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Charging forward: deploying EV infrastructure for Uber and Lyft in California

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Abstract
With recent policies such as the Clean Miles Standard in California and Lyft's announcement to reach 100% electric vehicles (EVs) by 2030, the electrification of vehicles on ride-hailing platforms is inevitable. The impacts of this transition are not well-studied. This work attempts to examine the infrastructure deployment necessary to meet demand from electric vehicles being driven on Uber and Lyft platforms using empirical trip data from the two services. We develop the Widespread Infrastructure for Ride-hail EV Deployment model to examine a set of case studies for charger installation in San Diego, Los Angeles, and the San Francisco Bay Area. We also conduct a set of sensitivity scenarios to measure the tradeoff between explicit costs of infrastructure versus weighting factors for valuing the time for drivers to travel to a charger (from where they are providing rides) and valuing the rate of charging (to minimize the amount of time that drivers have to wait to charge their vehicle). There are several notable findings from our study: (1) DC fast charging infrastructure is the dominant charger type necessary to meet ride-hailing demand, (2) shifting to overnight charging behavior that places less emphasis on daytime public charging can significantly reduce costs, and (3) the necessary ratio of chargers is approximately 10 times higher for EVs in Uber and Lyft compared to chargers for the general EV owning public.

Keywords Electric vehicles · Transportation network companies · Ride-hailing · Charging infrastructure · Electric Vehicle service equipment

Introduction

Over the last few years, the United States transportation sector has undergone a series of transformative "revolutions". These include an ongoing technological transformation from gasoline internal combustion engine (ICE) vehicles to plug-in electric vehicles (PEVs)—a transition spurred by a growing need to mitigate the effects of climate change in transportation. The commercialization of this technology in the US began in late 2010, with the first widely available electric vehicle models: the Chevrolet Volt and the Nissan Leaf. Cumulatively, over two million PEVs have sold in the US, with around half in California.

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Additionally, there are over 40 available vehicle models[1] with many more on the way[2] providing customers with additional choices on the market.

Simultaneously, transportation mode choice has also been rapidly altering away from privately-owned, personal transportation with the advent of the sharing gig economy. Transportation network companies (TNCs) such as Uber and Lyft have rapidly grown in the same timeframe as electric vehicles. While they currently constitute a small fraction of total miles traveled in the light-duty transportation sector, Uber and Lyft have combined 7 million drivers, are worth a combined value of over $100 billion, and offer millions of rides per day[3,4]. Many experts believe that properly managed TNCs represent an important future transportation solution by offering a platform for shared-rides, which can decrease total miles traveled (and hence emissions) while reducing congestion (Sperling 2018).

The combination of electrification and a sharing economy provides further synergies to improve sustainable mobility and combat climate change. As a result, several policies have passed to support the coupling of Uber and Lyft drivers with electric vehicles to realize these benefits. This includes legislation in California, SB 1014[5], which enabled the California Air Resources Board to create the Clean Miles Standard regulation that requires TNCs to begin improving the fuel efficiency and to electrify vehicles on their platforms. In addition to these regulatory efforts, TNCs themselves have given signals of a serious transition to PEVs: Lyft announced in June 2020 that they are committed to 100% electric vehicles on their platform by 2030[6]. This study attempts to understand the impacts of electrifying vehicles on TNC platforms in California. The high travel intensity of vehicles in ride-hailing services and difference in travel/charging behavior will lead to large impacts on the electric vehicle public charging infrastructure. This study employs empirical trip data from Uber and Lyft to strategically deploy chargers to meet demand from TNC fleets.

Both charging behavior and public EV charging infrastructure have been extensively studied in the literature. Often the deployment of infrastructure is modeled based on the charging behavior of EV drivers (Anderson et al. 2018; Davidov 2020; Globisch et al. 2019; He et al. 2018), dynamic traffic behavior of fleets (Ferro, Minciardi, and Robba 2020), or on the overall energy demand from the vehicles (Gnann et al. 2018). The benefits to consumers, economic gain, environmental impacts, and effects on EV adoption from the installation of charging infrastructure have also been demonstrated in several studies (Greene et al. 2020; Javid, Salari, and Jahanbakhsh Javid 2019; Levinson and West 2018).

However, few studies have examined the combination between ride-hailing specific fleets and charging infrastructure, the majority of studies associating electric vehicles and new mobility are with car-sharing (rather than ride-hailing) services. One example by Bauer et al. demonstrates that efficient deployment and use of infrastructure allows for ride-hailing fleets to electrify at minimal cost. They employ an agent-based simulation of BEV fleets in New York City and San Francisco and find that performance can be maintained even with a sparse distribution of chargers (Bauer et al. 2019). Similarly, Vosooghi et al. conduct a similar study, with a specific focus on charging types (normal and rapid charging, and battery swapping). They find that the best level of service is enabled through

1 https://evadoption.com/ev-models/

2 https://www.caranddriver.com/news/g29994375/future-electric-cars-trucks/

3 https://www.businessofapps.com/data/uber-statistics/

4 https://www.businessofapps.com/data/lyft-statistics/

5 Senate Bill No. 1014 California Clean Miles Standard and Incentive Program: zero-emission vehicles.

6 https://www.lyft.com/blog/posts/leading-the-transition-to-zero-emissions

battery swapping infrastructure (Vosooghi et al. 2019). Another study by Lokhandwala and Cai examines the optimization of charging infrastructure in shared fleets using New York City taxicab data as a case study. The authors demonstrate that charging infrastructure (and charging requirement) will not affect service provision of TNCs very dramatically (Lokhandwala and Cai 2020). Likewise, Gorka et al. use agent based modeling to examine charging behavior of car-share vehicles in public charging points (Gorka, Helmus, and Lees, n.d.). There are a few other studies based on taxi data case studies (Morro-Mello et al. 2019; Shahraki et al. 2015; Jäger, Wittmann, and Lienkamp, n.d.; Sellmair and Schelo 2019), but they are not necessarily accurate representations of shared-economy service travel behavior due to differences in affordability, reliability, and accountability (Brown and LaValle 2021; Brown et al. 2022).

The benefits of coupling electric vehicles and ride-hailing fleets are even rarer. Jenn et al. explores the potential benefits to EV adoption from exposure in ride-hailing (Jenn et al. 2018). Separate studies have examined the energy and environmental implications of this coupling through empirical data in California (Jenn 2020) and Austin, Texas (Wenzel et al. 2019). Asides from these benefits, there may be unexpected effects related to the sudden increase in demand for charging from EVs, including higher charger utilization, smart charging/vehicle-to-grid opportunities, and added business to charging service providers (and associated businesses). Our study focuses on the demand for electric vehicle charging infrastructure, specific to ride-hailing electric vehicles, using empirical data in California from Uber and Lyft trips. In the following sections, we provide an overview of our approach in the "Data and Methods" section, present our findings in the "Results" section, and discuss the significance of our work in the "Conclusion" section.

Data and methods

Ride-hailing datasets

We employ empirical datasets from both Uber and Lyft to conduct our study. The Lyft dataset contains trip level records from July 2016 through July 2018. The trips cover all electric vehicles in Lyft's San Diego, Los Angeles, and San Francisco as well as a representative sample of 5,000 gasoline ICE vehicles. Over the two years, we observe over 1.7 million trips across all three territories. Each trip record contains an anonymized driver ID number, allowing us to follow drivers over time (and hence accurate representation of *daily* behavior, rather than just trip behavior). Trip pickup attributes include the census tract of pickup as well as the time of pickup. Uber provided four separate datasets that are more aggregate in nature and covers July 2017 through the end of 2018 across California. The datasets contain information on:

- Proportion of rides given each hour of the day for EVs, broken down by day of the week, quarter of the year, and year
- Proportion of rides given each hour of the day for non-EVs, broken down by day of the week, quarter of the year, and year
- Number of trip miles driven each day by electric vehicles
- Approximate number of trips by electric vehicles in the 4th quarter of 2018 broken down by census tract

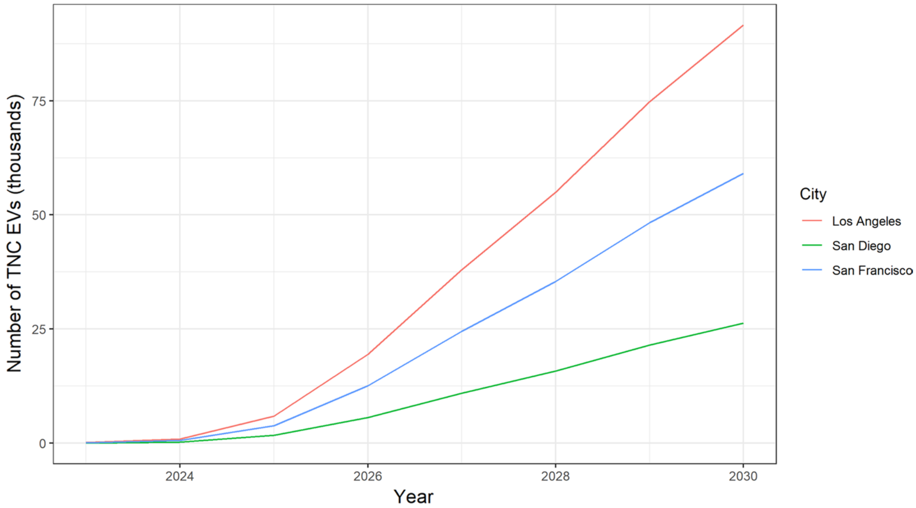

Fig. 1 Projection of electrified TNCs in San Diego, Los Angeles, and San Francisco based on California Air Resources Board's anticipated volumes required to meet the Clean Miles Standard

While the Uber data is at a much lower resolution than the Lyft data, we combine it with the trip-level detail of the Lyft dataset and provide weighting factors to simulate similar volumes of trips and miles travelled. Our analysis focuses on the number of trips in order to provide the correct number of draws in our bootstrap approach for a given number of electric vehicles. Since Uber and Lyft trips are distinctly separate (a rider cannot be taking both an Uber and a Lyft trip at the same time), the combination of trip counts provides an accurate volumetric representation of total trips across both services for a given number of electric vehicles. We employ trip characteristics solely from the Lyft data and reweight the data for total number of EVs using the Uber data, under the assumption that the spatial and distance characteristics of trips do not differ between Uber and Lyft.

In Fig. 1, we employ the California Air Resources Board's regulation targets[7] as our forecast scenario for the number of electric vehicles operating for TNC services such as Uber and Lyft over the next decade. The projections span all of California while our analysis operates over the three major cities of San Diego, Los Angeles, and San Francisco (based on our mobility data). We assume that approximately 80% of TNC services in California operate in these territories based on information on the number of Uber and Lyft vehicles operating in the three major cities compared to the entire state, and then scale the volume of vehicles based on the volume of unique vehicles operating in each region within our trip datasets from Uber and Lyft. Additionally, our infrastructure analysis focuses primarily on full battery electric vehicles (BEVs) as opposed to plug-in hybrids (PHEVs). We assume that TNCs PHEVs will have a negligible impact on public charging demand due to their lack of fast charging capability and lower overall battery range leading to substantially higher utilization of the gasoline engine. We derive the proportion of BEVs in conjunction with the California Energy Commission's projections, linearly increasing from

[7] Slide 9. "Clean Miles Standard Workshop: Proposed Regulation Targets". California Air Resources Board. November 19, 2020.

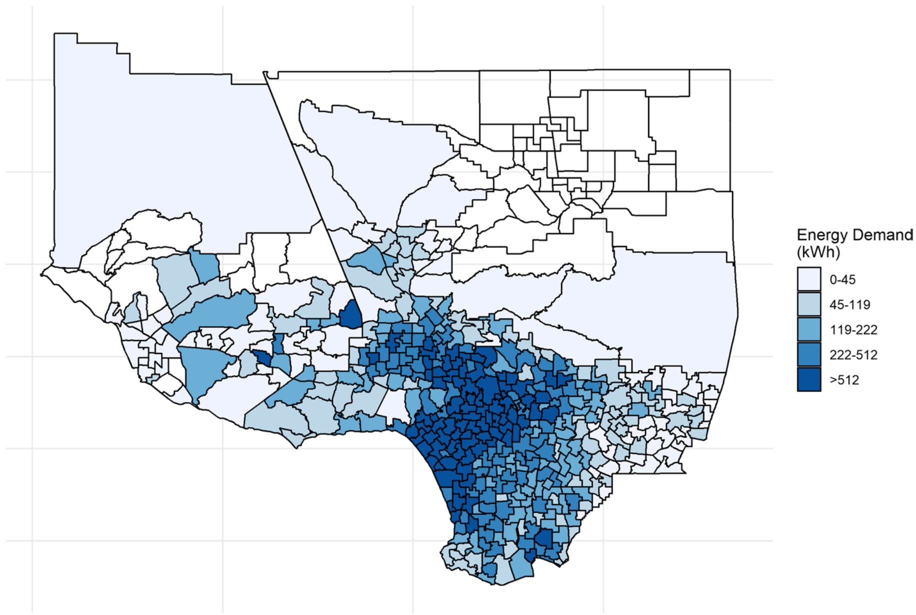

Fig. 2 Daily average energy demand over 90 simulated days of electric vehicles in Uber and Lyft at an aggregated census tract level in Greater Los Angeles in 2030

approximately 66% BEVs in 2023 up to 70% BEVs in 2030 (Alexander et al. 2021). By 2030, we observe over 80,000 TNC BEVs in Los Angeles, 50,000 BEVs in San Francisco, and 25,000 BEVs in San Diego. These figures serve as the baseline for the vehicle volumes within each of the three major cities in our analysis.

Bootstrap demand simulation

To fully account for variation of day-to-day energy demand and spatial travel patterns of ride-hail EVs, we bootstrap daily demand of trips using the Uber and Lyft datasets. This allows for a simulation of variable number of electric vehicles in the fleet while maintaining the spatial and temporal travel patterns seen in the empirical data. The bootstrap procedure to simulate a fleet of size n in a given region is as follows:

1. Draw n trips from weighted Uber and Lyft data
2. For each draw, extract all trips made by that driver in the date corresponding to the taken trip
3. Steps 1 and 2 represent the trips made in a single day by the ride-hailing fleet in a region, we repeat the first two steps a total of 90 times to represent 3 months of ride-hailing demand

An example of simulated average daily demand (based on distance traveled from the origin of the trip) is shown in Fig. 2. Note that we perform a distance-based hierarchical clustering algorithm that groups census tracts to reduce the complexity of the WIRED model. We reduce the number of regions by ~ 6–sevenfold depending on the region.

Infrastructure model

We developed the Widespread Infrastructure for Ride-Hailing EV Deployment (WIRED) model, a mixed integer linear optimization model that seeks to install infrastructure to meet the demand of electric vehicles providing service for ride-hailing companies while simultaneously meeting operational constraints and other cost concerns. The optimization has two decision variables: x^{install}, an integer variable that represents how many of each type of charger i to install in each region s (with alias r); and x^{charge}, a positive variable that represents how much vehicles charge in each region. The objective function is shown in Eq. (1) and is comprised of several cost components. The first cost component is a simple representation of the cost of installing the infrastructure $c^{\mathrm{stationCost}}$ (Nicholas 2019) and the cost of charging $c^{\mathrm{chrgPrice}}$. Two other non-traditional cost components include 1) the penalty for traveling greater distance to charge as a function of where the trips are taking place, c^{demand}, and how long it takes to travel to the charger c^{trvTime}; and 2) a penalty for time spent charging, a function of the charge rate c^{chrgRate}, for each type of charger.

Objective function

$$\min_{w.r.t:x_{ir}^{\mathrm{install}},x_{irs}^{\mathrm{charge}}} \sum_i \sum_r x_{ir}^{\mathrm{install}} c_i^{\mathrm{stationCost}} + \sum_i \sum_r \sum_s \left[x_{irs}^{\mathrm{charge}} c_i^{\mathrm{chrgPrice}} + w_1 \left(c_s^{\mathrm{demand}} c_{sr}^{\mathrm{trvTime}} x_{irs}^{\mathrm{charge}} \right) + w_2 \left(x_{irs}^{\mathrm{charge}} \middle/ c_i^{\mathrm{chrgRate}} \right) \right] \tag{1}$$

Subject to the following constraints:

Total charging demand must be fulfilled:

$$\sum_i \sum_r \sum_s x_{irs}^{\mathrm{chrgAmount}} - c_s^{\mathrm{demand}} \geq 0 \tag{2}$$

This constraint ensures that the amount of charging $x^{\mathrm{chrgAmount}}$ meets the total amount of charge demand c^{demand} as determined by vehicle efficiency and total distance travelled by ride-hailing vehicles over the course of a day.

Charging in each period cannot exceed charging capacity:

$$\left(x_{ir}^{\mathrm{install}} + c_{ir}^{\mathrm{existing}} \right) c_i^{\mathrm{chrgRate}} - \sum_s x_{irs}^{\mathrm{chrgAmount}} \geq 0; \forall ir \tag{3}$$

We construct a constraint based on the capability of infrastructure in each location to provide a specific rate of charging to ensure that the total amount of charging does not exceed the capability of infrastructure to charge it.

Allocate charging to original demand locations:

$$\sum_i \sum_r x_{irs}^{\mathrm{chrgAmount}} - c_s^{\mathrm{demand}} \geq 0; \forall s \tag{4}$$

Finally, this constraint is used to couple charging events to the original energy demand locations in order to account for travel times between charging events and where service is being provided by ride-hailing drivers.

In an initial parameter sweep of the model, we conducted a sensitivity analysis across the parameters of w_1 and w_2 which represent weights for the value of reducing the amount of time drivers would spend traveling to chargers and the time spent charging their vehicles respectively. We observe dynamic tradeoffs that are sensitive to the remaining parameters at values of $w_1 = 0.001$ and $w_2 = 1000$, which are then employed as baseline values for our analysis.

Existing chargers, c^{existing}, are background public infrastructure chargers that either exist already or are forecasted to be installed to meet non-TNC EV demand in the future. These forecasts are derived directly from the National Renewable Energy Laboratory's (NREL) Electric Vehicle Infrastructure Projection Tool (EVI-Pro), in conjunction with the California Energy Commission (Alexander et al. 2021). Charger deployment data from EVI-Pro are at the county level and we proportionally allocate the chargers to a higher spatial resolution based on the location of existing chargers. The results of these charger placements can be seen in Figs. 4, 6, and 8.

Sensitivity analysis

We conduct additional analysis to examine the sensitivity of our results to assumptions on the value of time for ride-hailing drivers as it pertains to both traveling to charge their vehicle and the amount of time it takes to charge the vehicle. These are represented as weights that push the model to favor a greater spatial distribution of chargers (when the weights for travel time [TT] are high) and faster charging infrastructure (when the weights for charging rates [ChrgRte] are high). We also examine the availability of "home charging" that would allow drivers to charge their vehicles overnight. The proportion of overnight charging is the most uncertain parameter input in the model (affecting the parameter $c_s^{\ demand}$) and simultaneously is one of the most influential parameters influencing the results. As a result, conduct a sensitivity analysis on this parameter, varying the proportion of a single battery charge fulfilled by home charging from 0 to 1 (if a single day's travel distance exceeds the range of the vehicle, the driver will still be forced to charged at a public charger). The baseline case for our analysis assumes that 40% of TNC EVs can employ home charging.

Results

In this section, we show the outcomes of the WIRED model: the charging infrastructure required for TNC vehicles to meet the sudden shift towards electrification required by the Clean Miles Standard in California. Due to the high daily travel intensity of electric vehicles on services such as Uber and Lyft, the per-EV charging infrastructure requirements are substantially higher and are subject to stronger behavioral constraints than the average EV driver. These constraints both the distance required to travel to the charger and the length of time spent charging. Both issues can interrupt a driver's ability to provide service and decrease revenue while the former can also increase deadheading and corresponding environmental burdens. Our model not only provides the total number of chargers necessary to meet the charging demand of TNC EVs, but also provides the spatial allocation of chargers by type (L1/L2/DCFC) to minimize the aforementioned issues regarding travel and charging times.

In Fig. 3, we observe that by 2030, electric vehicles on TNC services will require approximately 2,000 DC fast chargers across California's three major cities of San Diego, Los Angeles, and San Francisco assuming that 40% of drivers will have regular access to home charging. The large difference in number of chargers between San Francisco and Los Angeles compared to San Diego is primarily explained by the difference in number of TNC vehicles operating in the cities, though it should be noted that distances for trips are

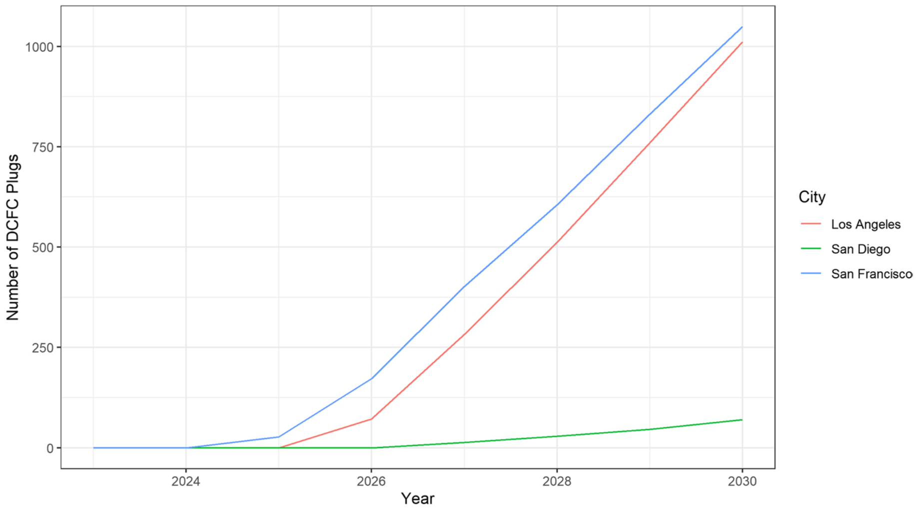

Fig. 3 WIRED projection of TNC EV DC fast charging infrastructure in the cities of San Diego, Los Angeles, and San Francisco

also slightly smaller in San Diego. We note that these chargers are in addition to the natural growth of public infrastructure to meet the demand of non-TNC electric vehicle demand. Most new chargers for TNC EVs are DC fast chargers due to the timing requirements for drivers to maintain the same level of service as a gas car. There are a small proportion of level 1 and level 2 chargers that TNC drivers employ to top off, particularly when there is a long period of downtime between rides. However, the volume of these chargers is relatively small compared to the DCFC requirements, which represents a pattern that is opposite of the proportions for regular electric vehicles.

Figure 4 through Fig. 9 show the respective charging station deployment (both public from EVI-Pro and for TNCs from WIRED) and energy from charging loads in the three cities of Los Angeles, San Francisco, and San Diego. In the lowest proportion of home charging scenario, the number of DC fast chargers necessary to support TNCs is over 50% of the existing 7,000 DC fast chargers currently deployed in California to support a volume of electric vehicles providing ride-hailing services that is a fraction of the volume of EVs on the road in California. However, our model also provides high spatial resolution of the charger deployment results. One of the common observations consistent across all three regions is that the highest demand occurs in two areas: the major airport in the region (SAN for San Diego, LAX for Los Angeles, and SFO for San Francisco) and in the downtown area of the city. It is therefore no coincidence that these locations feature prominently as areas for placing charging infrastructure—our results indicate that these zones tend to have more chargers placed in their vicinity in addition to being the areas where energy is being dispensed to charge ride-hail EVs. The remaining chargers are distributed throughout the rest of the region with a focus on high energy demand areas—though charging demand never exceeds the downtown and airport regions. In our base case scenario, the energy demand throughout the major cities often reaches several MWh per day in many regions (at times exceeding 3 MWh). Most stations charge under 500 kWh per day, though some of

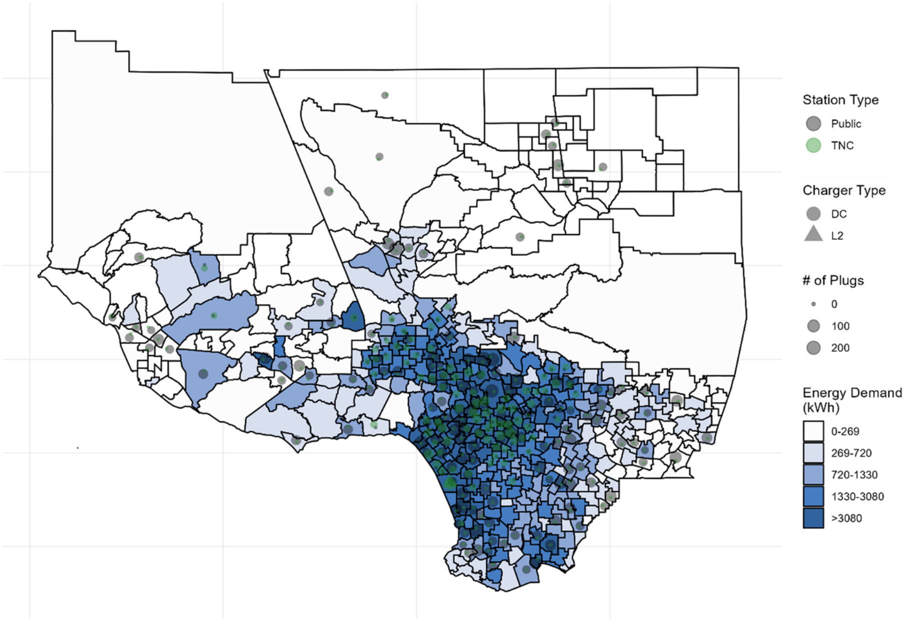

Fig. 4 WIRED projection of charging infrastructure required to meet TNC EV demand in the Greater Los Angeles region by 2030. Electric vehicles on Uber and Lyft services employ both existing public chargers (black dots) and TNC exclusive chargers (green dots) to meet the average daily energy demand (blue region shading)

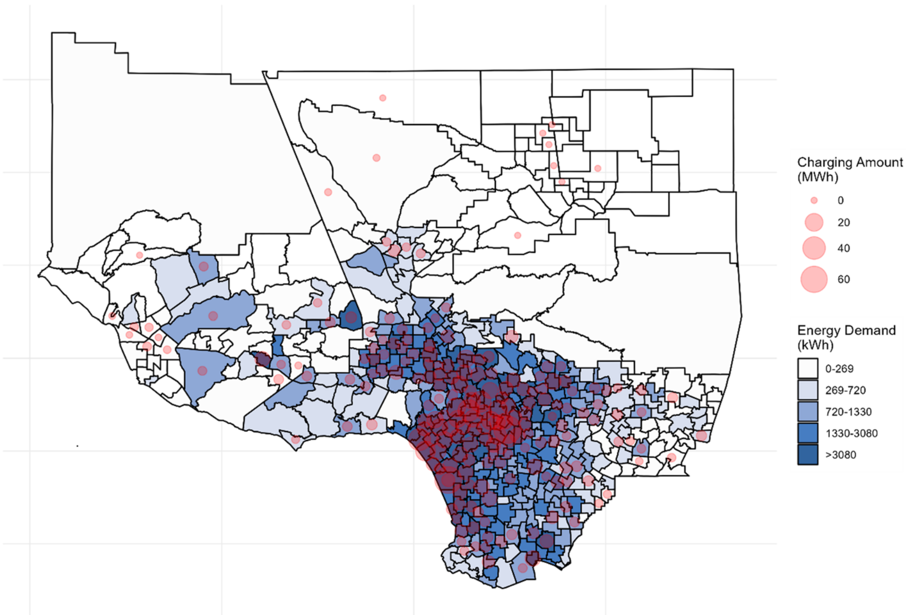

Fig. 5 WIRED projection of amount of daily EV charging (red dots) in each zone within the Greater Los Angeles region in 2030 to meet energy demand used to fulfill travel demand (blue region shading)

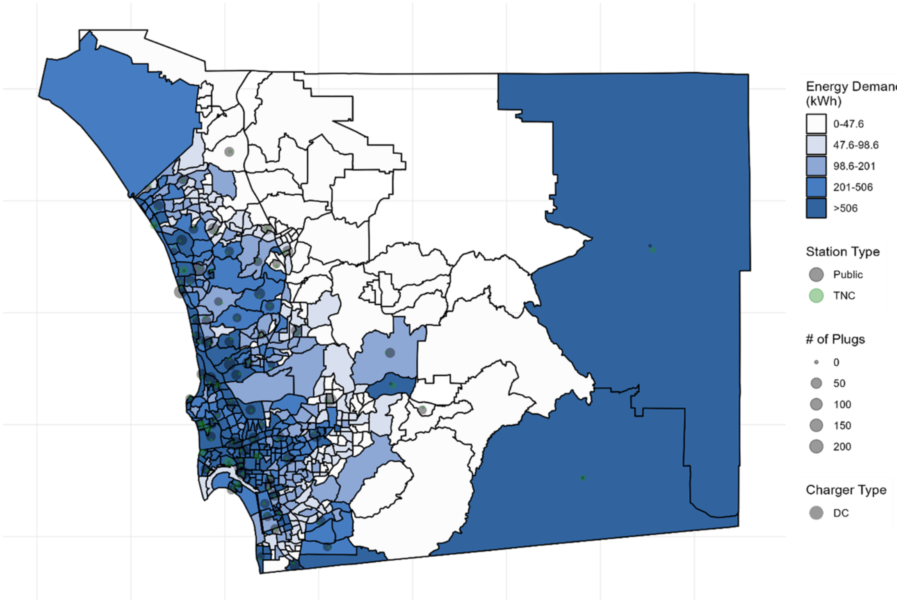

Fig. 6 WIRED projection of charging infrastructure required to meet TNC EV demand in the Greater San Diego region by 2030. Electric vehicles on Uber and Lyft services employ both existing public chargers (black dots) and TNC exclusive chargers (green dots) to meet the average daily energy demand (blue region shading)

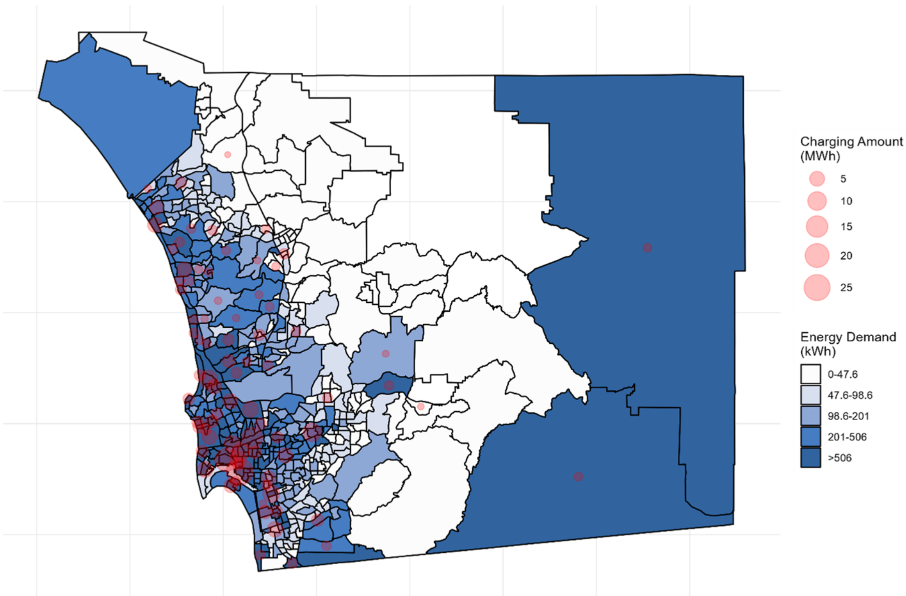

Fig. 7 WIRED projection of amount of daily EV charging (red dots) in each zone within the Greater San Diego region in 2030 to meet energy demand used to fulfill travel demand (blue region shading)

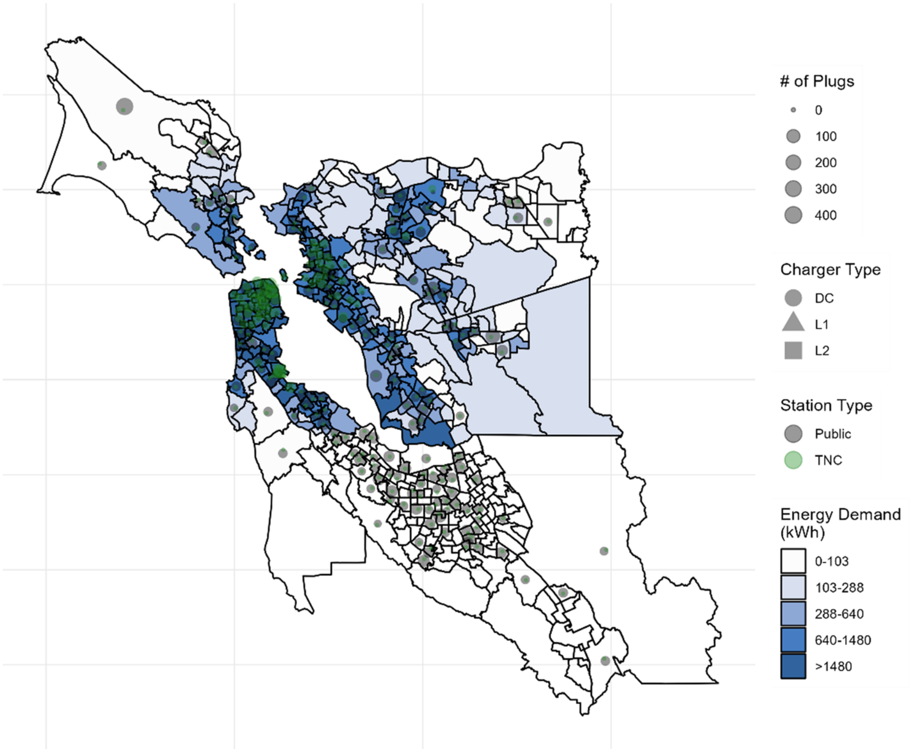

Fig. 8 WIRED projection of charging infrastructure required to meet TNC EV demand in the Bay Area (excluding South Bay, due to data limitations) by 2030. Electric vehicles on Uber and Lyft services employ both existing public chargers (black dots) and TNC exclusive chargers (green dots) to meet the average daily energy demand (blue region shading)

the most popular charging locations can dispense as high as 3 MWh in a single day (these have up to 6 DC Fast charging plugs at a single station location).(Figs. 5, 6, 7, 8, 9).

One of the most sensitive parameters affecting the quantity of infrastructure deployed depends on the assumed proportion of ride-hailing vehicles in TNC services that charge their vehicles at home. Unfortunately, this parameter is not well-understood and lacks empirical data for existing vehicles on TNC services—and importantly for future drivers/vehicles as electric vehicles penetrate to broader segments of ride-hailing driver populations. Depending on how much access to home charging is available to drivers, the number of DC fast chargers that need to be installed across California could vary tremendously. One of the reasons for the high sensitivity is because most of the vehicles in the TNC fleets have sufficient range to cover all of the trips in a given day, thereby substantially reducing reliance on public infrastructure. The California Energy Commission's charging infrastructure assessment report (Alexander et al. 2021) assumes approximately 40% of TNC drivers will have access to home charging, which would constitute about 2,000 DC fast chargers. This potentially represents a massive cost savings due to the discrepancy in the cost to deploy a public DC fast charger in comparison to slower Level 2 home charging—though accessibility may be a substantial barrier for drivers who do not have off-street garage parking. Nevertheless, it is certainly within the realm of possibility that future drivers may begin to shift to overnight charging. This behavior is potentially

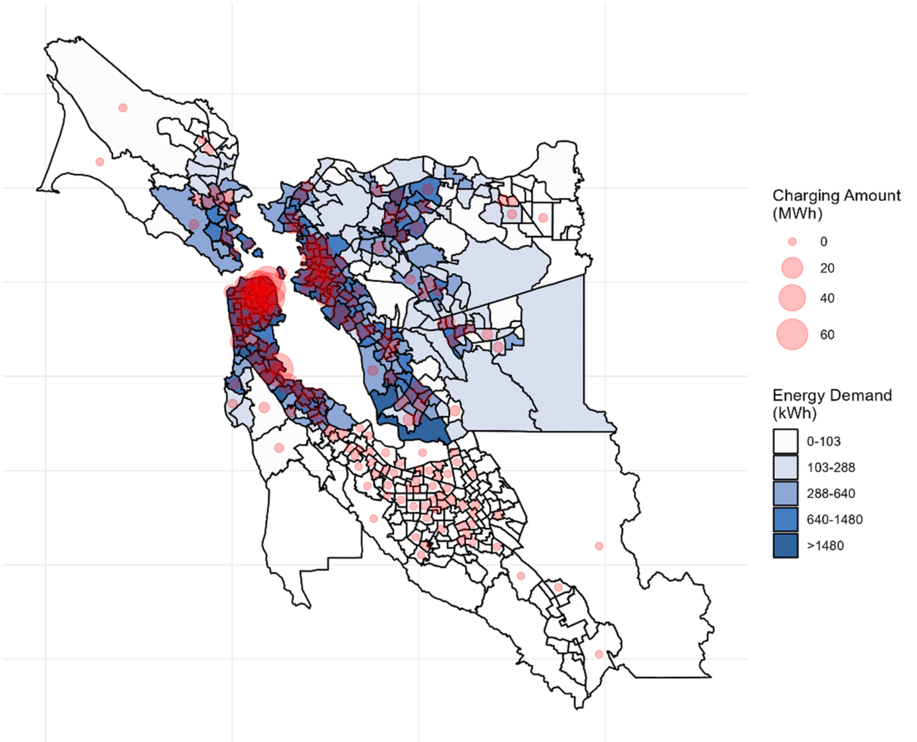

Fig. 9 WIRED projection of amount of daily EV charging (red dots) in each zone within the Bay Area (excluding South Bay, due to data limitations) region in 2030 to meet energy demand used to fulfill travel demand (blue region shading)

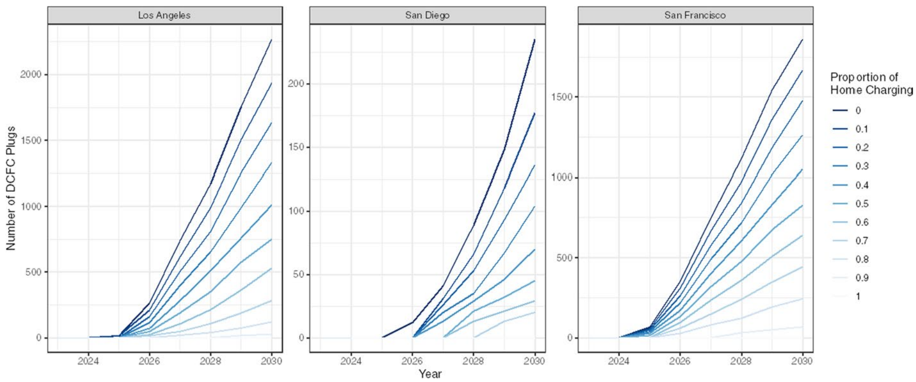

Fig. 10 DC fast charging deployment sensitivity analysis. The figure shows the number of plugs necessary to support TNCs across a range of assumed amount of home charging for ride-hailing vehicles

compelling because 1) it does not interfere with drivers' ability to provide their ride-hailing services, and 2) it may be cheaper than charging during the day. Therefore, we also investigate

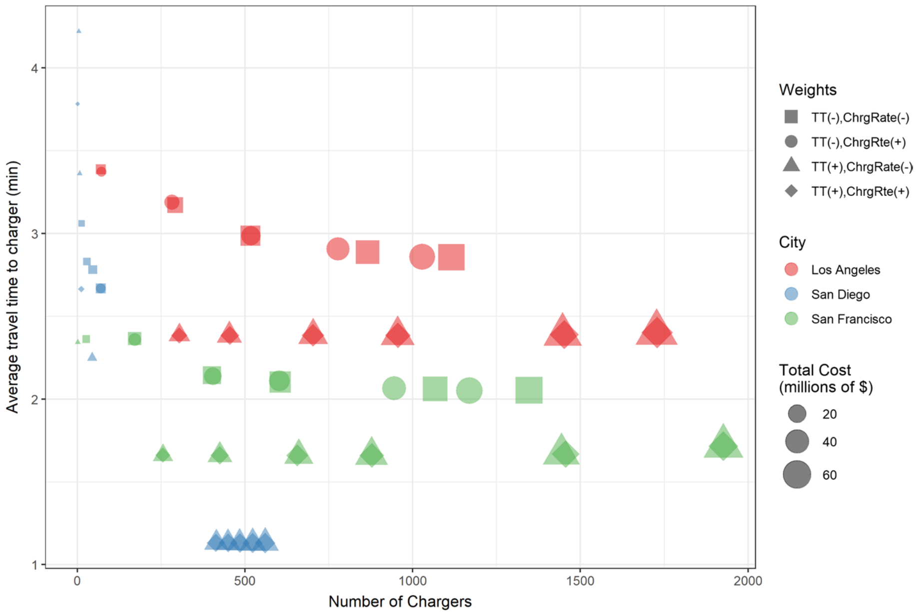

Fig. 11 Comparison of the average travel time to the number of chargers in the scenarios run from the WIRED model. There are four combinations of weights for high valuation (+) and low valuation (-) of travel time (TT) and charge rates (ChrgRte). Each point represents aggregated values from a single scenario run, with the city denoted by color and the total cost of all infrastructure installed denoted by the size of each point

the opposite end of the spectrum from our initial assumptions where drivers will only employ public chargers if they run out of charge in the vehicle in a given day. (Fig. 10).

In Fig. 11, we display the aggregate results of scenario runs across all combinations of weighting factors, number of vehicles, and public versus overnight charging patterns. It also contains information on the total cost of installing the charging infrastructure (denoted by the size of each point), the city (denoted by color), and the value of the weighting factors (denoted by shape) across all four combinations of values for travel time and charge rate. The figure displays a rapid tradeoff in the number of chargers and the average time for a vehicle to travel to a charger, there is a rapid decrease in the travel time to sub-5 min at around 100 chargers across all regions. As chargers continue to increase in number, the total cost continues to increase without the same magnitude of decrease in travel time observed within the increase up to the first hundred chargers. However, it should be noted that Fig. 11 does not display other key benefits of increasing the number of chargers. While travel time may not be decreasing, the WIRED model is making tradeoffs to meet higher demand for scenarios with a greater number of vehicles, as well as potentially transitioning between lower speed (L2) to higher speed (DC fast) chargers to reduce charge rates for drivers.

Conclusions

It is clear that the charging demand and behavior from TNCs is substantially different from charging from the general public. The tremendous demand on public infrastructure indicates that serious attention must be placed on the potentially tremendous charging demand coming from a rapidly growing segment of light-duty transportation. Despite the relatively small volume of electric vehicles operating for Uber and Lyft in California, they are already placing tremendous stress on the public charging infrastructure (Jenn 2020). Electrification of TNCs is relatively unexplored, and their associated impacts on infrastructure have only been studied in long-term scenarios, such as those that consider futures with complete ride-sharing and automation. Nevertheless, impacts of electrification in these fleets is evident even today—solving this issue will require a confluence of stakeholders including ride-hailing companies (Uber and Lyft), regulatory agencies (California Air Resources Board, the California Energy Commission, and the California Public Utilities Commission), charging network providers (EVGo, Electrify America, Chargepoint, etc.), local utilities, and local/regional planners. Our work is not intended to act as the primary planning resource for installation of future infrastructure for EVs operating on ride-hailing services, but rather to provide context and begin to lay the foundation for future studies in a sorely needed field of research.

While the current ratio of chargers to electric vehicles for the general public is about 1 slow charger (L1/L2) per 10 EVs and about 3–4 DC fast chargers per 1000 EVs. Our modeling indicates that this ratio must be approximately an order of magnitude higher for ride-hailing EVs. It is critical to note that the WIRED model attempts to maximize the utilization of chargers to reduce the associated costs of additional infrastructure installations. By increasing utilization, the availability of charging infrastructure is correspondingly decreased—in order to avoid issues such as charger congestion, maximizing utilization must include careful planning processes for drivers to strategically charge. Whether through a queuing model or congestion pricing at charging infrastructure, drivers must be provided a signal to maintain high utilization at chargers—without this our WIRED model serves only as a lower bound for the required number of chargers to meet demand.

Our work is not without shortcomings, the results are founded on assumptions including a fairly static view of the services provided by Uber and Lyft. If deeper penetration of TNCs occurs into the transportation sector, or if electrified mobility alters the patterns underlying driver and rider behavior, then the use of empirical trip data from Uber and Lyft may not be an accurate representation of ride-hailing services. Furthermore, the charging patterns of TNC drivers in our model is primarily constrained by the times that drivers provide their services to riders, but drivers may have separate preferences for charging which would not be directly captured in the model. If these charging behaviors differ drastically from those assumed in the model, this could have implications on the distribution and deployment of chargers that differ from the outputs of this work. Lastly, while many generalizations can be derived from the results, this work is in essence a case study of particular TNC behavior within three major cities in California—additional takeaways in other regions would require further research to arrive at results with similar levels of detail.

Future work will integrate existing stations and projections of public infrastructure to meet demand from EVs owned by the general public into the WIRED model. This will allow electric vehicles in Uber and Lyft to charge from existing (or potential new) public charging infrastructure. Further constraints will be necessary to accommodate the heterogeneity in availability of public chargers that may be occupied by vehicles from the general public—this can also extend to the network generated by WIRED (to allow anyone to use the charging network from this study).

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Data availability Non-confidential data is available upon request.

Declarations

Competing interests The authors declare no competing interests.

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