) $p = 8$, $N = 50$, and (BEV, PHEV) = (1%, 2%).

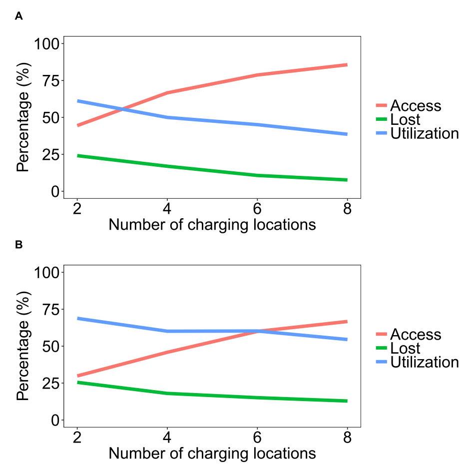

Fig. 9. Percentages for accessibility, lost demand, and charging utilization in the A) (BEV,PHEV) market shares are (1%,2%) and B) (BEV,PHEV) market shares are (2%,3%).

in Fig. 7 represents parking demand density for different areas. The darker the color, the higher the parking demand for the corresponding area. As shown in Fig. 9, the accessibility of the public charging service increases in both cases of the EV market share as more charging stations are installed in the community, but the utilization level of the stations simultaneously decreases. An increase in the EV market share can reduce the accessibility of the public charging network as much as 32% in both the optimistic and the pessimistic cases. However, this increase in demand will increase the utilization level up to 41% and the lost demand up to 68%.

Figs. 10 and 11 compare the average percentages for the hourly utilization levels of the charging stations on weekdays versus weekends in an optimistic case of willingness to walk and indicate a difference in the utilization patterns between weekdays and weekends. Utilization peaks around eight in the morning on weekdays, while it peaks around noon during weekends. These patterns match the expected arrival patterns of people in the community on weekdays and weekends. These plots also indicate that utilization for the charging stations decreases whenever the availability increases. This is important from a revenue perspective since the utilization level

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

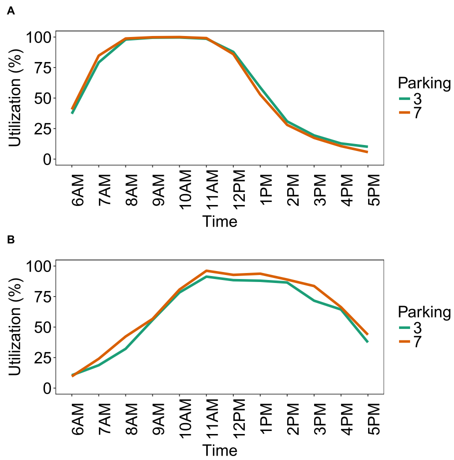

Fig. 10. Average percentages for hourly utilization on A) weekdays and B) weekends in an optimistic case when $p = 2$ and the (BEV,PHEV) market shares are (1%,2%).

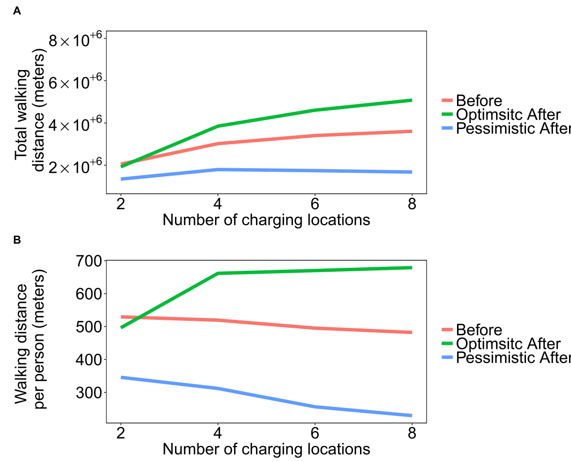

Fig. 12. A) Total walking distance and B) walking distance per capita for people who have access to a public EV charging service when the (BEV,PHEV) market shares are (1%,2%).

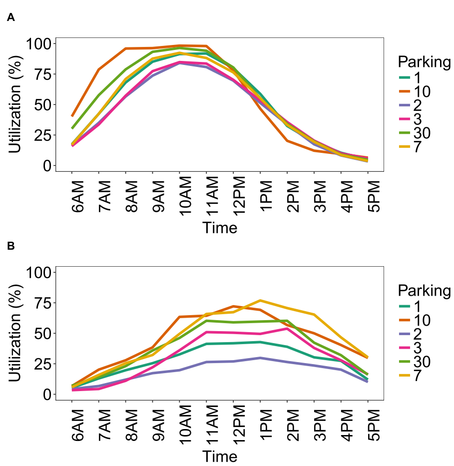

Fig. 11. Average percentages for hourly utilization on A) weekdays and B) weekends in an optimistic case when $p = 6$ and the (BEV,PHEV) market shares are (1%,2%).

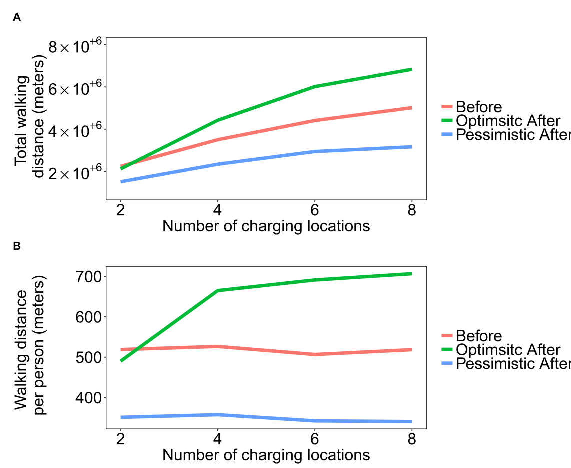

Fig. 13. A) Total walking distance and B) walking distance per capita for people who have access to a public EV charging service when the (BEV,PHEV) market shares are (2%,3%).

is a major driver to estimate profitability of an investment in public EV charging stations [34].

An important measure of livability analysis via transportation is an increase in travel options so that people can meet at least some of their travel needs through walking and biking and thereby improve their health [35]. It has been estimated that a shift from driving to walking could save an average person approximately 25c per vehicle-mile traveled and 50c under urban peak conditions, when emission and parking costs are high [36]. This indicates that an efficient design of EV charging network can also provide opportunities for people in the community to increase their levels of physical activity.

Figs. 12 and 13 compare the total walking distance and walking distance per capita among people who have access to a public EV charging service in the community before and after charging stations are installed. As earlier, two cases are evaluated, an optimistic case where we assume that people will always choose the farthest available parking lot for EV charging and a pessimistic case where people will always choose the nearest available parking lot. These plots show that increasing the number of charging stations in the community can increase the total walking distance and the walking distance per capita among people who have access to public EV charging stations as much as 40% in an optimistic case. However, the rate of increase in the total walking distance and walking distance per capita decreases as more charging stations are installed in the community. This is due to EV drivers getting closer to the charging stations from their final destinations and their need to walk is thus reduced.

Another interesting perspective is the relationship between the willingness to walk pattern and access to charging stations, as young and old people are expected to have different levels of willingness to walk. Young people tend to walk more, while elderly people are not willing to walk long distances. Fig. 14 shows that if the average walking distance preference drops to half, the accessibility of public EV charging stations will decrease by 4.23% and 1.32% when $p = 4$ and $p = 6$, respectively. However, if the average of the willingness to walk

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

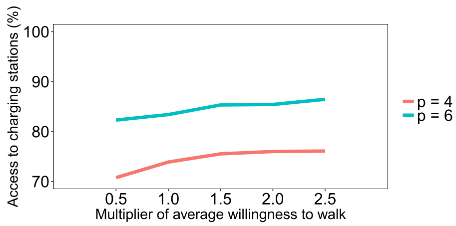

Fig. 14. Accessibility for different willingness to walk distribution averages when (BEV,PHEV) market shares are (1%,2%).

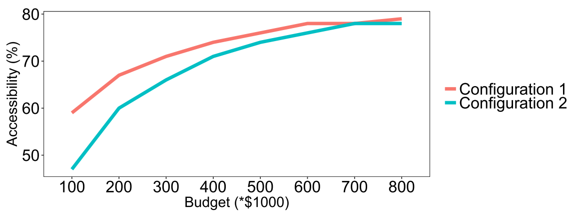

Fig. 15. Percentages for accessibility for two configurations when $p = 4$ and the (BEV,PHEV) market shares are (1%,2%).

distribution is doubled, accessibility increases by 2.86% and 2.43% when $p = 4$ and $p = 6$, respectively. This provides an additional perspective for policy makers and also indicates the robustness of the model to any changes in a community's pattern for willingness to walk.

D. Sensitivity Analysis

In the previous sections, all the installed charging stations are assumed to be level 2 type. To assess the robustness of the model parameters' uncertainties and their impact on accessibility, we considered a combination of levels for the experiment. Also, this provides an assessment for the city planners since the cost and performance vary for different types of chargers. We defined two configurations: configuration 1 - level 1 and level 3; configuration 2 - level 2 and level 3. Average unit costs for level 1, level 2 and level 3 charging stations are assumed to be \$900, \$3,450 and \$25,000, respectively [37]. In terms of charging time, for a 80-mile battery, level 1 and level 2 types take around 16 hours and 3.5 hours, respectively, while level 3 takes only around 30 minutes [38]. We assume that drivers with family, social, school, meal and shopping purposes along with drivers with work purpose having a short duration of stay are willing to use level 3 charging stations and will leave charging station once the vehicle is fully recharged. We also assume that charging stations in each parking lot are either slow (level 1 or level 2) or fast (level 3) depending on demand for these charging levels. Experiments were conducted by changing different values for budget parameter 'B' in the equation (11) and number of potential charging stations as four, $p = 4$. As shown in Fig. 15, configuration 1 provides better accessibility for the community in our data setup for the same budget since level 1 is much less expensive than a level 2 installation and more charging stations can be installed in case of configuration 1. Also the gap between the configurations reduced as the budget increased and this was due to the availability of additional funding for the installation of level 2

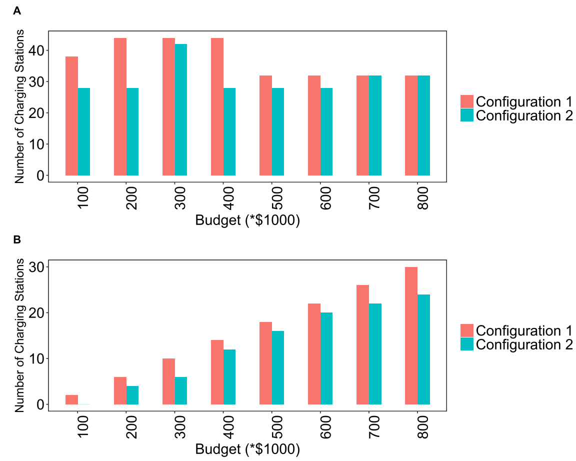

Fig. 16. A) Number of slow charging stations and B) Number of fast charging stations for two configurations when $p = 4$ and the (BEV,PHEV) market shares are (1%,2%).

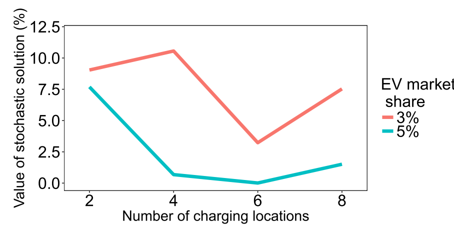

Fig. 17. Median value of the stochastic solution for five different runs and different values of p and the EV market share.

type chargers for configuration 2. This increased the access as charging time for level 2 is one fourth of level 1. The increase in level 3 charging stations was proportionate to the raise in the budget for both the configurations. The model without budgetary constraint utilized the entire capacity in each of the selected charging stations, and Fig. 16 provides the mix of charging equipment levels for each configuration during the runs in sensitivity analysis.

E. Value of the Stochastic Solution

The value of the stochastic solution was first introduced by Birge [39] and is a standard means to quantify the usefulness of the stochastic programming approach. Let the objective value of the recourse problem be given as $RP = E_{\Omega}[\varphi(x, z, \omega)]$; the *expected value problem* is obtained by replacing all random variables in scenarios with their expected values, $EV = \varphi(x, z, \bar{\omega})$, where $\bar{\omega}$ for the demand parameter will be $\sum_{\omega \in \Omega} p_{\omega} d_{\gamma,i,s}(\omega)$, with p_{ω} representing a scenario ω's probability of occurrence and $\sum_{\omega \in \Omega} p_{\omega} = 1$. Letting $\bar{x}, \bar{z}$ represent solutions for the EV problem, the expected result of using the expected value solutions $(\bar{x}, \bar{z})$ is $EEV = E_{\Omega}[\varphi(\bar{x}, \bar{z}, \omega)]$. The value of the stochastic solution can then be defined as $VSS = RP - EEV$. To obtain VSS, we use the same number of scenarios as for the SAA results. Based on five different runs and the data defining the uncertainties in the experiments, Fig. 17 exhibits that stochastic programming approach can increase the accessibility of the public EV charging network as much as 10.56% and 7.69%, when the EV market shares are 3% and 5%, respectively.

VI. Conclusion

In this paper, we presented a two-stage stochastic programming model for the public EV charging station network design problem in a community. We considered several uncertainties, such as the total EV flows, arrival and dwell times, batteries' SOCs at the time of arrival, the charging preferences of EV drivers, and their patterns for willingness to walk, when estimating the demand for a public EV charging service. We used the sample average approximation method, and for better computational performance, we proposed an effective heuristic that can solve large-scale problems and produce near-optimal solutions. In a post analysis, our model presented a number of insights about the design of a public EV charging network for an urban/community area. The results show that increasing the number of charging stations in the community will improve the accessibility of the charging service for EV owners but will also reduce the utilization level of the stations. Although all charging stations have similar demand patterns, increasing the number of charging stations will increase the differences in their utilization. While more charging stations in a community can potentially increase the total walking distance and walking distance per capita, the rate of increase for these measures decreases. Our model also exhibits robustness to any future changes in the community's pattern of willingness to walk. We believe that these analyses will provide better insights for policy makers. Apart from willingness to walk, other factors that could potentially affect drivers' choices are price for charging stations and accessibility of multi-modal transportation. From planners' perspective, population density, livability aspects and environmental consciousness are important. As a future study, a choice model representing the behavioral aspects of drivers can be embedded within the two-stage stochastic programming model, and this could present interesting perspectives. Although we have used the expected value function for the two-stage model, it will be interesting to study the benefits of including risk-measures for these strategic decisions.

References

[1] D. J. Berger and A. D. Jorgensen, "A comparison of carbon dioxide emissions from electric vehicles to emissions from internal combustion vehicles," *J. Chem. Educ.*, vol. 92, no. 7, pp. 1204–1208, 2015.

[2] W. Sierzchula, S. Bakker, K. Maat, and B. van Wee, "The influence of financial incentives and other socio-economic factors on electric vehicle adoption," *Energy Policy*, vol. 68, pp. 183–194, May 2014.

[3] C. Upchurch, M. Kuby, and S. Lim, "A model for location of capacitated alternative-fuel stations," *Geograph. Anal.*, vol. 41, no. 1, pp. 85–106, 2009.

[4] I. Frade, A. Ribeiro, G. Goncalves, and A. Antunes, "An optimization model for locating electric vehicle charging stations in central urban areas," *J. Transp. Res. Rec., J. Transp. Res. Board*, vol. 10, pp. 1–31, Jan. 2011.

[5] I. Capar and M. Kuby, "An efficient formulation of the flow refueling location model for alternative-fuel stations," *IIE Trans.*, vol. 44, no. 8, pp. 622–636, 2012.

[6] A. Y. S. Lam, Y.-W. Leung, and X. Chu, "Electric vehicle charging station placement: Formulation, complexity, and solutions," *IEEE Trans. Smart Grid*, vol. 5, no. 6, pp. 2846–2856, Nov. 2014.

[7] I. Capar, M. Kuby, V. J. Leon, and Y.-J. Tsai, "An arc cover–path-cover formulation and strategic analysis of alternative-fuel station locations," *Eur. J. Oper. Res.*, vol. 227, no. 1, pp. 142–151, 2013.

[8] Y. W. Wang and C.-C. Lin, "Locating multiple types of recharging stations for battery-powered electric vehicle transport," *Transp. Res. E, Logistics Transp. Rev.*, vol. 58, pp. 76–87, Nov. 2013.

[9] F. Baouche, R. Billot, R. Trigui, and N.-E. El Faouzi, "Efficient allocation of electric vehicles charging stations: Optimization model and application to a dense urban network," *IEEE Intell. Transp. Syst. Mag.*, vol. 6, no. 3, pp. 33–43, Jul. 2014.

[10] J. Cavadas, G. H. de A. Correia, and J. Gouveia, "A MIP model for locating slow-charging stations for electric vehicles in urban areas accounting for driver tours," *Transp. Res. E, Logistics Transp. Rev.*, vol. 75, pp. 188–201, Mar. 2015.

[11] F. He, Y. Yin, and J. Zhou, "Deploying public charging stations for electric vehicles on urban road networks," *Transp. Res. C, Emerg. Technol.*, vol. 60, pp. 227–240, Nov. 2015.

[12] Z. Liu, F. Wen, and G. Ledwich, "Optimal planning of electric-vehicle charging stations in distribution systems," *IEEE Trans. Power Del.*, vol. 28, no. 1, pp. 102–110, Jan. 2013.

[13] Y. Huang and Y. Zhou, "An optimization framework for workplace charging strategies," *Transp. Res. C, Emerg. Technol.*, vol. 52, pp. 144–155, Mar. 2015.

[14] N. Shahraki, H. Cai, M. Turkay, and M. Xu, "Optimal locations of electric public charging stations using real world vehicle travel patterns," *Transp. Res. D, Transp. Environ.*, vol. 41, pp. 165–176, Dec. 2015.

[15] J. Tan and W.-H. Lin, "A stochastic flow capturing location and allocation model for siting electric vehicle charging stations," in *Proc. 17th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2014, pp. 2811–2816.

[16] F. Pan, R. Bent, A. Berscheid, and D. Izraelevitz, "Locating PHEV exchange stations in V2G," in *Proc. 1st IEEE Int. Conf. Smart Grid Commun. (SmartGridComm)*, Oct. 2010, pp. 173–178.

[17] M. Hosseini and S. MirHassani, "Refueling-station location problem under uncertainty," *Transp. Res. E, Logistics Transp. Rev.*, vol. 84, pp. 101–116, Dec. 2015.

[18] F. Wu and R. Sioshansi, "A stochastic flow-capturing model to optimize the location of fast-charging stations with uncertain electric vehicle flows," *Transp. Res. D, Transp. Environ.*, vol. 53, pp. 354–376, Jun. 2017.

[19] A. S. Bergantino, C. Capozza, A. De Carlo, and A. Morone, "What drives parking choices: A laboratory experiment," Univ. Bari Aldo Moro, Bari, Italy, White Paper, 2014.

[20] R. P. Brooker and N. Qin, "Identification of potential locations of electric vehicle supply equipment," *J. Power Sources*, vol. 299, pp. 76–84, Dec. 2015.

[21] J. Krumm, "How people use their vehicles: Statistics from the 2009 national household travel survey," SAE Tech. Paper 2012-01-0489, 2012.

[22] M. Zhong, J. Hunt, and X. Lu, "Studying differences of household weekday and weekend activities: A duration perspective," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2054, pp. 28–36, Nov. 2008. [Online]. Available: https://trrjournalonline.trb.org/toc/trr/2008/2054/+

[23] S. Guner and A. Ozdemir, "Distributed storage capacity modelling of EV parking lots," in *Proc. 9th Int. Conf. Electr. Electron. Eng. (ELECO)*, Nov. 2015, pp. 359–363.

[24] S. Carley, R. M. Krause, B. W. Lane, and J. D. Graham, "Intent to purchase a plug-in electric vehicle: A survey of early impressions in large US cites," *Transp. Res. D, Transp. Environ.*, vol. 18, pp. 39–45, Jan. 2013.

[25] U.S. Environmental Protection Agency. *Midterm Evaluation of Light-Duty Vehicle Greenhouse Gas Emissions Standards for Model Years 2022-2025*. Accessed: Aug. 15, 2017. [Online]. Available: https://www.epa.gov/regulations-emissions-vehicles-and-engines/midterm-evaluation-light-duty-vehicle-greenhouse-gas

[26] Y. Yang and A. V. Diez-Roux, "Walking distance by trip purpose and population subgroups," *Amer. J. Preventive Med.*, vol. 43, no. 1, pp. 11–19, 2012.

[27] W.-K. Mak, D. P. Morton, and R. K. Wood, "Monte Carlo bounding techniques for determining solution quality in stochastic programs," *Oper. Res. Lett.*, vol. 24, nos. 1–2, pp. 47–56, 1999.

[28] T. Tsiligirides, "Heuristic methods applied to orienteering," *J. Oper. Res. Soc.*, vol. 35, no. 9, pp. 797–809, 1984.

[29] *Southeast Michigan Council of Governments (SEMCOG)—Data and Maps*. Accessed: Aug. 15, 2017. [Online]. Available: http://semcog.org/Data-and-Maps

[30] S. Vergis and B. Chen, "Comparison of plug-in electric vehicle adoption in the United States: A state by state approach," *Res. Transp. Econ.*, vol. 52, pp. 56–64, Oct. 2015.

[31] M. Dai, J. Zheng, M. Zhang, and W. Wang, "Optimization of electric vehicle charging capacity in a parking lot for reducing peak and filling valley in power grid," in *Proc. IEEE Int. Conf. Adv. Power Syst. Autom. Protection (APAP)*, vol. 2, Oct. 2011, pp. 1501–1506.

[32] Z. Luo, Z. Hu, Y. Song, Z. Xu, and H. Lu, "Optimal coordination of plug-in electric vehicles in power grids with cost-benefit analysis—Part I: Enabling techniques," *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 3556–3565, Nov. 2013.

[33] N. Lutsey, S. Searle, S. Chambliss, and A. Bandivadekar, "Assessment of leading electric vehicle promotion activities in United States cities," Int. Council Clean Transp., Washington, DC, USA, White Paper, 2015.

[34] D. Chang *et al.*, "Financial viability of non-residential electric vehicle charging stations," Luskin Center Innov., Los Angeles, CA, USA, White Paper, 2012.

[35] W. E. Marshall, "An evaluation of livability in creating transit-enriched communities for improved regional benefits," *Res. Transp. Bus. Manage.*, vol. 7, pp. 54–68, Jul. 2013.

[36] T. Litman, "Economic value of walkability," *World Transp. Policy Pract.*, vol. 10, no. 1, pp. 5–14, 2004.

[37] M. Smith and J. Castellano, "Costs associated with non-residential electric vehicle supply equipment: Factors to consider in the implementation of electric vehicle charging stations," Dept. Energy, Washington, DC, USA, Tech. Rep. DOE/EE-1289, 2015.

[38] *Driver's Checklist: A Quick Guide to Fast Charging*. Accessed: Oct. 15, 2017. [Online]. Available: http://www.chargepoint.com

[39] J. R. Birge, "The value of the stochastic solution in stochastic linear programs with fixed recourse," *Math. Program.*, vol. 24, no. 1, pp. 314–325, 1982.

Sina Faridimehr received the B.S. and M.S. degrees in industrial engineering from Sharif University of Technology, Tehran, Iran, in 2009 and 2011, respectively. He is currently pursuing the Ph.D. degree in industrial and systems engineering with Wayne State University, Detroit, MI, USA. His research interests are in service operations management and data-driven decision making.

Saravanan Venkatachalam received the M.S. and Ph.D. degrees in industrial and systems engineering from Texas A&M University, College Station, in 2003 and 2014, respectively. He is currently an Assistant Professor of industrial and systems engineering with Wayne State University. His research interests are in stochastic programming, large-scale optimization, and discrete event modeling and simulation, and applications of interest include supply chain management, healthcare, pricing and revenue management, and energy management.

Ratna Babu Chinnam received the M.S. and Ph.D. degrees in industrial engineering from Texas Tech University, Lubbock, in 1990 and 1994, respectively. He is currently a Professor of industrial and systems engineering and the Director of the Big Data and Business Analytics Group, Wayne State University. His research interests include business analytics, big data, supply chain management, freight logistics, operations management, sustainability, healthcare systems engineering, and smart engineering systems.