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Analysis of Fast Charging Station Network for Electrified Ride-Hailing Services

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Abstract

Today's electric vehicle (EV) owners charge their vehicles mostly at home and seldom use public direct current fast charger (DCFCs), reducing the need for a large deployment of DCFCs for private EV owners. However, due to the emerging interest among transportation network companies to operate EVs in their fleet, there is great potential for DCFCs to be highly utilized and become economically feasible in the future. This paper describes a heuristic algorithm to emulate operation of EVs within a hypothetical transportation network company fleet using a large global positioning system data set from Columbus, Ohio. DCFC requirements supporting operation of EVs are estimated using the Electric Vehicle Infrastructure Projection tool. Operation and installation costs were estimated using real-world data to assess the economic feasibility of the recommended fast charging stations. Results suggest that the hypothetical transportation network company fleet increases daily vehicle miles traveled per EV with less overall down time, resulting in increased demand for DCFC. Sites with overhead service lines are recommended for hosting DCFC stations to minimize the need for trenching underground service lines. A negative relationship was found between cost per unit of energy and fast charging utilization, underscoring the importance of prioritizing utilization over installation costs when siting DCFC stations. Although this preliminary analysis of the impacts of new mobility paradigms on alternative fueling infrastructure requirements has produced several key results, the complexity of the problem warrants further investigation.

Introduction

Today's electric vehicle (EV) owners charge their vehicles mostly at home and seldom use public direct current fast charger (DCFCs), reducing the need for a larger deployment of DCFCs for private EV owners. However, due to the emerging interest among transportation network companies (TNCs), whose operation may require quick fueling, there is potential for DCFCs to be highly utilized and become economically feasible in the future as EV ride-hailing business evolves.

Despite their ability to charge EVs quickly, the deployment of DCFCs is currently limited because of the high costs of both operation and installation that render the deployment economically infeasible. The potential for high utilization by ride-hailing EVs is a key to the economics of DCFC deployment; however, both the operation cost and installation cost can vary dramatically depending on various factors. Past studies pointed out great uncertainty in identifying and quantifying significant cost factors of DCFCs [1, 2]. At the same time, much uncertainty persists in the operational characteristics of TNC fleets and how they may evolve in the future [3, 4, 5, 6, 7]. Therefore, there is much interest in rigorous research on assessing economic feasibility of DCFCs for TNCs in both industry and academia.

The U.S. Department of Energy's SMART (Systems and Modeling for Accelerated Research In Transportation) Mobility Advanced Fueling Infrastructure Pillar team conducted simulations to estimate potential DCFC needs (location, number of plugs, and electricity demand) by a hypothetical EV ride-hailing service in Columbus, Ohio. Operation cost and installation cost were estimated using real-world data to assess the economic feasibility of DCFCs at the recommended locations. This paper describes the methodology developed for this study. It also provides key findings of simulation and analysis conducted by the three participating national laboratories-Argonne National Laboratory (ANL), Idaho National Laboratory (INL), and the National Renewable Energy Laboratory (NREL).

INRIX Global Positioning System Travel Trajectories

Understanding vehicle driving and parking patterns is key to determining EV charging infrastructure requirements. Shared vehicles likely have different driving patterns than personal-use vehicles. Therefore, analysis of ride-hailing vehicle use patterns was necessary as a first step in estimating DCFC needs for ride-hailing EVs. Given the lack of available ride-hailing data sets, this analysis first develops a procedure for synthesizing TNC activity patterns from personally owned vehicle datasets and applies said procedure to an example dataset from Columbus, Ohio.

Original INRIX GPS Data Set

NREL acquired individual anonymized global positioning system (GPS) travel trajectories from INRIX [8], which provided NREL with all GPS travel trajectories (mode imputed as driving trips by INRIX) that intersected the Columbus region at any time during 2016. Each trajectory features trip-level data such as start/end times and GPS coordinates (including origins, destinations, and intermediate waypoints). The INRIX data set contains a total of 7.82 million unique device identifiers, 32.9 million trips, 1.04 billion miles of driving, and 2.58 billion GPS waypoints. The spatial distribution of trip destinations in the Columbus area is shown in Figure 1.

Down Sampling and Processing

The GPS travel trajectories in the INRIX data set are an aggregation of data from several providers and were down-selected to include only light-duty vehicles. The subset of data from light-duty consumer vehicles consisted of data sourced from embedded GPS data (provided primarily by automotive manufacturers from in-vehicle navigation systems) and mobile devices (provided primarily by applications installed in cellular devices). Individual device identifiers from the embedded GPSs were systematically reset after each trip,

FIGURE 1 Heat map of Columbus trip destination frequency in INRIX data set (source [9]).

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making EV charging simulation impossible. As such, embedded GPS data were discarded, leaving only light-duty consumer vehicle data from mobile device sources. This down-sampling routine leaves approximately 14% of trips from the total INRIX data set available. This cleansed subset includes approximately 46.7 thousand unique device identifiers, 1.41 million full travel days, 4.48 million trips, and 35.8 million miles of driving.

Prior to using the INRIX data subset in plug-in electric vehicle (PEV) driving/charging simulations, several data processing steps were completed, including:

- Removing the first and last vehicle-day for each device identifier (in an attempt to remove incomplete travel days),
- Editing trip origins to match the previous destination in the trip chain,
- Computing trip driving distance as the sum of haversine distances between the original trip origin, each waypoint, and trip destination,
- Estimating home and workplace locations for each unique device and flagging trips to these locations for use in PEV driving/charging simulations,
- Implementing spatial joins on county, ZIP code, Traffic Analysis Zone, and land use data layers.

Categorizing charging events into home, workplace, and public charging requires knowledge of the location type of each trip destination. Unlike a typical travel survey, the INRIX GPS data set does not report trip purpose. Therefore, the destination type must be inferred from spatial and temporal heuristics applied at the vehicle level. The INRIX data set contains multiple travel days for each unique device identifier, which enables the analysis of dwell time patterns at recurring destinations. The home and workplace location assignment algorithm proceeds as follows:

- For each unique vehicle identifier, destinations with dwell times greater than a given threshold are selected and clustered geographically in ~100 m x 100 m cells. Nine-hour dwell locations are selected for home location identification, and 4-hour dwell locations at non-home locations are selected for workplace location identification.
- The cumulative dwell time over all travel days is calculated for each of these cells, and the cell with the greatest cumulative dwell time is flagged as the home or work location.
- Any trips ending within ¼ mile from the home or work flagged location are considered home or work trips respectively for this vehicle.

For both home and work/secondary locations, spatial attributes such as ZIP code, Traffic Analysis Zone, and land use were appended by spatially querying the respective databases and assigned to each vehicle. INRIX travel data were validated using two travel surveys, the 2012 California Household Travel Survey and the 2011 Massachusetts Travel Survey.

Ride-Hailing Emulation Algorithm

Methodology

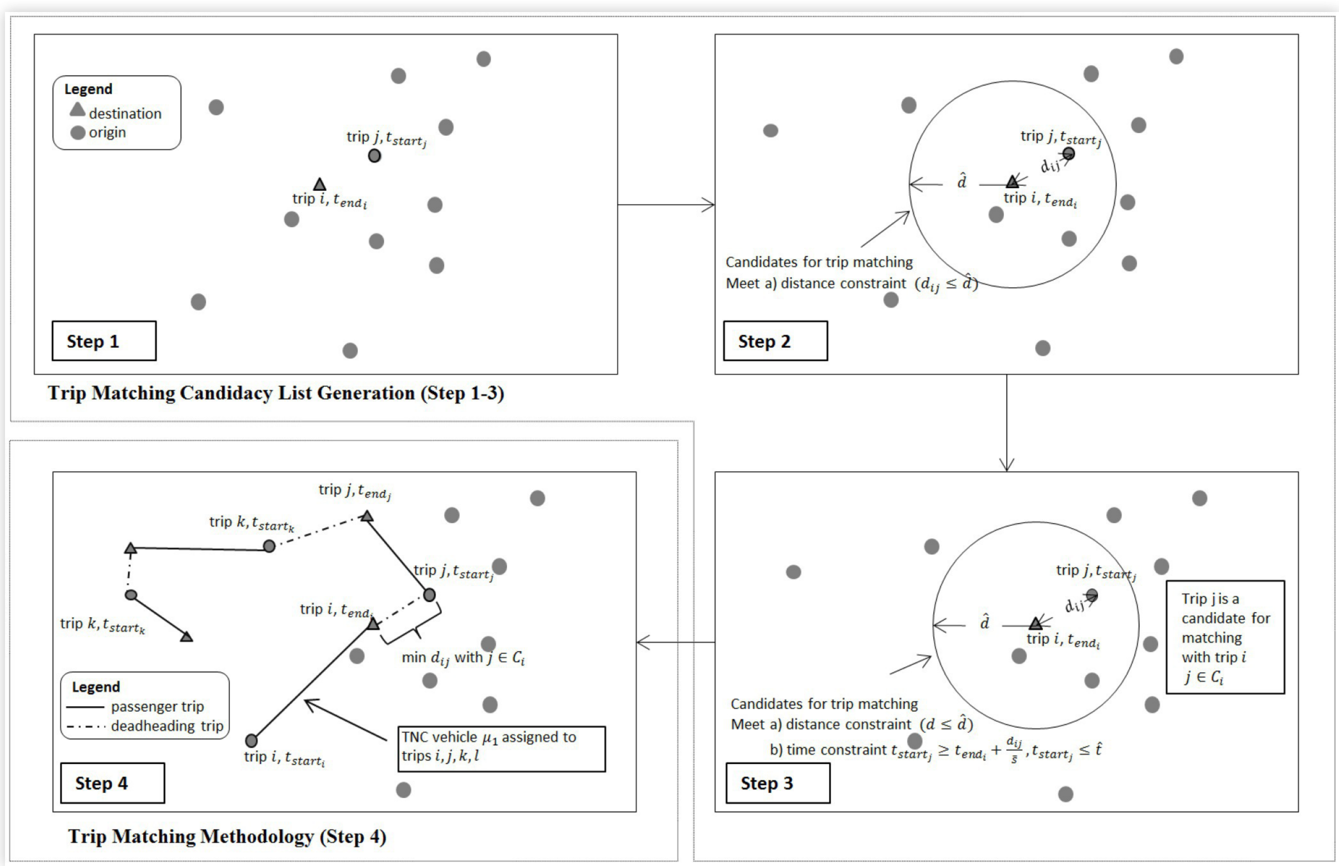
City-level analyses on the broad impacts of TNC systems have been conducted through surveys and field data collection [10] due to the lack of detailed data provided by TNCs. The absence of data sets that may uncover impacts of such mobility systems is a barrier in quantifying their benefits and drawbacks. In our study, due to the unavailability of data that describe TNC vehicle movements, a heuristic was deployed that emulated TNC vehicle data for ride-hailing systems, using as inputs personal trip data sets. The heuristic process objective is to enable matching of personal trips to TNC vehicle IDs, by essentially grouping together trips that can be conducted consecutively, and by allocating groups to TNC vehicle IDs.

The proposed algorithm, which is portrayed using a schematic representation in Figure 2, first identifies trip candidates that can be conducted consecutively based on the location and time of their destinations and origins. In this step, a candidacy list C_i was created that contains all trips j ≠ i whose origin is within a specified space and time distance from a certain trip's i destination (repeated for all trips in the set I where i,j∈I) by imposing two constraints: 1) the down time between trips is less or equal to an upper bound $\hat{t}$ and greater or equal to the required time t_d to cover the distance between the trip's i destination and the next trip's j origin with $t_d = d_{ij}/\bar{s}$ (note that d_{ij} is the distance between the trip's i destination and the next trip's j origin and $\bar{s}$ the average speed to cover that distance), and 2) the deadheading distance d_{ij} is less than or equal to an upper bound $\hat{d}$. There is no provision that allows prospective TNC riders to wait for TNC vehicles and depart later than the desired time (which is the time of departure as defined in the personal trip data set) since trip origin and destination times are strictly set and are not flexible. This assumption also implies that the trips' times and distances, as well as routes, have not changed or been impacted due to the TNC vehicle operation and are the same as the ones in the personal trip data set.

The second step of the heuristic involves determining which trip j that is included in the candidacy list of i will be conducted in sequence-this process constitutes trip-matching. The trip j that belongs to C_i with the minimum deadheading distance (MIN(d_{ij}), $j \in C_i$) is selected and conducted after i, under the assumption that the driver of the TNC automobile or the application that assigns that vehicle to the next trip goal is the minimum of the deadheading distance between the trips in a sequence.

Note that the heuristic described above does not assign trips that cannot be grouped with other trips to TNC vehicle IDs due to the time and location constraints set. The assumption was that those trips were conducted by a personal vehicle. The heuristic algorithm was implemented in Python 2.7.12 leveraging the processed INRIX data.

FIGURE 2 Schema of heuristic process for pseudo TNC trip data emulation.



Results and Discussion

The methodology was applied to 5,000 passenger travel-days from personal GPS trip data from Columbus. Trips are assumed to be completed in individual vehicles without allowing for sharing/pooling. The ride-hailing emulation attempts to match trips by minimizing deadheading distance and wait time with constraints of a maximum of 5 miles or 20 minutes between a given destination and potential next origins. Ride-hailing vehicles must satisfy the same travel demand (all trips are served by these vehicles). Trip chains are thus locally optimized, meeting the objective of minimum deadheading distance for each TNC vehicle, but not globally at the system level.

Table 1 compares summary statistics for the original and pseudo-synthetic ride-hailing data sets. Fewer ride-hailing vehicles complete more trips due to the addition of deadheading trips, connecting passenger drop-off and pick-up locations. These results are highly dependent on the constraints used for trip matching. With no time or distance constraints between two consecutive trips, the number of vehicles is reduced drastically while the total system vehicle miles traveled (VMT) increases further. In contrast, with a more stringent deadheading distance constraint of 2 miles, the number of ride-hailing vehicles deployed exceeds the number of original vehicles due to the inability to match a large share of trips. One last caveat is that due to computational limitations, a sample size of only 5,000 vehicle-days of travel was used. A larger sample size may increase the probability of matching trips and potentially increase system-wide efficiencies. The small sample set used here reflects an early-stage ride-hailing market. Simulating a larger sample set, potentially segregating "ride-hailing candidates" and "personal vehicles" would provide a better projection of a more mature ride-hailing market segmentation.

TABLE 1 Personal and simulated ride-hailing vehicles comparison.

Metrics	Personal vehicles	Ride-hailing vehicles
Number of vehicles	5,000 individual vehicles	4,834 total vehicles 3,726 ride-hailing vehicles chaining multiple trips 1,108 single-trip vehicles unable to chain trips
Number of trips	18,460 individual trips	25,115 total trips, including 7,112 additional "deadheading" trips
Total system VMT	143,139 miles	148,149 miles
Mean daily VMT	28.6 miles	37.0 miles *
Trip mean distance	7.8 miles	5.9 miles

* Note: the mean daily vehicle miles traveled (VMT) reported here are for the 3,726 ride-hailing vehicles that were able to chain trips and exclude the additional "single-trip vehicles" that would skew the mean daily VMT.

PEV Charging Infrastructure Simulation

EVI-Pro Methodology

NREL developed the Electric Vehicle Infrastructure Projection (EVI-Pro) tool in partnership with the California Energy Commission to estimate regional requirements for charging infrastructure to support consumer adoption of PEVs [11, 12]. EVI-Pro uses PEV market projections and real-world travel data to estimate future requirements for residential, workplace, and public charging under a variety of scenarios. The model aims to anticipate spatially and temporally resolved consumer charging demand while capturing variations with respect to residents of single-unit dwellings (SUDs) and multi-unit dwellings (MUDs), weekday/weekend travel behavior, and regional differences in travel behavior and vehicle adoption. A graphical representation of the input/output relationships in EVI-Pro is shown in Figure 3.

EVI-Pro's charging behavior emulation assumes that consumers aim to complete all their existing travel electrically while minimizing operating cost. Several charging scenarios are simulated for each consumer. To identify the optimal charging scenario, individual travel days from the INRIX travel data set (originally completed using a conventional gasoline vehicle) are simulated in the model under different assumptions for charging infrastructure availability. The latter include residential Level 1 (L1) and Level 2 (L2) charging stations at SUDs, residential L2 charging stations at MUDs, workplace L2 charging stations, public L2 charging stations, and public DCFC.

EVI-Pro repeats this charge behavior selection routine for all travel days in the study and for all vehicle types under consideration. The modeled PEV fleet consists of 20% plug-in hybrid electric vehicles with a range of 20 miles (PHEV20), 20% PHEV50, 20% battery electric vehicles with a range of 100 miles (BEV100), 20% BEV250, 10% PHEV20 sport utility vehicles (SUVs), and 10% BEV250 SUVs for both personal and ride-hailing vehicles. The default charging behavior is

FIGURE 3 Graphical representation of inputs/outputs and data flow in EVI-Pro.

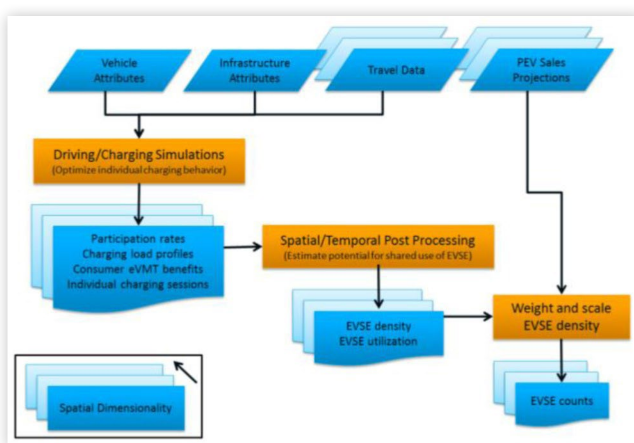


TABLE 2 Infrastructure requirements that would be necessary to support electrification of the two vehicle groups (5,000 personal vehicles; 3,726 ride-hailing vehicles plus 1,108 personal vehicles).

Charger type	# plugs (personal vehicles)	# plugs (ride-hailing vehicles)	Ratio $\left(\frac{\textit{ride-hailing}}{\textit{personal}}\right)$
Home SUD L1	3,732	3,555	0.95
Home SUD L2	172	212	1.23
Home MUD L2	702	702	1.00
Work L2	222	160	0.72
Public L2	211	387	1.83
Public DCFC	13	24	1.85

"home-dominant," meaning that consumers prefer to charge at home, then at their workplace, and then in public locations. All drivers, whether of personal or ride-hailing vehicles, are modeled as having access to charging at their residence. In an automated and driverless future where ride-hailing vehicles would be owned by fleet operators, these vehicles would potentially have reliable access to charging at a depot.

This charging demand simulation generates a set of charging sessions required to satisfy the travel patterns displayed in the data in a way that maximizes electric miles traveled and minimizes operational cost. These charging sessions are then post-processed spatially and temporally to output electric vehicle supply equipment requirements and use for the Columbus region.

Simulation Results

Estimated PEV charging infrastructure requirements are shown by mode and plug type in Table 2. Uncertainty in these estimates is driven by several factors that were not explicitly modeled in EVI-Pro, including: uncertainty in PHEV demand for public charging, consumer access to home charging at MUDs, consumer ability to make shared use of public charging stations, and consumer tolerance for station/destination proximity. EVI-Pro provides a range of values in an attempt to quantify these uncertainties. The values presented below are midpoints.

While residential charging requirements remain similar for personal and ride-hailing vehicles, the demand for non-residential charging is drastically different. Shorter dwell times at work reduce the demand for workplace charging by 28%, while more frequent dwell events in public locations combined with higher daily VMT increases the need for public L2 and DCFC by 83% and 82%, respectively.

PEV Charging Infrastructure Cost Analysis

Siting DCFC where use is expected to be high is important to increase the economic feasibility of DCFC for station owners. However, demand for charging is not the only factor that should be considered when choosing DCFC site locations. The cost to install and operate DCFC also should be considered. Not only can costs be high, but they also vary widely depending on how the DCFC is used and where it is located.

Operating and capital costs were estimated for the DCFC candidate locations output by EVI-Pro to show relationships between cost, use, and location.

Operation Cost of Charging Infrastructure

EV charging station operators must buy electricity from local utility companies unless the station is owned by a utility company or generates its own electricity on-site. In this section, the operation costs of a group of EV charging stations were assessed. The analysis includes two major assumptions: 1) the station operator must buy all the station's electricity from utility companies, and 2) the operator is a standalone business, that is, it buys electricity exclusively for the charging station.

Cost Estimation The monthly electricity bill is determined by the applied rate plan of the utility company, as well as the electricity consumption and maximum demand of the charging station.

Rate Schedules. Utility companies usually have multiple rate plans designed for different groups of users with varying voltage requirements and maximum demands. A rate plan is composed of base charges including monthly charge, energy charge, demand charge, and so on, as well as riders, which may be flat rates, may depend on energy or power consumption; or may be a percentage increase on the base bill. In addition, some utilities have rates that differ depending on the season and the time of day. For example, some utilities charge higher rates during the summer or daytime when electricity demand tends to be higher [13]. Disincentivizing electricity use during these times reduces peak demand (peak power usage) and puts less strain on the utility's generators [14]. A customer may be eligible for more than one rate plan. Peak demand usually determines rate plan eligibility.

Table 4 lists types of utility charges and corresponding symbols for use in bill calculation equations. Table 5 lists some of the rate plans used by Columbus Southern Power Company [15], one of the two American Electric Power (AEP) companies that operate in Ohio and dominates the electricity supply in Columbus, Ohio, the location of the 12 hypothetical charging stations modeled in this analysis.

To determine which rate plan to use for the simulated charging station electricity bills, their user type and eligibility need to be identified. Residential rate types are excluded since the DCFC stations in this study are targeted for commercial use. Rates for the primary distribution system, subtransmission, and transmission at greater than 480-V service are excluded [16]. Rates with power demand requirements below 24 kW are also excluded because even low-power DCFC stations charge at a minimum of 24 kW [17]. Eligibility is determined by the charging station maximum demand.

TABLE 4 Types of charges composing utility electric bills.

Type of Charge	Symbol	Unit	Description
Monthly charge	M_c	$	Customer, metering, and other monthly charges
Energy charge	E_c	$/kWh	Energy, regulatory, and other kWh charges
Demand charge	D_c	$/kW	Charge for highest power demand this month
Non-IDR power charge	$NIDR_c$	$/NCP kW	Power charge for loads <700 kW, calculated with max power demand during this month
IDR power charge	IDR_c	$/4CP kW	Power charge for loads > = 700 kW, calculated with max power during four critical time periods specified by the utility
Summer seasonal energy charge	$S_{c,s}$	$/kWh	Energy rate during the summer
Summer on-peak energy charge	$ON_{c,s}$	$/kWh	Charge for energy used during the on-peak during the summer
Summer off-peak energy charge	$OFF_{c,s}$	$/kWh	Charge for energy used during the off-peak during the summer
Summer demand charge	$D_{c,s}$	$/kW	Charge for maximum power demanded during the summer
Winter seasonal energy charge	$S_{c,w}$	$/kWh	Energy rate during the winter
Winter on-peak energy charge	$ON_{c,w}$	$/kWh	Charge for energy used during the on-peak during the winter
Winter off-peak energy charge	$OFF_{c,w}$	$/kWh	Charge for energy used during the off-peak during the winter
Winter demand charge	$D_{c,w}$	$/kW	Charge for maximum power demanded during the winter
Riders	R_c	$	Total rider contribution; fees utilities charge to compensate for various losses, such as energy loss in electricity transmission
Additional variable costs	A_c	$	Various other costs (primarily included in subsequent equations to accommodate complicated energy, demand, and rider pricing schemes)
On-peak energy charge	ON_c	$/kWh	Charge for energy used during the on-peak
Off-peak energy charge	OFF_c	$/kWh	Charge for energy used during the off-peak
On-peak demand charge	OND_c	$/kW	Charge for maximum demand during the on-peak
Off-peak demand charge	$OFFD_c$	$/kW	Charge for maximum demand during the off-peak
Minimum bill	MB_c	$/day	The minimum amount the customer must pay this month
Surcharge	SUR_c	%	A percent increase on the total bill

Table 6 shows the basic profiles of 12 charging stations simulated by NREL, including energy usage, maximum demand, number of charging sessions, and time spent at the station for one day of various theoretical conditions in a future Columbus. According to Table 6, maximum demand ranges from 20.5 kW (Stations 10 and 12) to 82.06 kW (Station 1), indicating GS-2 Secondary Service is the most appropriate rate schedule.

Customer Inputs. In addition to the utility company rate schedule, estimating the charging station monthly bill requires knowing its electricity usage. The monthly energy usage is estimated by multiplying the daily energy usage by 30. Table 6 is the major source of customer data, and Table 7 lists the customer inputs needed to estimate the monthly bill.

This study uses the Ohio Power Company - Columbus Southern Power Rate Zone Bill Calculation Spreadsheet to estimate monthly electricity bills [15]. The spreadsheet receives a month-long hourly energy usage profile (in kilowatt-hours) and outputs the approximate monthly bill from that data for each applicable rate plan. For the GS-2 Secondary Service rate plan, the simplified equation for the monthly bill is:

$$\text{Monthly bill} = M_c + D_c D_u + R_c, \tag{1}$$

where M_c is monthly charge, D_c is demand charge, D_u is customer maximum demand, and R_c is total applicable riders.

If more than one utility supplies the target charging station, the equation for a monthly electricity bill must include all types of charges in the relevant rate plan of each utility. The equation is:

$$\begin{aligned}\text{Monthly bill} = \text{MAX}\big(&MB_c DAYS,\ E_c E_u + D_c D_u + ON_c ON_u \\ &+ OFF_c OFF_u + OND_c OND_u + OFFD_c IF \\ &\left(OFFD_u - OND_u > 0,\ OFFD_u - OND_u,\ 0\right)\big)\left(1 + \frac{SUR_c}{100}\right),\end{aligned} \tag{2}$$

where.

MB_c	minimum bill
DAYS	number of days this month
E_c	energy charge
E_u	energy usage
ON_c	on-peak energy charge
ON_u	on-peak energy usage
OFF_c	off-peak energy charge
OFF_u	off-peak energy usage
OND_c	on-peak energy demand charge
OND_u	on-peak energy demand

TABLE 5 Columbus Southern power rate plans [13].

Schedule	Rate Plan		Eligibility
R-R	Residential service		Available for residential electric service through one meter to individual residential customers
RLM	Residential Optional Demand Rate		Available for optional residential electric service through one meter to individual residential customers. Requires the installation of demand metering facilities.
RS-ES	Residential Energy Storage		Available to residential customers who use energy storage devices with time-differentiated load characteristics approved by the Company
RS-TOD	Residential Time-of-Day		Available to individual residential customers. Availability is limited to the first 500 customers applying for service under this schedule.
RS-TOD 2	Experimental Residential Time-of-Day		Available to individual residential customers on a voluntary, experimental basis. Availability is restricted to customers served by the circuits designated for the Company's gridSMART pilot program.
GS-1	General Service - Small		Available for general service to customers with maximum demands less than 10 KW.
GS-2	General Service - Low Load Factor	Secondary distribution system[3]	Available for general service lo customers with maximum demands of 10 KW or greater.
		Primary distribution system	
		Subtransmission	
		Transmission	
GS-2-TOD	General Service - Time-of-Day		Available for general service customers with maximum demands less than 500 kW, Availability is limited to secondary service and the first 1,000 customers applying for service under this schedule.
GS-3	General Service - Medium Load Factor	Secondary distribution system	Available for general service to customers with maximum demands of 50 KW or greater.
		Primary distribution system	
		Subtratismission	
		Transmission	
GS-4	General Service -Large	Primary distribution system	Available for general service to customers with maximum demands in excess of 1000 KVA.
		Subtransmission	
		Transmission	

Source: Public Utilities Commission of Ohio, "AEP Ohio Standard Tariff" AEP Ohio (2017)

TABLE 6 Simulated Charging Stations in Columbus, Ohio.

No.	Sessions	No. of plugs	Daily energy usage (kwh)	Maximum demand (kw)
1	6	2	117.81	82.06
2	17	4	297.11	61.5
3	2	2	85.24	61.5
4	2	2	91.51	61.5
5	6	2	94.17	66.85
6	6	2	155.66	61.5
7	48	7	638.35	78.91
8	2	1	17.58	28.93
9	3	1	30.75	28.75
10	2	1	26.63	20.5
11	7	2	52.91	33.55
12	3	1	23.36	20.5

$OFFD_c$ off-peak energy demand charge
$OFFD_u$ off-peak energy demand
SUR_c surcharge

The function MAX(val_1, val_2) returns the greater of val_1 and val_2, and the function IF(condition, val_1, val_2) returns val_1 if the condition is true, and val_2 otherwise.

TABLE 7 Customer inputs needed to calculate electricity bills [14].

Input	Symbol	Unit	Description
Monthly Energy usage	E_u	kWh	kWh used this month
Maximum demand	D_u	kW	Highest power needed this month
Maximum demand from previous year	AD_u	kW	Highest power demand last year
On-peak energy usage	ON_u	kWh	Total on-peak energy used this month
Off-peak energy usage	OFF_u	kWh	Total off-peak energy used this month
On-peak demand	OND_u	kW	Maximum on-peak demand
Off-peak demand	$OFFD_u$	kW	Maximum off-peak demand
Number of days this month	$DAYS$	days	Total number of days in this month

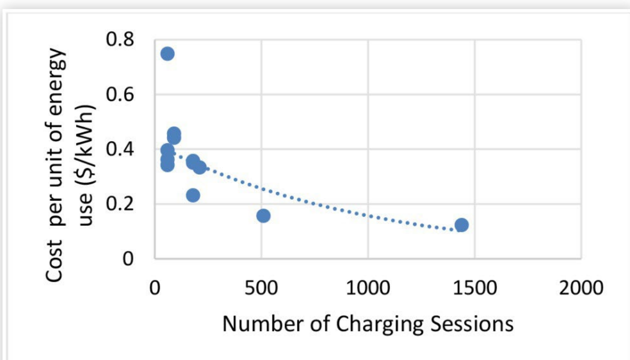
Results Table 8 shows the estimated monthly electricity bill for the 12 simulated charging stations in Columbus. The total electricity cost ranges from $316.5 to $1,397.11. Cost efficiency is calculated by dividing the monthly electricity

TABLE 8 Simulated Charging Stations' Monthly Electricity Bill Estimation.

Location	No. of Sessions (monthly)	Daily Total Energy Usage (kWh)	Monthly Total Energy Usage (kWh)	Maximum Demand (kW)	Monthly Charge ($)	Demand Charge ($)	Riders ($)	Total ($)	Cost Efficiency ($/kWh)
1	180	117.81	3,534.40	82.06	9.04	331.11	899.14	1,239.29	0.35
2	510	297.11	8,913.42	61.5	9.04	248.03	1,140.04	1,397.11	0.16
3	60	85.24	2,557.22	61.5	9.04	248.03	669.19	926.26	0.36
4	60	91.51	2,745.31	61.5	9.04	248.03	683.12	940.19	0.34
5	180	94.17	2,825.13	66.85	9.04	269.81	730.34	1,009.19	0.36
6	180	155.66	4,669.68	61.5	9.04	248.03	825.67	1,082.74	0.23
7	1,440	638.35	19,150.64	78.91	9.04	318.20	2,029.16	2,356.40	0.12
8	60	17.58	527.32	28.93	9.04	116.55	268.79	394.38	0.75
9	90	30.75	922.40	28.75	9.04	115.75	296.71	421.49	0.46
10	60	26.63	922.40	20.5	9.04	82.68	224.78	316.50	0.40
11	210	52.91	1,587.35	33.55	9.04	135.51	383.75	528.30	0.33
12	90	23.36	700.90	20.5	9.04	82.68	217.48	309.19	0.44
Average	260	135.92	4,077.73	50.50	9.04	203.7	697.35	910.09	0.36

Note that for AEP Southern Power Company's GS-2 Secondary Service, the nominal energy charge is not included. All the charges related to energy usage are included in applicable riders. For information about GS-2 Secondary Service, please check "2017-08-28_AEP_Ohio_Standard_Tariff" 6th Revised Sheet No.221-1, available at: https://www.aepohio.com/global/utilities/lib/docs/ratesandtariffs/Ohio/2017-08-28_AEP_Ohio_Standard_Tariff.pdf

FIGURE 5 Correlation between cost efficiency and number of sessions



bill by the total energy usage. Figure 5 shows a negative correlation between cost efficiency and number of charging sessions in a month. Cost per unit of energy usage decreases as number of charging sessions increase at a charging station. This relationship is caused by the monthly demand charge averaging out with increased energy use from more charging sessions.

Installation Cost of Charging Infrastructure

DCFC operation is important to the DCFC vendor's long term economic viability; at the same time, installation costs can be a significant burden in materializing a DCFC vendor business. Installation costs of DCFCs can vary depending on many different technical and environmental factors. Cost data for EV charge infrastructure are currently limited and can be found in few peer-reviewed journal articles [1, 2].

DCFC installation costs were collected from the U.S. Department of Energy's EV Project and are summarized as follows:

- Average cost = $23,662
- Median cost = $22,626
- Minimum = $8,500
- Maximum = $50,820

The total cost of the installations cited above includes only costs paid to the electrical contractors to install Blink DCFCs. This cost would typically include permit costs, engineering drawings, contractor's installation and administration labor, subcontracted construction labor or equipment (e.g., concrete, asphalt, trenching, and boring), and materials other than the DCFC itself. To evaluate the cost drivers for DCFC installations during the EV Project, some of the features of the installed hardware and site conditions were examined. The following were found to be significant DCFC installation cost drivers observed during the EV Project that are not specific to the Blink dual-port DCFC. Their impact on installation costs would be applicable for any installation of a DCFC unit rated at 20 kW or more:

1. Electrical service upgrade
2. Ground surface conditions
3. Materials

DCFC installations often require new electrical service to be added to the host's site. The cost of these installations was significantly higher than those that did not require new service. The magnitude of this cost increase depends on existing electrical services at the host site and costs from the electric utility to install a new metered electrical service. Electrical service extension costs also varied depending on

TABLE 9 Attributes data collected.

Variable Name	Description
Service Upgrade	Binary variable where 1 indicates that new service was required and 0 indicates new service was not required
Underground Service	Binary variable where 1 indicates that new service was required and 0 indicates new service was not required
Gravel	Binary variable where 1 indicates that ground surface is gravel and 0 indicates either asphalt or concrete
Distance	Distance of underground power feed in feet

the electric utility's policies for aboveground or underground service. Overhead service is typically less expensive and quicker than trenching for an underground service extension. The cost of underground service extension varies depending on the distance (i.e., the length of the underground passage) from the transformer. Therefore, to determine the economical suitability of the location for DCFC installation, each site needs to be vetted for available power and proximity to existing power service. To quantify association between total installation cost and the above-mentioned cost drivers, several attributes of the DCFC sites from the EV Project were collected via invoices and interviews with the contractors as needed.

An ordinary least-squared regression was estimated to examine the statistical association between total cost and the identified cost drivers. The coefficient estimates and the 95% confidence intervals are shown in Table 10. The mean DCFC installation cost at a site without electricity service upgrade is estimated to be $18,290. This installation cost is significantly affected by the electricity service upgrade, which adds an additional cost of between $1,354 and $7,763. The cost of service upgrade depends on whether the service is overhead or underground. If the electricity service is underground, the cost of service upgrade is affected by the type of ground service and the distance of the needed underground power feed. If the ground surface is gravel rather than concrete or asphalt, installation cost is estimated to reduce by between $231 and $9,143 and the cost of trenching or boring for DCFC installation, if required, is estimated at between $38.79 and $174.59 per foot.

Low-cost installations require sufficient electrical power at the site to accommodate the DCFC and a simple installation with either short underground conduit runs or surface-mounted conduit. All suggested locations that are within AEP Ohio's service territory have adequate facilities to serve a 60-kwh DCFC. Because service upgrade is not necessary, the relative difference in installation costs among the proposed DCFC installation sites primarily would be affected by the costs of trenching and boring that are required to extend the service lines if the service lines are underground. Figure 6 shows the map of Location #10 as a location with a potentially low installation cost. As shown in the map, overhead power lines, which are shown with blue lines, conveniently extend around the parking lot of a large retail store, making it convenient for installing DCFCs on parking space without a need for extensive underground work. As discussed above, installation cost can be compounded by long underground conduits and surface conditions that are expensive to restore. On the other hand, Location #5 (Figure 7) has limited access to the overhead service line. In Location #5, electrical service is provided to the nearby amenities mostly via underground lines. Therefore, if DCFC is to be installed in the nearby parking space, a considerable amount of trenching and boring would be required, which is estimated to cost from $38.79 to $174.59 per foot. Moreover, because the ground surface is either concrete or asphalt, installation costs for this location can potentially be much more expensive; the above estimates for the cost model show the cost increase would be between $231 and $9,143 relative to when the ground surface is gravel.

Total Cost of Charging Infrastructure

Total capital expenditure was calculated on a monthly basis and combined with monthly operating expenses to determine the total cost of charging infrastructure. Capital cost of a single DCFC unit (i.e., one plug) was assumed to be $40,000. Each additional DCFC plug per site was assumed to add an additional $40,000. Because the exact installation location of DCFCs at each of the recommended sites is unknown and a slight change in the installation position may significantly affect the installation cost, a range of installation costs was computed based on the results from Table 10. Capital costs for each site were added to the range of expected installation costs for each site to provide total capital cost. The total cost was amortized over 10 years at an 8% discount rate to determine a monthly capital expenditure. Total operating costs for each site were assumed to be the electricity cost, as shown in Table 8, plus $100/month for warranty, maintenance, network service, and other fees. Total monthly cost for each site was determined by adding the total monthly capital cost and the total monthly operating cost.

To put total cost in terms that are relatable to revenue, the total cost of charging infrastructure at each location was divided by the number of charging sessions. Figure 8 shows this cost. The horizontal bar represents the total operating

TABLE 10 Coefficient estimates.

	Coefficient	Standard. Error	P-value	2.5%	97.5%
Intercept	18,290.26	863.02	<0.01	16,574.63	20,005.88
Service Upgrade	4,559.02	1,611.92	<0.01	1,354.61	7,763.41
Underground × Distance	106.69	34.15	<0.01	38.79	174.59
Underground × Gravel	−4,687.10	2,241.56	<0.05	−9,143.19	−231.02
R-squared: 0.204					
Adjusted R-squared: 0.176					

FIGURE 6 Map of Location #10. Satellite imagery credit: © 2017 Google, Map Data © 2017 Tele Atlas.

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FIGURE 7 Map of Location #5. Satellite imagery credit: © 2017 Google, Map Data © 2017 Tele Atlas.

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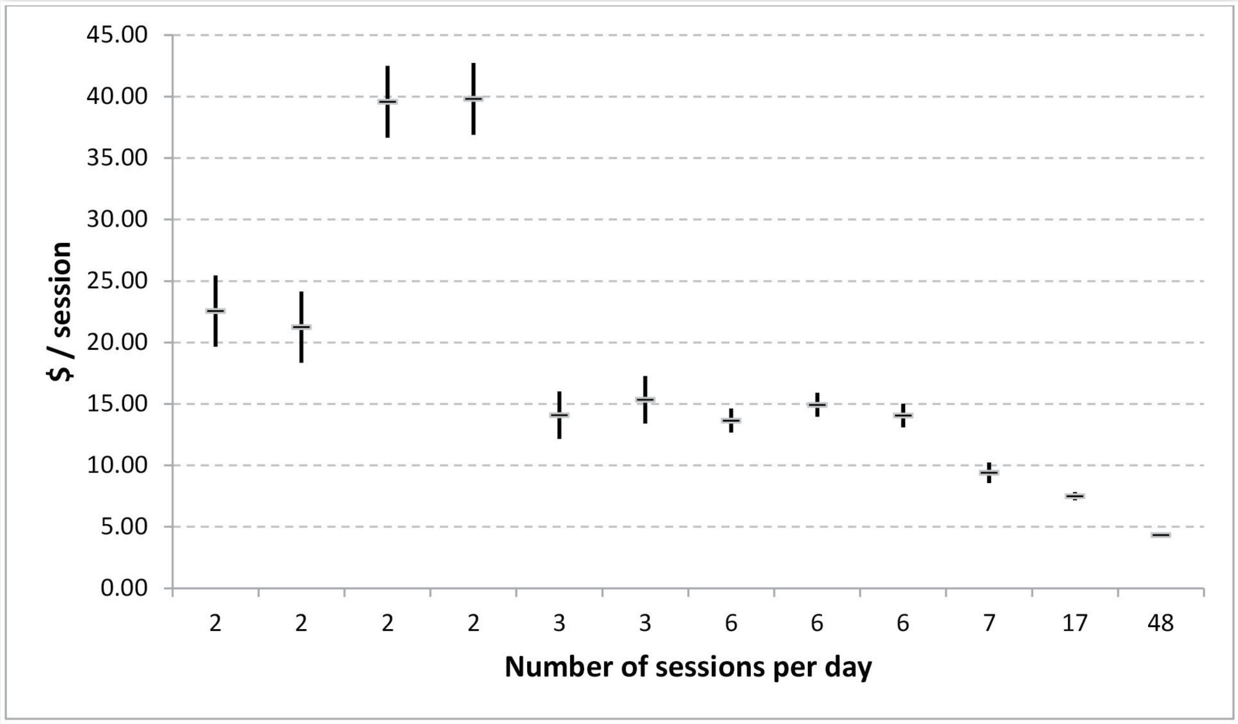
FIGURE 8 Total cost of charging infrastructure per site, calculated on a per-session basis. Error bars represent the expected range of installation cost, which varies depending on the specific location chosen for the charging site.



cost plus the mean total capital cost. The error bars represent the range of expected installation costs.

Because some of the recommended locations expect low utilization, the uncertainty in the installation cost can affect their total cost per session considerably. However, as the number of sessions increases, the effect of installation cost variation is minimized, and operation costs dominate the total cost. Therefore, when siting DCFC stations, priority should be placed on choosing a location with potential for high utilization rather than choosing a location with minimal installation cost.

Conclusions

EVI-Pro recommended 12 sites for DCFC installations to support a hypothetical PEV ride-hailing service in Columbus, Ohio. The total electricity cost at the recommended sites was estimated to range from $316 to $1,397. Cost per unit of energy use decreases as sites experience more charging sessions because fixed demand charges are distributed across a greater number of kilowatt-hours.

Among the recommended sites, the sites with overhead service lines are recommended for hosting the DCFC as trenching and boring that are required for underground service line extension can be a considerable cost driver. Although the cost of service upgrade generally is a significant cost driver, all the recommended sites that are within AEP Ohio's territory were found to have enough service capability to support DCFCs. However, some of the sites have limited overhead service lines and underground service line extension may be required.

The uncertainty in the actual installation cost may affect the total cost; however, as the level of utilization increases, the operation cost dominates the total cost. Therefore, for DCFC site selection for a ride-hailing service, priority should be placed siting DCFC at locations with the potential for high utilization rather than choosing locations based on low cost.

Recommendations for Future Work

Although this preliminary analysis of the impacts of new mobility paradigms on alternative fueling infrastructure requirements has produced several key results, the complexity of the problem warrants further investigation. Repeating the ride-hailing emulation process with a larger travel data sample would increase the probability of matching trips to TNC vehicles, increasing the overall efficiency of the ride-hailing fleet. Simulating a larger data set in EVI-Pro would also shed light on the ability to share infrastructure as the EV market for TNC operations grows. Refining the input assumptions for ride-hailing vehicle operations would add realism to the proposed process for ride-hailing data emulation. For example, it would be useful to constrain the first and last trips of the day for each driver, as those should start or end either at the driver's residence or at a depot where all ride-hailing vehicles would be parked to charge overnight. In addition, vehicles completing long out-of-area trips may be excluded from the ride-matching pool of candidates, as they are unlikely to be used for ride-hailing services for such trips.

Modifying the algorithm to allow for ride-pooling (i.e., shared, multi-passenger ride-hailing) would shed light on the potential to achieve VMT reductions due to this mobility option. Developing algorithmic processes for other mobility paradigms, such as car-sharing or car-pooling, would be interesting additions. A comparison of the ride-hailing data emulation results with real-world ride-hailing data would be invaluable for validating our methodology.

It is also important to point out that the site selection criteria in this study were solely based upon potential charging demand: a location with a high level of simulated charging needs is recommended for the DCFC installation. However, in reality, the property owner provides the space for the DCFC installation, and it is uncertain if the recommended site would be available for hosting the charging stations. The monthly energy consumption was estimated based on the simulation of energy use within a single day in the summer. However, variability across different seasons and between weekdays and weekends needs to be considered for a more accurate estimation. Additionally, a charging station can be either owned by a utility or run as a standalone business. Future research can investigate the difference in operational cost between a utility-owned charging station and a charging station operated by a non-standalone business.

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Definitions/Abbreviations

AEP - American Electric Power

BEVxx - battery electric vehicle with a range of xx miles

DCFC - direct current fast charger

EVI-Pro - Electric Vehicle Infrastructure Projection tool

L1 - level 1 charging station

L2 - level 2 charging station

MUD - multi-unit dwelling

PEV - plug-in electric vehicle

PHEVxx - plug-in hybrid electric vehicle with a range of xx miles

SUD - single-unit dwelling

TNC - transportation network company

VMT - vehicle miles traveled

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