DEPLOYMENT OF PUBLIC PLUG-IN ELECTRIC VEHICLE (PEV) STATIONS IN MID-OHIO REGION

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ABSTRACT

We apply a simulation-optimization approach developed by Xi et al. (2013) to optimize the PEV charging station location in Mid-Ohio region. This approach consists of a simulation model that formulates relations between service levels and numbers of chargers built at candidate stations, and an optimization model that determines a location plan by maximizing the overall service levels in the region. Our study find that a combination of the level-one and -two chargers can serve more PEVs than level-two only given a limited deployment budget, and that although the location plan is greatly affected by the type of service levels that is optimized, the actual service levels are relatively insensitive to the optimization strategy.

KEY WORDS:

Plug-in Electric Vehicles (PEV), Charging Infrastructure Location

1. INTRODUCTION

Electric vehicles (EVs) have been a distant star, shining and visible, but out of reach due to many obstacles in the past several decades. However, with the recent breakthroughs in the battery technology, many electric models are finally taking over the market at a promising pace, such as Toyota Prius, Nissan Leaf, and Chevy Volt. According to the sales data from Electric Drive Transportation Association, nearly 487,500 of the 14.4 million vehicles (about 3.4%) sold in U.S. in 2012 are electric, and about 53,000 of them are plug-in electric vehicles (PEVs). Although the current PEV market share is still low, the sales data indicates a potential exponential increase. PEVs are forecast to reach 400,073 annual sales in the United States by 2020 in the most recent projection by Pike Research.

Availability of public charging stations plays an important role in customers' purchasing decision of PEVs. Many early adopters experience a feeling of 'range anxiety', wherein they are concerned about being stranded with a depleted battery, and many customers also express that they are unlikely to consider purchasing PEVs until they see sufficient public charging stations. Therefore, wide adoption of PEVs requires careful planning for public charging stations.

Current PEV charging technology offers 3 types of charging methods (Table 1.1): level one charging, level two charging, and DC fast charging. Level one charging usually uses a standard power outlet of 110 VAC and 15 amp, which can be found in most residential or public buildings in United States. It can take about 12-18 hours to fully charge a vehicle battery in most existing vehicle models. Level two uses a 220 VAC circuit with 15-30 amp and thus takes less time to charge. DC fast charging uses a high direct current (i.e. 400-500 VDC) and is expected to require no more than 30 minutes to charge. However, since fast charging method requires special charging equipment and is beyond the power capacity of most residential infrastructures, DC charging is not expected to be implemented in residential areas.

Table 1.1

Charging Method	Voltage	Usage	Power	Time to Charge
Level 1	110 VAC	Home/Public	1.4 kW	12-18 hours
Level 2	220 VAC	Home/Public	3.3-6.6 kW	4-8 hours
DC fast charging	400-500 VDC	Public	50 kW	15-30 min

The fundamental questions of charging station location planning are: (1) where to put the charging stations, (2) how many charging stations are needed, (3) and what type of charging technology to use. These questions are important in the sense that the availability of convenient and affordable recharging infrastructure will directly affect customers' purchase decision. Moreover, a location plan might indicate potential power congestion and help utilities companies get ready.

The location problem of PEV charging station, in general, is a refueling infrastructure problem, which has been studied in the literature. Kuby et al. (2009) develop a model that locates hydrogen stations by maximizing the volumes of the vehicle flows that pass through the stations. The vehicle flows are measured either by the number of vehicle-trips or the vehicle-miles traveled. The inputs of the optimization model include a network with nodes of origins and destinations, origin-destination flow volumes of conventional vehicles from weekdays, and a set of candidate locations which are either on the nodes or the origin-destination paths. Stephens-Romero et al. (2010) introduce a model that determines the location of hydrogen stations by travel time analysis between current gasoline stations and candidate hydrogen stations. Each gasoline station is considered as a hydrogen demand point, the objective is to minimize the total number of hydrogen stations required to cover all the gasoline stations within a certain travel time distance. Other similar studies include Nicholas et al. (2004), Melaina (2003), etc. There are also studies exploiting location models for PEV charging stations. Ip et al. (2010) determine the location of fast charging stations using a hierarchical clustering method. This method converts road traffic information into demand clusters and each cluster is assumed to be assigned with one fast charging station. However, the exact location of the charging station in the cluster is not determined. Frade et al. (2011) propose a maximal covering model, which determines the location of level-one charging stations by maximizing the demand covered within an acceptable distance of the stations. The demands are determined based on the number of vehicles at each city block. An implicit assumption of this approach is that the demands can be satisfied, without regard to EV arrival and departure times.

Despite the body of the existing researches, there are still numerous issues and nuances that are not well addressed by the existing models and thus limit their application in PEV charging stations. First, most of the existing models are more appropriate for fast refueling systems, such as gasoline and hydrogen. These models usually neglect the charging time, and assume that all the vehicles arrive at the stations can be served. While this assumption is acceptable for hydrogen and gasoline charging, it is not appropriate for slow charging technology such as level-one and –two charging. Considering the fact that PEV charging takes a decent amount of time, a flow that arrives to a station might be rejected if there’s no free chargers in the station and the customer is unwilling to wait; or a vehicle might only be partially charged because its parking duration is not long enough for full charging.

Second, many of the earlier studies use conventional vehicle flows or gasoline sales data to estimate the new vehicle flows, with an implied assumption that the new vehicle flows are proportional to conventional ones. This assumption is problematic to estimate PEV flows as many recent studies indicate that PEV adoption is strongly related to customers’ economic and demographic characteristics. Curtin et al. (2009) conduct an interview about people’s interest in electric vehicles, finding that households with higher income and education level are more likely to buy electric vehicles. Besides, vehicle usages, such as number of cars in the house hold and daily highway miles, also have a significant influence. Households with more vehicles, smaller average vehicle ages indicate stronger interests in electric vehicles. Gallagher and Muehlegger (2009) find that people who are more concerned with environmental and energy security issues are more likely to purchase HEVs. Similar results are also found in Ren et al. (1994), Melendez and Milbrandt (2006).

A third issue with the existing models is that they can’t decide how many chargers are needed for each PEV charging station. This question is important for PEV charging station planning because the number of chargers directly affects the amount of the PEVs that can be served due to the prolonged charging duration.

Given the limitations of existing refueling infrastructure models, Xi et al. (2013) develop an infrastructure location model that is specifically for slow charging technologies such as level-one and –two charging. Their model maximizes PEV service level while accounting for the impact of vehicle arriving pattern and parking time on actual flows that can be served. The PEV flows are weighted by factors of vehicle usage, economic and demographic characteristics of households. We apply this model to study the optimal station location plan for level-one and –two charging stations in mid-Ohio region under different deployment plans and PEV adoption levels.

The remainder of this report is organized as follows. Section 2 describes the data used for our study of mid-Ohio region. Section 3 describes how data are processed using the location model by Xi et al. (2013). Section 4 summarizes our study results of mid-Ohio region.

2. VEHICLE ELECTRIFICATION IN OHIO AND DATA STRUCTURE

The state of Ohio has always shown great interest in renewable energy and alternative fuels. In 2002, Clean Fuels Ohio was founded, a non-profit organization interested in the utilization and deployment of advanced fuel and vehicle technologies. Later in August 2008, a program named Ohio Green Fleets was launched by Clean Fuels Ohio, which has engaged hundreds of fleets across the state through workshops, seminars and individual meetings, and helped them displace a combined total of 4,814,095 gallons of petroleum and eliminated over 180 tons of nitrogen oxide (NOx). The Ohio State University has always been an active researcher in clean technology. In 2009, the university's Center for Automotive Research (CAR) received state approval for the first $500,000 of a $3 million Ohio Third Frontier Grant designed to promote commercial electric vehicles, including buses and trucks. Ohio companies Vanner, Inc. and American Electric Power, along with STMicroelectronics of Michigan, and Fil-Mor Express of Minnesota, have been collaborating with CAR on the initiative to create more than 900 new clean-energy jobs. In 2011, the Ohio State University and Clean Fuels Ohio received a combined $1.4 million funding from the federal government to develop a comprehensive electric vehicle infrastructure and planning initiative for Ohio. This project is partially sponsored by this funding. Great supports are also received from Mid-Ohio Regional Planning Commission (MORPC), an organization that aims for the overall improvement of the mid-Ohio in land use, transportation, energy efficiency and environmental quality. All of the following data, which are used for our study, are provided by MORPC.

2.1 Traffic Analysis Zones (TAZs) and Demographics

MORPC divides the whole mid-Ohio region into 1805 traffic analysis zones (TAZs), (see Figure 2.1). For each TAZ, economic and demographic, and current vehicle usage data from year 2010 are collected, which are listed as follows:

- Number of households in the TAZ
- Number of population in the TAZ
- Average household population
- Average household income
- Median household income
- Total employment in TAZ
- Number of households with 2 or more cars
- Average household travel time
- Average of highway travel time
- Population 25 years and over (denominator for calculating education percents)
- Population 25 years and over with high school degree
- Population 25 years and over with some college degree
- Population 25 years and over with associate degree
- Population 25 years and over with college degree

These data are used to estimate the likelihood of a household purchasing PEV, so as to estimate the volume of PEV flows. More details are given in section 3.1.

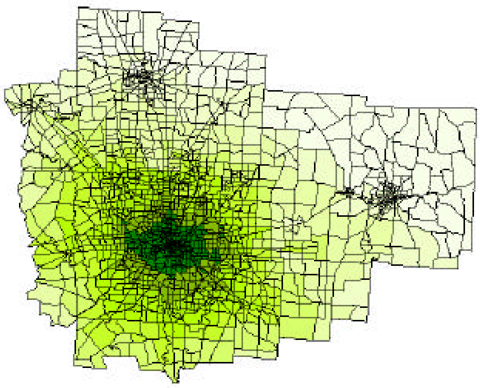


Figure 2.1 Traffic Analysis Zones of Mid-Ohio Region

2.2 Tour Record Data of Conventional Vehicles

A second important data set from MORPC is the tour record data, which contain detailed vehicle travels information of a typical weekday in the mid-Ohio region. These data are generated from the MORPC tour-based model system (Schmitt et al.(2006), Sener et al.(2009)).

The MORPC tour-based model system (see Figure 2.2) first generates a list of synthetic households (and individuals) for each TAZ through the "population synthesizer", which takes the TAZ-level socioeconomic (e.g. total population, number of households, age and labor force participation, and average household income) and land-use data as inputs, and creates a synthetic population of households drawn from PUMS[1] allocated to TAZs. Then based on the socioeconomic and structure of a household, each individual in the household is assigned with a daily travel plan drawn from MOPRC household travel database. This database is based on the 1999 Household Interview Survey, which collected single weekday travel data from 5,555 households and contains 13,500 full person day observations and almost 18,000 tours for various purposes. Although the household travel database is from 1999, statistics are adjusted to consider changes of travel behavior over time when generating travel tours of future years.

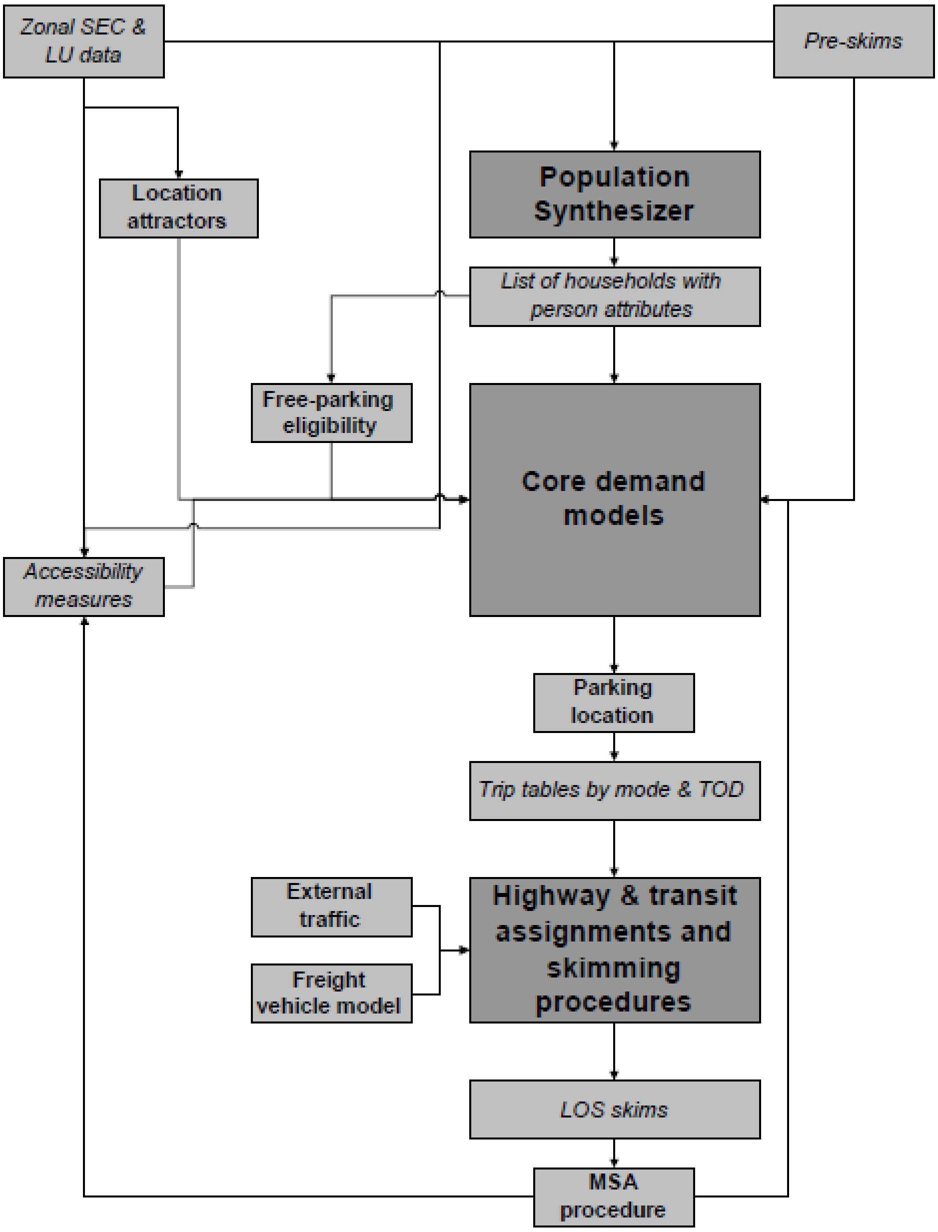


Figure 2.2 MORPC Tour-Based Modeling system

The tour assignment of synthetic individuals is achieved household by household through "the core demand model". The inputs of this model include: (1) socioeconomic of the households and individuals, (2) land-use data of the simulation year, (3) auxiliary data such as location attractor and accessibility variables, which define how an individual chooses among different destinations for each travel purpose. Based on the car ownership and age and labor force participation, the core demand model first generates a list of mandatory travels (i.e. work, university, and school). Then, in the next stage of the modeling, non-mandatory tours -- any travel except for work, university and school, such as eating out, friends visit -- are generated given the time remained for each individual after mandatory

[1] Public use microdata sample data: a sample of population and housing unit records from the American Community Survey

travels. Statistics of mandatory and non-mandatory tour frequencies are taken as inputs of in this procedure, and tours of individuals from the same household can be combined into a single tour under certain rules and probability. The destinations of tours are determined the location attractor variables and the accessibility variables. In the final stage of the core model, sub-stop is added into the tours between origin and destination, and travel modes (i.e. public transportation, vehicle, walk) are determined for each segment of the tours.

The current MORPC model system is able to generate travel tours of mid-Ohio region for a typical weekday of 2010, which are used for our study. This data set contains about 2.05 million vehicle tours that travel within the 1805 TAZs. Each tour is a vector of more than 70 elements, defining details such as the origin and destination TAZs, travel distances, times when tours start and end, travel purposes, etc. Table 2.1 shows an example of tour records. Each vehicle, each individual and each household in the data set has an unique ID (i.e. VehicleID, PPID, HHID). The first 2 rows of Table 2.1 shows that a person (ID=18273), who lives in TAZ 321, leaves for work (in TAZ 324) at 8 am and comes back home at 4 pm. During his stay at work, he drives to TAZ 273 for lunch.

Table 2.1 Tour Record Example

VehicleID	PPID	HHID	HomeTAZ	OriginTAZ	DestTAZ	StHr	EndHr	Purpose	…
132	18273	7283	321	321	324	8	16	Work	…
132	18273	7283	321	324	273	12	13	Eat	…
133	18274	7284	322	322	543	9	17	University	…

2.3 Other Data

The following data are also collected from MORPC:

- A list of major groceries and shopping centers, and their locations
- A list of employers and their size of employment within each TAZ
- A list of garages and park lots (in downtown area), and their sizes and locations
- A list of universities, and parking garages and their sizes

These data sets are used to define candidate locations for charging stations and to allocate PEV flows among locations within a same TAZ (section 3.2).

3. MODELING TECHNIQUE AND USE OF MORPC DATA

In this section, we discuss how we use the MOPRC data and apply the location model in Xi et al. (2013) to determine the location plan for public PEV charging stations in mid-Ohio region. In the first two subsections, we generate the PEV flows by estimating the adoption probabilities of individuals living in each TAZ. We then formulate the service level of each candidate location as a function of the number of the chargers to install (Section 3.3). Finally, an optimization model is used to determine the number of chargers to build at each candidate location by maximizing the total service level of the region subject to a fixed budget constraint.

3.1 Convert Conventional Vehicle Tours into PEV Tours

To estimate the PEV flows for our study, we use the regression model in Curtin et al. (2009) to estimate the PEV adoption probability by TAZ. This model accounts for the impact of customers' economic and demographic characteristics. There are 4 sets of explanatory variables included in the regression model:

- Vehicle ownership: number of vehicles owned, vehicle ages, current types of vehicles owned, new or used purchase, age of vehicle,
- Current driving behavior: average miles per day, percent of highways miles, monthly gas usage

- ●Economic and demographic: household income, education in years, gender, locations (urban/suburban/rural, northeast/south/west), age of respondents,
- ●Others: gas prices, electricity prices, concern of green technology, year to break even

The average number of vehicles owned, average vehicle miles, average miles of highway, average household income, average education years by TAZ are used to estimate the PEV adoption probability of individuals of each TAZ, while the values of the other explanatory variables are takens as the average values reported by Curtin et al. (2009). Figure 3.1 shows the density distribution of adoption probability among the 1805 TAZs, with an average value equal to 30%.

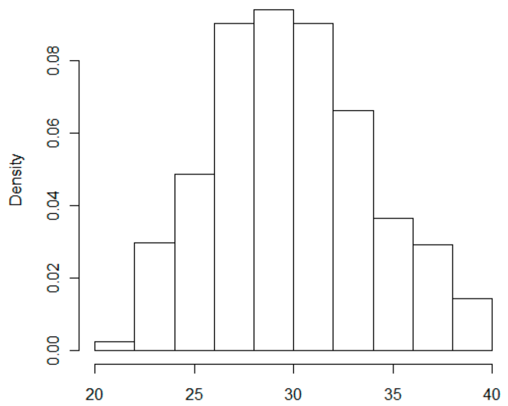


Figure 3.1 Distribution of Purchasing Probability

In our case study of Section 4, we explicitly assume the adoption level in the whole mid-Ohio region. In order to reach a certain adoption level we can scale the adoption probability of TAZ *i*, W_i, by letting,

$$W_i = (\overline{W} / \overline{W}_0) \bullet W_{i0},$$

where, W_{i0} is the original adoption probability from the regression model of TAZ *i*, $\overline{W}_0$ is original adoption level of the whole region, and $\overline{W}$ is the assumed the adoption level.

Since the tour record data (section 2.2) keep track of the home TAZ for each vehicle, we can decide if a particular vehicle from TAZ i is PEV by generating a random number (between 0 and 1). If the random number is smaller than W_i, then this vehicle is considered as a PEV, and all the tours of that vehicle are consider as PEV trips. By going through all the vehicles in the tour record data, we can obtain a PEV tour record data set.

3.2 Determine Candidate Locations for Charging Stations

Since level-one and -two charging generally takes several hours to fully charge a vehicle, a candidate location must require customers to have sufficiently long parking durations. For this reason, we pick 3 types of locations as candidates for PEV charging stations: working places, universities, and shopping places. From the MORPC data, we identify all such possible locations in the mid-Oho region. Besides, in order to be economically viable, a charging station must have sufficient PEV arrivals. In our study, we only model those locations with at least one daily expected arrival.

Figure 3.2 shows the TAZs that have candidate locations in our case study of mid-Ohio region at 1% adoption level. A green-area TAZ means that there are at least one working candidate inside, blue-area means university candidates, and red-area means shopping candidates. Table 3.1 summarizes the number of candidate locations, the number of TAZs with locations inside, and the number of daily PEV arrivals by location type.

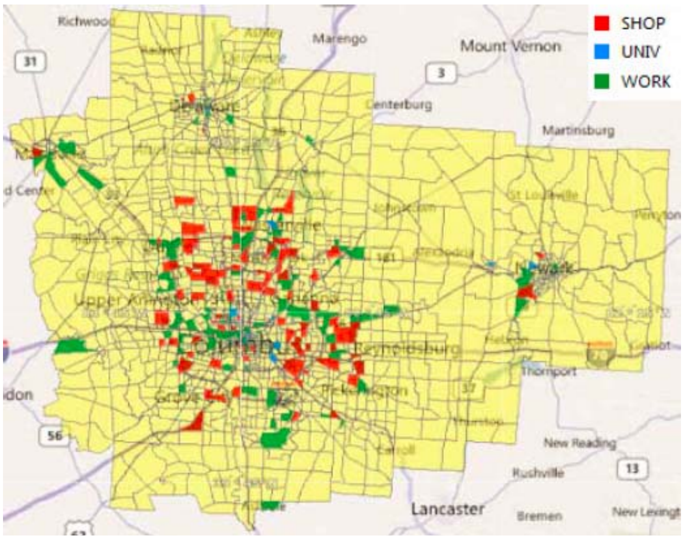


Figure 3.2 TAZs with Modeled Candidate Locations

Table 3.1 Candidate Locations by Type

Purpose	Work	University	Shop
# of candidate locations	275	25	158
# of TAZs	199	11	139
# of PEV arrivals (1%)	2725	276	501

3.3 Simulation Service Level at Each Candidate Location

Weather a PEV arrival can be successfully charge depends on if there's any free charger available when the vehicle arrives into the station. If not, a customer will park at a spot without charging. And even if there are free chargers available when a PEV arrives, it does not necessarily mean that the vehicle can be fully charged. Instead, the amount of energy charged depends the parking duration. Overall, the service levels, which can be measured either by number of PEV charged or by amount of energy charged, are dependent on the number of chargers, the power of the chargers, the arriving patterns of PEVs, and their times spent in the stations.

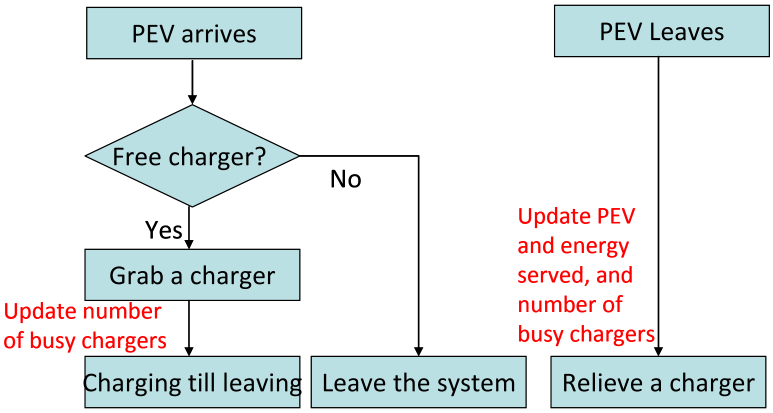


Figure 3.3

We build a simulation model to formulate the service level as a function of the number of chargers built for each candidate station. Figure 3.3 shows the procedures of the simulation model. Events of arrivals and leaving and the charging time are determined by the tour data of PEVs (section 3.2) that arrive into station i. After a PEV arrives, it checks if there are any free chargers available. If so, the PEV occupies a free charger and keep charging until the battery is full or the vehicle leaves.

When a PEV leaves from the system, the charger that is originally in use is relieved. The number of PEVs and amount of energy charged are recorded by the simulation system. The amount of energy is defined as,

*min {energy required, power rate of charger * time of charging}. (3.2)*

The first term in equation 3.2 is the energy required to fully charge the PEV given the state of charge (SOC) when the vehicle arrives into the station. We assume that each vehicle leaves from home with a fully charged battery in the morning; hence the SOC of vehicle will be dependent on the distances that it travels before arriving the station. We assume a constant fuel economy, 0.25 kWh/mile, in our case study of section 4; hence, the energy required is computed by,

*min {distance in miles * 0.25 kWh/mile, battery range},*

which is the minimum of the energy for travelling and battery range, because a PHEV might travel longer than the battery range can offer, in which case, the vehicle has to run on gasoline.

The total number of chargers built in the station, n_i, is parameterized as an input, which limits the maximum number of PEVs can be served at the same time. We assume different values of n_i, and for each value of n_i, we run 500 iterations[2] of simulation to compute the expected service levels, $f(n_i)$, i.e., the daily average number of PEVs charged, and the daily average amount of energy charged. It's apparent that the service levels (i.e. energy) are dependent on the power rate of the chargers. Therefore, for different type of chargers we formulate different functions of service level -- $f(n_{i,1})$ represents the service level functions of level-one stations, and $f(n_{i,2})$ represents level two stations. Figure 3.4 shows the service levels as functions of the number of level-two chargers (i.e., 4kW). Each line represents for one particular candidate location.

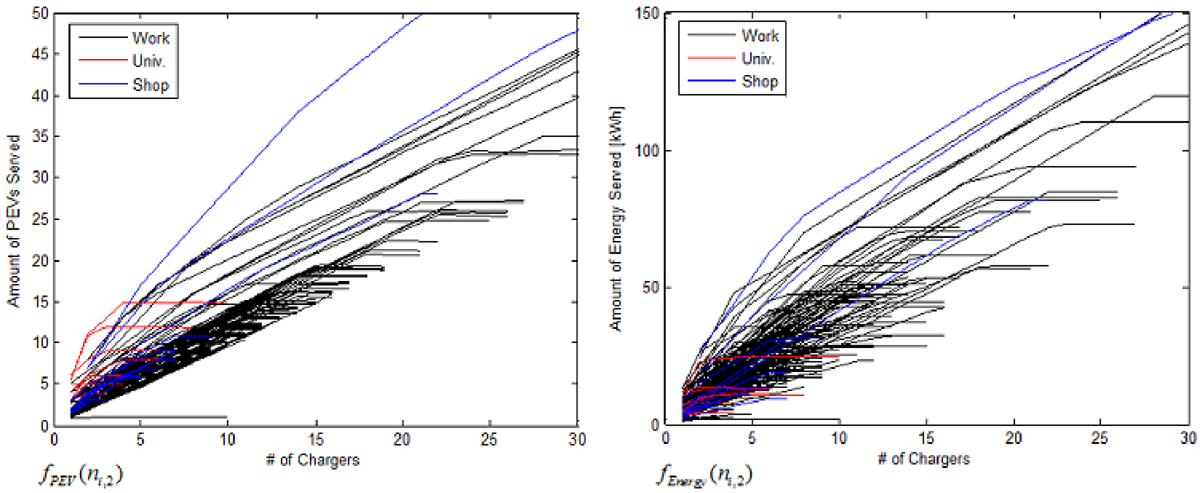


Figure 3.4

3.4 Optimize the Location Plan

From the simulation model in section 3.3, we obtain the service levels, $f(n_{i,1})$ and $f(n_{i,2})$, as functions of the number of level-one or -two chargers built at each candidate location. An optimal infrastructure location plan can be obtained by solving an integer program (IP). The objective function of the MIP is defined as,

$$Max \sum_i f(n_{i,1}) + f(n_{i,2}), \quad (3.3)$$

[2] Note that different iterations have different inputs of PEV arrivals, which are generated by the procedures from section 3.1 through 3.2.

which is to maximize the summation of service levels (either energy or PEVs charged) over all the candidates locations by deciding the number of chargers to built at each location, $n_{i,1}, n_{i,2}$.

In our case study of Section 4, we assume that only one type of chargers can be picked in a single station. Hence, we introduce a set of auxiliary binary variables A_i and set up constraints as follows:

$$\begin{aligned} n_{i,1} &\le M \bullet A_i \\ n_{i,2} &\le M \bullet (1 - A_i) \end{aligned}, \quad (3.4)$$

where, M is a large number, and $I_i = 1$ means that station i is a level one type station, and level two otherwise.

In order not to cause reliability issue in the distribution system, we assume that transformer upgrade is needed at each charging station, and that the minimum upgrading capacity is the sum of the power rates of all the chargers built in the station. In our case study of section 4, it's assumed that only 3 sizes of transformers are available to choose due to industry practice -- 25 kW, 50kW, and 75kW[3] -- and a upgrading cost of is associated with each type of transformer. Hence, the distribution level constraint can be formulated as,

$$n_{i,1}P_1 + n_{i,2}P_2 \le 25m_{i,25} + 50m_{i,50} + 75m_{i,75} \quad (3.5)$$

where, $m_{i,25}, m_{i,50}, m_{i,75}$ are the action variables denoted as the numbers of transformers upgraded at location i, and P_1, P_2 are the parameters denoted as the power rates of level one and two chargers.

We also assume that the project planner has a limited budget plan, $\$B$; hence, the budget plan constraints can be defined as,

$$\sum_{i=1}^{I} C_1 n_{i,1} + C_2 n_{i,2} + C_{25} m_{i,25} + C_{50} m_{i,50} + C_{70} m_{i,75} \le B, \quad (3.6)$$

where $C_1 (C_2)$ is the cost to build a level one (two) charger, and C_{25} (C_{50} or C_{75}) is the cost to upgrade a 25 kW (50 kW or 75 kW) transformer.

4. NUMERICAL RESULTS OF MID-OHIO REGION

We study a diverse set of scenarios to examine the optimal location for PEV charging stations in mid-Ohio region. The scenarios vary by objective functions (i.e. maximization of energy or PEV arivals served), budget plans, technology availability (i.e. level one and two, or level two only), and PEV penetration level (1%-5%). Following is a list of facts and assumptions of our numerical study:

- Vehicle flows represent a typical weekday in mid-Ohio region.
- All PEVs have a battery capacity of 16kWh, with a usable range from 30% to 95% (4.8 kWh to 15.2 kWh), and the fuel economy is 0.25 kWh/mile.
- In the simulation of formulating relations between service level and number of chargers (section 3.3), we assume:(1) The battery is full when PEVs leave from home in the morning; (2) PEV owners charge their cars whenever there are free chargers available in the station; (3) A charger in use will not be released until the PEV leaves; in other word, even if a PEV is fully charged after being charged for a while, the charger can't be used for others as long as the PEV doesn't leave.
- We distinguish candidate locations by their service functions, and only 3 types of locations are considered: shopping, working, and university places (section 3.2).
- We only consider slow charging technology (i.e. level one and two), and all level one chargers have a name power rate of 1.4kW, and level two of 4kW, with charging efficiency equal to 90%.

[3] One can choose a combination of transformers if the capacity required exceed 75kW, e.g. one 25kW and one 75 kW transformers give a total capacity of 100kW.

- Each candidate location can build at most one type of chargers.
- Each charger of level one is assumed to have a building and material cost of $425 and level two of $825 (see Morrow, Karner, and Francfort (2008)). No fixed cost is incurred if a station is built in some location.
- Transformer upgrading includes costs of material, installation and maintenance. Material costs are offered by AEP (i.e. $1100, $1450, and $1800 for 25, 50 and 75 kW). Costs of installation and maintenance are estimated to be 15% of material cost.

4.1 Maximization of Energy Served

We first examine the optimal charging station location plan when maximizing the total amount of energy recharged.

Figure 4.1 shows the TAZs that are built with chargers under different budget plans (i.e. $1,2,3 million), and Table 4.1-a summarizes the numbers of chargers built for each type of stations and the number of locations built with charging stations. The results show that level one dominates level two when there is a limited budget (i.e., $1 million). This is because level one charger is cheaper and more chargers can be built under small budget plan; hence, more energy can be served. Moreover, in locations like working places, people tend to have prolonged parking time, which is sufficient to fully charge a vehicle using level-one chargers. Only 1 shopping station is built at $1 million because people stay shorter in shopping places than at work or university. However, as the budget increase, more level two stations are built, and the number of level one stations starts to drop when budget is sufficiently larger (i.e. from $2 million to $3 million). Table 4.1-b summarizes the charger density of stations that are successfully built with charging stations. As we can see that most of the stations build no more than 10 chargers. The total number of locations where stations are built is almost doubled (i.e. from 186 level one locations to 259 level one plus 119 level two locations) when the budget increases from $1 million to $2 million, which indicates that it's more efficient to disperse the chargers when budget plan is limited.

Figure 4.1

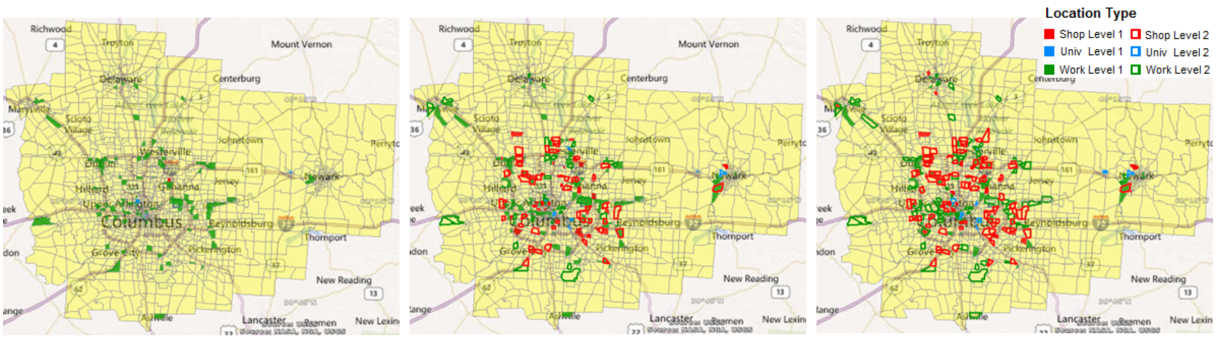


Table 4.1-a

Budget ($)	***$1M***		***$2M***		***$3M***	
Energy Served (kWh)	***7450***		***10322***		***10699***	
# of Chargers by Type	**Level 1**	**Level 2**	**Level 1**	**Level 2**	**Level 1**	**Level 2**
Work	806	0	1024	185	350	867
Univ.	55	0	58	22	8	73
Shop	1	0	31	70	22	137
Total	862	0	1113	277	380	1077

Table 4.1-b

Budget ($)	***$1M***		***$2M***		***$3M***	
# of Chargers / Location	**Level 1**	**Level 2**	**Level 1**	**Level 2**	**Level 1**	**Level 2**
1->10	174	0	244	118	121	287

11->20	10	0	10	1	0	11
21->30	2	0	4	0	0	4
30+	0	0	1	0	0	1
Total	186	0	259	119	121	303

4.2 Maximization of Number of PEVs Served

In this case study, we allocate the charging stations by maximizing the total number of PEVs served. Figure 4.2 shows that, different from energy maximization (Figure 4.1), no level two chargers are built when maximizing the number of PEVs served. This is because level one charger is cheaper. With a limited budget, more chargers can be built and thus can serve more PEVs. However, this result is only true under the assumption that a charger in use won't be released until a PEV leaves even if the PEV is fully charged before its departure. Suppose technology allows a charger to be released right after a PEV is fully charged, a faster charger (i.e. level two) might serve more PEVs than a slower one.

Table 4.2-a summarizes the total number of chargers built by location type. At budget of $1 million, 41 out of 862 chargers are built in shopping places -- this is larger than 1 out of 862 in Table 4.1-a -- indicating that more shopping chargers are built when maximizing PEVs served. This is because PEVs stay less longer in shopping places than places like working or university; hence, a charger built in a shopping place can be reused by more PEVs. Table 4.2-b summarizes the charger density of those stations successfully built with chargers.

Figure 4.2

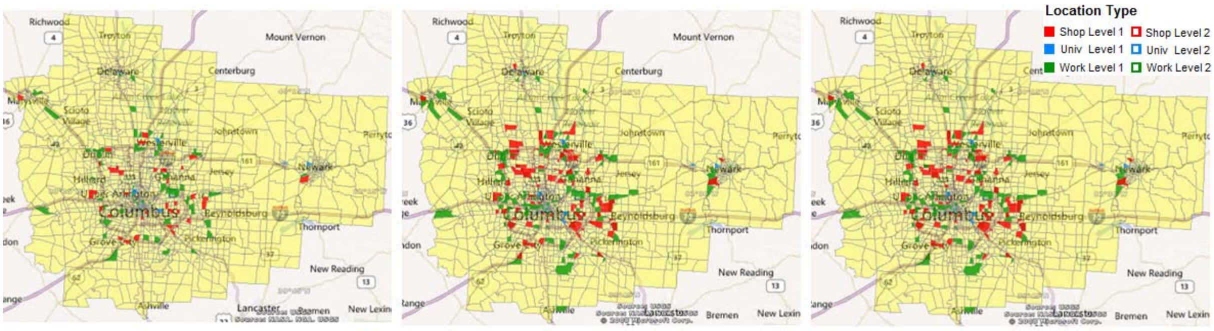


Table 4.2-a

Budget ($)	***$1M***		***$2M***		***$3M***	
# of PEVs Served	***2368***		***3502***		***3521***	
# of Chargers by Type	**Level 1**	**Level 2**	**Level 1**	**Level 2**	**Level 1**	**Level 2**
Work	749	0	1307	0	1678	0
Univ.	72	0	93	0	145	0
Shop	41	0	183	0	200	0
Total	862	0	1583	0	2023	0

Table 4.2-b

Budget ($)	***$1M***		***$2M***		***$3M***	
# of Chargers / Location	**Level 1**	**Level 2**	**Level 1**	**Level 2**	**Level 1**	**Level 2**
1->10	179	0	412	0	412	0
11->20	6	0	11	0	11	0
21->30	1	0	4	0	4	0
30+	1	0	1	0	1	0
Total	187	0	428	0	428	0

4.3 Level Two Chargers Only

In this study, we assume that only level two chargers can be built in the candidate locations. Table 4.3 summarizes the expected service levels under different budget and optimization criteria. As it's shown in the table that the service levels from level-two-only cases are much smaller than level-two-and-one cases, especially when budget is limited.

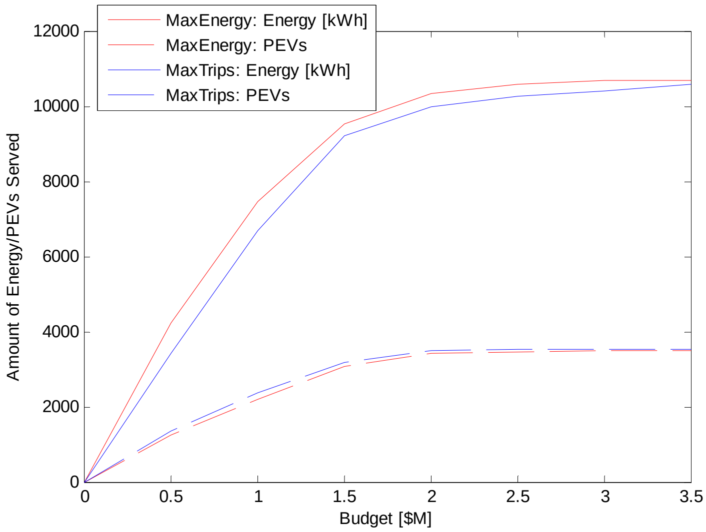
Table 4.3

Maximization	*Energy Served*			*PEVs Served*		
Budget ($)	***1M***	***2M***	***3M***	***1M***	***2M***	***3M***
Objective Value	*4797*	*8255*	*10507*	*1433*	*2448*	*3319*
% of Level 1+2 Obj.	*64.39%*	*79.97%*	*98.21%*	*60.52%*	*69.90%*	*94.26%*

4.4 Service level under Different Maximization Objectives.

Figure 4.4 shows the service level -- total amount of energy and PEV arrivals served -- under different scenarios. Although the optimal location policy seems to be very sensitive to what type of service level is maximized, as we see in sections 4.1 and 4.2, the service level themselves are close, in other words, less sensitive to the maximization objectives.

Figure 4.4



4.5 Impact of PEV Adoption Level

In this case we examine the impact of PEV adoption lelve, where the budget of each scenario is assumed to be $1 million. The adoption level is adjusted by scaling the purchase probability by TAZ (see section 3.2).

Figure 4.5-a

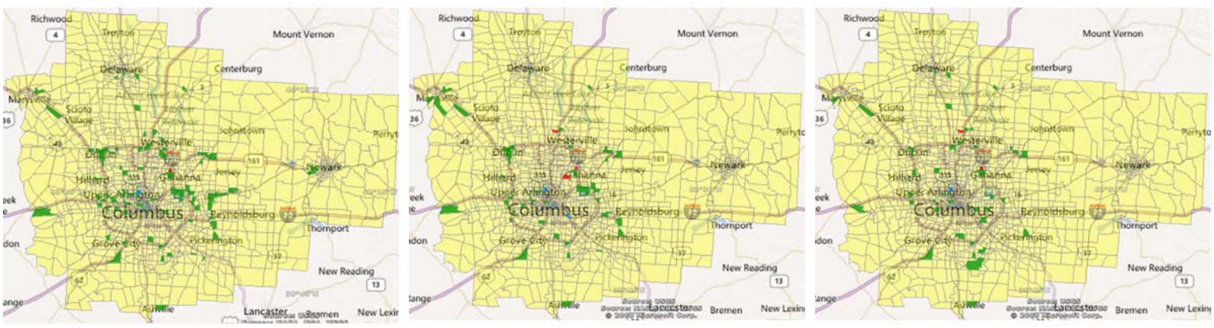


Table 4.5-a

Penetration Level	***1%***		***3%***		***5%***	
Energy Served (kWh)	***7450***		***9655***		***10468***	
# of Chargers by Type	**Level 1**	**Level 2**	**Level 1**	**Level 2**	**Level 1**	**Level 2**
Work	806	0	906	0	911	0
Univ.	55	0	51	0	57	0
Shop	1	0	3	0	8	0
Total	862	0	960	0	976	0
# of Locations	186	0	113	0	98	0

Figure 4.5-b

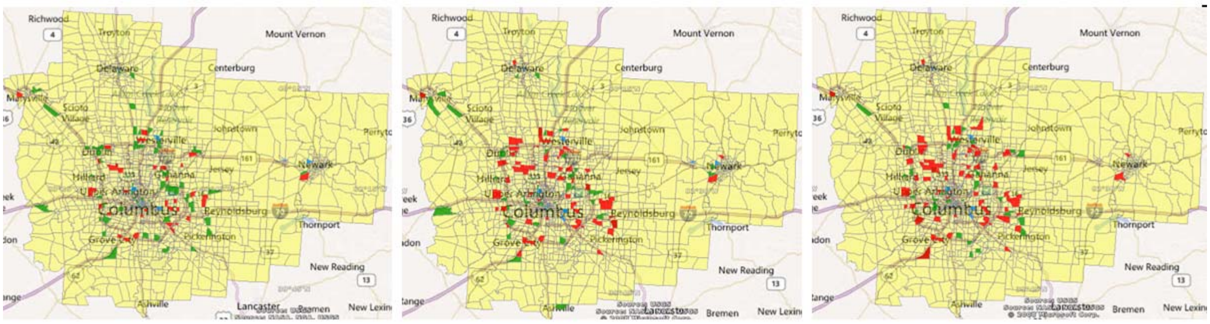


Table 4.5-b

Penetration Level	***1%***		***3%***		***5%***	
# of PEVs Served	***2368***		***3539***		***4452***	
# of Chargers by Type	**Level 1**	**Level 2**	**Level 1**	**Level 2**	**Level 1**	**Level 2**
Work	749	0	551	0	458	0
Univ.	72	0	137	0	126	0
Shop	41	0	143	0	237	0
Total	862	0	831	0	821	0
# of Locations	187	0	205	0	210	0

Table 4.5 summarizes the total number of chargers built by type and the total number of locations selected under different adoption level. As we can see, no level 2 stations are built at all in any case. The number of chargers built at shopping places increases as adoption level increases, especially when maximizing the number of PEVs served. This is because, as we point out in section 4.2, a charger in a shopping place can serve more vehicles as vehicles spend less time in shopping places than others; and this effect will be amplified as the number of PEV arrivals increases with the adoption level.

In the case where we maximize the total energy recharged, the number of locations built with chargers decreases as the penetration level increases; however, in the case where we maximize the number of PEVs served, the number of locations decreases. This is because that a charger in working places is efficient in serving more energy while a charger in shopping places is efficient in serving more PEVs. When penetration level increases, those a few working locations -- where people travel long distances to work -- will have more PEV arrivals with large energy demand; as a result, chargers originally built in other locations are moved to those locations, which leads to the decrease in the number of locations selected for stations. On the second hand, the PEV arrivals in shopping places also increase among all shopping locations; but the flows, in terms of both the number of PEV arrivals and energy, are pretty dispersed and similar over all different locations since people tend to shop near where they live. As a result, the chargers for shopping stations will be dispersed among different locations, leading to increase in the number of locations selected for stations.

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