

Estimating Fast Charging Infrastructure Requirements to Fully Electrify Ride-Hailing Fleets across the United States

Matthew Moniot, Yanbo Ge, and Eric Wood

Abstract—Ride-hailing electrification is made challenging by a variety of factors including limited driver access to overnight charging and a nascent network of public direct-current fast chargers (DCFCs). This paper projects the DCFC infrastructure needed to electrify ride-hailing across 384 cities in the United States. Research leveraging a novel infrastructure projection tool, EVI-OnDemand, estimates that 25,400 DCFC ports capable of charging vehicles at a mean power of 150 kW are required to electrify 1.45 million ride-hailing vehicles in the baseline scenario. Results show that ride-hailing vehicles require 17.5 DCFC ports per 1,000 vehicles, three times that of personal electric vehicles. Infrastructure demand is also shown to vary across cities; 63% more DCFC ports are needed to support 1,000 battery electric vehicles in Chicago versus Miami. The analysis also includes sensitivity studies that explore variation in charging demand across input assumptions, finding that charging power, vehicle class, overnight charging access rates, and port utilization each influence the network size needed. Projections vary from 18,600 to 41,300 DCFC ports across sensitivity scenarios, indicating that ride-hailing electrification will require significant expansion of access to fast charging even in the most optimistic scenarios, and that investments into supporting assets can reduce the scale of the public charging expansion needed.

Index Terms—ride-hailing, electrification, infrastructure, fast charging, electric vehicle.

I. INTRODUCTION

THE light-duty transportation sector in the United States is undergoing rapid disruption. Although historically comprising vehicles relying solely on internal combustion, environmental concerns are increasingly motivating a shift toward more low-emitting electrified powertrains worldwide [1]–[4]. Although plug-in electric vehicles (PEVs) made up only 2% of U.S. vehicle sales nationally in 2019 [5], automakers are announcing pledges to increase PEV sales volumes [6]–[9] simultaneous to a federal executive order aimed at reaching 50% of light-duty sales as zero-emission vehicles by 2030 [10]. Enthusiasm for PEVs has developed alongside significant investments into charging

infrastructure [11], without which widespread PEV adoption is not viable [12]. Simultaneous to the emergence of electrified powertrains and a novel fueling paradigm, ride-hailing through transportation network companies (TNCs) such as Uber and Lyft has emerged as a growing use case for light-duty vehicles. Although TNC services exhibit many similarities to taxi fleets, the TNC business model innovated the ride-hailing sector through flexible shifts for drivers and the exclusive use of a mobile app for riders to hail drivers. These innovations contributed to TNCs rapidly growing in market share since their emergence in the early 2010s. For instance, the largest ride-hailing company in the United States, Uber, took 6 years to service 1 billion trips worldwide by December 2015, and only 6 additional months to service an additional 1 billion trips by June 2016 [13]. By 2018, the company had serviced 10 billion cumulative trips worldwide [14]. This growth is not limited to Uber; other prominent ride-hailing companies such as Didi and Lyft have also experienced substantial growth since their inception [15], [16]. The prominence of TNC services motivates generalizing TNC operations as reflective of the ride-hailing segment at large throughout this study.

The transportation disruptions of vehicle electrification and ride-hailing are currently disparate, as the ride-hailing fleet predominantly comprises gasoline-powered vehicles. For instance, electric vehicles (EVs) accounted for less than 1% of miles traveled for major ride-hailing companies in California in 2018 [17]. However, the deployment of battery electric vehicles (BEVs) within ride-hailing services is forecasted to increase dramatically in the near future. The California Air Resources Board formally adopted the Clean Miles Standard in 2020, which regulates ride-hailing companies on the basis of energy per passenger mile, motivating electrification of ride-hailing vehicles [18]. Uber and Lyft, the major U.S. ride-hailing companies, have reacted by pledging to meet and exceed these regulations; both companies have announced intentions to fully electrify their fleets nationwide by 2030 [19], [20].

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Literature pertaining to BEVs in ride-hailing contexts is limited, although contributions have accelerated in recent years. Early findings indicate both challenges and opportunities associated with ride-hailing electrification. Although EVs are typically cheaper to operate than internal combustion vehicles [21], they require access to charging infrastructure and current charging times are significantly longer than fueling internal combustion vehicles, cutting into available time to collect revenue-servicing trips. The opportunity cost associated with vehicle downtime contributes to a negative value proposition for BEVs compared to internal combustion vehicles, especially for vehicles with limited battery range [22]. Additionally, vehicles operated within ride-hailing contexts are predominantly owned by drivers who have lower-than-average income and difficulty accessing the necessary capital to acquire EVs for which there is a nascent used market [23]. Driver demographics and residence types also contribute to reduced likelihood of access to an overnight charger [24], which has been shown to dramatically reduce the downtime associated with mid-shift charging [25]. High-mileage TNC vehicles and limited access to overnight charging has resulted in early deployments of EVs in TNC fleets being heavily reliant on fast charging infrastructure. For instance, a study analyzing a population of EVs leased for ride-hailing purposes in California showed that ride-hailing vehicles charging at public stations comprised 35% of the total direct-current fast charging (DCFC) energy demand despite representing only 0.5% of the EVs in the state [26]. These statistics underscore the need for understanding the scale of the DCFC network needed to support ride-hailing as TNCs pursue aggressive EV targets.

Despite the stated challenges, the benefits of electrifying ride-hailing fleets are noteworthy. Jenn [26], who analyzed the operations of over 1,000 real-world EVs in TNC applications, found that replacing a gasoline ride-hailing vehicle with an electric ride-hailing vehicle produced emissions savings equivalent to replacing *three* gasoline vehicles used for personal travel. Beyond societal-level benefits associated with emissions reductions, research conducted by Klock-McCook et al. [27] has indicated that ride-hailing electrification can bring disproportionate benefits to underserved communities through targeted infrastructure investments in lower-income neighborhoods, where a disproportionate number of ride-hailing drivers reside. These benefits are further compounded by additional knock-on effects, including improved economics for DCFC station operators due to greater utilization demanded by ride-hailing vehicles [27] and increased exposure of EVs to TNC passengers who may be unfamiliar with the technology [28].

The momentum toward electrifying ride-hailing services and associated benefits motivates planning for charging infrastructure that future electric ride-hailing fleets will depend on. Prior studies investigating infrastructure requirements for ride-hailing fleets have typically focused on individual cities [24], [25], [29]. These studies leverage findings that emerge from analyzing real-world ride-hailing data. While comprehensive in a local sense, they are limited in geographic scope given the difficulty in obtaining representative ride-

hailing data at the national scale. The authors are aware of one study that estimates national infrastructure requirements for ride-hailing vehicles in the United States, which found that approximately 42,000 DCFC ports would be necessary to electrify ride-hailing services nationally [30]. The researchers arrived at this figure through assumed ratios of public and private ride-hailing charging demands from early deployments of ride-hailing EVs. The study also estimates the opportunity for ride-hailing vehicles to take advantage of underutilized chargers by comparing charging demands by time of day between the ride-hailing fleet and the broader light-duty EV fleet. Although the authors find the national estimation of 42,000 ports plausible, the research does not explore results on a city-by-city basis or investigate the sensitivity between the size of the charging network and variables that may change over time, such as vehicle class, access to overnight charging, or charging speed. Disaggregation of these factors is vital, as ride-hailing companies are exploring business model innovations such as providing subsidized charging access to drivers [31], vehicle leasing programs [32], or even controlling the shift lengths of drivers [33].

This report investigates the infrastructure requirements necessary to fully electrify ride-hailing operations in the United States. This paper aims to provide greater regional granularity in infrastructure projections, outputting required DCFC ports for all U.S. metropolitan statistical areas. Additionally, the level of modeling fidelity is considered to be the most comprehensive in the literature, outside of individual studies leveraging granular trip data, which are not available nationally. The Electric Vehicle Infrastructure Tool for On-Demand Mobility Services model (EVI-OnDemand) considers a wide variety of factors including local housing stock, ambient temperature, local traffic speeds, and more. These variables are explored in-depth in this work through sensitivities surrounding a baseline infrastructure charging network. Sensitivity model results quantify the implications of possible strategies for achieving full fleet electrification, including greater access to overnight charging, investment into higher charge power, and adjustments in driver shift lengths. Additionally, while the study focuses on the U.S. market, outcomes are also considered to be informative for ride-hailing fleets internationally; the diverse geography of the United States includes cities with a wide range of climates, driving speeds, and housing stock affordability. Beyond leveraging relationships ascertained from U.S. cities, EVI-OnDemand requires limited city-level data and can be simulated for any geography where data are available. The paper will proceed by introducing the EVI-OnDemand model, outlining input data and assumptions, and concluding with a discussion of results and implications for stakeholders in the ride-hailing ecosystem.

II. EVI-ONDEMAND SIMULATION

EVI-OnDemand was created to anticipate charging network designs necessary to support electric ride-hailing operations. EVI-OnDemand was formulated in response to the data limitations associated with ride-hailing operations, particularly at the national level. While numerous travel surveys and

telematic data sets are readily available for personal use vehicles, data describing the operations of ride-hailing fleets are difficult to obtain outside of key metropolitan areas such as New York City, Chicago, and San Francisco. The modeling framework developed almost exclusively leverages publicly available data, reporting infrastructure requirements for core-based statistical areas (CBSAs). For each metropolitan CBSA, EVI-OnDemand considers local factors specific to the geography, such as local traffic, local climate, and the likelihood of access to overnight charging through consideration of the local housing stock. These considerations are critical for differentiating the charging infrastructure needs across CBSAs with varying characteristics, such as dense cities with cold climates versus sprawling cities with a high percentage of detached family homes, faster roadway speeds, and more temperate climates. A high-level description of the model follows, including how the simulation framework produces vehicle- and fleet-level results in response to a diverse set of input variables. For a more comprehensive overview of the model, please refer to the source code [34]. Finally, input data (and relevant processing) are discussed before proceeding to the study results.

A. Driver Simulation

The core of EVI-OnDemand is the driver simulator (Fig. 1), which characterizes the driving and charging behaviors associated with ride-hailing vehicle operation in response to numerous inputs, most notably shift duration, overnight charging access, and vehicle parameters, including electric range and maximum charge acceptance rate (step 1). The driver simulator progresses through successive days through the procedure outlined in . The driver simulation is initialized with a fully charged vehicle (regardless of overnight charging access) just before starting a ride-hailing shift (step 2). The model assesses whether the vehicle has enough energy to complete a shift of predetermined duration, and if so, depletes the simulated battery (based on shift duration, driving speed, and ambient temperature) and advances to an off-shift period (step 3). If the vehicle is unable to complete its shift due to limited battery energy, a mid-shift DCFC event is modeled, after which the vehicle resumes driving if there is still time remaining on the shift (step 4). When the vehicle transitions to an off-shift state, the simulator assesses whether overnight charging is available. If it is available (step 5), the vehicle will charge at a lower power level corresponding to Level 2 charging. If charging is not available (step 6), it will dwell until its next shift event the following day. Days are simulated in succession to account for day-to-day variability in charging demand (step 7). Once a specified number of days have been simulated, the model finishes and outputs statistics such as miles driven per day and charging events per day (step 8).

No driving is considered outside of ride-hailing contexts given the lack of data pertaining to vehicle miles traveled (VMT) typical of ride-hailing drivers when they are not on shift. Additional infrastructure will likely be needed to support off-shift travel, although these demands are not explicitly modeled within this framework. Outcomes from this analysis are intended to specify only the incremental charging infrastructure needed to support ride-hailing vehicles while they are in

service; in reality, the full extent of the charging network will be broader to support personal travel. It is assumed that travel taken by ride-hailing drivers while off-shift will be accommodated using this larger network.

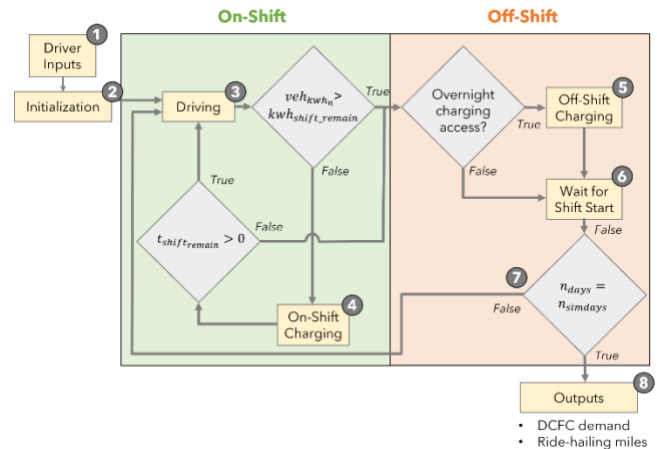


Fig. 1. Driver simulation structure.

Where:

- t_{shift_remain} = remaining time on the current driver shift
- veh_{kwh_n} = current amount of battery energy
- kwh_{shift_remain} = battery energy required to finish the remainder of the shift without charging
- n_{days} = the number of days simulated thus far
- $n_{simdays}$ = the number of days specified to be simulated per driver.

Sample driver simulations across 6 successive days are shown in Fig. 2, illustrating the data generated for each driver through two sample simulations. All variables are identical between drivers (e.g., shift length, battery size) except for access to overnight charging. Removing access to overnight charging induces a large amount of on-shift fast charging, from zero DCFC events to six across the 6 simulation days. This increase in on-shift charging also comes at the detriment of vehicle uptime to accrue miles; the vehicle with access to home charging is shown to accrue 150 miles per shift versus a slightly lower 143 miles per shift without access. The mile reduction between these vehicles being so slight (4.6%), despite a large amount of on-shift charging, is due to large charging powers (150 kW) and the slow average driving speed assumed (15 mph).

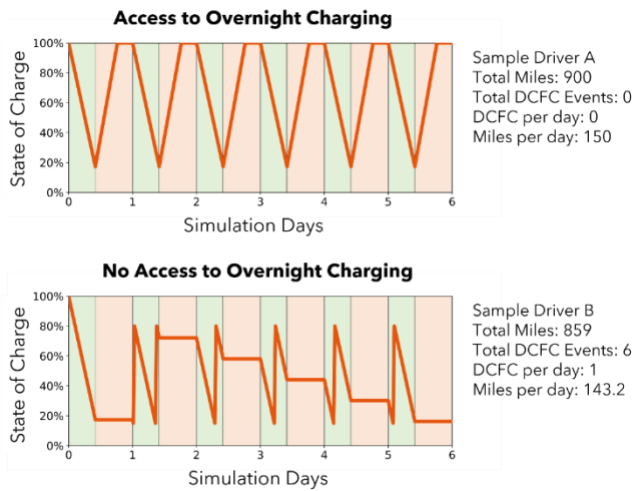


Fig. 2. Sample driver simulations for two identical drivers, except for access to overnight charging.

Key outputs from the driver simulations include the number of miles and on-shift DCFC events accrued per day. Note that while only 6 days are shown for demonstration purposes in Fig. 2, many more days (up to 50) are typically simulated to reduce the impact of initializing the vehicle at 100% from the simulator outcomes. Miles per day and DCFC events per day are leveraged by the fleet simulator, described in the following section.

B. Fleet Simulator

EVI-OnDemand produces fleet-level results at the scale of a given CBSA through outcomes from repeated driver simulations. The workflow of the fleet simulator is introduced in Fig. 3, whereby the model aggregates the driving and charging results observed from numerous driver simulations. The fleet simulator may be best thought of as a wrapper around the driver simulator, orchestrating which inputs are fed into the driver model and the quantity of driver simulations performed. For instance, fleet simulations for the CBSA of Minneapolis would entail identifying variables specific to the geography, including the corresponding climate, likelihood of overnight charging access, and average shift speed for input into the vehicle simulation. A final CBSA-specific variable, of total ride-hailing miles to electrify, is used to determine the number of driver simulations to perform before aggregating observed charging demand into a charging network. Note that some variables are assumed to generalize across CBSAs; the distribution of driver shift duration and the efficiency of the vehicle powertrain (less ambient and traffic effects) are universal across geographies simulated.

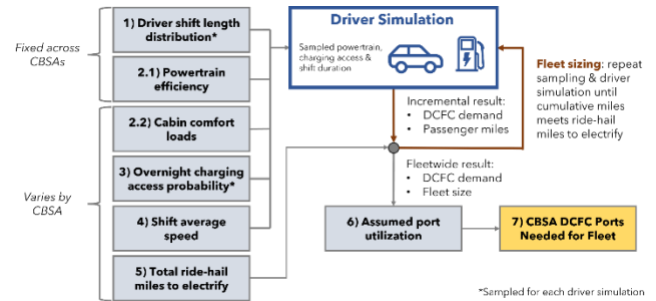


Fig. 3. Fleet simulation structure.

Inputs into the fleet simulator include the following key variables:

- Driver shift duration distribution: Frequency of driver shift durations in hours.
- Powertrain efficiency: Distance-based energy efficiency of the EV modeled.
- Cabin comfort load: Time-based auxiliary load of the EV, sensitive to the local climate.
- Overnight charging access probability: Percentage of drivers participating in the ride-hailing fleet who are considered to have access to overnight charging.
- Shift average speed: Average rate of mileage accrual while on shift (miles per hour).
- Total miles to electrify: Total miles traveled by the ride-hailing fleet in the CBSA, including deadheading miles. This mileage is expressed across all ride-hailing fleets—heterogenous fleets and ride-hailing competition are not considered.

Combined, these variables are input into the driver simulation, which outputs the number of direct-current fast charging events (DCFC) and achieved ride-hailing miles, including deadheading miles. The fleet simulator continues to orchestrate driver simulations, sampling from the driver shift length distribution and overnight charging likelihood, until the CBSA-level fleet VMT target is reached. Note that the VMT target is assumed to be across all participating ride-hailing fleets in each geography; heterogenous ride-hailing fleets/competing services are not considered. A more detailed fleet simulation example, which estimates charging infrastructure requirements for Denver, Colorado, can be found in the Supplemental Materials.

III. EVI-ONDEMAND INPUT DATA

A. Vehicle Efficiency

Assumptions regarding vehicle efficiency are required to translate vehicle activity into energy consumption, and by proxy, charging demand. Vehicle efficiency is calculated using (1), which assumes a baseline vehicle efficiency of 300 Wh/mi. This selected baseline value is consistent with U.S. Environmental Protection Agency-rated efficiencies of popular EV options, such as the 2021 Tesla Model 3 (250 Wh/mi), 2021 Tesla Model Y (260 Wh/mi), 2021 Chevy Bolt (290 Wh/mi), and 2021 Ford Mac-E (360 Wh/mi) [35]. Ride-hailing vehicles are assumed to be consistent with new model EV sedans, given

the prominence of sedans in the current ride-hailing fleet and the bias toward newer vehicles. An additional penalty scalar, ρ_{CBSA} , is applied to the baseline vehicle efficiency to incorporate ambient effects, which have shown to heavily influence infrastructure requirements for a population of EVs [36]. Note that no changes in the energy consumption rate arising from roadway grade are included across geographies; while roadway grade varies by city and has been shown to influence energy consumption, the impact of grade on BEV energy consumption is considered minor, especially relative to ambient effects [37].

$$\eta_{CBSA} = \eta_{Baseline} * \rho_{CBSA} \quad (1)$$

Where:

- $\eta_{Baseline}$ = baseline powertrain efficiency (300 Wh/mi)
- ρ_{CBSA} = ambient penalty factor, specific to a given CBSA depending on local weather
- η_{CBSA} = ambient-influenced powertrain efficiency, specific to a given CBSA.

The ambient penalty factor was modeled to vary by geography, incorporating the variability in climate throughout the United States. CBSA-specific penalty factors were calculated through use of the typical meteorological year (TMY3) data set, which describes representative ambient conditions for over 1,000 locations in the United States [38]. This data set was used in conjunction with a relationship between ambient temperature and relative EV efficiency (Fig. 4), produced using a validated thermally sensitive powertrain model, FASTSim Hot [39], that incorporates variable component efficiencies and auxiliary cabin comfort loads. The relationship in Fig. 4 was developed by simulating a large number of trips across a wide range of ambient conditions and comparing the energy consumed against ideal ambient conditions (22°C).

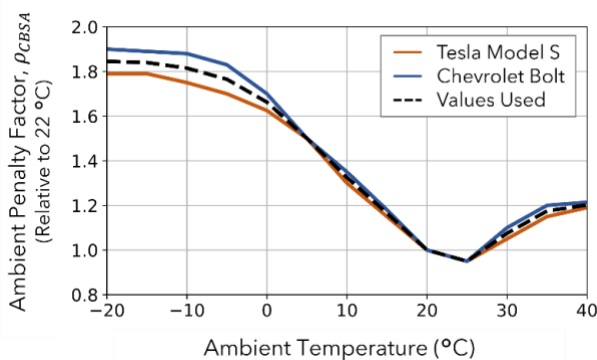


Fig. 4. Ambient penalty factors versus ambient temperature, calculated using FASTSim Hot.

Ambient penalty factors reflective of each CBSA were then calculated using the following procedure:

1. For a given CBSA, identify the nearest TMY3 station.

2. Join ambient penalty factors against the TMY3 data by interpolating ambient temperature data occurring at the nearest weather station.
3. Average the ambient penalty factors for each CBSA and day of the year. Day-level ambient penalty factors are sorted from least to most severe.
4. Select a day of the year for each CBSA based on the sizing scenario of interest—50th percentile values of penalty factors correspond to typical vehicle efficiencies at a given location, whereas 100th percentile values correspond to the worst day of the year. The average penalty factor across the day selected is used for simulation.

It is assumed that a successful infrastructure network must be capable of meeting fleet charging needs across the majority of days of the year, although it is subjective whether the worst day of the year is appropriate for infrastructure sizing. The vehicle efficiency workflow developed thus enables adjusting which day of the year is selected for sizing for each location. Additionally, the procedure ensures that challenging days of operation are selected for each location, whether driven by cabin heating in cold climates or air conditioning in hot climates. Fig. 5 illustrates the process for identifying vehicle efficiencies specific to each CBSA on a percentile basis. Fig. 5a demonstrates how ambient-influenced vehicle efficiency changes throughout the year for a cold and warm location and percentile values are selected, and Fig. 5b shows the range of efficiency values selected at the 75th, 85th, and 95th percentile levels for each CBSA in the study. In general, worst-case ambient conditions occur during the coldest times of year for the vast majority of CBSAs given the greater energy penalty associated with cold temperatures. The small number of CBSAs that experience worst-case vehicle efficiencies during warm conditions feature climates with high summer temperatures and mild winters.

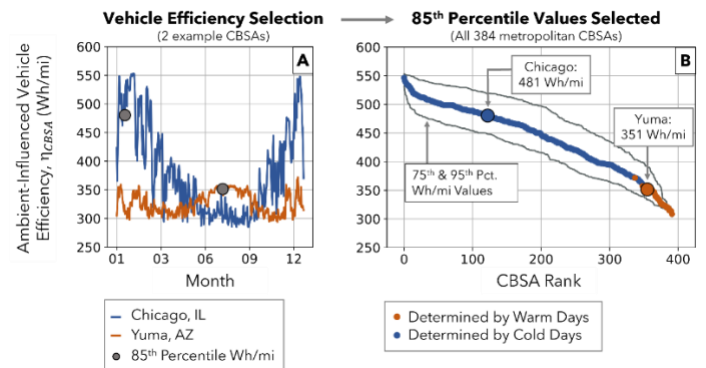


Fig. 5. (a) Variability in powertrain efficiency throughout the year for two example CBSAs, with relevant values selected for sizing days specific to each location (winter in Chicago, summer in Yuma). (b) Selected powertrain efficiency values across all metropolitan CBSAs studied.

B. Vehicle Battery Size and Charge Rates

Battery size and charge power assumptions are required to inform how frequently vehicles will require charging and the

rate at which fast charging occurs. It is unclear whether future ride-hailing fleets will comprise newer, more capable vehicles with greater battery sizes and charge acceptance rates, or if future ride-hailing fleets will instead rely primarily on older, used EVs with powertrain parameters similar to existing EV offerings. A baseline battery size of 75 kWh is assumed alongside a baseline mean charge acceptance rate of 150 kW throughout a full charge event—values considered reflective of existing EV sedan options. Additional vehicle parameters—found in Table —are explored through sensitivities to understand the implications of different battery sizes and charge powers and the corresponding infrastructure required. The total time per DCFC is calculated using (2) and (3), which assume charging will occur between 20% and 80% with an ingress/egress time of 5 minutes.

$$t_{chg} = \frac{veh_{kwh}(SOC_f - SOC_i)}{chg_{kw}} \quad (2)$$

$$t_{chg_{tot}} = t_{chg} + t_{ingress/egress} \quad (3)$$

Where:

veh_{kwh} = battery energy (kWh)

SOC_i, SOC_f = initial and final state of charge for DCFC event, assumed to be 20% and 80%, respectively

chg_{kw} = mean DCFC charge power

t_{chg} = time per DCFC event spent charging

$t_{ingress/egress}$ = access time associated with DCFC charging

$t_{chg_{tot}}$ = total time a plug is considered occupied during a DCFC event.

TABLE I.
BATTERY SIZE, CHARGE POWER, AND RESULTING CHARGE TIMES FOR EACH SCENARIO SIMULATED.

Vehicle name	Battery size (kWh)	Mean charge power (kW)	DCFC charge time (hours)	Total time per DCFC (hours)
Baseline	75	150	0.40	0.48
Vehicle class (low)	60	150	0.32	0.40
Vehicle class (high)	90	150	0.48	0.56
Charge power sensitivity (low)	75	100	0.60	0.68
Charge power sensitivity (high)	75	200	0.30	0.38

C. Driver Home Charging Access

The percentage of overnight charging access across ride-hailing drivers in a region is expected to heavily influence the size of the fast charging network. For instance, prior research on taxi fleet electrification has indicated that ubiquitous access to overnight charging can nearly eliminate the number of fast charging ports needed [25]. However, estimating the potential likelihood of overnight charging access for ride-hailing drivers is challenging, as overnight charging access depends on many variables, including parking location (e.g., street, garage), housing type (e.g., apartment, detached home), and housing tenure (rent or own) associated with a population of heterogenous drivers that are assumed to drive their own personal vehicles and dwell them at their home location. Additionally, drivers for ride-hailing services are disproportionately lower-income, complicating opportunities to leverage data sources representative of the general population. The following analysis introduces a means of characterizing the likelihood of access to overnight charging for ride-hailing drivers. Note that emerging business models, such as leased vehicles with overnight charging at a depot location or leases where public charging is included in the lease of the vehicle, are not explicitly considered. However, such models could be evaluated in the future by assuming greater rates of overnight charging access irrespective of driver housing status or through a driver preference for midday fast charging.

Recent survey data gathered by the National Renewable Energy Laboratory assessing the likelihood of access to overnight charging [40] were leveraged to estimate the probability that drivers may have access to overnight charging. Although this survey is intended to be representative of the broader population, the survey produced relationships between housing descriptors—tenure and housing type—and overnight charging access (Table , repeated from original source), which allows for the estimation of ride-hailing drivers' residential charging access if their housing type/tenure distributions are known. Rates of access to overnight charging are displayed in response to assumptions regarding driver parking behavior and the respondent's perception regarding whether a charging port could be installed at their overnight location. Home charging rates by housing characteristics are obtained using a survey among U.S. citizens on both where they park their vehicles when at home and the electrical access and possibility to install new outlets at each parking option at home. The following three scenarios are considered to capture the uncertainty of residential charging access rates:

- Existing parking and 120-V perception: Assumes home charging is available if a vehicle is parked near electrical access and its owner believes standard outlet can be used to charge EVs.
- Parking behavior modification and existing perception: Assumes home charging is available if a vehicle is either currently parked near electrical access or can be moved to a charging location at home that has electrical access.
- Parking and perception modification: Assumes home charging is available if a vehicle can be moved to a

parking location where electrical access is either currently available or can be installed.

For more information regarding the survey assumptions, refer to Ge et al. [40]. Note that the “existing parking and 120-V perception scenario” is highly conservative and included from survey results to represent an absolute lower bound on overnight charging access; it is unlikely that ride-hailing drivers will have rates this low for overnight charging access, and the scenario is included primarily for exploration through the sensitivity analysis presented later in the paper.

TABLE II.
LIKELIHOOD OF ACCESS TO OVERNIGHT CHARGING IN
RESPONSE TO HOUSING TYPE AND HOUSING TENURE [40].

Housing type	Tenure	Existing parking, 120-V perception	Parking behavior modification, existing perception	Parking and perception modification
Single-family, detached	Own	17%	72%	89%
Single-family, detached	Rent	10%	49%	68%
Single-family, attached	Own	16%	53%	70%
Single-family, attached	Rent	7%	28%	47%
High-rise apartment (20+ units)	Rent	5%	19%	29%
Mid-rise apartment (5–19 units)	Rent	3%	11%	19%
Low-rise apartment (2–4 units)	Rent	2%	12%	26%
Other		9%	41%	59%

As there is no credible source on the distributions of ride-hailing drivers’ housing types and tenures, instead of estimating residential charging access directly by leveraging Table II, we had to build an indirect connection by using ride-hailing drivers’ income distribution as a bridge. To interpret the residential access values in a manner specific to ride-hailing drivers, driver household income data¹ ([41], repeated from original source in Table) were conflated against data from the Public Use Microdata Sample (PUMS) [42], which provides anonymized household-level information from the U.S. Census. To preserve the anonymity of participants, PUMS records are reported at a coarse spatial resolution known as Public Use Microdata Areas (PUMAs).² For a given CBSA, PUMS households were sampled from associated PUMAs and assigned an overnight charging access likelihood based on PUMS statistics (residence type and tenure). Next, households were categorized by household income using thresholds

¹ Driver household income data are used instead of the income obtained exclusively from ride-hailing services. Household income includes additional revenue from separate forms of employment and across all household members. This value is considered to be a more accurate indicator of the type of housing the driver lives in, and also enables direct comparison against PUMS.

consistent with Table III. Overnight access rates across households within a given income bin were then averaged. Finally, a single rate of overnight access across all income bins for ride-hailing drivers was determined through an average of overnight access rates by income bin weighted by the share of drivers affiliated with the household income bin (Table). This procedure, performed for each CBSA, enables differentiation across geographies by accounting for variability in housing stock and household income, leading to consideration of lower overnight charging access in expensive dense CBSAs (such as New York City) versus more sprawling CBSAs with a greater availability of more affordable housing options with more favorable rates of overnight charging (such as Houston).

TABLE III.
HOUSEHOLD INCOME DISTRIBUTION ACROSS 1,000
SURVEYED RIDE-HAILING DRIVERS [41].

Range	Share of respondents
\$0–\$14,999	3%
\$15,000–\$29,999	16%
\$30,000–\$39,999	14%
\$40,000–\$49,999	14%
\$50,000–\$659,999	11%
\$60,000–\$74,999	9%
\$75,000–\$99,999	11%
\$100,000–\$149,999	8%
\$150,000 or more	3%
Prefer not to answer	10%

Outcomes regarding the likelihood of overnight charging access are shown in Fig. 6 for three different assumptions explored in the residential access survey. As expected, more generous assumptions for improved parking locations and driver perceptions are correlated with greater access to overnight charging. These CBSA-specific rates are used by the fleet simulator when determining how frequently to provide access to overnight charging to each vehicle.

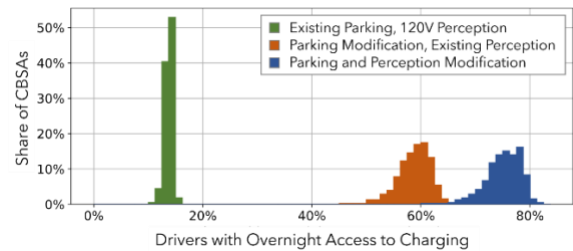


Fig. 6. Likelihood of overnight charging access for ride-hailing drivers by overnight access scenario and across all metropolitan CBSAs.

² PUMAs are geographies that were found to not necessarily align with CBSA boundaries. A spatial join was performed to affiliate PUMAs with CBSAs on the basis of an inclusive geographic join. The overwhelming majority of PUMAs that overlapped with CBSAs were found to be fully confined (100% overlap).

D. Driver Shift Durations

A key variable influencing the charging demands of ride-hailing vehicles is the time vehicles are assumed to be spent on shift. Full-time drivers operating vehicles for ride-hailing services accrue significantly more miles than part-time drivers and will thus induce greater demand for charging. However, a greater share of full-time drivers may also reduce the total population of vehicles given the fleet sizing procedure introduced in Section II B. Accurately characterizing drivers on the basis of hours driving per shift or shifts per week is difficult given the lack of publicly available data pertaining to ride-hailing drivers. One study from 2019 found 11% of drivers to be full-time using data from RideAustin [43]. More recently, a blog post published by an Uber economist [44] suggested that the vast majority of drivers are part-time through analysis of proprietary driver data sourced from all Uber drivers in California (reproduced in Table). These values are sourced from all Uber drivers in California and are considered to be the best reflection of hours worked per week across ride-hailing drivers in the United States. Ride-hailing drivers were assumed to operate 5 days per week, producing the assumed shift time column in Table IV.

TABLE IV.
RIDE-HAIL DRIVER SHIFT DURATION PROBABILITIES.
COLUMNS 1 AND 2 REPRODUCED FROM [40].

“Online” hours per week (survey)	Share of drivers	Assumed shift time (hours)
0–10	45%	2
10–25	29%	4
25–40	17%	6.5
40+	9%	10

E. Driver Shift Average Speed

The driving simulator requires assumptions regarding average driving speed to translate time spent on shift into feasible rates of mileage accrual, which is used to determine both charging requirements at the vehicle level and fleet sizing requirements at the fleet level. Although ride-hailing driving is predominantly urban across the United States, the mean driving speed within CBSAs was assumed to vary across cities with different characteristics; for instance, mileage accrual rates for ride-hailing drivers in cities with significant congestion (such as New York City) are likely lower than cities with less concentrated urban cores (such as Denver). Over 50 million GPS trips from January 2020 sourced from INRIX, a commercial telematics data provider, were joined against CBSA geographic boundaries. A single representative speed for each CBSA was then identified by finding the median speed across all trips affiliated with a given CBSA. Outcomes from this step are shown in Fig. 7, with assumed driving speeds varying between 15 mph and 28 mph across CBSAs.

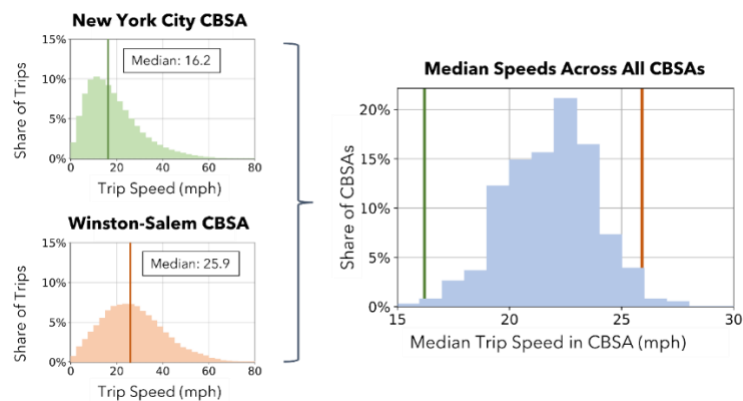


Fig. 7. Median speeds assumed across CBSAs.

F. Total Fleet Miles to Electrify, Deadheading Ratio

EVI-OnDemand requires the total number of passenger miles to electrify to determine fleet size. Few data are available in the literature regarding the share of miles affiliated with ride-hailing fleets outside of an analysis performed by Fehr & Peers [45]. In the analysis, the authors aggregated real-world ride-hailing miles across P1, P2, and P3 phases³ provided by Uber and Lyft from September 2018 across the six metropolitan areas of Seattle, San Francisco, Los Angeles, Chicago, Washington, D.C., and Boston. The authors compared the total miles across the ride-hailing fleets for each region against the overall amount of vehicle miles traveled for the month as reported by the local metropolitan planning organization. The study found that ride-hailing fleets comprise between 2% and 3% of VMT within the six regions analyzed, with greater rates of penetration within the urban cores of each region. The authors explored opportunities to correlate relevant statistics (e.g., vehicle registrations, household income) affiliated with the TNC penetration rates reported by Fehr & Peers, but ultimately determined that the small sample size of six CBSAs was an insufficient foundation for a regression model. The VMT shares found by Fehr & Peers are used for the six regions the authors analyzed, and a VMT share of 1.5% is assumed for all other regions in lieu of access to more granular data. The VMT shares reported by Fehr & Peers are assumed to have above-average rates of VMT penetration given the high household incomes and prominence of technology and information workers in the regions analyzed. VMT penetrations for each CBSA were multiplied by the inferred number of vehicle miles traveled in each CBSA. Total VMT values were obtained at the CBSA-level by disaggregating state-level VMT values reported in Table VM-2 of the 2019 Highway Statistics Report [46] on the basis of vehicle registrations, which were separately sourced from IHS Markit [47] at the ZIP code level and aggregated to CBSA and state levels.

Ride-hailing demand and VMT accrual outside of metropolitan CBSAs is acknowledged, although not explicitly considered in this analysis. It is assumed that ride-hailing operations in micropolitan and rural areas comprise a small

³ Miles accumulated with ride-hailing services are categorized by type: P1 miles correspond to mileage accrued between trips without a dispatch instruction, P2 miles correspond to mileage accrued while dispatching to a

known pickup location, and P3 correspond to trip miles with a passenger. Commuting miles are not considered in the analysis by Fehr & Peers or in this study.

fraction of the national ride-hailing fleet, and charging demands associated with ride-hailing vehicles in these areas will largely be fulfilled by the charging network deployed for broader personal use. Finally, estimates regarding current ride-hail market share are used in lieu of growth estimates for the year 2030. It is unclear whether ride-hailing services will continue to grow, especially as TNCs begin to electrify their vehicle fleets.

G. Port Utilization

The final input into EVI-OnDemand is the assumed port utilization, necessary for translating observed time spent charging into a network size for each CBSA. Although DCFC ports could theoretically be utilized 24 hours per day, real-world utilization is much lower due to variability in charging demand by time of day. Ports are typically utilized less frequently during overnight hours, with greater charging demand occurring when vehicles are being utilized. Inspection of DCFC charging data from ride-hailing vehicles presented by Jenn [26] shows increased demand in the evening hours, which coincides with observed DCFC demand from the general public. However, ride-hailing demand also persists through overnight hours when charging demand from the general public is lower, suggesting that ride-hailing charging demand may be partially met through chargers demanded by the general population. Existing research pertaining to ride-hailing charging utilization suggests that current utilization levels are approximately 20% in Los Angeles and Shenzhen, China, with opportunities for greater utilization in the future through growth of the electric ride-hailing segment and coordinated charging instructions [27], [48].

Review of the available electric ride-hailing literature motivated assuming a baseline daily average utilization of 30% for a forward-looking use case when TNC services are fully electrified. Sensitivities regarding utilization are explored with 20% on the low end, reflecting current station utilization for ride-hailing applications, and 40% on the high end, reflecting a possible future scenario with greater market share and coordinated charging.

Emerging research [24], [27], [30] also assumes that ride-hailing charging demand may be complementary to demands by the general public, presenting an opportunity for some ride-hailing charging to occur at underutilized chargers with the primary purpose of providing charging access for personal use EVs. These assumptions leverage load profile data published by Jenn [26], who published load profiles describing ride-hailing charging demands by time of day. Although the authors agree that infrastructure sharing is worth consideration, the load profiles are not necessarily considered reflective of future ride-hailing charging demand by time of day. The charging demand data presented by Jenn [26] are aggregated from EVs that were made available through vehicle leasing programs to drivers who almost exclusively drove full-time and did not have access to home charging. While the charging demand curves are the best data available, the authors have chosen to not explicitly incorporate port sharing opportunities between ride-hailing vehicles and chargers sited for public use. As a result, final infrastructure values are believed to be conservative.

IV. SIMULATION SCENARIOS & RESULTS

EVI-OnDemand was used to estimate the infrastructure required to support a fully electric ride-hailing fleet in the United States. An overview of this process can be found in the Supplemental Materials, illustrating the modeling outputs generated at the CBSA level for a sample simulation of Denver. National results from the baseline simulation are introduced next, with results for sensitivities exploring the impact of different input values following thereafter. Infrastructure results at the CBSA level are also available across the baseline results and each sensitivity performed in the Supplemental Materials.

A. Baseline Results

Producing national results required EVI-OnDemand simulations across each of the 384 metropolitan CBSAs in the United States. Aggregate demand for on-shift charging was observed across each of the driver simulations and translated into a DCFC network through assumptions regarding port utilization. This process also provides insight into the relative fleet size of BEVs needed in each CBSA, as illustrated by the number of unique driver simulations needed to meet the TNC miles to electrify. Modeling results indicate that 25,400 DCFC ports will be needed nationally to accommodate a fleet size of 1.45 million vehicles. The national fleet size of BEVs calculated is consistent with available estimates of the current ride-hailing fleet in the United States [49]. Overall, an average of 17.5 DCFC ports are needed per 1,000 ride-hailing BEVs, far more than ratios obtained by infrastructure analyses related to personal use of light-duty vehicles. For instance, a study assessing infrastructure requirements for BEVs owned and operated by the general population in California found that approximately 30,600 DCFC ports were needed to support the daily travel requirements of a fleet of 5.2 million BEVs, a rate of 5.8 ports per 1,000 BEVs [50]. Additionally, the national estimate of approximately 25,400 fast charging ports to support full ride-hailing electrification is also notably smaller than a similar estimate conducted by Bauer et al. [30], which found that 42,000 dedicated fast chargers would be needed in addition to use of underutilized chargers primarily used by the general population. The larger estimate for ride-hailing charging network size is likely due to larger assumptions regarding ride-hailing market share; Bauer et al. [30] assume that ride-hailing fleets may continue to grow, reaching 2.5% nationally by 2030 and reaching up to 5% in some cities.

Analysis of CBSA-level results from EVI-OnDemand provides additional insight into which regions comprise the greatest demand for charging. As one would expect, larger areas with greater TNC mileage necessitate larger local fleet sizes and greater demand for charging ports. However, this relationship is not absolute; the local climate of cities was also found to influence charging network size at the CBSA level. This relationship is demonstrated in Fig. 8, wherein colder climate conditions (as illustrated through vehicle efficiency assumptions) induce more frequent charging. At the city level, effects are significant; for instance, 91.1 ride-hailing vehicles were supported per DCFC port in Miami versus only 42.7 vehicles per port in Chicago. Inspection of Fig. 8 also supports approximating the per-vehicle demand for fast charging in

cities outside the United States with corresponding climates—such as warm cities with results similar to Miami—assuming the fundamentals of the ride-hailing business model are similar.

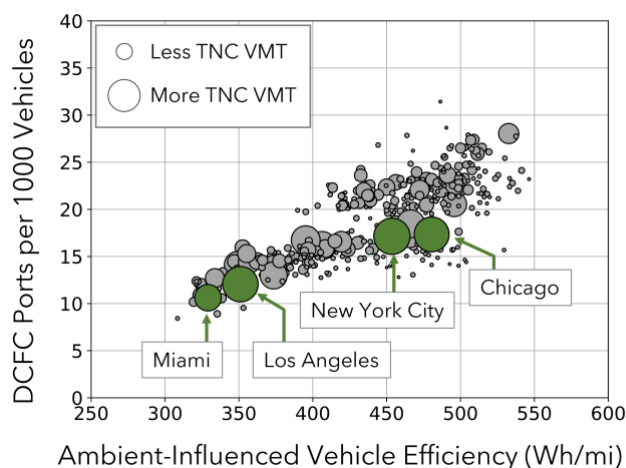


Fig. 8. CBSA-level results relating charging infrastructure required per vehicle expressed as a function of the local vehicle efficiency.

B. Sensitivity Results

Uncertainty is acknowledged surrounding the baseline results, arising largely from input assumptions. Although the best estimates were used for each input variable, actual parameters associated with real-world electric ride-hailing may evolve differently due to technological, business model, and policy factors. The uncertainty inherent in baseline assumptions motivated a sensitivity study to understand how the requisite charging network size and corresponding fleet size varies in response to different input assumptions. The sensitivity study was performed by adjusting inputs individually while holding all others constant. In total, 12 additional national EVI-OnDemand simulations were performed exploring pessimistic and optimistic values for port utilization, ambient condition assumptions, full-time driver share, DCFC power, rate of overnight charging access, and vehicle class. Overnight charging access sensitivities were explored through different assumptions regarding driver behavior and perception. While the baseline scenario used survey results corresponding to the “existing perception, parking modification” category, the sensitivity study included simulations assuming “existing parking and existing 120-V perception” and “possible parking modification and perception modification” (Fig. 6, Table). The authors acknowledge that some variables may be inherently linked, such as rates of access to overnight charging and the share of drivers that are full-time. These variables are kept uncoupled within the sensitivity study due to limited empirical data defining relationships between scenario input values.

The size of the ride-hailing charging network needed varies considerably throughout sensitivity runs, from 18,600 to 41,300 DCFC ports versus the baseline result of 25,400 ports (Fig. 9). Sensitivity results indicate that the charging network size is influenced by two broad considerations: absolute charging

demand and how infrastructure is used to meet charging demand. On one hand, changes in absolute charging demand (defined as the total time across DCFC events required to support the fleet) induce changes in the aggregate network size. For instance, fleets with greater access to overnight charging start each shift at a full battery capacity and require fast charging infrequently. Changes in total charging demand may also be observed through the vehicle class sensitivity, whereby the network size required to support a fleet of compact sedans, despite having identical range to the baseline sedan and crossover vehicle classes, is smaller due to less charge time required per DCFC event due to the smaller battery size. On the other hand, sensitivity results indicate that the charging network size may vary even between scenarios with a fixed total demand for charging through greater port utilization and faster charge power. Greater utilization of assets and faster charge power both enable a single DCFC port to accommodate more events per day. Although the polarity of the results is intuitive—such as higher-powered ports reducing the total network size—the relative impacts of each variable on aggregate network size are striking. For instance, while increasing overnight charging access to 73% in the optimistic case versus 57% in the baseline case reduces the total DCFC network size, a similar reduction in the requisite charging network size can be obtained by increasing port utilization from 30% to 40%. Findings from the sensitivity study underscore the variety of pathways available to stakeholders in the ride-hailing ecosystem to keep the size of the fast charging network manageable, including incentives favoring more efficient vehicles, investments in home charging, centralized charging coordination, and more.

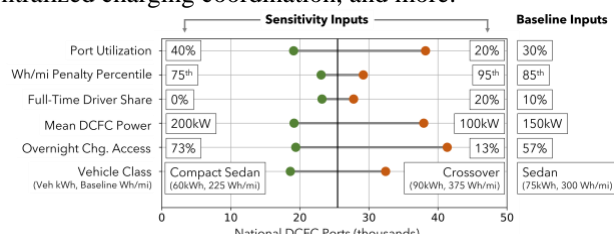


Fig. 9. Ride-hailing charging infrastructure network size in response to varying input assumptions.

Varying assumptions in EVI-OnDemand also implicate the fleet size calculated by the model. Reductions in on-shift charging enable fewer vehicles to meet VMT requirements through greater on-shift time available to drive. The impact of input values in the sensitivity study on national ride-hailing fleet size are shown in Fig. 10. Slight relationships are observable between fleet size and variables that influence the prominence of on-shift charging, such as reduced overnight charging access increasing the total fleet size by approximately 30,000 vehicles nationally. However, these relationships are found to be minor in comparison to the impact of the share of full-time drivers and the national fleet size. This finding is intuitive; increasing the average number of hours simulated per driver enables vehicles to accumulate a greater number of miles, and thus fewer drivers are needed overall. Implications from this finding motivate prioritizing providing full-time drivers access to EVs in cases where vehicle supply is low and

considering opportunities to increase the full-time share of drivers within the ride-hailing fleet.

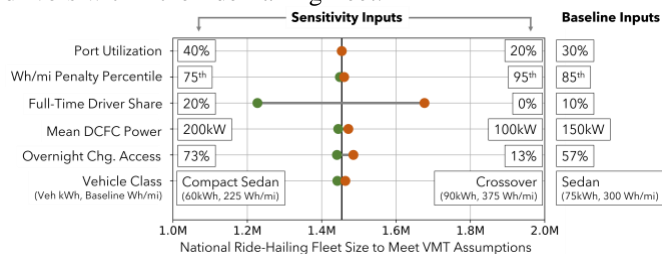


Fig. 10. Ride-hailing fleet size in response to varying input assumptions.

V. DISCUSSION AND CONTRIBUTIONS

Anticipating the charging infrastructure needs of electric ride-hailing fleets is a challenging problem requiring knowledge of vehicle technology, driver behavior, and residential charging access. Analysis of the literature reveals that the DCFC infrastructure demands of electric ride-hailing fleets are understudied. Numerous research articles assess infrastructure requirements in specific cities where detailed trip data are available but do not produce results generalizable to other locations [24], [25], [27]. Moreover, the limited research available estimating national DCFC requirements estimate plausible port counts but do not consider local factors such as climate or housing stock and neglect to report city-level counts [30]. The EVI-OnDemand model fills this gap in the literature by leveraging the best available data at the city level, aiding planning efforts at the national scale with city-level resolution. The following high-level insights are recommended from this analysis:

- Significant expansion of public fast charging infrastructure will be needed to fully electrify the U.S. ride-hailing fleet. Simulation results indicate that 25,400 fast charging ports are needed nationally using baseline assumptions, far more than the roughly 8,700 public ports currently available as of September 2021 [51]. Additionally, sensitivity results indicate that investments into longer-range vehicles or increasing rates of overnight charging do not avoid the reality that growth of the nation’s fast charging network size will be required.
- Ride-hailing vehicles disproportionately demand fast charging as compared to personal use vehicles. Simulation results show that approximately 17.5 DCFC ports are needed per 1,000 ride-hailing BEVs compared to 5.8 ports per 1,000 BEVs from a separate study [50] exploring electrification of more general light-duty vehicle travel in California. Comparison of infrastructure demand rates reveals that electric ride-hailing vehicles demand three times the DCFC infrastructure compared to personally owned and operated vehicles.
- Several variables are shown to influence the size of the charging network on a city-by-city basis, most notably vehicle efficiency, which varies in response to the local climate. Stakeholders responsible for providing

DCFC for ride-hail drivers should prepare to invest differently in each market, with the greatest investment per driver in colder climates associated with lessened EV efficiency.

In addition to the high rates of mileage accumulation, ride-hailing electrification is also challenging due to the segmented ecosystem. Although modeled as a singular fleet in each city, ride-hailing electrification in reality consists of competing ride-hailing fleets and disparate charging networks, and is made possible by a large number of predominantly self-employed drivers each individually making vehicle purchase decisions outside of ride-hailing leasing programs. Successful business models are still emerging, and additional insights are recommended based on research results:

- If securing access to fast charging infrastructure for drivers is a challenge, investments in other physical assets are shown to reduce the size of the requisite fast charging fleet. These assets include vehicles with greater range (whether through rebates or lease fleet purchase decisions) and proliferation of home chargers, which are both shown to reduce the number of fast charging ports needed per vehicle. These opportunities are challenging, however, given the current paradigm whereby ride-hailing fleets do not own the vehicle fleets or the supporting infrastructure.
- Charging infrastructure size may also be reduced through investments into non-physical assets through effective charging coordination. Increasing charger utilization was found to be one of the most influential variable considered in the sensitivity study, and ride-hailing fleets are uniquely positioned to observe and schedule the charging demand of their fleets, which has been found to be highly flexible [52]. In addition to satisfying more charging demand per port, ride-hailing fleets may also be effective stewards at coordinating ride-hailing drivers to charge outside peak hours from the general public, thus minimizing the number of incremental chargers needed.
- If securing access to vehicles is a challenge, BEV access should be prioritized to full-time drivers, as they are able to accrue significantly more miles on a per-vehicle basis. There are trade-offs with this approach, however—increasing the share of full-time drivers with BEVs also increases the size of the fast charging infrastructure required given the greater miles traveled per day, increasing the likelihood of a mid-shift DCFC being demanded.

Strategic investment into infrastructure and vehicles may be further leveraged through business model innovation. Although not explored within this study, there are additional opportunities to limit the size of the fast charging network needed by strategically determining the shift length of each vehicle and determining when each vehicle charges. The authors acknowledge one ride-hailing fleet, Revel, which fully employs and coordinates a fleet of drivers servicing trips and charging at fleet-owned fast charging stations in New York City. However,

this approach is antithetical to the gig-economy model wherein drivers select their own shifts and through which the vast majority of ride-hailing drivers are employed.

VI. CONCLUSIONS

Initial deployments of EVs in ride-hailing services and corresponding research have shown that ride-hailing electrification will require satisfying disproportionately large demand for fast charging, arising from both high-mileage days and limited access to overnight charging [24], [26], [27]. To estimate the size of the expansion needed at the national scale with city-level resolution, this paper introduces a novel simulation platform, EVI-OnDemand, which produces requisite infrastructure network sizes using the best available data. The modeling framework developed considers a variety of pertinent variables, including access to overnight charging, driver shift lengths, mean driving speed, local climate, and more. Results show that approximately 25,400 ports capable of providing a mean charging rate of 150 kW will be needed to electrify a fleet of approximately 1.45 million ride-hailing vehicles (17.5 ports per 1,000 vehicles) throughout the United States, which satisfy 1.5% of current VMT across 384 CBSAs. (Note that the maximum charge power per port may be higher than 150 kW depending on the charge acceptance of the vehicles in the fleet). When compared to prior infrastructure projections focused on electrifying the broader light-duty fleet [50], ride-hailing vehicles demand three times the number of fast charging ports per vehicle. The authors note that the fast charging demand modeled within this report is assumed to exclusively rely on a network of dedicated fast chargers; in reality, there are likely opportunities to leverage underutilized charging assets intended for public consumption, which could serve to reduce the size of the incremental network needed to support electric ride-hailing fleets.

City-by-city results indicate that charging investments will vary, most notably due to local climate. For instance, 63% more DCFC ports will be needed to support 1,000 BEVs in Chicago versus 1,000 BEVs in Miami (17.3 DCFC ports per 1,000 BEVs vs. 10.6 DCFC ports per 1,000 BEVs, respectively). A sensitivity study was also performed by varying key variables to understand their impact on the aggregate network size. Variables such as charging port utilization, vehicle class, and overnight charging access rates were each shown to influence the size of the total charging network needed, which varied from 19,000 ports to 41,300 ports across the 12 sensitivity simulations performed. Results indicate that full electrification of the ride-hailing fleet in the United States will require significant expansion of access to fast charging even in the most optimistic scenarios considered.

Before concluding, the authors note some limitations with the analysis performed, most of which are attributed to the lack of high-fidelity data describing TNC operations and the heterogeneity in driver behavior. Key assumptions were required to produce conclusions from the data available in the literature, including no variability in day-to-day shift lengths, constant deadheading ratios across CBSAs, and no off-shift VMT or off-shift fast charging. Additionally, there is nontrivial uncertainty associated with forecasted future dynamics, such as plausible port utilization across scenarios, possible growth of

the ride-hailing market above 1.5% of urban VMT, increase in goods delivery services facilitated by ride-hailing fleets, and the role ride-hailing fleets will play through interventions such as coordinated charging or vehicle lease models. Future work is recommended to revisit the modeling performed as ride-hailing fleets begin to electrify and empirical data become available. More research is recommended regarding the feasibility of coordinating ride-hailing charging under gig economy scenarios with unpredictable driver shifts, investigation into opportunities to harmonize ride-hailing charging by time of day versus charging dynamics by the general public, and consideration of centrally operated automated fleets.

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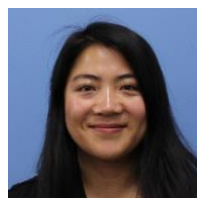
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