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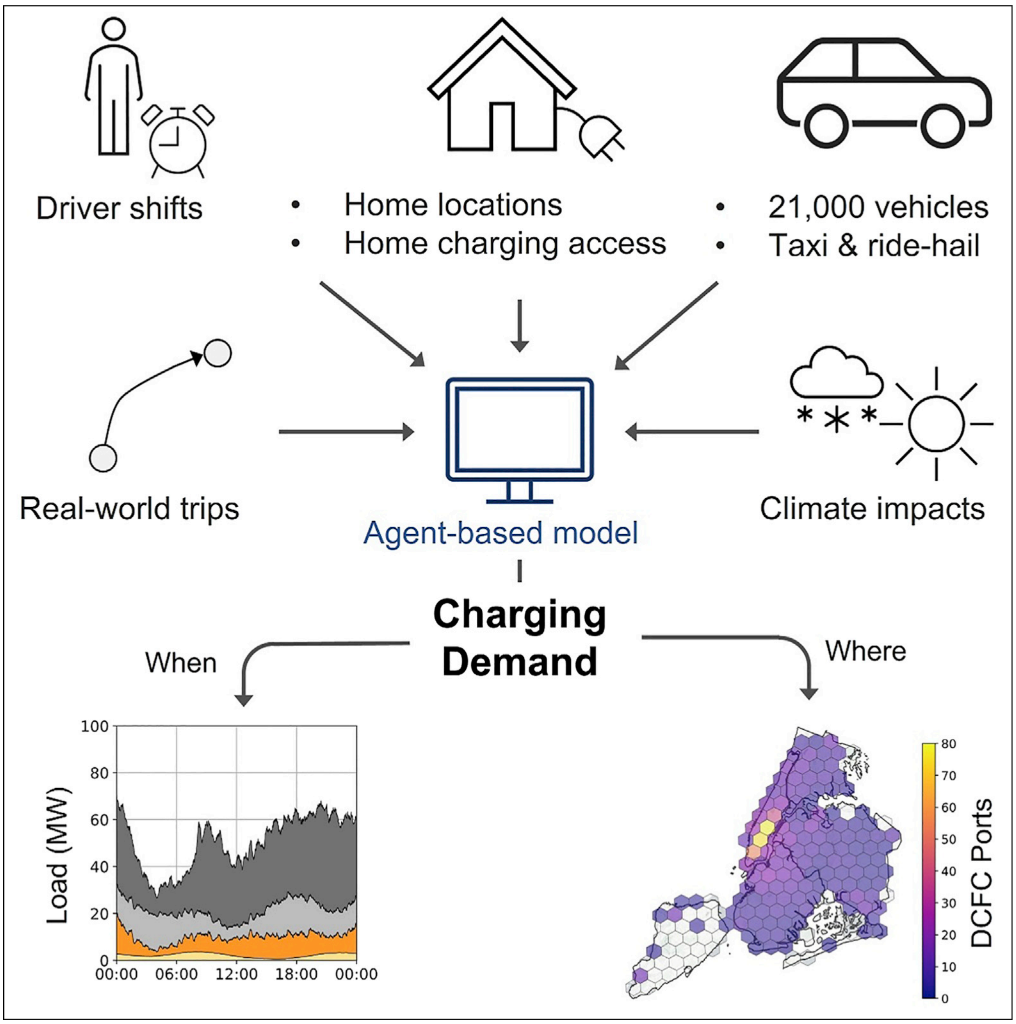


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## Highlights

Roughly 1k 150 kW DCFC ports needed to support 20k EV ride-hailing vehicles in NYC

Ubiquitous access to overnight charging does not eliminate the need for DCFC access

Highest demand for charging ports nearby trip demand and driver home locations

Overnight charging access reduces DCFC demand but does not reduce fleet peak load

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# Electrifying New York City Ride-Hailing fleets: An examination of the need for public fast charging

Matthew Moniot,[1,3,*] Brennan Borlaug,[1] Yanbo Ge,[1] Eric Wood,[1] and Jason Zimbler[2]

## SUMMARY

**This report assesses the scale of public fast charging needed to electrify approximately 20,000 vehicles across the yellow cab and for-hire segments in New York City. The analysis considers real-world trip data in conjunction with driver home locations, overnight charging access rates, driver schedules, and more. Outcomes indicate that the existing charging network in New York City is not adequate even in the most optimistic scenario; 1,054 150-kW ports are required when 15% of drivers have access to overnight charging, whereas 367 150-kW ports are needed when 100% of drivers have access. Results also indicate that although charging is demanded in areas nearby high trip demand, fast charging ports are also demanded in areas near driver residences as a supplement for home charging in scenarios with limited overnight charging access. These findings motivate investment into both overnight charging and public fast charging to meet the charging demands of ride-hailing fleets.**

## INTRODUCTION

Ride-hailing electrification has gained momentum in recent years as regulators have set aggressive targets for fleet electrification (California Air Resources Board, 2018). Successful fleet electrification would help reduce the negative externalities associated with ride-hailing, such as increased emissions (Anair et al., 2020; Ward et al., 2021). Major ride-hailing companies, most notably Uber and Lyft, have responded by setting aggressive goals of their own; both companies have pledged to fully electrify their fleets by 2030 (Khosrowshahi, 2020; Lyft, 2020). Meeting this goal will require significant expansion in access to fast charging, as ride-hailing drivers are less likely to have access to overnight charging than the general population (Nicholas et al., 2020) and likely to accrue high mileage while servicing passenger demand for trips (Wenzel et al., 2019). The significant infrastructure demands of electric ride-hailing vehicles are not just hypothetical; for instance, a study analyzing a population of electric vehicles (EVs) leased for ride-hailing purposes in California showed that ride-hailing vehicles charging at public stations comprised 35% of the total DC charging energy demand despite comprising only 0.5% of the EVs in the state (Jenn, 2020).

Momentum toward ride-hailing electrification is occurring alongside a broader push to accelerate light-duty vehicle electrification, as evidenced by zero-emission vehicle programs (Northeast States for Coordinated Air Use Management, 2018) being adopted by numerous states (Brown et al., 2013). New York has established a goal of deploying 850,000 zero emissions vehicles across the state by 2025 (Rushlow et al., 2015). These factors lead to a particular emphasis on New York City (NYC), which contains a ride-hailing fleet of over 100,000 vehicles across the traditional yellow cab (YCB) taxi and for-hire vehicle (FHV) segments. Although ride-hailing vehicles comprise a small share of the total light-duty vehicle fleet in New York state, the challenges of meeting statewide goals within the context of barriers to transportation network company electrification motivated investigation of plausible rates of ride-hailing electrification and corresponding infrastructure requirements in NYC within the context of a 2025 timeframe.

The large fleet size and generous data availability has led to a rich history of research focused on the NYC ride-hailing fleet. This research is broad, with studies exploring questions pertaining to ride-pooling potential (Alonso-Mora et al., 2017), vehicle automation (Bauer et al., 2018), electrification (Bauer et al., 2018; Hu et al., 2018; Tseng et al., 2019), and even a ride-hailing service integrated within public transit (Wang and

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Ross, 2017). This study is most closely affiliated with a paper by Bauer et al. (2019), which studied the implications of electrifying a ride-hailing fleet in NYC operated by human drivers. In the study, the authors employed an agent-based model characterizing the operations of an all-electric ride-hailing fleet to explore the outcomes of scenarios with various vehicle types, charging infrastructure assumptions, and charging strategies. The research finds that a modest number of chargers at a relatively low power level is sufficient for supporting a fleet of EVs. For instance, in a baseline scenario, the authors find that a charging network of 750 50-kW chargers placed at a density of three chargers per square mile supporting a fleet of EVs each with 238 miles of driving range produces equivalent service to a similarly sized fleet comprising gasoline-powered vehicles.

An additional study estimating ride-hailing charging infrastructure demands explored infrastructure deployment needs across several cities, including NYC (Nicholas et al., 2020). The authors find that 55 chargers are needed beyond the predicted growth of the public charging network to electrify 60,000 ride-hailing vehicles by 2025, assuming that a portion of the ride-hailing charging demand may be met by public infrastructure. One limitation of the study is the assumption that part-time drivers represent 94% of drivers. The NYC market is unique, wherein drivers must register with the Taxi and Limousine Commission (TLC), biasing the driver population toward full-time drivers who disproportionately demand fast charging. Additional factors contributing to increased demands for local charging include the local climate in NYC, which contributes to worsened vehicle range as well as a high volume of trip demand. The authors consider the analysis to be a reasonable estimate of charging infrastructure for typical cities, although the unique characteristics of dense urban cities motivate additional consideration of local factors.

This research seeks to build upon the available literature with specific emphasis on the charging infrastructure necessary to transition the NYC ride-hailing fleet to battery-electric vehicles. This study is distinct from prior research through its incorporation of key input parameters that were not available to the authors of prior studies, including FHV trip data (comprising the majority of NYC ride-hailing trips) and additional data fields made available by the *2018 TLC Factbook* (NYC Taxi and Limousine Commission, 2018), which provides critical information ranging from driver residence location, shift start times, and dynamic fleet sizing that is fundamental to this analysis. In addition, this study also explores the relationship between access to overnight charging and the corresponding fast charging network demanded by the fleet. The analysis employs novel survey data and driver residence data obtained through a Freedom of Information Law (FOIL) request to characterize plausible rates of overnight infrastructure access by ride-hailing drivers. Finally, the study evaluates the charging demands of the YCB and FHV segments simultaneously, which feature different trip dynamics, driver populations, and driver shift considerations.

To take advantage of the large amount of data available in NYC, the Highly Integrated Vehicle Ecosystem (HIVE) framework (Fitzgerald et al., 2021) is employed, which simulates the operations of a dispatchable vehicle fleet using agent-based modeling. This paper proceeds by briefly introducing HIVE and detailing how the model leverages data published by the TLC. Next, scenarios consistent with 2025 timing are outlined with input simulation values defined. Results for each scenario follow, as well as a discussion of major findings and conclusions.

## HIVE simulation platform

HIVE is an agent-based transportation platform that simulates the operations of a dispatchable fleet of EVs accommodating exogenous travel demand. Key simulation parameters include a supply of fleet assets (vehicles and charging infrastructure), which are servicing the demand for transportation (passenger trip requests) occurring on a roadway network. As the simulation progresses, passenger trip demand is iterated through sequentially, and trips are paired with eligible vehicles with sufficient range to complete the trip and the ability to arrive at a given trip origin within a specified wait time. When the driving range of a vehicle drops beneath a given threshold, the vehicle seeks charging infrastructure (either slow charging at a vehicle's home location or fast charging at a network of public stations) to replenish powertrain energy capacity before continuing to service trips. This cycle of trip service and vehicle charging continues throughout the course of the simulation, with a centralized controller influencing the state of the fleet (vehicle request matching and repositioning instructions) and individual agents making vehicle-level decisions (commuting, shift behavior, and charging behavior). Further information regarding the functionality and structure of HIVE may be found in supporting documentation (Fitzgerald et al., 2021).

This study employs HIVE to investigate the operations of an EV fleet operated by human drivers servicing ride-hail trips in NYC. Both YCB and FHV fleets are characterized using input data made available by the TLC (NYC Taxi and Limousine Commission, 2018). HIVE models these fleets simultaneously to understand potential synergies or conflicts between the charging demands of each segment. (Although FHVs may not service YCB requests—and vice versa—these fleets may rely upon the same public fast charging infrastructure.) Individual drivers were assigned vehicles and assumed to drive for a single ride-hailing segment, either YCB or FHV. (The FHV segment itself comprises multiple entities, most notably Uber and Lyft. Individual fleet membership across these two competitors was not explicitly modeled given the limited data specific to each company and the frequency of "multi-apping," whereby drivers are on-shift for both services simultaneously. Charging demand and performance metrics for the FHV segment are thus considered across all drivers affiliated with one or more companies within the FHV segment.). Drivers take the vehicles used for ride-hailing operations to their home locations when off-shift (TLC registration data were considered to infer locations of likely YCB depots, although inspection of these locations using satellite imagery frequently revealed small commercial storefronts where vehicles were registered but likely did not dwell while off-shift. Absent reliable data, vehicles were assumed to be taken by the drivers to their home location when off-shift.) and travel to recent locations of trip demand when transitioning from off-shift to on-shift. When transitioning from on-shift to off-shift, vehicles complete any ongoing requests before commuting home (charging en route, if required). Upon arriving at the home location, vehicles are plugged into an AC charger if the driver has access to residential charging; otherwise, no charging occurs. Ride-hail vehicles do not accrue off-shift mileage (e.g., for personal travel) after arriving at home because the travel data set used for this analysis is limited to ride-hailing trips only.

HIVE simulations used a "conditioning day," whereby the simulation progresses to a realistic state after the first day. The second simulation day—a direct continuation of the prior day—is an "evaluation day" over which all relevant performance statistics are calculated. This approach is frequently observed in the literature (Bauer et al., 2018; Loeb et al., 2018) and is an effective method for inducing realistic initial conditions at the beginning of the evaluation day. Finally, the average state of charge (SOC) of all fleet vehicles is compared between the beginning and the end of the evaluation day and confirmed to be within 5%. This step ensures the fleet does not undercharge (and is thus poorly prepared for the following day) or overcharge (in response to the initial condition of the conditioning day).

## Scenario definition and assumptions

Given the objective of infrastructure sizing, the set of input data selected for simulation was intended to characterize the operations of a ride-hailing fleet in NYC operating under challenging conditions. Although results from a typical day may be more representative, sited infrastructure will be inadequate for days with large trip counts or extreme weather. Thus, the HIVE inputs selected for this analysis are intended to characterize a near-worst-case scenario, namely a large number of trips on a cold weather day reflecting NYC's climate. Analysis of historical TLC trip request volume data (Schneider, 2021) (Figure 1, top left) revealed that March 2019 was the most active month across both the YCB and FHV fleets, with an average of over 1 million trips per day throughout the month. This month also contained the largest active fleet in historical data, with an average of over 70,000 vehicles operating per day (Figure 1, top right). Additional subplots compare March 2019 with other months throughout the same year.

Data from March 2019, discussed further below, were selected as the foundation for estimating infrastructure requirements to support an electrified ride-hailing fleet. More recent data, especially after the impacts of the COVID-19 pandemic, are not chosen to avoid undersizing the charging network for fleet operations, which have shown signs of recovery (Blumberg, 2021). No growth beyond observed trip and vehicle volumes in March 2019 is assumed given the lack of available data or goals.

### *Fleet size*

Investigation of infrastructure requirements corresponding to a timeline of 2025 contributed to an assumption of partial fleet electrification; although ride-hailing companies have announced ambitious targets for electrifying their fleets, it is considered unlikely that the NYC ride-hailing fleet will be fully electric by 2025. Instead, an estimation of the evolution of the NYC ride-hailing fleet was performed

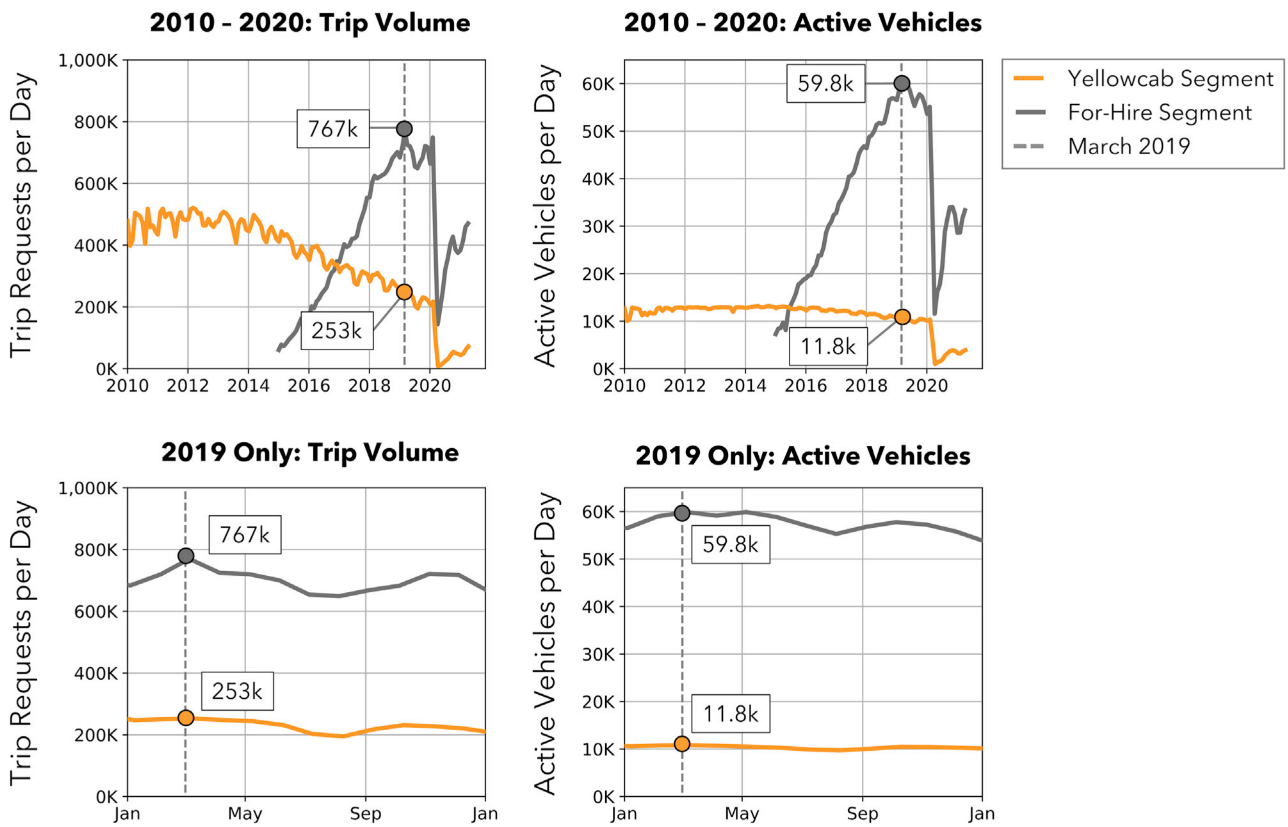


**Figure 1. Historical trip requests and active fleet sizes by month for the FHV and YCB segments**

to produce plausible electric fleet sizes corresponding to aggressive rates of electrification under the following assumptions:

- Initial fleet size of 13,587 YCB vehicles and 107,435 FHVs (NYC Taxi and Limousine Commission, 2018), all assumed to be internal combustion engine (ICE) vehicles.
- Average vehicle age of 5 years.
- EV sales for ride-hailing increasing linearly from 0% in 2020 to 100% in 2030, corresponding to the timing of full electrification announcements by major transportation network company fleets.

These assumptions, iterated annually, estimated that EVs would comprise 30% of the NYC ride-hailing fleet by 2025 (Table 1). Note that this is not a formal forecast of EV adoption, but rather a means of identifying a plausible scenario that aligns with announced electrification goals.

Although the YCB and FHV segments comprise over 120,000 total vehicles, only a fraction of these vehicles operate on a given day. This is observable in Figure 1, whereby the busiest month's data show a fraction of the total fleet size in operation (71,600 out of 121,000). Applying the 30% EV penetration rate obtained from the simplified vehicle turnover model previously mentioned produces a total fleet size of roughly 21,000 EVs for simulation, comprising 3,244 YCB vehicles and 17,967 for-hire EVs operating in 2025 with travel demand equivalent to observations from March 2019.

### *Trip requests*

Friday, March 8, was identified as having the largest number of trip requests in March 2019. Note that this day (the busiest day from the busiest month) does not necessarily select the most active day in the historical data; extreme days such as major holidays were avoided to ensure that results are more generalizable. Trip-level records containing information for pickup times, pickup locations, and drop-off locations for both FHV

**Table 1. Ride-hailing electrification by year using simplified assumptions regarding fleet turnover**

| Year | YCB – ICE | YCB – EV | FHV – ICE | FHV – EV | EV Percent |
|---|---|---|---|---|---|
| 2020 | 13,587 | 0 | 107,435 | 0 | 0% |
| 2021 | 13,315 | 272 | 105,286 | 2,149 | 2% |
| 2022 | 12,772 | 815 | 100,989 | 6,446 | 6% |
| 2023 | 11,957 | 1,630 | 94,543 | 12,892 | 12% |
| 2024 | 10,870 | 2,717 | 85,948 | 21,487 | 20% |
| **2025** | **9,511** | **4,076** | **75,205** | **32,231** | **30%** |
| 2026 | 8,044 | 5,543 | 63,602 | 43,833 | 41% |
| 2027 | 6,522 | 7,065 | 51,569 | 55,866 | 52% |
| 2028 | 5,000 | 8,587 | 39,536 | 67,899 | 63% |
| 2029 | 3,533 | 10,054 | 27,933 | 79,502 | 74% |
| 2030 | 2,174 | 11,413 | 17,190 | 90,245 | 84% |

Bolded values correspond to the target year of the study (2025).

and YCB segments were obtained from the TLC for March 7 (conditioning day) and March 8 (evaluation day), 2019 (NYC Taxi and Limousine Commission, 2021). Pickup and drop-off locations provided by the TLC are available at the ''taxi-zone level,'' a geography intended to approximate neighborhoods (NYC Open Data, 2021). Locations within a given taxi zone were assumed to be distributed uniformly to avoid stacking passengers exactly at a precise origin or destination location, which could contribute to unrealistically low empty miles traveled between trips.

Finally, aggregated trip counts across both the conditioning day and evaluation day were scaled in accordance with the number of EVs being simulated. Exposing the partially electric fleet to all requests would induce an unrealistically large number of trips per vehicle. In reality, EVs will be competing with ICE vehicles, which comprise 70% of the fleet and accommodate the majority of the requests in this 2025 scenario. It is assumed that a given ICE vehicle and a given EV are equally likely to pick up a given passenger and that exposing a proportional share of requests to the EV fleet is an adequate proxy for incorporating competition for demand. (The approximation of competition through request reduction was tested through a series of smaller-scale experimental HIVE runs with a fleet size of 3,000 vehicles. The performance of a partial fleet exposed to a corresponding share of requests (such as 30% of vehicles exposed to 30% of requests) was found to be very similar to a partial fleet exposed to all requests while competing with a counterpart ICE fleet (30% of vehicles modeled as EVs competing with 70% of vehicles modeled as ICE vehicles all exposed to 100% of requests). Applying the 30% sampling rate to trip data produces approximately 84,000 YCB trips and 249,000 FHV trips occurring throughout the evaluation day (Figure 2). Trip counts are low during overnight hours, with an initial peak during the morning commute. Trip counts rise again during evening hours, corresponding to Friday night demand for ride-hailing.

### *Charging infrastructure*

Vehicles in HIVE rely on public charging infrastructure to replenish battery energy while on-shift. Public DC charging power levels were assumed to be 150 kW given the increasing proliferation of vehicles capable of accepting higher DC charge rates, deployment of high-power infrastructure at or above 150 kW (Brown et al., 2021), and the driver incentive to maximize vehicle uptime and minimize time spent charging (Pavlenko et al., 2019). Public network size (number of 150-kW ports) and geography (locations of ports throughout NYC) were determined using the infrastructure siting workflow described in Section Infrastructure modeling approach. DC ports simulated in this study were assumed to be available to both ride-hailing fleets, but no general-purpose use by the public is modeled owing to absent available data. Consideration of competition for charging by the public is a topic of future inquiry and a noted limitation of this study.

Prior research has shown that access to overnight charging can dramatically affect the size of the infrastructure needed to support daily electric operations (Moniot et al., 2019; Nicholas et al., 2020; Rushlow et al., 2015). Drivers with access to off-shift overnight charging can start shifts with higher battery SOC and may not require use of public DC stations while on-shift, in contrast with drivers who do not have access to overnight charging and are fully reliant on the public charging network. However, access to overnight charging

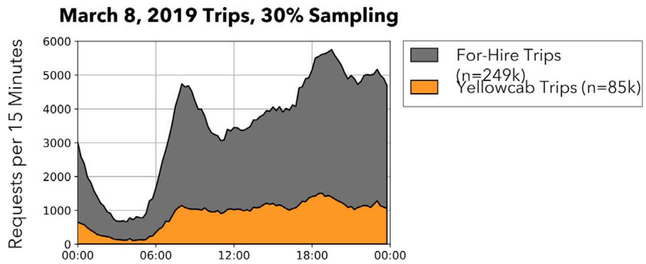


**Figure 2. Trip counts by time of day and by fleet segment for the day selected using a 30% sampling rate**

is not ubiquitous, requiring reliable parking, and is typically restricted to individuals living in single-family homes with garages. Access to overnight charging has been found to correlate positively with income (Bauer et al., 2021). Ride-hailing drivers are disproportionately lower-income (Benenson Strategy Group and GS Strategy Group, 2020), and thus anticipated to have more limited access to overnight charging.

The importance of access to overnight charging—in addition to the unique density and demographics of ride-hailing drivers in NYC—contributed to detailed estimation of plausible access to overnight charging. Access to overnight charging (summarized in Figure 3) was calculated by synthesizing several data sources:

- Percentage of ride-hailing drivers by residence type. These data were obtained through a FOIL request facilitated by the TLC comparing driver address locations with zoning data to infer what housing type the drivers likely reside in. Raw driver address location was not shared given the sensitivity of the data. These data are outlined in the orange column in Figure 3.
- Home charging access ratio by dwell type. These values were generated based on a survey (Ge et al., 2021) conducted among New York state residents. The survey collected information on the respondents' parking options available at home, outlet availability of each parking option and their perceived potential for new outlet installation if not currently available, and where each vehicle is typically parked at home. Home charging access likelihood by dwell type from 408 respondents in NYC is outlined in green in Figure 3, whereas the results from 397 respondents in New York State but outside NYC are outlined in gray. Residential charging access is described by two scenarios, which respectively capture the lower and upper bound. Scenario 1 shows the percent of vehicles that are currently parked near electrical access, whereas the more optimistic Scenario 2 considers overnight charging as available if the vehicle can be moved to a parking option at home that either has electrical access already or where new electrical access can be installed. Admittedly, the home charging access of transportation network company drivers can differ from the general population even when housing type is controlled, and a survey targeting transportation network company drivers would be ideal for assessing their residential charging access in a future research effort.
- When drivers' residence locations were not available or did not correspond with zoning data, they were assumed to have access to overnight charging at a rate of 20% likelihood for existing parking behavior and 50% likelihood for Scenario 2, assuming the possible parking behavior changes and new outlet installation. These values are outlined in red in Figure 3.

The final column included in Figure 3 assumes ubiquitous access to overnight charging regardless of the dwelling type. Although this is not realistic—especially in NYC—the scenario was included to investigate the relationship between overnight charging access and DC network size. Aggregating the percentage of drivers by residence type and the likelihood of overnight charging access by residence type produces values of 17% overnight charging access for existing parking behavior, 42% overnight access for parking behavior with a possible behavior modification and new electrical installation, when necessary, and 100% overnight access. Aggregated values were rounded slightly and approximated through the following scenarios:

- Business as Usual: 15% of ride-hailing drivers have access to overnight charging.
- Residential Investment: 45% of ride-hailing drivers have access to overnight charging.
- Home Charging for All: 100% of ride-hailing drivers have access to overnight charging.

| Dwell Type | Driver Share | Scenario 1: Business as Usual | Scenario 2: Residential Investment | Scenario 3: Home Charging for All |
|---|---|---|---|---|
| Apartment | 41% | 7% | 23% | 100% |
| Townhome | 27% | 17% | 45% | 100% |
| Detached | 8% | 28% | 61% | 100% |
| Not in NYC | 13% | 41% | 77% | 100% |
| No data | 10% | 20% | 50% | 100% |
| N/A | 1% | 20% | 50% | 100% |
| **Weighted Access:** | | **17%** | **42%** | **100%** |

**Figure 3. NYC ride-hailing driver residency and overnight charging access likelihood by dwelling type**

### *Vehicle specifications*

The current ride-hailing fleet is dominated by relatively fuel-efficient sedans. It is assumed that the current fleet composition by vehicle size will persist, which motivated the selection of values for battery size and charge acceptance (Table 2) reflective of existing and emerging four-door EV sedan options. Also included in Table 2 are energy consumption rates corresponding to an optimal day and an extremely cold day. An increase in energy consumption per mile of 100% is assumed based on observed reductions in EV performance in cold ambient temperatures versus ideal ambient temperatures (Yuksel and Michalek, 2015) and the climate of NYC in the winter.

### *Driver shifts*

Human drivers in HIVE are modeled as operating on shifts with defined start and end times. Shift start time data were obtained from the *2018 TLC Factbook* (NYC Taxi and Limousine Commission, 2018) for both YCB and FHV segments. Shift end times are not provided; instead, shift lengths were synthesized randomly between 6 and 8 h for FHV drivers and between 10 and 14 h for YCB drivers. These shift times reflect observed shift times from TLC driver data, with YCB drivers operating more hours per day on average (Schneider, 2021). Shift times strongly correlate with trip demand, with a greater number of drivers on-shift during periods of high requests.

The small share of part-time drivers within the FHV segment is unique to NYC. Part-time drivers constitute the majority of ride-hailing drivers in other markets (Benenson Strategy Group and GS Strategy Group, 2020). The large number of full-time drivers is largely attributable to the regulatory requirements (NYC Taxi and Limousine Commission, 2022) faced by drivers in NYC. Regulatory constraints enforced by TLC-licensed drivers bias the population toward full-time drivers who are more likely to drive for ride-hailing companies as their main source of income (NYC Taxi and Limousine Commission, 2018).

### *Driver home locations*

When drivers are off-shift, vehicles are assumed to be at a home location. The 2018 TLC Factbook provides home locations for drivers across both ride-hailing segments at the borough level (Figure 3). Overall, drivers are observed to live in locations where housing is more affordable, with more drivers living outside NYC than in Manhattan. Specific home locations within each borough were approximated by randomly sampling coordinates and snapping points to the road network (ensuring that drivers live in locations that can be driven to). Drivers living outside NYC were synthesized to live on the edges of the outer boroughs (all but Manhattan). This approach effectively captures long commute distances without necessitating the need for a road network outside of the NYC boroughs. Note that rates of overnight charging

**Table 2. Assumed vehicle parameters for EVs simulated**

| Parameter | Value |
|---|---|
| Battery capacity | 50 kWh |
| Maximum charge acceptance | 150 kW |
| Energy consumption rate, cold day | 450 Wh/mi |
| Energy consumption rate, optimal day | 225 Wh/mi |

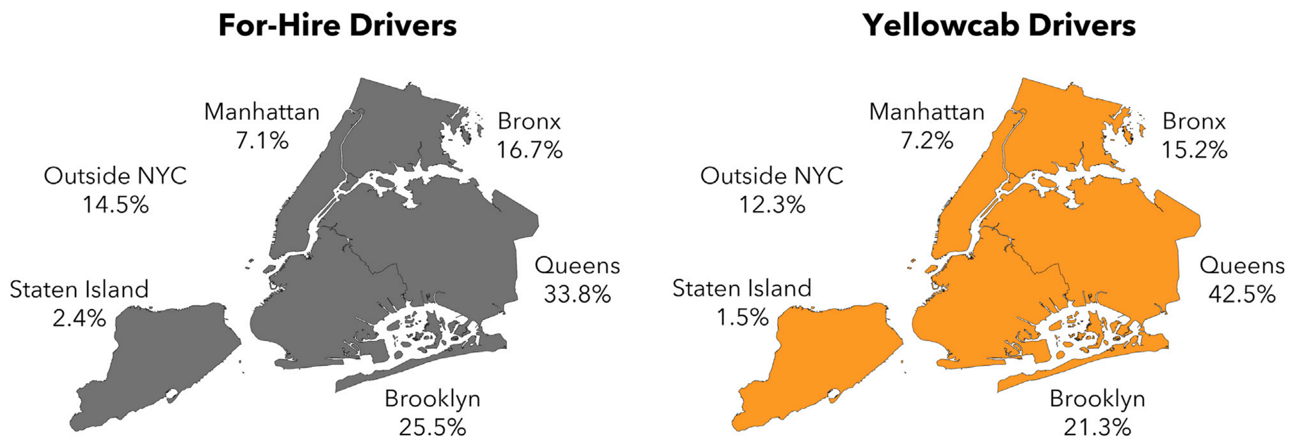


**Figure 4. Share of driver residence locations by borough and ride-hailing fleet segment**

access, estimated previously, are not varied for drivers in response to driver home location. Data limitations regarding the contents of the FOIL request response did not enable estimation of variation in home charging access across NYC.

## Infrastructure modeling approach

The DC charging network is both an input to HIVE and a desired output from this analysis. To discover requisite infrastructure demanded by the fleet, a modeling pipeline was developed using HIVE to quantify the performance of candidate networks. The workflow, outlined in Figure 4, contains the following steps:

1. An initial HIVE simulation is performed (including a conditioning day and an evaluation day) using input values corresponding to the scenario in question, including variables such as rates of overnight charging access and ambient temperature assumptions influencing vehicle energy consumption rates. This simulation sites ubiquitous DC charging in the form of finely sited stations with no port count restrictions for on-shift charging needs.
2. Charging demand from the simulation evaluation day, defined as instances when vehicles transition from servicing trips to dispatching to the nearest DC charging station, is aggregated by space and time. In space, demand is aggregated to the hex level using the H3 Python package. H3 hexagons are preferred for evaluating charging demand across equal-area geographies versus arbitrarily defined political boundaries. A hexagon resolution of 7, corresponding to an average area of 2 miles, is chosen given the dense road network of NYC. (Larger hexes may be justified when aggregating charging demand from other geographies, such as rural areas.) In time, demand is aggregated by the 30 min bin (corresponding to a typical DC charge time plus allocation for ingress/egress). Spatial aggregation provides a suggestion of the charging demand of the fleet throughout the city, whereas temporal aggregation provides insight into the number of ports needed at a given location, accounting for opportunities for distinct charging demand events in the same location to be accommodated by a single port if they occur in different time bins.
3. Processing of the spatial-temporal charge event aggregation facilitates insight into potential port utilization. Ports are prioritized based on utilization and ranked from highest to lowest. Charging networks are generated using this ranking, iterating from sparse networks containing only the most highly demanded ports (top *n*% ports) to generous networks containing all ports demanded during the seed run. All ports demanded within a given hex are aggregated into a single station at the centroid.
4. HIVE is run numerous times with the same inputs originally used during the seed run but with candidate DC charging networks instead of a ubiquitous network. Key performance indicators (KPIs) are evaluated for each run to determine whether a charging infrastructure was deemed to provide a sufficient level of performance. KPIs used to assess the adequacy of a given network within this study are at the fleet (a) and vehicle (b) level:

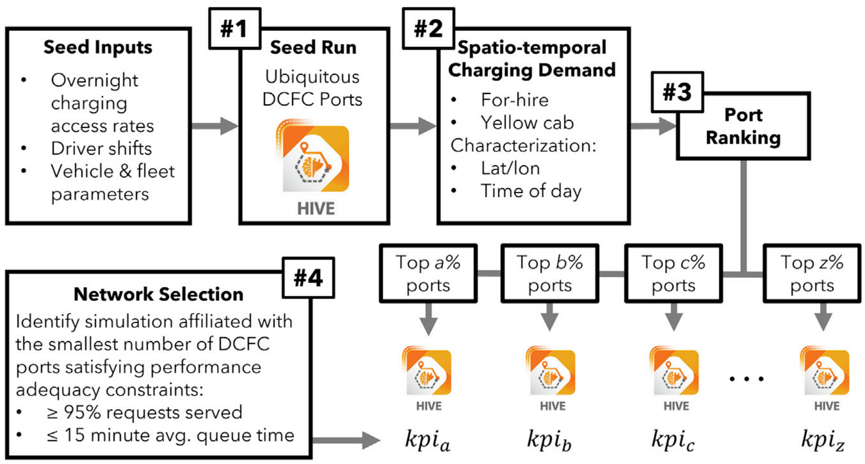


**Figure 5. Infrastructure modeling approach using HIVE to identify a sufficient charging network for each scenario (DCFC = DC fast charging)**

a. At the fleet level, infrastructure must enable service of at least 95% of all trips simulated as being requested. Note that the *requested* trips simulated in HIVE are actually *served* trips as reported by the TLC. There are also many unserved trips not taken by passengers that are not present in the data but could have been possibly served by the simulated vehicle fleet. Diminishing returns were found when increasing the number of fleet vehicles or infrastructure ports, suggesting that servicing trips at or near a 100% rate would require more sophisticated supply/demand balancing or incorporation of heterogeneous driver behavior. Achieving 95% quality of service is considered to meet a similar level of service to the real world.
b. At the vehicle level, infrastructure must be sufficient such that the average queue time encountered by drivers at DC charging stations does not exceed 15 min. It is assumed that drivers will not be tolerant of significant delays to access charging infrastructure.

This approach is similar to others in the literature that site infrastructure for electric fleets in accordance with the observed or inferred demand for charging (Bauer et al., 2018; Chen et al., 2016), with the added benefit of being able to identify charging networks that satisfy specific KPIs.

## RESULTS AND DISCUSSION

### Results: infrastructure network sizing

Candidate infrastructure networks were generated and assessed for three scenarios corresponding to increasing share of drivers assumed to have home charging access (Business as Usual: 15%, Residential Investment: 45%, Home Charging for All: 100%). These three scenarios were evaluated assuming a high vehicle energy consumption rate—450 Wh/mi—corresponding to cold ambient conditions typical of NYC winters. In each case, spatiotemporal charging demand was generated using seed runs of HIVE wherein ubiquitous DC charging access was provided. Candidate networks, generated based on simulated port utilization from an unconstrained network, were re-simulated using HIVE for each infrastructure-constrained scenario. Figure 5 shows the results of this process for all three scenarios, comparing the size of the DC charging network against KPIs used to assess adequacy of the charging network (request service percentage and mean queue time).

Applying performance constraints—minimum of 95% requests served and maximum average queue times of 15 min—enabled selection of a charging network size for each scenario, described in Table 3. Increasing the magnitude of the charging network was shown to improve both KPIs of interest, as greater access to infrastructure increased fleet uptime through reduced dispatching distances to chargers and reduced driver queue times. However, results in Figure 5 also indicate diminishing returns across KPIs as the network size grows. Diminishing returns with respect to trip service and driver queue times underscore the importance of selecting strategic KPI thresholds; requirements of 95% request service and maximum average

**Table 3. DC charging infrastructure network sizes necessary to accommodate 21,211 human-driven ride-hailing vehicles servicing trips in NYC on a challenging day**

| Scenario | Share of Vehicles with Overnight Charging Access | Number of Overnight Chargers | Number of DC 150-kW Ports Sited |
|---|---|---|---|
| Business as Usual | 15% | 3,176 | 1,054 |
| Residential Investment | 45% | 9,540 | 806 |
| Home Charging for All | 100% | 21,1211 | 367 |

queue times of 15 min were selected as targets by the authors. Although these thresholds produced an effective charging network, stakeholders in the ride-hailing ecosystem responsible for providing access to charging may deem separate thresholds to be more strategic.

Further analysis of network sizing results in Figure 6 indicates a strong relationship between the number of drivers with access to overnight charging and the number of DC ports needed to support an adequately performing fleet. Increasing the number of vehicles with access to overnight charging from 15% to 100% reduced the number of DC ports needed by 65% (1,054 ports to 367 ports). On a per-port basis, results indicate that one less DC port is needed for every 26 drivers who gain access to overnight charging. This finding is consistent with other literature suggesting that increased access to off-shift charging reduces the need for on-shift charging (Jenn, 2021; Nicholas et al., 2020). However, results indicate that a substantial DC charging network will still be needed even by populations with access to overnight charging. The network size demanded by drivers with access to overnight charging is much higher than in a similar study performed by the authors (Moniot et al., 2019), which found that providing overnight charging access to taxi drivers in Columbus, Ohio, would nearly eliminate the need for DC charging infrastructure entirely. Major contributors to the size of the DC charging network in the ''Home Charging for All'' scenario include incorporation of NYC's cold climate using a high vehicle energy consumption rate (450 Wh/mi) and the long shift lengths (up to 14 h), which induce charging for some vehicles despite starting their shifts with a full battery capacity.

In addition to quantifying total port counts, the infrastructure siting approach provides visibility regarding where ports are sited throughout NYC. Figure 6 contains results by H3 hex of sited stations and port counts for each of the three scenarios. Note that a single station is sited within each hex and assumed to contain all ports within the hex; in reality, a given geography may be served by many stations, although this was not explicitly modeled. It was assumed that a single large station may support a similar number of vehicles, as multiple smaller stations with the same number of overall ports provided sufficient driver information regarding queues and station proximity.

In each case, the area with the greatest demand for ports was found to be in midtown Manhattan, which corresponds with the largest amount of trip demand. These results are consistent with prior research, which

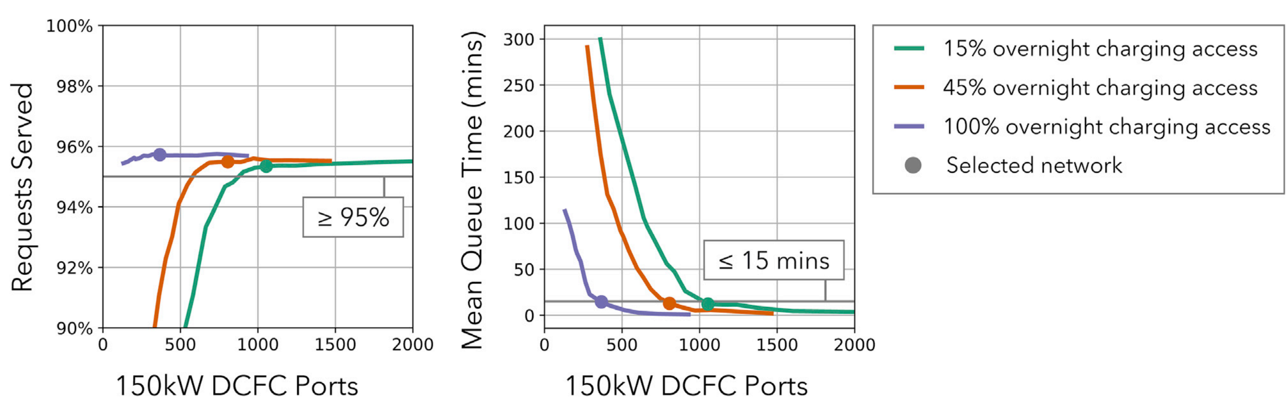


**Figure 6. Simulation results regarding request service and mean queue time across home charging access scenarios in response to candidate DC charging networks**

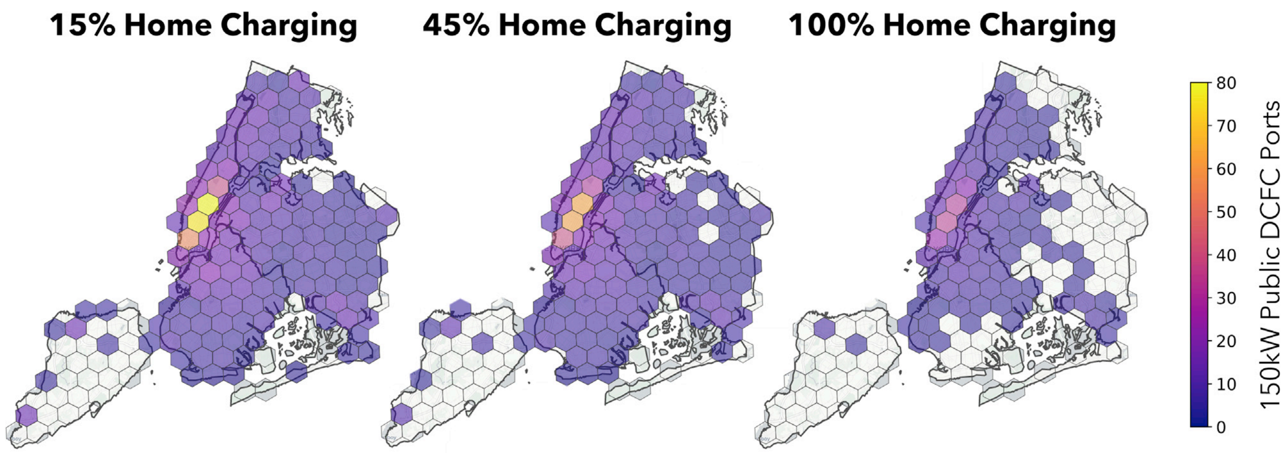


**Figure 7. Concentration of sited ports across scenarios throughout NYC**

has found a strong relationship between request density and effective infrastructure siting (Bauer et al., 2019). However, trip demand alone is not shown to be fully predictive of charging network geography; access to overnight charging is also shown to influence the location of demanded charging infrastructure. Scenarios with lower shares of overnight charging access demand a larger share of charging in outer boroughs away from dense trip demand and nearby home locations. This charging corresponds to on-shift demand for charging but also the commuting needs of vehicles as they start and end their shifts with low SOCs because of limited access to overnight charging. These findings support multiple infrastructure paths for electrifying a fleet of ride-hailing vehicles that balance investment in DC charging in areas of high travel demand (such as urban cores) and investment in overnight charging access (such as in residential neighborhoods). Cost calculations comparing the trade-offs between these approaches were not explored given the uncertainty in estimating infrastructure costs for both DC charging stations and overnight chargers across a variety of overnight parking locations.

## Results: fleet simulations using sized networks

Fleet load profiles were developed for each simulation to understand the magnitude of the electrical load demanded by time of day. These loads, broken out by ride-hailing segment and port type, are shown in Figure 7 for each scenario. Inspection of the load profiles reveals that FHVs contribute the majority of charging demand, which is to be expected considering the larger fleet size relative to YCB vehicles. In addition, the load profiles indicate that greater shares of home charging access result in less energy dispensed through public DC charging stations, as expected. A more surprising finding, however, is that the peak load across scenarios is relatively similar. Although overnight charging uses a lower power level relative to DC charging, ubiquitous access to overnight charging leads to a high percentage of the fleet charging simultaneously. Having said this, peak charging demand from overnight charging is more dispersed across the electric network and may be less likely to exceed local grid hosting capacity versus fewer centralized high-power stations.

Loads from scenarios with ubiquitous overnight access are contrasted with fleets primarily relying upon public DC charging. Note that the charging behavior in this study is uncoordinated; prior research pertaining to personal vehicles and automated ride-hailing fleets has indicated that charging loads may be highly flexible without interrupting travel requirements (Moniot et al., 2020; Sheppard et al., 2021). Finally, in addition to assumptions regarding unmanaged charging, the authors emphasize the importance of driver behavior with respect to load shape. For instance, the early morning peak observed in the Business-as-Usual scenario (15% overnight charging access) is induced by a large number of drivers beginning their shifts, commuting to the city, and requiring a charge because of a low overnight SOC and no access to home charging. In practice, drivers may develop more sophisticated charging strategies that avoid queues and reduce peak demand.

In addition to fleetwide profiles, HIVE outputs were analyzed using smaller geographies. Load profiles for all ports in each hex, modeled as belonging to a single station, are shown for exemplar stations from the

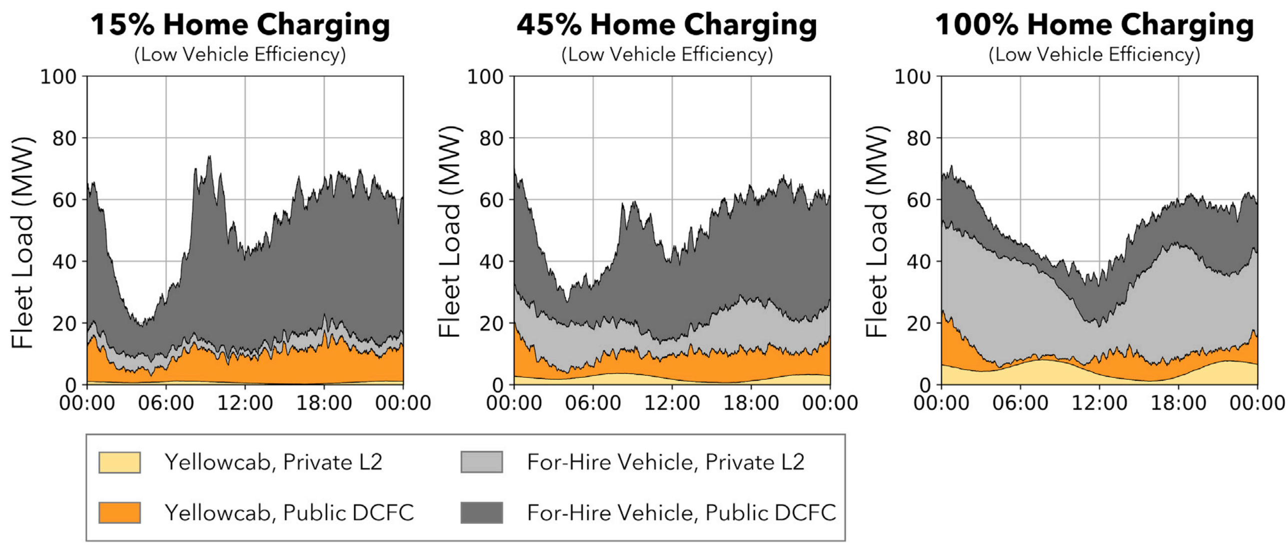


**Figure 8. Fleetwide load profiles corresponding to simulations using sized infrastructure networks for each scenario across infrastructure type (DC and Level 2 [L2]) and fleet segment (YCB and FHV)**

"Business-as-Usual" case in Figure 8, with the largest station in the urban core (79 ports in the midtown Manhattan hex) and a smaller station supporting neighborhood travel (5 ports in a Brooklyn hex). The authors reiterate that the large number of ports per station in dense regions is an artifact of modeling resolution and these areas with a high density of ports could be spread across multiple station locations. However, this abstraction does not impact the demand for ports by time of day or the utilization of ports averaged across a hex.

Comparison of these load profiles reveals that the Manhattan station heavily contributes to the fleetwide morning peak, driven by many low-SOC vehicles transitioning on-shift and commuting into the city, requiring an early shift charge event and demanding charging simultaneously. However, after this peak event, the station is not highly utilized throughout the remaining day and especially not during overnight hours when the majority of the fleet is off-shift and commutes home. This load shape is contrasted with the neighborhood station, which accommodates a more consistent stream of charging events throughout the day and the overnight hours. The Brooklyn station's location enables it to service en route trips for on-shift vehicles, as well as low-SOC vehicles commuting to or from a home location. These charging dynamics contribute to a higher utilization (calculated using Equation 1) for the neighborhood DC charging station in Brooklyn (41%) versus the DC charging station in Manhattan (26%).

$$\mu_{station} = \frac{\sum_n^p t_n}{24p} \qquad \text{(Equation 1)}$$

Where $\mu_{station}$ = station-level utilization, $t_n$ = total time in hours port, $n$ dispensed energy in a day, $p$ = number of ports affiliated at station $\mu_{station}$, 24 = number of hours in a day.

Finally, the load profiles also vary by fleet segment. The Manhattan station charges a disproportionate number of YCB vehicles relative to fleet size given the consolidation of YCB requests to Manhattan. This is contrasted against the Brooklyn station, which primarily services FHVs that can accommodate trips throughout all boroughs. The few charging events demanded by YCB vehicles at the Brooklyn station correspond to drivers commuting to or from their home location nearby.

The relationship between station location and utilization was explored further across all stations sited in each HIVE scenario. Distributions of station utilization are communicated by borough in Figure 9 for each scenario. Results indicate a pattern: stations sited in Manhattan experience less utilization than neighborhood stations, which contain a fewer number of ports but provide charging benefits to the fleet during broader time periods (as opposed to primarily servicing the morning rush for charging). Utilization results also contain a handful of stations with very high utilization in the 15% Home Charging scenario; although

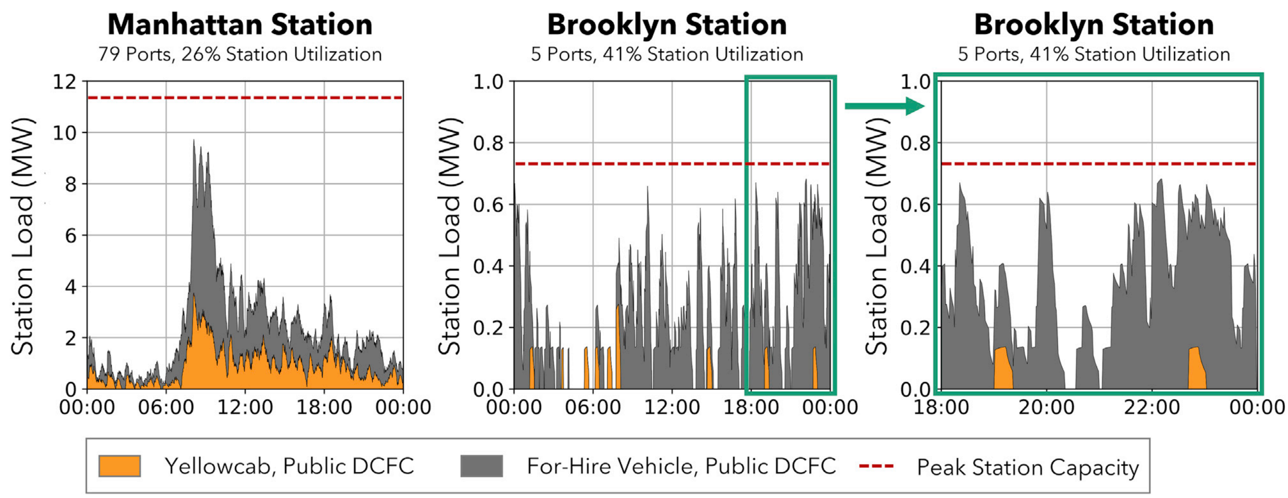


**Figure 9. Sample load profiles from a large and small DC charging station from the Business-*as*-Usual scenario**

these stations enjoy consistent demand for charging throughout the day, they are also smaller in size and comprise a small fraction of the total ports on the network. Finally, when interpreting the figure, readers should note that the total network size is changing across each scenario as demanded by the fleet and determined by constraints in the prior section. The variability in charging demand across cases contributes to consistent station-level utilization across scenarios despite an increase in overnight charging access.

Despite differences in average utilization, all ports sited on the network are required at least once throughout the day. For some stations, all ports at a given station are simultaneously demanded frequently; however, at other stations, complete use of plugs occurs only briefly, such as at the Manhattan station in Figure 8. (Inspection of Figure 8 may lead readers to conclude that all ports are not in use at any time given that the peak station load does not reach the station capacity. All ports are indeed in use at approximately 8 a.m. for the Manhattan station; the station load does not reach the stated capacity due to nonlinear charging rates resulting in many vehicles charging below 150 kW.). In some locations, investment into additional charging ports results in accommodating marginal charging demand. As discussed earlier, although these additional ports were found to be necessary to meet network sizing KPIs, investments into chargers accommodating diminishing charging demand may not be strategic depending on the motivations of the stakeholders in the ride-hailing ecosystem.

Finally, before concluding discussion of baseline results, the authors would like to acknowledge the trade-offs corresponding to outcomes from a single design day, Friday, March 8, 2019. Analysis of a single design day introduces limitations because of the larger-than-normal number of requests and the emphasis of weekday travel patterns. First, simulation of more typical weekday travel days with fewer trips would be expected to coincide with a reduction in the fleet charging demand; prior research leveraging simulations with a fractional share of the total requests in a given day has indicated that the resulting fleetwide load is approximately proportional to the number of requests simulated while also being similar in shape. In other words, halving the travel demand was shown to halve the demand for charging in magnitude when controlling for economic fleet size (Moniot et al., 2020). Second, weekend travel demand is distinct from weekday travel demand by time of day and across geographies given the difference in travel behavior, such as reduced trip demand corresponding to commuting and increased trip demand corresponding to recreational opportunities. Although a single travel day was explored in this study to accommodate computational resources and to keep the quantity of results tractable, it is acknowledged that a charging network satisfying the needs of both weekend and weekday travel patterns may be slightly larger than the network introduced in this section and is a recommended topic for future work.

## Sensitivity results: fleet simulations on a warm day

Results from HIVE introduced thus far correspond to simulations assuming a very cold day and high vehicle energy consumption rates. An additional set of HIVE simulations was performed assuming a more ideal

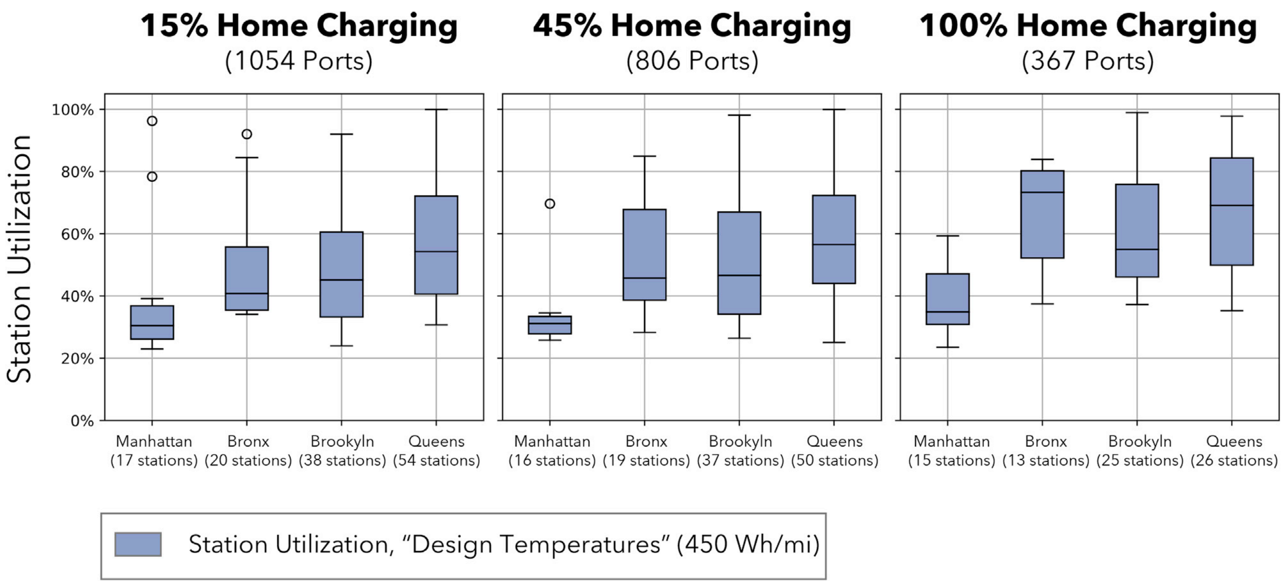


**Figure 10. Utilization rates broken out by station borough and scenario**

energy consumption rate of 225 Wh/mi. All other variables (e.g., DC charging network, trip data) were kept constant to isolate the impact of fleet consumption rate on charging demands and station utilization.

Load profiles from simulations assuming a low vehicle energy consumption rate are shown in Figure 10, with inclusion of the aggregated load from the corresponding high vehicle energy consumption rate simulation (originally introduced in Figure 7) shown for reference. Most notable is the reduction in load across cases; more energy-efficient vehicles are observed to demand less charging. In addition, the relative share of fleet charging demand corresponding to private L2 chargers is higher. Overnight charging access was found to provide sufficient energy for vehicles to complete a full shift in most cases. The limited DC charging loads shown in Figure 10 are almost exclusively attributable to the vehicles in the fleet with no access to overnight charging. This trend is most notable in the "Home Charging for All" scenario, wherein only a small fraction of YCB vehicles with long shifts require DC charging.

Although there are many differences between the cold and warm simulations, comparison between cases does reveal similarities. Most notably, the peak load is similar across overnight charging access scenarios, and the overall shape of the loads is similar between cold and warm simulations. These findings suggest that the peak load of the fleet generalizes across home charging access scenarios when controlling for a given climate, and that the timing of the peak demand generalizes across energy consumption assumptions for a given collection of trip requests that must be served.

The relationship between station utilization and location was also explored for simulations with higher ambient temperature, which assumed lower vehicle energy consumption rates. In all cases, stations experienced lower utilization during the warmer simulations, as shown in Figures 11 and 12. This lower utilization is driven by two factors. First, vehicles without access to overnight charging still rely upon DC charging to replenish battery energy but do not necessarily require a DC charging event each day given the lower energy consumption rate. This finding is evidenced by the reduced utilization in the "Business as Usual" and "Residential Investment" scenarios, wherein a significant portion of the fleet is still reliant on public DC charging. Second, vehicles with access to overnight charging can satisfy their charging needs without mid-shift charging in nearly all cases, as evidenced by the DC charging utilization rates of nearly zero for the "Home Charging for All" scenario.

Outcomes from the sensitivity study indicate a high degree of variability in overall charging demand and corresponding station utilization in response to vehicle energy consumption rates, which vary because of ambient conditions. Findings motivate consideration of trade-offs between minimizing queueing on cold days at the expense of poor station utilization, which may be uneconomical during warmer days.

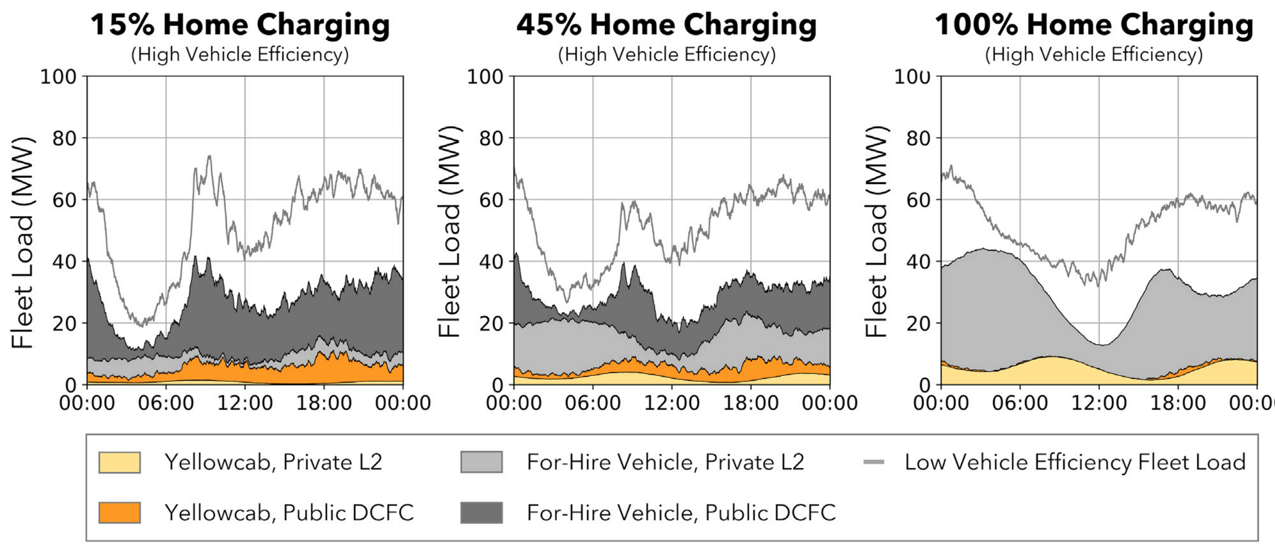


**Figure 11. Fleetwide load profiles corresponding to simulations using sized infrastructure networks and warm ambient temperatures for each scenario across infrastructure type (DC and AC L2) and fleet segment (YCB and FHV)**
Traces are also included for the peak fleet load from corresponding cold simulations.

This balance is also affected by trip volumes, whereby days with high trip volumes induce a large demand for fast charging, whereas simulations with reduced trip volumes induce less demand for fast charging.

## Conclusions and limitations of study

This paper examines the infrastructure demands of an electric ride-hailing fleet of over 20,000 vehicles in NYC. Infrastructure demands were calculated using the HIVE modeling tool, a simulation platform that models the operation of shared vehicle fleets. HIVE considered a broad number of real-world inputs provided by the TLC, including real-world trip data, driver shift timing, and driver home locations. Additional data pertaining to access to overnight charging supplemented the study through administered surveys of residents in the NYC metropolitan area. HIVE was leveraged to understand the fleet demand for charging in space and time, siting networks that met performance metrics at the fleet and vehicle level. Results indicate that electrifying 30% of the NYC ride-hailing fleet by 2025 will require a robust charging network, ranging in size from 367 to 1,054 DC ports each rated at 150 kW (depending on the level of home charging access assumed). In addition to these findings, the analysis performed extends beyond what is typically available in similar studies. Key contributions include simulation of heterogeneous fleets relying on shared infrastructure and added realism through consideration of real-world data, including driver shifts and overnight charging access informed by survey data.

There are many factors unique to the NYC environment that are important to consider when interpreting the results. First, the ride-hailing market in NYC is uniquely regulated by the TLC, which biases the driver population to be predominately full-time. Second, the congested nature of NYC limits the total mileage accrued within a given shift, meaning charging needs are greatly influenced by time-based loads including cabin heating. Third, the presence of a high-volume public transit system may bias the types of trips taken by the ride-hailing fleet. Finally, the dense nature of the housing market constrains plausible upper bounds on home charging access. Additional modeling limitations—not specific to NYC—include the absence of off-shift vehicle miles traveled outside of commuting, assumption of homogenous charging behavior, simulation of only a single evaluation day, assessment of the opportunity for taxi depots to host overnight charging, simulation of partial fleet electrification, and neglected consideration of the charging competition between ride-hailing drivers and the broader light-duty vehicle fleet. These topics warrant future inquiry as ride-hailing electrification accelerates.

These caveats aside, the authors emphasize the following insights:

- Access to overnight charging dramatically reduces the size of the public DC charging network required to support ride-hailing operations. Off-shift charging access enables vehicles to start their

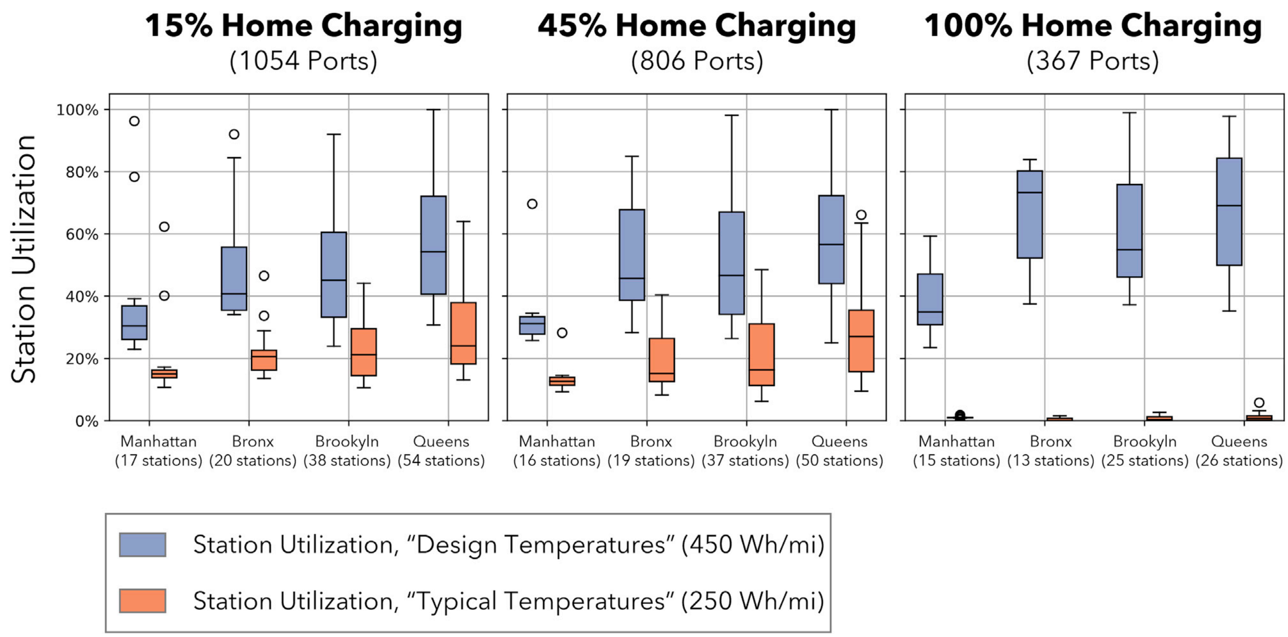


**Figure 12. Utilization rates broken out by borough, home charging access scenario, and assumed ambient temperature**

shifts fully charged, as opposed to frequent use of public DC charging alone. Increasing the share of overnight charging from 15% of the fleet to 100% reduced the required DC charging network size from 1,054 to 367 150-kW ports for a fleet of approximately 20,000 vehicles.

- A robust network of DC ports will be needed even by fleets with overnight charging access. The existing availability of DC charging within NYC—68 public DC fast charging ports as of November 2021 (U.S. Department of Energy, n.d.)—pales in comparison to what will be needed to support successful ride-hailing operation regardless of scenario. Although overnight charging does support the majority of charging needs for drivers with access, full-time drivers are still expected to demand public charging, particularly on cold days with high travel demand.
- The demand for charging is highly correlated with trip density, with areas of greatest public charging demand adjacent to high-volume pickup and drop-off locations. However, scenarios with fewer vehicles modeled as having overnight charging access demand DC charging nearby their residence, despite relatively little trip demand.
- DC charging station utilization is impacted by many factors, most notably station geography, ambient temperature, and fleet access to overnight charging. DC charging stations located in the urban core are observed to accommodate a large number of simultaneous charge events, but feature lower utilization overall when compared to DC charging stations located within neighborhoods. In addition, a natural relationship between station utilization and demand for charging was observed, with demand for public charging driven by vehicle energy consumption rate and overnight charging access.

## STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

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  - Materials availability
  - Data and code availability
- METHOD DETAILS
  - Fleet simulator
  - Infrastructure siting

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## AUTHOR CONTRIBUTIONS

Conceptualization, M.M., Y.G., E.W., and J.Z.; Analysis, M.M.; Writing, M.M. and Y.G.; Reviewing, E.W. and J.Z.; Software, M.M.

## DECLARATION OF INTERESTS

The authors declare no competing interests.

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## STAR★METHODS

### KEY RESOURCES TABLE

| REAGENT or RESOURCE | SOURCE | IDENTIFIER |
|---|---|---|
| Other | | |
| Trip records, 2019 | NYC TLC | https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page |
| TLC data aggregations | Todd Schneider | https://toddwschneider.com/dashboards/nyc-taxi-ridehailing-uber-lyft-data/ |
| Driver home locations by borough | 2018 TLC Factbook | https://www1.nyc.gov/site/tlc/about/fact-book.page |
| Driver shifts | 2018 TLC Factbook | https://www1.nyc.gov/site/tlc/about/fact-book.page |

### RESOURCE AVAILABILITY

#### Lead contact

Further information about the protocols and requests for resources and reagents should be directed to and will be fulfilled by the lead contact, Matthew Moniot (matthew.moniot@nrel.gov).

#### Materials availability

This study did not generate new unique reagents.

#### Data and code availability

This paper analyzes existing, publicly available data. These accession numbers for the datasets are listed in the key resources table. This paper does not report original code. Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

### METHOD DETAILS

#### Fleet simulator

We characterize the operations of ride-hailing fleets using the HVIE simulation platform (Fitzgerald et al., 2021). HIVE enforces various physical constraints, including battery range, vehicle state transitions, road network routing, request and vehicle matching, and more. The study employed HIVE through use of several real-world input datasets pertaining to ride-hailing in New York City, including real-world trips, aggregated driver residence locations, driver shifts, and more. A key variable, likelihood of driver overnight charging access, was inferred from data provided by the TLC describing driver domicile type and survey data originally introduced by Ge et al., (2021) correlating likelihood of charging access by domicile type. These inputs supported HIVE simulations which induced demand for fast charging.

#### Infrastructure siting

Infrastructure locations and power levels are both an input to the HIVE simulation and the focus of the study. To identify the demand required, the following simulations were performed:

1. A "seed" simulation, whereby the fleet has access to ubiquitous infrastructure spatially and with no plug constraints
2. Candidate infrastructure networks are sited in response to this seed run, where plugs are distributed based on observed demand from the seed run.
3. HIVE simulations are iterated with increased infrastructure network sizes until KPI's are met at the fleet level (quality of service constraint) and at the driver level (mean queue times to charge).

4. Once KPI's are met, the corresponding charging infrastructure in both space (location of stations) and quantity (number of ports per location) are retained.

Simulations to identify demand for infrastructure assumed cold climate conditions with low vehicle efficiencies under the presumption that sited infrastructure must adequately support a fleet on a challenging day of operation. Additional simulations were performed with more favorable energy efficiency assumptions to understand more typical fast charging demand from the fleet.