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Planning charging infrastructure for plug-in electric vehicles in city centers

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ABSTRACT

Installing charging facilities in existing parking lots in city centers is considered an effective measure to encourage the adoption of plug-in electric vehicles (PEV). This article is concerned with the problem of locating these facilities so as to minimize the total system cost. The problem is formulated as a fixed charge facility location model with charging capacity constraints. The proposed model extends the existing work by allowing unserved demands and considering drivers' preference for familiar parking lots. Accordingly, inconvenience costs are introduced for unserved demands and for those who have to change their parking lots in order to charge at work. The proposed model is not only always feasible, but also introduces a pricing mechanism so that the level of service (measured by the cost of unserved demands) can be traded off with the infrastructure cost. In addition, a stochastic version of the proposed model is developed to address the effects of uncertain PEV market penetration rate on the planning of charging facilities. A case study is conducted to analyze the sensitivity of the models to different cost components, and to compare the results of the stochastic and deterministic models.

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Charging infrastructure; demand uncertainty; fixed charge facility location problem; plug-in electric vehicles

1. Introduction

Traditional vehicles powered by gasoline and diesel fuels have been a major source of air pollution and greenhouse gas (GHG) emissions. Together, the transportation sector contributes roughly 27 percent of the U.S. total GHG emissions.[1] A portfolio of strategies is needed to reduce the transportation sector's dependence on fossil fuels. Of these, promoting the use of alternative fuel vehicles (AFV), especially vehicles powered fully or partially by electricity, is considered an effective tool that promises far-reaching impacts. Indeed, the importance of promoting alternative fuel vehicles has been recognized by policymakers around the world. In the United States, President Obama has pledged to make the United States become the first country to have one million electric vehicles on the road by 2015.[2] According to the Electric Drive Transportation Association, the number of plug-in electric vehicles (PEVs) in the United States exceeded 190,000 (or more than 0.5% of the new vehicle market) between January of 2011 and March of 2014.[3]

Relevant questions at present are how soon a full-scale transition to AFV will take place, to what types of AFV, how much will it cost, and what policies can be implemented to facilitate the process. The work presented in this article tackles the last question. Specifically, we focus on the problem of locating public charging facilities for plug-in hybrid electric vehicles (PHEV) and battery electric vehicles (BEV), which we shall refer to as plug-in electric vehicles (PEV) throughout this article. One of the greatest hurdles to growing EV market share is the inconvenience caused by the limited range of the batteries and the lack of public charging infrastructure. Making charging facilities conveniently available to motorists could help overcome this hurdle.

With the current technology, EVs require relatively long charging times (Monica & Nick, 2011; Morrow, Karner, & Francfort, 2008; Shiau, Samaras, Hauffe, & Michalek, 2009). At present there are three types of charging facilities available in the United States, each associated with a different range of charging power. The maximum power for level-I and level-II chargers is around 1.5 and 10 kW, respectively, whereas Level-III can provide a charging power up to 60–150 kW (Morrow et al., 2008). Because Level-III chargers operate with high voltage (440V), they are generally much more expensive to build and only available at commercial charging stations (Morrow et al., 2008). Even with a Level-III charger, fully charging a typical BEV (such as Nissan Leaf with a range of about 100 miles) would still take more than 30 minutes, which is considerably longer than refilling the fuel tank of conventional vehicles. A full charge will take several hours to complete using the lower level chargers. Therefore, an attractive solution is to place the charging facilities at the driver's home, workplace, or other places where they are likely to stay for an extensive period of time (e.g., shopping malls and recreational facilities; Pound, 2012). Of these options, the workplace in the central business district (CBD) is especially worth noting because (a) the high

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[1] United States Environmental Protection Agency, http://www.epa.gov/oms/climate/basicinfo.htm
[2] Institute for Energy Research, http://www.instituteforenergyresearch.org/2011/03/10/ obama-administration-pushes-electric-vehicles
[3] *Source.* http://electricdrive.org/index.php?ht=d/sp/i/20952/pid/20952 Note that the data excludes hybrid models such as Toyota Prius.

concentration of workers in CBD promises economics of scale, and (b) the typical working hours are long enough to allow fully charging most existing EVs, even with lower level chargers.

The question we ask in this article is how to minimize the implementation cost of providing such charging facilities while fulfilling EV drivers' needs as much as possible. This problem belongs to a class of fixed charge facility location problems that have been studied extensively in the literature; see, for example, Daskin (1995) for a review. Specifically, the objective here is to find the locations of the chargers and to assign chargers to EV drivers so as to minimize a total cost that consists of the cost of installing chargers and the "inconvenient cost" of the EV drivers (such as the time it takes to walk from their office to the charging location). Fixed charge facility location problems may or may not consider the capacity at each location, leading to capacitated (Akinc & Khumawala, 1977; Sridharan, 1995) and uncapacitated (Kuehn & Hamburger, 1963) versions. The models considered in this article are capacitated.

For the remainder of this article section 2 reviews the literature and explains how the proposed work is related to the existing studies. Section 3 states the formulation of the basic model. Section 4 proposes and analyzes variants of the CBD charging facility location model that consider inconvenience costs and demand uncertainty. Section 5 explains how important inputs such as the unit inconvenience cost may be estimated. Section 6 reports the results of numerical experiments, and section 7 concludes the study.

2. Related studies

Locating charging facilities for EVs has only received attention recently. According to the type of trips that the charging facilities aim to serve, the location problems may be classified as *intracity* and *intercity* problems. While the intracity problems focus on the issue of charging accessibility within the boundary of urban centers, the intercity problems are more concerned with the range anxiety issue associated with longer (intercity) trips. Nie and Ghamami (2013) propose a conceptual intercity model to analyze travel by EVs along a long corridor. The objective of their model is to select the battery size and charging capacity to meet a given level of service in such a way that the total social cost is minimized. In a similar spirit, Sathaye and Kelley (2013) develop a continuous facility location model (Daganzo, 2005) for the optimization of EV charging facility deployment for highway corridors. Unlike Nie and Ghamami (2013), their model does not consider the battery cost. Rather, the focus is to complement private charging infrastructure by publicly funded charging stations, while considering demand uncertainty.

One of the early intracity EV facility location models, first proposed by Dashora et al. (2010), aims to minimize the total cost of converting existing parking lots to accommodate charging and the cost of walking between parking lots to office buildings. The parking lot conversion cost includes the cost of installing charging units, solar shade, and connecting the lot to the electrical grid. Minimizing walking distances is also considered in a similar model by Chen, Khan, and Kockelman (2013). In Frade, Ribeiro, Goncalves, and Antunes (2011), an intracity EV charging location problem is formulated as a maximum covering model, that is, maximizing the number of users covered by charging stations while maintaining the level of coverage by each station. He, Wu, Yin, and Guan (2013) consider the interactions between charging station deployment, power grids, and route/destination choices.

The work proposed herein deals with an intracity problem. In particular, it extends the model of Dashora et al. (2010) in several aspects. First, the proposed model does not require all PEVs be served. Instead, those PEVs that are not assigned a charger will incur an inconvenient cost (estimated based on extra fuel consumption, emission cost, or the cost of acquiring supplementary transportation). One focus here is to analyze the sensitivity of the location design to this inconvenience cost. Second, the proposed model attempts to avoid as much as possible relocating a worker from his/her previous parking location. To this end, another inconvenience cost is introduced whenever a PEV driver has to change his/her parking location in order to charge at work. Third, since the adoption rate of EVs is difficult to predict, it seems more appropriate to model it as a random variable. Accordingly, a stochastic version of the charging location model is proposed to explicitly address this demand uncertainty.

3. Problem statement and the base model

Consider commute trips by private automobiles ending in a densely populated CBD area. It is assumed that all commuters who drive would park their vehicles in public parking lots and walk to their office buildings. Each commuter's working and current parking locations are assumed to be given. To encourage the use of PEVs, some parking lots may be converted to PEV-compatible lots by installing chargers at a certain number of parking spaces. This conversion entails two costs. First, a fixed cost is needed for each conversion project, which may involve upgrading the connection between the parking lot and the local electrical grid to accommodate the extra load, as well as installing signs and canopies. The second cost has to do with purchasing and installing chargers, which depends on the number and type of chargers installed in each PEV-compatible lot.

The design objective is to select PEV-compatible lots and the number of chargers to minimize the total system cost, which includes not only the facility cost but also the user cost. The user cost may be defined in different ways. The simplest one may be to assume it as a function of the total walking distance of the PEV users.

With the above background, we are ready to present the basic location model that closely resembles that proposed by Dashora et al. (2010). Let F and P denote the sets of office buildings and parking lots, respectively, and $|P| = N_P$, $|F| = N_F$. Without loss of generality, we assume that the parking lots are numbered from 1 to N_P, whereas the office buildings are numbered from 1 to N_F. Table 1 presents the description of parameters and variables used in this study, in which H_f is the number of workers in the office building f who drive to work, and α is the estimated market penetration rate of PEVs. Thus, αH_f is the number of PEV drivers in f and d_{pf} denotes the distance between parking lot $p \in P$ to an office building $f \in F$. The fixed cost of converting the parking lot p to a PEV-compatible lot is denoted as $C^g{}_p$. The purchase and installation cost of each

Table 1. Parameters and variables definitions and units.

		Parameters	
Costs	C^c	Charger cost per unit charging power	$\frac{\$}{kw}$
	C^g	Fixed cost of building charging station	$
	C_w	Walking cost	$\left(\frac{\$}{mile}\right)^2$
	C^u	Unserved demand cost	$\frac{\$}{\text{unit demand}}$
	C^t	Switching cost	$\frac{\$}{\text{unit demand}}$
Demand	H_f	The number of workers in office building f who drive to work	—
	α	Market penetration rate of PEVs	—
	ρ	Percent of PEV users assigned to a parking lot to be served simultaneously	—
	V_{pf}	Number of EV drivers in building f who park at lot p before the charging facilities are provided	—
Distance	d_{pf}	Minimum walking distance between building f and parking lot p	*mile*
	$\tilde{d}_f$	Minimum walking distance between building f and the nearest parking lot	*mile*
Capacity	q_p	Maximum capacity of parking lot p	—
		Variables	
Decision variable	X_p	Parking lot p converted or not	
	Y_p	Number of chargers installed in parking lot p	
State variable	Z_{pf}	The number of PEV drivers who work in the office building f and park in the parking lot p	
	E_f	Unserved PEV charging demand at the office building f	
	S_{pf}	Number of EV drivers in building f who can no longer use lot f	
	$\tilde{S}_f$	Excessive distance to be traveled as a result of switching	

charger is C^c, which is assumed to be the same regardless of where the chargers are installed. The cost of walking, C_w, is assumed to be a quadratic function of the walking distance. Note that this differs from Dashora et al.'s model. We adopted this assumption because the literature suggests that the inconvenience associated with walking would increase nonlinearly with the distance (Jara Díaz, 1982; Kasilingam, 1998).

There are three sets of decision variables: X_p is a binary variable that dictates whether or not the parking lot p is converted; Y_p denotes the number of chargers installed in the parking lot p; and Z_{pf} is the number of PEV drivers who work in the office building f and park in the lot p. The problem of selecting PEV-compatible lots and the number of chargers to minimize the system cost can be formulated as the following fixed charge facility location problem.

$$\min_{X_p, Y_p, Z_{pf}} \quad \sum_{p=1}^{N_P} \left(C^c Y_p + C_p^g X_p \right) + \sum_{p=1}^{N_P} \sum_{f=1}^{N_F} C_w d_{pf}^2 Z_{pf} \tag{1}$$

subject to

$$Y_p \leq q_p X_p \quad \forall p \in P \tag{2}$$

$$\rho \sum_{f=1}^{N_F} Z_{pf} \leq Y_p \quad \forall p \in P \tag{3}$$

$$\sum_{p=1}^{N_P} Z_{pf} \geq \alpha H_f \quad \forall f \in F \tag{4}$$

$$Z_{pf} \geq 0 (integer) \quad \forall f \in F, p \in P \tag{5}$$

$$Y_p \geq 0 (integer) \quad \forall p \in P \tag{6}$$

$$X_p \in \{0, 1\} \quad \forall p \in P \tag{7}$$

As mentioned before, the objective function combines the facility cost and the user cost. The latter converts the total walking distance to a monetary cost through a quadratic function.

Constraint (2) dictates that the number of chargers installed in a parking lot must be less than the capacity of the parking lot q_p. Constraint (3), called the level of service constraint, ensures each parking lot should have enough chargers to accommodate ρ percent of all PEVs assigned to it simultaneously. Constraint (4) ensures that all PEVs from any building must be served at a PEV-compatible lot. Constraint (5)–Constraint (7) are feasibility constraints. In particular, the demand allocation to parking lots and the number of chargers in each parking lot are required to be integer numbers (Constraints [5] and [6]).

4. Proposed models

The base model presented above requires providing enough chargers to serve all EV drivers, which may be too expensive or even infeasible given the limited budget and the restriction of the local electrical grid. Because simply imposing a budget limit may not resolve the infeasibility issue, we propose to leave some PEVs unserved. Accordingly, an extra inconvenience cost associated with these unmet demands is introduced. In addition, we postulate that workers would prefer to stay in their current parking lot. To capture this preference, a switching cost is introduced if one has to switch to another parking lot to keep one's PEV plugged. In what follows, the first subsection presents a model that implements these extensions. The second subsection explains how the uncertainty in the PEV's market penetration rate may be incorporated into the design.

4.1 *Unserved demand and switching cost*

Let E_f be the unserved PEV charging demand at the office building f. We assume that each PEV driver who is unable to find a charger at work will incur an inconvenience cost, C^u. C^u may be estimated based on the type of PEVs. For a BEV, because electricity is the only fuel option, it must have enough electricity to finish the trip back home. We assume that, due to the lack of access to charging at the workplace, BEV users may charge the battery at an alternative facility. The extra time and cost associated with these extra charging activities can be used to estimate the inconvenience cost.

For PHEV, C^u may be measured as the difference between the costs of driving home on electricity and on gasoline. It is assumed that unserved EV users would park at the closest available parking lot. That is, the walking distance of an unserved user from building f is estimated as

$$\tilde{d_f} = \min_p\{d_{pf}\}.$$

Moreover, let V_{pf} be the number of EV drivers in building f who park at lot p before the charging facilities are provided, and S_{pf} be the number of EV drivers in building f who can no longer use lot f. We also use C_t to denote the unit inconvenience cost of switching to a new parking lot (see Table 1). The extended model considering unserved demands and switching costs may be formulated as follows:

$$\min \sum_{p=1}^{N_P}\left(C^c Y_p + C_p^g X_p\right) + \sum_{p=1}^{N_P}\sum_{f=1}^{N_F} C_w d_{pf}^2 Z_{pf} + \sum_{f=1}^{N_F} E_f C_w \tilde{d_f}^2 + \sum_{f=1}^{N_F} E_f\left(C^u - C^t\right) + \sum_{f=1}^{N_F}\sum_{p=1}^{N_P} C^t S_{pf} + \sum_{f=1}^{N_F} C_w \widehat{S_f} \tag{8}$$

subject to constraints (2), (3), (5)–(7) and

$$\sum_{p=1}^{N_P} Z_{pf} \le \alpha H_f \quad \forall f \in F \tag{9}$$

$$E_f \ge \alpha H_f - \sum_{p=1}^{N_P} Z_{pf} \quad \forall f \in F \tag{10}$$

$$S_{pf} \ge V_{pf} - Z_{pf} \quad \forall f \in F, p \in P \tag{11}$$

$$S_{pf} \ge 0 \quad \forall f \in F, p \in P \tag{12}$$

$$\sum_{p=1}^{N_P} d_{pf}^2 Z_{pf} - \sum_{p=1}^{N_P} d_{pf}^2 V_{pf} \le \widehat{S_f} \quad \forall f \in F \tag{13}$$

$$\widehat{S_f} \ge 0 \quad \forall f \in F \tag{14}$$

where $\widehat{S_f}$ measures the excessive distance to be traveled as a result of switching.

In addition to the facility cost and walking cost, the objective function now also includes the distance to be traveled by unserved users (the third term), the inconvenience cost of unserved demand (the fourth term), the cost of getting acquainted with the new environment after switching parking lot (the fifth term), and the excessive distance to be traveled by switching users (last term). Note that the switching demands account for all the demands that have switched from their regular spot due to the adoption of PEVs, which also include the unserved users. Therefore, the term (C^u–C^t) in the objective function reflects the fact that switching cost does not apply to unserved users.

Constraint (9) states that the number of PEVs from building p that are served in any parking lot should be less than or equal to the total demand of p. Constraint (10) requires that the unserved demand in building f must be larger than or equal to the difference between the total number of PEV users and those that are served. Similarly, constraint (11) specifies the switching demand must be larger than or equal to the difference between the previous and current EVs from f allocated to lot p. Constraint (13) finds the excessive walking distance caused by switching in the system. Constraints (12) and (14) assure the nonnegativity of switching demand and excessive walking distance caused by switching.

4.2 *Demand uncertainty*

In our problem, the demand for charging facilities depends on the EV's market penetration ratio α. Yet, the predictions of the overall market share of EVs are subject to large variations. Thus, it is appropriate to anticipate such uncertainty when planning charging facilities. To this end, the EV market penetration rate $\vec{\alpha}$ is modeled as a discrete random variable with a known support $\Xi = \{\alpha_1, \alpha_2, \ldots, \alpha_L\}$. The probability of $\vec{\alpha}$ taking α_r is denoted as B_r and $\sum_r B_r = 1$. The stochastic version of the model can then be formulated as follows, along the line of Kalvelagen (2003).[4]

$$\min \sum_{p=1}^{N_P}\left(C^c Y_p + C_p^g X_p\right) + \sum_{r=1}^{R}\sum_{p=1}^{N_P}\sum_{f=1}^{N_F} C_w d_{pf}^2 B_r Z_{pf,r} + \sum_{r=1}^{R}\sum_{f=1}^{N_F} C_w \tilde{d_f}^2 B_r E_{f,r} + \sum_{r=1}^{R}\sum_{f=1}^{N_F}\left(C^u - C^t\right) B_r E_{f,r} + \sum_{r=1}^{R}\sum_{p=1}^{N_P}\sum_{f=1}^{N_F} C^t B_r S_{pf,r} + \sum_{r=1}^{R}\sum_{f=1}^{N_F} C_w B_r \widehat{S_{f,r}} \tag{15}$$

subject to constraint (2), (6)–(7)

$$\rho \sum_{f=1}^{N_F} Z_{pf,r} \le Y_p \quad \forall p \in P, r \in R \tag{16}$$

$$\sum_{p=1}^{N_P} Z_{pf,r} \le H_f \alpha_{f,r} \quad \forall f \in F, r \in R \tag{17}$$

$$E_{f,r} \ge H_f \alpha_{f,r} - \sum_{p=1}^{N_P} Z_{pf,r} \quad \forall f \in F, r \in R \tag{18}$$

$$S_{pf,r} \ge V_{pf}\alpha_{f,r} - Z_{pf,r} \quad \forall f \in F, p \in P, r \in R \tag{19}$$

$$S_{pf,r} \ge 0 \quad \forall f \in F, p \in P, r \in R \tag{20}$$

$$\left(\sum_{p=1}^{N_P} d_{pf}^2 Z_{pf,r} - \sum_{p=1}^{N_P} d_{pf}^2 V_{pf,r}\right) \le \widehat{S_{f,r}} \quad \forall f \in F, r \in R \tag{21}$$

$$\widehat{S_{f,r}} \ge 0 \quad \forall f \in F, r \in R \tag{22}$$

$$Z_{pf,r} \ge 0 (integer) \quad \forall f \in F, p \in P, r \in R \tag{23}$$

Note that all the constraints in this model are the same as the constraints in the deterministic model except that they are scenario dependent.

5. Specification of model inputs

5.1 *Allocation of demand*

The original allocation of demands to parking lots (V_{pf}) may be obtained from empirical data. When such data is not readily

[4] Note that the probability space in Kalvelagen (2003) is defined by the number of scenarios and the occurrence probability of each scenario. In our case, if we define $B = \{B_1, B_2, \ldots, B_L\}$, then our probability space is defined by (Ξ, B).

available, the following allocation model can be used to estimate V_{pf}.

$$min \sum_{p=1}^{N_P} \sum_{f=1}^{N_F} d_{pf}^2 V_{pf} \tag{24}$$

subject to

$$\sum_{f=1}^{N_F} V_{pf} \le Q_p \quad \forall p \in P \tag{25}$$

$$\sum_{p=1}^{N_P} V_{pf} \ge H_f \quad \forall f \in F \tag{26}$$

$$V_{pf} \ge 0(integer) \quad \forall f \in F, p \in P \tag{27}$$

Constraint (25) dictates that a parking lot can only serve demands up to its capacity (Q_p). Constraint (26) ensures that all the demands from different buildings have to be served at available parking lots. For the stochastic model, we assume that the allocation of demand to parking lots is proportional to the demand in each scenario, that is, $V_{pf}\alpha_{f,\ r}$.

In reality, the assignment of workers between some building–parking pair may be forbidden for various reasons, for example, parking permit regulation. Such restrictions can be implemented in a preprocess rather than by adding extra constraints in the model. In this study, we assume that parking permits are only offered to the workers who are working in office buildings located within a maximum allowable distance from the parking lot. Accordingly, the solution variables associated with those building–parking pairs are excluded from the model, which promises to improve the computational efficiency. Note that this assumption is adopted consistently across all models.

5.2 Facility cost

The cost of purchasing and installing a charger depends on the charging power. The unit cost is estimated as $500(\frac{\$}{kw})$ (Nie & Ghamami, 2013). Currently most of the charging stations in the United States use level-II chargers (U.S. Department of Energy, 2013). Considering an average power of 6(kW) (Plugin America, 2012) for level-II chargers, the unit charger cost would be \$3,000. The cost of converting a parking lot to a PEV-compatible lot, C_p^g, is composed of different costs, such as cost of cords, wall boxes, branch circuits, meters, breaker panels, and administration costs. In this study, C_p^g is estimated as \$2,000 for level-II charging facilities (Morrow et al., 2008). In reality, C_p^g may depend on the location of parking lots, which may affect, among other things, the cost of connecting to electrical grids. Because this study does not consider the integration between electrical grids and charging facility locations, the same $C^g{}_p$ is adopted for all parking lots.

Table 2. Penetration rate and probability of different scenarios for each building.

Scenarios	Low	Medium	High
Penetration rate	0.12	0.23	0.58
Probability	0.33	0.33	0.33

Table 3. Distance matrix between the building and parking lots (feet).

Node number	1	5	8	18	20	23	13
10	2,970	1,320	1,485	1,155	1,815	2,145	2,310
11	2,310	1,320	2,310	1,980	2,640	1,320	1,485
15	3,795	2,310	1,980	1,650	1,155	1,155	1,980
17	3,300	2,145	1,155	825	990	1,980	2,805

5.3 Walking cost

To estimate the walking cost, we assume the average walking speed as $3\left(\frac{mile}{hr}\right)$, and use the average hourly wage in 2012 in the United States, which is $23.5(\frac{\$}{hr})$ (Bureau of Labor Statistics Data, 2013), to evaluate the time spent on walking. This leads to a unit walking cost of about $0.001\left(\frac{\$}{feet}\right)$. Because the walking cost is a quadratic function of distance, the unit walking cost C_w is set to $10^{-6}\left(\frac{\$}{feet^2}\right)$.

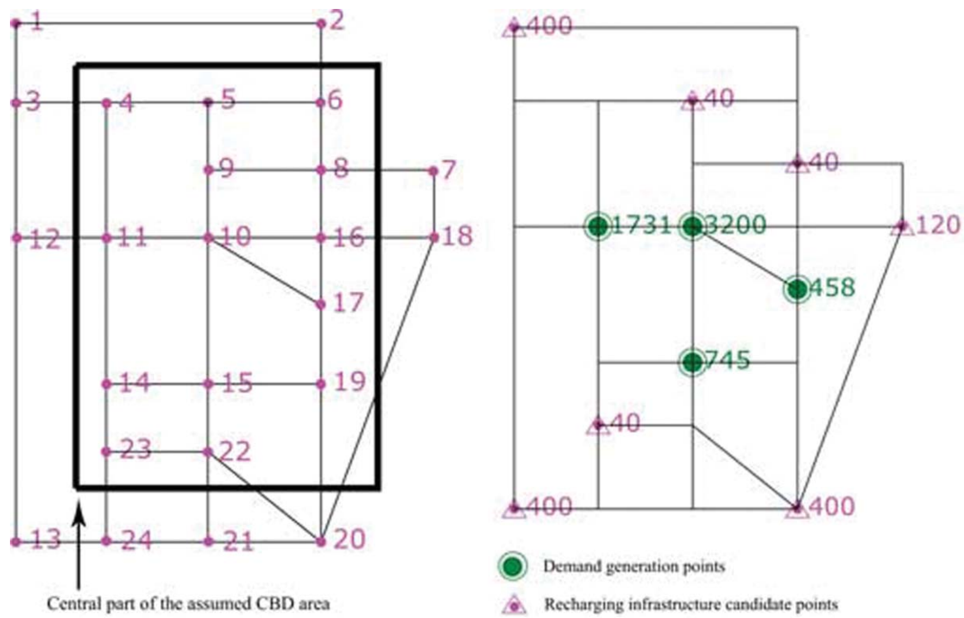
5.4 Unserved demand cost

The cost of unserved demand for PHEVs is calculated as the difference between gas and electric miles. The unit distance cost of gas is estimated based on the average United States gas price ($3.55(\frac{\$}{gallon})$) for 2012 (U.S. Energy Information Administration, 2012) and the average conventional vehicle fuel efficiency (35.6 mpg for 2012) (U.S. Department of Transportation, 2012). Therefore the per unit distance cost of gas is $0.1(\frac{\$}{mile})$ while the same cost for electricity is about 0.04 $(\frac{\$}{mile})$ (U.S. Department of Energy, Alternative Fuels Data Center, 2013). Assuming a daily vehicle miles traveled (VMT) of 30 (Santos, McGuckin, Nakamoto, Gray, & Liss, 2009), the cost of unserved demand for PHEVs is estimated as \$1.8. The cost of unserved demand for BEVs is estimated based on the time for charging at a public charging station. With fast charging at a public charging station, this time is estimated as about 15 minutes,[5] and valued at about \$5.8. Clearly, the inconvenience cost is higher for BEV users than for PHEV users. In this study, an average of \$3.8 is adopted to represent the unserved demand cost for both PHEVs and BEVs.

5.5 Switching cost

Users may incur two different types of costs upon switching their parking lots. One is the cost of additional walking distance and the other is the cost of getting acquainted with the new environment. We assume that during the first month after a user switches his/her parking lot, an extra time of ten minutes is needed to find a spot in the new parking area, to locate amenities such as elevators and exits and to find the most desirable walking path. Using the same value of time of $23.5(\frac{\$}{hr})$, the inconvenience cost of switching to a new environment would be equal to \$4. We assume that this confusion in the new environment diminishes after the first month.

[5] U.S. Department of Energy, Alternative Fuels Data Center, Developing infrastructure to charge plug-in electric vehicles, http://www.afdc.energy.gov/fuels/electricity_infrastructure.html



(a) Network topology of the case study
(b) Demand generation points and candidate charging stations *(The numbers show demand and maximum capacity of nodes)*

Figure 1. Description of the case study.

5.6 *Life span*

It is worth noting that some of the above costs occur once in a lifetime (e.g., the capital cost and switching cost) and the others (e.g., the walking cost) are routine daily costs. To address this issue, a 10-year analysis period is assumed (Chang et al., 2012) and all the costs in the former category are amortized to a day considering a zero percent interest rate.

5.7 *Stochastic demand scenarios*

For the stochastic model, three different penetration scenarios are considered: low, medium, and high, as shown in Table 2. Note that the penetration rates are estimated based on 2030 market predictions[6] according to different assumptions. Because the assumptions leading to these estimates are independent from each other, we assume that they all have an equal probability to occur.

6. Numerical experiments

After describing the case study, this section will present and compare the results for the base and proposed models. A comprehensive sensitivity analysis is then performed to test the model's sensitivity to various cost components as well as other parameters. Finally, the results obtained from the stochastic and deterministic models are compared. All models are implemented in AMPL[7] and solved using Knitro solver.[8] The default values of the input parameters are introduced in section 5 and remain the same unless otherwise specified. For the base and the proposed deterministic modes, the market penetration rate is assumed to be 0.23.

6.1 *Case study description*

A hypothetical network with a topology as described in Figure 1 (a) is used to represent a CBD area. The central part of this CBD area (marked in Figure 1) is assumed to be denser and thus have less capacity available. In the base scenario, $P = \{1, 5, 8, 13, 18, 20, 23\}$ and $F = \{10, 11, 15, 17\}$. Figure 1(b) highlights the demand generation points and the candidate nodes for building charging facilities.

The shortest distance matrix between buildings and candidate points is presented in Table 3. Also it is assumed that only candidate points located within 2,500(*ft*) (Bossard et al., 2002; NJ Transit, 1994) from a building can serve the building as potential parking lots.

6.2 *Comparison between base and proposed deterministic model*

Figure 2 compares the optimal number of chargers installed at each candidate lot obtained from the base and the proposed deterministic models. Notably, the candidate site at the upper left corner (node 1) has zero chargers in the proposed model, whereas in the base model it has 303 chargers. The reason for this difference is that this lot is at a relatively remote location. (As shown in Table 3, the distances between node 1 and the office buildings are significantly higher than the other candidate lots.) In other words, drivers prefer not being served to parking their EVs at a remote lot that requires excessive walking. This implies that the walking cost associated with the lot is actually higher than the inconvenience cost of being unserved. Therefore, if the candidate parking lots are not located close

[6]Long Term Electric Report for Maryland (LTER) Plug-In Electric Vehicles, White Paper, 2010, http://esm.versar.com/pprp/pprac/Docs/PEV_White_Paper.pdf
[7]http://www.ampl.com/
[8]http://www.ziena.com/knitro.html and http://www.ampl.com/solvers.html

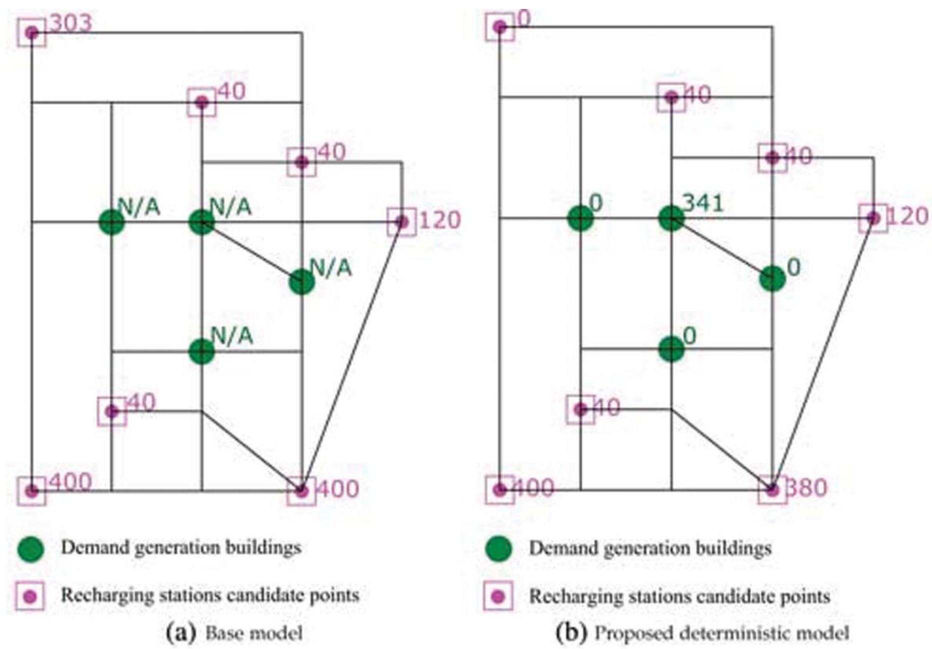


Figure 2. Comparing the number of recharging spots in each lot for the base model and the proposed deterministic model. The numbers beside recharging stations candidate points represent the optimum capacity charging stations and the numbers beside demand generation buildings show the amount of unserved demand in these buildings.

enough to demand generation buildings, they may not be used as an incentive for adopting electric vehicles.

6.2.1 *Sensitivity to various costs*

Nie and Ghamami (2013) showed that the current per unit power charger cost may be estimated at about $500\left(\frac{\$}{kw}\right)$. We assumed that this cost may decrease to $100\left(\frac{\$}{kw}\right)$ as the technology advances. Accordingly, the unit charger cost varies between \$600 to \$3,000 for type-II chargers (with a 6(kW) power), and between \$9,000 to \$45,000 for type-III chargers (with a 90(kW) power). In our sensitivity test, the range for the unit charger cost (C^c) is assumed to be between \$600 and \$27,000.

Figure 3(a) shows that the system cost increases with the walking cost in the base and the proposed deterministic model. The increase rate is small at the beginning but when the walking cost exceeds a certain threshold, the slope becomes much steeper, thanks to the quadratic distance function. Moreover, a small walking cost leads to a smaller number of charging stations by avoiding locations with small available capacities. The reason is that with small walking costs, walking is less of a burden for the system than the fixed cost required to convert a new parking lot. As the walking cost increases, more charging stations are converted but distant locations become less attractive, suggesting that walking cost outweighs the cost of building charging stations. Clearly, larger walking costs also lead to more unserved demand in the proposed deterministic model.

Figure 3(b) also shows that the system cost increases linearly with the unit charger cost (C^c) in the base model. In the proposed deterministic model, however, when the conversion becomes too expensive, all demands will remain unserved and no charging station will be built. This explains why the total cost becomes a constant after the unit charger cost exceeds a certain threshold (Figure 3[b]). Moreover, the optimal configuration of charging stations in the base model is not sensitive to the unit charger cost, indicating that the walking cost is the dominating factor in the base model. In contrast, in the proposed models, a large

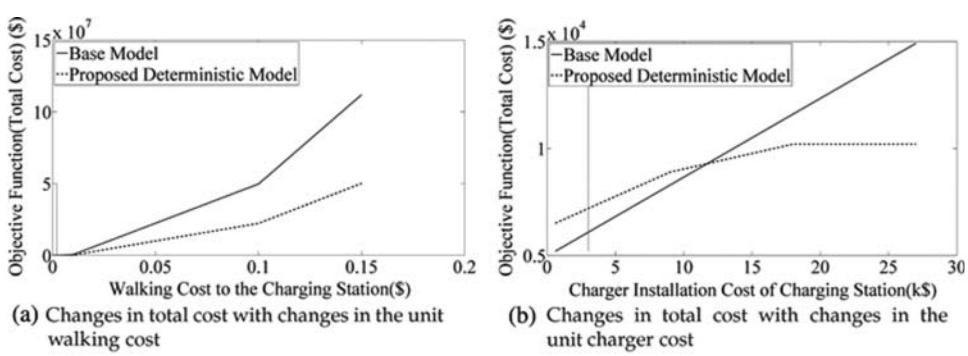


Figure 3. Sensitivity of the base and the proposed deterministic model to various cost parameters. *Note*. The vertical line represents the base parameter values.

Table 4. Comparison of the base model and proposed deterministic model results for different penetration rates.

Node number		Optimum capacity of charging stations at candidate points							Unserved demand in buildings			
Node number		1	5	8	18	20	23	13	10	11	15	17
Penetration rate = 0.06	Base model	0	40	25	120	70	40	57	N/A	N/A	N/A	N/A
	Proposed model	0	40	38	120	70	40	43	1	0	0	0
Penetration rate = 0.12	Base model	0	40	40	120	304	40	158	N/A	N/A	N/A	N/A
	Proposed model	0	40	40	120	190	40	156	120	2	0	0
Penetration rate = 0.18	Base model	12	40	40	120	400	40	400	N/A	N/A	N/A	N/A
	Proposed model	0	40	40	120	333	40	256	234	1	0	0
Penetration rate = 0.23	Base model	303	40	40	120	400	40	400	N/A	N/A	N/A	N/A
	Proposed model	0	40	40	120	400	40	380	341	0	0	0
Penetration rate = 0.31	Base model				Infeasible				N/A	N/A	N/A	N/A
	Proposed model	0	40	40	120	400	40	400	735	73	0	0
Penetration rate = 0.58	Base model				Infeasible				N/A	N/A	N/A	N/A
	Proposed model	0	40	40	120	400	40	400	1646	542	11	266

unit charger cost makes it better not to build a station and to leave charging demands unserved.

6.2.2 *Sensitivity to penetration rate*

Table 4 reports the sensitivity of the base and proposed models to the penetration rate. As expected, increasing the penetration rate always leads to building more chargers and stations in the base model. When the demand exceeds the system capacity, the base model becomes infeasible. In the proposed model, however, as the penetration rate increases, a significant portion of the additional demand is left unserved.

6.2.3 *Total system cost decomposition*

Table 5 shows the percent of various user and facility costs in the total system cost using the base value of parameters. Notably, walking cost in the base model has the largest portion of the system costs. In the proposed deterministic model the users have the flexibility of walking from distant parking lots or experiencing the unserved demand cost. Thus, a considerable portion of the cost in the proposed deterministic model is unserved demand cost. However, switching cost is negligible relative to the other costs of the system.

6.3 *Comparison between deterministic and stochastic models*

6.3.1 *Sensitivity to various costs*

In this section, we compare the proposed stochastic model with a corresponding deterministic model, which uses the average market penetration rate, estimated from the given discrete distribution, as the input. The main purpose is to examine the benefits of modeling the market penetration rate as random variable (as opposed to using a nominal average).

In Figure 4(a), the total system cost increases with the walking cost following the trend of the quadratic function. In other words, the rate is small at the beginning but as the walking cost exceeds a certain threshold the rate increases.

Total system cost also increases with the charger installation cost (Figure 4[b]). After a certain threshold building charging stations becomes too expensive and no charging station will be built. Thus, the total cost remains constant after that threshold. Also, as unit charger cost is the only non-scenario dependent section of the objective function, building no charging stations makes the proposed deterministic and stochastic models objective functions similar, as averaging the demand inside or outside the model does not make any difference.

Figure 4(c) shows that increasing the unit unserved demand cost will eventually force all demands to be served in the proposed deterministic model. Also, after the unit unserved demand cost exceeds a certain threshold, the total cost will be fixed. The sensitivity of the stochastic model is different in this case, with the total cost continuously increasing without an upper bound. The reason for this difference is that for the highest penetration rate in Table 2, the unserved demand is inevitable. As long as there are unserved demands, the total cost is bound to increase with the unit unserved demand cost.

Finally, Figure 4(d) indicates that the sensitivity of the model with respect to the unit switching cost is rather weak. This is expected because the switching cost (about 10 minutes for the first month after switching) has to be spread out in a period of 10 years.

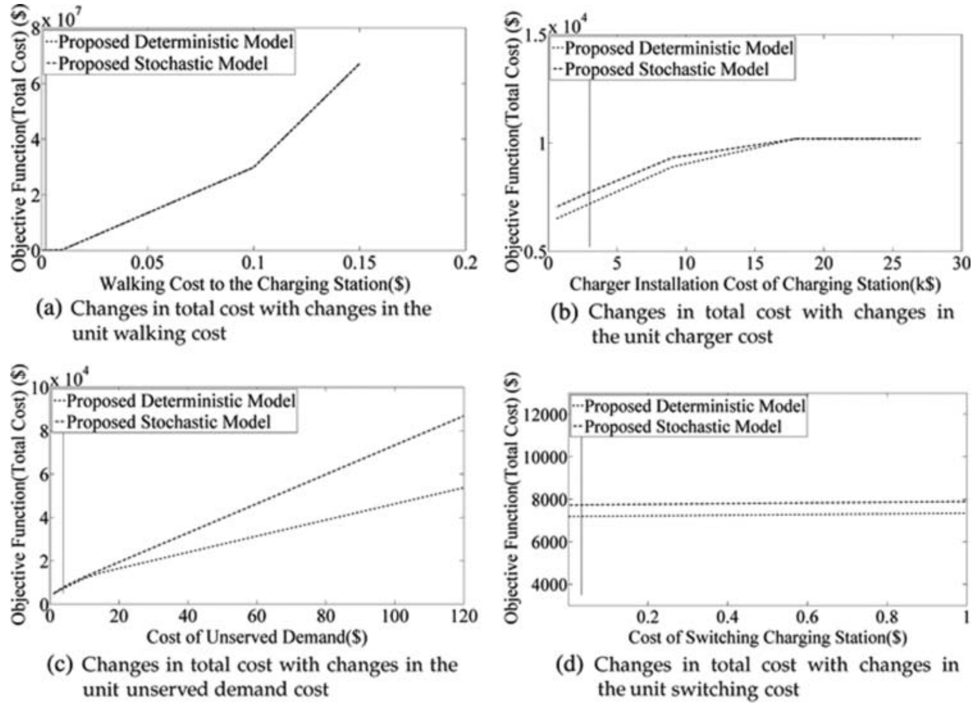
6.3.2 *Total system cost decomposition*

Table 6 shows that the portion of various costs in the proposed stochastic model and the equivalent proposed deterministic model are comparable.

Table 5. Share of various costs in the base and proposed deterministic model total cost.

Model	Construction cost	Walking cost	Unserved demand cost	Switching cost
Base model	18.2%	81.8%	—	—
Deterministic model	16.5%	42.3%	36.9%	4.3%

Note. The penetration rate of PEVs is assumed to be 0.31.



(a) Changes in total cost with changes in the unit walking cost

(b) Changes in total cost with changes in the unit charger cost

(c) Changes in total cost with changes in the unit unserved demand cost

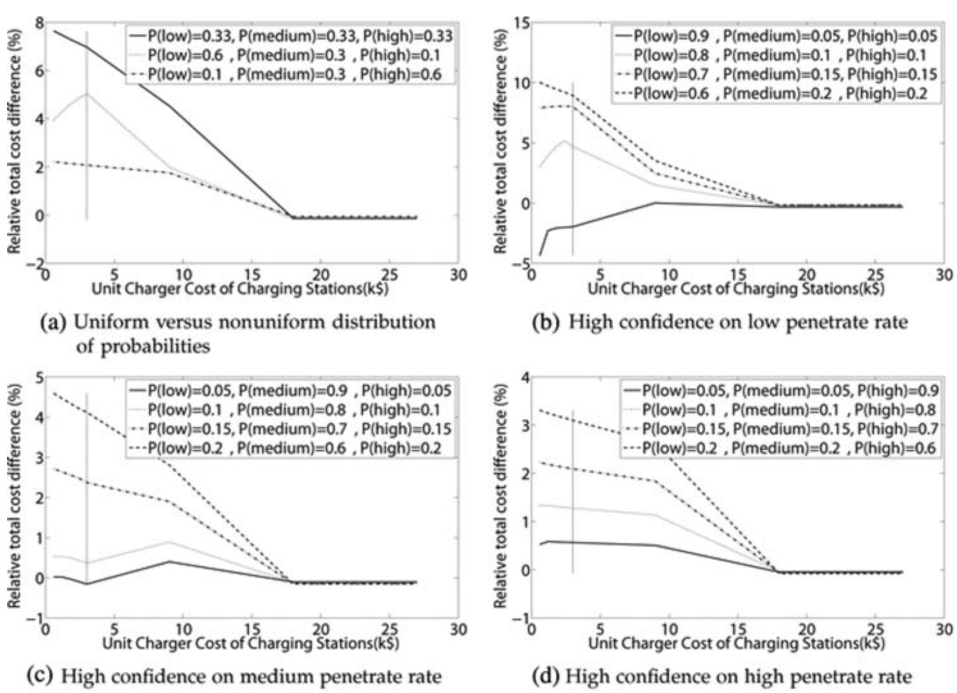
(d) Changes in total cost with changes in the unit switching cost

Figure 4. Sensitivity of the base and the proposed models to various cost parameters. *Note*. The vertical line represents the base parameter values.

6.3.3 *PEV penetration scenarios*

Because the cost of installing the charging facilities (including both fixed and variable costs) is not scenario dependent, we compare the stochastic and the associated deterministic models against various values of these costs, as reported in Figure 5. The percent of relative difference in this figure is calculated as the total cost of the stochastic model minus the total cost of the deterministic model divided by the total cost of the stochastic model.

Figure 5(a) compares the sensitivity of the total system cost to the unit charger cost under three different penetration distributions. First, note that the difference between the



(a) Uniform versus nonuniform distribution of probabilities

(b) High confidence on low penetrate rate

(c) High confidence on medium penetrate rate

(d) High confidence on high penetrate rate

Figure 5. Relative total cost difference of the proposed deterministic and stochastic models under different penetrate rate distributions. *Notes*. The percent of relative difference is equal to the total cost of the stochastic model minus the total cost of the deterministic model divided by the total cost of the stochastic model. The Vertical line represents the base parameter values.

Table 6. Share of various costs in the proposed deterministic and stochastic models total cost.

Model	Construction cost	Walking cost	Unserved demand cost	Switching cost
Deterministic model	11.8%	26.7%	61.1%	0.4%
Stochastic model	11.1%	24.3%	64.1%	0.5%

Note. The penetration rate of PEVs is assumed to be 0.31.

deterministic and stochastic models diminishes as the unit charger cost increases. This is because a higher unit charger cost leads to less charging facilities. When no charging facility is built, the system cost only depends on the scenario-dependent user cost. In other words, whether the demand is averaged outside or inside the model does not make any difference. So the stochastic model and its nominal deterministic counterparts produce exactly the same results in this case. Another useful finding from Figure 5(a) is that the largest difference between the stochastic and deterministic models always occurs when the likelihood of having low, medium, and high penetrate rate is the same. This is expected because a uniform distribution implies low confidence on any projected penetration scenario. Thus, properly hedging against such high uncertainty involves higher cost. Also clear from Figure 5(a) is that, as the confidence over some scenarios is strong, the cost caused by uncertainty decreases.

Figures 5(b)–5(d) test more distribution scenarios, each corresponding to a strong confidence on one of the three penetration realizations (low, medium, and high). Figure 5 (b) shows that when the confidence on low market penetration is 0.6, the difference between the two models peaks. As this confidence increases, however, the difference decreases, and finally even reverses the sign (i.e., the stochastic model actually yields a lower total cost). Figures 5(c) and 5(d) generally demonstrate the similar trend. However, the difference between the models seems to become smaller when the higher penetration projection receives strong confidence.

We emphasize that using a nominal penetration rate in the proposed deterministic model generally underestimates the total system cost. In the worst case, the difference can be as high as 10 percent in this example. Adopting the stochastic model is useful to avoid such a suboptimal solution.

7. Conclusions and future study

This study is concerned with the problem of locating charging stations in city centers so that workers can charge their plug-in electric vehicles at their workplace. The problem is formulated as a fixed charge facility location model, which extends the model of Dashora et al. (2010) by allowing unserved demands and considering drivers' preference for familiar parking lots. Inconvenience costs are introduced for unserved demands and for those who have to change their parking lots for the purpose of charging. One advantage of the proposed model is that it is always feasible regardless of the demand level, since the unserved demand is "priced" by the inconvenience cost and can be traded off with other system costs. In addition, the proposed model also addresses the effects of uncertain market penetration rate on the design of charging facilities.

Findings from the numerical experiments are summarized as follows:

- Increasing walking cost makes parking lots located far away from the demand generation points less attractive. In the proposed model, distant parking lots may be abandoned as the drivers would rather be unserved than walk an excessively long time to access parking.
- The base model is insensitive to the unit charger cost because all demands have to be served. In contrast, the proposed model will respond to the increase in the unit charger cost by leaving more demands unserved. Thus, the proposed model better reflects the trade-off between the infrastructure cost and the level of service. Indeed, a large unit charger cost may reduce the level of service of the charging facilities, hence discouraging the adoption of PEVs.
- Ignoring uncertainty in the EV penetration rate underestimates the total system cost in most tested cases. Such differences increase with the level of uncertainty in general.

Numerical results from the proposed model show that, when the unit walking cost is high, remote parking lots are not attractive to EV users even if they are equipped with charging facilities. To make more effectively use of these remote parking spaces requires providing better access to them from CBD. One possibility is to connect the remote lots to the CBD area using an alternative mode of transportation such as a shuttle bus service. This would lead to a new model that includes multimodal transportation between office buildings and parking lots (walking and taking bus), and the cost of providing alternative transportation. The analysis of such a model seems an interesting direction for future research.

Finally, the focus of this article is to understand the properties of the proposed model. No attempt has been made to design specialized solution methods for the underlying integer programs, which could be a significant challenge in real-world applications. We leave this important task also to future studies.

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