Electrifying the NYC Yellow Taxi Fleet: A simulation-based analysis of the relation between charging infrastructure requirements and lithium-intensity

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Short summary

Road transportation electrification, a key element of the transition towards net-zero carbon emissions, is one of the lead drivers of demand for critical raw materials (CRM) for batteries such as lithium, nickel, and cobalt. While securing the supply of such materials is paramount to support the transition to green energy, mitigating their demand by making transportation operations more material-efficient can relieve some of the pressure on the supply side, enabling the development of more socially and environmentally sustainable supply chains. This study uses simulation and optimization to explore the charging infrastructure implications of potential strategies for reducing lithium demand in an electrified New York City taxi fleet. In particular, as strategies of interest, we consider battery downsizing and shallow charging, a charging dispatching rule that mitigates battery stress. Our analyses show that reducing the initial lithium intensity of mobility fleets by battery downsizing requires considering trade-offs between fleet investment and infrastructure investment. Further research integrating battery degradation models to the framework used in this study is however needed to evaluate long-term lithium consumption of taxi fleet operations.

Keywords: Charging infrastructure, Critical raw materials, Lithium intensity, Electric vehicles, Taxi fleets.

1 Introduction

Road transportation electrification, a key element of the transition towards net-zero carbon emissions, is now one of the lead drivers of demand for critical raw materials (CRM) for batteries such as lithium, nickel, and cobalt (Gibb, 2021; IEA, 2021). Securing a socially and environmentally sustainable supply of such materials is paramount to supporting green energy transitions, but it is challenging. The deposits and the processing capacity of some of these materials are severely concentrated. For example, 97% of the global lithium supply lithium is currently mined in 5 countries (Australia, Chile, China, Argentina, and Zimbabwe), and 65% of the lithium processing capacity is in China. This means that CRM supply for EV batteries is vulnerable to geopolitical tensions and other external shocks to global supply chains (e.g., pandemics). Furthermore, the extraction CRM, such as lithium, can have significant environmental and cobalt is often marred by social injustices ("Raw materials for a truly green future", 2021; Herrington, 2021). Steep production increases are exacerbating these negative impacts (Barber, 2024). Reducing CRM demand by more efficiently using CRM in electric mobility might partially relieve the pressure on CRM supply chains, enabling socially and environmentally sustainable practices in exporting countries and mitigating the vulnerability to supply chain shocks of transportation systems in importing countries. While it has been suggested that promoting EVs with smaller batteries might reduce CRM requirements (IEA, 2022), detailed analyses on the implementation requirement of such solutions are lacking. This study contributes to filling this gap by analyzing the charging infrastructure deployment implications of two potential strategies for lithium demand reduction for the NYC taxi fleet: a) battery downsizing, and b) shallow charging, a charging dispatching strategy that avoids EV batteries'

*This study was undertaken while Pei-Yu Chang was enrolled in Columbia University's Master of Science in Civil Engineering and Engineer Mechanics, cohort 2022-2023 state of charge lower than 60%. The first enables short-term lithium savings, and the second one, by mitigating battery degradation, has the potential to save lithium over longer operational horizons. Previous studies of e-mobility service fleet electrification have analyzed charging infrastructure requirements (Zhang et al., 2020; Ahadi et al., 2021; Moniot et al., 2022) decarbonization potential (Kinsella et al., 2023) of mob. However, the relationship between lithium demand and infrastructure and fleet configurations has not been considered.

2 Methodology

This study combines the HIVE fleet simulator with a charging infrastructure location-allocation model formulated as a MIP Optimization model to identify charging infrastructure requirements for a given trip demand under different fleet scenarios. This paper uses this approach to analyze how charging infrastructure requirements change under different vehicles characterized by different battery sizes to explore the trade-offs between charging infrastructure requirements and the lithium intensity of the fleet. It also analyses the charging infrastructure requirements between a baseline charging dispatching strategy and a battery-life-preserving one, which we call "shallow charging".

HIVE Fleet simulator

HIVE (Highly Integrated Vehicle Ecosystem), developed by NREL (National Renewable Energy Laboratory), simulates mobility fleet operations given known trip rquests by combining agent-based modeling of individual vehicles and refueling infrastructure with a centralized vehicle dispatch system (Fitzgerald et al., 2021; Moniot et al., 2022). HIVE allows the specification of electric vehicles, charging infrastructure characteristics, EV agent's charging behavior, and vehicle agent shifts. Given such inputs, it can be used to analyze charging infrastructure utilization and fleet level of service performances under alternative vehicle fleet and charging infrastructure characteristics as well as alternative charging behavior scenarios.
In this study, HIVE simulates fleet and charging infrastructure operation for an all-electric Medallion taxi (Yellow Taxi) fleet serving Manhattan, New York City. HIVE was previously used to simulate ride-hailing fleets in New York City to study their charging infrastructure requirements (Moniot et al., 2022). Our methodology for the location and sizing of the charging infrastructure for the fleet is, however, different from that by Moniot et al. (2022). In particular, following Ahadi et al. (2021), we formulate a demand covering location-allocation model. The details of the charging infrastructure location-allocation model are provided in the following section. Furthermore, this study also implements a shallow charging mode within HIVE to limit EV charging to particular depths of discharge to simulate discharging/charging scenarios with different battery degradation impacts, as the lithium intensity of EV fleet operations depends on the battery replacement rate of the fleet.

Charging infrastructure optimization model

To locate and size the charging infrastructure for an electric taxi fleet, this study builds on the location-allocation formulation by Ahadi et al. (2021). The optimization decides the charging stations' locations and number of chargers, given an initial ubiquitous charging demand obtained from HIVE, by including a relocation penalty. The main inputs of the model involve charging demand (under ubiquitous charging), the maximum number of chargers in a region, and costs (including vehicle relocation penalties and charger installation costs). As compared to Ahadi et al. (2021)'s, the formulation in this study allows for a more nuanced installation cost reduction profile as more DC chargers are installed per site, as it is discussed in the 2019 study "Estimating electric vehicle charging infrastructure costs across major U.S. metropolitan areas" by the International Council on Clean Transportation (Nicholas, 2019). Sets, parameters, and decision variables used in our optimization formulation are listed below.

Sets

- N: Set of stations
- T: Set of time steps

Parameters

- D_it: Demand in station i at time t
- L_ij: Distance between station i,j per KM
- M_i : The chargers amount limit in the station i
- $C_{ik}, k = 1, 2, ..., 5$: Installation cost for the first through fifth chargers in station i
- C_i^{add}: Installation cost of additional(more than 5) chargers in station i
- $Beta$: Relocation penalty rate for charging in other stations
- H: Number of days in the horizon time
- $MaxRange$: The maximum distance the vehicle can relocate to charge in the other station.

Variables

- $x_{ik}, k = 1, 2, ..., 5$: Binary variables of installing the first through fifth chargers in zone i
- y_i: Integer variable of the number of installed chargers in zone i
- a_{ijt}: Number of chargers in zone i allocated to the demand of zone j at time t

The optimization problem, minimizing the total installation costs, is formulated as:

$$\min \sum_{i \in N} \left(\frac{\sum_{k=1}^{k=K} x_{ik} C_{ik} + \left(y_i - \left(\sum_{k=1}^{k=K} x_{ik} \right) \right) C_i^{\text{add}}}{H} + \beta \sum_{j \neq i \in N} \sum_{t \in T} a_{ijt} L_{ij} \right) \tag{1}$$

Subject to

$$y_i \leq (k-1) + (M-k+1) x_{ik} \quad \forall i \in N, \forall k \in \{1, \dots, 5\} \tag{2}$$

$$x_{ik} \leq x_{i(k+1)} \quad \forall i \in N, \forall k \in \{1, \dots, 4\} \tag{3}$$

$$\sum_{k=1}^{k=K} x_{ik} \leq y_i \quad \forall i \in N, \forall k \in \{1, \dots, 5\} \tag{4}$$

$$D_{jt} \leq \sum_{i \in N} a_{ijt} \quad \forall j \in N, t \in T \tag{5}$$

$$\sum_{j \in N} a_{ijt} \leq y_i \quad \forall i \in N, t \in T \tag{6}$$

$$a_{ij}(1 - I(L_ij \geq MaxRange)) \leq 0 \quad \forall i \in N, j \in N, t \in T \tag{7}$$

$$x_{ik} \in \{0, 1\} \quad \forall i \in N \forall k \in \{1, \dots, 5\} \tag{8}$$

$$y_i \in \mathbb{Z}_{\geq 0} \quad \forall i \in N \tag{9}$$

$$a_{ijt} \in \mathbb{Z}_{\geq 0} \quad \forall i \in N, j \in N, t \in T \tag{10}$$

The first part of the objective function 1 represents the total installation cost across all regions, considering that for gradually decreasing costs for up to 5 chargers. Note that this cost is divided by the number of days in the planning horizon. The second part represents the cost incurred if vehicles need to relocate from one location to another for charging.
Constraints 2 limit the number of charging stations installed to be less than M—the maximum installation limit for a single site. Constraints 3 and 4 pertain to the installation logic of the charger at the station at each site, such as the requirement for the first charger to be in place before a second charger can be installed. Constraints 5 indicate that the charging stations must meet all charging demands. Constraint 6 restricts the charging demand transferred to any station i from exceeding the number of chargers at that location. Constraints 7 limit the maximum straight-line distance for demand to be transferred from j to i, with a specific MaxRange. In this study,

MaxRange is set to 5.5km, indicating that demand transfers can span across two contiguous Uber H3 hexagonal areas[1].

Scenarios' definition

We investigate the lithium requirements for an electrified Yellow Taxi Fleet serving under three scenarios. A baseline scenario in which BEVs have a 50 KWh battery (and a range of), a small battery scenario in which BEVs have a 25kWh battery and a shallow charging scenario in which the SOC of the battery is constrained to fluctuate between 60% and 80%. The shallow charging scenario is applied to 50 KWh battery BEVs. On the one hand, halving the battery size to 25kWh is an intuitive approach to reduce the initial use of lithium. On the other hand, limiting the depth of discharge of the battery cycles can significantly increase the number of cycles before failure, as the depth of discharge is a significant stress factor in battery degradation (Xu et al., 2018). In the baseline scenario and the small battery scenario, the charging behavior is HIVE'd default: taxi agent looks for charging when the range is less than 50km, or the vehicle has a range buffer of no more than 20km above the distance of the nearest charging station. In the shallow charging scenario, the charging behavior was changed so that the SOC does not reach below 60%. In all scenarios, the upper SOC is 80%, as only DC charging is considered in this study. In DC charging, the charging rates slow down dramatically past the 80% mark, so vehicles are charged only to 80% in the simulations.

Basic simulation inputs

Trip Demand - For the HIVE simulation, we use NYC yellow cab trip data from March 2, 2013. This was the busiest day of the busiest month of 2013. This data was extracted from the University of Illinois at Urbana-Champaign's New York City Taxi Trip Data (2010-2013) (Donovan & Work, 2016). Unlike more recent datasets of New York City taxi data, this dataset has precise pickup and drop-off coordinates, necessary inputs to HIVE. Only Manhattan trips were considered to hone in on the urban core's high demand, yielding 490,505 data points.
Fleet size - The same trip dataset provided vehicle medallion data, identifying 12,612 active vehicles for the selected day.
Drivers shifts and home locations - Following Moniot et al. (2022) shift start times and drivers' home locations were randomly allocated within to NYC boroughs to partly reflect the distributions of drivers' home locations in the 2018 Taxi and Limousine Commission Factbook TLC (2018), except for the fact that our simulation assumes that all drivers resided within NYC. Vehicle shift durations were randomly drawn from a shifted and rescaled beta distribution.
Charging infrastructure All charging ports are modeled as 50 kW DC fast chargers and our simulation assumes that these are the only charging facility available to the driver. Charging station locations are assumed to coincide with hexagonal areas of approximately 2 square miles, obtained with Uber's H3 (hex resolution 7).

Integration of simulation and optimization

To investigate the optimal charging infrastructure configuration the above-mentioned scenarios, we integrated the HIVE simulator above with the location-allocation charging infrastructure optimization. The simulation generates ubiquitous charging demand, and the optimization identifies the charging station location and the number of chargers at each station to satisfy this demand aggregated over time intervals of a size allowing a full charge in each scenarios. An adaptive search was implemented to fine-tune parameter M (i.e., the maximum level of chargers per station) for each scenario. The is involved in iterating between the simulator and optimizer to identify the minimum M, allowing trip serve rates above 95% and average charging queue times up to 15 minutes in the simulation. Figure 1 depicts the iterative approach adopted.

3 Results and discussion

Table 1 shows the charging infrastructure requirements and costs and the *initial lithium demand* for the fleet in the three scenarios. Figure 2 shows how the charging infrastructure is spatially

[1] Uber H3 is an s an open-source Hexagonal hierarchical Geospatial indexing system to partition Earth Surface into hexagonal cells, https://h3geo.org/

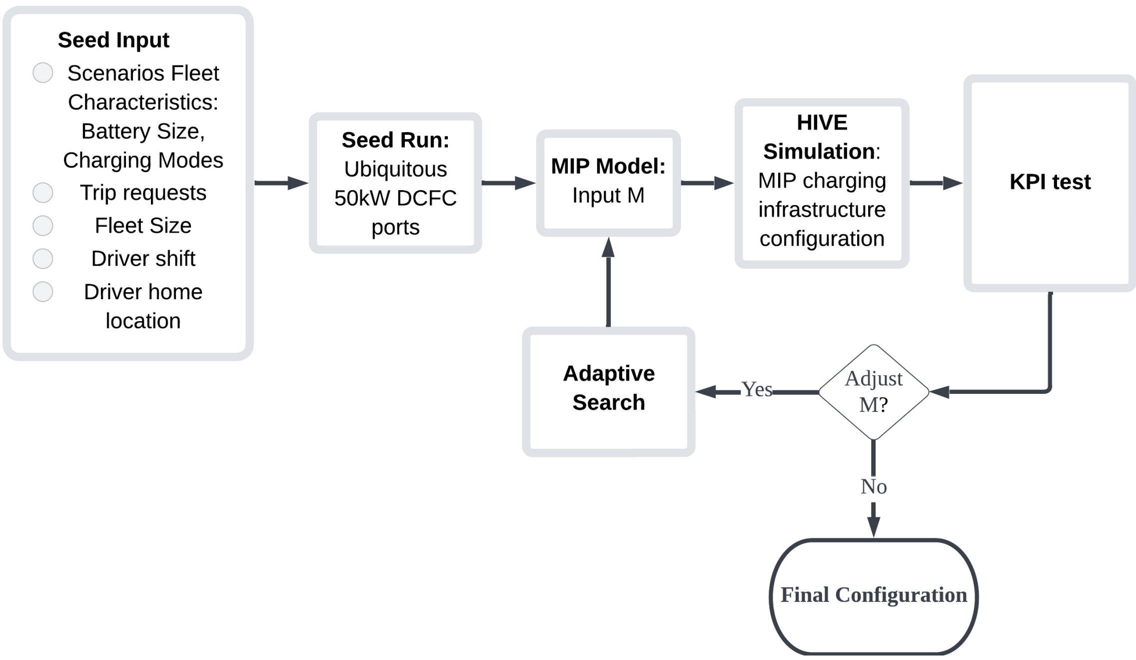

Figure 1: Iterative approach

distributed. We define the *initial lithium demand* as the total lithium used in the fleet operating in a day in our simulation, i.e., not over a long time period, which would require accounting for battery degradation in a life-cycle assessment. The initial lithium demand is calculated under the assumption that LFP batteries are used in all scenarios; these have an intensity of 0.09 kg/kWh.
The small battery scenario requires half of the lithium of the other two scenarios but requires 21% more chargers than the baseline scenario. It also requires 14% more chargers than the shallow charging scenario. This is surprising considering that to allow a State of Charge (SOC) fluctuation between 60% and 80%, the shallow charging scenario implies a usable battery capacity of 10 kWh. This lower total number of chargers in the shallow charging scenario might be the result of the higher M. To enable the fleet performance KPIs to be met, the shallow charging scenario requires a less stringent limit on the number of chargers per station location than the small battery scenario, perhaps leading to a lower total number of chargers but a higher chargers' concentration in the central areas of Manhattan. Nevertheless, further investigations to explain this counter-intuitive result are required.
The comparison between these scenarios suggests that limiting the initial lithium demand by battery downsizing requires a higher infrastructure investment. Without considering battery life implications, the initial cost savings for smaller battery vehicles could offset this greater infrastructure investment. Considering a \$153/kWh cost for a vehicle battery pack (VTO, 2023), and assuming that other capital cost components of the vehicles are fixed, the vehicle cost savings in the small battery scenarios are \$48M. These savings are well above the the increase in charging infrastructure costs for the small battery scenario compared to the baseline and shallow charging scenarios, respectively: \$14.7M and \$9.2M. It should be however noted that, over the long term, more battery replacements in the small battery vehicle fleets, due to likely shorter battery lives, might make battery downsizing a less cost-effective lithium-saving strategy than what appears from these initial analyses.
Table 1 also shows that shallow and small battery scenarios are characterized by more charging and discharging cycles than the baseline scenario over the simulation day than the baseline scenario. A higher number of cycles per unit of time means that the battery's end of life occurs earlier. However, a deep DoD of charging cycles accelerates the battery degradation. So, both the small battery and baseline scenario will reach a capacity fade of 20%, considered the end of life for an EV battery, in fewer cycles than the shallow charging scenario. Hence, an in-depth analysis considering battery life is paramount for an assessment of the long-term lithium demand for the fleet. In particular, battery replacement needs over operational horizons of several years (e.g. 10, 15, or 20 years) need to be quantified. This further analysis, which requires detailed battery degradation models, is left to future work.
The analyses completed so far demonstrate that reducing the lithium intensity of mobility fleets

requires considering the trade-offs between fleet investment and infrastructure investment. Our discussions of such analyses and the results in terms of the mean depth of discharge and the mean number of charging-discharging cycles in each scenario highlight the need for a comprehensive evaluation of the long-term effects of battery degradation implied by the alternative strategies for lithium demand intensity mitigation we considered.

	Baseline Scenario	Small Battery Scenario	Shallow Charging Scenario
Chargers per station limit (M)	116	109	142
Total Chargers	1356	1646	1441
Installed capacity, MW	67.8	82.3	72.05
Infrastructure cost, M$	67.7	82.4	73.2
Initial lithium use, metric ton	56.8	28.4	56.8
Average number of daily charging-discharging cycles (*)	1.1	2.3	3.73
Mean cycles depth % of full charge	72	69	21

Table 1: Charging infrastructure requirements and initial lithium use for each scenario. (*) Charging-discharging cycles are approximately counted as the number of charging events.

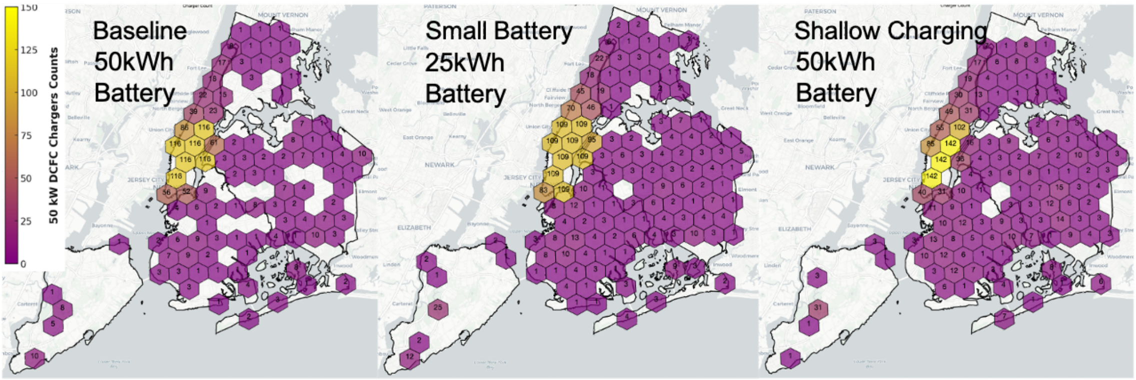

Figure 2: Charging infrastructure configurations in the three scenarios

4 Conclusions

This study analyses the charging infrastructure implications of strategies for mitigating the lithium demand of an electrified New York City taxi fleet. Our analyses reveal that decreasing the initial lithium intensity of mobility fleets requires careful consideration of trade-offs between fleet and infrastructure investments. As battery downsizing affects battery cycling in fleet vehicles, impacting battery lifespans, further research is needed to evaluate the long-term effects on lithium consumption resulting from battery downsizing and charging dispatching rules that mitigate battery stress.

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