

Simulation-Optimization Model for Location of a Public Electric Vehicle Charging Infrastructure

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Abstract

The paper develops a simulation-optimization model that determines where to locate electric vehicle chargers to maximize their use by privately owned electric vehicles. Applying this model to the central-Ohio region, we demonstrate that a combination of level-one and -two chargers is preferable to level-two chargers only. We further explore interactions between the optimization criterion used and the budget available. We finally show that although the optimal location is sensitive to the specific optimization criterion considered, overall service levels are less sensitive to the optimization strategy.

Keywords: Electric vehicles, charging infrastructure location, vehicle charging

1. Introduction

An important electric charging infrastructure design question focuses on what charging technology to use. There are currently three major EV charging technologies available. Level-one charging uses a standard wall outlet, providing a 110 V/15 A connection. Typical EV batteries, which range between 16 and 25 kWh, can take 12 to 18 hours to fully charge using such a connection. Level-two charging uses a larger ‘appliance circuit,’ which is typically rated at 220 V and between 15 and 30 A. DC fast charging uses high-voltage (often 400 to 500 V) direct current and can fully charge a typical EV battery in as little as 30 minutes. Since DC fast charging requires special equipment, it is not expected to be deployed in standard residential settings.

Another challenge is where to locate charging stations. Charging station location belongs to the general class of refueling infrastructure problems, however most of the existing approaches to solving them are more appropriate for ‘fast’ refueling. Indeed, most works typically neglect fueling times and assume that all customers that arrive at or pass by a station are served. While valid for gasoline and hydrogen fueling, this assumption is inappropriate for slower level-one and -two charging. A vehicle that arrives or passes through a charging station may be ‘rejected’ if there are no free chargers and the driver is unwilling to wait. Moreover, a vehicle may only be partially charged as the driver may be unwilling to wait for a full charge. Thus, it is more appropriate to focus on EV arrival and departure times from parking lots, since this is when slow charging can be reasonably done. Existing models do not determine the number or type of chargers to install at each location, only where to place stations. This question is important for EVs because the number of chargers directly affects how many vehicles are served (due to charger occupancy). Moreover, the number of chargers determines infrastructure deployment cost. [Upchurch et al. \(2009\)](#) refine these typical assumptions by restricting the number of vehicles that a station can serve. Thus, multiple stations might be

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required at a single location to capture a large flow. Their model assumes, however, that every station and charger has a fixed flow-capture capacity. That is, the marginal service level is independent of the vehicle arrival pattern. Furthermore, most existing studies use conventional vehicle flows or gasoline sales data to estimate EV vehicle flows, with the underlying assumption that EV adoption rates are uniform within a region.

This paper develops a charging infrastructure location model that maximizes EV service levels. It is explicitly designed to model slow charging technologies (*e.g.*, levels one and two) and accounts for the impact of EV driving patterns and the chargers installed on flows that can be served.

2. Modeling Approach

Our modeling approach assumes a fixed study region, which is divided into sub-regions that can represent specific vehicle origins and destinations, or aggregations of such locations. Our model assumes that tour record data for vehicle trips between the sub-regions are available. At a minimum, these data should identify the times during which vehicle trips occur. In our case study we also make use of more detailed data that associate driving trips with specific vehicles, allowing complete vehicle tours to be constructed. Our tour record data further specify the home sub-region of each vehicle owner and the purpose of each vehicle trip.

Our modeling approach consists of three steps. The first is to determine the volume of EV flows between the sub-regions. We determine EV flows by assigning an EV adoption probability, which depends on demographic data, to vehicle owners living in each sub-region. The second step is to develop a simulation model to determine the expected number of EVs that successfully charge at a candidate location, as a function of the number of chargers built. The final step uses a linear integer programming (IP) model to determine the location and size of charging stations.

[Curtin et al. \(2009\)](#) use a linear model of the form, $y = X\beta + \epsilon$, to estimate EV adoption probabilities (more specifically, they examine plug-in hybrid electric vehicle adoption) as a function of household demographic and macroeconomic variables. The household-specific explanatory variables in their model are: the number and age of vehicles owned, average total and highway km driven daily, average monthly gasoline usage, income, education level, gender, age, interest in green technologies, and urban versus rural location. The macroeconomic variables are gasoline and electricity prices and the purchase price premium for an EV, relative to a conventional vehicle.

We use this linear model, and the β estimated by [Curtin et al. \(2009\)](#), to estimate EV adoption probabilities for individuals living within the sub-regions. We let \hat{y}^i denote the estimated adoption probability for residents of sub-region i . The analysis assumes that a fixed proportion of the vehicles in the region are EVs. To model this desired EV penetration, we assume that a fraction, w^i , of the vehicles owned by individuals in sub-region i are EVs and that the w^i 's are proportional to the \hat{y}^i 's, or that:

$$w^i = \alpha \cdot \hat{y}^i, \forall i \in I,$$

where α is a scaling factor. If we let ϕ denote the assumed EV penetration level and v^i the vehicles owned by individuals living in sub-region i , then the EV penetration condition gives:

$$\alpha = \frac{\phi \sum_{i \in I} v^i}{\sum_{i \in I} \hat{y}^i \cdot v^i}.$$

Since each vehicle in the tour record data is assigned a home sub-region, we can use the w^i 's to determine which of the vehicles are EVs by bootstrapping. This is done by randomly generating Bernoulli trials. We use the trips in the tour record taken by the randomly assigned EVs to determine EV flows between the different sub-regions.

We assume that we have a set, J , of candidate locations within the study region at which charging stations can be built. The set J can, but must not necessarily, correspond to I . Ideally, the candidates constituting J are sufficiently small in geographic area to correspond to a single location at which EVs park.

The EVs that successfully charge and the amount of energy recharged at a candidate charging station location depend on vehicle arrival and departure patterns, the chargers installed at the location, and charging behavior. We capture these effects by simulating EV arrivals, departures, and charging at each candidate location, using a simulation model with the structure illustrated in Figure 1. This model estimates the EVs that successfully charge and the amount of energy recharged in EV batteries as a function of the chargers installed at each location.

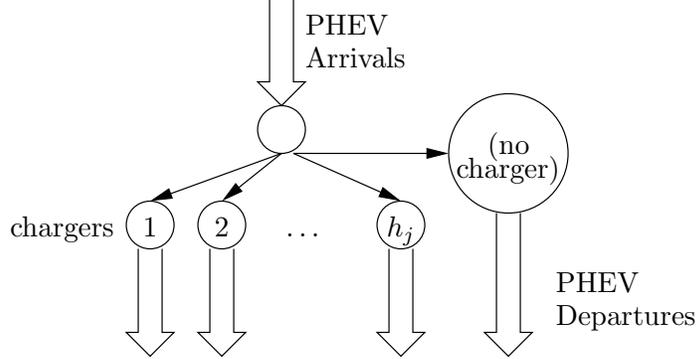


Figure 1: Schematic of charging model at a single candidate location with h_j chargers.

The model first determines when EV arrivals and departures occur at each candidate location and uses two simple rules to determine how many of the EVs that arrive charge. The first is that an EV charges if and only if there is an unoccupied charger available upon arrival. If so, the EV occupies the charger and charges for the entire parking duration. Otherwise, the EV parks at a spot without a charger and does not charge. We also later examine cases in which some of these rules are relaxed. Because vehicle charging decisions at each location are independent of the chargers installed elsewhere, we simulate each location individually. We let $f_j(h_j)$ denote the number of EVs that are simulated as successfully charging at candidate location j if h_j chargers are installed.

We use the same simulation model to estimate the battery energy recharged in EV batteries that use a public charger. To do so, we compute the charge level of each EV battery upon arrival. If we let V denote the set of EVs and $\mathcal{N}_{v,j}$ the times vehicle v arrives at location j , our model computes this charge level as:

$$c_{v,j,n} = \max\{c_v^-, c_v^+ - \eta_v \cdot d_{v,j,n}\}, \quad \forall v \in V, j \in J, n = 1, \dots, \mathcal{N}_{v,j}. \quad (1)$$

The c_v^- and c_v^+ terms denote the minimum and maximum charge levels, respectively, within which the battery operates. The η_v term is EV v 's average efficiency, measured in kWh of battery energy consumed per km driven. The $d_{v,j,n}$ term is the cumulative distance driven by EV v upon the n th arrival at location j , including any intermediate stops en route.

Equation (1) assumes that each EV battery is fully charged (i.e., has c_v^+ kWh of energy stored) at the beginning of the study period. It also assumes that the charge level of each EV depends only on the cumulative distance upon arrival. This second assumption ignores the possibility of charging in other locations, and allows us to simulate EV charging at each location independently. Otherwise, one would have to simulate all of the candidate locations jointly to account for intermediate charging elsewhere. We use a more detailed simulation model to examine whether this independence assumption affects the results.

We compute the amount of energy recharged in the battery as:

$$e_{v,j,n} = \min\{c_v^+ - c_{v,j,n}, t_{v,j,n} \cdot r_j\}, \quad \forall v \in V, j \in J, n = 1, \dots, \mathcal{N}_{v,j}, \quad (2)$$

if the vehicle recharges, where $t_{v,j,n}$ is the parking duration, and r_j is the net of efficiency losses charger power capacity. Otherwise, if there are no unoccupied chargers upon arrival, $e_{v,j,n} = 0$. Equation (2) assumes that all of the chargers installed at each location are homogeneous, with the same power capacity.

We can simulate charging with different values for r_j , which would represent replacing all of the chargers with a different technology. We make this homogeneity assumption because if different charger types are installed, an additional assumption is required about what charger type EVs occupy upon arrival. We define:

$$\tilde{f}_j(h_j, r_j) = \sum_{v \in V} \sum_{n=1}^{\mathcal{N}_{v,j}} e_{v,j,n},$$

as the amount of energy recharged in EV batteries at charging station j if h_j chargers with charging rate r_j are installed.

The optimization model determines the chargers to place at each candidate location, with the objective of maximizing fleet-wide EV charging. We consider two variants of this objective—maximizing the EVs that charge and the amount of battery energy recharged. Our model includes two sets of constraints. One is that enough distribution-level transformer capacity be installed at each location to accommodate the chargers. The second is a general budget constraint.

To formulate our model, we first define the following model sets and parameters:

G : set of charging technologies available

S : set of transformer types available

P_g : gross power capacity [kW] of a type- g charger

W_s : power capacity [kW] of a type- s transformer

κ_g : cost of a type- g charger

ω_s : cost of a type- s transformer

B : total budget available

We also define the following decision variables:

h_j^g : type- g chargers installed at candidate location j

A_j^g : binary variable that is 1 if type- g chargers are installed at j , equals 0 otherwise

m_j^s : type- s transformers installed at candidate location j

The formulation of the optimization model that maximizes the EVs that charge is:

$$\max \sum_{j \in J} \sum_{g \in G} f_j(h_j^g) \tag{3}$$

$$\text{s.t. } h_j^g \leq A_j^g \cdot \sum_{v \in V: \mathcal{N}_{v,j} > 0} 1, \quad \forall j \in J, g \in G; \tag{4}$$

$$\sum_{g \in G} A_j^g \leq 1, \quad \forall j \in J; \tag{5}$$

$$\sum_{g \in G} P_g \cdot h_j^g \leq \sum_{s \in S} W_s \cdot m_j^s, \quad \forall j \in J; \tag{6}$$

$$\sum_{j \in J} \left[\sum_{g \in G} \kappa_g \cdot h_j^g + \sum_{s \in S} \omega_s \cdot m_j^s \right] \leq B, \tag{7}$$

$$h_j^g \in \mathbb{Z}^+, \quad \forall j \in J, g \in G; \tag{8}$$

$$A_j^g \in \{0, 1\}, \quad \forall j \in J, g \in G; \tag{9}$$

$$m_j^s \in \mathbb{Z}^+, \quad \forall j \in J, s \in S. \tag{10}$$

Objective function (3) maximizes the number of EVs that charge. Constraint set (4) only allows type- g chargers to be built at location j if $A_j^g = 1$. The:

$$\sum_{v \in V: \mathcal{N}_{v,j} > 0} 1,$$

terms on the right-hand side of these constraints are the EVs that arrive at each location during the study and represent upper-bounds on the chargers that may be optimally installed at each location. Constraint set (5) allows at most one charger type to be installed at each location. Constraint set (6) requires sufficient transformer capacity to be installed at each location to serve the potential peak load of the chargers. Constraint (7) is the budget limit. Constraint sets (8) through (10) impose integrality restrictions on the decision variables.

When maximizing the amount of energy recharged, the IP retains the same set of decision variables and constraint sets (4) through (10). The objective function changes to:

$$\max \sum_{j \in J} \sum_{g \in G} \tilde{f}_j(h_j^g, \zeta \cdot P_g), \quad (11)$$

where ζ is the charger efficiency.

3. Case Study: Central-Ohio Region

The case study is based on the central-Ohio region; the city of Columbus and its surrounding metropolitan area. The area of study covers about 6000 km² and included 1.7 million inhabitants and 1.1 million light-duty vehicles in 2010. Most of the data used are obtained from the Mid-Ohio Regional Planning Commission (MORPC). The study period is a typical workday in 2010, as modeled by the MORPC. We examine a case in which EVs constitute 1% of the light-duty vehicle fleet.

For purposes of transportation modeling, the MORPC divides the central-Ohio region into 1805 traffic analysis zones (TAZs). The MORPC collects demographic, socioeconomic, and vehicle ownership and usage data for inhabitants of each TAZ. It also generates typical weekday travel tours for the central-Ohio region using the multi-step tour-based approach of [Sener et al. \(2009\)](#). The data include about 2.4 million trips, of which 2.1 million involve a personal vehicle. Each vehicle tour is a round trip, with the trip having a primary purpose. A tour can also include a side-trip. Although an individual tour is a round trip with a single destination, a single vehicle can make multiple tours. When concatenated, these tours result in a vehicle having multiple stops in the course of a day. The MORPC also has data regarding possible vehicle destinations within each TAZ, which are used as candidate charging stations. Specifically, it tracks the employers, categorized by the number of employees, retail shopping and grocery stores, and the number of large public, private, and university-owned parking lots, categorized by the number of parking spaces available, in each TAZ.

To estimate EV adoption probabilities we consider the average number of vehicles owned, highway kilometers driven daily, household income, and education level of inhabitants of each TAZ. The MORPC classifies each TAZ as being either urban or rural, which is used in the model. The values of the remaining explanatory variables are based on more aggregate averages. [Santos et al. \(2011\)](#) estimate average U.S. vehicle and driver ages in 2009, which are 6.85 and 37 years, respectively. We use data from the U.S. Department of Energy’s Energy Information Administration to estimate the average retail price of gasoline and electricity to be about \$0.92/l (\$3.50/gallon) and \$0.0988/kWh. We combine a conventional vehicle fuel efficiency of 20 miles/gallon—the survey average reported by [Curtin et al. \(2009\)](#)—with average daily household driving distances for each TAZ to estimate monthly gasoline usage. We use a value of 0.5 for the gender indicator variable. We use survey averages reported by [Curtin et al. \(2009\)](#) for interest in green technologies, and a \$5000 purchase price premium for an EV over a conventional vehicle, which is their base case assumption. The EV adoption probabilities estimated for the TAZs range between 0.21 and 0.39 and have a mean of 0.30. An $\alpha = 0.033$ scaling factor is used to achieve the desired 1% penetration.

Since the level-one and -two chargers that we focus on require multiple hours to fully recharge an EV, public chargers must be at locations with long parking times. Moreover, for a charging station to be viable, it needs a sufficient number of expected EV arrivals to make the investment cost-effective. For these reasons, we model the parking lots of workplaces, universities, and retail shopping locations as candidate stations. Trips to such locations typically entail extended stays. Moreover, each TAZ has few workplaces, universities, and retail shopping locations, compared to the possible destinations for other trip types. For instance, an EV traveling to visit a friend has thousands of possible destinations within a TAZ.

The tour record data specify each trip’s destination TAZ and purpose, and we use these data to assign EVs to candidate locations upon arrival. A TAZ can, however, contain multiple locations of a single type (*e.g.*, multiple workplaces). We use a set of heuristic rules to assign EV arrivals to the different potential locations. For retail shopping locations, we model each individual shopping center as a separate candidate location and assume that EVs are equally likely to go to any of these shopping centers within a TAZ.

We assume that each employer that is located in a TAZ that is outside of downtown Columbus has dedicated parking spaces for its employees. We model the parking lot of each of these employers as a separate candidate location. We randomly allocate EVs that arrive to a TAZ for work to the different candidate work locations in proportion to the employment size of the workplaces. Due to restricted land availability, employers in downtown Columbus are assumed to use shared public parking garages. We model public parking garages within a downtown TAZ as candidate locations and allocate work-related EV arrivals to them in proportion to the number of parking spaces that they have.

The region that we model has one large university, The Ohio State University’s main campus, and a number of smaller ones. The Ohio State University occupies a single TAZ and has multiple parking garages. We model each of these garages as an individual location, and allocate arrivals in the same manner used for work-related arrivals to TAZs in downtown Columbus. We model each of the smaller universities in central-Ohio as individual candidate locations.

Considering the complete set of candidate locations yields a computationally intractable IP. Thus, we filter out candidate locations with fewer than one expected daily EV arrival and neglect them in the IP. Table 1 provides summary statistics of the set of candidate locations and the ones modeled in the IP. Although we only model 13% of the candidate locations, our model considers 39% of the expected work-, university-, and shopping-related EV arrivals.

Table 1: Candidate Location Summary Data

	Working	University	Shopping
All Locations	3029	25	350
Modeled Locations	275	25	158
Expected Total EV Arrivals	7422	286	1330
Expected Modeled EV Arrivals	2725	276	501

We assume that the EVs modeled are pure EVs with a 117 km (73 mile) driving distance and a 0.21 kWh/km (0.34 kWh/mile) driving efficiency. This driving efficiency accounts for inverter and battery losses. The values are based on tested efficiency and range data for the Nissan Leaf reported by the U.S. Environmental Protection Agency.

Our case study assumes that two charging technologies, level-one and -two, are available. These have 1.4 kWh and 4 kWh power capacities and \$425 and \$925 per-charger installation costs, respectively, based on values reported by [Morrow et al. \(2008\)](#). We assume that 25 kW, 50 kW, and 75 kW transformers, with per-unit costs of \$1265, \$1668, and \$2070, respectively, are available, based on values reported by American Electric Power. We consider cases in which up to \$3.5 million are allocated for charging infrastructure.

4. Results

To simulate expected service levels with different numbers of chargers we conduct 500 replications of the simulation by bootstrapping EV trips from the tour record data. Figure 2 shows expected service levels at six selected candidate locations, as a function of the number of level-two chargers installed. The figure and the simulation results illustrate some relationships between the service levels of the candidate location types. Charging stations at universities tend deliver the highest service levels. This is because EVs tend to have extended parking times, but do not park the full eight or nine hours that an EV at a workplace does. Thus, a charger can be used by multiple EVs daily, yet EVs are parked for a sufficiently long time that much of the depleted battery energy is replaced. Installing two chargers at a university parking location captures, on average, about 87% of expected EV arrivals and recharges about 90% of the battery energy that can be recharged with an unlimited chargers. Significantly fewer EVs are able to charge at the average workplace and shopping location—40% and 43%, respectively—if only two chargers are installed. Shopping locations have multiple arrivals, that tend to be concentrated in the morning and afternoon, and two chargers can only serve a small subset of the vehicles, despite being reused multiple times.

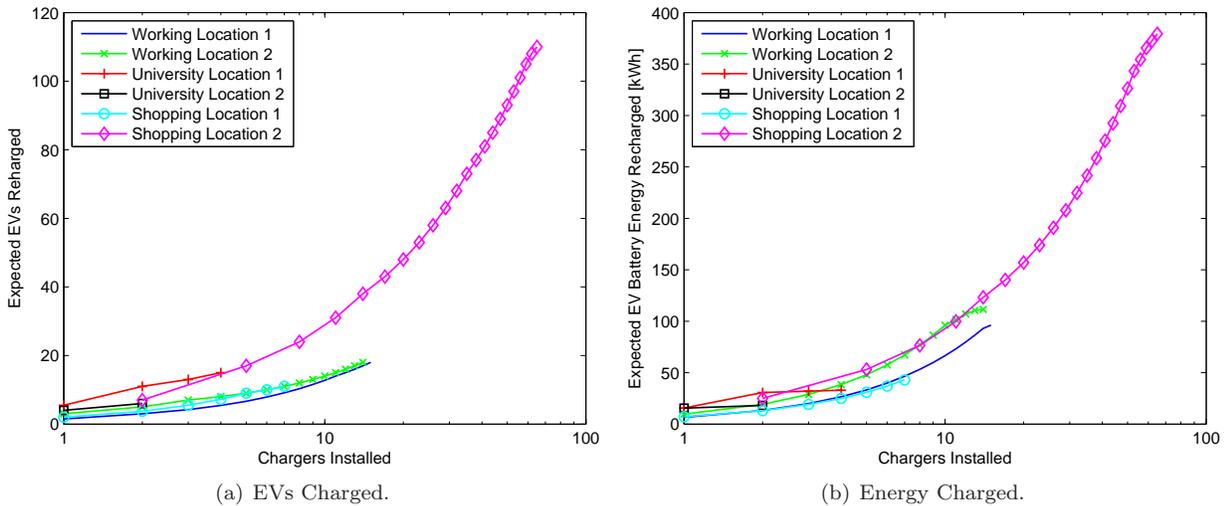


Figure 2: Service Levels at a Select Set of Candidate Locations as a Function of the Number of Level-Two Chargers Installed.

Table 2 summarizes the deployment of chargers that maximizes the expected amount of EV energy recharged with a \$1 million and \$3 million budget. The table shows that most charging stations are built at workplaces. This is because the relatively long parking times at workplaces result in more energy being provided compared to the other location types. Moreover, because of the prolonged parking times, there is little incremental benefit of deploying level-two chargers, since most vehicles can be fully recharged using level-one technology. Of the 847 chargers deployed among the 194 charging stations built with a \$1 million budget, only 14 are level-two.

As the budget increases, more chargers are deployed in retail shopping locations. Due to the short parking time of vehicles at shopping locations (relative to workplaces), a greater proportion of the chargers installed in retail shopping locations are level-two. For instance, with a \$3 million budget 1191 chargers, of which 77% are level-two, are installed in workplace charging stations. Conversely, 84% of the 153 chargers installed in shopping centers are level-two.

Table 3 summarizes the charger deployment that maximizes the expected EVs charged. As opposed to the energy-optimization case, level-two chargers are never installed in this case. This is because the faster charging rate has no benefit in increasing the EVs charged. More stations are built in university and shopping locations compared to the case in which energy charged is the optimization criterion. This is due to the short parking durations at these locations (relative to workplaces), which allows a single charger to be

Table 2: Charging Stations and Chargers Built at Location Types Under Energy-Maximization Optimization Criterion

	Charging Stations				Chargers			
	\$1 million		\$3 million		\$1 million		\$3 million	
	Level-1	Level-2	Level-1	Level-2	Level-1	Level-2	Level-1	Level-2
Working	172	9	82	193	778	13	279	912
University	12	0	3	22	55	0	9	72
Shopping	0	1	25	109	0	1	25	128

reused multiple times daily. Because university and shopping locations have fewer daily EV arrivals relative to workplaces, the majority of chargers are still deployed at workplaces.

Table 3: Charging Stations and Chargers Built at Location Types Under EV-Maximization Optimization Criterion

	Charging Stations		Chargers	
	\$1 million	\$3 million	\$1 million	\$3 million
Working	136	275	731	1198
University	19	25	74	81
Shopping	48	145	45	165

Note: All Chargers Are Level-One

With both optimization criteria, the charging stations built with a \$1 million budget are also built with a \$3 million allocation. Thus, the station locations are ‘robust,’ in that they are used if the budget constraint is relaxed. When maximizing energy recharged, however, 151 of the level-one stations built with a \$1 million budget are upgraded to level-two technology with a \$3 million budget allocation.

Tables 2 and 3 show that locations of charging stations are somewhat sensitive to the optimization criterion used. Figure 3 compares the charging station locations obtained using the two optimization criteria in terms of the actual service level (objective function value) achieved. The figure shows the expected EVs and kWh of energy recharged daily as a function of the budget with the two optimization criteria. The expected EVs that successfully charge is relatively insensitive to the optimization criterion used. For any budget level, the energy-maximizing infrastructure deployment allows at least 91% of the EVs that recharge with the vehicle-maximizing deployment to charge. The amount of energy recharged is more sensitive to the optimization criteria used. This is, in part, due to level-two chargers not being deployed when maximizing the expected EVs that recharge. A \$2.1 million investment in level-one chargers allows every EV to charge (in expectation). However, not all EVs are able to fully recharge relative to the other optimization criterion. For the purposes of actual infrastructure planning, these findings suggest that the particular performance metric considered is relatively unimportant. The limitation of using the EVs charged as an optimization criterion, however, is that it does not determine what charging stations should be upgraded to level-two technology.

Figure 4 shows the expected EVs that cannot complete their daily tours when public charging infrastructures are built. About 96% of owners drive less than the assumed 117 km range of the EVs modeled, meaning that 4% cannot complete their tours without midday recharging. Public chargers reduce the number of EVs that cannot complete their tours by up to 16%. Between 80% and 96% of the EVs that cannot finish their tours drive to locations that are not modeled and would, thus, not have access to the public chargers built. If we only consider EVs that drive to locations modeled in the IP, then 99% to 100% of EVs are able to complete their daily tours.

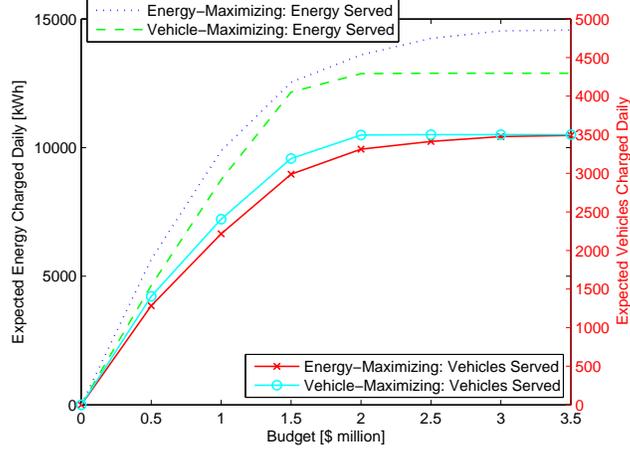


Figure 3: Service Levels Achieved with Different Optimization Criteria.

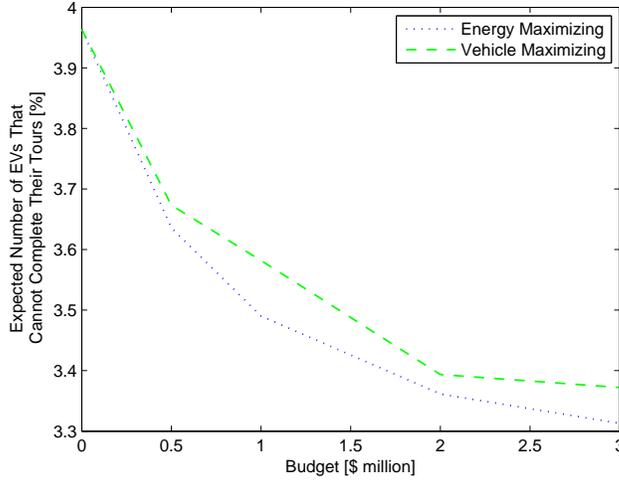


Figure 4: Expected Number of EVs That Cannot Complete Their Tours.

5. Sensitivity Analysis

The model used to estimate $\tilde{f}_j(h_j^g, \zeta \cdot P_g)$ considers candidate locations independently, not accounting for the possibility that an EV may have charged at other stops earlier in the day. This can result in overestimating the energy recharged. To validate this assumption we develop a more detailed simulation, a schematic of which is shown in Figure 5, which considers such interdependencies. The model takes as inputs EV trips and an optimized charging station layout. When a simulated EV arrival occurs, the model updates the vehicle's charge level based on the cumulative distance traveled and other charging events before the EV's arrival. Specifically, we define \mathcal{M}_v as the set of stops, in chronological order, made by EV v at the candidate locations; $d_{v,m}$ as the distance driven by EV v between stops $m-1$ and m ; $c_{v,m}$ as v 's charge level upon arrival at stop m ; and $e_{v,m}$ as the amount of energy recharged by v during stop m , which is defined in equation (13). EV v 's charge level upon arrival at stop m is defined as:

$$c_{v,m} = \begin{cases} \max\{c_v^-, c_v^+ - \eta_v \cdot d_{v,m}\}, & \text{if } m = 1; \\ \max\{c_v^-, c_{v,m-1} + e_{v,m-1} - \eta_v \cdot d_{v,m}\}, & \text{otherwise;} \end{cases} \quad \forall v \in V, m = 1, \dots, \mathcal{M}_v. \quad (12)$$

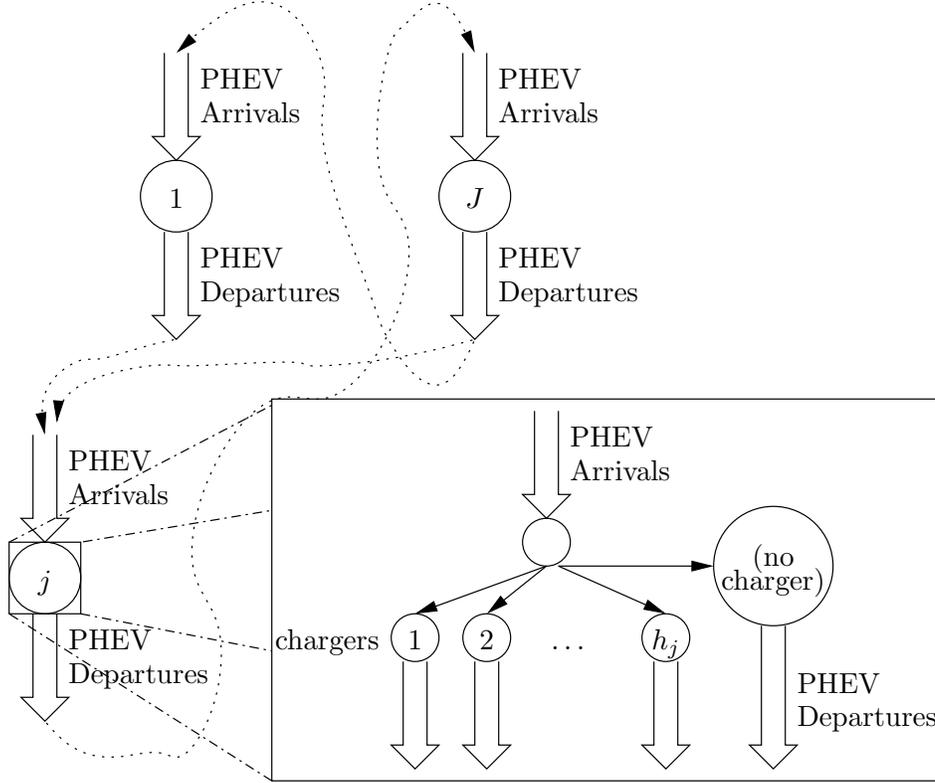


Figure 5: Schematic of Validation Simulation Model.

The amount of energy that vehicle v recharges during stop m is:

$$e_{v,m} = \begin{cases} \min\{c_v^+ - c_{v,m}, t_{v,m} \cdot r_{v,m}\}, & \text{if EV } v \text{ charges during stop } m; \\ 0, & \text{otherwise;} \end{cases} \quad \forall v \in V, m = 1, \dots, \mathcal{M}_v, \quad (13)$$

where $t_{v,m}$ is the duration of vehicle v 's m th stop and $r_{v,m}$ is the power capacity of the charger installed at the location of the m th stop, if a charger is unoccupied when the EV arrives. Alternatively, it is assumed to not charge. Equations (12) and (13) reinforce equations (1) and (2), because they account for midday recharging. We conduct 500 replications of this simulation, in which the EV set is randomly sampled, to estimate the expected amount of energy recharged in EV batteries by a given infrastructure. We compare this to the optimized value of objective (11) to test the sensitivity of the results to the independence assumption.

Table 4 summarizes the energy recharged estimated by the two models, using infrastructure that maximizes the energy objective. As expected, the optimization model slightly overestimates EV charging, but by less than 3.5% of the expected charged energy predicted by the simulation model. This suggests that the simple approach of modeling locations independently is relatively accurate in capturing the amount of energy charged because most EVs only use at most one charging station daily.

The base model assumes that if a charger is available upon arrival, an EV owner always occupies it. In practice, they may not always charge, depending on several factors, including the price levied, the necessity of charging (based on the distance of subsequent trips), and the duration that the vehicle is parked. Because the exact effect of these factors is not well understood, we use an extreme assumption to bound the possible effect of such factors on charging behavior and infrastructure design.

Specifically, we assume that a vehicle owner only 'attempts' to use a public charging station if it is needed to complete all of the trips of the day, or if the EV battery could not be fully recharged before the first trip of the following morning when it returns home at the end of the day. As before, a driver that attempts to

Table 4: Expected Daily Energy Charged Estimates Provided by Optimization and Simulation Models

Budget [\$ million]	Energy Charged [kWh]	
	Optimization Model	Simulation Model
0.5	5659	5487
1	9873	9604
2	13606	13174
3	14540	14058

charge only does so successfully if a charger is available upon arrival at a location. The first condition can be written as:

$$\sum_{m \in \mathcal{M}_v} \eta_v \cdot d_{v,m} > c_v^+ - c_v^-, \quad (14)$$

or that the amount of energy required by EV v to complete its trips is greater than the usable range of the battery. The second is:

$$\sum_{m \in \mathcal{M}_v} \eta_v \cdot d_{v,m} > \tilde{r}_v \cdot \tilde{t}_v, \quad (15)$$

where \tilde{r}_v is the power capacity of the charger installed at the home of EV v 's owner and \tilde{t}_v is the parking duration between the last trip of the night and the first trip of the following morning. We assume that EV owners have a level-one charger, with a 1.4 kW power capacity, available at home.

Tables 5 and 6 summarize the location of chargers under the new charging conditions. This results in significantly less infrastructure investment being needed, because of reduced charging demand. Indeed, a \$2 million budget allocation is sufficient to serve all of the EVs that have need for charging in the energy-maximization optimization case, while \$1 million is sufficient if maximizing EVs being charged. The difference in budget stems from level-two chargers being used with the former optimization criterion. The tables also show that almost all of the chargers are built at workplaces with none installed at retail locations. This is because most shopping involves short trips, relative to commutes.

Table 5: Charging Stations and Chargers Built at Location Types Under Energy-Maximization Optimization Criterion if Only EVs Requiring it Charge

	Charging Stations				Chargers			
	\$0.5 million		\$2 million		\$0.5 million		\$2 million	
	Level-1	Level-2	Level-1	Level-2	Level-1	Level-2	Level-1	Level-2
Working	113	38	70	154	213	55	81	274
University	2	2	4	4	3	5	4	9
Shopping	0	0	0	0	0	0	0	0

Despite the charging station ‘saturation,’ 3% of EVs are unable to finish their tours, even if \$2 million of infrastructure is installed. Most of these travel to destinations that are not modeled in the IP. Less than 1% of EVs that travel to at least one location modeled in the IP are unable to complete their tours, and these remaining EVs have unusually long trips at the end of the day or short midday parking durations, which do not allow for charge level recovery.

6. Conclusions

This paper optimizes the locations of slow chargers to serve EVs. The modeling steps consist of predicting where EVs owners live, simulating the relationship between service rates and the chargers deployed,

Table 6: Charging Stations and Chargers Built at Location Types Under EV-Maximization Optimization Criterion if Only EVs Requiring it Charge

	Charging Stations		Chargers	
	\$0.5 million	\$1 million	\$0.5 million	\$1 million
Working	172	224	298	351
University	7	8	12	13
Shopping	0	0	0	0

Note: All Chargers Are Level-One

and optimizing the deployment with an IP. We apply the model to the central-Ohio region. Our results demonstrate that a combination of level-one and -two chargers maximize the charging energy available. If sufficient funds are not available, level-one chargers are more economical. We also conduct sensitivity analyses to validate our modeling approach and determine the effect of more conservative use of public charging stations.

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