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

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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.

M o n Appro

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 co

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.

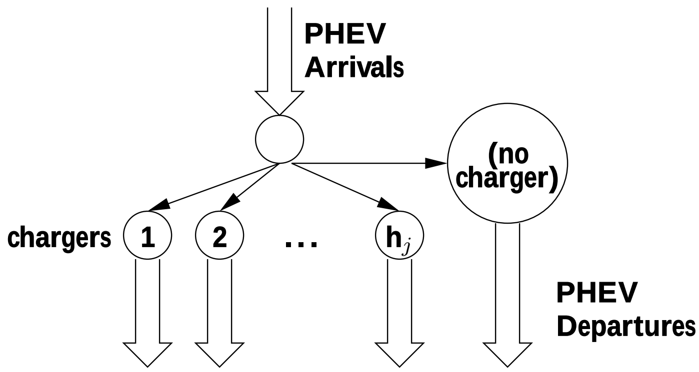


Figure 1: Schematic of charging model at a single candidate location with h_j chargers.

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 $N_{v,j}$ the times vehicle v arrives at location j, our model computes this charge level as:

$$c_{v,j,n} = \max\{c_v^-, c_v^+ - \eta_v \cdot d_{v,j,n}\}, \quad \forall v \in V, j \in J, n = 1, \dots, N_{v,j}. \tag{1}$$

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 nth 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:

$$e_{v,j,n} = \min\{c_v^+ - c_{v,j,n}, t_{v,j,n} \cdot r_j\}, \quad \forall v \in V, j \in J, n = 1, \dots, N_{v,j}, \tag{2}$$

if the vehicle recharges, where $t_{v,j,n}$ is the parking duration, and r_j is the net of efficiency losses charger

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 chargers types are installed, an additional assumption is required about what

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.

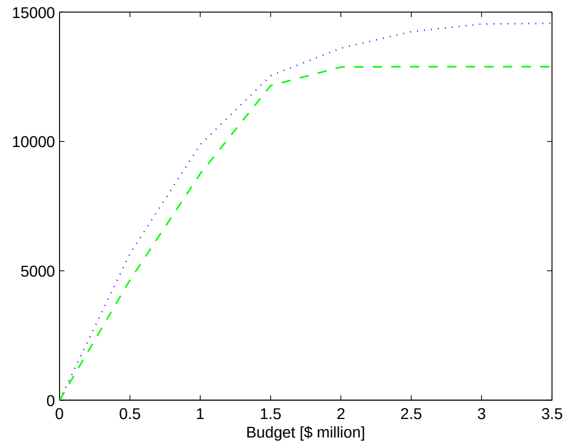
The tour record data specify each trip's destination TAZ and purpose, and we use these data to assign EVs to candidate locations upon arrival. A TAZ can, however, contain multiple locations of a single type (e.g., multiple workplaces). We use a set of heuristic rules to assign EV arrivals to the different 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 lo

4 Results

To simulate expected service levels with different numbers of chargers we conduct 500 replications of the

Table 2: Charging Stations and Chargers Built at Location Types Under Energy-Maximization Optimization Criterion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0.5
1
1.5
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3.5
Budget [$ million]

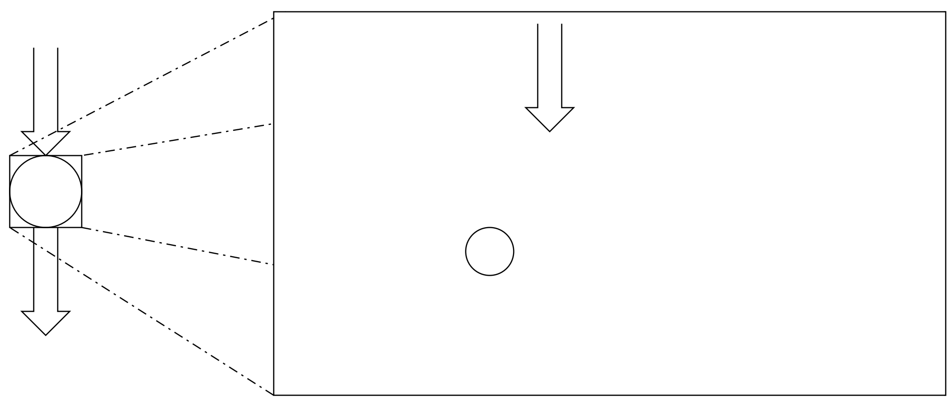

Table 4: Expected Daily Energy Charged Estimates Provided by Optimization and Simulation Models

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