Electrification of mobility on-demand vehicle services: infrastructure and fleet design, operations, and policy recommendations

by

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Abstract

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To avert catastrophic climate change, society must rapidly shift to decarbonized forms of transportation; recent reductions in the cost of batteries has made battery electric vehicles (BEVs) a promising alternative. Meanwhile, mobility on-demand vehicle (MODV) services have grown explosively in recent years, in some cases threatening targets for local air pollution and global carbon emissions. Mobility on-demand is a novel form of transportation that represents a shift from private ownership to commodification, in which users request transportation services for individual trips via smartphone apps. Despite evidence that these services are ripe for electrification, adoption of BEVs in fleet applications has been even slower than in the private market. In this dissertation, I combine agent-based simulation with empirical methods to identify pathways for rapidly electrifying MODV services, including requirements for charging infrastructure and battery range, routing strategies, and regulatory tools.

In Chapter 1, using taxi trip data from New York City, I develop an agent-based model to predict the battery range and charging infrastructure requirements of a fleet of shared automated electric vehicles (SAEVs) operating on Manhattan Island. I also develop a model to estimate the cost and environmental impact of providing service, and I perform extensive sensitivity analysis to test the robustness of my predictions. I estimate that costs will be lowest with a battery range of 50-90 miles, with either 66 chargers per square mile rated at 11 kilowatts or 44 chargers per square mile rated at 22 kilowatts. I estimate that the cost of service provided by such an SAEV fleet will be \$0.29-\$0.61 per revenue mile—an order of magnitude lower than the cost of service of present-day Manhattan taxis and \$0.05-\$0.08/mi. lower than that of an automated fleet composed of any currently available hybrid or internal combustion engine vehicles (ICEVs). I estimate that such an SAEV fleet drawing power from the current NYC power grid would reduce GHG emissions by 73% and energy consumption by 58% compared to an automated fleet of ICEVs.

In Chapter 2, I build on this analysis to study the electrification of ridesourcing services (also known as transportation network companies, or TNCs) in the U.S. in the present day. Ridesourcing/TNC fleets present an opportunity for rapid uptake of battery electric vehicles (BEVs), but adoption has largely been limited to small pilot projects. Lack of charging infrastructure presents a major barrier to scaling up, but little public information exists on the infrastructure needed to support ridesourcing electrification. With data on ridesourcing/TNC trips for New York City and San Francisco, and using agent-based simulations of BEV fleets, I show that given a sparse network of three to four 50kW chargers per square mile, BEVs can provide the same level of service as ICEVs at lower cost. This suggests that the cost of charging infrastructure is not a significant barrier to ridesourcing/TNC electrification. With coordinated use of charging infrastructure across vehicles, I also find that fleet performance becomes robust to variation in battery range and charger placement. My analysis suggests that mandates on ridesourcing/TNCs, such as the California Clean Miles Standard, could achieve electrification without significantly increasing the cost of ridesourcing services.

In Chapter 3, I shift to look at real-world barriers to MODV electrification based on empirical data. Leveraging over two weeks of high-resolution GPS and battery data from almost 20,000 EVs in the all-electric Shenzhen taxi fleet, I analyze the potential to improve fleet-wide operations by optimizing both the location and timing of vehicle charging. I construct machine learning models to predict travel time, queuing time at charging stations, and charge consumption by time of day. Contrary to the emphasis on charging station siting in the literature, I find that optimizing charging locations would have a relatively limited impact. Instead, providing drivers with better real-time information about queuing times at charging stations, and enabling flexibility in battery charge during shift changes could reduce down-time per vehicle by over 30 minutes per day, while increasing the number of economically viable charging stations by over 50%. Moreover, taking full advantage of break periods and nighttime to charge could reduce downtime per vehicle by over one hour per day, reducing revenue losses due to charging by roughly 90%. These results are verified with evidence from real-time charging station data and driver shift-change data.

Contributions:

This dissertation contributes to the knowledge of sustainable transportation engineering through advances in theory, methodology, and empirical results that can help guide MODV electrification policy and implementation world-wide. Previous literature has claimed that MODV services are hard to electrify due to challenges with battery range and charging. In particular, operations research literature has used rigid models that either do not accurately reflect real-world constraints or require BEVs to operate in the same way as ICEVs. I hypothesize that allowing vehicles to charge during short windows in between trips and relocating to new areas to anticipate demand can greatly increase BEV fleet performance. To test this hypothesis, in Chapter 1 I develop a novel agent-based modeling method in the field of operations research, including a new theoretical approach to fleet rebalancing based on the equivalence between efficient demand forecasting and retrospective assignment. I hypothesize that by having vehicles "look back in time" to relocate to areas with unmet demand and to charging stations in the present, the model can evaluate minimum requirements for fleet size, battery range, and charging infrastructure with a fraction of the computational cost of other approaches. To test this hypothesis, I also developed a fleet rebalancing framework based on demand forecasting and show that the retrospective approach returns equivalent results in much less time.

As a result, I show that BEVs can provide MODV service at scale and at lower cost than gasoline vehicles with present-day technology, while resulting in more rapid reductions in air pollution and greenhouse gas (GHG) emissions than comparable investments in private vehicle electrification. By maximizing flexibility in the design, this method also enables application to new environments, as explored through the development of a national scale model at the end of Chapter 1, and a TNC-specific model in chapter 2.

Previous studies and pilot projects have found that there is insufficient charging infrastructure to support TNC electrification, in part because this infrastructure is prohibitively expensive. I hypothesize that the cost of charging is largely driven by usage rates, such that efficiently operated TNC fleets can drive down the cost of public fast charging for all users. To test this hypothesis, in Chapter 2 I develop a simple theoretical approach to estimating requirements for TNC charging infrastructure based on driver wage rates, driving speeds, and relocation times. I then adapt the model developed in Chapter 1 to show that drivers do in fact have sufficient idle time to charge, and that charging infrastructure is relatively cheap given reasonable usage rates.

Finally, chapter 3 applies these analyses to current BEV taxi operations in Shenzhen, China, where drivers have complained of lost revenue and long queues at charging stations. Based on my previous findings, I hypothesize that simple strategies to improve operations could greatly reduce these problems. Whereas previous studies have conducted analyses based on incomplete vehicle data, I integrate qualitative methods from in-person interviews (n=30) with quantitative insights from analysis of multiple detailed datasets, web scraping and machine learning in an interdisciplinary approach. I hypothesize that such a mixed-methods approach would result in more nuanced findings than any one method could provide on its own. I show that reduced revenue from BEVs results from irrational charging behavior that can be mitigated by simple software and policy interventions. In turn, I find that real-time data collection and analysis efforts are crucial to efficient MODV electrification.

Policy recommendations from this dissertation include establishing firm electrification targets to catalyze investment in fast-charging infrastructure; establishing citywide open data platforms to integrate real-time data on vehicle trajectory, battery charge, and charger availability; and providing drivers and companies with training on best charging practices. Such capabilities may also require labor policy reform to incentivize fleet operators to manage their drivers' charging behavior. In turn, digitization enabled by fleet electrification holds the potential to enable a host of smart urban mobility strategies, including integration of public transit with innovative transportation systems and emission-based pricing policies. As a number of cities worldwide move toward fully electrified MODV fleets, this analysis has large-scale implications for decarbonized, cleaner urban areas.

Limitations and directions for future research: This dissertation does not explore how changes in vehicle supply and cost may impact trip demand. I have conducted a variety of sensitivity analyses to ensure my results are robust to changes in trip demand, but this is a topic that deserves further examination in the future. Similarly, I have not analyzed how changes in fleet operation or trip demand might impact congestion, which was critical to enabling computational efficiency and geographic flexibility. I have made a variety of conservative assumptions to counteract this omission, such as slightly increasing travel times and giving trip requests a 10-minute buffer, but future work should address this topic more thoroughly. Future work should also expand geographic scope, especially focusing on issues specific to suburban and rural settings. I have not closely examined the impact of vehicle charging on the power grid or potential benefits coordinated charging might provide. Future work should also seek to incorporate charging activity by other types of BEVs, such as private vehicles and taxis, while further exploring behavioral factors that influence charging decisions, such as availability of rest places and food, opportunities to meet friends and other drivers, and range anxiety.

Finally, this study does not deeply analyze impacts on social equity, which deserves further analysis in future research. Academics, social justice advocates, and policymakers must work to ensure these new technologies help redress past and present injustices rather than exacerbating them or merely maintaining the status quo.

To my parents,

my first and forever advisers

much love

Table of Contents

List of Figures

List of Tables

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Finally, many thanks to my parents, my brother Aaron, and my beloved partner, Samira, for providing unconditional love, guidance, affirmation and support, not least during these past few months of quarantine during the COVID-19 pandemic.

Preface

This dissertation combines work from five papers that have been published in academic peer-reviewed journals. In four of the five cases I was the lead author, developing and communicating the research as the main contributor. In the last case, Sheppard et al. (2019), the research I led and have included in this dissertation served as a key component to a larger project. References to each article are listed here:

Bauer, G.S., Greenblatt, J.B., Gerke, B.F., 2018. Cost, Energy, and Environmental Impact of Automated Electric Taxi Fleets in Manhattan. Environ. Sci. Technol. https://doi.org/10.1021/acs.est.7b04732

Sheppard, C., Jenn, A., **Bauer, G.S.**, Gerke, B., Greenblatt, J., Gopal, A., 2019. A Joint Optimization Scheme for the Planning and Operations of a Regional Electrified Fleets of Ride Hailing Vehicles Serving Mobility on Demand. Transp. Res. Rec. 1–19. https://doi.org/10.1177/0361198119838270

Bauer, G.S., Phadke, A., Greenblatt, J.B., Rajagopal, D., 2019. Electrifying urban ridesourcing fleets at no added cost through efficient use of charging infrastructure. Transp. Res. Part C Emerg. Technol. 105, 385–404. https://doi.org/10.1016/j.trc.2019.05.041

Bauer, G.S., Zheng, C., Shaheen, S., Kammen, D.M., 2020. Leveraging Big Data and Charging Coordination for Effective Taxi Fleet Electrification: A Case Study of Shenzhen, China, in: Transportation Research Board 2020 Annual Meeting. Transportation Research Board, Washington, D.C.

Bauer, G.S., Zheng, C., Greenblatt, J.B., Shaheen, S., Kammen, D.M., 2020. On-Demand Automotive Fleet Electrification Can Catalyze Global Transportation Decarbonization and Smart Urban Mobility. Environ. Sci. Technol. https://doi.org/10.1021/acs.est.0c01609

Introduction

In the following section, I provide an overview of the challenges and policies regarding transportation electrification. I then discuss the emergence of mobility on-demand vehicle (MODV) services, and the potential synergies with electrification. Finally, I provide a brief introduction to each subsequent chapter, including previous studies and key contributions.

Transportation electrification

Transportation is entering a period of transformative change. Transportation represents the fastest-growing source of the world's greenhouse gas (GHG) emissions, with passenger cars accounting for close to a sixth of carbon dioxide emissions,[1] and car sales set to more than double by 2050.[2] To meet the 2-degree and 1.5-degree targets established in the Paris Agreement, transportation must shift rapidly to low-carbon technologies.[2,3] In the U.S., transportation recently became the single largest source of GHG emissions. Emissions have grown by over 20% since 1990, while emissions from almost all other sectors have decreased or remained constant.[4]

Battery electric vehicles (BEVs) have emerged as a market-ready technology with the potential to reduce the carbon intensity of private transportation,[5,6] and costs are falling to the point where BEVs may become cheaper than internal combustion engine vehicles (ICEVs) for private use within the next five to ten years.[1] BEVs could reduce transportation-related carbon emissions and urban air pollution,[6,7] but despite years of strong public support, several barriers have slowed adoption.[8,9] BEVs typically have higher upfront cost than similar conventional and hybrid vehicles, and they provide a shorter driving range.[10,11] Consumers worry about the safety and reliability of new technologies like batteries and electric motors.[8,9] Charging infrastructure incurs additional cost, and the vast majority of public charging infrastructure consists of Level 2 chargers,[12] which require several hours to fully recharge longer range BEVs. Public DC fast charging requires much less time (providing 60–80 miles of range in 20 minutes),[13] but relatively few fast-charging stations are available, and low utilization increases charging costs.

Meanwhile, car ownership and vehicle-miles traveled (VMT) are projected to increase several fold by 2050, potentially leading to massive increases in energy consumption.[14] My previous research has suggested that providing incentives for personal BEVs may lead to significant rebound effects in both vehicle ownership and usage.[15]

Furthermore, focusing on electrifying privately owned vehicles ignores the fundamental inequities of this system. While low-income neighborhoods are often burdened with greater air pollution, BEVs are disproportionately owned and driven by residents of higher-income neighborhoods.

In California in particular, there has been increasing focus on improving accessibility of BEVs to low- and moderate-income groups. Low-income customers are eligible for an additional $2,500 rebate when trading in an older car for an EV. In addition, SB350, which established the zero-emission vehicle (ZEV) mandate for 2030, also required that the California Air Resources Board study ways to overcome barriers to ZEV access for low-income customers. A 2018 executive order from Governor Jerry Brown also expanded ZEV incentives for low-income groups, including targeted investment in charging infrastructure.

But resolving transportation inequity will also require shifting away from a system based primarily on private vehicle ownership. For many households, ownership represents a major financial burden, but today's transportation system often makes owning a vehicle a prerequisite to accessing jobs, education, healthcare, and food. As shown in Figure 1, travel by private vehicles dominates across all income groups, but lower levels of vehicle ownership lead to greatly reduced travel among low income households. Yet, due to fixed costs that make up a large proportion of the cost of vehicle ownership, low-income households that own vehicles spend a higher fraction of their income on transportation and each mile they drive costs more (as shown in Figure 2).

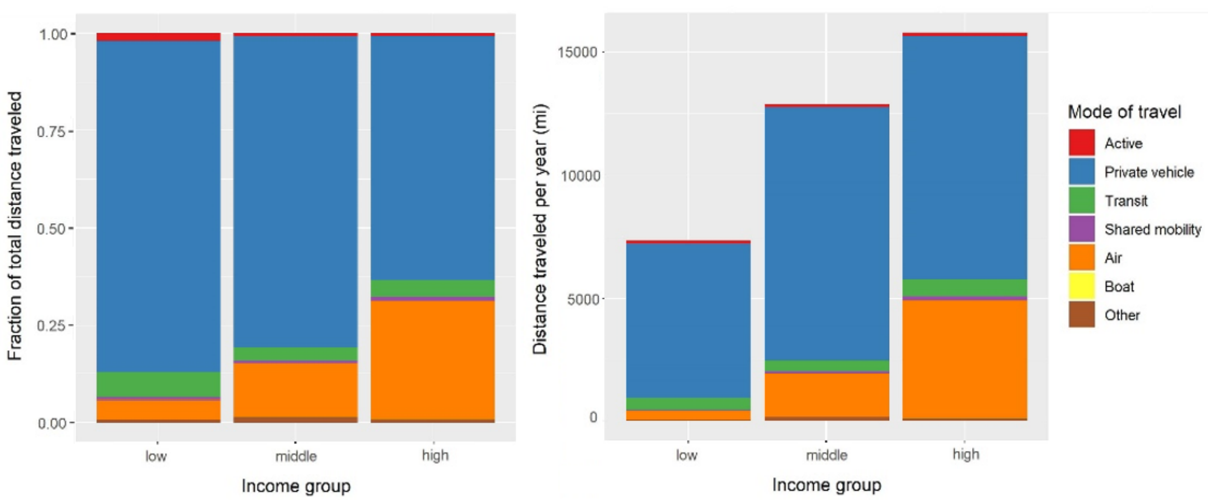


Figure 1. Mode share and distance traveled by mode and annual household income group (low < $35,000, middle $35,000 - $75,000, high > $75,000). Data from the 2017 National Household Travel Survey (NHTS).[16]

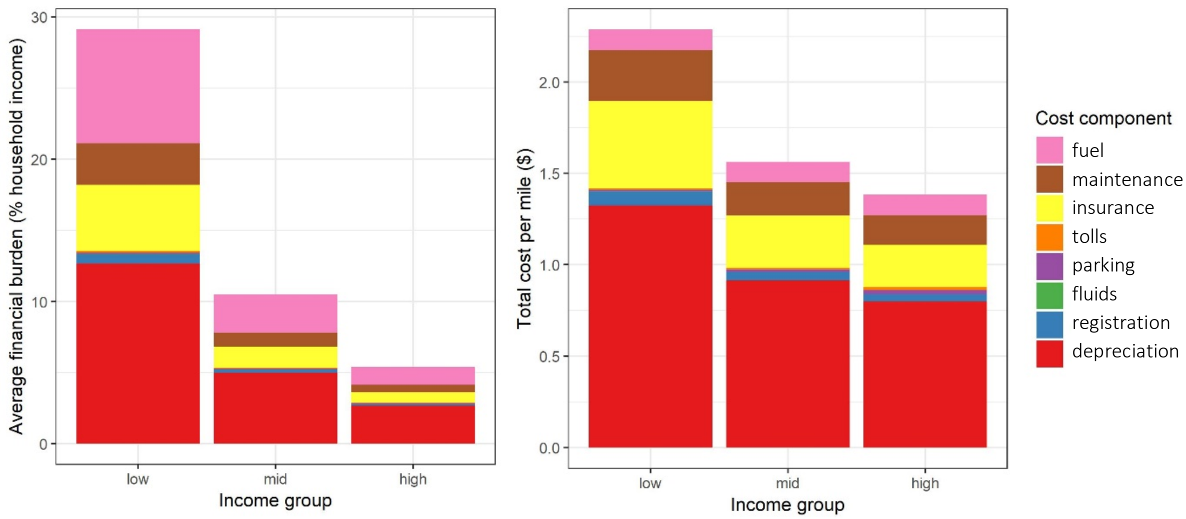


Figure 2. Financial burden and cost per mile of vehicle ownership and operation by cost component and income group (same boundaries as in Figure 1). Analysis based on data from NHTS, Kelley Blue Book,[17] and Consumer Expenditures Survey.[18]

Mobility on-demand and the "three revolutions"

Meanwhile, the market for personal mobility is changing rapidly. Innovative mobility concepts and strategies, from bikesharing and carsharing systems to innovative demand response bus and shuttle services, are providing travelers with new, flexible, and tailored transportation options. The widespread adoption of smartphones has enabled the rise of a new form of transportation, the "mobility on-demand" (MOD) platform, in which users order transportation services for an individual trip via smartphone apps.[19–23] MOD is based on the transformation of transportation modes and trips into interchangeable commodities with comparable costs and benefits, including price, trip duration, wait time, and comfort. In other words, MOD converts transportation into a marketplace where companies match vehicles and drivers with consumers in need of travel; this can also include e-commerce. This marketplace requires system operators, which can lend itself to implementation of various transportation demand management strategies to improve social outcomes such as equal access and reducing traffic congestion.[24]

Arguably, early versions of MOD have existed for decades in the form of carsharing[25] and carpooling[26] services, but it has gained increased traction and attention since the advent of transportation network companies (TNCs), also known as ridesourcing and ridehailing,[1] which typically leverage digital marketplaces to connect travelers to drivers who provide prearranged and on-demand transportation services in private vehicles for compensation.[22] TNCs entered the mainstream with the launch of Lyft and Sidecar in San Francisco around 2012, and they have since spread around the globe, providing service similar to taxis but eclipsing them in many markets. More recently, MOD has expanded to include shared micromobility – i.e., shared bikes

[1] Note that the term ridehailing was coined by the media and does not clearly distinguish between taxis and TNCs/ridesourcing, so these latter two terms are preferred and will be used exclusively in subsequent sections.

and scooters – and microtransit, a technology-enabled transit service that typically uses shuttles or vans to provide on-demand or fixed-schedule service with either dynamic or fixed routing.[22,27] These latter services have gained rapid adoption: as of May 2018, there were almost 50,000 shared bicycles in the United States.[28] Especially with the advent of the COVID-19 pandemic, they may become an important feature of urban transportation in the future – for example, and the collapse of public transit ridership may lead to an increased use of microtransit in some places to provide a more flexible service model. Also, there are early indications that shared micromobility may be growing in part due to its ability for travelers to maintain social distancing. The global pandemic may also be contributing to longer shared micromobility trips, enabling new use cases.

Similarly, goods delivery services such as Amazon, UPS, along with grocery and restaurant food delivery services like Uber Eats and Instacart, have become an increasingly important element of the MOD ecosystem. As people make fewer trips and remote work facilitates more suburban and rural living, goods delivery will likely continue to grow rapidly in the coming decades. Meanwhile, advances in automation technology and drone delivery will likely further increase the affordability and "on-demand" nature of these services.[29]

This diversity of on-demand transportation modes has given rise to a related by separate concept called mobility as a service (MaaS) in which travelers can access a range of different modes through a single platform and subscription.[28] MaaS will likely be an important part of the sustainable transportation future, but it falls outside the scope of this dissertation.

In this dissertation, I focus on a subset of MOD services using automobiles, which I term "mobility on-demand vehicle" (MODV) services, to distinguish from MOD services without automobiles, such as shared micromobility. These services include both TNCs and e-hail for taxis, as well as microtransit. Furthermore, while many of the insights also apply to goods delivery services, the focus of my work is on passenger transportation services.

Although MODV services currently represent a relatively small share of all vehicle miles traveled, the sector has experienced explosive growth in recent years,[30] largely due to advances in technology, changes in consumer patterns, and a combination of other economic, environmental, and social forces.[28] Some forecasts expect the global market to increase almost three-fold by 2030.[22,31] In some emerging economies with low labor costs such as India and South Africa, these services already represent over 10% of vehicle kilometers traveled (VKT). In several megacities in emerging economies, MODV services represent over one third of VKT (see Table 1 for sources and calculations). With urban areas expected to add 2.5 billion people by 2050, urban sustainability will be a defining challenge of the 21st century, and MODV services will represent a key element.[32] While the ongoing COVID-19 pandemic has drastically reduced MODV ridership, this trend has been partially offset by increases in demand for delivery services,[33] and ridership will likely rebound as the pandemic subsides.

Another technology on the horizon that could disrupt this trend and enable MODVs to dominate the transportation market is vehicle automation.[34,35] Automation could lead to a series of cascading impacts on transportation and urban form, like allowing many consumers to sell their personal vehicle and rely on MOD services, and the conversion of parking spaces to increase network capacity or access for non-motorized modes; conversely, increased comfort of travel could increase suburban sprawl as people become willing to move further from their work.[36] Over a dozen pilot projects are underway in the U.S. exploring the use of automated vehicles in MODV fleets. All of these projects operate only within a restricted geographic area, and most require safety drivers in the vehicles at all times, but the technology could progress rapidly in coming years.[28]

Table 1. Summary of data used to determine fleet VKT proportion in select locations.

Location	Fleet VKT	Total automobile VKT	% fleet	Sources
		Nations		
China	142B taxi km/yr + 48.8B pkm Didi * 2 km/pkm = 236B km/yr	15k km/yr/veh * 250M veh = 3.75T km/yr	6	[37] [38] [39] [40]
India	1.3B TNC trip/yr * 4 total/TNC * 7 pkm/trip * 2 km/pkm = 73B km/yr	12k km/veh/yr * 33M veh = 396B km	16	[41] [42] [43] [44]
South Africa	450k R/yr/veh * 20 R/mi * 200k veh * 2 km/pkm = 14B km/yr	17M hh * 0.3 veh/hh * 16600 km/veh/yr = 83 B km/yr	14	[45] [46] [47]
Germany	56k vehicles * 50k pkm/veh * 2 km/pkm = 5.6B km/yr	14k km/yr/veh * 64M veh = 893B km/yr	0.6	[48] [49]
England	62mi/p/yr * 56M ppl * 2 total/passenger * 2 (TNC + taxi)/taxi = 22B km/yr	38M vehicles UK * 7k mi/yr * 56M ppl England/66M ppl UK = 370B km/yr	6	[50] [51]
USA	38B pkm/yr * 2 km/pkm	3.2T km/yr	2	[30]
		Cities		
Delhi	150k veh * 100k km/yr = 15M km/yr	3M veh * 10k km/yr = 30M km/yr	33	[52]
Beijing	100k veh * 100k km/yr = 10M km/yr	6M veh * 10k km/yr = 60M km/yr	14	[53]
Mexico City	140k taxi * 100k km/yr * 2 total/taxi = 28M km/yr	5M veh * 10k km/yr = 50M km/yr	36	[54]
Bangkok	140k taxi * 100k km/yr * 2 total/taxi = 28M km/yr	5M veh * 10k km/yr = 50M km/yr	36	[55]
Cairo	80k taxi * 100k km/yr * 2 total/taxi = 16M km/yr	2M veh * 10k km/yr = 20M km/yr	44	[56]

Meanwhile, recent studies have shown that ridesourcing can increase both GHGs[57] and congestion.[58] Without rapid decarbonization, the corresponding growth in transportation emissions could easily offset carbon reductions in other sectors. Local governments are increasingly concerned by ridesourcing's adverse emissions impacts,[59] and BEVs offer a potential solution.

As shown in Table 2, several countries have enacted policies to pursue MODV electrification. California has set a timeline to set target reductions in TNC emission intensity,[60] and India has announced a ban on sales of new fossil-fuel vehicles for use in commercial fleets after 2026.[61] In California, the public utility commission is tasked with establishing targets for emissions reductions for ridesourcing companies,[62] Uber has announced that all its vehicles in London will be electric or hybrid by 2025,[63] and Lyft has set a goal of 1 billion autonomous electric rides per year by 2025.[64] In addition, 15 countries have announced sunset dates on new fossil-fuel vehicle sales.[65]

Table 2. Summary of on-demand automotive fleet electrification policies around the world.

Location	Policy	Year	Notes	Source
Oslo, Norway	Electrification mandate	2023	100% taxi fleet electrification	66
Amsterdam, Netherlands	Electrification mandate	2025	100% taxi fleet electrification	67
Washington D.C., USA	Pilot project	2019	127 EV drivers, many complaints	68
New York City, USA	Electrification mandate	2013, 2020	Conducted pilot project with 5 BEVs in 2013 and planned to electrify one-third of taxi fleet by 2020; no progress made	69
India	Electrification mandate	2026	All new commercial vehicle sales must be electric, 40% of TNC fleets	61
Nagpur, India	Pilot project	2018	200 drivers given EVs, planned 50 charging piles at four locations but only 12 built. Most drivers reverted to fossil-fuel vehicles	70
Costa Rica	Electrification mandate	2035, 2050	70% bus and taxi electrification by 2035, 100% by 2050	71
London, UK	Electrification mandate, emissions fee	2018-2025	New taxis must be electric starting in 2018, emission-based congestion zone expanding in 2021, Uber plans to be fully electric by 2025	72
Medellin, Colombia	Electrification mandate / pilot project	2022	1,500 of 20,000 taxis will be electric	73
California, USA	Emissions mandate	2020-2023	Establish baseline for TNCs in 2020, establish targets by 2021 deadlines every two years starting in 2023	60
Bogota, Colombia	Electrification mandate	2025	50% electric taxis (progress not updated since pilot project in 2015)	74

Previous studies have suggested that MODVs represent a ripe market for the adoption of battery electric vehicles (BEVs), with the potential to overcome the barriers and inequities discussed above and drive a step-change in transportation electrification. Vehicles used for MODV services accumulate mileage more quickly than vehicles used for personal purposes only, such that BEVs used for ridesourcing can provide greater benefits to vehicle owners due to lower costs per mile,[75,76] and they provide better returns on public electrification investments in terms of reduced carbon emissions and air pollution per vehicle.[77] My previous research has suggested that due to higher utilization and more rapid vehicle turnover, a complete shift to shared electric fleets could have a greater impact on cumulative emissions reductions from transportation than complete electrification of the personal vehicle market combined with rapid grid decarbonization.[78] This impact does not include the potential for shared fleets to increase penetration of renewable energy sources on the power grid by shifting load to different times of day.

In addition, because ridesourcing vehicles are typically driven in urban cores, ridesourcing BEVs could increase public health benefits, especially in disadvantaged communities, while exposing many consumers to the technology, which might increase private BEV sales.[79,80] The focus on dense urban areas and short trips can also help overcome barriers related to limited battery range and long charging times.[8,75,81,82]

MODV services also offer a new potential pathway to providing ZEV access to low-income groups, through electric shared mobility services offered by ridesourcing companies. Previous studies have shown that taxis can improve access for low-income families without cars,[83,84] but at great expense. Ridesourcing services have been shown to serve more diverse groups than taxis,[23,85] and low-income groups are much more likely to use ridesourcing than to own a BEV, adopting pooled ridesourcing at similar rates to other income groups.[86] However, barriers still remain, including access to smartphones and electronic finance, distrust of outsiders,[84,87] and other non-monetary factors.[88,89]

The convergence of automation, ridesourcing, and electrification has been coined the "three revolutions,"[90] resulting in a new form of transportation called shared automated electric vehicles (SAEVs).[91] Previous studies have estimated that SAEVs deployed in 2030 could reduce GHG emissions per mile by more than 90% relative to privately owned conventional vehicles while substantially reducing cost.[75] It is possible that such cost savings will increase overall vehicle miles traveled as a result of induced demand, but some studies have predicted that the efficiency gains would outweigh any resulting potential increases in emissions.[81]

But the nature and magnitude of these impacts is hardly inevitable. In particular, without effective policies, these technologies could do little to change the status quo, leading to a future where ever-increasing travel offsets any improvements in efficiency, resulting in worse congestion and pollution. In this dissertation, I propose to study the social and environmental impacts of shared fleets, as well as the barriers stopping the use of electric vehicles in taxi and ridesourcing fleets today. I test the hypothesis that if electrified and operated in a coordinated way, taxi fleets hold the potential to overcome these barriers and drive dramatic increases in transportation electrification.

Outline and key contributions

Chapter 1:

My initial research focuses on a future where advances in automation technology have enabled the use of shared automated electric vehicles (SAEVs).[92] SAEVs would offer on-demand transportation in electric and self-driving cars similar to the service provided by current transportation network companies such as Uber and Lyft but likely at much lower cost and carbon intensity. Because each SAEV need only have enough seats (known as "right-sizing," see below for details) and battery range for the trip requested, and charging can be split over many short periods in between trips, they could enable the use of smaller cars with shorter battery range, overcoming the barriers of slow charging speed and high capital cost.[75,93]

Several previous studies have employed agent-based modeling techniques to explore the feasibility of a fleet of automated taxis operating in an urban environment.[92,94–100] Building on these results, I develop an agent-based model to predict the system costs of a fleet of SAEVs operating in New York City (NYC). Manhattan is a good test case because it is likely one of the world's best-suited cities to implement an SAEV fleet. With 1.6 million people living in an area of 23 square miles, it is also the most densely populated region in the U.S. Car ownership in Manhattan is both challenging and expensive; average household vehicle ownership in Manhattan is about 0.3 vehicles,[101] compared with 1.9 in the U.S. as a whole.[102] As a result, taxi usage is relatively high—taxi trips currently represent about 8% of all daily trips taken by Manhattan residents.[103]

Previous studies have shown that electric taxi fleets are viable options under certain circumstances. However, those studies have chosen fixed values for various fleet parameters. To my knowledge, ours is the first study that explores a variety of vehicle, operational, and infrastructure parameters to identify the fleet configuration with lowest cost, and the corresponding environmental and energy impacts. In contrast to previous work, my analysis also assumes that taxis can relocate to charge whenever they are idle, which may reduce both the required battery range and overall cost as well as the impact of the vehicle fleet on the power grid. Furthermore, instead of assuming that batteries will be replaced on a fixed schedule, I study the optimal battery replacement schedule by investigating the impact of battery degradation on the number of taxis required to serve demand. Including this flexibility in my model allows me to make substantive recommendations regarding how SAEV fleets should be designed, the greatest barriers facing implementation, and how the impact of this technology might differ from adoption of personal BEVs.

Results: I estimate that costs will be lowest with a battery range of 50-90 miles, with either 66 chargers per square mile rated at 11 kilowatts or 44 chargers per square mile rated at 22 kilowatts. I estimate that the cost of service provided by such an SAEV fleet will be \$0.29-\$0.61 per revenue mile—an order of magnitude lower than the cost of service of present-day Manhattan taxis and \$0.05-\$0.08/mi. lower than that of an automated fleet composed of any currently available hybrid vehicle or ICEV. I estimate that such an SAEV fleet drawing power from the current NYC power grid would reduce GHG emissions by 73% and energy consumption by 58% compared to an automated fleet of ICEVs.

Key contributions:

Theoretical – Current notions in business, policy, and research contend that BEVs require long battery range and fast charging, both of which lead to higher costs. On the contrary, I hypothesize and test in the MODV context, more efficient operations enable shorter battery range and slower charging, such that BEVs can serve demand at lower cost than ICEVs with present-day technology. In particular, because MODV services are dominated by short-distance trips and fleets are sized to meet peak demand, I hypothesize that each vehicle may only need enough battery range to serve a single trip and often will have time to recharge in between trips.

Previous studies in operations research have looked at the performance of BEV fleets using agent-based models, but these models have failed to simulate efficient fleet operating strategies, employing only rigid and simplistic fleet rebalancing strategies. For example, Chen et al. (2016) and Loeb et al. (2018) only allowed vehicles to charge when they did not have enough range to serve a trip, while Bischoff and Maciejewski (2014) only allowed vehicles to charge while waiting at a taxi stand. Hu et al. (2018), Yang et al. (2017), and Jia et al. (2018) assumed each BEV must serve the same trajectory as a present-day ICEV, and that charging would only occur when the taxis currently had idle time.

These simplistic assumptions have resulted in the false conclusion that BEVs inevitably will increase cost. In part these models' simplicity comes from constraints on computational resources. I hypothesize that a more flexible modeling structure can enable simulating efficient fleet operation at low computational cost, and so reveal the true potential for MODV electrification.

Methodological – I develop a novel agent-based modeling framework, employing "retrospective" rebalancing to efficiently assign a fleet of shared vehicles to serve mobility demand, and show that this method is equivalent to an efficient demand forecasting algorithm. I apply this new modeling framework to study the case of electrifying taxi operations in Manhattan. I also couple the simulation with a model to evaluate cost and environmental impact, along a model predicting battery degradation. Finally, I develop a method for optimizing fleet size and battery capacity to minimize total cost, given that battery lifetime is determined by the amount batteries are oversized relative to minimum required range, which in turn is a function of fleet size.

Empirical – I find that given efficient operations, BEVs can serve demand at lower cost than any ICEV or hybrid vehicle, while greatly reducing cost, GHG emissions, and air pollutants.

Chapter 2:
The results of Chapter 1 beg the question, why aren't MODV fleets already electrifying? In particular, in this chapter I focus on modeling pathways to ridesourcing electrification. Early efforts at ridesourcing electrification have experienced mixed results. In a London pilot project, Uber found that over 80% of BEV drivers lacked access to home charging, and insufficient public infrastructure prevented drivers from serving as many rides as they could with ICEVs.[79] Elsewhere, ridesourcing BEV drivers have reported declining rides because their vehicles lacked sufficient charge as well as losing revenue owing to time spent charging and looking for charging stations.[104,105] In a pilot in South Korea, BEV taxis provided a much lower benefit-to-cost ratio compared with natural-gas-powered taxis because of limited charging infrastructure and battery range.[106] In China, electric taxi drivers exhibit significant range anxiety, driving

relatively short distances between charging events.[107] In Beijing, researchers found that EV taxis with 130 to 160 km of battery range travel only 118 km per day, compared to 250 km for conventional vehicles, suggesting that they do not earn nearly as much revenue.[108] In Hong Kong, surveys with taxi drivers and owners revealed that both the location of chargers and charging time are two of the most important factors affecting perception of BEV adoption.[109] In India, the TNC company Ola launched a highly publicized pilot with BEVs in the city of Nagpur but ended the project prematurely due to driver strikes arising from long queues at charging stations and lost revenue.[70]

While it is thus evident that ridesourcing electrification will require convenient and inexpensive public fast-charging charging infrastructure, there is limited public information regarding optimal infrastructure design and BEV fleet operation. Wood et al. (2018) built an optimization model of a hypothetical ridesourcing fleet in Columbus, Ohio, based on GPS data from cell phones.[110] However, these data did not distinguish ridesourcing trips from trips taken by other modes, and the authors assumed that all drivers have access to home charging, whereas ridesourcing electrification in major cities likely will depend on public charging as discussed above. Ke et al. (2019) developed an optimization model to study scheduling of charging sessions in an electric ridesourcing fleet but did not base their analysis on real-world data and did not incorporate spatial constraints in the model.[111] Tu et al. (2019) analyzed current trajectories of ridesourcing vehicles in Beijing and found that ubiquitous Level 2 charging at all driver homes and dwell locations would be required to electrify 90% of the fleet, but the authors did not account for the possibility that BEVs could have different trajectories than ICEVs.[112]

This study builds on the work discussed in Chapter 1 by extending the agent-based model to present-day ridesourcing fleets in San Francisco and New York City, which incorporates flexibility as to when drivers relocate to charge. Previous studies have determined charging and trip assignment separately, leading to much less flexibility in the timing of charging than if the two are determined simultaneously. Also, most previous studies have only allowed vehicles to charge when battery range falls below a threshold, and they have required vehicles to remain charging until at full capacity.[96,98,113,114] I hypothesize that flexibility both in terms of when to charge and the extent of charge may be even more important for ridesourcing than for other BEV applications, because the vehicles return to the drivers' homes at the end of shifts, where charging stations may not be available. This hypothesis is consistent with Keskin and Çatay (2016), who found that allowing partial-charge sessions improves electric fleet performance.[115]

Results: I show that given a sparse network of three to four 50kW chargers per square mile, BEVs employed in TNC fleets can provide the same level of service as ICEVs at lower cost. This suggests that the cost of charging infrastructure is not a significant barrier to ridesourcing electrification. With coordinated use of charging infrastructure across vehicles, I also find that fleet performance becomes robust to variation in battery range and placement of chargers.

Key contributions:

Theoretical – Previous studies and industry reports have argued that TNC operations are challenging to electrify due to the lack of fast charging infrastructure, and that drivers lose revenue when they go to charge. On the contrary, I hypothesize that due to the nature of TNC operations: a) TNC drivers have sufficient time in between trips to charge without losing revenue; and b) cost of charging is largely dependent on usage rates, and MODV services can provide sufficient charging demand to fund the development of public fast-charging infrastructure.

Methodological – To test the above hypothesis, I develop an approach to estimating charging infrastructure requirements and the opportunity cost of charging based solely on wage rates, driving speed, and relocation distances. I then apply and extend the modeling framework developed in Chapter 1 to analyze the cost and barriers to electrifying present-day TNC operations in both New York City and San Francisco. This effort includes integration of survey data regarding driver earnings, shift lengths, and commute distances. I also develop new methods for modeling different charger siting strategies and fleet operational capabilities.

Empirical – I find that electrification does not necessarily result in increased cost, and that long charging times do not inevitably lead to revenue losses given that drivers only spend a fraction of their shift serving trips. I find that providing drivers with information regarding charger availability and future demand reduces requirements for both charging infrastructure and battery range.

Chapter 3:
Naturally, simulation can never capture all of the barriers experienced in real-world implementation. In this final chapter, I turn my focus to Shenzhen, China, where the taxi fleet has already been completely electrified. To build a sustainable roadmap for taxi electrification that can be adapted and adopted elsewhere, the Shenzhen electric fleet must provide the same level of service as a conventional fleet at low cost and with significant carbon benefits. Local interviews conducted with drivers and reports in the media suggest, however, that time spent charging – in some cases over three hours per day – results in lost revenue, compounded by problems with queuing at popular charging stations.[116]

In this chapter, I use over two weeks of GPS and battery state of charge (SOC) data from about 20,000 electric taxis in Shenzhen to evaluate the potential of different interventions to the problems described above. The data come from January, May, and June 2019, and they consist of snapshots taken every five minutes from each vehicle. Using these data, I develop several machine learning models to predict operational characteristics of the taxi fleet and present a framework for how this modeling platform can be implemented in practice.

In particular, I analyze the impact of four proposed interventions that could reduce the charging burden: 1) optimizing the location of charging stations to minimize travel time to charging stations, 2) optimizing the dispatch of vehicles to charging stations to minimize both travel and queuing times, 3) shifting more daytime charging to early morning hours when demand for taxi trips is low, and 4) shifting charging to times when vehicles are idle. I conduct simulations to estimate and compare the potential impact of these various interventions on fleet performance, driver revenue, and charging infrastructure use. Finally, using one day of driver shift-change data, I compare the performance of groups of drivers with different charging patterns to verify the simulation results.

Results: Contrary to the emphasis on charging station siting in the literature, I find that optimizing charging locations would have a relatively limited impact. Instead, providing drivers with better real-time information about queuing times at charging stations, and enabling flexibility in battery charge during shift changes could reduce down-time per vehicle by over 30 minutes per day, while increasing the number of economically viable charging stations by over 50%. Moreover, taking full advantage of break periods and nighttime to charge could reduce downtime per vehicle by over one hour per day, reducing revenue losses due to charging by roughly 90%. These results are verified with evidence from real-time charging station data and driver shift-change data.

Key contributions:

Theoretical – BEV taxi drivers in Shenzhen have complained of lost revenue and long queues at charging stations, leading the media to report that BEVs are not ready for widespread adoption in MODV services. Based on my previous findings, I hypothesize, test, and demonstrate that simple strategies to improve operations (i.e., showing drivers accurate estimates of queue times at each charging station and encouraging drivers to charge during breaks and nighttime) could greatly reduce these problems. I also hypothesize, test, and demonstrate that such strategies will require a mixed-methods approach combining insights from both qualitative and quantitative research methods. I employ a range of qualitative and quantitative methods to demonstrate this: semi-structured interviews, big data analysis, web scraping, machine learning, and simulation.

Methodological – I integrate driver interviews (n=30) with web scraping, data analysis and machine learning techniques to conduct a mixed-methods analysis of barriers to taxi electrification in Shenzhen, China, and evaluate the impact of potential solutions.

Empirical – I find that simple software and policy interventions could greatly reduce revenue losses currently caused by electrification, decreasing queue times at charging stations while shifting charging activity to times of day when vehicles are currently sitting idle. In turn, I find that real-time data collection and analysis efforts are crucial to efficient MODV electrification.

Chapter 1:
Simulation of Shared Automated Electric Vehicle (SAEV) fleets serving urban mobility

1.1. Introduction

In both the literature and public discourse, common perception holds that BEVs are currently inferior to conventional vehicles because a) the high cost of batteries leads to limited range and higher upfront cost, and b) relatively slow re-charging times make usage in high-mileage contexts infeasible.[8,117] My collaborators at LBNL and I hypothesize that with shared fleets, these barriers can be overcome because a) vehicles need only enough battery range to serve individual trips, which are typically less than 10 miles, and b) vehicles can use idle time between trips to re-charge. To test this hypothesis, I built an agent-based simulation framework to route shared vehicles to serve trips and to charge, and tested the performance of a variety of fleet scenarios using real-world data from Yellow Cabs in Manhattan.

Several previous studies have employed agent-based modeling techniques to study taxi fleets, but most focus on self-driving cars, and few have modeled BEVs.[94,95,99] Of those that do consider BEVs, the charging relocation strategy is typically either absent or simplistic. Chen et al. (2016) and Loeb et al. (2018) only allowed vehicles to charge when they did not have enough range to serve a trip, while Bischoff and Maciejewski (2014) only allowed vehicles to charge when at taxi stands. Hu et al. (2018) studied the feasibility of electrifying Yellow Taxis in NYC, defining "feasibility" as able to serve 99% of the same trips as an ICEV. They found that only 7% of the fleet could be electrified with current charging infrastructure, and half of the fleet could be electrified by installing approximately 400 additional charging stations. However, the authors did not consider charging congestion or relocation times after charging. They also placed several restrictions on when the vehicles could charge, such as being within half a mile of the nearest station. Yang et al. (2017) simulated electrification of taxis in Beijing to determine optimal charging siting, but they assumed charging would only occur when the taxis currently had idle time, i.e., they did not allow for relocation to charging stations. Similarly, Jia et al. (2018) used this data to simulate trip chains of distance equal to electric taxis' assumed range (150km), and used the end points of these chains to estimate optimal locations for charging stations.

Fagnant and Kockelman[94] developed an agent-based model of self-driving conventional taxis on a 10 mi. by 10 mi. grid network (16 km by 16 km), and found that shared vehicles could serve all trips with roughly one-tenth of the number of vehicles, and only 10% additional miles from vehicle relocation, resulting in GHG savings of about 5%. In a subsequent study, the group used MATsim to model a more realistic grid network based on the Austin, Texas metropolitan area, and obtained similar results.[95] Chen et al. extended this model to look at the impact of electrifying this self-driving taxi fleet, and found that taxis with a battery range of 80 miles (129 km) could replace about three vehicles each, while increasing the battery range to 200 miles (322 km) resulted in a replacement ratio of over five to one.[92] A deeper analysis of this model determined that shifting from Level 2 (240V, AC, 7 kW) to Level 3 charging (480V, DC, 50 kW) increases vehicle replacement to 5:1 and 7:1, respectively.[96] It was estimated that this electric fleet would cost between $0.40-$0.50/mi. ($0.25-$0.31/km) to operate, and capture as much as a third of overall travel mode share.[96]

Meanwhile, Bischoff and Maciejewski[97] used the MATSim framework to model 50 electric taxis serving 5% of inner city travel demand in a small city in Poland, with 50 kW fast chargers at each taxi stand. They found that electric taxis can serve demand just as well as conventional vehicles during normal demand conditions, but may incur negative impact during periods of high demand. Building on these results, they developed a cost model to determine the feasibility of a fleet of electric taxis in Berlin, assuming one charger for every 10 taxis, all charging at 50 kW (i.e. level 3 DC fast charging), and battery replacement every second year.[98] Their main finding was that under these circumstances, electric taxis could only become cost-competitive with conventional vehicles if the cost of electricity falls below 0.20€/kWh or battery warranties improve.

Burns et al.[103] used three case studies to investigate the environmental and travel impacts of shared automated mobility systems, including a study of New York City taxis. They found that customer wait time and empty vehicle miles decrease exponentially with fleet size, such that a fleet of 9,000 shared automated vehicles (about two-thirds the size of the current taxi fleet) could serve all Manhattan yellow taxi trips with a mean wait time of less than one minute.

1.2. Methods

1.2.1 Taxi trip data

All trip data for my analysis were downloaded from the NYC OpenData 2015 database of yellow taxi trips. For most of my simulation runs, Wednesday, February 4, 2015 was used as a typical weekday (415,249 total trips) during the winter months when demand is at its highest. To test for stability over time as well as the impact of higher demand on two consecutive weekends, the simulation was also run with trip data for a 10-day period, February 6-15, 2015. To test the impact of fluctuations in seasonal demand (taxi demand is somewhat lower during summer months), this longer-period simulation was repeated using data from August 7-13, 2015. Figure 3 shows the total daily number of NYC taxi trip requests for all of 2015, whereas Figure 4 shows the number of trip requests by hour across an average week. Table 3 summarizes descriptive statistics of baseline simulation results.

Table 3. Summary statistics of simulation results over 24 hours

	Minimum	Lower quartile	Median	Mean	Upper quartile	Maximum
Number of charging events per vehicle	2	11	13	13.13	16	29
Number of trips served per vehicle	4	22	26	25.48	29	47
Relocation time per charging event (min)	0	3	4	4.95	5	32
Relocation distance per charging event (mi)	0	0.3	0.4	0.79	0.6	14
Relocation time per trip (min)	0	0	0	2.414	4	51
Relocation distance per trip (mi)	0	0	0	0.33	0.4	17.9
Trip durations (min)	0	7	11	12.64	17	59
Trip distances (mi)	0	1	1.5	1.9	2.4	21.9
Duration of charging events (mi)	1	3	7	16.55	18	299
Time spent charging per vehicle (min)	0	175	215	213.4	259	437
Trip distance served per vehicle (mi)	24.4	91.3	101.1	99.9	110	153.7
Time spent serving trips per vehicle (min)	163	644	700	681	740	892
Distance relocated per vehicle (mi)	5	21.7	26.1	26.44	30.7	56.7
Time spent relocating per vehicle (min)	39	161	184	184.4	209	315
Wait times (min)	0	0	0	2.148	4	10

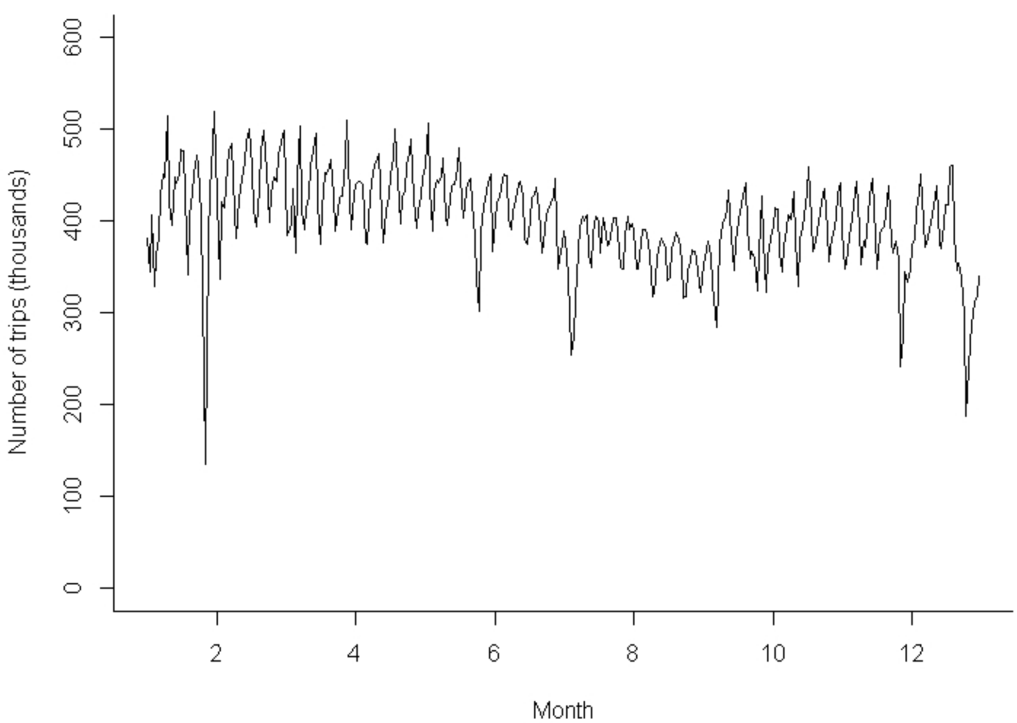


Figure 3. Number of taxi trips by day of the year.

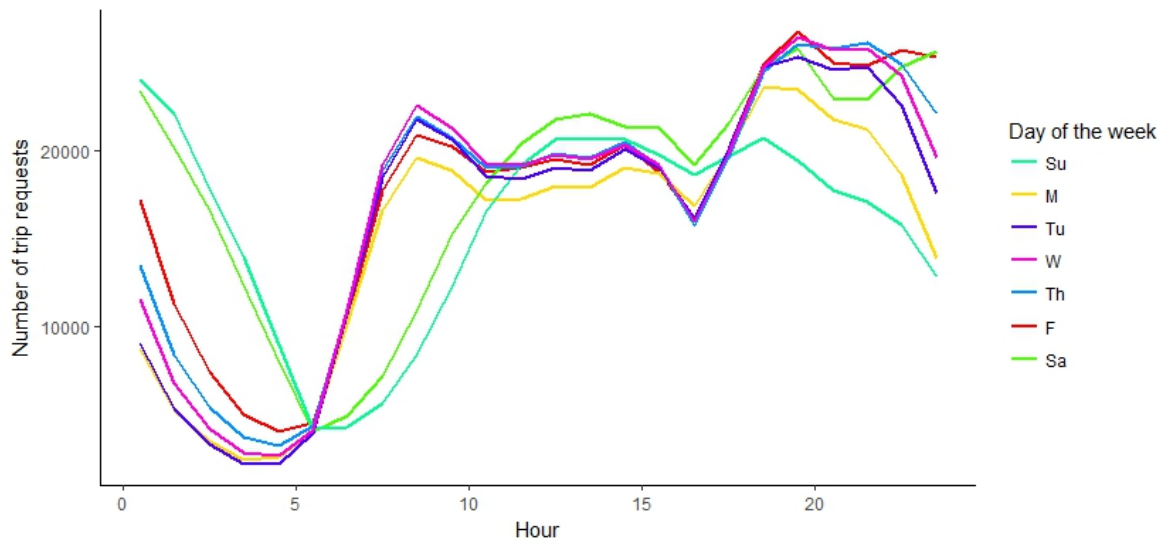


Figure 4. Demand profile during each hour of the day, for each day of the week.

As with current pilot projects,[120] automated vehicles will likely need to remain within a defined geo-fenced area for the foreseeable future (i.e., level 4 automation),[121] so, for both realism and computational simplicity, the data set was restricted to trips that both started and ended on Manhattan Island. Trips outside of Manhattan would presumably be served by a different fleet entity, as they largely are today by Green Cabs.[122] Removing trips falling outside these boundaries on my representative day left me with 349,026 trips or 84% of total demand. Other potential limitations of level 4 automation (inclement weather, accidents, road construction, etc.) fall outside the scope of this study.

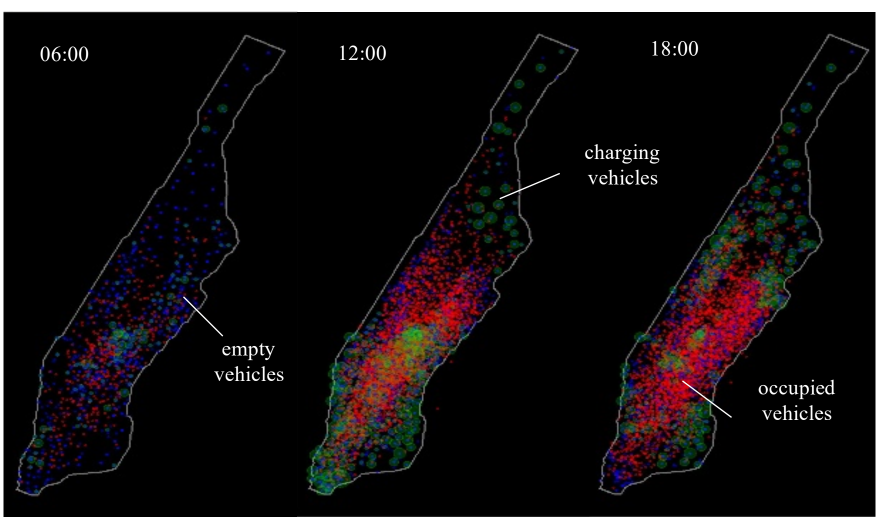


Figure 5. Snapshots of simulation activity at three different times of day. Red dots show vehicles serving trips, blue dots show empty vehicles, and green circles show charging stations with the size denoting the number of vehicles charging there. An animation of a 48-hour taxi trip simulation model run can be found at https://youtu.be/gQgIjuN2gDY.

The data retrieved from NYC OpenData contain starting and ending trip times, geolocations, and distances for all taxi trips, but do not include times and distances that taxis traveled between drop-offs and pickups. To estimate these data, Google Maps API was used to retrieve bidirectional times and distances for a 498-point set of points of Manhattan (248,004 point pairs), which were then used to interpolate values for a total of 4,482 points approximately representing each street corner. To account for congestion, Google Maps was used to estimate times and distances for a subset of 50 points (2,500 point pairs) at every hour of the day, which were then used to extrapolate delays for the rest of the data set. This data was verified by running simulations with random error based on correlation to trip times and distances in the taxi dataset, and found my estimates to be conservative.

As shown in Figure 6, of the three data sources I used for relocation times, Google Maps with traffic prediction had the best correlation with times taken from the taxi trip data, with an r-squared value of 0.62 and a standard deviation of 5 minutes. Distance predictions were somewhat better, with an r-squared value of 0.85 and a standard deviation of 0.6 mi. Both distances and times predicted by Google were slightly longer on average than those reported in the taxi dataset (0.2 mi. and 2 minutes, respectively), which I considered conservative because SAEVs will likely drive less aggressively than NYC taxi drivers.

To test the impact of this error on results, I performed several simulations in which relocation datasets were multiplied by an error distribution matrix with a mean of one and standard deviation of 0.3 (equivalent to the 5-minute standard error shown above). As shown in Table 4, both normally distributed and gamma-distributed errors consistently produced fleets that were 10-15% smaller than simulations with the baseline relocation matrix. I hypothesize that this result stems from the fact that trip assignment prioritizes the closest taxi, and multiplying by error matrices increases the likelihood that some taxi will be more close by (others will be further away, but this does not affect the result). In turn, reducing relocation times reduces the over number of vehicles required to serve demand. Thus, I consider my baseline results to provide conservative estimates of cost of service. Note that the smaller fleet sizes resulted in significantly more empty miles, as taxis tend to be further from trip requests (distance error was not correlated with time error, since error in times was assumed most likely due to congestion).

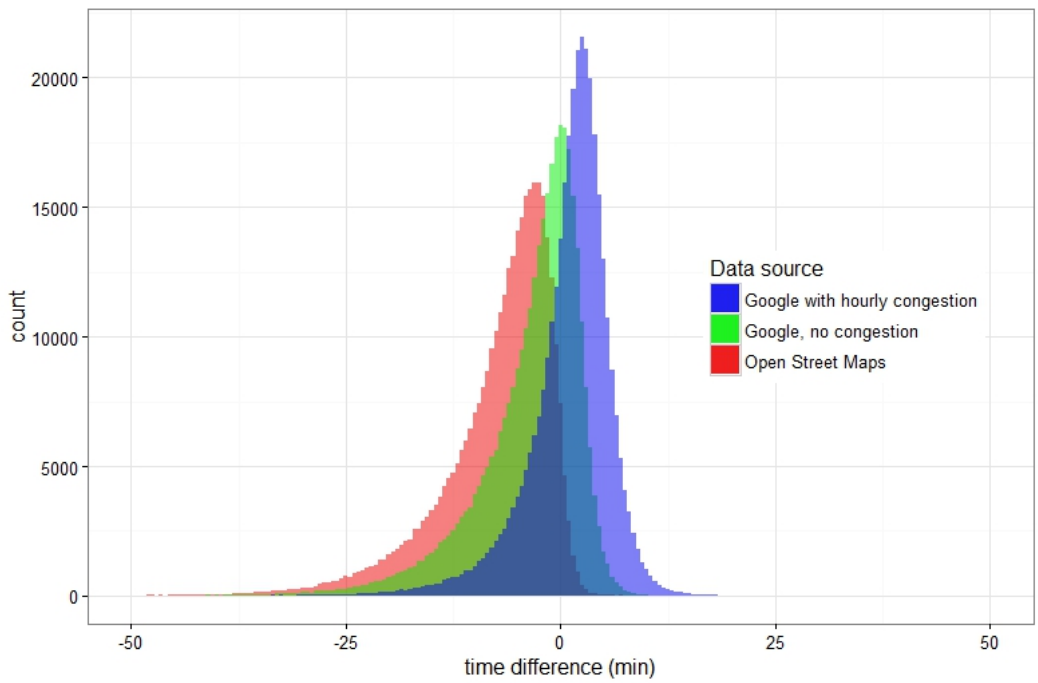


Figure 6. Distributions of the difference between travel times predicted by Google Maps API and OSRM, and those given for passenger trips in the actual taxi dataset.

Table 4. Simulation results with modifications to relocation matrix

Relocation error	Battery range (mi.)	Chargers	Charging stations	Charging power (kW)	Fleet size	Empty miles (% of total)
Baseline	100	2000	500	7	6553	20
Normal	100	2000	500	7	5709	35
Normal	100	2000	500	7	5689	35
Normal	100	2000	500	7	5711	35
Gamma	100	2000	500	7	5981	23
Gamma	100	2000	500	7	5980	23

1.2.2 Taxi routing model description

Using the R coding platform version 3.3.3, I developed an agent-based model to simulate the movement of taxis around Manhattan throughout the day. This model has since been named Routing and Infrastructure for Shared Electric vehicles (RISE), and has an open-source license through Lawrence Berkeley National Laboratory. Agent-based modeling is well-suited to my research question because as compared to other analysis techniques, it allows for more realistic interaction between vehicles, passengers and charging stations, and easy modification of various assumptions such as strategies for charging, trip assignment, and vehicle relocation.[123]

The model proceeds chronologically, assigning taxis to trips in each minute throughout the day. Trip timestamps are used to represent the time when the trip was requested via a smartphone app, and priority is given to the first trip requested within the minute. The model assigns to each trip the closest available taxi that has at least enough range to both serve the trip and then make it to the closest charging station. In cases where more than one taxi meets these criteria, the model assigns the taxi with the greatest battery range. Given that Uber has already become the single-largest taxi service in NYC,[124] and industry experts predict that automation will give further monopoly power to large fleets,[125] I assume that all trip assignments are managed by a single operator.

To assess a constant level of service across all model runs, I chose 10 minutes as the maximum amount of time a passenger would be willing to wait between trip request and pickup. If no taxi is able to reach a trip request within this window, a new taxi is created to serve the trip. As such, the simulated taxi fleet grows gradually over the course of the day, and the simulation is designed to produce the minimum number of taxis required to serve the demand given constraints in battery range and charging infrastructure. It is assumed that "created" taxis represent vehicles that had been idle up until that point in the day.

To manage vehicle relocation between trips, I assumed that the fleet operator would have a well-trained algorithm to predict the spatial distribution of future trip demand and efficiently route taxis between trips when necessary, to ensure vehicles are located within a 10-minute radius of trip requests whenever possible. Assuming perfect foresight, in cases where no taxi can reach a trip request within 10 minutes, the model allows taxis to start relocating as soon as they ended their previous trips. For example, a taxi that had been idling for five minutes could, within the 10-minute tolerance window, reach trips requests up to 15 minutes away. This assumption was verified with simulations that managed vehicle relocation based on historic trip data, and I explore the impact of changing relocation algorithms in my sensitivity analysis (see below for details). In reality, relocation times will be stochastic, such that some trips will not be served within the 10-minute threshold. In this study I use 10 minutes merely as a benchmark for comparison between different fleets; real-world fleet operators must weigh the value of decreasing wait times against the cost of increasing fleet size.

1.2.3 Charger routing simulation

In between trips, taxis must also decide whether or not to drive to a charger. Again assuming accurate demand prediction, in each minute, each taxi identifies the charging locations where it could have driven and spent enough time charging to at least replenish the energy expended to get there. It is assumed that chargers are automated (either wireless or employing a robotic arm), such that vehicles begin to charge as soon as they arrive at a station. Each vacant charging point accepts the closest feasible taxi that has not already been assigned and is then designated as occupied until the taxi either accepts a trip request or its battery is fully charged. Note that this method differs significantly from previous models because it allows taxis to charge for very short periods in between trip requests instead of waiting to run out of charge and then remaining at a charger until the battery is fully charged. My hypothesis is that this method allows for greater flexibility in charging, thus allowing the system to adjust to both shorter battery ranges and dynamic electricity pricing. In my simulations, the empty miles that taxis spent relocating to charge and to pick up passengers represented about 20-25% of passenger miles, or about 25 miles per vehicle per day. While this is significantly more than that found by other studies, over half of trips are served by vehicles less than 0.1 mi. away, so I expect that increased empty miles are an artifact of the short average distance of Manhattan taxi trips (1.9 mi.; see below for more details). Simulations of a fleet of ICEVs suggest that empty miles are almost the same as for an electric fleet, so I do not expect that electrifying Manhattan's taxi fleet would increase congestion.

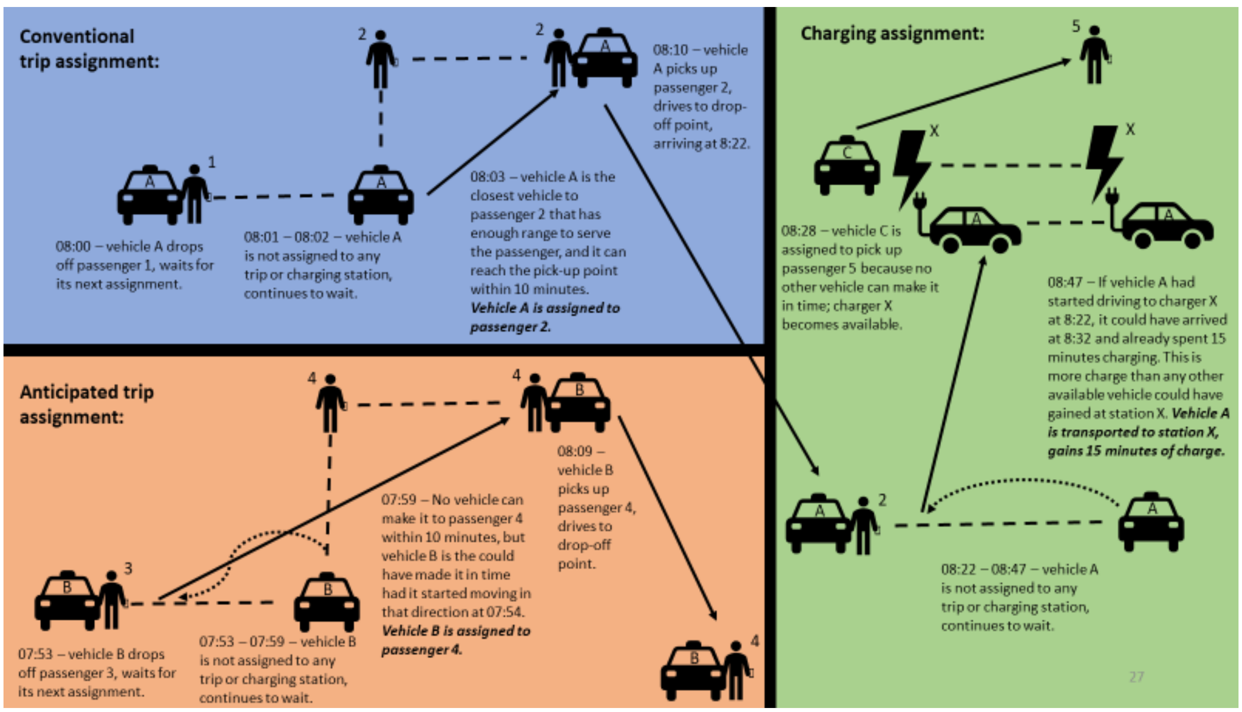


Figure 7. Schematic describing original RISE vehicle routing algorithms.

1.2.4 Charger distribution model

To rationally populate my model with a network of chargers, I used an elimination method, starting with all possible charging points and iteratively removing the location whose absence caused the least impact on the system. In an initial simulation, taxis charged whenever idle, no matter where they were located. This initial iteration was run with several different battery ranges, and it was found that the charger distributions produced with 20-mile battery range resulted in the smallest fleet sizes. For each location, the algorithm then calculated the total amount of charging time that would be lost if all the taxis at that point were forced to relocate to the next nearest point with chargers, and the charging location with the lowest loss was removed. The chargers at that location were transferred to the next nearest point and the process was repeated. By removing the lowest-loss location in each iteration, this algorithm runs the risk of missing a globally optimal solution that could entail a different combination of removal steps. To protect against falling into a locally optimal but globally suboptimal solution, 100 points were randomly added back each time the algorithm had removed 500.

After synthesizing each distribution of charging locations, I ranked the importance of each individual charger by calculating the amount of time for which it was occupied on the simulated day. When limiting the number of individual chargers, chargers were removed in order of occupancy time, from least to most.

As shown in Figure 8, I compared the simulation results from four different strategies for synthesizing the charging network, using two dichotomies: whether the charging infrastructure synthesis algorithm described in the methodology was applied to the charging locations or to each station individually, and whether the initial network was obtained from a simulation using a battery range of 20 miles, or 100 miles. Based on these results, in order to minimize the number of taxis, I ran all simulations using the charging network based on a 20-mi. range fleet with the network selected by locations. Six of these distributions are displayed in Figure 9.

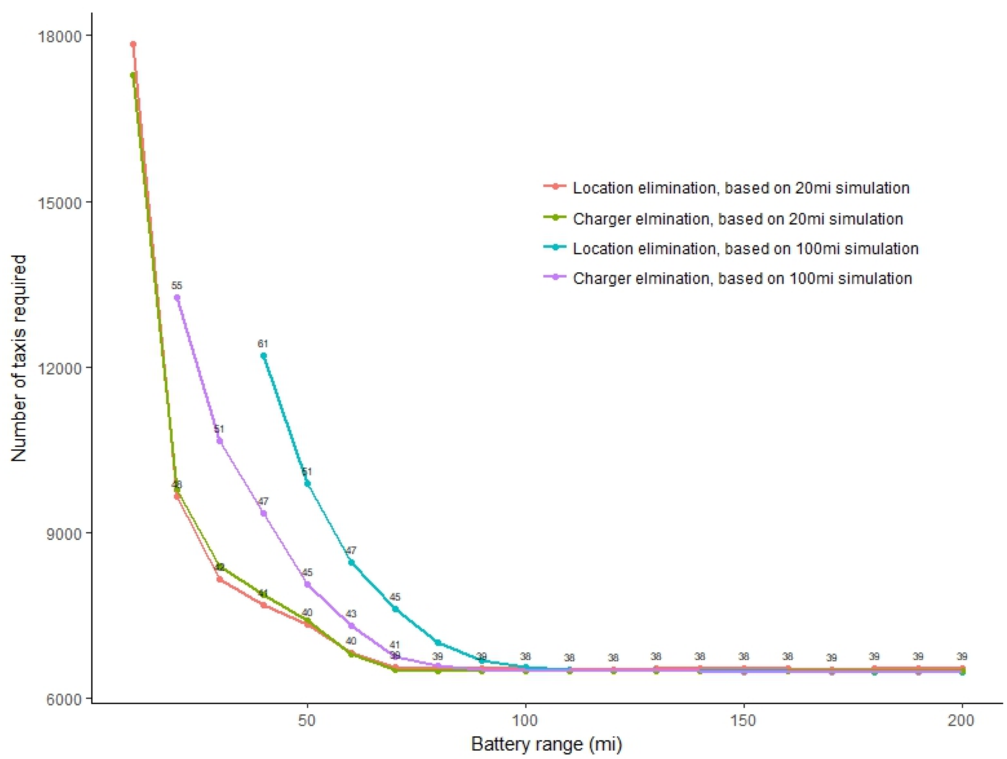


Figure 8. Comparison of simulation results from four different charging networks using different rules to rank charging stations. Numbers show the cost of the fleet in cents per mile served.

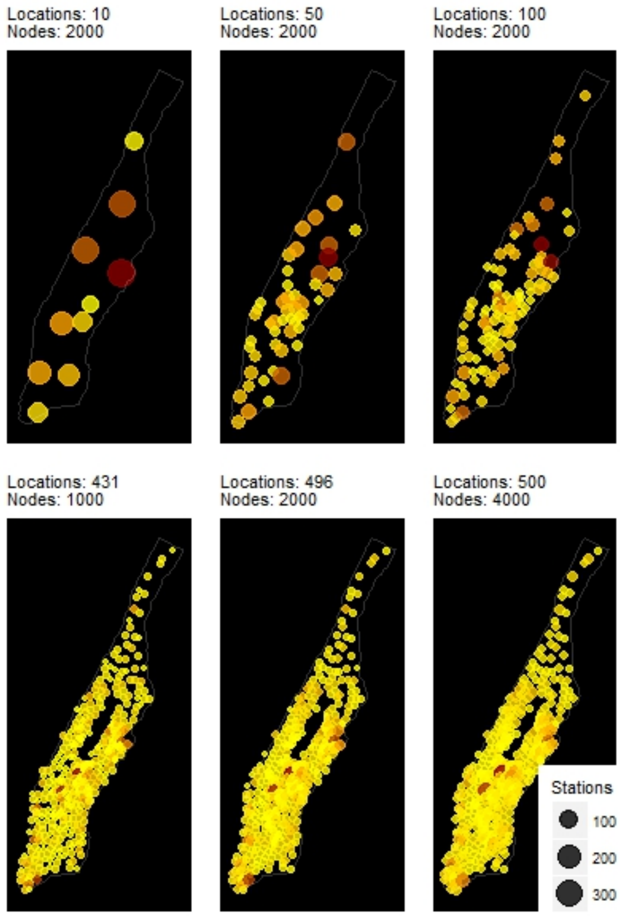


Figure 9. Distributions of charger stations with varying number of locations (first number) and total stations (second number). Size represents the absolute number of charging stations at a given point, while color represents the number relative to other points in the distribution.

1.2.5 Battery degradation model

As shown in Equation 1, degradation is composed of two parts: calendar loss, and cycle loss.[126]

$$Q_{loss,\%} = k_1 e^{k_2 I} Ah + k_3 e^{-E_a/RT} t^{\frac{1}{2}} \qquad (1)$$

The parameters k_1 and k_2 are quadratic functions of temperature (approximately 0.0008 and 0.4 at 20°C, respectively), while k_3 is a constant equal to 14,876 days$^{-0.5}$. *Ah* is charge throughput (expressed in cumulative ampere-hours), *I* is current (expressed in C-rate, the fraction of total capacity discharged per hour), E_a is the activation energy (24.5 kJ/mol), *R* is the ideal gas constant (8.314 J/mol/K), and *t* is time in days. For temperature (*T*), I made the simple assumption that battery temperature is held constant at 20°C while driving to optimize performance, and used an overall average of 15°C to calculate calendar loss, given that temperature will fall when the vehicle is idling (about half the time), and the annual average temperature in New York is 10°C.

Using the Nissan Leaf as a model, where each battery cell has a voltage of around 4 V, I assumed that charge throughput is equal to energy throughput divided by 4 (energy throughput is equal to miles traveled multiplied by vehicle efficiency in kWh/mi.). I converted EPA drive cycle data[127] to power using Equation 2,

$$P_{in} = \frac{P_{out}}{\eta} = Fv = (ma + F_{air})v/\eta = \left(m\frac{\Delta v}{\Delta t} + \frac{1}{2}C_D\rho A v^2\right)v/\eta \qquad (2)$$

where P is power, a is acceleration, F is total force, F_{air} is force required to counter air resistance, v is velocity, η is engine efficiency, m is the mass of the vehicle (assumed to be 1100 kg plus 7 kg per kWh of battery capacity, derived from correlations between weight and battery size of currently available vehicles), C_D is the drag coefficient, assumed to be 0.3, A is the frontal area of the vehicle, assumed to be 0.66 m^2 (both based on published numbers for currently available EV models) and ρ is the average density of air, 1.225 kg/m^3.

Assuming that η is independent of speed, since I know the total energy consumption over the driving cycle, I can calculate the relative energy consumption of the vehicle in each second, removing η from the equation. To get the C-rate, I then divide this rate of energy consumption by the battery capacity. Figure 10 shows the C-rate profile for a range of battery capacities in the EPA drive cycle for New York City.

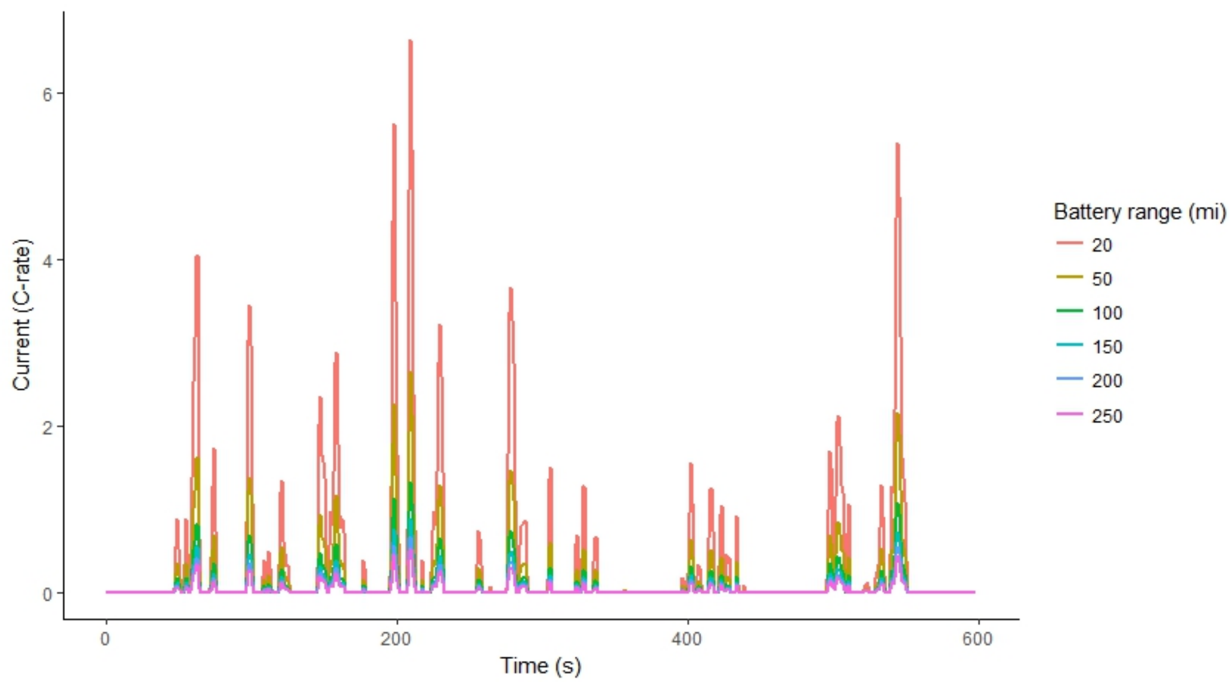


Figure 10. Estimated current profiles over the course of the EPA driving cycle for New York City, expressed as the fraction of total capacity discharged in an hour (C-rate).

The original model assumed current was identical during charging, so to include degradation from charging, I took the mean of charging and discharging degradation on each day, assuming the same amount of charge throughput for each. Figure 11 shows capacity loss over time for a range of battery sizes, assuming a fleet size of 7,000 taxis serving February demand.

Note that this model assumes degradation proceeds linearly with charge throughput throughout the battery's lifetime. Other studies have found that, depending on the charge rate, battery capacity begins to fall off exponentially after reaching a tipping point.[128] In my sensitivity analysis, I explored the impact of both eliminating battery degradation from the cost model, as well as accounting for non-linear degradation. I found that non-linear degradation becomes significant at higher charging powers, but does not significantly change my main results.

Instead of choosing an arbitrary interval at which to replace the batteries, I assumed that batteries would be replaced when the fleet could no longer satisfy constraints placed on maximum wait time, in this case 10 minutes. Because larger fleets need less battery capacity to satisfy demand, this assumption means that the fleet operator must add vehicles to increase battery lifespan, creating a trade-off between vehicle purchase cost and battery replacement costs. Taking results from the fleet sizing model, I used exponential fits to interpolate the minimum required fleet size at any battery range. I then swept through a range of fleet sizes to find the least-cost combination of fleet size and battery replacement rate; as shown in Figure 12, there is a simple convex relationship between fleet size and cost with a global minimum. As shown in Figure 13, as battery range increases, the least-cost fleet size approaches the minimum number of vehicles required to serve demand, while the lifespan of the battery and the amount of range remaining at the end of the battery's life increase.

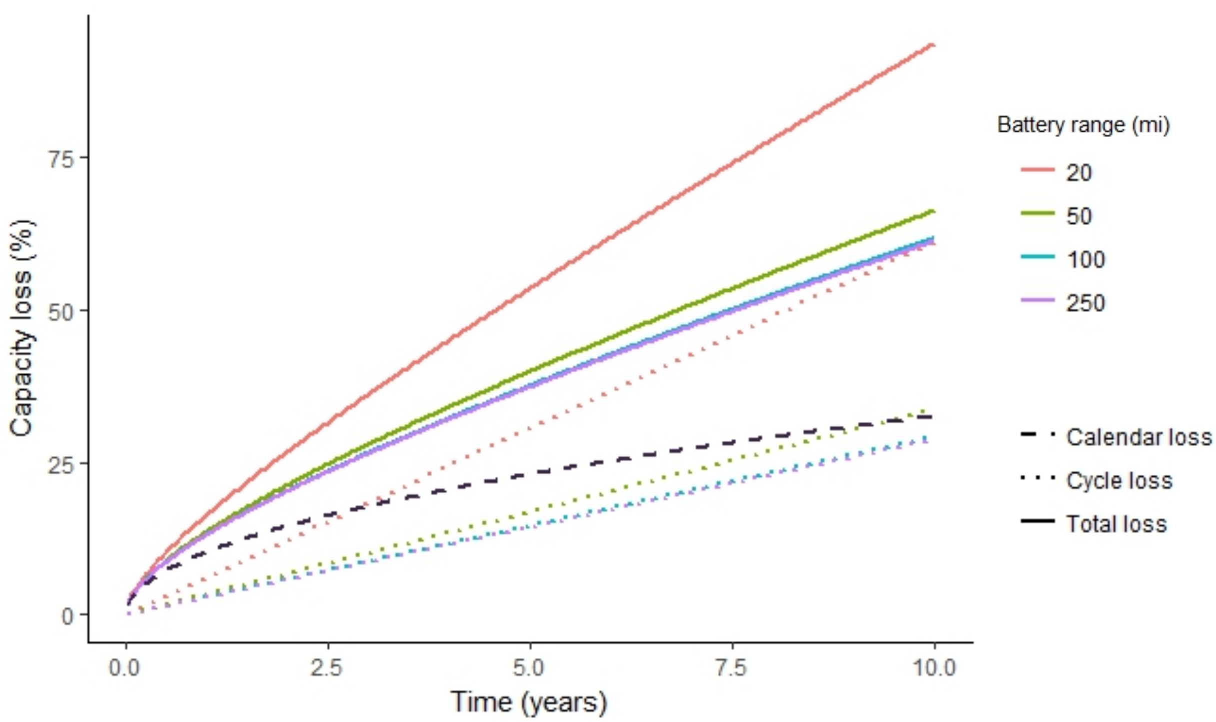


Figure 11. Loss of battery capacity over time for various battery ranges, assuming that each taxi drives 128 mi. per day (approximately the distance driven by each taxi in a fleet of 7,000).

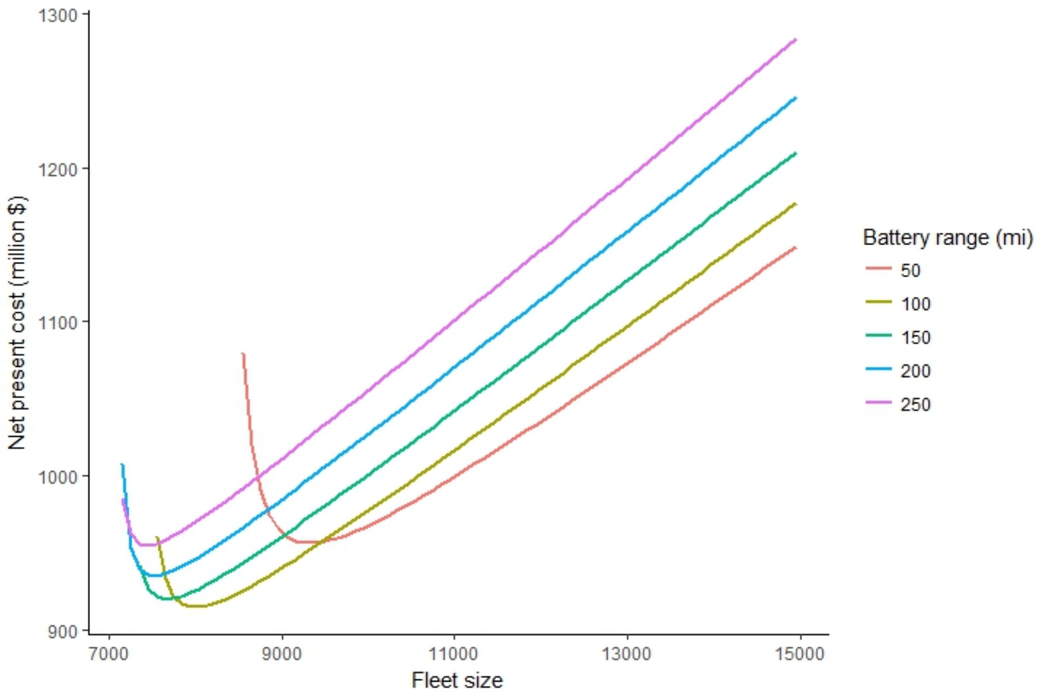


Figure 12. Net present value of the taxi fleet by number of vehicles and battery range. Decreasing the number of taxis increases the distance traveled by each vehicle, and reduces the lifespan of both vehicles and the battery. If no extra taxis are added over the minimum fleet size, due to capacity loss the batteries must be replaced almost continuously to meet demand. This situation creates a tradeoff between vehicle purchase, vehicle lifespan, and battery lifespan, such that each battery range leads to a distinct optimal fleet size.

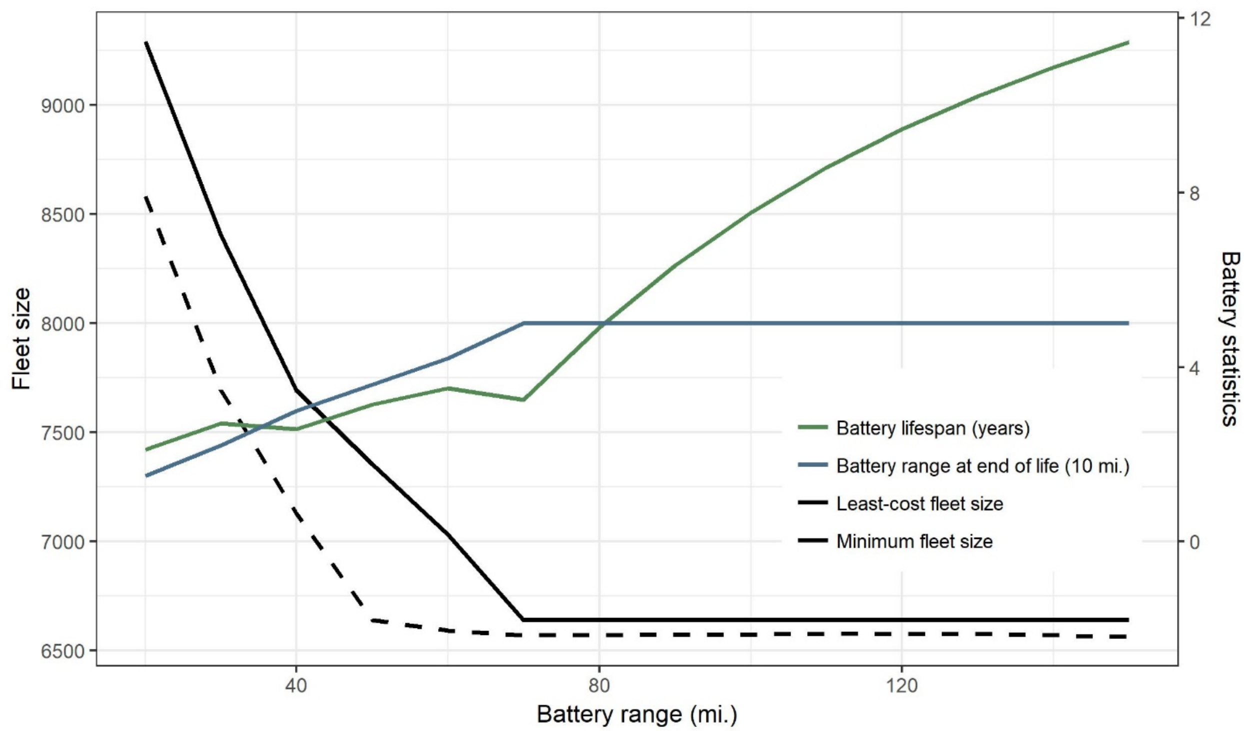


Figure 13. Change in battery replacement time, the final capacity, and the optimal number of buffer taxis as battery range increases.

1.2.6 Greenhouse gas emissions model

In order to estimate the environmental and energy impacts of my simulated fleets, I calculated the life-cycle production of greenhouse gas emissions, air pollution, and energy. Components of each of these calculations are shown in Table 5, and Table 6 provides a more detailed breakdown of the components that went into the air pollution calculation.

Table 5. Summary of emissions model components

Component	*Value (tons CO_2-eq)*	*Sources*
BEV vehicle production	6.5/vehicle	Based on [129], assuming medium-sized BEV
BEV battery production	0.11/kWh	[130]
BEV end of life	0.6/vehicle	[129]
ICEV vehicle production	5.2/vehicle	[129]
ICEV end of life	0.5/vehicle	[129]
Electricity consumption	0.280/MWh	Carbon intensity of electricity consumed in New York City in 2015 ([131])
Gasoline consumption	0.012/gallon	Life-cycle impact of conventional gasoline ([132])
BEV charging infrastructure	0	Life-cycle impact is comparable to that of refueling infrastructure for ICEVs, so net impact is negligible ([133])
Parking	0	Assume conversion from existing spaces

Table 6. Air pollution emissions data

	VOC	CO	NOx	PM2.5	SO_2	Source
ICEV tailpipe (g/mi)	0.2	2.9	0.1	0.0	0.0	[134]
ICEV upstream (g/mi)	0.1	0.1	0.2	0.0	0.1	[134]
ICEV manufacture (kg)	34.2	23.8	9.7	2.3	24.7	[134]
BEV manufacture (kg)	34.0	24.1	9.4	2.2	27.9	[134]
BEV battery manufacture (g/kWh)	50.6	94.9	224.2	101.1	1025.2	*Based on* [134]
NYC electricity (g/kWh)	0.4	0.1	0.3	0.1	0.2	[131], [135]
HEV tailpipe (g/mi)	0.1	2.9	0.1	0.0	0.0	[134]
HEV upstream (g/mi)	0.1	0.1	0.2	0.0	0.1	[134]
HEV manufacture (kg)	34.5	26.7	10.4	2.4	35.2	[134]

Note: NYC's electricity mix is about 48% natural gas, 42% nuclear, 8% renewables, 1.5% petroleum, and less than 1% coal.[131]

1.2.7 Cost model

The taxi service's cost per mile was estimated using a model with the components summarized in Table 7. As shown in Equation 3, where *CRF* represents the capital recovery factor and c_i represents the annual cost of the *i*th component in the cost model, levelized cost of service was found by dividing total net present value (NPV) of costs by NPV of passenger miles. I used a discount rate of 5% and a system time horizon of 20 years, assuming constant costs and demand throughout this period. In my sensitivity analysis, I varied the cost of each of these components to study the impact that different future cost trajectories would have on my conclusions. Note that vehicle lifetimes were significantly shorter than the 20-year system time horizon, about 8.2 years for the cost-optimal configuration. This life-span is longer than that of current taxis because I expect electrification and automation will result in lower maintenance requirements, and because my simulated vehicles travel significantly fewer miles searching for passengers.

$$Cost\ of\ service = \frac{NPV_{cost}}{NPV_{miles}} = \frac{\sum_i C_i \cdot CRF}{\sum passenger\ miles \cdot CRF} \qquad (3)$$

$$CRF = \frac{1 - 1.05^{-20}}{0.05} \approx 12.5$$

Table 7. Summary of cost model components

Component	Value	Source
Vehicle purchase	$20,000/vehicle	*Based on* [99], [100]
Vehicle lifetime	300,000 mi.	*Based on* [75], [103]
Automation	$10,000/vehicle	[96], [136]
Battery cost	$200/kWh plus 30% fleet discount	[137], [100]
Battery lifetime	Rate of degradation estimated using semi-empirical model (see methods section for more details)	[126], [127], [128]
Charging infrastructure	$700/charger/kW + $15/charger/kW/year + $10000/location	*Based on* [138], [34], [100]
Electricity consumption	$0.12/kWh	[139]
Vehicle efficiency	0.25 kWh/mi. + 0.0006 kWh/mi. per kWh battery capacity [a]	[98], [117]
Parking	$300/space-month [b]	*Based on* [140], [141]
Insurance	$600/vehicle-year + $0.05/mi.	[142], [96], [103]
Maintenance	$0.04/mi.	[143], [34]
Administrative overhead	$2.50/vehicle-day	*Based on* [103], [34]

a) When calculating the cost of electricity, I corrected vehicle efficiency for the additional weight of the battery.
b) Although I recognize that it is unclear who will pay for SAEV parking, I included the total cost to society of providing parking so that I could compare the total cost of various fleet configurations. It was assumed that the operator would need to buy a parking space to store all idle vehicles at the point of lowest demand, or about 90% of the total fleet size.

1.3. *Results and Discussion*

1.3.1 Fleet-sizing simulation results

As shown in Figure 14, I found that the minimum fleet size required to serve all trips within 10 minutes of requests decreases asymptotically with increasing battery range and number of chargers, ultimately falling to 6,470 vehicles at battery ranges of 70 mi. and greater. This minimum fleet size requires at least 2,000 chargers rated at 7 kW (88 chargers per square mile, or one for every 3.2 vehicles), but adding more chargers beyond this point has diminishing returns, especially at higher battery ranges. Increasing the number of charging locations has a much smaller effect than increasing battery range or number of chargers; this effect becomes negligible once battery range exceeds 50 mi.

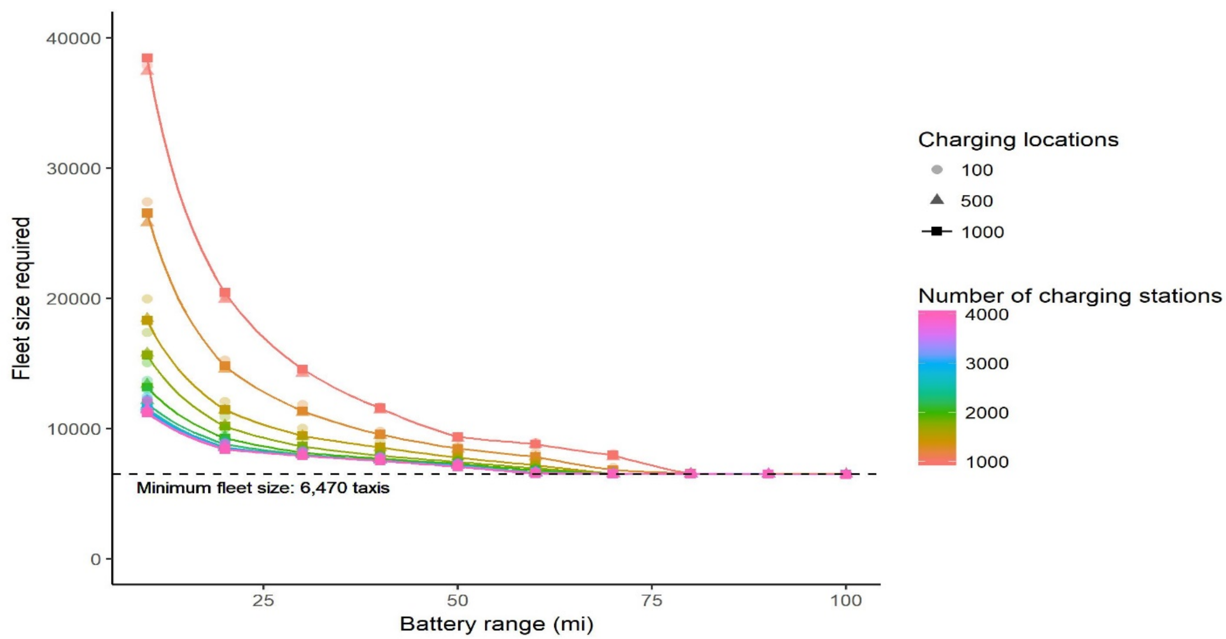


Figure 14. Required fleet size by battery range and charging network. Lines represent exponential fits for simulation results, which were collected at 10-mi. intervals in battery range.

In multi-day simulations, I obtained similar results to those displayed above, with a slightly higher minimum fleet size of 6,510 vehicles, and at least 2,000 Level 2 chargers. I also found that higher charging speeds can reduce both the number of chargers and the battery range required to reach the lower limit of required fleet size. Increasing charging power to 11 kW reduced the battery range required to 50 mi and the number of chargers to 1,000 (44 per square mile, or one for every 6.5 vehicles), and increasing to Level 3 charging (50 kW) allowed fleets with around 6,500 vehicles and over 80-mi. battery range to meet demand with only 200 chargers (9 per square mile, or one for every 32.5 vehicles).

These results suggest that the main challenge to introducing SAEV fleets is not battery range—currently available models like the Nissan Leaf more than suffice for meeting demand in Manhattan. The greater challenge may be building out sufficient charging infrastructure. In contrast with the scenarios of thousands of chargers considered above, according to the charger database ChargePoint, there are currently only 456 chargers in Manhattan, including many proprietary stations only accessible by Tesla owners.[144]

1.3.2 Cost model results

Given the results of the fleet-sizing simulation, I can see that there are several trade-offs between different fleet parameters. Increasing battery range, charging speed, and the density of chargers can decrease the number of vehicles required, but also increases other costs. For example, Level 3 chargers reduce the number of chargers required, but cost on the order of ten times as much as Level 2 chargers[138], and also increase battery degradation. As shown in Figure 15, taking all these trade-offs into account, I identify a lowest-cost configuration at a battery range of 90 mi., 1,500 chargers, and a charging power of 11 kW, with an estimated cost of service of $0.42 per revenue-mile. As shown in Figure 16, when paired with the appropriate charging infrastructure, all battery ranges between 30 mi. and 150 mi. result in costs of less than $0.45/mi. As battery range increases beyond the point at which fleet size reaches a plateau, cost continues to fall briefly because batteries can degrade further before being replaced. After battery range surpasses 90 miles, however, the cost of battery purchase becomes the dominant factor, and overall cost begins to rise again.

While these costs may seem optimistic, it should be noted that they do not include cost reductions from improvements in battery technology or charging agreements, improvements in BEV efficiency, right-sizing (see below for details), dynamic ride-sharing,[100] bulk purchasing contracts, or optimal trip assignment algorithms, and so could be considered conservative. These cost estimates are also consistent with Burns et al.'s finding that a fleet of conventional SAVs could replace Yellow Cab trips on Manhattan with a cost of $0.50/mi.,[103] as well as Chen et al.'s estimate that an SAEV fleet could serve taxi demand in Austin, Texas at a cost of $0.40-$0.50/mi.[96]

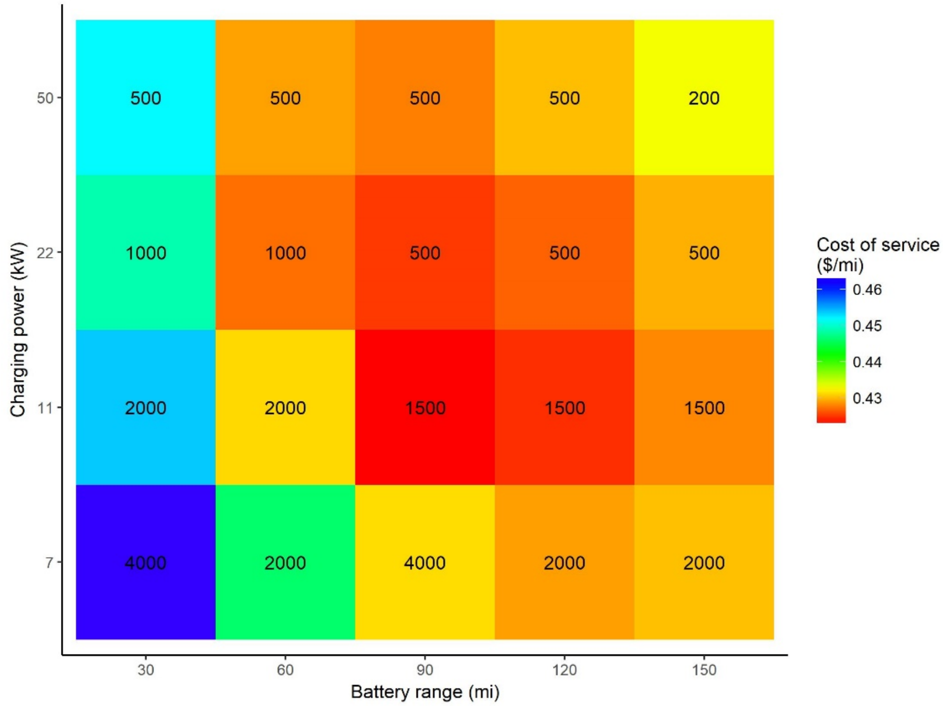


Figure 15. Estimated cost per mile of simulated taxi fleets with a given charging network and battery range. Numbers represent the number of chargers that returned the least cost for each combination of battery range and charging speed.

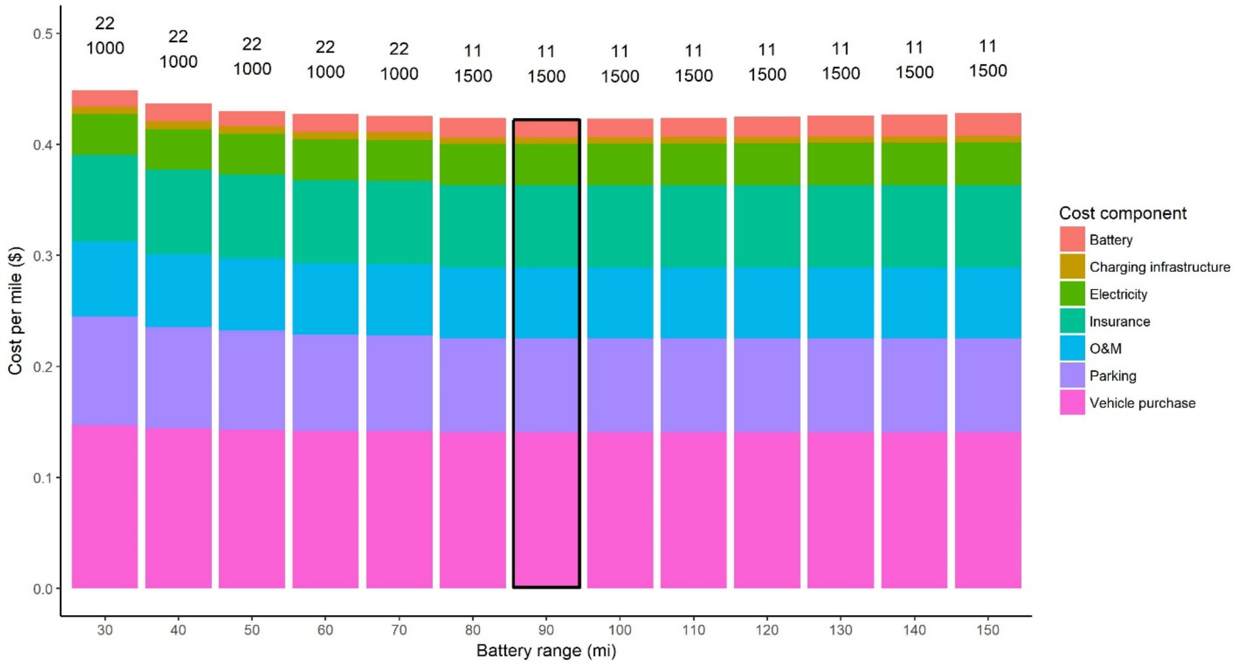


Figure 16. Breakdown of cost of service by component. The outlined column, representing results for a fleet with 90-mi. battery range, represents the lowest-cost configuration. Numbers represent the lowest-cost charging power (top), and number of chargers (bottom) for each battery range.

Looking at the breakdown of cost by component, I find that the cost of vehicle purchase varies only slightly with battery range, despite a large difference in the number of vehicles required. This result arises from the assumption that vehicle lifespan is based on distance traveled (taxis are replaced after 300,000 miles), rather than being based on a fixed amount of time. Because each additional taxi added to the fleet reduces the average daily distance traveled by all taxis, each new taxi extends the lifespan of the fleet as a whole, such that the net present cost of each additional taxi purchase of only about $10,000. If taxis were instead replaced on a fixed-time schedule, my results would become more sensitive to fleet size. At the same time, each additional taxi has associated costs: insurance (estimated at $600/vehicle/year plus mileage), administrative overhead ($2.50/vehicle-day), and parking ($300/vehicle-month). Together, these costs add close to $60,000 of NPV per vehicle, shifting the overall cost structure in favor of the smallest possible fleet size.

1.3.3 Comparison with conventional taxi fleets

Comparison with a hypothetical fleet of conventional vehicles reveals that, unless both fuel prices and conventional vehicle purchase prices fall dramatically, a battery electric vehicle fleet will be cheaper. Simulation results show a minimum fleet size of 6,469 conventional vehicles, slightly less than the lowest result for a fleet of battery electric vehicles. The lack of relocation to chargers also reduces the total distance traveled by 1.4%. To determine the cost of service of this hypothetical fleet, I used a similar cost model to that for electric vehicles but with a maintenance cost of $0.06/mi and no costs for electricity, batteries, or charging infrastructure. As shown in Figure 17, I then calculated the cost for a range of combinations of vehicle cost and fuel cost and compared them with estimates for four commercially available models: Toyota Prius, Chevrolet Volt, Smart Fortwo, and Toyota Corolla. As with the electric vehicles in my earlier analysis, I added $10,000 to the purchase price to account for the cost of automation. In each case, even when using the cheapest model configuration and the cheapest U.S. gasoline price ($2.15 in June, 2017), all four of these models would cost significantly more than a comparable fleet of electric vehicles. Using mean values, the cost increase ranges from $0.05/mi. for the Prius to $0.08/mi. for the Volt.

Relative to the current cost of Manhattan taxis—median fare was $5.42/mi. in August, 2015[145]—our estimated cost for the operation of an SAEV fleet represents roughly an order of magnitude reduction (assuming about 10% profit margin). Aside from savings due to electrification, the elimination of driver labor reduces cost by roughly $1.30/mi,[34] with the remainder of the savings coming from the increased efficiency of a single-operator, smartphone-based system (fleet size is reduced by half), and the lack of medallion fees.

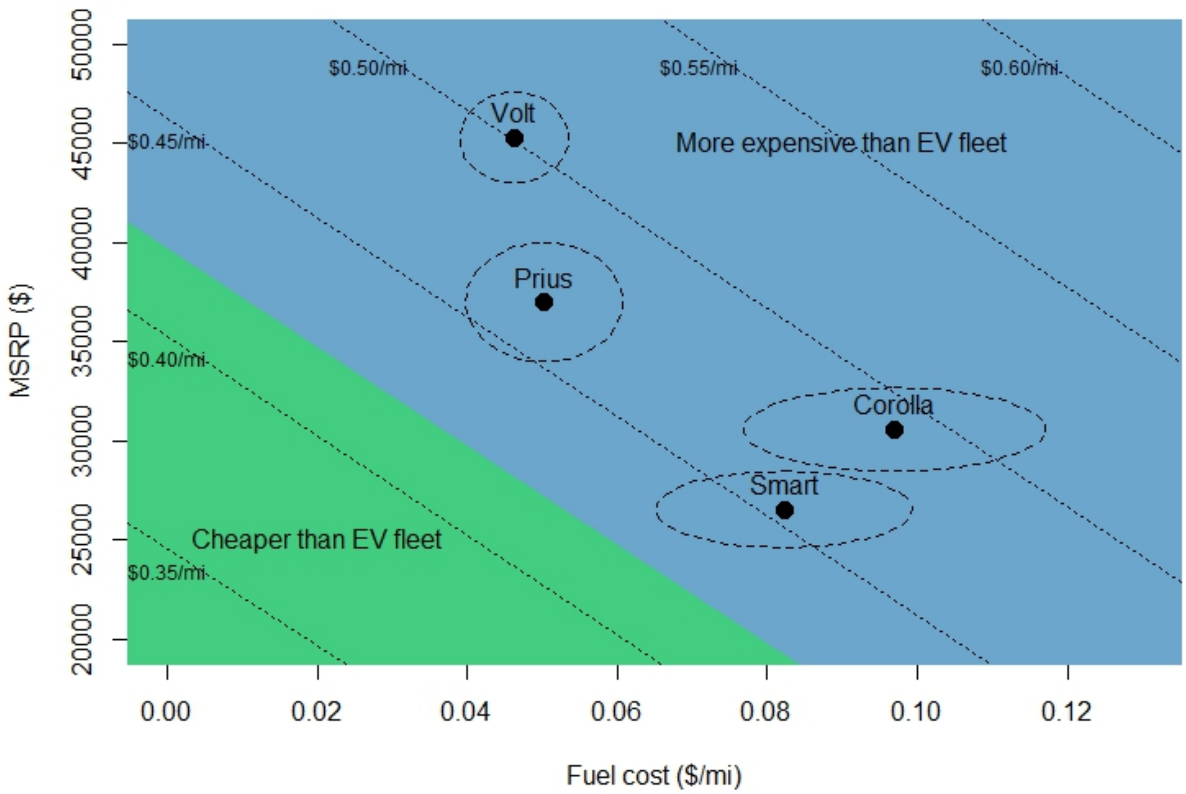


Figure 17. Comparison of estimated fleet costs for four different models of conventional vehicles. Ellipses represent ranges in manufacturer suggested retail prices and gas prices across the U.S. in June, 2017.

Using data cited elsewhere,[129–135] I can also project the energy, GHG and air pollution emission savings that would result from taxi fleet electrification. As shown in Table 8, SAEV fleets result in significantly lower impact in every case except for sulfur dioxide emissions, which would increase by 10% due to high emissions from battery production with the current power grid. Naturally, the air pollution caused by electric vehicles comes from manufacturing facilities and power plants that tend to be located in relatively rural areas, and so will likely result in much lower health impacts than emissions from ICEVs.[146,147] Meanwhile, NYC plans to reduce the carbon intensity of its electricity mix by half by 2030,[148] which would further reduce the GHG emissions of electric vehicle fleets by a third, and substantially reduce air pollution as well. Serving the same trips with personal electric vehicles driven 15,000 miles per year and 300 miles of battery range would lead to 74,000 tons CO_2-eq per year, meaning that replacing personal vehicles with short-range SAEVs could reduce GHG emissions by more than half. Table 9 and Table 10 show more detailed results.

Table 8. Comparison of energy, GHG, and air pollution emissions

tons/yr, unless noted otherwise	BEV	ICEV (BEV % savings)	HEV (BEV % savings)
Energy (GWh/yr)	205	460 (55)	280 (27)
GHG (ktCO$_2$-eq/yr)	33	122 (73)	76 (57)
Carbon monoxide	43	932 (95)	922 (95)
Nitrogen oxides	40	101 (60)	96 (58)
Particulate matter	11	20 (45)	20 (45)
Volatile organic compounds	70	132 (47)	104 (33)
Sulfur dioxide	78	71 (-10)	70 (-11)

Table 9. Fleet air pollution emissions results

Type of vehicle	Pollutant	Total emissions (kg/yr)	Vehicle manufacture (kg/yr)	Battery (kg/yr)	Fuel/ electricity	Percent reduction from electrification
ICEV	VOC	131688	40557	—	91131	46.7%
HEV	VOC	103605	40826	—	62779	32.3%
BEV	VOC	70141	40725	1578	27838	—
ICEV	CO	931841	28223	—	903619	95.4%
HEV	CO	921788	31670	—	890118	95.3%
BEV	CO	42902	28856	2961	11084	—
ICEV	NOx	101254	11472	—	89781	60.2%
HEV	NOx	95986	12280	—	83706	58.0%
BEV	NOx	40275	11270	6990	22014	—
ICEV	PM2.5	19758	2747	—	17011	44.8%
HEV	PM2.5	19866	2855	—	17011	45.1%
BEV	PM2.5	10904	2613	3153	5137	—
ICEV	SO_2	71288	29300	—	41988	-9.2%
HEV	SO_2	69905	41688	—	28217	-11.4%
BEV	SO_2	77860	33375	31971	12514	—

Note: Air pollution emissions from BEVs are essentially flat with respect to battery range because as battery size increases, increased emissions from production are offset by increased lifespan in the baseline battery degradation model.

Table 10. Fleet energy consumption.

	BEV	ICEV	HEV	Sources
Vehicle energy consumption (kWh/mi)	0.25	1.2	0.72	[149]
Production efficiency (%)	43	80	80	[150,151]
Energy intensity (kWh/mi)	0.58	1.5	0.9	
Usage energy consumption (GWh/yr)	184	449	270	
Vehicle manufacturing (GWh/yr)	13	10	10	
Battery manufacturing (GWh/yr)	7.8			
Total consumption (GWh/yr)	205	460	280	
Energy savings from electrification (%)		55	27	

Note: Production efficiency calculation for BEV fleet based on NYC generation mix.

1.3.4 Sensitivity analysis

To test the robustness of my results, I performed a variety of sensitivity analyses. First, I ran a subset of my simulations for a full 10 days, and found that this increases the minimum required fleet size from 6,500 to 7,000, as well as increasing the lowest-cost battery range by 10 miles. This result suggests that as demand increases, if the taxi operator wishes to maintain the same level of service, costs must rise, and battery range may need to increase moderately. Of course, if taxi fares were to actually fall by an order of magnitude as predicted here, demand might shift dramatically, and so I do not expect that these results more accurately represent reality than those based on a single day of data.

Second, I conducted simulations with naïve relocation algorithms to test the impact of my assumption regarding perfect foresight. If taxis do not relocate until they are assigned a trip, I found that the number of taxis required increased to more than 10,000, and cost of service increased to around $0.50/mi., but fleet size became less sensitive to battery range so that the lowest-cost battery range at 7-kW charging decreased from 110 mi. to 70 mi. The effect of assuming taxis cannot predict when they should relocate to charge is the opposite: overall cost does not increase significantly, but battery range becomes more critical, with a lowest-cost battery range of 140 mi. Thus, any errors in my assumptions regarding the two relocation algorithms have counterbalancing effects, suggesting that my results are robust to inaccuracies in my relocation assumptions. Given that the taxi operator has information on the location and state of charge of all taxis at any point in time, most likely charging availability will be easier to predict than trip demand. In turn, this means that my result for battery range represents an upper bound, while that for cost of service represents a lower bound.

Next, I tested the effect of restricting chargers to a few locations, using the algorithm described in the methods section. Given the challenges of obtaining permits and property, SAEV charging might take place primarily in a few discrete parking garages that each have a large number of chargers. However, I found that with an efficient charging algorithm, results for fleet size and battery range do not change appreciably until the number of locations falls below 50. Given that there are already charging stations at over 100 locations in Manhattan,[144] I expect the impact of constraints on charging locations to be minimal.

Finally, as summarized in Table 11, I tested the sensitivity of my results to a variety of changes in cost components, including cost of parking, vehicles, batteries, and electricity. These scenarios result in cost of service estimates ranging from $0.29/mi. to $0.61/mi. and a lowest-cost battery range of 50 - 90 mi. This result contrasts with current trends in electric vehicle development to expand battery range until it equals the travel range of ICEVs, i.e., more than 300 mi. My study shows that battery range will not be the main obstacle for SAEV fleets. Currently available ranges more than suffice, and significant cost savings could result from reducing battery range from current levels.

Table 11. Summary of results of cost model sensitivity analyses

Scenario	Explanation	Changes to cost model	Minimum cost of service ($/mi.)	Lowest-cost fleet configuration
Baseline	See methodology section	None	$0.423	90 mi. battery 1500 chargers 11 kW
Dynamic electricity rates	Power utility bases electricity rates on time of use to reduce peak system load.	Electricity: $0.17/kWh on-peak $0.11/kWh off-peak[139] No change in charging patterns	$0.427	90 mi. battery 1500 chargers 11 kW
Cheap batteries, expensive vehicles	Cost of batteries falls quickly, but automation costs are more than expected.	Vehicle: $50,000 with automation 200,000 mi. lifespan Battery: $100/kWh to buy $50/kWh to sell	$0.608	90 mi. battery 1500 chargers 11 kW
Cheap vehicles, expensive batteries	Effective battery capacity is reduced by cold weather and aggressive driving, but vehicle cost is reduced by right-sizing and cheap automation.	Vehicle: $17,500 with automation 50% reduction in parking and insurance Battery: $250/kWh to buy $0 to sell	$0.294	70 mi. battery 1000 chargers 22 kW
No battery degradation	Battery technology improves so that degradation becomes negligible	Batteries replaced when vehicles reach 300,000 mi. (no battery resale value)	$0.419	50 mi. battery 1500 chargers 11 kW
Nonlinear battery degradation	Batteries degrade non-linearly after reaching cut-off [128]	$Loss > 0.4 - \frac{I_{charge}}{5} \Rightarrow$ $Loss_{cycle} \propto Ah^2$	$0.428	70 mi. battery 1500 chargers 11 kW
No parking costs	Society bears the cost of parking, providing it for free to the taxi operator	No parking costs	$0.339	90 mi. battery 1500 chargers 11 kW

The following sections provide more details on the sensitivity analyses. Unless specified otherwise, all of the following simulations were performed with a charging network of 4,000 7-kW chargers distributed across 1,000 locations.

a) Variable taxi demand

To test the impact of changing demand, I also ran a subset of simulations for a full 10 days (see Figure 18 and Figure 20). Similar to the single-day results, the results of the one-week simulations showed diminishing returns to increasing the number of chargers beyond 2,000. Adding more charging nodes allows the fleet to reach minimum size with a range of 10 miles less, while requiring the fleet to meet weekend demand increases this benchmark by 10 miles, and also increases the minimum fleet size by about 500 taxis, from 6,500 to 7,000. On the other hand, decreasing the number of chargers below 2,000 had a much larger effect in the one-week simulation, since the fleet cannot keep up with demand day after day unless it has adequate charging. With 1,500 chargers, fleet size does not plateau until battery range reaches 120 miles, while with only 1,000 chargers, fleet size is twice as large even with a battery range of 140 miles. I also ran 1-week simulations using data from August 7-14, 2015, and found that the lower level of demand results in a required fleet size of only about 6,000 taxis, but the impact of charging stations and battery range is similar. Finally, as shown in Figure 19, I ran a single-day simulation with 80 miles of battery range and 1500 11kW chargers on every day of January, when demand is greatest. On no day did fleet size surpass 7,500, and on most days it fell below 5,000.

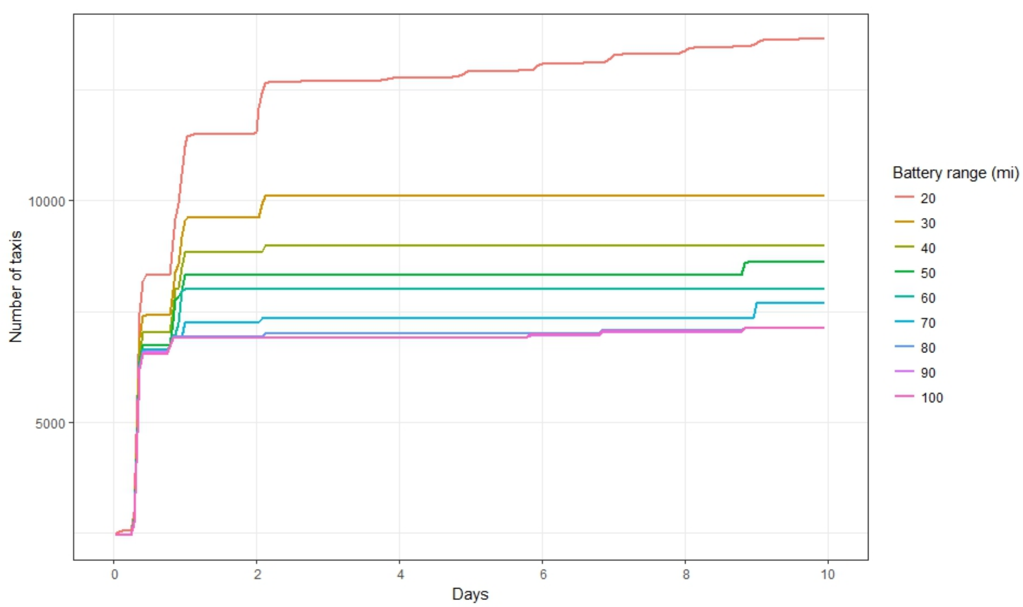


Figure 18. Evolution of the taxi fleet over the course of the 10-day simulation, at varying battery range (4,000 chargers at 7 kW).

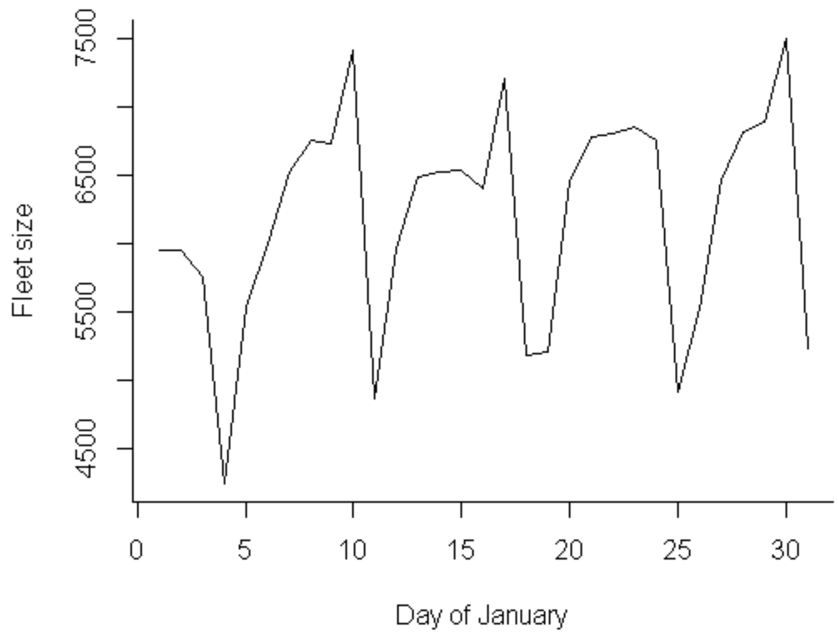


Figure 19. Fleet size required to serve demand with 80 miles of battery range and 1500 11kW chargers on each day of the month of January, 2015.

However, it would not be profitable for the fleet operator to size the fleet such that it can serve all trips within 10 minutes even on days with highest demand. For example, on weekend nights customers would likely be willing to wait somewhat longer than during weekday commutes. If I relax the requirement that all trips be served within 10 minutes, I find that a smaller fleet designed for weekday peak demand can also serve demand on weekends with a reasonable level of service. As shown in Table 12, using a fixed fleet of 6,571 vehicles, i.e. the fleet generated with 80 mile battery range and 1500 chargers at 11kW, I find that even on Saturdays with high demand, mean wait time is still less than 7 minutes, and less than 10% of all trips must wait longer than 10 minutes.

Table 12. Distribution of wait times from fixed fleet simulations

	Percentage of total trips						
Wait times (min)	**Sunday**	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**
0	52	53	54	54	52	50	45
1	8	8	7	7	8	9	11
2	6	4	4	4	4	5	5
3	11	10	10	10	10	10	9
4	9	9	8	8	8	8	8
5	5	4	4	4	4	4	5
6	2	2	2	2	2	2	3
7	2	2	2	2	2	2	2
8	1	1	1	1	1	1	1
9	1	1	1	1	1	1	1
10	4	6	6	5	5	3	3
>10	0	0	0	1	3	4	8
Mean (min)	2.0	2.1	4.9	3.9	6.0	3.6	6.5

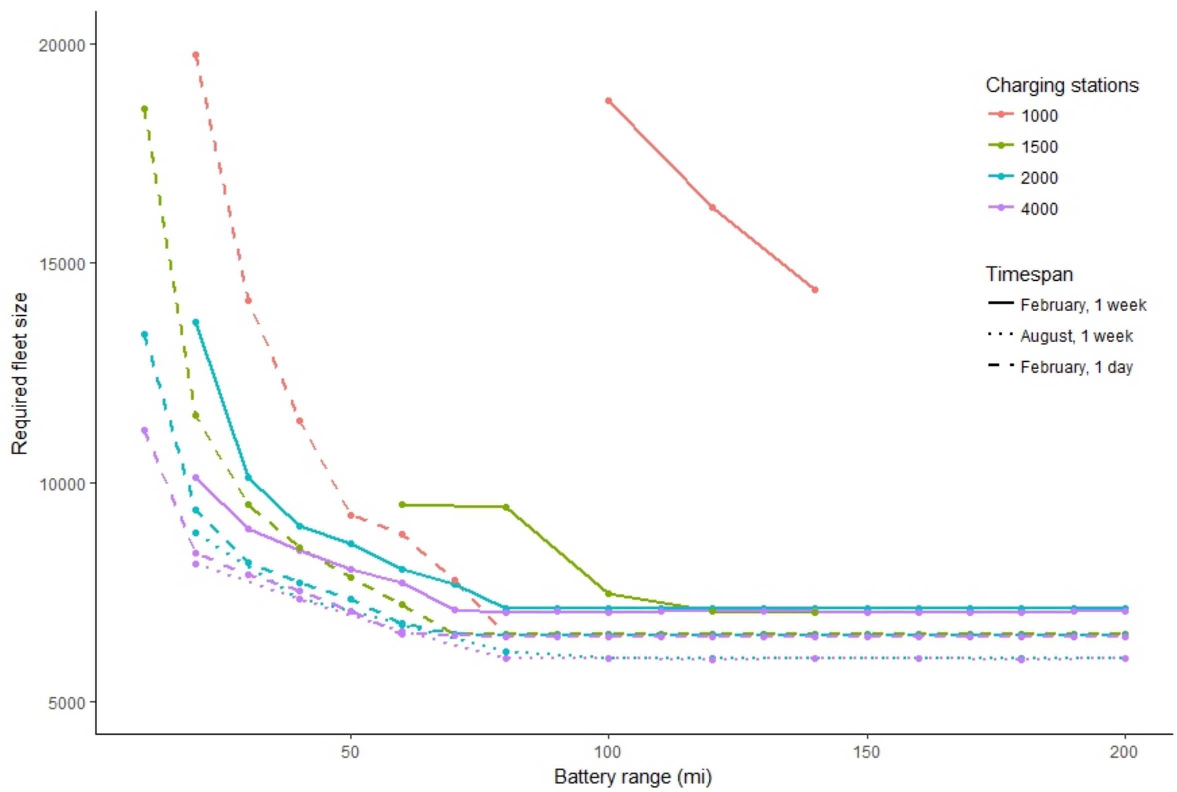


Figure 20. Comparison of the number of taxis required to serve demand by battery range and charging configuration. Dashed lines represent results from 1-day simulation runs, while solid lines represent results after a full week. Note that week-long simulations with 1,000 chargers never converged to the minimum fleet size. All simulations assume charging at 7 kW.

b) Abundance and distribution of charging stations

As one might expect, the result of my simulation is contingent on having adequate access to charging. As implied by Figure 20, at 7 kW charging power, reducing the number of chargers from 4,000 to 2,000 increases the lowest-cost battery range by 10 miles. With only 1,500 chargers, the cost minimum shifts out at least 20 miles more, while with only 1,000, it may shift out to larger than 200 miles.

A similar effect can be observed by restricting the number of charging locations. If the regulatory environment does not allow for charging stations dispersed throughout Manhattan, it is possible that fleet charging would be restricted to only a few locations, with several hundred charging stations at each location. As shown in Figure 21, if one reduces the number of available charging locations below 50, the required fleet size for taxis with 100-mi. range begins to increase significantly. At less than 10 locations, the same effect spreads to a simulated fleet with 125mi-range.

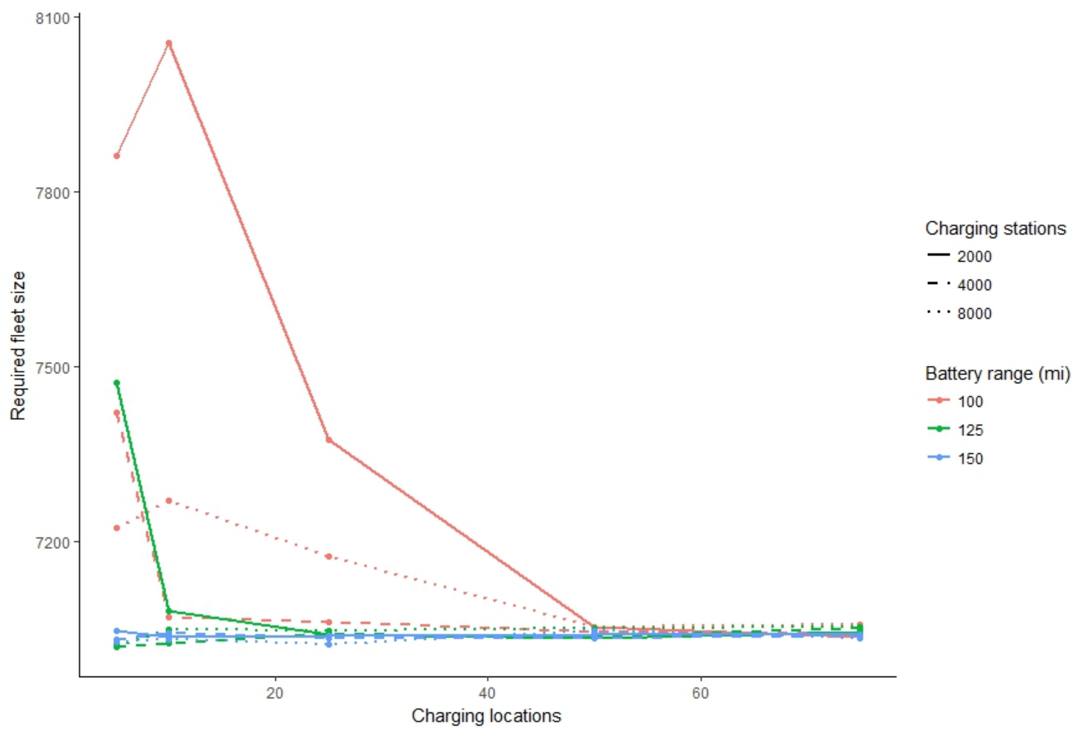


Figure 21. Simulation results with severe restrictions on the number of charging locations shows that such a situation may favor longer battery range (assuming charging at 7 kW).

In turn, these restrictions on charging will result in a higher system-wide cost. In addition to higher battery costs, concentrating charging stations at a few locations could result in much greater costs for electricity and charging infrastructure. This restrictive distribution would require massive charging garages with several hundred charging stations each, with power demands on the order of a few megawatts. Few such charging centers currently exist, but I know that this power demand is about the same as a large office building, which typically require custom-designed transformers, along with a full-time team of electrical engineers for maintenance (P.

Phanivong, pers. commun., 2017). Such charging centers will be difficult to convert from existing garages, and so will require either greenfield space (essentially non-existent in dense city centers like Manhattan), or demolition of existing structures, followed by construction from the ground up.

c) Relocation algorithms

I considered the possibility that my assumption of perfect demand prediction is too optimistic. To test the impact of this assumption, I conducted simulations with various battery sizes both with and without predictive relocation, and determined that my assumption does not significantly bias my results. In simulations without foresight, taxis never move unless they are the best taxi to serve a trip and can drive to the pickup location within 10 minutes. As shown in Figure 22, excluding relocation significantly increases the number of taxis needed to serve all trips, but the change is largely uniform across battery sizes. Meanwhile, because relocations requiring foresight are relatively rare events, representing less than 10% of all taxi relocations, eliminating prediction only decreases the total distance traveled by each taxi by 1-2 miles per day. Due to Manhattan's high density, over half of trips were served by taxis at the same point (requiring no relocation), while over 90% were served by taxis less than a mile away.

The results for simulations without demand foresight predict a lowest-cost battery range of around 80 miles, so it is possible that my model overestimates range requirements. However, I also looked into the effect of removing all foresight in relocation to charging stations (represented by the purple and blue lines in Figure 22), and found the opposite effect. If taxis only move to charging stations after the stations become available, and never take into account whether or not there is enough time to make it worth the trip, the lowest-cost battery range shifts out to closer to 150 miles, with similar cost per mile to that when charging foresight is included. These opposing results suggest that inaccuracies in my assumptions to some extent will cancel each other out, such that true fleet activity may be closer to that predicted by my model. Removing demand foresight does increase the cost of providing service by about 15%, so it is possible that I have slightly underestimated the cost per mile. However, all of the costs included in my model will likely continue to fall in the future, counteracting this error. Furthermore, as machine learning and artificial intelligence (AI) continue to improve, demand forecasting will become more and more accurate. By the time the first commercial SAEV fleet picks up its first ride, with the combined computing power of several thousand automated vehicles, the difference between perfect foresight and that obtained by an efficient AI algorithm may become negligible.

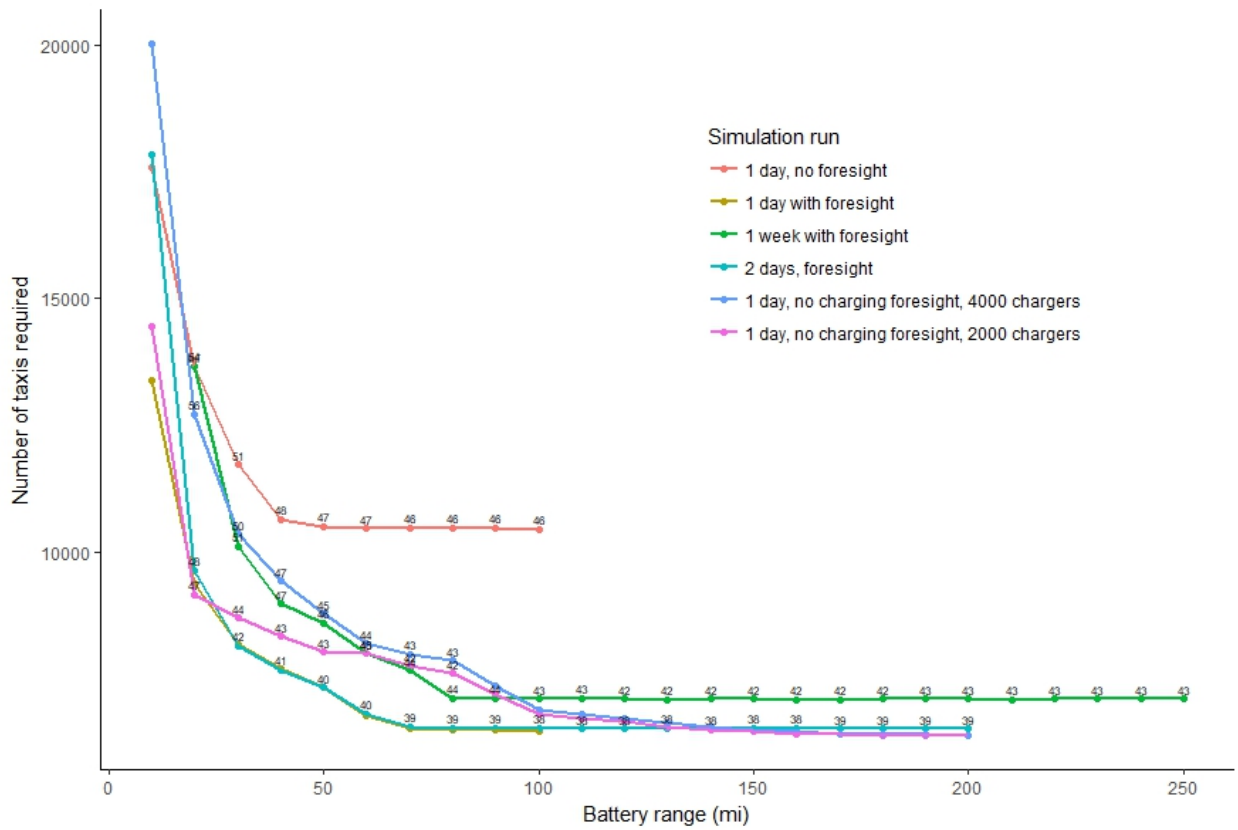
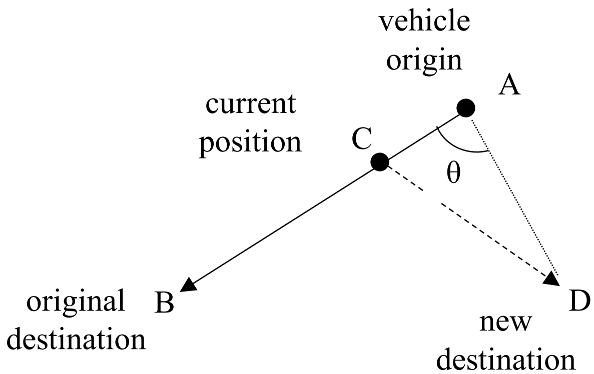


Figure 22. Results of simulations for battery ranges between 10 and 250 miles, varying relocation strategies and time horizon. Data labels show the estimated cost of the taxi service, in cents per mile.

To further test my relocation algorithm, I developed a more rigorous model that determines when idle vehicles should relocate to charge or serve trip demand using trip data from the week before. In each minute, after completing trip assignment, the model runs forward in time, using trip data from the week before to assign vehicles to hypothetical trips. Idle vehicles assigned to hypothetical trips further than 10 minutes away (i.e. when no closer vehicle is available) are ordered to begin relocating to that point. Vehicles that are predicted to remain idle for long enough to relocate to a charger and replenish the energy expended to get there are ordered to relocate to charge. The model continues to progress into the future in this way until any vehicle could have made it to any hypothetical trip request. When the model progresses to the next minute, vehicles are again assigned to trips using the real trip data from the simulated day. If there are trip requests which no available taxi can reach within 10 minutes, relocating vehicles that could make it to the trip within 10 minutes are allowed to be reassigned. Vehicles relocating between two points are assumed to move at a constant rate, and the distance and time from their current position to a new destination are calculated using the law of cosines, as shown in Figure 23.



known: T_{AB}, T_{AD}, T_{BD}, D_{AB}, D_{AD}, D_{BD}, T_{AC}
(T = time, D = distance)

$$D_{AC} = D_{AB} * \frac{T_{AC}}{T_{AB}}$$

$$cos\theta = \frac{(T_{AB}^2 + T_{AD}^2 - T_{BD}^2)}{2T_{AD}T_{AB}}$$

$$T_{CD} = \sqrt{(T_{AC}^2 + T_{AD}^2 - 2T_{AC}T_{AD}cos\theta)}$$

$$D_{CD} = \sqrt{(D_{AC}^2 + D_{AD}^2 - 2D_{AC}D_{AD}cos\theta)}$$

Figure 23. Schematic of calculation for re-assignment times and distances for relocating taxis.

As shown in Table 13, for both weekdays and weekends, regardless of battery range, this forward-looking model with historical data (labeled "Historical") performs almost as well as the backward-looking model described in the methods section (labeled "Perfect")—fleet size differs by 11% at most, and in most cases by much less than that. Empty miles also increase slightly in each case, but again the difference is marginal. In each case, the simulation was performed with 2000 chargers rated at 11kW distributed across 500 locations.

Table 13. Summary of results of forward-looking simulation.

Relation algorithm	Date	Battery range (mi.)	Fleet size	% change	Fraction empty VMT	% change
Perfect	2/13	50	7554		0.193	
Historical	2/13	50	7844	3.84	0.206	6.98
Perfect	2/14	50	8275		0.193	
Historical	2/14	50	8303	0.34	0.206	6.32
Perfect	2/15	50	6913		0.214	
Historical	2/15	50	7272	5.19	0.226	5.65
Perfect	2/13	100	7047		0.187	
Historical	2/13	100	6943	-1.48	0.202	8.18
Perfect	2/14	100	7120		0.192	
Historical	2/14	100	7100	-0.28	0.204	6.28
Perfect	2/15	100	5549		0.211	
Historical	2/15	100	6192	11.59	0.222	5.04
Perfect	2/4	100	6553		0.203	
Historical	2/4	100	6635	1.25	0.225	10.46

Finally, I also tested the effect of imposing a constraint that taxis can only charge when they fall below 20% of full charge. As shown in Figure 24, this provides a very small benefit to fleets with longer battery range, but adversely affects fleets with shorter battery range. Given that longer battery ranges will degrade over the lifetime of the fleet, such that they will behave like shorter-range fleets at the end of battery life, I do not expect that introducing this constraint would significantly change my results.

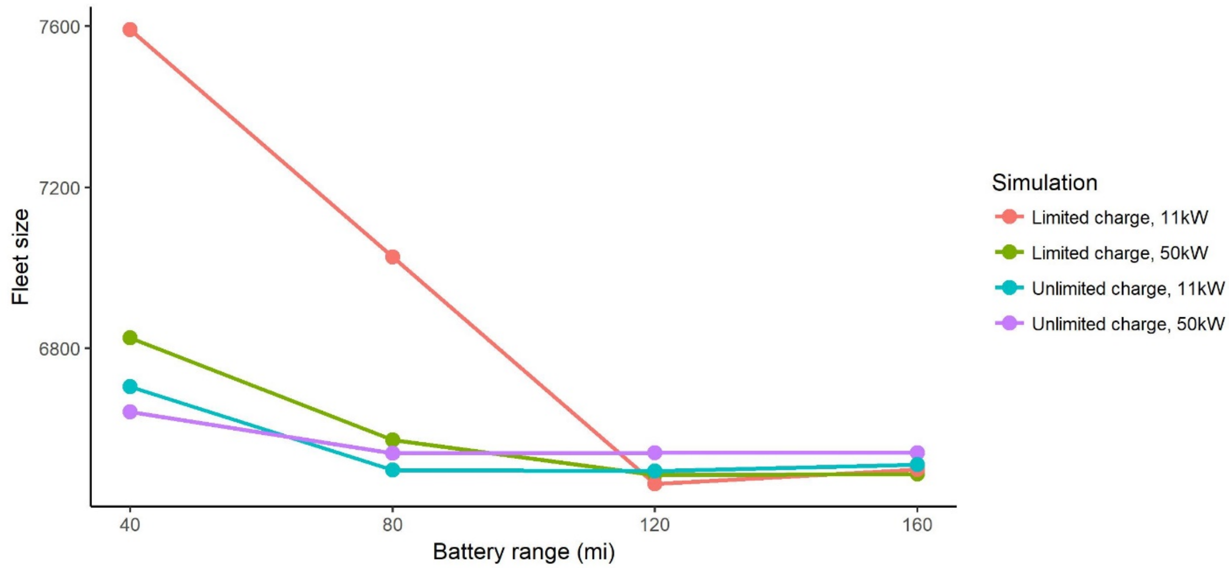


Figure 24. Effect on fleet size of imposing a constraint that taxis only change when at less than 20% of full charge (limited charge), at both 11kW and 50kW charging speeds.

d) Electricity pricing

In this study, I have assumed a flat rate for electricity, but most likely, electricity rates for charging electric vehicles will vary based on the time of the day. Consolidated Edison Company of New York (the electricity utility serving Manhattan) offers a time-of-day rate structure for electric vehicle home-charging with \$0.17/kWh for on-peak use (8am-10pm on weekdays), and \$0.11/kWh for off-peak use (all other times). As shown in Figure 25, simulated charging station use peaks twice—once at night, and again in mid-day—resulting in off-peak charging of about 46%. This result is stable across a wide range of battery sizes (see Figure 26), and changes only marginally with different charging networks, reaching 56% with 4000 charging points at 50 nodes. It is possible that a fleet with large battery range could save some money on charging by shifting all charging activity to the middle of the night. However, compared to my simulation with uncontrolled charging, this could only save a maximum of \$0.023/kWh, or about \$0.006/mi, much of which would be offset by increased need for charging infrastructure.

It is possible that in the future, the difference between peak and off-peak electricity rates might be much greater than this. However, most of the charging in the simulation occurs in the middle of the day, when generation from solar energy will be greatest. Thus, this charging does not coincide with net peak electricity demand hours, and could actually provide substantial benefits to a grid with greater penetration of intermittent resources such as solar.

Comparing the simulated load profile with that of current New York City electricity demand suggests that only a moderate amount of control would be required to shift taxi charging to partial-peak and off-peak hours. The largest peak in taxi charging occurs on weekend mornings, after periods of peak activity on Friday and Saturday nights. Conveniently, as shown in Figure 27, this peak coincides with a period of relatively low demand in the rest of the system. The other charging peak, at 5pm on weekdays, does coincide with system-wide peak demand, but it quickly drops off as taxis become active during the afternoon rush hour, so it would not be too difficult to set stricter limits on charging during this time (e.g. set a maximum state of charge above which taxis will not charge between 4-9pm). Meanwhile, the peak power demand for charging represents less than 1% increase in the total power demand of the system, and so should not require any extreme system upgrades on its own.

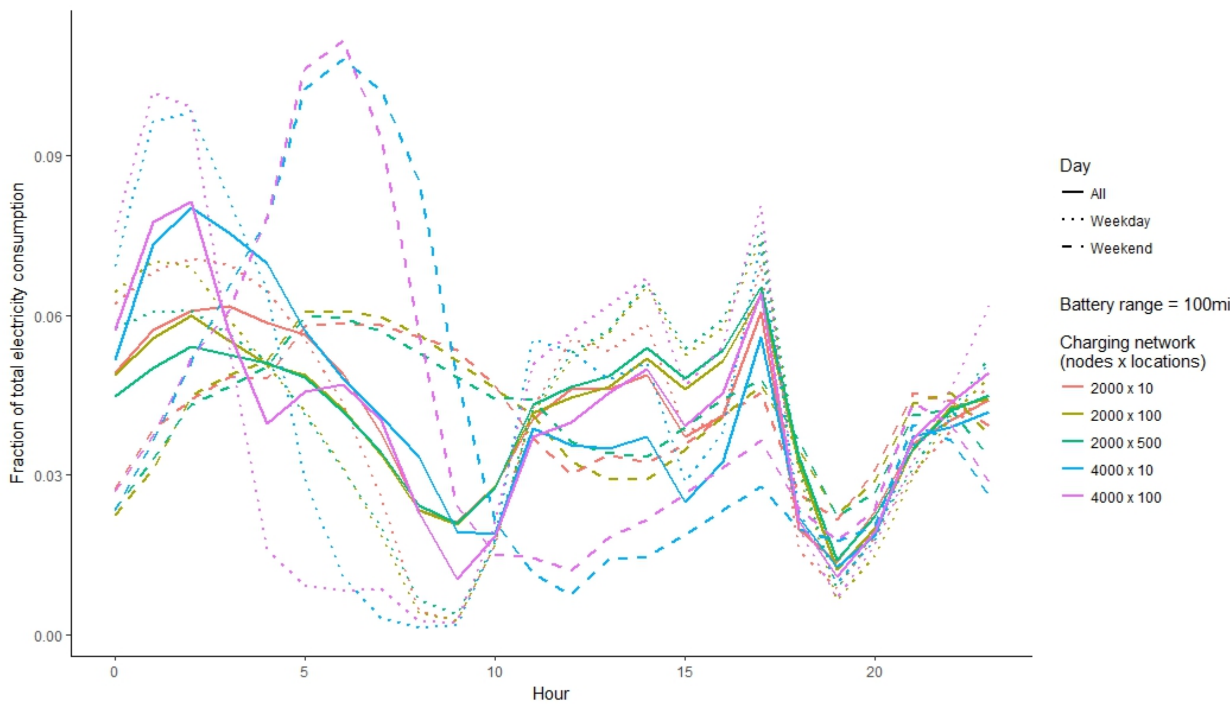


Figure 25. Charging load profile of simulated taxi fleets with 100mi battery range and varying charging distributions, on both weekdays and weekends (charging power = 7 kW).

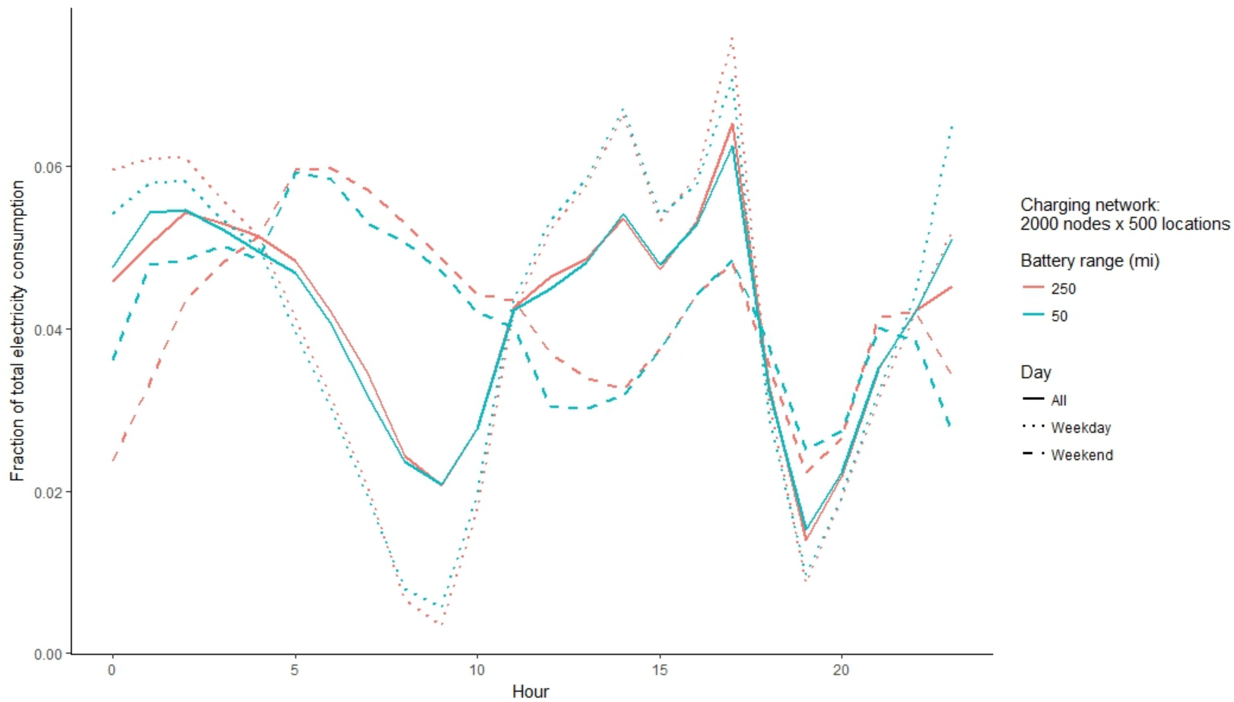


Figure 26. Comparison of charging load profile of simulated taxi fleets by battery range (charging power = 7 kW).

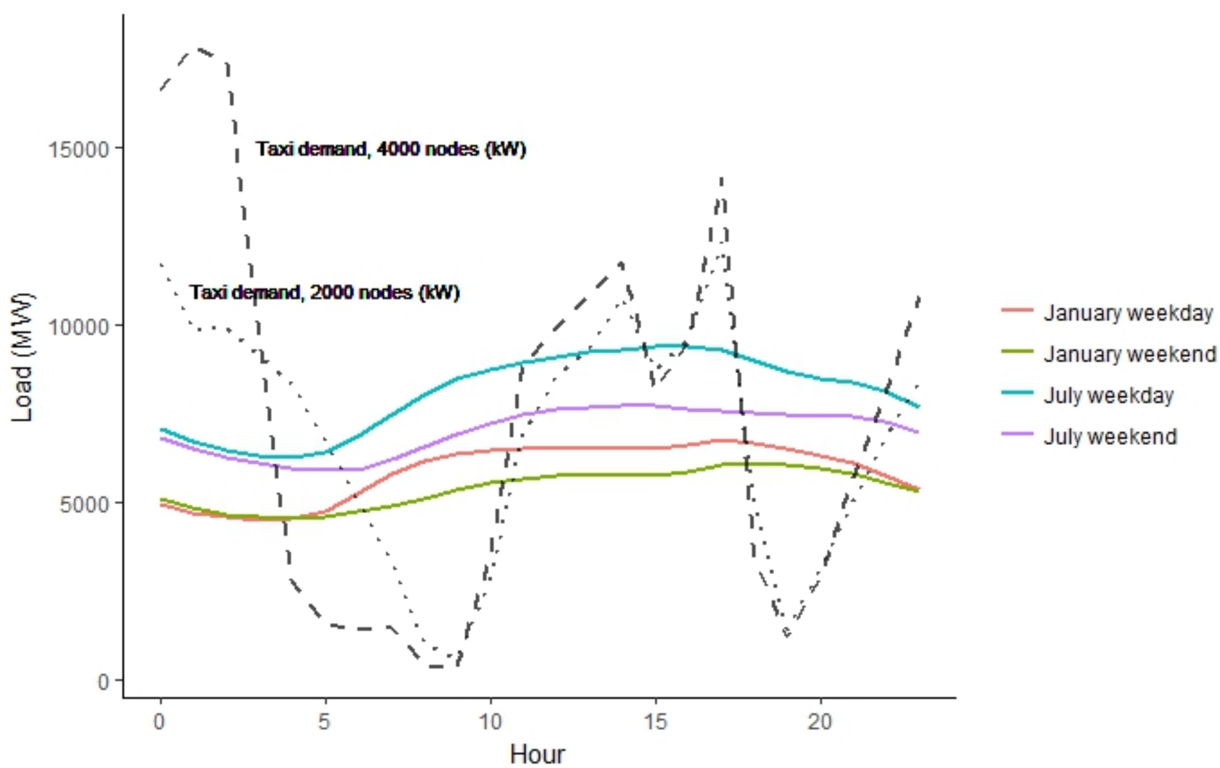


Figure 27. Comparison of simulated charging profiles with actual New York City electricity demand for different days of the week and seasons. Note that the taxi charging profiles have been magnified 1000 times in order to show them on the same scale as overall electricity demand (each charger rated at 7 kW).

e) Vehicle right-sizing

It is possible that further efficiencies could be gained by varying the number of seats in each vehicle. While I conducted the above modeling assuming all vehicles have four seats, this need not be the case. Most taxi trips taken in Manhattan have only one or two passengers, and so could be served more efficiently by vehicles with less than four seats. In fact, on February 4, my base simulation day, 73% of trips had only one passenger, and an additional 12% has only two passengers. While this topic deserves further investigation, I present some preliminary results in Figure 28 below. I used a similar fleet sizing algorithm as above, creating a new vehicle whenever there was a trip that could not be served within 10 minutes, but requiring that this vehicle have the same number of seats as passengers in that trip. Each simulation was conducted with 100 miles of battery range and 4000 chargers rated at 7kW, using a full week of data. Fleet size ranged from roughly 7300 to 7900 vehicles, about a 500-1000 more than simulations with only four-seater vehicles. However, the majority of these vehicles had fewer than four seats, suggesting significant savings could be achieved by right-sizing the fleet—I estimate that the lowest-cost fleet with 1-seat, 2-seat, and 4-seat vehicles would cost \$0.40/mile, roughly 10% less than a fleet with only four-seat vehicles. In particular, requiring that each vehicle size only serve trips with the same number of passengers results in reducing the vehicle size of a much larger proportion of the fleet at relatively small cost in increased fleet size (see "strict" scenarios below).

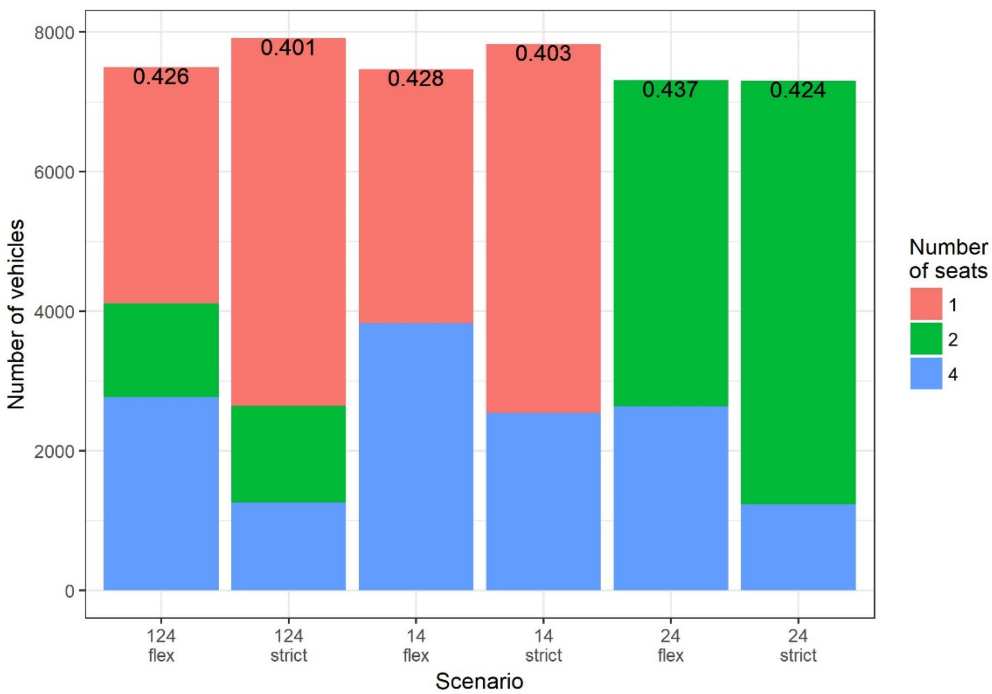


Figure 28. Fleet-sizing simulation results for scenarios allowing for different numbers of seats in each vehicle. "Flex" scenarios allowed larger vehicles to serve trips with fewer passengers, while "strict" scenarios required that four-seat vehicles serve only trips with at least three passengers. The numbers on each scenario represent the alternatives for vehicles allowed in the fleet, e.g. "124" scenarios represent fleets with one-, two-, and four-seat vehicles. The number shown at the top of each bar shows results for cost of service.

1.3.5 Limitations and directions for future research

The first limitation to my results arises from my assumption of exogenous demand—if costs fall as dramatically as projected in this analysis, demand for taxis will likely skyrocket. More research is needed to study the optimal vehicle parameters for a fleet serving the majority of all Manhattan trips, as well as those to and from the outlying boroughs. If SAEVs begin to replace other modes of travel, empty miles may lead to increased congestion, which also deserves further study.

Furthermore, my results apply only to the densest area in the U.S., and it is difficult to generalize my conclusions to other areas. Another next step will be to ask: what is the impact of changing the geography of the network in which the fleet operates? It will be interesting to apply my model to other cities (particularly those of lower density) and compare results.

Accounting for higher demand and less dense geography would both likely require larger fleets, and so operating these fleets could cost more than I have estimated in this study. On the other hand, I did not consider the possibility of a heterogeneous fleet, in which some chargers have higher speeds than others, and some taxis have more or less battery capacity, or different numbers of seats. Because the average occupancy of NYC taxi trips is less than two people,[40] if there is no need to provide space for a driver, then most shared vehicles need have no more than two seats. Given that these vehicles will be smaller and rarely get into collisions,[136] they might also enable significant reductions in weight, leading to substantial reductions in energy consumption, cost and GHG emissions [75].

I also have not considered issues of equity in this study, which deserve further analysis in future research. My simulated fleet can only serve customers with smartphones, and fleet rebalancing based on demand forecasting could lead to worse service in low income neighborhoods. However, these issues already exist with services like Uber and Lyft, and smartphone ownership is approaching ubiquity in urban areas,[152] such that my simulation can still provide useful insights as to the future of shared mobility.

1.3.6 National fleet model

The low cost of automated shared fleets leads to the question, what would happen if such fleets served all light-duty vehicle mobility in the US? Working with researchers at Lawrence Berkeley National Laboratory, Emerging Futures, LLC, and University of California, Davis, I helped developed a convex optimization program to identify the number of vehicles, infrastructure, and battery range required to serve mobility demand nationwide. This optimization program included a number of parameters that needed to be verified with agent-based simulation modeling, including:

- **charger distribution factor:** ratio between the peak charging occupancy and the total number of chargers required.
- **fleet size correction factor:** correction to account for the fact that it might not be feasible to utilize all vehicles during periods of peak demand.
- **trip deadheading factor:** ratio between trip duration and distance and total driving, including relocation to pick-up locations.
- **charging deadheading factor:** correction to account for time and energy spent relocating to charge, resulting in lower effective charging speed and higher energy consumption.

Whereas the Manhattan study relied on travel times and distances downloaded from Google Maps API, issues with computational complexity and data availability arising from simulating entire metro areas required estimating times and distances as distributions between zones. Building on the simulation work in Manhattan, I ran the simulation on a set of 11 diverse cities around the country, leveraging GPS and cell phone data from StreetLight Data, a company that aggregates data from cell phones and GPS devices to produce transportation metrics like travel times and volumes.

First, I obtained shapefiles from the Census Bureau website with census tracts for a series of combined statistical areas. I then uploaded these shapefiles to the StreetLight Data portal, and obtained two types of data. "Trip attributes" files contained distances, times and speeds between each pair of census tracts. Data was only provided for zone pairs with a significant number of trips, as determined by StreetLight Data. "Trip Counts" data contained the volume of trips between each census tract origin and every traffic analysis zone (TAZ) with a significant volume, again as determined by StreetLight. The data also contained significant trip counts between each origin TAZ and destination census tract.

Since Streetlight trip attributes were binned into larger intervals (e.g. percent trips with durations between 10-20 minutes, or 5-10 miles), the first processing step was to interpolate distributions with increased resolution, binning distributions by 1 min, 0.1 mi, and 1 mile per hour for trip duration, distance, and speed, respectively. To interpolate missing values, I found the average distributions from the three nearest zones, along with data from the nearest zones in the hour before and after. This process was repeated iteratively until over 99% of all O-D pairs had data in all hours for all three attributes.

While this interpolation process introduces a source of error into my model, I consider it acceptable for two reasons: all trip data between census tracts comes from zone pairs with actual data, and as discussed above, I found that modifying trip relocation times by distributions with mean zero did not significantly change my results. Trip counts data was binned by hour, so I again interpolated the data to estimate the number of trips starting in each minute.

These pre-processing steps resulted in trip counts for each origin-destination pair by minute, and distributions of duration, distance, and speed for each origin-destination pair by hour. I then used this data as inputs for RISE simulations similar to those conducted in Manhattan.

The model proceeds chronologically over one day of data, repeating until the fleet's aggregate battery capacity at the end of the day is within 5% of that at the beginning of the day. In each minute, trips are assigned to the nearest vehicle, and idle vehicles are routed to charge or rebalanced in anticipation of future demand. Travel times and distances between each taxi and trip or charging point are imputed by drawing random values from the corresponding distribution obtained from StreetLight Data. To ensure a reasonable relationship between time, distance, and speed for each trip, distances are re-sorted in order to best match the relationship between draws for duration and speed. If a trip can only be served by a vehicle with insufficient battery capacity, the vehicle's range is increased by 50-mi increments until capacity is adequate. If no vehicle can serve a trip within a 10-min wait time, a new vehicle is added to the fleet. Thus, both battery range and fleet size increase organically over the course of the simulation, providing estimates of the minimum values required to serve demand. Vehicles serving trips that end outside the CSA are removed from the fleet; trips starting outside the CSA are served by new vehicles that are then added to the fleet.

To validate the accuracy of describing relocation times and distances with distributions instead of Google Maps predictions as in the original work, I compared results in New York City using the same input parameters. I found that using at least one zone per 100,000 inhabitants was sufficient to obtain similar results to those obtained with the previous method. I also tested the sensitivity of the results to the number of zones in Dallas, and found that using zones six times as large as TAZs returned similar results.

Finally, to test the sensitivity of results to correlation between distribution draws made for the same vehicle, I divided each zone into 100 parts, and randomly assigned each trip pick-up and drop-off and each charging station a grid cell within its corresponding zone; the relative Euclidean distance between grid cells in two zones was used to weight the probability distributions described above (i.e. cells relatively closer to each other were more likely to receive draws from the lower end of distance and travel time distributions, and vice versa). I found that this addition to the model increased deadheading predictions by less than 10%, but I retained it for the final simulation runs to be conservative.

Simulations were conducted for each city with 20k, 40k, 100k, 200k, 400k, and 800k trips, and with both 15kW and 50kW charging power. Locations of chargers were determined by k-means clustering of trip origins and destinations, which was determined to work as effectively as the siting algorithm described above. Simulations were then run with sufficient chargers to recharge the fleet assuming 25% empty miles and 50% charger utilization, then again assuming 100% charger utilization. In each case, every charger was occupied during peak charging times, so I concluded that a charger distribution factor of 1 would be sufficient.

While the simulation ran, I recorded the empty distance and time traveled to each passenger pick-up and charging event to determine the average ratios of empty-to-trip ratios for each city. These simulations allowed me to estimate the relationship between urban form and a variety of fleet parameters, including the empty distance to trips and charging stations. As shown in Figure 29, I found that deadheading ratios increase roughly with the square root of area per trip. To develop correction factors for estimated fleet size and battery ranges, I also compared results from GEM and RISE using the same inputs. Using ordinary least squares regression techniques, I extrapolated these ratios to all other CSAs and urbanized areas in the country based on population and area. Finally, I took population-weighted means to extrapolate from cities to determine the average deadheading ratios for rural and urban areas in each census division.

Interestingly, if fleets serve all driving demand, I found these correction factors to have consistently low values (e.g. empty miles represent 10% of revenue miles) in most areas of the U.S. These values were then used as correction factors to refine a convex optimization program to model the operations of the fleet on the national scale, based on data from the 2017 National Household Travel Survey (NHTS). Somewhat surprisingly, we found that when we allowed for heterogeneous battery range and charging speeds, average requirements did not increase dramatically from the Manhattan case, resulting in very low cost of service. This work was published in Transportation Research Record in January 2019,[153] and the final results integrated with a grid dispatch model are currently under review.

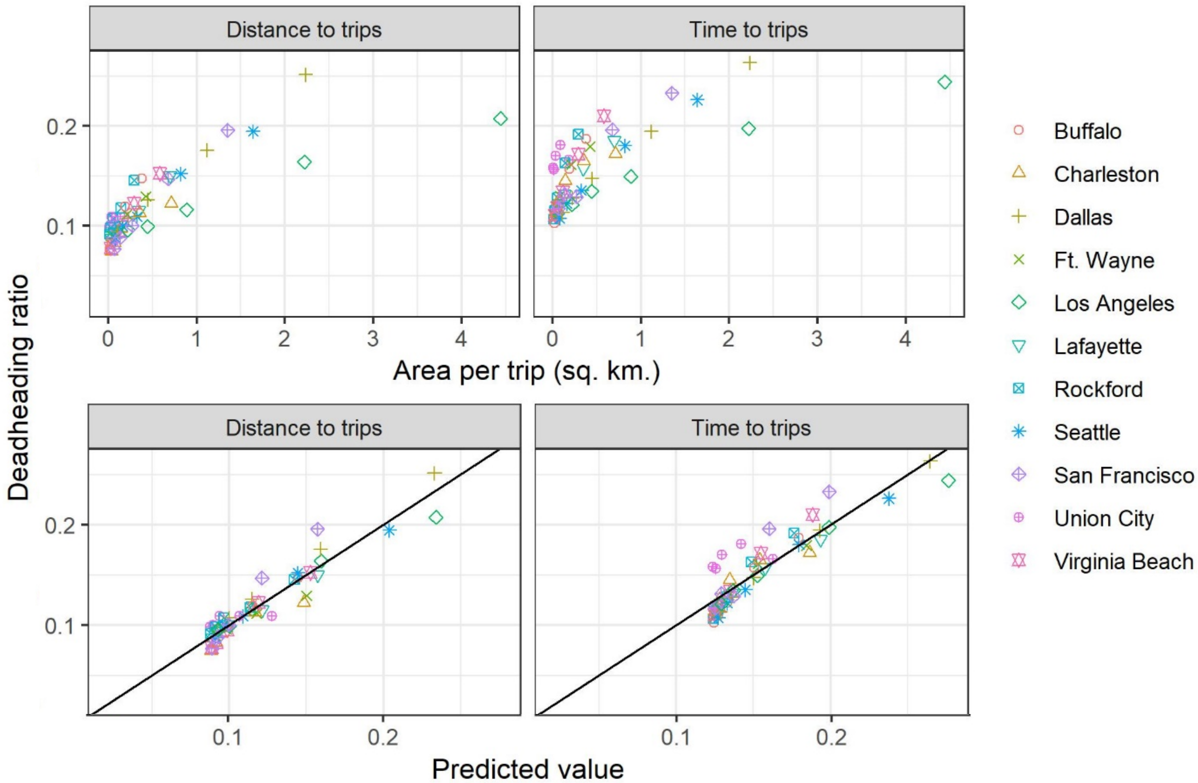


Figure 29. Relationships between area per trip and deadheading ratios for distance and time to trips in all simulated cities (top), along with actual versus predicted values from non-linear regression.

Chapter 2:
Electrifying urban ridesourcing/transportation network company (TNC) fleets at no added cost through efficient use of charging infrastructure

2.1. Introduction

The results described in the previous chapter imply that BEV fleets can serve demand at lower cost than gasoline vehicles. While the focus was on automated vehicles, many of the same advantages and modeling assumptions apply to human-driven vehicles as well, which leads to the question, why aren't fleets already electrifying?

In this chapter, I focus on the electrification of human-driven vehicles in ridesourcing services, or Transportation Network Companies (TNCs). I use data on ridesourcing trips and vehicle supply in San Francisco (SF) and New York City (NYC) to test the feasibility of meeting demand with supply given a variety of different input values, including for battery range and charging infrastructure. I show that (1) modest additions of public fast-charging infrastructure make urban ridesourcing electrification practical under a range of vehicle battery capacities and operating strategies, and (2) the current economics of urban ridesourcing can support vehicle electrification and the required charging infrastructure at total costs lower than the costs of the ICEV-based ridesourcing system. In addition, the increased utilization of charging infrastructure due to ridesourcing BEVs could reduce public charging costs for all BEV users and further support large-scale transportation electrification. Therefore, electrifying the urban ridesourcing sector could be a cost-effective approach to reducing transportation-related greenhouse gas emissions and urban air pollution, and properly designed policies could realize these benefits with little or no cost burdens to governments, transportation network companies, or ridesourcing drivers.

This chapter will proceed as follows. In section 2, I use fleet-wide average statistics to motivate my hypothesis that BEVs employed in ridesourcing fleets have sufficient time to charge, and that given reasonable levels of charger utilization, infrastructure cost becomes affordable. In section 3, I present the methods used to conduct agent-based simulations to verify this hypothesis, results of which are presented in section 4. In section 5, I conclude with policy implications and directions for future research.

2.2. Theory

Contrary to common perception, simple economic reasoning suggests that ridesourcing drivers have adequate time to charge during their shifts, and that—given sufficient utilization—fast-charging infrastructure could pay for itself. As previous studies have noted,[154] the short rider wait times that are key to ridesourcing's value proposition are predicated on having a significant number of drivers waiting for ride requests at any given time. This idle time represents time when drivers could charge BEVs without losing revenue. As shown in Equation 4, the amount of idle time for drivers (t_{idle}) can be expressed as a relation between driver wage rate (w), the ratio of empty miles to passenger miles (deadheading ratio, r) and the rate that could be earned by serving trips continuously (f) multiplied by the time period (t_{tot}), minus average refueling time (t_{fuel}).

$$t_{idle} = t_{tot} * (1 - w/f * (1+r)) - t_{fuel} \quad (4)$$

For instance, in NYC, a Uber riders' fare is determined as the sum of a fixed \$2.55 per trip base charge, a \$1.75 per mile charge and \$0.35 per minute charge, with 75% of this total accruing to the driver and the remaining 25% to Uber.[155] Given an average speed of roughly 12 miles per hour and an average trip distance of 3 miles,[145] a driver carrying passengers for a full hour would serve 4 trips, earning \$39.15 (f). Assuming gross driver earnings (w) average \$24 per hour,[154,156] and a deadheading ratio (empty miles divided by passenger miles) of 0.25,[157] I can estimate that drivers in NYC are moving for roughly 46 minutes out of the hour, and have roughly 14 minutes in which to recharge the 9.2 miles they traveled. As shown in Figure 30, a 50-kW charger can provide this amount of charge in roughly 3 minutes, suggesting that drivers have more than enough time to charge during their shift. Based on these assumptions, the average driver would have to charge less than once per shift, such that time spent relocating to charge is negligible.

On the other hand, data suggests that, in the U.S., public charging infrastructure is utilized less than 10% of the time,[158,159] which often makes DC fast charging more expensive than gasoline on a per-mile-driven basis. As shown in Figure 31, once utilization surpasses about 15% (roughly 3.5 hours per day), the combined cost of infrastructure and electricity becomes less than the equivalent cost of gasoline in both NYC and San Francisco (SF), and operational savings start to accrue. This suggests that the cost of charging infrastructure is highly sensitive to utilization.

These calculations suggest that neither the time required to charge nor the cost of infrastructure should pose significant barriers to ridesourcing electrification. This conclusion is based on several major assumptions: that charging in between trips does not affect the ability to serve demand for rides, that time spent relocating to charge is not significant, and that charger utilization greater than 3.5 hours per day is feasible when accounting for relocation time and queuing at stations.

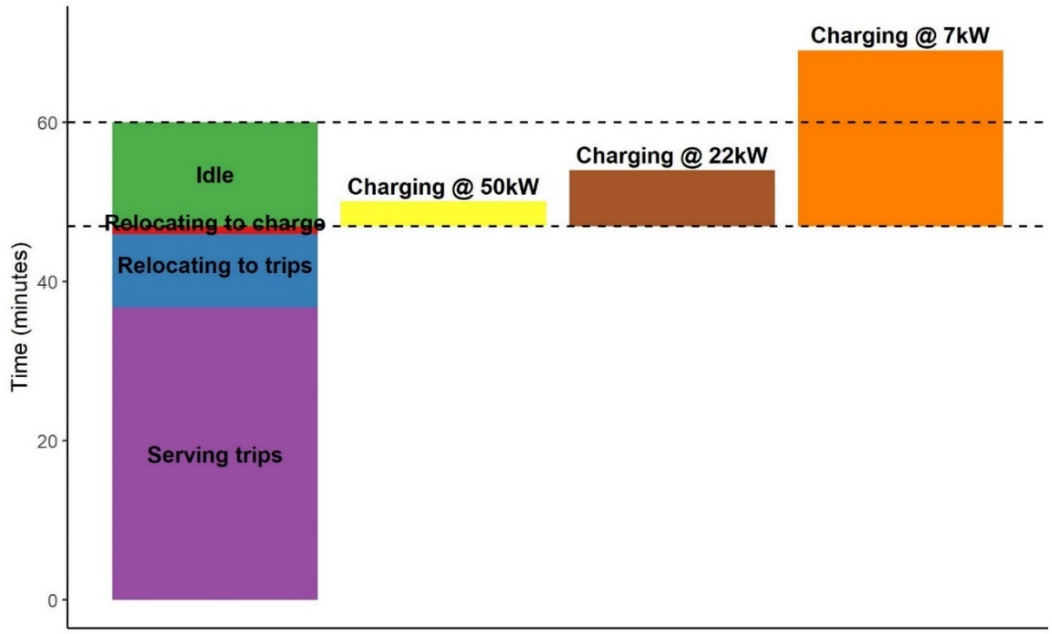


Figure 30. Distribution of time spent by an average NYC ridesourcing driver, with time cost of charging for both DC fast charging (50 kW) and Level 2 charging (22 kW or 7 kW). I assume a vehicle energy consumption of 0.28 kWh/mile, equivalent to the performance of the 2018 Chevrolet Bolt.[160] For relocating to charge, I assume one charging session per 8-hour shift and an average relocation distance of 2.5 miles at a speed of 10 miles/hour.

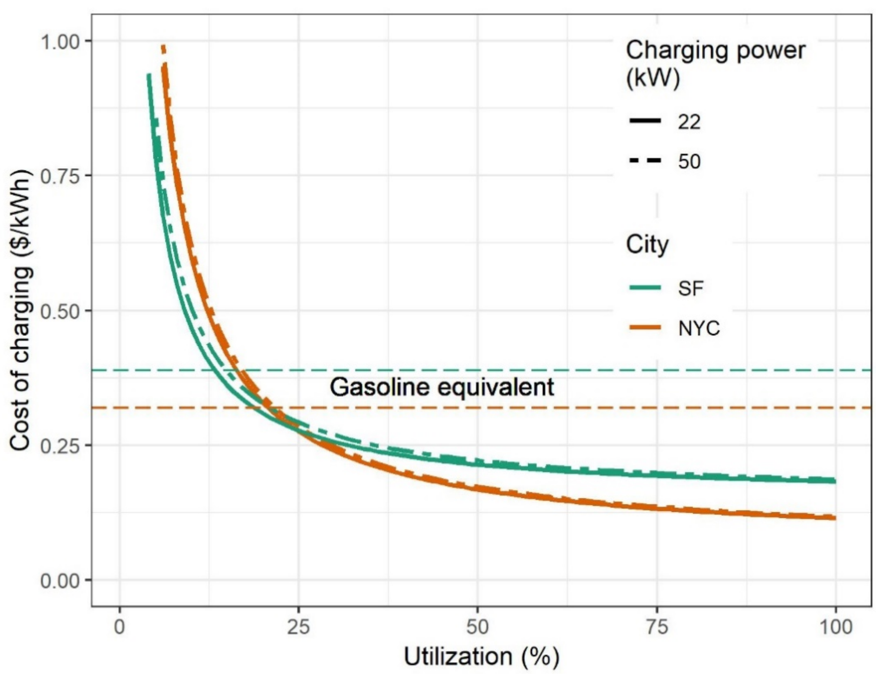


Figure 31. Relationship between the total cost of charging infrastructure (capital cost, electricity, and demand charges) and percent utilization by time. Cost assumptions are shown in Table 15 in the methods section. Note that the curves for 50kW and 22kW chargers appear roughly the same because capital costs scale roughly linearly with the power rating.

2.3. *Methods*

To test the assumptions listed above, I developed an agent-based model that routes a fixed number of active vehicles to trips, rebalances idle vehicles to match demand, and determines the best times for vehicles to charge given a fixed number of charging points and locations. I repeated this analysis numerous times for different combinations of the fixed input parameters (see Table 16) to determine the minimum charging infrastructure required for BEVs to generate at least as much revenue per shift-hour as ICEVs. I conducted this analysis with data for ridesourcing trips in both SF and NYC, integrated with data on travel times and distances from cell phones and GPS devices, along with driver characteristic data from government records and existing surveys.

2.3.1 Fleet modeling

To route vehicles to trips and charging, I used a modified version of the agent-based model originally described in chapter 2. Figure 32 shows a flow-chart of the model process. Basically, the model heuristically relocates vehicles between trips to better serve demand and charge opportunistically. Proceeding chronologically, the model assigns each trip to the closest available vehicle that would have at least enough range to serve the trip, make it to the closest charging station, and commute home. Other studies have found that such an approach to trip assignment is equivalent to more optimal algorithms when there are enough idle vehicles [161]. When more than one vehicle meets these criteria, the model assigns the one with the least earnings per hour to decrease disparity in earnings between drivers. If no vehicle can serve a trip within 10 minutes, it is allowed to be served by an idle vehicle that could have arrived at the pick-up point within 10 minutes of the request time, assuming it anticipated the demand and started driving in that direction immediately after its last drop-off. As discussed above, this "clairvoyant" approach was verified to be realistic through sensitivity analysis. I also ran simulations in which vehicles do not relocate in between trips, which support my main results. In practice, there is no way to guarantee that all trips will be served within 10 minutes of the request time; I merely use this threshold as a basis for comparison between simulations.

If a trip request is not served within 15 minutes, it disappears and its revenue is lost. This constraint results in less than 4% lost revenue for ICEV fleets in NYC, and no lost revenue for ICEV fleets in SF. After trip assignment, idle vehicles are routed to charging stations using the following heuristic approach. Vehicles only relocate if they have been idle for enough time that they could have made it to the charging station, regained any charge lost in transit, and spent at least 15 additional minutes charging. Charging time is also limited by the amount of time chargers have been available, and occupied chargers are not available to accept vehicles. Assignments are made in order of the amount of energy gained. To test the impact of this routing algorithm, I conducted simulations with restrictions on charging (Table 16). The fixed charger locations are predetermined using k-means clustering of trip origins and destinations, which resulted in equivalent performance to the charger location algorithm described in chapter 2. This result is consistent with He et al. (2016),[162] who found a similar clustering algorithm to be superior to other siting algorithms. In simulations with a fixed number of charging locations, placement of both the locations and chargers were determined with k-means clustering, and then each charger was moved to the nearest location.

The main difference between the model developed for this study and that reported previously is that, at each minute, vehicles in the present study were removed or added to the fleet to match the time-varying fleet size determined exogenously. Each vehicle was assigned a shift length and commute distance (to and from home) randomly selected from a distribution based on survey data (see below for details). At the end of the shift, after serving any active trip, vehicles were designated as inactive as soon as they had enough range for their commute. When starting a new shift, initial vehicle range was selected randomly from the ranges of vehicles already to have completed their shifts, and the simulation repeated on the same 24-hour period until the average range of all vehicles (both active and inactive) at the end of the day was within 5% of what it was at the beginning of the day. Model inputs and outputs can be summarized as follows (see Table 16 for details):

Inputs: battery range, charging speed, number of chargers, number of charging locations, number of active vehicles by minute, driver shift length, driver commute distance, vehicle routing algorithms

Outputs: wait time by trip, revenue per shift-hour by vehicle, utilization by charger, deadheading distance and time by vehicle

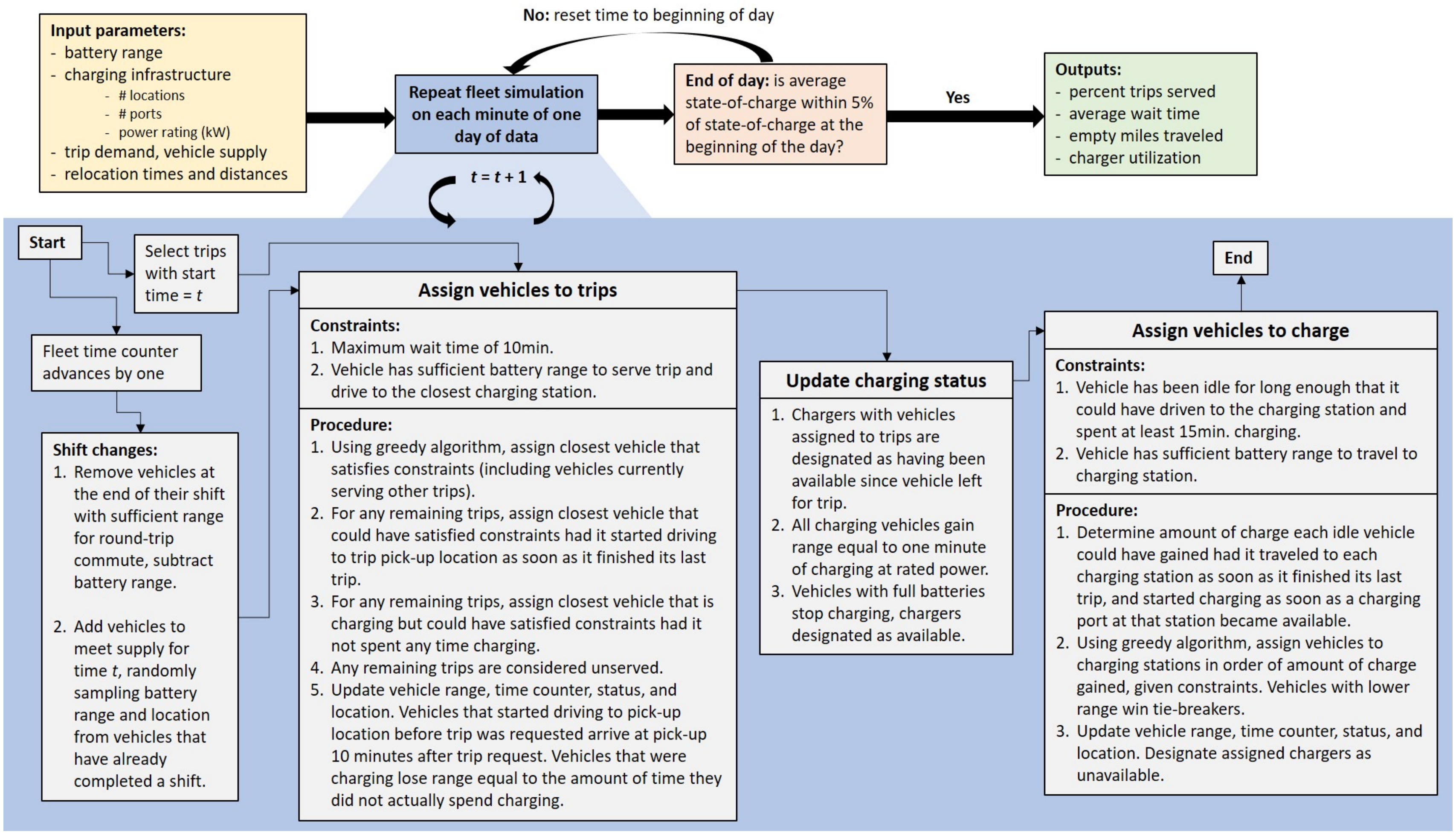


Figure 32. Flow chart depicting agent-based simulation for BEV fleet operations.

2.3.2 Trip data

I conducted fleet simulations in both SF and NYC. To estimate trip data for NYC, I obtained data from the NYC Taxi and Limousine Commission (TLC) on trips taken by Yellow Taxis, Green Taxis, and For-Hire Vehicles (FHVs), the latter of which includes all ridesourcing vehicles. The taxi datasets included geolocations and timestamps for trip pick-up and drop-off points, as well as trip distance, whereas the FHV dataset included only the number of trips by pickup zone and hour. To estimate individual trip records, I sampled trips from the combined taxi dataset to create a trip record with the same distribution by hour and pickup zone as the FHV data from February 2017, with 422,000 trips (the average for a weekday). This method accounts for the fact that FHVs tend to serve different neighborhoods, but it assumes that trips within each neighborhood are similar to taxi trips, which introduces a potential source of error. Pick-up and drop-off coordinates were clustered into cells with radius 250 meters such that the maximum difference in travel time would be 1 minute assuming an average speed of 15 miles per hour. This clustering resulted in 6,500 total cells. Origin-destination matrices with times and distances between each of these cells were estimated using data downloaded from Google Maps API, as described in Chapter 2.

Table 14. Summary of city characteristics.

Parameter	San Francisco	New York City
Area (square miles)	47	303
Number of trips	162,707	422,652
Average trip distance (miles) and duration (minutes)	2.7 miles 14 minutes	3.1 miles 15 minutes
Total number of active drivers	14,735	27,275
Average commute distance (miles)	12.4	10.0
Average shift length (hours)	4.6	7.0
Average driver earnings ($/shift-hour)	18.55	24
Sources	San Francisco County Transit Authority; San Francisco Tax Collector's Office	NYC Taxi & Limousine Commission; Hall and Krueger (2018); Parrott and Reich (2018)

The SF simulations are based on data obtained from the San Francisco County Transportation Authority (SFCTA) for Uber and Lyft trips starting and ending within city limits in November and December 2016. The data were aggregated by hour and traffic analysis zone (TAZ), and pickup minutes were estimated using LOESS regression, with the number of trips in each minute adjusted such that the total number of trips in each hour was equal to that in the original data. To estimate times and distances for each trip, I integrated the SFCTA data with data obtained from StreetLight Data Inc. based on GPS data from smartphone apps and in-vehicle devices. These data include the distribution of times and distances for vehicle trips taken between TAZ pairs by hour. While this GPS data is primarily sourced from personal vehicles, I assume that ridesourcing trips will have similar distance and time to trips made by personal vehicles between the same two points. StreetLight Data metrics were also used to create relocation matrices between each zone pair, similar to the data from Google described above. As shown in Figure 33, for each unique vehicle-trip and vehicle-charger pair, relocation times and distances are drawn randomly from the corresponding distribution provided by the data.

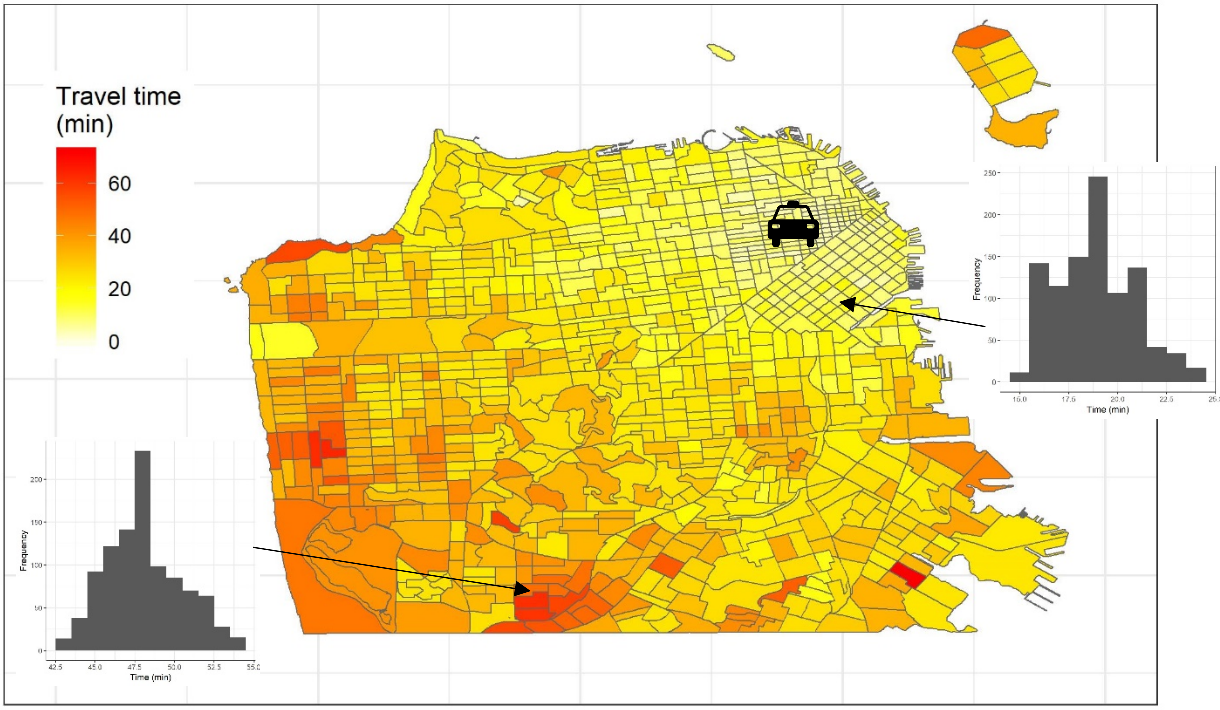


Figure 33. Maps showing average travel times between a vehicle in downtown SF (depicted by the taxi icon) and every other TAZ in SF. Distributions of travel times to selected TAZ's are shown in inset histograms; these distributions are derived from GPS data provided by StreetLight Data. Note that distributions appear discontinuous due to rounding; the distributions they are drawn from are discrete but relatively smooth.

2.3.3 Driver commutes and shift lengths

In both cities, I used survey data of Uber drivers [156] and NYC TLC data on ridesourcing driver working hours [154] to estimate the distribution of shift lengths for drivers. To estimate commute distances, in SF I obtained data on the home cities of about 1,000 Uber/Lyft drivers within the Bay Area [163], and I used the Google Maps distance from each city to SF to create a sampling distribution. Drivers originating outside the Bay Area were excluded, because I assumed they would have to charge somewhere in the Bay Area on their way to and from home, such that these "super-commuters" would not affect charging infrastructure requirements. Based on the distribution for SF, in NYC I estimated commute distances by sampling from a gamma distribution with a scale factor of 2 miles and shape factor of 5 miles.

2.3.4 Number of drivers active

In SF, I obtained data from SFCTA on the average number of drivers active in each hour, then used LOESS regression to estimate the number active in each minute. In NYC, I calculated the total amount of revenue generated in each minute based on Uber fares,[155] and I used this to determine the number of drivers that would be active if the average gross earnings were

$23/hour, the average of values found in surveys.[154,156] I then used LOESS regression to create a smooth curve for number of active drivers, adjusted such that the average earnings over the entire day were equal to $23/hour.

2.3.5 *Cost analysis*

Each component used to estimate the average cost per mile of each scenario is described in Table 15. The energy costs used are standard rates for small commercial entities, corresponding to the power range of charging stations considered. This does not include overhead expenses for a charging operator, assuming stations may be either publicly owned or managed by the ridesourcing companies themselves. All amortization calculations assume an annual discount rate of 5%, a value commonly used to evaluate the cost of long-term projects [164]. I ran a cost sensitivity using a 10% rate (roughly the long-term average stock market return, see MoneyChimp, 2018),[165] but found that results for the difference in net revenue between ICEVs and BEVs changed by only -$0.07 to +$0.04 per shift-hour, which is a very small percentage of total revenue.

Table 15. Cost model components.

Component	Value	Source
Vehicle purchase	BEV 238: $29,120 (2019 Chevrolet Bolt after federal tax credit; assumed that battery lasts at least as long as vehicle) ICEV: $23,845 (2019 Toyota Camry)	17
Vehicle lifetime	200,000 miles	166
Vehicle maintenance	BEV: $0.04/mile ICEV: $0.06/mile	143
Charger installation	7 kW: $5,000 22 kW: $20,000 50 kW: $50,000	138,167
Electrical connection	Same cost as two additional chargers per location (includes cost of transformer upgrades)	138,167
Vehicle insurance	$150/vehicle-month	168
Energy costs	<u>BEV</u> NYC: $0.061/kWh + $30.90/kW SF: $0.151/kWh + $15.90/kW (per-kW fees represent demand charges on peak power usage) <u>ICEV</u> NYC: $0.09/mile ($2.68/gallon, 30 miles/gallon) SF: $0.11/mile ($3.27/gallon, 30 miles/gallon)	169–172 Gasoline prices reflect 5-year averages

2.3.6 *Simulation runs*

As shown in Table 16, I conducted simulations for a variety of scenarios for vehicle range, charging infrastructure, and charging relocation strategy (i.e. the rules that determine when vehicles go to charge), for a total of 360 BEV fleet simulations (180 for each city). I also conducted an ICEV fleet simulation in each city for comparison. I then determined whether each BEV fleet provided equivalent service to the ICEV fleet, defined as earning at least 95% as much revenue per hour, with no more than 5% additional empty miles and average wait times no more than 1 minute longer.

Table 16. Description of simulation runs.

Parameter	Values simulated
Battery range	90 miles (based on 2019 Nissan LEAF with decreased range from winter driving or capacity fade), 238 miles (based on 2019 Chevy Bolt advertised range)
Charger utilization	25%, 50%, 75%, 100%
Charging speed	7.7 kW (present-day Level 2 charging), 22 kW (next-generation Level 2 charging),[173] 50 kW (public DC fast charging)
Number of chargers	Total distance * 1.4 / (Charging rate per hour * 24 hours * charger utilization)
Number of charging locations	Unrestricted, 10 locations
Charger distribution strategy	k-means clustering (“optimal”), random point selection after k-means clustering to 5,000 points (“random”), random point selection from bottom 20% of points by total number of trips within a 1.5-mile radius (“perimeter”) (tested only with 50% charger utilization and 50-kW charging)
Charging relocation strategy	Optimal routing (“opportunity”), optimal when < 20% state of charge (SOC) (“threshold”), move to closest available charger when < 20% SOC (“baseline”)

2.4. *Results & Discussion*

2.4.1 *Feasibility of ridesourcing electrification by scenario*

As shown in Figure 34, my simulation results suggest that BEVs with 238 miles of range (equivalent to the Chevrolet Bolt EV) can provide equivalent service to ICEVs in a range of different infrastructure scenarios in both cities. However, the ability of the fleet to serve demand is sensitive to both charging speed and charging relocation strategy. Using chargers rated at 7kW—the most common form of public infrastructure today—does not allow for equivalent service in any of my simulations, suggesting that such slow charging is not sufficient for ridesourcing electrification. This result is consistent with the analysis summarized in Figure 30. Using 22-kW charging works in the “opportunity” relocation scenario in SF and when the number of locations is unrestricted in NYC, while using 50-kW charging (DC fast charging) allows BEVs to provide equivalent service across a wide range of scenarios. This result suggests that DC fast charging infrastructure rated at 50kW is both necessary and sufficient for ridesourcing electrification.

In the “baseline” scenario, in which drivers have no information on when they should charge and only have information on which chargers are available when they start moving there, only 50-kW charging allows for equivalent service in both cities. This scenario represents how BEVs currently operate, suggesting that 50kW charging will be necessary to initiate BEV penetration. In NYC, 22-kW charging can provide equivalent service if there is no restriction on the number of charging locations, but when BEV penetration is low, there will not be enough utilization to support more than a few locations. On the other hand, the fact that 22-kW charging works in many cases suggests that 50-kW charging may work even if my model is too optimistic, and effective charging speed is lower in practice when accounting for time spent parking and plugging in.

If fleet operators are able to direct vehicles to charge only when they have enough idle time to do so ("opportunity" and "threshold" scenarios), the number of 50-kW chargers required decreases to two per square mile in NYC (512 total chargers), and three per square mile in SF (175 total chargers). In the "threshold" scenario, vehicles are only available to charge once their battery range falls below 20%, whereas in the "opportunity" scenario, vehicles are available to charge whenever idle. The former scenario performs slightly better in NYC, while the latter performs better in SF, likely because the larger area or greater congestion of NYC induces a larger penalty for charging frequently. This result suggests that some form of scheduling system for charging stations can greatly improve electric vehicle reliability, which is consistent with findings from previous studies.[174–176]

In some ways, 238-mi. range represents an ideal case; to account for the impact of colder temperatures, more aggressive driving, using vehicles with less battery range, and capacity fade over time, I also ran each simulation with 90 miles of battery range. As shown in Figure 35, such vehicles can also provide equivalent service to ICEVs in both cities with 50-kW charging so long as timing of charging is managed efficiently ("opportunity" scenario), suggesting that such a capability makes fleet performance insensitive to battery range. In turn, using vehicles with less range could decrease operating costs by reducing vehicles' up-front costs and extending batteries' functional lifetime.

As shown in Figure 36, fleet performance is also relatively robust to how the chargers are sited. Relative to clustering chargers by trip origins and destinations ("optimal" scenario using k-means clustering), results remain largely unchanged when chargers are placed semi-randomly ("random" scenario, i.e. selecting locations randomly after using k-means clustering to narrow down selection to 5,000 points), suggesting that mildly perturbing placement does not affect fleet performance. Even if chargers are placed only on the periphery ("perimeter" scenario, randomly selecting points from areas with low trip density), revenue remains stable in both cities, and in NYC overall service with the "threshold" charging relocation strategy remains comparable to the ICEV fleet. If this scenario is modified such that charging at the beginning and end of shifts is incorporated into drivers' commutes ("commute" scenarios), fleet performance in NYC becomes equivalent to the "optimal" charger placement scenario. Average wait time remains roughly 3 minutes longer in SF, but this may be because the trip data does not include trips entering or leaving city limits. This result suggests that in some cases, if many ridesourcing drivers come from outside the city (e.g. over half in SF),[163] placing charging near popular commute routes may be sufficient. In summary, it appears that charging placement has relatively little impact as compared to coordinated charging management, as the latter enables the use of short-range BEVs. A map of each charging distribution is shown in Figure 37.

Figure 38 and Figure 39 show more details related to vehicle activity: the first shows overall averages for the amount of time devoted to each activity, while the second shows vehicle counts disaggregated by activity and minute in SF.

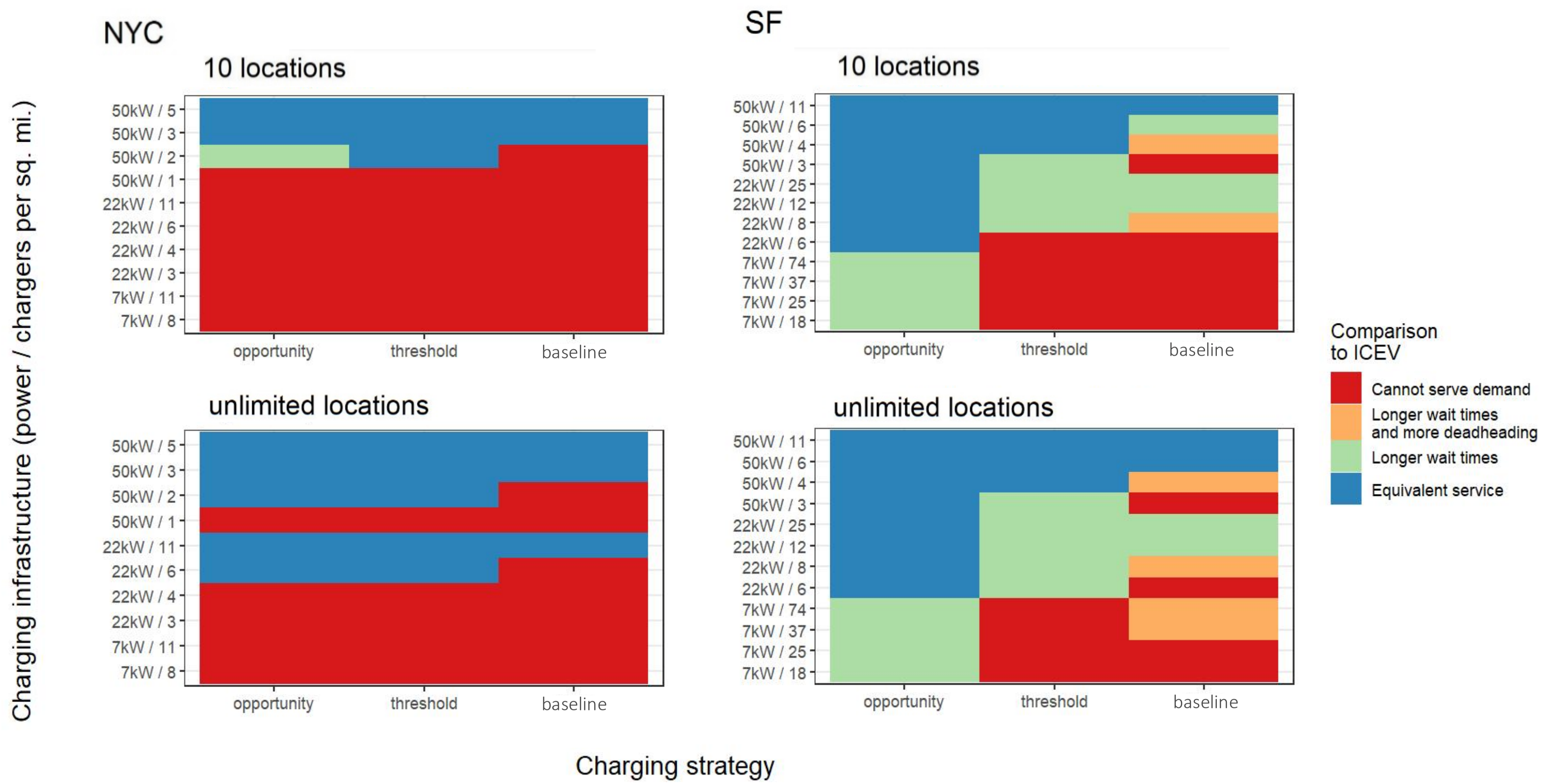


Figure 34. Results for all simulations, showing the performance of a fleet of BEVs with 238-mi. range relative to a fleet of ICEVs for each combination of charging infrastructure, battery range and charging relocation strategy. “Opportunity” represents simulations where vehicles are routed to charge whenever they have enough idle time to make it worthwhile, “threshold” represents simulations where vehicles are only allowed to charge when below 20% state of charge, and “baseline” means that as soon as vehicles reach 20% state of charge, they move to the closest available charger whether or not they have enough time to gain a meaningful amount of charge, and whether or not there is another vehicle moving to the same charger. Ten was chosen as the number of charging locations for the restricted-location scenarios because this was considered a lower bound on the number of charging sites that could be feasibly deployed in a city.

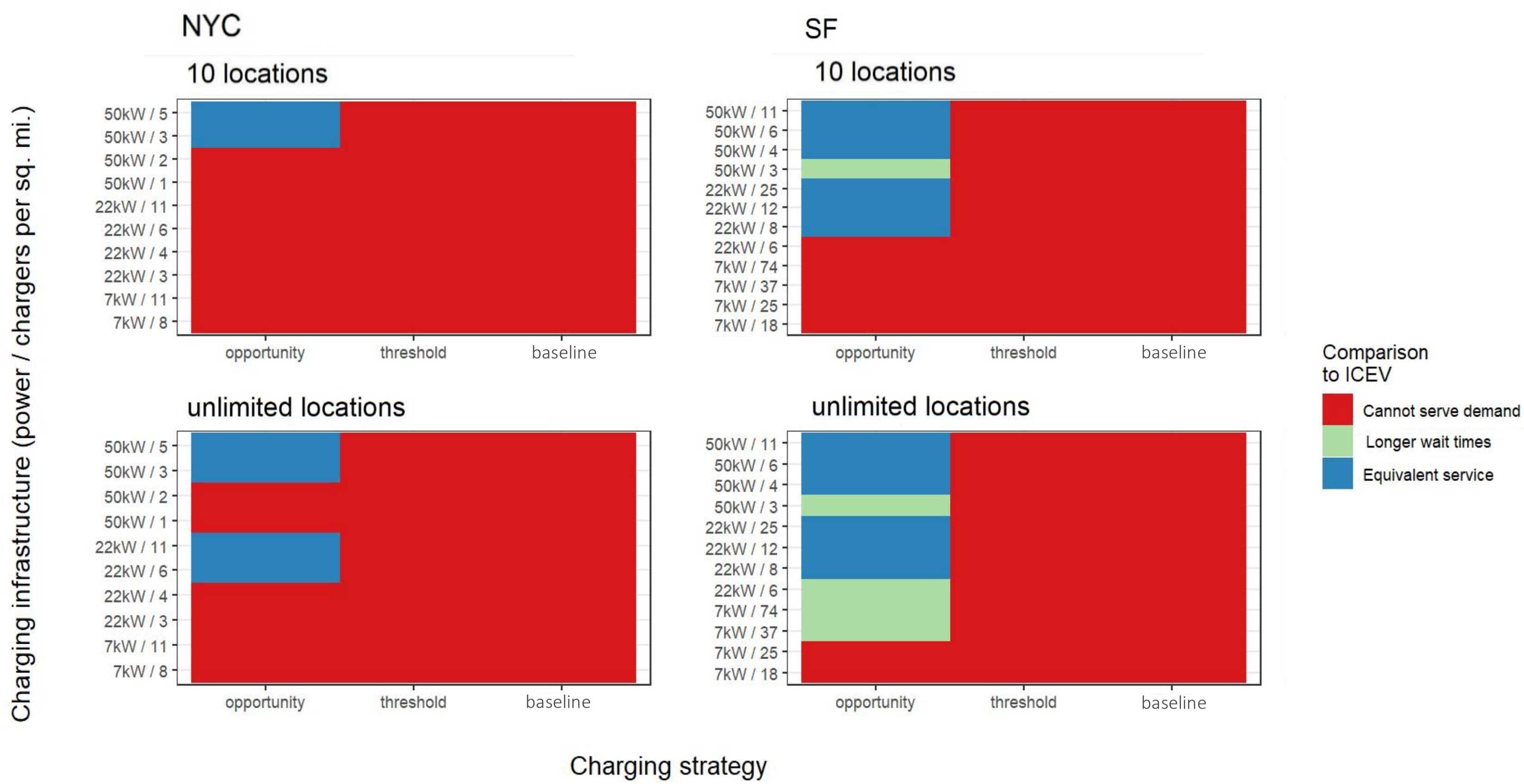


Figure 35. Results for all simulations with 90-mi. battery range. Labels are the same as in Figure 34.

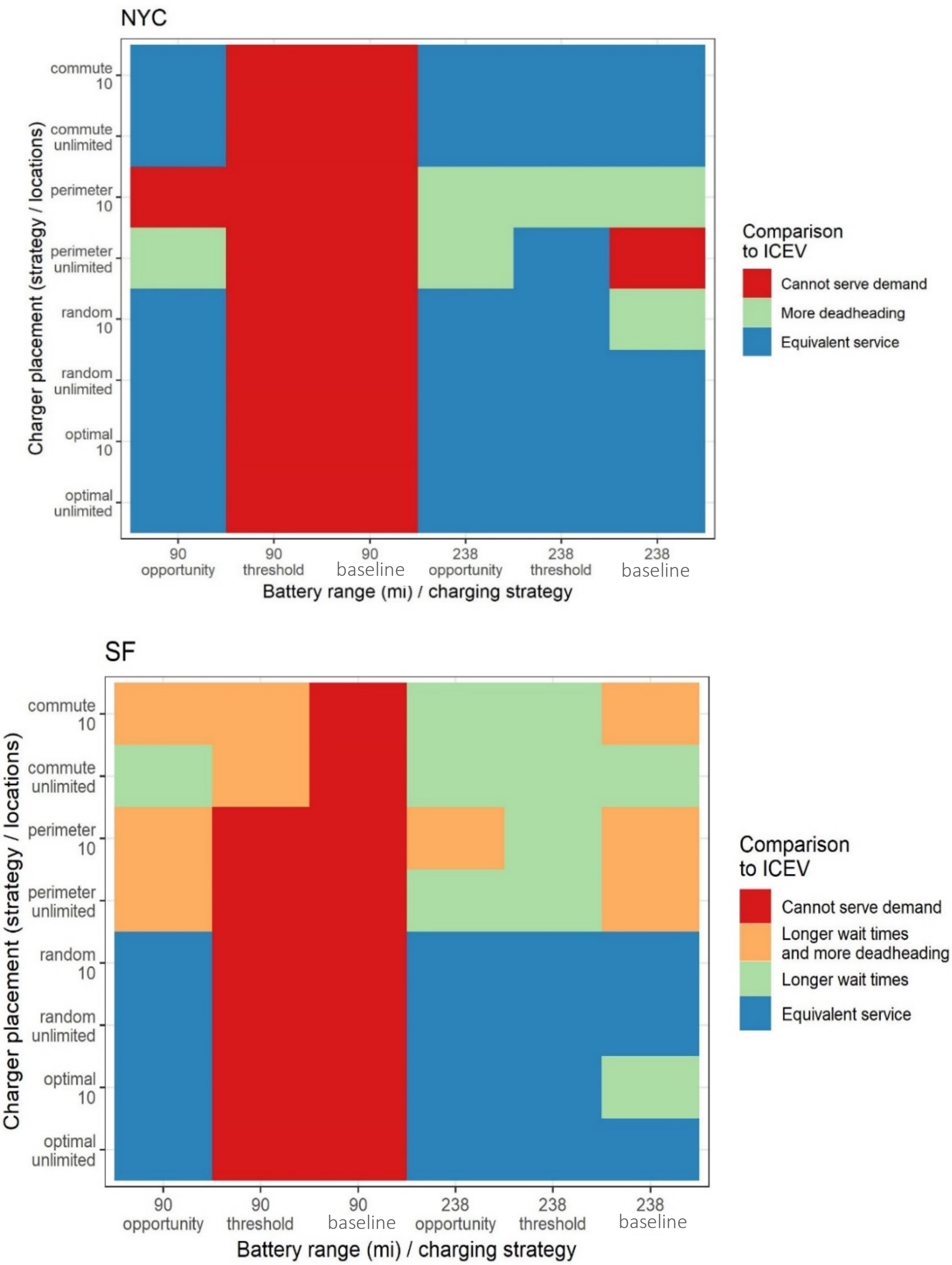


Figure 36. Results for simulation runs with different strategies for charging relocation and charger placement. In "optimal" simulations, chargers were clustered based on trip origins and destinations. In "random" simulations, charger locations were selected randomly after clustering trip origins and destinations to 5,000 points, and in "perimeter" and "commute" simulations, charger locations were selected randomly from points in the lowest 20% of trips per square mile. Each simulation was run with three and four 50-kW chargers per square mile for NYC and SF, respectively.

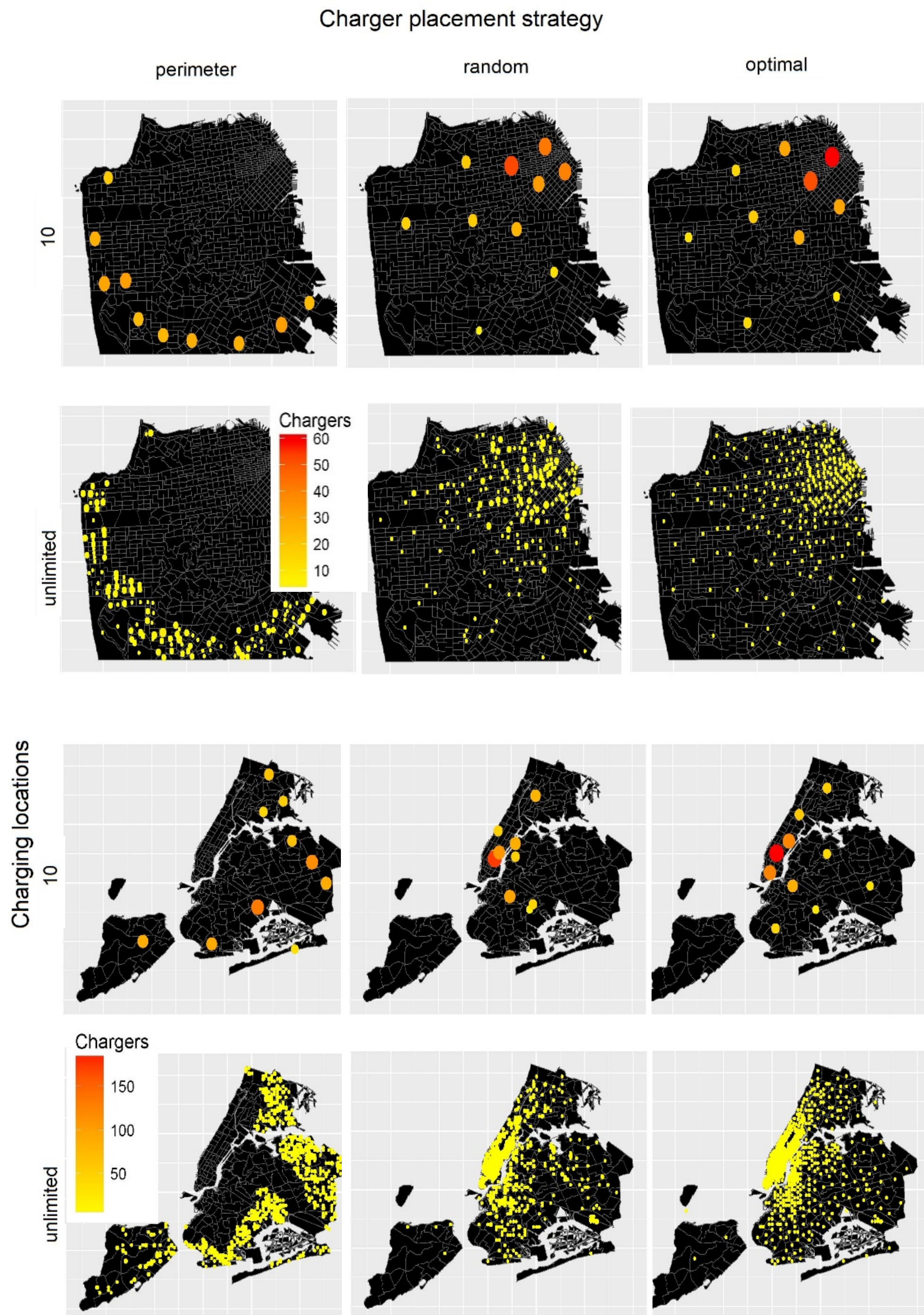


Figure 37. Maps of distributions of chargers in SF (top) and NYC (bottom) for each placement strategy and for both unlimited locations and placement restricted to 10 locations. The color and size both represent the number of chargers at each location.

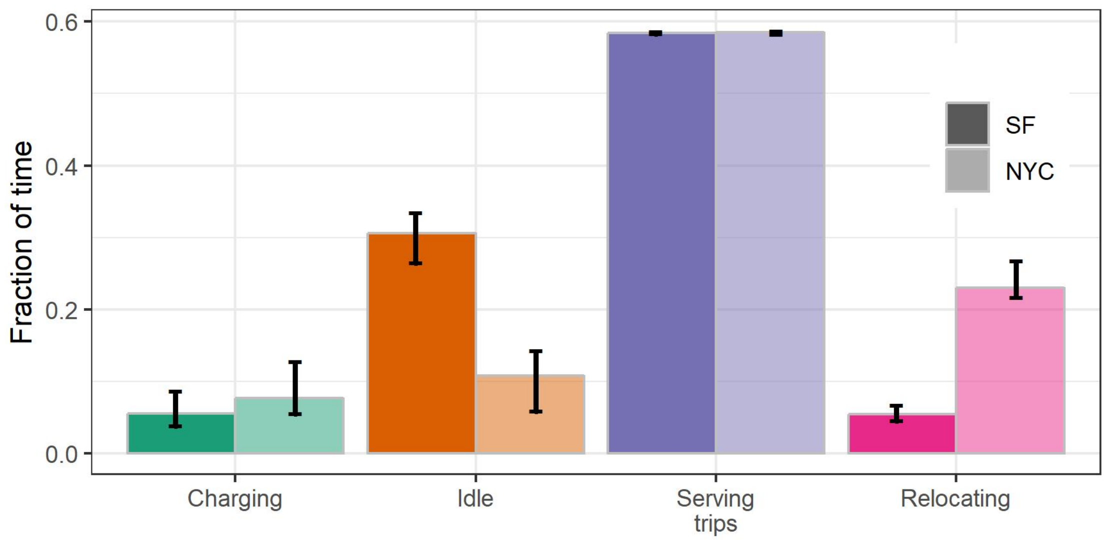


Figure 38. Fraction of time devoted to each activity in each city for all simulations resulting in equivalent service to ICEV fleets.

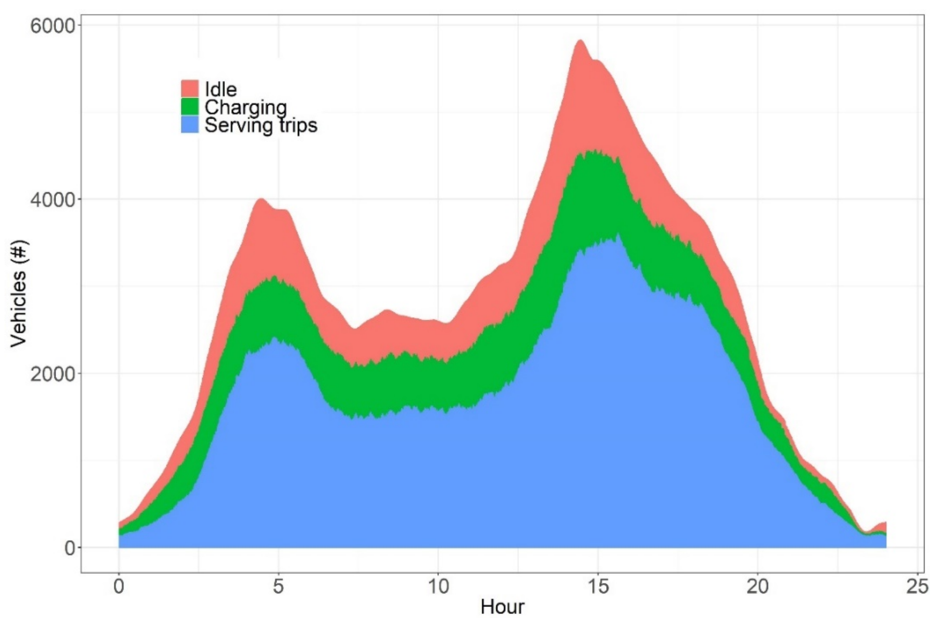


Figure 39. Vehicle activity by time of day with 7kW charging in San Francisco.

2.4.2 Total costs of ridesourcing electrification

The results presented above suggest that ridesourcing fleets can provide high levels of charger utilization. In both cities, fleets with average charger utilization of over 12 hours per day were feasible with both 22-kW and 50-kW charging. With 50-kW charging and some management of charging timing ("opportunity" and "threshold" scenarios), fleets in both cities achieved charging utilization of up to 20 hours per day while providing equivalent service to ICEVs. These results correspond to about 750 50-kW chargers in NYC, and 175 in SF, with densities of about three chargers per square mile in both cities (NYC covers an area roughly five times as large as SF). These quantities are roughly equivalent to the total number of gasoline pumps in each city.[177] In comparison, NYC currently only has 16 public fast chargers, but it plans to build up to 1,000 more by 2020.[178] SF currently has 20 fast chargers spread across 13 locations,[179] but there is public funding for the installation of several thousand additional chargers (power ratings have not been publicly announced).[180,181] Based on my results, these existing plans are more than sufficient to fully electrify ridesourcing in these cities provided that chargers are rated to at least 50kW. I find that adding more charging infrastructure beyond this threshold does not significantly improve fleet performance, consistent with previous studies that have found diminishing returns to adding more charging infrastructure.[119,182]

As a result of high utilization, I estimate that the cost of installing these fast chargers is quite low: \$0.07/shift-hour in SF and \$0.17/shift-hour in NYC, including demand charges (see Table 15 for cost model details). In contrast, I estimate that all other ridesourcing BEV expenses fall in the range of \$3.27–\$3.40/shift-hour including both operating costs and amortized capital costs. The impact of BEVs on net revenue is either positive or close to zero in all scenarios (Figure 40). In other words, even if the charging infrastructure is significantly overbuilt, resulting in only 5-10 hours of utilization per day (11 and 5 chargers per square mile for SF and NYC, respectively), the cost still represents at most 2% of driver earnings and an even lower proportion of total revenue. My sensitivity analyses show that—in every case I tested—differences in revenue between ICEV and BEV fleets fall within the range of -\$0.80 to \$0.80/shift-hour, or a few percent of total revenue. This comparison assumes that fleets or their drivers pay for charging infrastructure; any public infrastructure funding will increase potential savings for ridesourcing fleets.

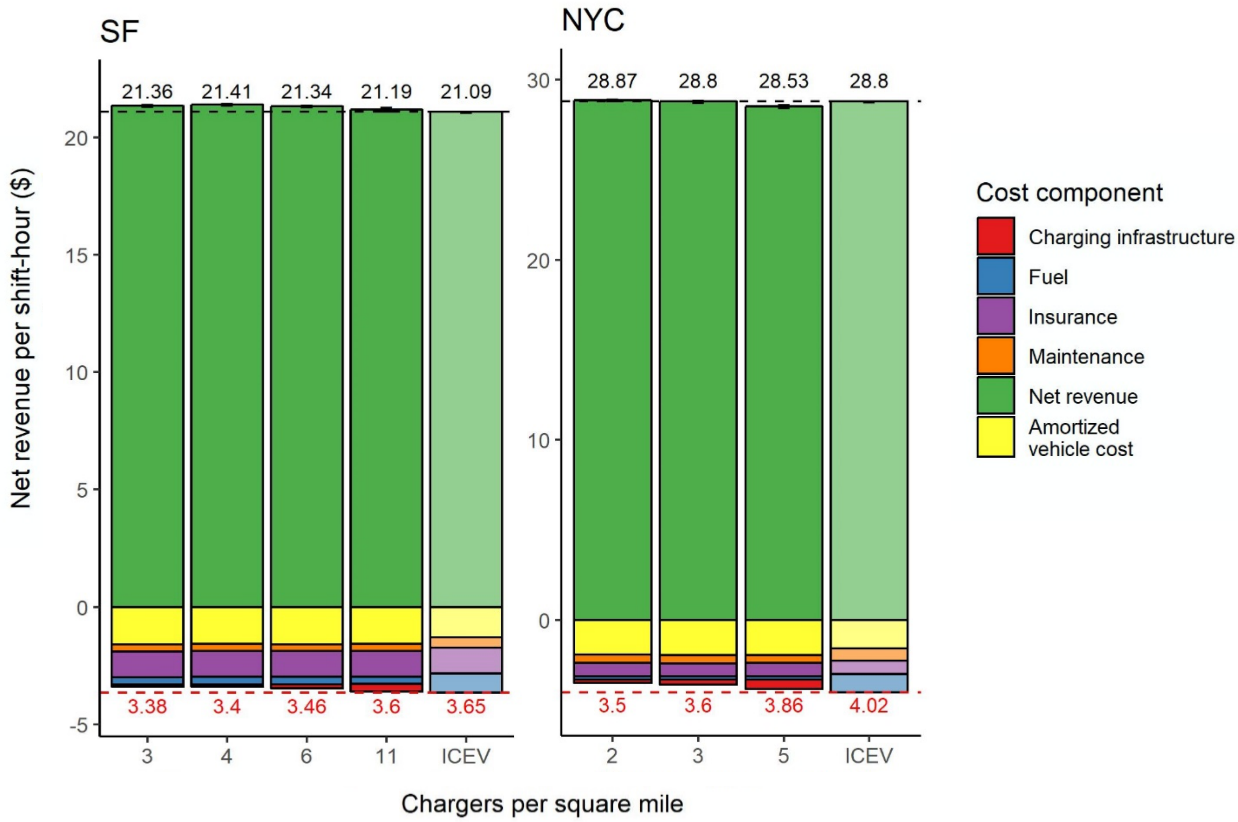


Figure 40. Average expenses and net revenue of operating a ridesourcing BEV per shift-hour, broken down by component for each city. Dashed lines show comparison to total ICEV cost and net revenue, while red numbers show total expenses and black numbers show net revenue after expenses. Error bars show difference between BEV scenarios (only 50-kW scenarios that provide equivalent service to ICEVs are shown).

Charging infrastructure could be paid for with less than 1% of revenue from the rideshare tax in NYC,[183] or less than 4% of the proposed rideshare tax in SF.[184] While I do not make any claim about the specific levels of utilization required to support charger deployment, these results suggest that utilizations as low as 20% may be sufficient. Below this point, the net revenue from BEVs will decrease as charging costs per kWh increase exponentially.

2.4.3 Extended simulation results

NYC

Figure 41 to Figure 46 show results for each city for each measure of fleet performance: demand served (and correspondingly driver revenue), average wait times, and deadheading (the ratio of empty miles to passenger miles).

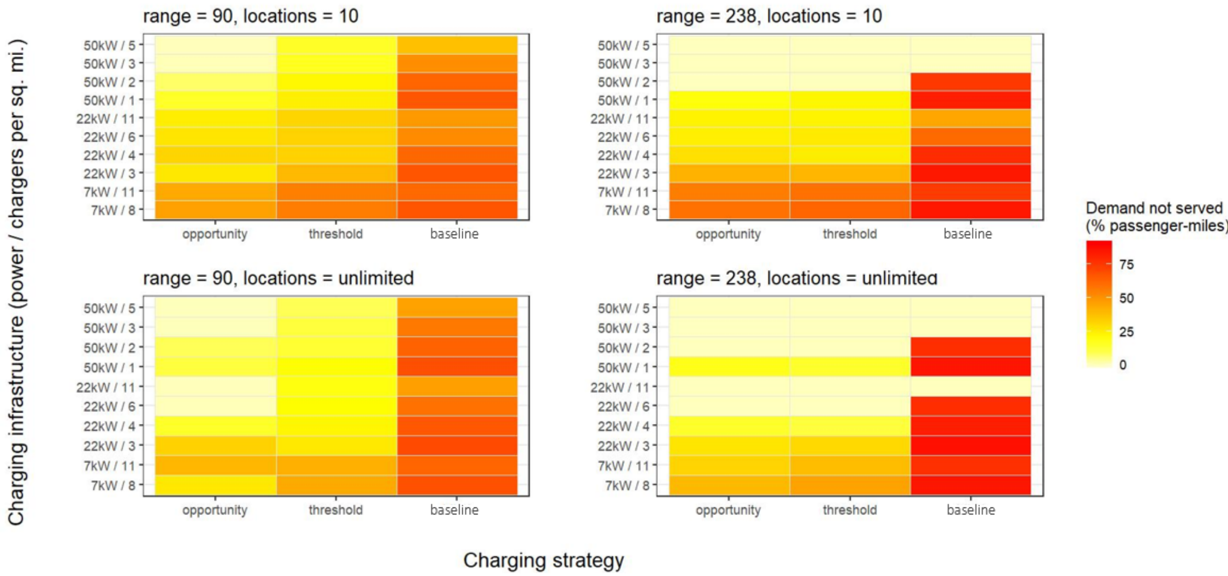


Figure 41. Percent passenger-miles served by BEV fleets in NYC under different charging and vehicle scenarios.

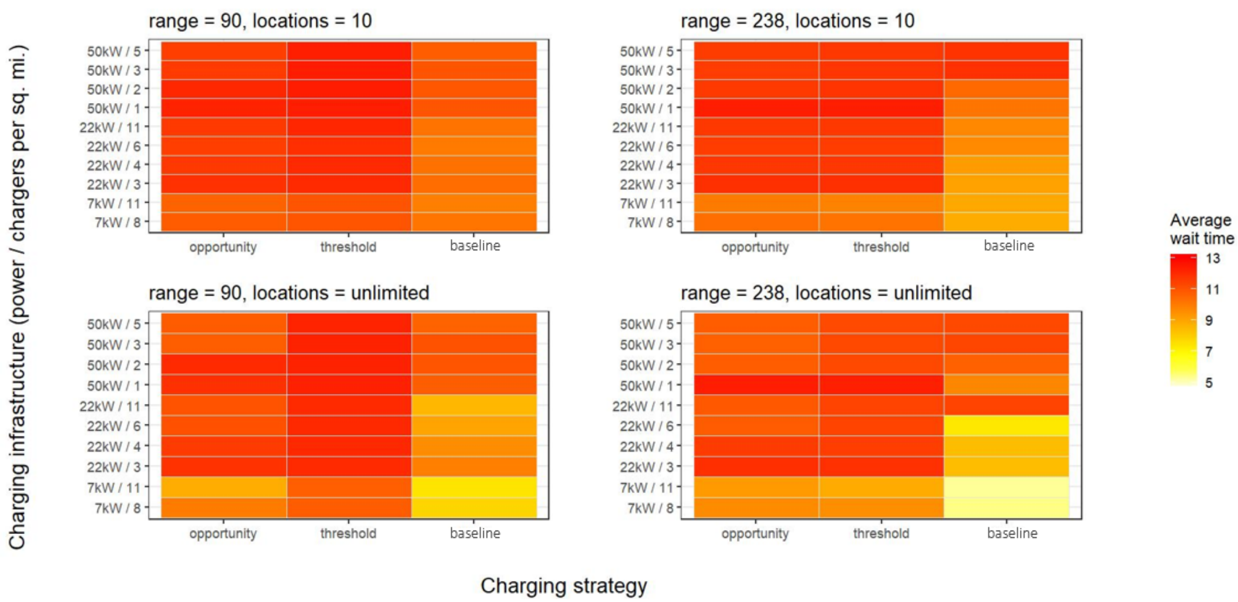


Figure 42. Average wait times in NYC by simulation scenario.

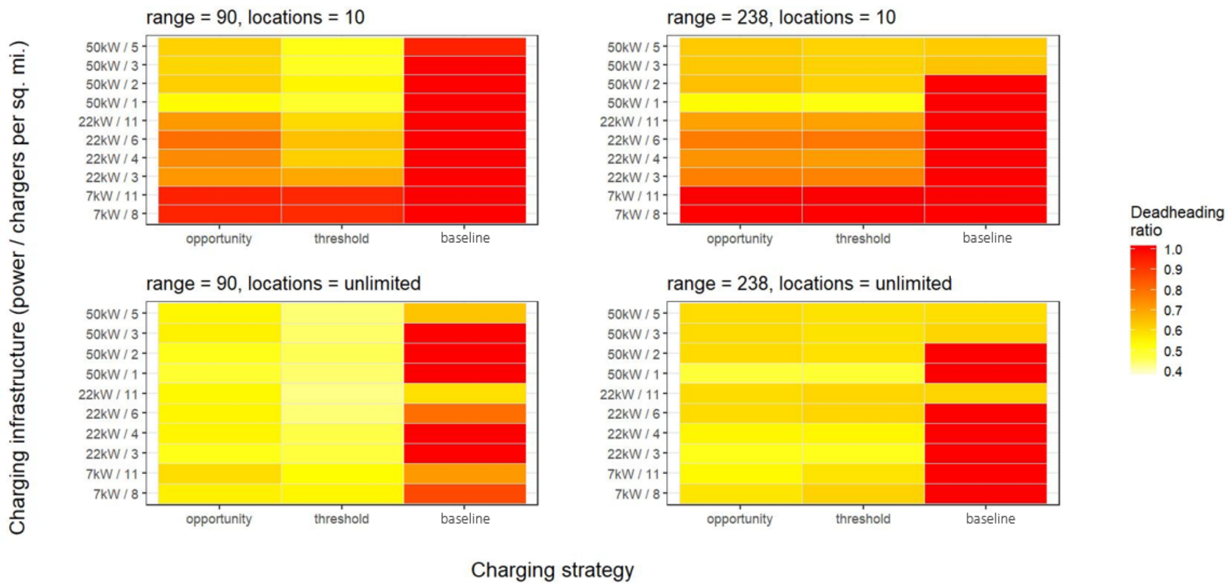


Figure 43. Ratio of empty miles to passenger miles in NYC by simulation scenario.

San Francisco

Figure 44. Percent passenger-miles served by BEV fleets in SF under different charging and vehicle scenarios.

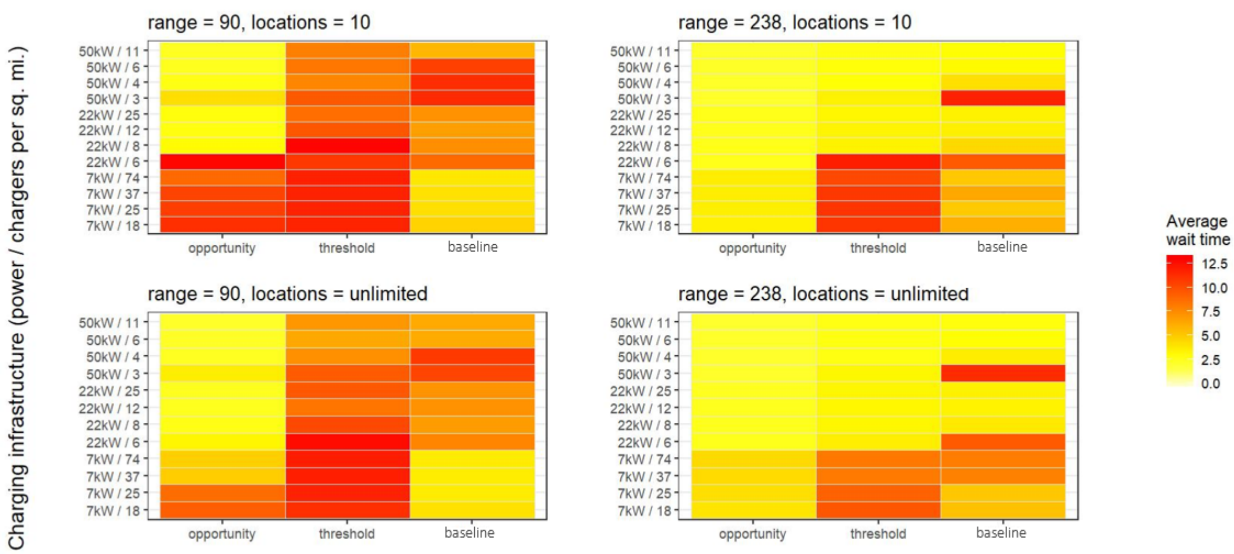


Figure 45. Average wait times in SF by simulation scenario.

Figure 46. Ratio of empty miles to passenger miles in SF by simulation scenario.

2.4.4 Sensitivity analysis

Figure 47 shows the impact of changing cost assumptions on the difference in net revenue between BEV and ICEV fleets in each city, with each scenario described in Table 17. Figure 48 shows the impact of changing the assumption that idle vehicles rebalance in anticipation of future demand.

Table 17. Description of cost model sensitivity analysis scenarios.

Scenario	Description
base	Base scenario, described in Table 15
low_gas	Gas prices decrease by $1/gallon
hi_gas	Gas prices increase by $1/gallon
low_eff	ICEV fuel economy = 25 miles/gallon
hi_eff	ICEV fuel economy = 50 miles/gallon
nofedsub	No federal tax subsidy for BEVs
parity	BEV 238 purchase price is the same as ICEV ($23,845), and BEV 90 price decreases accordingly
chgsub	Cost of charging installation is ignored, assuming it is paid for through public funding
hiutil	Vehicles are used by multiple drivers, increasing vehicle utilization to 20 hours per day

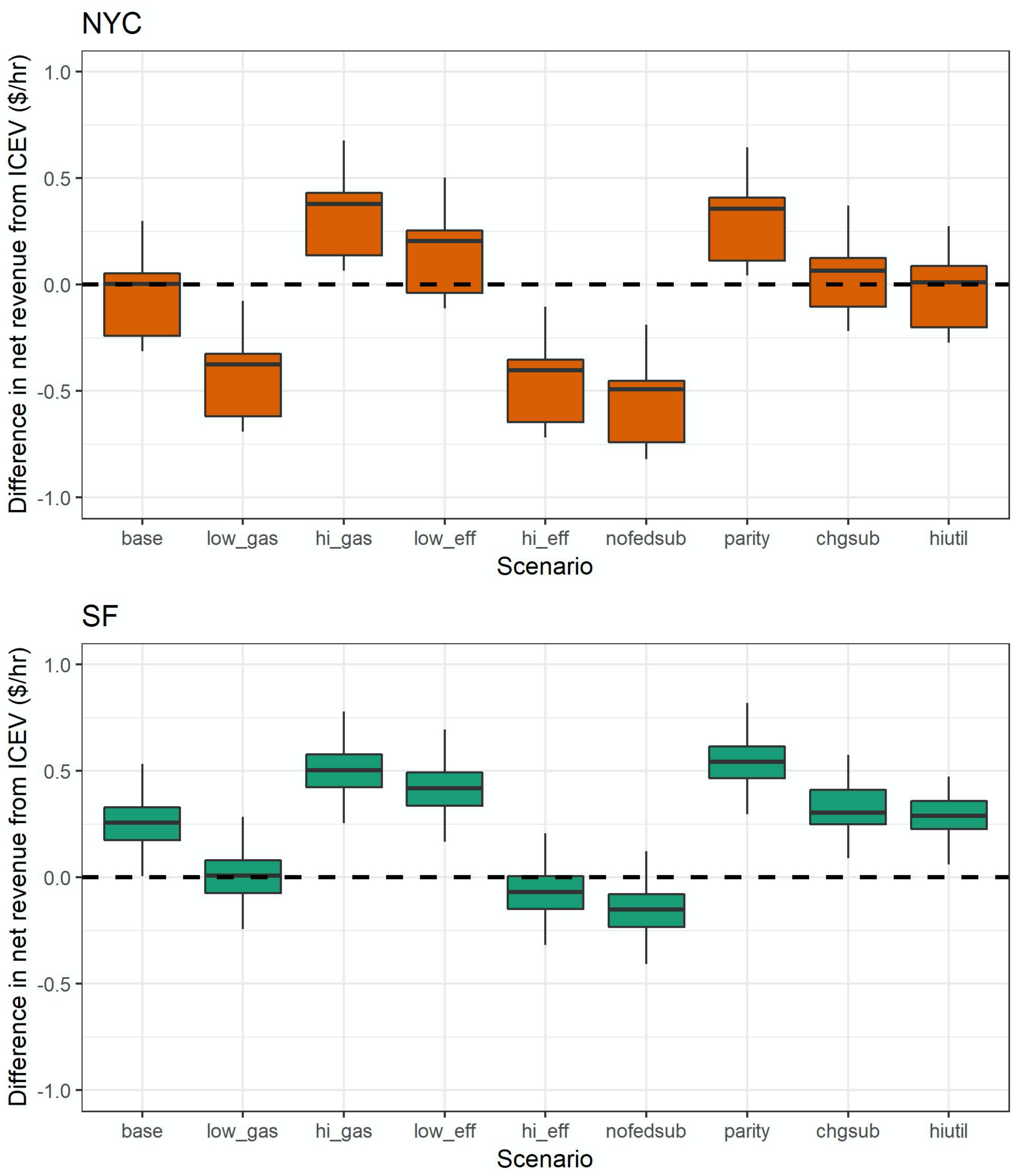


Figure 47. Impact of changing cost assumptions on potential savings from switching to BEVs. For more details on each scenario, see Table 17.

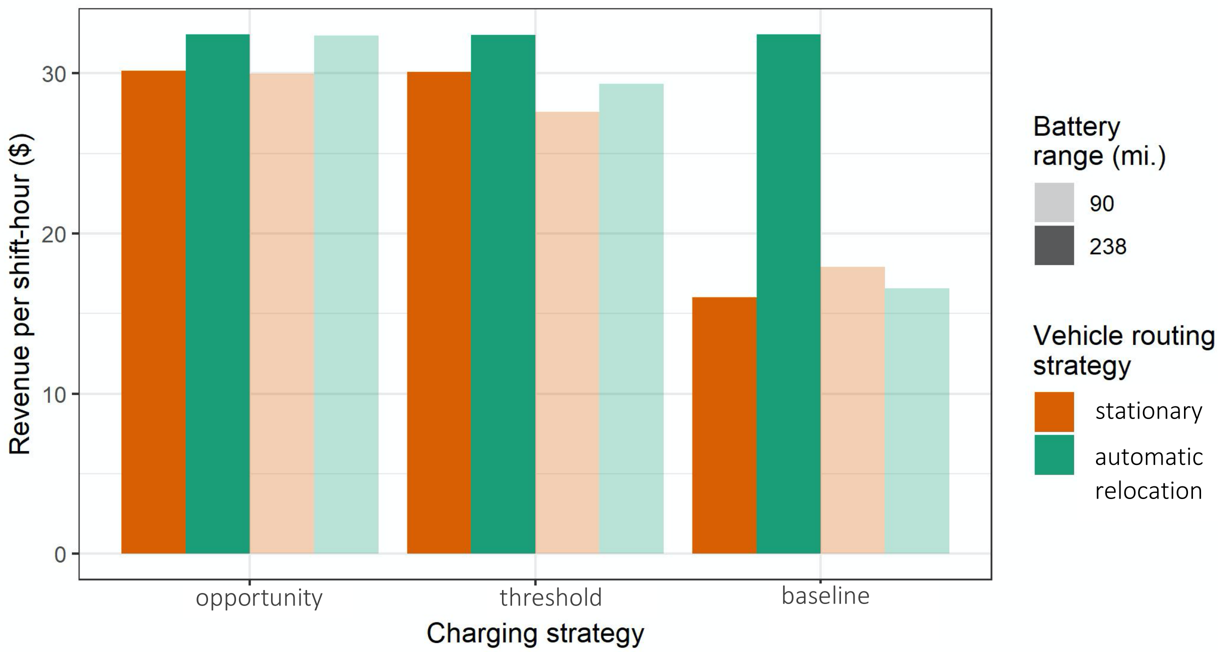


Figure 48. Comparison of simulation results by vehicle routing strategy ("stationary" represents simulations in which vehicles never rebalance in between trips to match demand, while "automatic relocation" represents the base scenario with clairvoyant rebalancing). Results show that removing clairvoyance decreases vehicle revenue somewhat, but the impact of charging relocation strategy and battery range remain the same, with the exception of the "baseline" scenario, where longer-range BEVs can no longer serve demand.

2.5. Conclusion

While my analysis is focused on two cities, it yields some general implications. My analysis suggests that ridesourcing fleets can be electrified while maintaining or potentially even increasing net revenues. The cost of charging infrastructure is a relatively small fraction of the total cost of an electric, ride-sourced trip, indicating that it might be prudent to slightly overbuild capacity to ensure high-quality service. For instance, 50-kW chargers placed at a density of roughly three to four chargers per square mile would allow the fleet to better serve demand while also increasing revenue slightly.

Efficiently routing vehicles to charge makes fleet performance insensitive to changes in vehicle range, which may enable batteries to be used much longer than currently expected, further lowering costs. Although short-range BEVs may not readily serve all of drivers' personal trips, leasing or renting vehicles for ridesourcing is already common, and almost two-thirds of ridesourcing drivers in NYC report acquiring a new vehicle for the sole purpose of working in the ridesourcing industry.[154]

From a policy perspective, justification for public intervention has centered on the environmental benefits of shared, electric vehicles. However, this analysis suggests that when chargers are utilized efficiently switching to BEVs could be achieved without increasing the cost of ridesourcing services. A combination of mandates on ridesourcing companies coupled with public investments in charging infrastructure can help ensure that ridesourcing companies invest in driver adoption of BEVs while freeing them of concerns related to availability and utilization of charging infrastructure. Mandates that require industry to obtain a certain percentage of miles from zero-emission vehicles would naturally spur the development of innovative financing and leasing strategies for BEVs as well as the development of efficient charging-routing algorithms. One of the first instances of such a mandate is the California Clean Miles Standard and Incentive program, which sets targets for reduction in emissions per passenger-mile for ridesourcing companies beginning in 2023.[62] My work is the first to suggest that such policies are not only feasible but could deliver emissions reductions at low cost.

It is important to note that my work can be extended to address the following limitations. First, I do not have data regarding actual driver behavior in between trips, so it is possible that the way I have modeled deadheading activity and charging behavior could bias my results. For example, I assume that drivers never wait at charging stations with their app turned off. In the "opportunity" and "threshold" cases, drivers will only relocate to charge when there is a charger available for the whole time they wish to charge. In the "baseline" scenario, if there are no available chargers when a driver arrives at a station, they are either routed to serve a trip or relocate to the closest charging station with available spots. Similarly, I did not have access to actual ridesourcing trip data for an entire metropolitan area in either of the cities I analyzed; in each case, data from several sources are combined to extrapolate individual trips. In both cities, these data consisted of only an average weekday, ignoring variation across days of the year. Future work could improve on this approach, especially with access to proprietary data. That said, because I modeled the ICEV and BEV fleets consistently, I expect my comparisons to be robust to inaccuracies in driver behavior. Given the difficulty of obtaining and publishing analysis of proprietary data, my approach for developing insights with limited data may prove useful in future work. Regardless, I hope this study shows the value of detailed ridesourcing data and thus encourages more data sharing in the future.

Future work should also seek to incorporate charging activity by other types of BEVs, such as private vehicles and taxis. In particular, previous studies have shown that ride-sourcing and taxis may provide complementary services,[185] so charging activity by electric taxis could either increase charger utilization or interfere with ridesourcing charging.

In addition, future work could incorporate dynamics of a fleet that changes over time with the introduction of both electric and automated vehicles. While in this work I focus on currently available vehicle models to study present-day ridesourcing fleets, future technology may include a variety of different options. For example, it is likely that performance could be further improved by using a heterogeneous mix of vehicles with different battery ranges, as shown in Sheppard et al. (2019).[153] To provide recommendations for managing gradual electrification over time, it will also be important to conduct simulations of fleets with both ICEVs and BEVs at varying levels of BEV penetration.

Finally, while I have relied on average literature values for modeling cost components, true costs may vary greatly from location to location, especially for charging infrastructure. Future work could also incorporate cost components I have ignored, such as the cost of acquiring land and maintaining parking spaces at charging stations, and the cost of developing and operating routing software. However, even if I have under-estimated charging infrastructure costs by several fold, my main conclusions would not change.

Chapter 3:
Leveraging big data and coordinated charging for effective taxi fleet electrification: the 100% EV conversion of Shenzhen, China

3.1. Introduction

China is rapidly pushing toward the adoption of BEVs, and an increasing number of cities have set ambitious targets for taxi fleet electrification including: Taiyuan,[186] Shenzhen,[187] Guangzhou,[188] Chengdu,[189] and Beijing.[190] Shenzhen, China represents an especially interesting case study because it is the first top-tier Chinese city to have fully replaced its taxi fleet of over 20,000 vehicles with BEVs, using the BYD e6 model with 400 km battery range (80 kWh capacity with an average consumption of 0.2 kWh/km).[191]

To build a sustainable roadmap for taxi electrification that can be adapted and adopted elsewhere, the Shenzhen electric fleet must provide the same level of service as a conventional fleet at low cost and with significant carbon benefits. Local interviews conducted with drivers and reports in the media suggest, however, that time spent charging – in some cases over three hours per day – results in lost revenue, compounded by problems with queuing at popular charging stations.[116]

Many studies have developed methods to optimize the siting of charging stations,[113,162,192,193] but despite the unplanned nature of charging infrastructure siting in Shenzhen, sub-optimal station locations may not be the fundamental cause of operational inefficiencies. Drivers report that charging activity is concentrated during the afternoon because dayshift drivers feel obligated to fully charge their vehicle before delivering it to the nightshift driver – most vehicles are driven by two drivers for 12 hours per day each, and most dayshift drivers end their shift between 5 and 7 PM.[194] Some drivers use apps to find available stations, but others go to the same preferred station each day near the shift change location, leading to problems with queuing at popular stations. In turn, this uncertainty in waiting time means drivers go to charge two to three hours before a shift change, long before they typically need to: most drivers go to charge around 50% state of charge, and most afternoon charging events take less than one hour (this charging pattern is similar between weekdays and weekends). If left with extra time between charging and the end of their shift, drivers are often unwilling to accept trips that travel too far from the shift change location, reducing revenue opportunities during this period.

In this chapter, I use over two weeks of GPS and battery state of charge (SOC) data from about 20,000 electric taxis in Shenzhen to evaluate the potential of different interventions to the problems described above. The data come from January, May, and June 2019, and they consist of snapshots taken every five minutes from each vehicle. Using these data, I conduct simulations of four proposed interventions that could reduce the charging burden: 1) optimizing the location of charging stations to minimize travel time to charging stations, 2) optimizing the dispatch of vehicles to charging stations to minimize both travel and queuing times, 3) shifting more daytime charging to early morning hours when demand for taxi trips is low, and 4) shifting charging to times when vehicles are idle.

In addition to my own work described in previous chapters, several previous simulation studies have found that optimization strategies could improve the efficiency of electric taxi fleets. Lu et al., (2012) showed that having a dispatching strategy for electric taxis in Taipei, Taiwan successfully reduces charging wait times.[195] Tian et al. (2016) proposed a framework to recommend charging station locations to e-taxi drivers in Shenzhen.[174] However, the study was limited as the SOC data were crudely inferred from estimated charging locations. Tian et al. (2017) considered the scenario of a major shutdown of an EV charging station in Shenzhen and developed a strategy to re-allocate the charging demand to reduce queuing time and increase the usage rate of charging stations.[196] Finally, Dong et al. (2018) proposed a real-time framework to recommend location and charging time to electric taxi drivers in Shenzhen, and conducted simulations that showed significant potential improvements in charging station use and queuing times at charging stations.[175]

No previous study, however, has analyzed impact on revenues or compared the effectiveness of multiple interventions. More importantly, no previous study has explored the underlying causes of the apparent inefficiencies in fleet operations. In particular, I find that inefficient charging behavior may be caused in large part by taxi drivers' preference for changing shifts at full charge in the afternoon, and that changing shifts at partial charge could significantly improve fleet operations.

In this study, I develop several machine learning models to predict operational characteristics of the taxi fleet and present a framework for how this modeling platform can be implemented in practice. I conduct simulations to estimate and compare the potential impact of these various interventions on fleet performance, driver revenue, and charging infrastructure use. Finally, using one day of driver shift-change data, I compare the performance of groups of drivers with different charging patterns to verify the simulation results.

3.2. Methodology

Our study methodology consists of the following steps employing GPS and charging data. Vehicle data for approximately 19,224 electric taxis in Shenzhen were prepared by Aspiring Citizens Cleantech (ACC) between May 27 and June 9 and between January 17 to 19, 2019, for a total of 17 days of data. Data include snapshots of location, state of charge (% of battery capacity), and operation status (hired or available) every five minutes for each taxi while the vehicle is turned on. To verify simulation results, ACC also provided vehicle data and driver shift change data for July 25, 2019, including timestamps for when each driver logged in or out of each vehicle. Finally, ACC also provided summaries of interviews conducted with approximately 30 drivers in June and July 2019. These interviews were conducted with drivers who were approached at charging stations by ACC or while ACC staff were taking taxi trips. My analysis with these data consists of four key methodologies: 1) charging inference; 2) queuing inference; 3) predictive models; and 4) heuristic optimization analysis focused on four intervention strategies: a) charging station location, b) dispatch to charging stations, and c) shifting more charging to nighttime and d) shifting more charging to break periods.

3.2.1 Charging inference

To begin my data analysis, I first inferred charging events by finding locations where the vehicle SOC increased by at least 10%. I then performed hierarchical clustering on all of these locations, using 200 m as the maximum distance between any two vehicles in the same cluster. To infer charging locations, I then took the mean values of latitude and longitude of all points in each cluster, and then removed outlier charging events greater than 200 m from the closest charging location. To estimate the number of chargers at each station, I found the maximum number of vehicles charging simultaneously at the location across the total period in the dataset.

Note that this estimate of the number of chargers at each station does not account for usage aside from taxis. To validate these inferred estimates, I collected data on actual charger availability for 18 charging stations, whose locations match the charging station locations I inferred from the taxi data. I collected these data by taking a sequence of screenshots of two different charging apps each hour over the course of four days between July 19 to 22, 2019, then using Google Vision API [197] to extract the number of available chargers from each screenshot. The estimated availability for these 18 charging stations inferred from the taxi data closely tracks the availability displayed by the apps, especially during peak charging periods in the early morning and late afternoon (see Figure 49). As such, I assume my estimates of the number of chargers at each charging station is sufficiently accurate for the simulations conducted in this work. In future work, I plan to improve accuracy by expanding data collection from the charging apps and integrating it with taxi data more thoroughly.

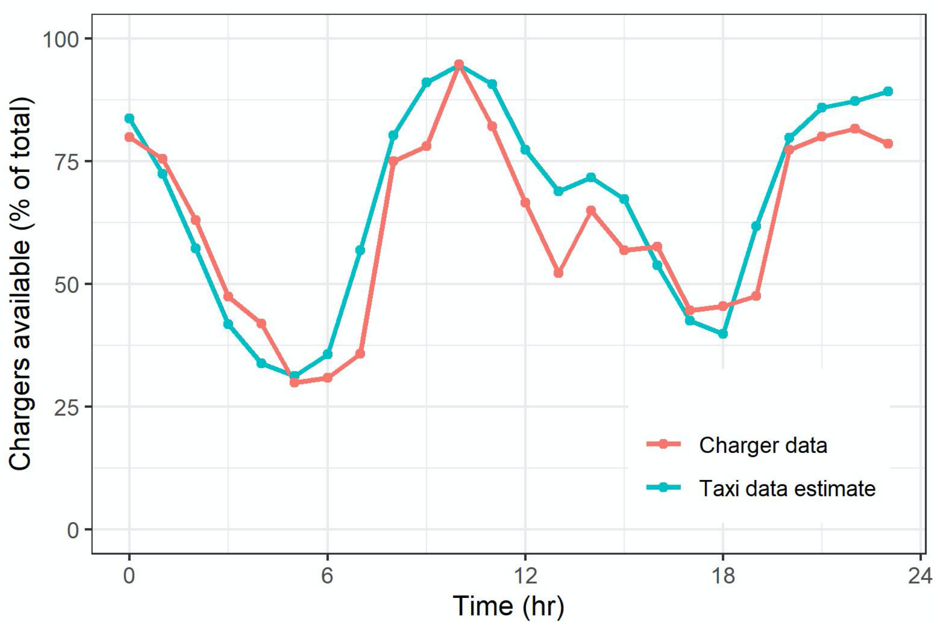


Figure 49. Comparison of total availability at charging stations by time of day between estimates from taxi data with actual data collected from charging companies' smartphone apps.

3.2.2 Queuing inference

For every timestamp, I identified which vehicles were relocating to each charging station (i.e., idle vehicles whose next activity was charging). I inferred these vehicles to be queuing, if they satisfied the following criteria: 1) the vehicle moved less than 1 km over the previous five minutes and was either: a) the closest vehicle to the charging station and within 500 m or b) within 100 m of another vehicle queuing at the same station. In other words, after finding the closest queuing vehicle to each station, I inferred lines of queuing vehicles by sequentially adding the next-nearest queuing vehicle. I define queuing time as the time elapsed between the start of a vehicle joining a charging queue and the beginning of the charging event.

3.2.3 Predictive models

I developed all predictive models with the h2o package using R 3.5.1. I tuned hyper-parameters using five-fold cross-validation, and I validated model performance with 10% of the data left out of model training for testing purposes. I found the difference in performance between the gradient boosting models and other model types to be negative or insignificant, so I only report results using gradient boosting for all models.

First, I constructed a model to predict the average queuing time before charging at each charging location for 30 minutes into the future. The predictive model includes the following features: the number of vehicles queuing at the charging station, the number of vehicles charging, the flows in and out of the station and queue, the size and location of the station, fixed effects for each station, and a variety of transformations of each of these variables. As reliable prediction requires sufficient charging events at each charging station, I only applied the predictive model to charging stations with at least 20 inferred chargers, resulting in 93 charging stations accounting for over 75% of charging events, for a total of approximately 375,000 observations. The model prediction tracks the actual queuing time during peak hours quite well, with a root mean squared error of 4.3 minutes.

Second, I also constructed a model to estimate travel time between any two points in the city of Shenzhen, using 7.3 million trip durations as training outcomes. I clustered trip origin and destination locations into 500-meter grid cells and downloaded travel-time estimates between each pair of grid cells from OpenStreetMaps. These travel-time estimates do not account for traffic congestion and served as inputs in my model to predict trip durations, along with straight-line distance, time of day, day of week, and origin and destination locations. Over 85% of predictions fall within five minutes of the actual trip duration, with a root mean squared error of 4.7 minutes. Figure 50 shows comparison of predictions with data for both of these models.

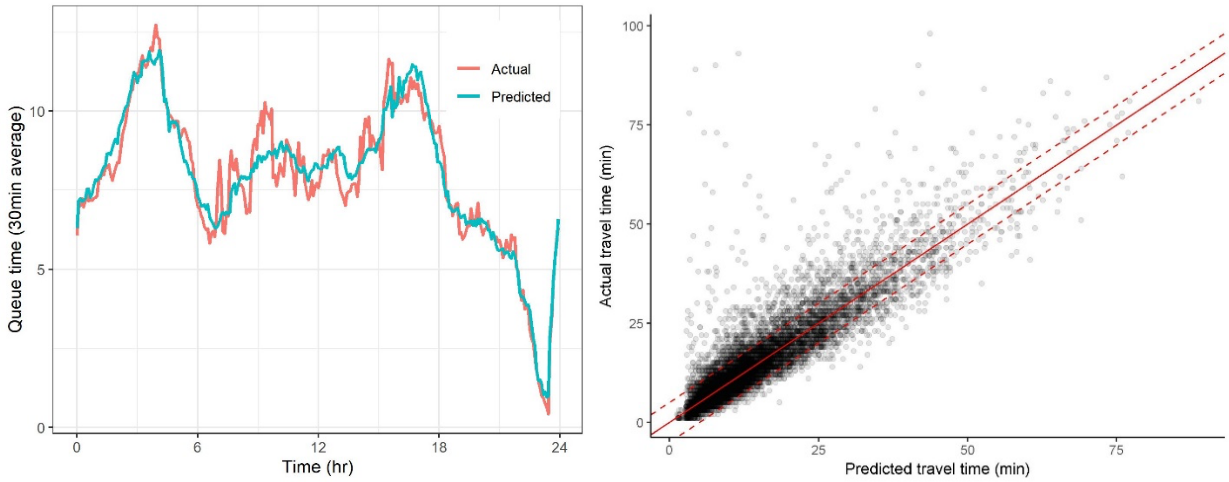


Figure 50. Performance of predictive models for queue time at the top 93 charging stations (top) and travel time between all locations (right). Dotted lines show five-minute error bounds.

3.2.4 Optimization analysis

Relocate charging stations:
Using the travel time model described above, I identified the detour time required to visit a charging station at each point C, defined as the additional travel time from the last drop-off point A to the next pick-up point B via the charging station C ($t_{AC} + t_{CB}$), compared with the travel time directly from point A to point B (t_{AB}, see Figure 51 below).

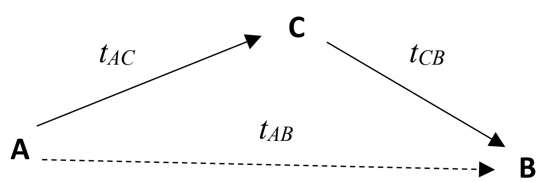


Figure 51. Schematic of the calculation of detour time caused by driving to a charging station.

I then used a heuristic approach to analyze the impact of optimally locating charging stations. I relocated each existing charging station to a location C that minimized total detour time of all charging events taking place there and reassigned each charging event to the charging station that minimized detour time, following the objective function shown in Equation 5 below. I repeated these two steps until the simulated detour times converged.

$$\min \sum_i \; t_{A_iC} + \; t_{CB_i} - t_{A_iB_i} \qquad (5)$$

Dispatch to charging stations:
Using the queuing and travel time models described above, I predicted the average queuing time at all stations for the next 30 minutes and assigned vehicles to the station with available chargers

that minimized the total delay (the sum of detour time plus queuing time). Given potential inaccuracies in my estimate of the number of chargers available, as a conservative approach I only relocated vehicles to a new charging station if I estimated less than 90% of the chargers to be occupied. After reassignment, I updated the estimated queuing time and the number of available chargers at each station. I repeated these two steps until the simulated queuing times converged. This process is described by the objective function and constraints listed in Equation 6 below, where q_C is the estimated queuing time, d_C is the travel detour time seen in Equation 5, and p_C is the number of charging ports at the charging station.

$$\min(d_C + q_C);$$
$$d_C = t_{A_iC} + t_{CB_i} - t_{A_iB_i},$$
$$n_{charging} < 0.9 * p_C \qquad (6)$$

Shift more charging to nighttime:
Based on my analysis and results from the driver interviews, I assumed that charging has a negligible opportunity cost between 1 AM and 7 AM on weekdays and between 2 AM and 8 AM on weekends due to low trip demand. As such, I argue that the SOC that the nightshift driver had at the start of this "zero-cost" period could be interpreted as surplus SOC that the dayshift driver did not need to charge before the shift change.

I defined these before-shift-change charging events as the last charging events for each vehicle before 8 PM or the first charging event after 8 PM in cases where there was no charging event between 10 AM and 8 PM. Based on the average amount of surplus SOC that each vehicle had on other days, the time of day, and the starting SOC, I trained a model to predict how much surplus SOC a vehicle would have at the start of the "zero-cost" period, if the dayshift driver charged to 100% immediately before changing shifts. For each prediction, I then calculated the SOC at the shift change that would give the vehicle a 95% and 99% chance of reaching the "zero-cost" time without falling below 10% SOC. Based on the average power of the charging station selected for the before-shift-change charging event, I then calculated the amount of time that could be saved by following my recommendation for the SOC at shift change. This process is described in Equation 7 below, where $t_{n,d}$ is the time savings of taxi n on day d, t is time of day, and P is the power of the charging station. Figure 52 shows a comparison of predictions with outcomes for this predictive model, along with curves representing 95% and 99% reliability.

$$t_{n,d} = f(t, SOC) * P \qquad (7)$$

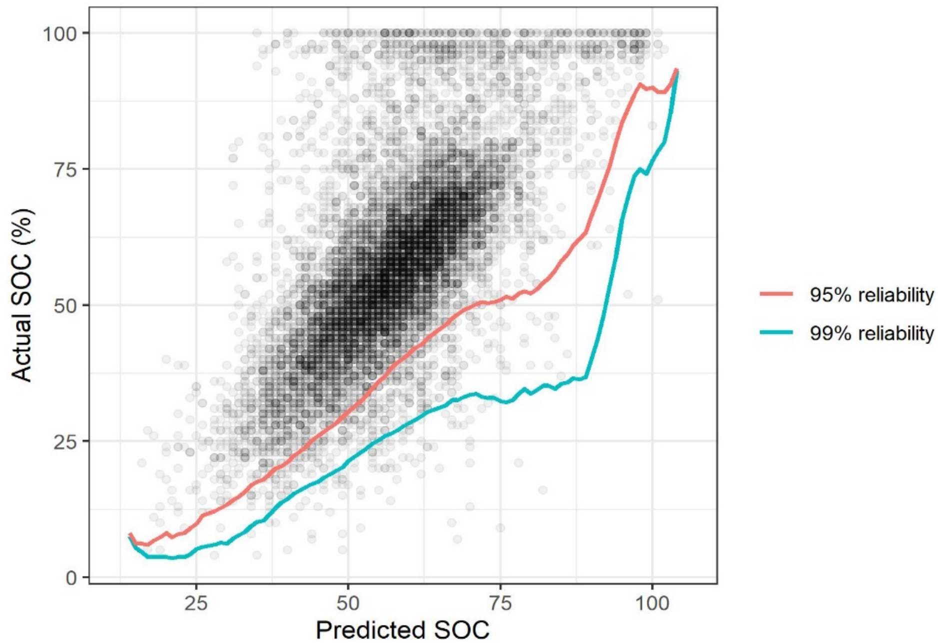


Figure 52. Comparison between predictions and actual data for SOC in early morning hours (1 AM on weekdays, 2 AM on weekends) based on SOC at the start of the dayshift driver's last charging event. Red and blue lines show the 5th and 1st percentile of predictions respectively, representing the lower bounds placed on predictions to ensure high levels of reliability.

Shift more charging to break times:

First, I identified break periods for each vehicle, defined as periods when the vehicle was neither serving a trip nor charging and the vehicle's odometer reading did not increase for more than 30 minutes. Using the queuing and travel time models described above, I estimated the amount of time available for charging during each break period, and the maximum amount of SOC that could be charged. I then conducted a simulation to determine the potential to satisfy charging needs during these break periods by removing all charging events, i.e. assuming the vehicles' SOC did not change during existing charging events. I then added charging during break periods incrementally to keep SOC between 0% and 100% and calculated the amount of additional charging time needed to maintain SOC above 10% between each break. This process is described by the objective function and constraints listed in Equation 8 below.

$$
\begin{gathered}
min(SOC_{emerg})\,; \\
SOC_{end} > 10, \\
\Delta SOC_{max} = (t_{idle} - \min d_C + q_C) * P_C, \\
\Delta SOC_{break} = \min(\Delta SOC_{max}\,, 100 - SOC_{start}), \\
SOC_{end} = SOC_{start} + \Delta SOC_{break}, \\
\Delta SOC_{emergency} = \max(0, -1 * SOC_{end}), \\
SOC_{start} = SOC_{end} + \Delta SOC_{emergency} \qquad (8)
\end{gathered}
$$

3.2.5 Study limitations

There are several limitations to this analysis that can be addressed with expanded data access. First, without complete real-time data from existing charging stations, there may be inaccuracy in my estimates of charger availability. In future research, I could expand charging station data collection efforts to conduct more accurate and detailed charger availability analysis. Similarly, I could also obtain and integrate data on driver shift change locations and times to inform my estimates of detour time and surplus SOC during the afternoon shift change. Finally, this analysis does not consider a variety of behavioral factors that influence decisions on where and when to charge including: the availability of rest places and food, opportunities to meet friends and other drivers, and desire to maintain a large SOC buffer at all times (for example, it appears some drivers never let their batteries fall below 50% SOC). To analyze these factors in depth and to test potential strategies in the real world, future research should include a pilot project via a smartphone app that will provide drivers with real-time information on queuing times at charging stations as well as an accounting tool to keep track of SOC charged across shifts, to facilitate changing shifts at partial charge.

3.3. Results

As shown in Figure 53 below, analysis of the Shenzhen taxi data shows there are two major peaks in charging events in the early morning and late afternoon (likely preceding shift changes), along with a smaller peak during the lunchtime period. Each peak is accompanied by a significant number of taxis queuing at charging stations, especially in the afternoon. Notably, this afternoon peak is also accompanied by a decreased number of hired vehicles serving trips and an increased total number of active vehicles, suggesting that these charging events result in significant lost revenue. A comparison with TNC trip volumes in Shenzhen across three months in 2019 shows correlation between decreased taxi trip volumes and increased TNC trip volumes during the afternoon period, suggesting that taxi trip volumes are constrained by vehicle supply (TNC data are not shown here due to issues with confidentiality).

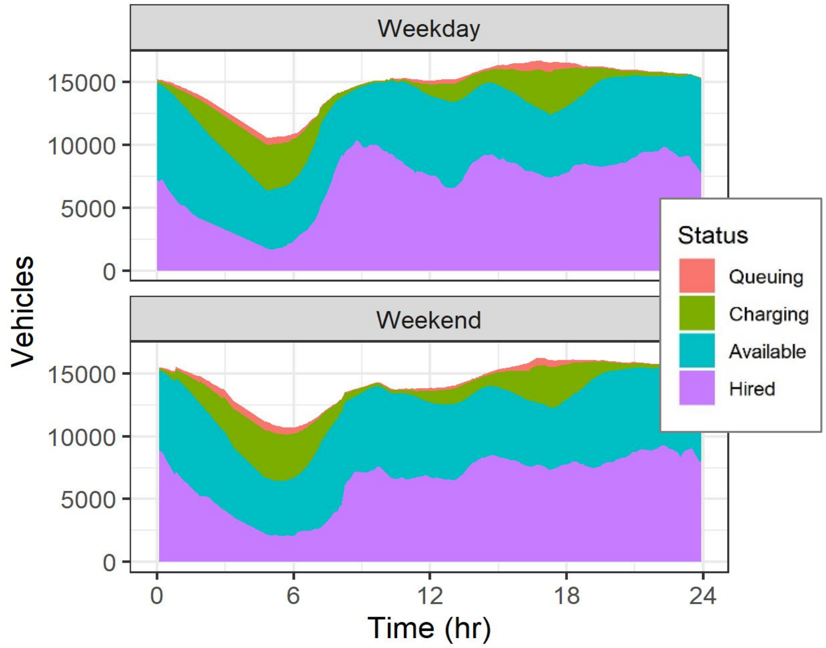


Figure 53. Number of taxis by operating status over time of day, for both weekends and weekdays.

Drawing on my literature review, my analysis, and taxi driver interviews, I identify three key problems in taxi fleet operations: 1) queuing time due to inefficient routing of vehicles to charging stations, 2) spatial mismatch between charging station locations and charging demand, and 3) temporal mismatch between charging events and the time periods of lowest opportunity cost of charging. In the following sections, I analyze each of these problems and the impact of proposed interventions. Table 18 below summarizes the intervention results.

Impact on revenue is estimated by multiplying the daytime savings by the average revenue generated per vehicle during that time. Results for flexible shift change SOC are derived from the scenario providing 99% reliability of maintaining a 10% buffer in SOC between the last daytime charging event and early morning hours. Exchange rate between USD and Chinese Yuan (RMB) (0.14:1) was recorded on August 1, 2019.

3.3.1 Optimal charging locations

The charging market in Shenzhen is highly fragmented with over 100 different charging station operators,[198] and planning has not been integrated with charging demand data, potentially leading to a spatial mismatch. Meanwhile, drivers report that they prefer larger charging stations to smaller ones due to greater reliability in expected queuing time. This is reflected in charger usage data; concentrating chargers into fewer large stations at the best locations may increase usage rate. Many studies have suggested siting taxi charging stations close to areas with high trip density can improve fleet performance,[113,162,192,193] but given that drivers in Shenzhen typically charge near their shift-change location, I assume that drivers seek to minimize the detour time incurred by visiting a charging station on the way to their next destination, as described in the methodology. As shown in Figure 54 below, relocating charging stations to the locations that minimize detour time results in a much higher density of charging stations in densely populated areas of the city close to major corridors. I find that on average, optimizing charging station locations could save each vehicle eight minutes per day.

Table 18. Summary of impacts of all proposed interventions.

Strategies/ interventions	**Time savings (min/vehicle/day)**		**Revenue generated (USD/ vehicle/day)**	**Electricity savings (USD/ vehicle/day)**
	dayshift	total		
Optimal charging station locations	5	8	0.72	0
Optimal dispatch to charging stations	10	14	1.45	0
Flexible SOC during shift change	25	0	3.77	0.43
Optimal charging during break periods	72	123	11.16	0.58

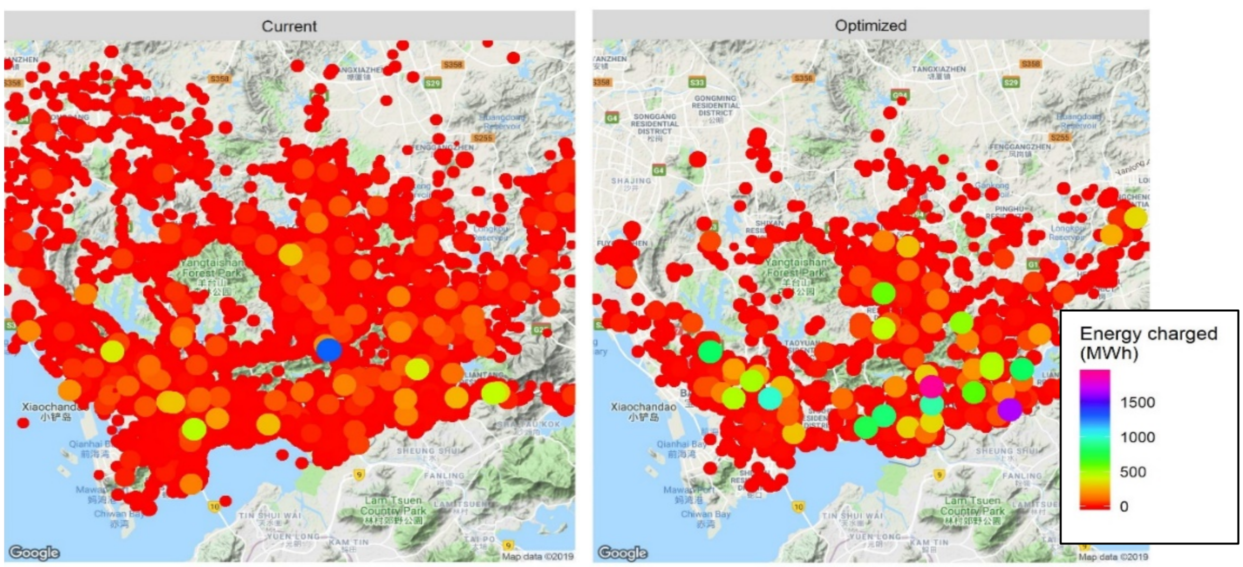


Figure 54. Heat maps comparing the distribution of energy charged at current charging stations with the distribution after relocating stations to the locations that minimize the detour time.

3.3.2 Optimal charging dispatch

While existing charging network apps show real-time availability at charging stations, these data are fragmented between platforms and may not reflect actual queuing times due to many vehicles arriving during a short time window. Accurate queuing time predictions may help drivers locate charging stations with less queuing time and improve the certainty of the total time needed to charge, allowing drivers to start charging closer to the end of their shift.

Using the queuing model described earlier, I estimated the amount of time vehicles could save if they charged at the station causing the least delay, which is defined as the sum of the detour and queuing time. I find that through optimization it is possible to reduce the time spent queuing per charging session by almost 50%, from over 10 minutes to about five, with a total time savings of 14 minutes per vehicle per day. While over 26% of vehicles currently spend over 30 minutes queuing per day, in the simulation I find that this proportion could be reduced to less than 10%. I find that optimizing the dispatch of vehicles to charging stations could save almost 4,500 hours of downtime per day, potentially resulting in over $10 million per year in additional revenue (see Figure 56).

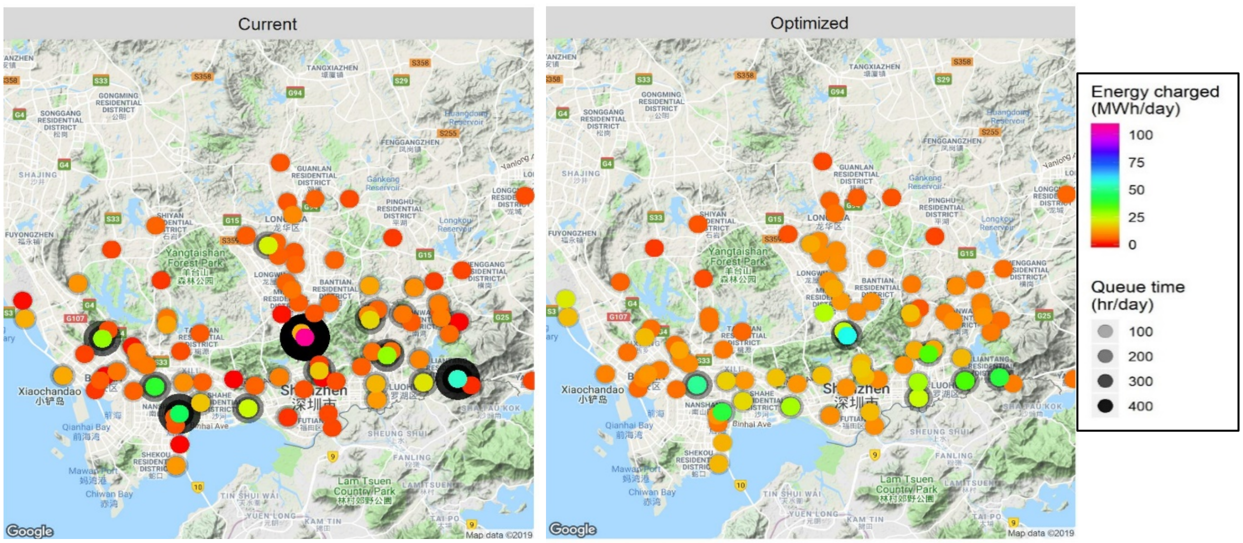


Figure 55. Heat maps depicting charger use and total queuing time (black rings) before (top) and after (bottom) dispatching optimization.

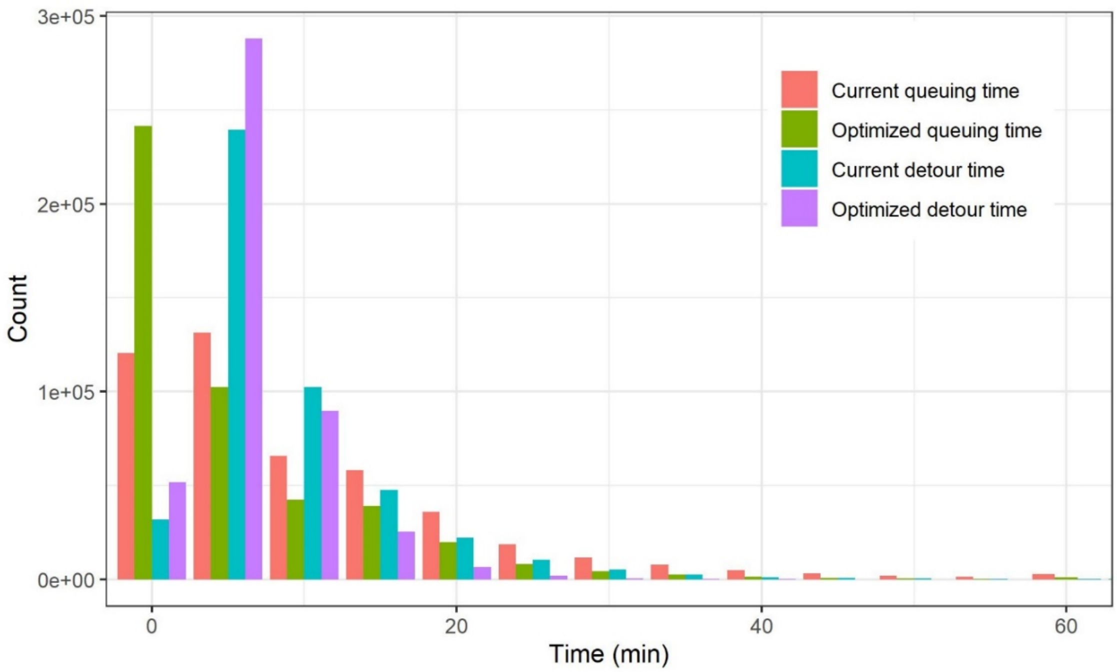


Figure 56. Distributions of time lost due to detouring to charging stations and queuing at charging stations, both before and after dispatch optimization.

Optimizing the dispatch of vehicles to charging stations could also greatly increase the economic sustainability of the charging network, which may be threatened by the pending removal of charger installation subsidies.[199] As shown in Figure 55 above, currently most charging is concentrated in a few large charging stations with over 100 inferred chargers each, resulting in large total queuing times at each of these stations (shown by the black rings). Drivers report that they prefer larger stations because the queuing time is more certain due to higher turn-over rates. Not surprisingly, by providing accurate estimates of the expected queuing times at each station, I find that charging events can be dispersed among more charging stations.

Due to the non-linear relationship between usage and amortized cost per kilowatt-hour (see Figure 57), I find that this dispersion can have positive impacts on charging economics. Using the cost parameters reported by Crow et al. (2019),[198] including costs for charger construction, maintenance, and land, I calculated the cost of charging amortized per kilowatt-hour, assuming a 10% discount rate and a 10-year charging station lifetime. As shown in Figure 58 below, the increased usage rate at many stations results in much lower amortized cost. Under the current pricing regulation, charging stations are not allowed to charge customers more than $0.11 per kWh on top of the electricity price [198]. Without subsidies on charger installation, less than 10% of inferred charging stations would be economically sustainable, including less than 50% of the top 93 inferred charging stations. In contrast, with optimal dispatching of vehicles to charging stations, 75% of inferred charging stations would be profitable without subsidies.

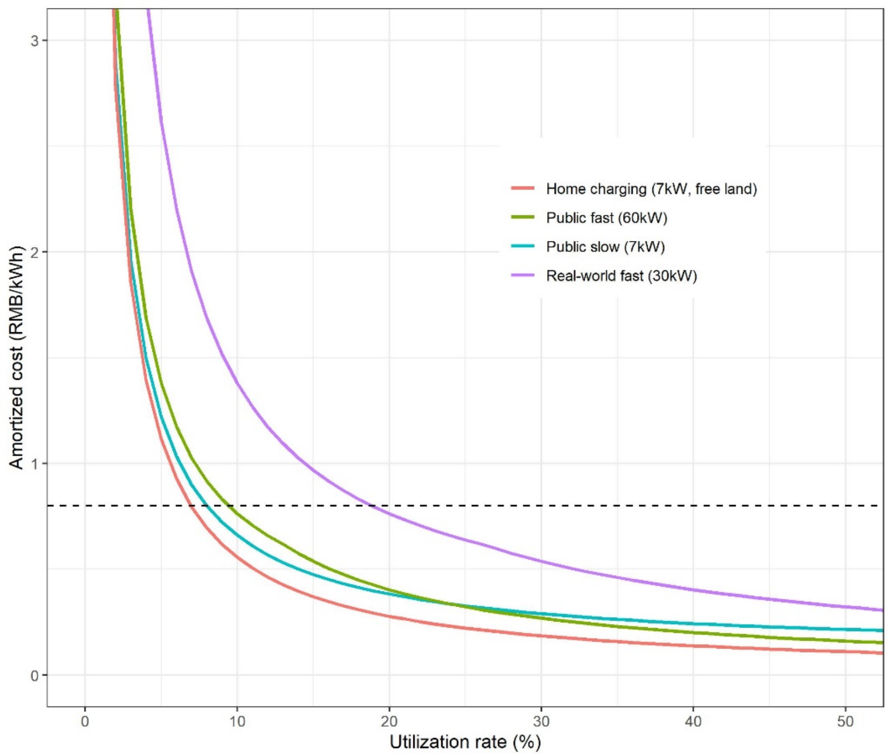


Figure 57. Impact of usage rate (measured as percent of total hours charger is being used) on amortized cost of electricity, by charger type.

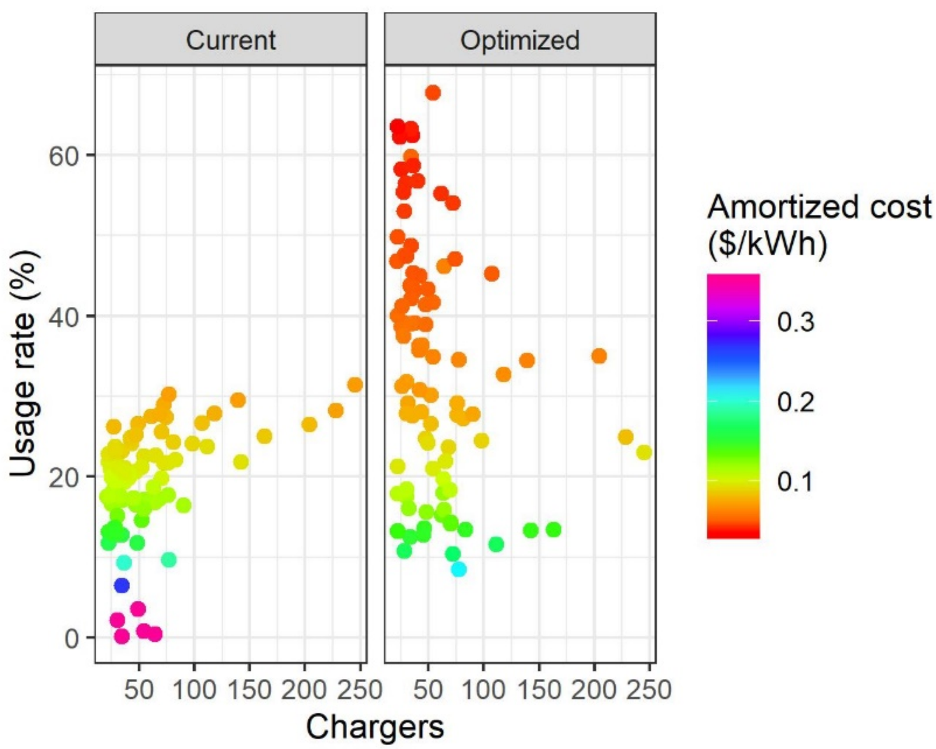


Figure 58. Usage rate of major charging stations (average percent of time each charger is occupied) by number of chargers at each station, before (top) and after (bottom) dispatching optimization.

Interestingly, once vehicles have been dispatched to optimal charging stations, repeating the heuristic location optimization described in the first section has little effect. As shown in Figure 59, I find that only stations on the city's periphery are significantly affected, resulting in time savings of less than one minute per vehicle per day.

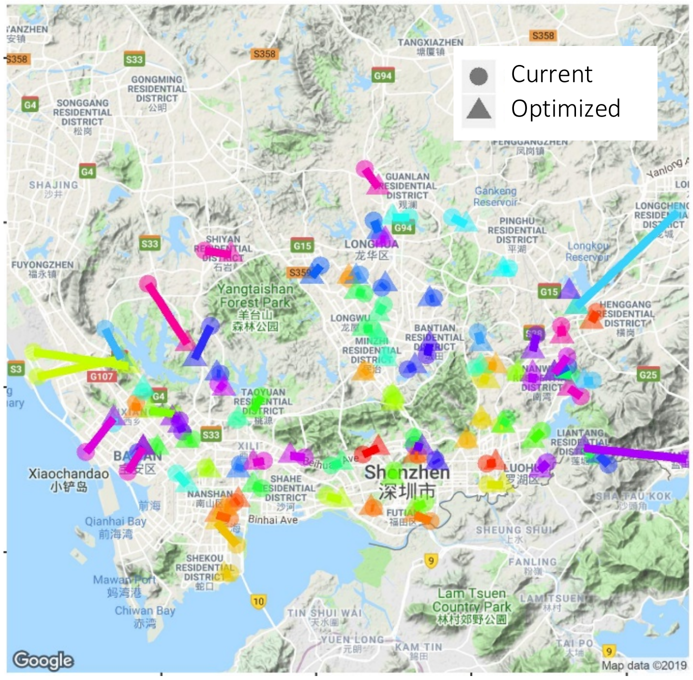


Figure 59. Difference in charging locations before after location optimization, given optimal dispatch.

3.3.3 *Shift more charging to early morning hours*

I also studied the potential for enhancing efficiency by shifting some charging from the dayshift to early-morning hours, when charging carries a lower opportunity cost due to lower demand for taxi trips. As shown in Figure 60, most drivers consume less than 50% SOC between the afternoon charge and early morning hours when trip demand plummets, suggesting large potential for arbitrage.

As seen in Figure 61, during early-morning hours both the proportion of the fleet that is hired and the hourly revenue per vehicle drop substantially, suggesting there are more idle vehicles than are needed to serve demand. Based on this finding, I estimated the number of "surplus vehicles" that could go charge without affecting the fleet's capacity to serve trip demand. This value is defined as the number of idle vehicles that could be removed from duty while maintaining the ratio of hired vehicles to idle vehicles at or below 1:1.25, the minimum hired ratio observed during the daytime. I find that the number of vehicles charging during early-morning hours (defined as 1 AM - 7 AM on weekdays and 2 AM – 8 AM on weekends) could almost double without affecting the fleet's capacity to serve trip demand.

Despite this apparent incentive to charge more during the nightshift, most drivers interviewed reported that they feel an obligation to charge to full SOC before the afternoon shift change to ensure that dayshift and nightshift drivers both pay for a fair share of the electricity and have an equal opportunity to serve long trips.

There is no established policy by regulators or companies that requires drivers to change shift at full SOC. If there were a data-driven accounting tool to facilitate payment between drivers to compensate for time spent charging, the barrier to optimizing charging times among drivers could be overcome. Based on the prediction model described in the methodology, I find that starting with a 72% SOC during the afternoon shift change gives the nightshift driver a 95% probability (on average) of reaching the early-morning hours without falling below 10% SOC (see methods section for details). Based on the derived charging power of each charging station (33 kW on average), adding this SOC flexibility to the afternoon shift change would save each dayshift driver 40 minutes per day and increase their fare revenue by over me $5 per day. Given that electricity prices are also lower between 11 PM and 7 AM, this intervention would also reduce charging costs by over me $1 per vehicle per day. Even if nightshift drivers require 99% probability that they will maintain at least 10% SOC, a flexible SOC policy during shift changes would save each dayshift driver over 25 minutes per day. In aggregate, this intervention could save day shift drivers 8,000 to 12,000 hours per day, potentially yielding over $25 million per year in additional revenue. This analysis does not include the potential for reducing queuing and detour times by increasing flexibility in when and where drivers charge, and so these estimates are likely conservative.

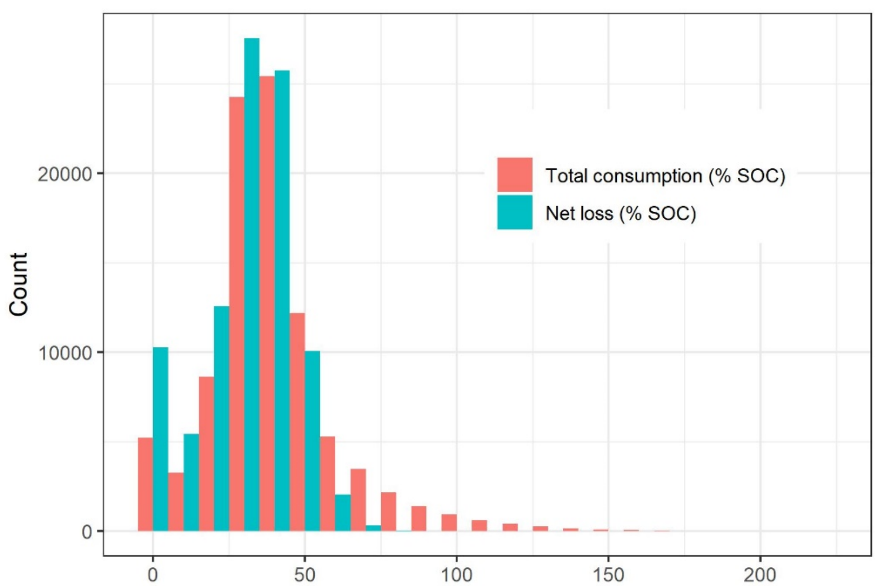


Figure 60. Distributions of net loss and total consumption of SOC between last charging event before 8pm and the start of low-demand hours (1am on weekdays, 2am on weekends). Total consumption is equivalent to net loss for vehicles with no charging between 8pm and low-demand hours.

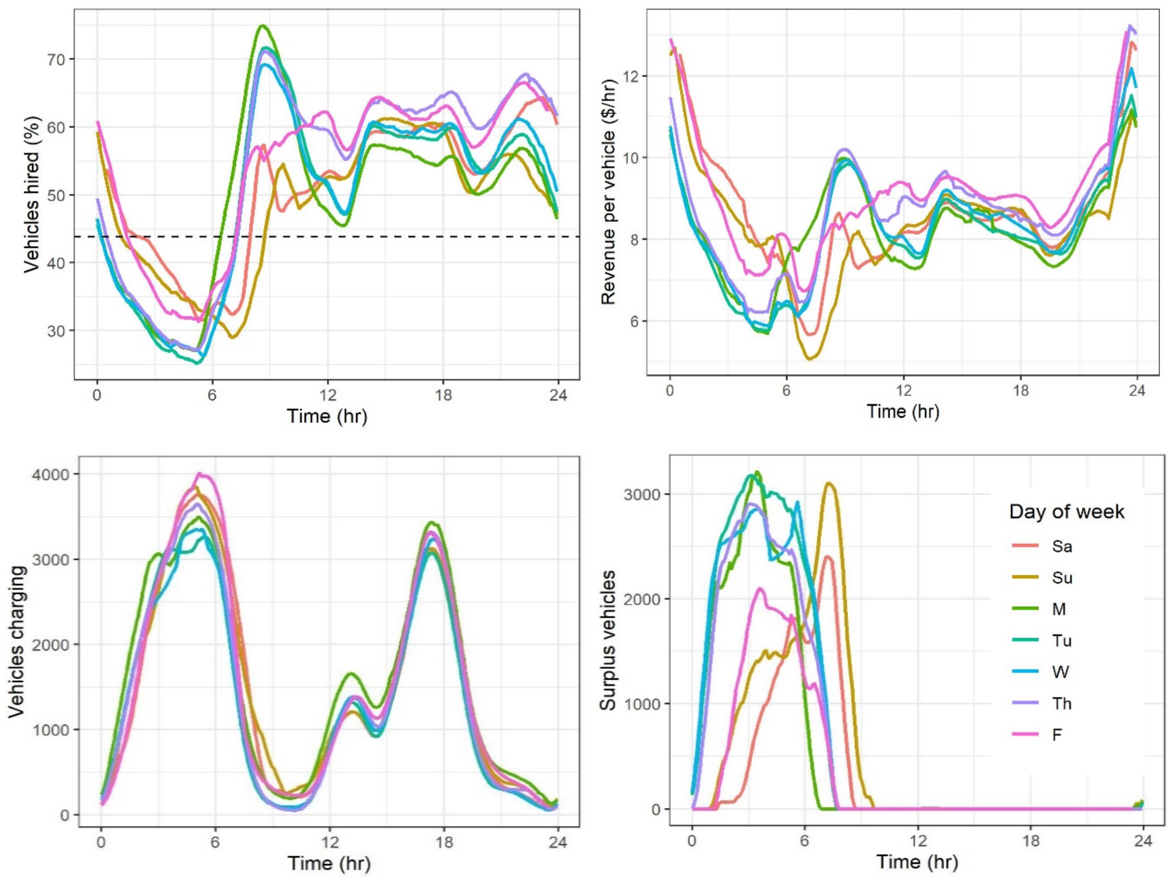


Figure 61. Clockwise from top left (all hourly moving averages disaggregated by both time of day and day of week): a) proportion of vehicles hired (not including vehicles that are disengaged or charging); b) average net revenue per vehicle per hour (fare revenue minus electricity cost); c) number of "suplus vehicles," defined as the number of vehicles in the fleet that could be charging while keeping the fraction of vehicles hired below the minimum value observed during the daytime (44%); d) number of vehicle charging.

3.3.4 Shift charging to break periods

Early-morning hours are not the only time of day when charging has a negligible opportunity cost. I estimate that each vehicle takes over two hours of breaks per day on average, even when only including periods when the vehicle spends at least 30 minutes idle in the same location (not including charging). Over 60% of vehicles spend at least as much time on these breaks as they spend charging during the dayshift. When asked why they do not currently use break periods to charge, several drivers reported that they see no need to do so, because they must charge to full SOC before changing shift regardless. Without the constraint of changing shift at full SOC, drivers could save time by charging during breaks. Such an intervention could also reduce fatigue driving and improve safety by encouraging drivers to take longer breaks every few hours to ensure that they remain alert while driving.

As described in the methodology, I developed a simulation model to estimate the minimum amount of additional charging time required given full use of both break periods and early morning hours, finding that on average vehicles could satisfy all their charging needs with only

10 additional minutes, saving over 70 minutes per vehicle per day. This optimization strategy, shown as the “optimized” vehicle charging profile in Figure 62, results in a larger early-morning peak, a broader lunchtime peak, and a substantially smaller afternoon peak. This reduced demand for charging during the afternoon increases the fleet’s capacity to serve trip demand during afternoon peak hours, yielding over $75 million per year in additional revenue.

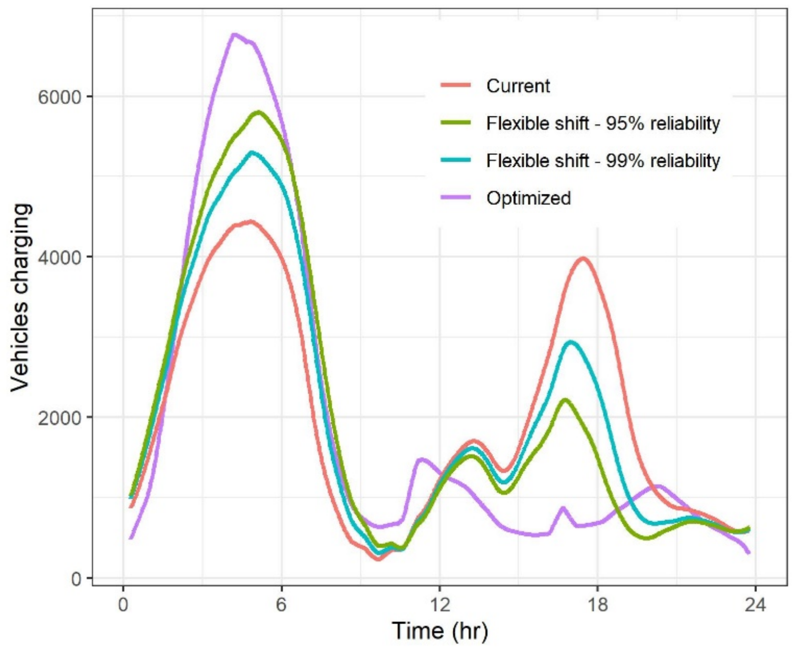


Figure 62. Number of vehicles charging by time of day in four different scenarios. The “flexible shift” scenarios allow drivers to change shift at a sufficient SOC to provide either 99% (green) or 95% (blue) confidence for the nightshift driver to operate without charging until the early morning hours (defined as 1am on weekdays and 2am on weekends). The optimized scenario assumes full usage of both break periods and early morning hours for charging. The large nighttime peak introduces the possibility of scarcity of available chargers. However, given that I inferred over 12,000 chargers in the taxi data, I expect that the dispatching optimization, described above, would be able to mitigate this potential issue.

3.3.5 Evidence from current driver behavior

Using the fleet’s driver shift-change data, I find that some drivers have already adopted charging patterns aligned with some of the strategies described above. For example, for 1,251 vehicles or roughly 7% of the fleet, dayshift drivers ended their shift with a 60 to 85% SOC. Compared with “full SOC” dayshift drivers in Figure 63 below, “flexible SOC” dayshift drivers tend to charge earlier in the afternoon, likely coinciding with their lunch break, and “flexible SOC” nightshift drivers tend to charge slightly earlier in the early-morning hours.

As shown in Table 19 below, compared with drivers that change shifts at full charge, on average these “flexible SOC” drivers earn more revenue ($5 per vehicle per day), operate for slightly more time, and continue accepting trips with less time before their shift change (1.42 hour versus 2.25 hour). They also charge further from the shift-change location (6.1 km versus 2.9 km), meaning they have more choice of where to charge. This increased choice likely results in less queuing time and greater certainty of charging time, both of which reduce the overall opportunity cost of charging.

Table 19. Comparison of descriptive statistics by vehicle charging strategy.

Attribute	SOC at afternoon shift change (%)		p-value
	60 to 85 (flexible SOC)	>85 (full SOC)	
Number of vehicles	1251	10616	n/a
Total revenue (USD/vehicle/day)	211.62	206.15	***
Dayshift revenue (USD/vehicle/day)	107.09	102.31	***
Distance between charging station and shift change location (km)	6.1	2.9	***
Time between charging and shift change (hr)	3.63	2.30	***
Time between shift change and last trip dropoff (hr)	1.42	2.25	***
Operating time (hr/day)	19.67	19.48	*
Revenue per operating hour (USD/vehicle/hr)	10.79	10.57	**
Starting SOC of charging events (%)	53	52	
Ending SOC of charging events (%)	92	96	***
Charging time (hr)	1.09	1.26	***

p-values describe results of two-tailed t-tests, with the following significance levels: * < 0.05, ** < 0.01, *** < 0.001

Additionally, on average "flexible SOC" dayshift drivers stop charging at 92%, saving 10 minutes per charging event by avoiding slow charging speeds at close to full SOC. These findings are consistent with my simulation results that suggest that flexibility in the SOC required at shift changes can increase driver earnings by enabling drivers to charge during break times and at charging stations with shorter queuing times.

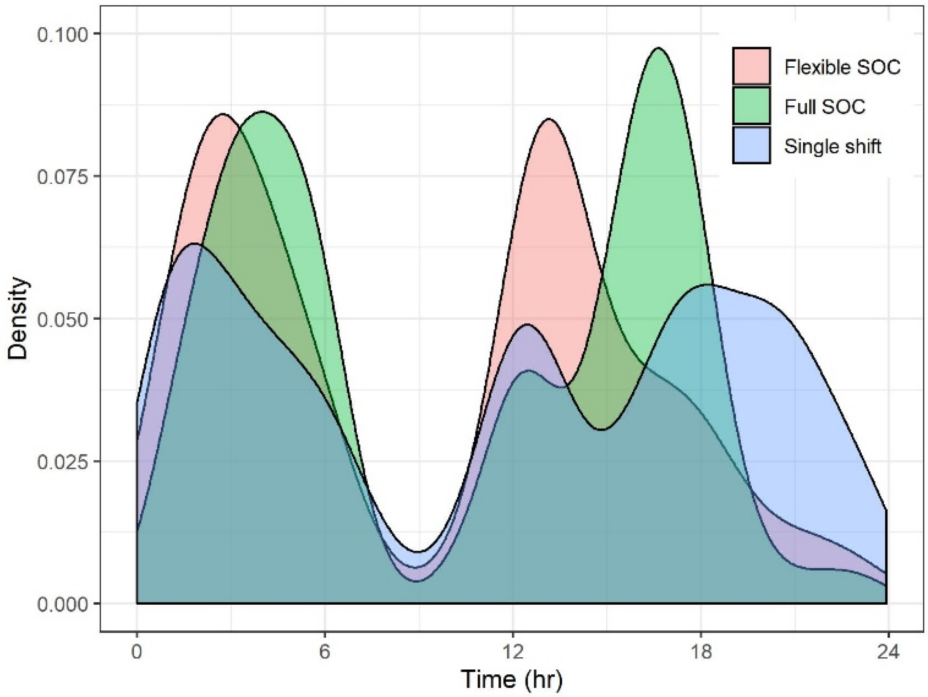


Figure 63. Density profile of charging events by start time on July 25, 2019, grouped by shift-change type. “Flexible SOC” represents vehicles changing shift in the afternoon at 60 to 85% SOC, “full SOC” represents vehicles changing shift in the afternoon at 85 to 100% SOC, and “single shift” represents vehicles that did not report a shift change on this day.

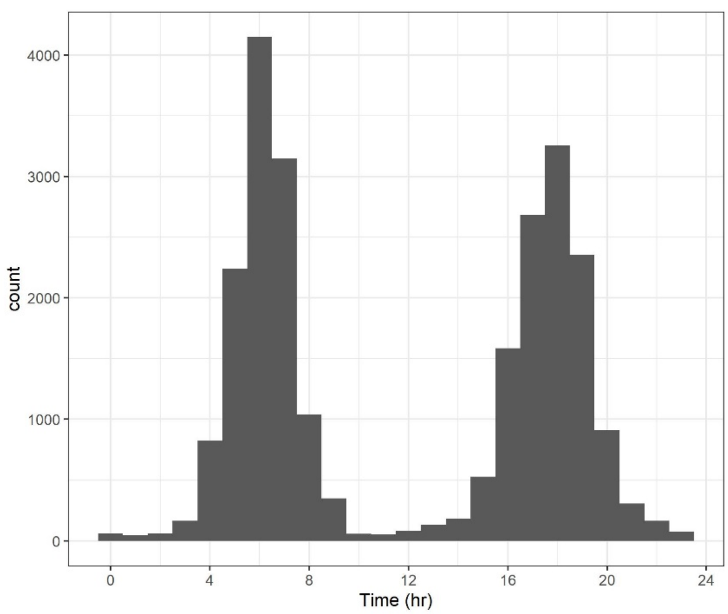


Figure 64. Distribution of shift change times on July 25, 2019.

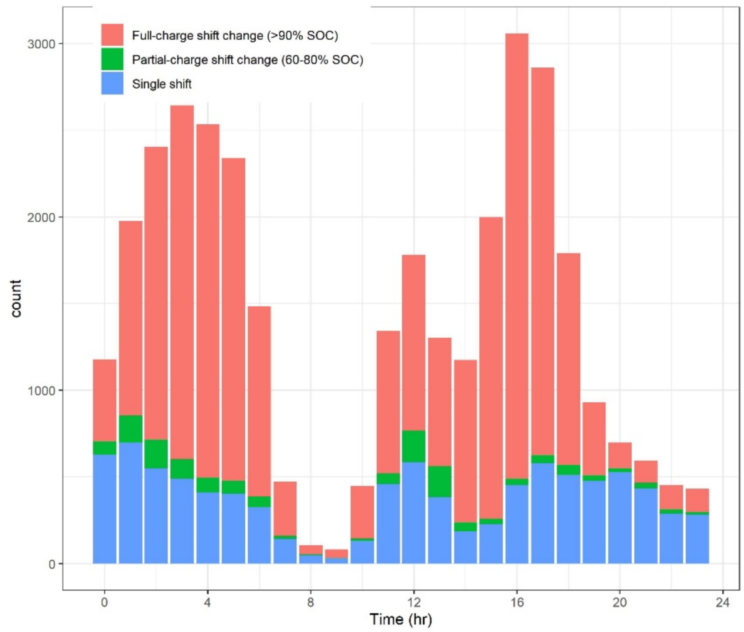


Figure 65. Distribution of charging start times by driver shift-change type.

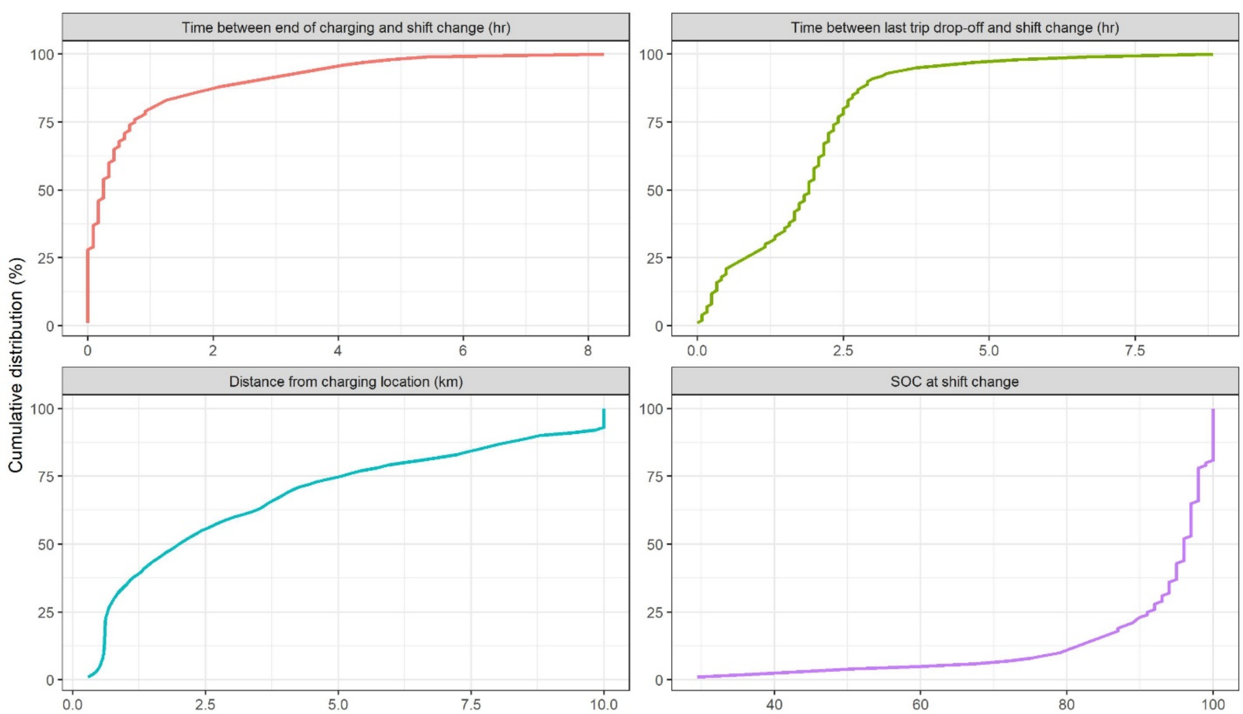


Figure 66. Cumulative distributions of different characteristics of driver shift change data.

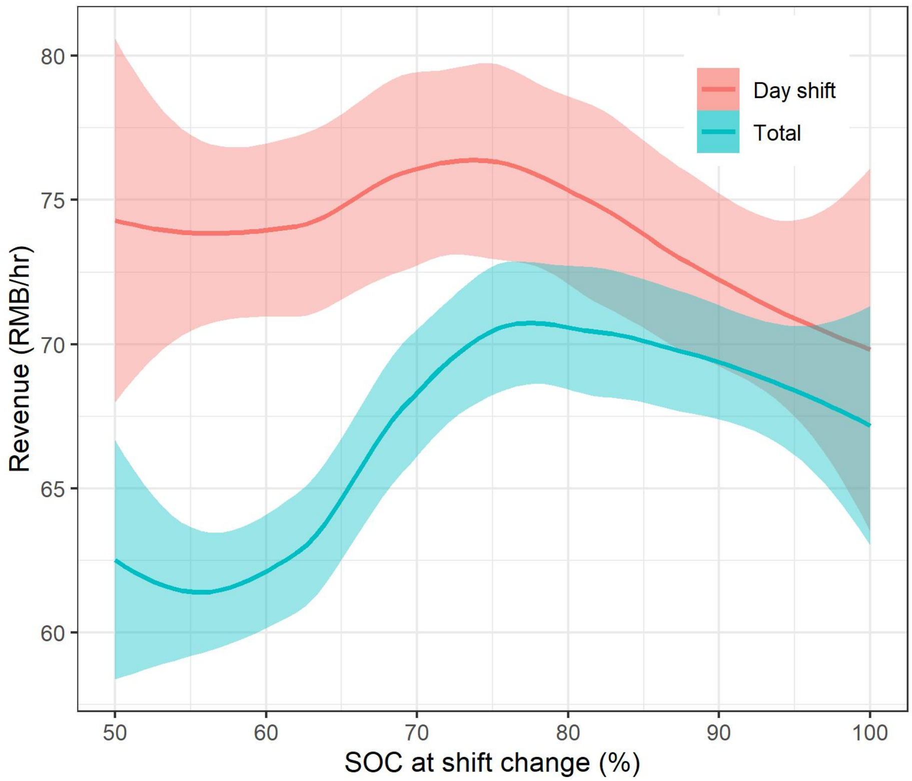


Figure 67. Impact of SOC at driver shift change on average revenue per hour both during the dayshift and across the day.

3.4. Conclusion

With the Shenzhen taxi fleet data on vehicle trajectory and battery state of charge, I illustrate the capability of big data to reveal system-level inefficiencies and inform simple optimization strategies to facilitate effective total electrification. Enabling flexible SOC during the afternoon shift change could reduce aggregate vehicle downtime by over 10,000 hours per day, while fully using break periods and early morning hours to charge could save over 20,000 hours per day. I also find that optimizing vehicle dispatching to charging stations could improve the economic sustainability of charging infrastructure by increasing the percentage of viable chargers without subsidies from less than half to 75%.

These findings naturally lead to recommendations for policies that encourage driver behavioral change and coordinated charging. By testing and implementing such strategies, cities and fleet operators could greatly alleviate the operating burden arising from electrification. For more effective fleet electrification, cities should consider developing data platforms that integrate demand-side data on the charging needs of various transportation modes with supply-side data on charger availability and construction. This combination would enable critical feedback control so cities can predict and balance the demand and supply for electrified transportation. Aside from the real-time fleet optimization discussed in this study, data integration can also be used to minimize the stress vehicle charging places on the power grid and maximize usage of intermittent renewable energy resources. Meanwhile, switching from conventional vehicles to BEVs effectively will require significant behavioral changes, and both taxi drivers and fleet operators could benefit from targeted training to better understand how to best use this new technology.

Shenzhen provides a strong leadership model for municipal governments to consider as they seek full electrification of both fleets and private transportation. Given China's goal of phasing out conventional vehicles over the next several decades,[200] the findings of this study have large-scale implications for other Chinese megacities aiming to shift to low-carbon transportation.

Conclusion:
On-demand automotive fleet electrification can catalyze global transportation decarbonization and smart urban mobility

In the previous three chapters, I have conducted analysis and modeling to show the feasibility of rapidly electrifying MODV services worldwide. Figure 68 summarizes these findings. As shown in Figure 68a, MODVs often spend over 25% of their time idle while waiting for trips,[201] suggesting that if this downtime could be harnessed effectively, drivers would have plenty of time to charge. As shown in Figure 68b, less than 0.5% of taxi trips are over 50 km in a variety of cities, and my work discussed above has shown that BEV fleets could serve present-day mobility demand in dense urban areas with less than 160 km of battery range.[77] Given that these vehicles are typically driven in urban cores, BEV fleets could also more effectively reduce air pollution, especially in lower-income communities where private BEVs may remain prohibitively expensive for many years.[202]

One factor that complicates MODV electrification is that some companies – mainly TNCs – do not own and operate their vehicles but rather operate a software-based marketplace where drivers working as independent contractors provide mobility services to consumers requesting rides. However, as I discuss below, many of the same opportunities, barriers, and policy needs apply to TNCs as well.

Electrification of the MODV sector also presents an opportunity for large potential spill-over benefits for other areas of sustainability. MODV electrification would expose many consumers to BEV technology and spur investment in charging infrastructure for those without access to home charging (especially common in low-income areas), both of which would likely broaden the market for private BEVs.[80,203] While MODV charging could exacerbate peak electricity loads, coordinated charging could eliminate peak-load growth, spreading charging to hours of the day when electricity is cheaper and/or underused.[153,204] Individual charging stations can also moderate power supply to vehicles to align with grid capacity. Furthermore, as I describe in detail below, MODV electrification can facilitate the collection and analysis of vehicle trajectory data to inform the design, integration and operation of innovative mobility services, including bus rapid transit, shared micromobility (bike and scooter sharing platforms), and partnerships between MODVs and existing public transit service. Beyond its application to transportation innovation and policy, this vehicle trajectory data may also become an important tool to enable contact tracing in the fight against the COVID-19 pandemic.

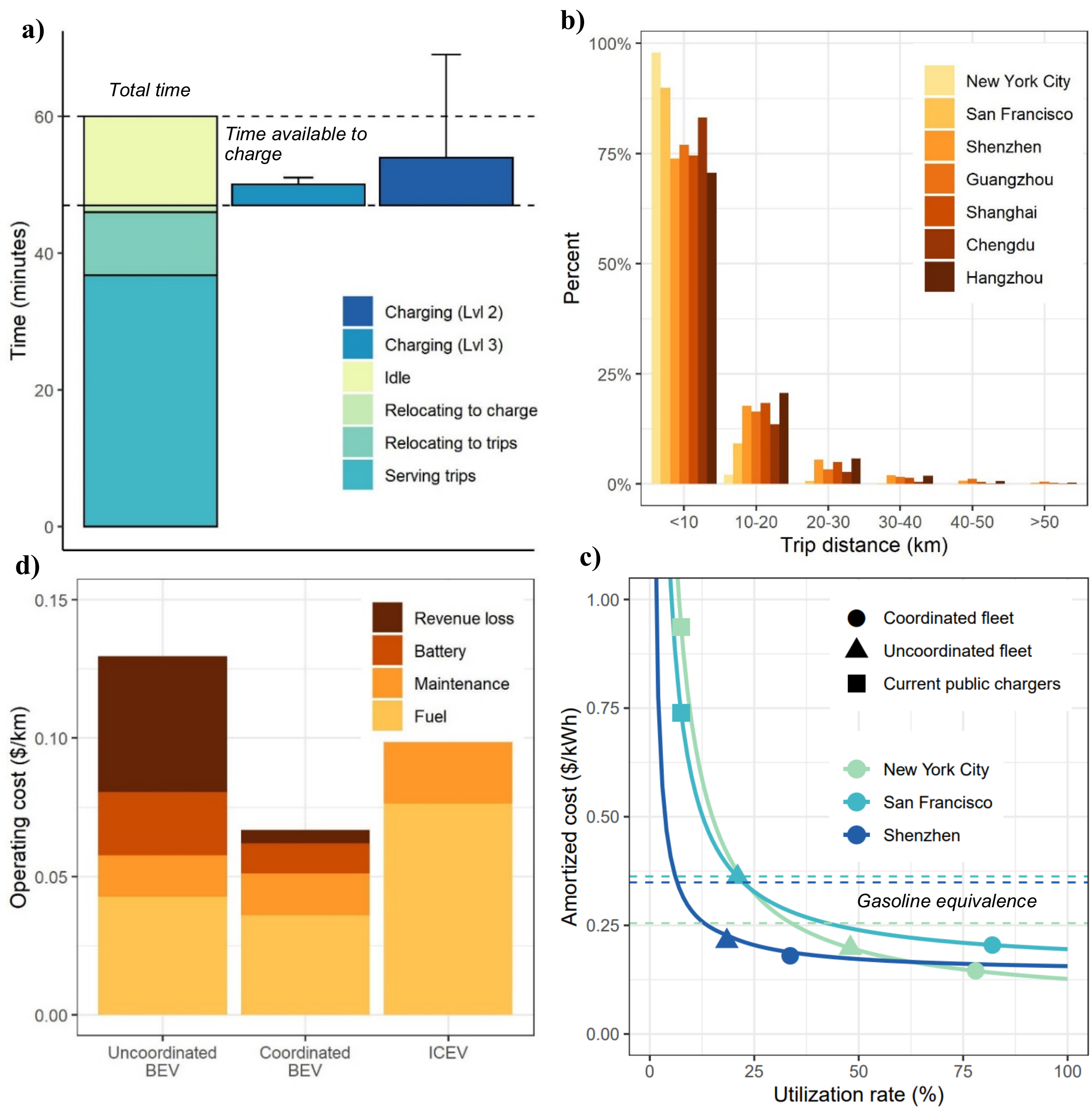


Figure 68. Clockwise from top left: a) distribution of time spent by an average New York City (NYC) ridesourcing driver.[145,201] I assume a vehicle energy consumption of 0.17 kWh/km, equivalent to the performance of the 2018 Chevrolet Bolt.[160] For relocating to charge, I assume one charging session per eight-hour shift and an average relocation distance of 4 km at a speed of 16 km/hour. b) Distribution of taxi trip distances in cities in the United States (U.S.) and China (data provided by city governments of respective cities). c) Relationship between the total cost of charging infrastructure (capital cost, electricity, and demand charges) and percent utilization by time, along with the impact of fleet coordination.[138,198,201] Note that these costs only include the cost of electricity and charger installation, not the opportunity cost of queuing and charging; the reduction of the cost of charging with coordination is due to the reduced quantity of chargers needed. d) Operating cost by vehicle type and fleet coordination based on cost estimates in Shenzhen. I use cost parameters from chapter 2, and I assume battery lifetime of 1,500 cycles when uncoordinated, and 3,750 cycles when coordinated, based on my review of battery degradation literature. I assume that vehicles must be replaced at 80% of original capacity when uncoordinated, and at 50% when coordinated, as found in chapter 2.[77] Revenue lost due to charging is based on results from chapter 3, and includes the opportunity cost from time spent both queuing and charging.[205,206] In both c) and d), I assume an annual discount rate of 5%. See Table 20 to Table 22 for details on calculations, sources, and assumptions.

Table 20. Variable definitions and values for Figure 68a

Variable	Definition	Value	Source
fare_mi	fare per mile	\$1.75	[155]
fare_min	fare per minute	\$0.35	[155]
f_{base}	base fare	\$2.55	[155]
v	velocity	12 miles/hour	[145]
w	wage	\$24/hour	[154,156]
avg_dist	average trip distance	3 miles	[145]
t_shift	shift duration	5 hours	[154,156]
kpm	energy consumption	0.28 kWh/mile	[160]
C	TNC commission	25%	[155]
d_rel	empty distance ratio	25%	[157]
full_wage	theoretical wage if serving trips 100% of the time		
t_pass	time actually serving trips given wage rate		
t_trprel	times spent relocating to trips		
d_tot	distance traveled per hour		
t_chgrel	time spent relocating to charge		

Calculations:

*full_wage = (60 * fare_min + vel * fare_mi + vel / avg_dist * fare_trp) * (1 - C)*

*t_pass = 60 * w / full_wage*

*t_trprel = t_pass * d_rel*

*d_tot = vel * (t_pass + t_trprel) / 60*

*t_chgrel = 1 / vel * 60 / t_shift*

time required to charge *= d_tot * kpm * 60 / charger power*

total time busy with non-charging activities *= t_pass + t_trprel + t_chgrel*

Table 21. Variable definitions and values for Figure 68c.

Variable	Definition	Value			Sources
		SF	NYC	SZ	
fee	annual fee	$0	$0	$1,344/year	[198,201]
capex	installation cost	$50,000	$50,000	$24,500	[138,198]
opex	O&M cost	$1,500/year	$1,500/year	$700/year	[138,198]
dmnd	demand charge	$15.90/kW/month	$30.9/kW/month	$0	[198,201]
elec	electricity cost	$0.151/kWh	$0.061/kWh	$0.14/kWh	[198,201]
dur	charger lifetime	10 years	10 years	10 years	[198,201]
disc	discount rate	0.05	0.05	0.05	[198,201]
power	charger rating	50kW	50kW	42kW	[198,201,205]
util	utilization rate of charging infrastructure	current: 7.5% uncoordinated: 21% coordinated: 82%	current: 7.5% uncoordinated: 48% coordinated: 78%	current: unknown uncoordinated: 18% coordinated: 34%	[158,159,201,206]

Calculations:

*annual kWh = util * power * 24 hours/day * 365 day/year*

discount rate = (1 + disc) ^ (1 / annual kWh) – 1

total cost per kWh =

*capex * (discount rate / (1 – (1 + discount rate) ^ (-1 * annual kWh * dur))) +*

*opex * (discount rate / (1 – (1 + discount rate) ^ (-1 * annual kWh))) +*

*fee * (discount rate / (1 – (1 + discount rate) ^ (-1 * annual kWh)))*

Table 22. Variable definitions and values for Figure 68d.

Variable	Definition	Value			Sources
		Coordinated BEV	Uncoordinated BEV	ICEV	
fuel_price	cost of electricity or gasoline	$0.18/kWh	$0.21/kWh	$1.02/L	[207]
cons	rate of fuel consumption	0.2 kWh/km	0.2 kWh/km	0.075 L/km	[198,206]
bat_price	battery purchase price	$150/kWh	$150/kWh	n/a	[201]
capacity	battery capacity	80 kWh	80 kWh	n/a	[206]
cyc_deg	battery capacity degradation per cycle	.013%	.013%	n/a	[208]
soc_end	capacity at which batteries must be replaced	50%	80%	n/a	[77,201,208]
rev_loss	revenue lost due to time spent charging	$1.50/day	$15/day	$0	[206]
maint	maintenance cost	$0.015/km	$0.015/km	$0.025/km	[77,198]
dist_day	average distance traveled	306 km/day			[206]
disc	daily discount rate	0.05 / 365 = .00014			[77]
bat_dur	battery lifetime, in days				

Calculations:

*bat_dur = (100 – soc_end) / (cyc_deg * dist_day / (capacity / cons))*

total cost per km = *bat_price * capacity **

disc (disc + 1) ^ bat_dur / ((r + 1) ^ bat_dur – 1) / dist_day* **+** *fuel_price * cons + maint + rev_loss*

Barriers

Despite such high stakes and promising opportunities, as discussed above, in most areas MODV electrification lags even the slow pace of private-vehicle electrification. While many major TNC companies have announced initiatives to promote electrification, most goals amount to electrifying less than 5% of operations.[209]

Current understanding is that fast-charging infrastructure is prohibitively expensive to build and operate without high levels of public subsidy, but the truth is more complex. Because cost is dominated by installation and demand charges, it is highly dependent on usage rates: as usage increases, the per-energy cost decreases exponentially. As shown in Figure 68c, the amortized cost of charging at public fast-charging stations in the U.S. costs over twice as much as gasoline because usage rates are very low; private BEV owners typically charge at home and only use fast-charging stations in emergency situations or on rare long-distance trips. In contrast, BEV fleets need to use fast chargers in urban areas daily and are available to charge in between trips throughout the day. Studies have shown that even use by unmanaged fleets could drive costs below that of gasoline;[92,114] coordinated charging could reduce costs even further.[201]

Even with sufficient charging infrastructure, MODV services may not electrify without additional policy support. Drivers are typically responsible for fuel expenses, leading to a principal-agent problem (i.e., the actor able to solve a problem and the actor affected by the problem are separate entities)[210] as the service operator is much better equipped to facilitate electrification. In many places, fuel costs represent less than 10% of driver earnings, and studies have shown that consumers tend to undervalue savings from efficiency,[211] such that drivers may not prioritize efficiency over other factors (e.g., comfort and style) when choosing a vehicle. Prior to updated regulation in 2009, NYC taxis had an average gasoline fuel economy of 15 miles per gallon (16 L/100 km), much lower than the nationwide average. Even today, though the total cost of ownership of hybrid vehicles is lower than that for gasoline vehicles, only 60% of the taxi fleet in NYC is hybrid, and less than 20% of TNC vehicles.[212]

Both these trends point to the need for policymakers to set firm targets for MODV electrification. Without BEV demand for fast chargers in the urban core, it is not surprising that a lack of infrastructure remains a problem. But if charging operators have confidence in high levels of demand, private companies will invest in infrastructure, resulting in sufficient supply. As shown in Figure 68, high levels of usage from BEV fleets enables charging operators to make a return on their investment, spurring further investment.

Electrification trends in China provide a model for how this can work in practice. Mandates on bus and taxi fleet electrification in Shenzhen, China spurred heavy investment in charging infrastructure, resulting in over 12,000 fast-charge points spread across the city within five years, owned and operated by over 10 different private companies.[198] Electrification mandates for buses and taxis in several Chinese cities have already electrified billions of kilometers, suggesting such policy represents a viable pathway to rapid electrification at scale (see Figure 69).

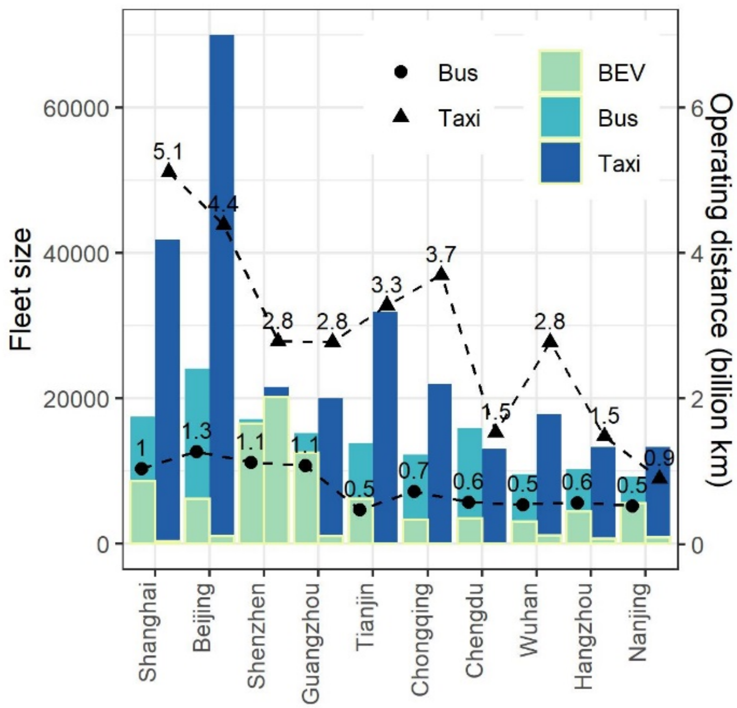


Figure 69. Number of vehicles and operating distance in bus and taxi fleets in 10 of the largest Chinese cities, along with rates of electrification. Data provided to authors by Aspiring Citizens.

Incentives and pricing play an important role in accelerating adoption of BEVs and installation of charging infrastructure. The city government in Shenzhen and the Chinese national government provided subsidies for charging stations amounting to 30% of installation cost.[198] However, subsidies for charging stations and vehicles do not guarantee adoption, and no level of subsidy is sufficient without demand. For example, analysis of current incentives in the U.S. showed that every US$1,000 of monetary incentive has increased BEV sales by less than 3%, equivalent to a cost of over US$30,000 per additional sale.[213] While incentives will likely be necessary to reward early actors and compensate them for risk, they cannot replace firm electrification targets. One possible strategy would be to combine incentives with targets through a credit-trading scheme, as employed with fuel economy standards for private vehicles in the U.S. and elsewhere. Cities in other regions have now also set electrification targets, including London, Amsterdam, and Oslo. These governments should look to China for lessons on how to electrify quickly, as well as learn from past mistakes.

The Chinese political context enables rapid policy implementation, and electrification will likely proceed more slowly in other regions. Most of the same challenges and policy recommendations still apply, but a more gradual transition introduces another barrier related to driver equity. When all vehicles are electric, they will need the same amount of downtime to charge, and so have the same opportunity to earn revenue. In contrast, while there are some ICEVs remaining, they may earn more revenue than BEVs that must go to charge. As such, it is likely that TNC companies will need to cross-subsidize BEV vehicles, or schedule charging sessions more carefully.

On the other hand, a more gradual electrification timeline offers the advantage of allowing drivers to opt in based on how amenable their driving habits are to electrification; e.g., those who drive full-time and those who lease vehicles specifically for TNC driving will be likely to adopt a BEV before part-time drivers and those who use their own vehicle. Furthermore, while TNC driving is largely concentrated in urban areas, there are also TNC operations in lower density areas, which may prove more difficult to electrify due to the larger requirement for charging infrastructure; these operations can be given lower priority.

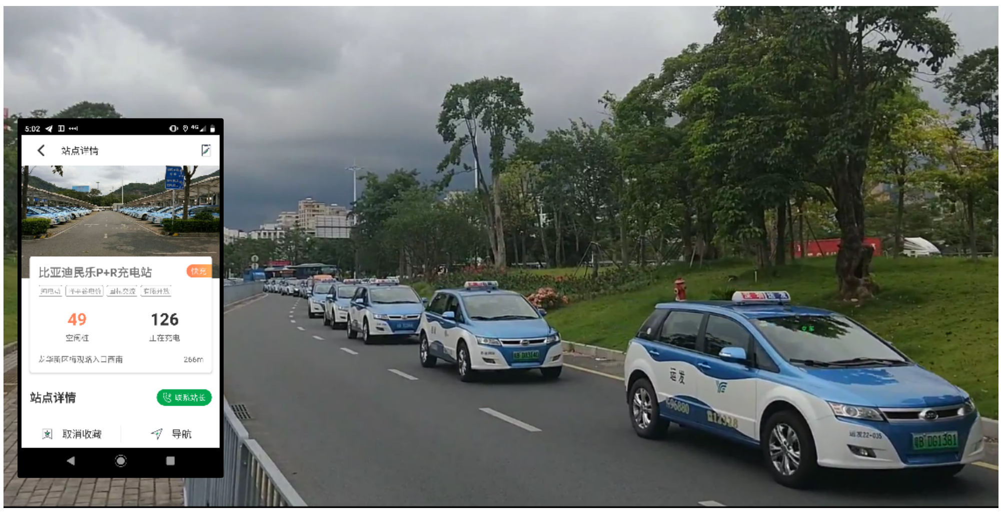


Figure 70. Taxis waiting to charge at Minle station in Shenzhen on July 30, 2019. As shown in the inset, at the same time there were over 100 taxis waiting to charge, a popular charging app by automaker BYD showed 49 available charging ports, suggesting that vehicle data may be necessary to provide real-time charging availability. Minle station is the largest charging station in the world, with over 500 fast chargers,[214] and drivers see it as more reliable than other smaller stations, leading to disparities in usage rates and long queuing times.

Solutions

While important, adequate infrastructure supply does not ensure efficient charging operations. As shown in Figure 70, and discussed in the previous chapter, taxis in Shenzhen often wait over 30 minutes to enter charging stations, despite real-time charging apps that show plenty of availability. Downtime for charging currently costs drivers US$15/day, more than the cost of electricity itself. A few large charging stations receive a disproportionate share of charging demand, while most other charging stations are not economically viable.

As discussed in the previous chapter, my research has showed that this inefficiency is largely due to a lack of data: without proper information on the best places and times to charge, drivers tend to charge at large stations right before they end their shifts, during afternoon peak demand. The authors found that providing drivers with complete information including forecasts of trip demand could reduce revenue losses by up to 90%, and even just providing accurate information on queues at each charging station could reduce overall queuing time by half. As shown in

Figure 68d, the combined cost reductions of fleet management in Shenzhen could reduce operating costs by almost 50%, from 130% of the cost of ICEVs to 66%.

Whether to coordinate shift changes and minimize downtime for charging, or to minimize battery range requirements, data are essential. To ensure electrification programs succeed, governments need to start building public data platforms to host several critical datasets, including vehicle trajectories, charging station availability and location, and potential charging location costs.

In the planning stage, charging companies should have access to aggregated vehicle trajectory data and grid capacity availability data from power grid operators to predict optimal station locations. Charging companies currently waste significant resources searching for the best sites for charging stations; many studies have developed methods to optimize the siting of charging stations,[113,162,192,193] but all require data for proper implementation. In the operational stage, charging station status (i.e., number of plugs available and occupied and estimated time until free) should be aggregated across operators and integrated with vehicle trajectories to provide drivers with an accurate measure of expected wait time at each charging station. Public agencies should also actively monitor charging behavior to identify context-dependent barriers, such as those found in Shenzhen. In the longer term, such data can enable MODV service operators to provide drivers with recommendations for where and when to charge, minimizing electricity prices and grid capacity constraints, downtime for charging, and requirements for battery range. Note that coordinated charging does not require the fleet to be operated by a single company with monopoly power; as long as all operators and drivers have the data necessary to forecast total trip demand and charging availability, several operators working independently could still conduct their own operations more efficiently.

MODV service operators rarely give up data easily,[215] but electrification targets provide a powerful justification for data transparency. In Shenzhen, BEV incentives were tied to providing vehicle trajectory data as part of a broader modernization effort, and in California, the state government successfully requested vehicle trajectory and trip data from TNCs to establish a carbon footprint baseline.[216] These strategies suggest that not only can smart data policy enable electrification, but electrification policy may facilitate mobility data collection as well. Another option could include offering subsidized BEV leases for vehicles equipped to transmit data.

But acquiring data is not enough; policy must also ensure that this data is accessible to key stakeholders, including charging infrastructure developers and operators, along with third-party software developers providing services for efficient fleet operation. While real privacy concerns exist, fleet data is also much less sensitive than data from personal vehicles, and data can be aggregated to the intersection or census tract level to ensure anonymity without reducing benefits. Another possibility would be increasing consumers' access to their data and notification of data collection, as mandated by the European Union's General Data Protection Regulation.[217] Several cities around the globe already collect TNC trip data (e.g., Toronto, Mexico City, Sao Paolo), in some cases also publishing parts of it publicly (e.g., Chicago, NYC);[218] it is not hard to imagine expanding these existing regulations to aid charging infrastructure development and operation.

Policy recommendations and spill-over effects

MODV companies have increasingly relied on treating their drivers as independent contractors to minimize labor costs, which means they have a strong incentive to refrain from interfering with how their drivers perform their work.[219] For example, directing drivers to charge at times with relatively low trip demand or collecting data on vehicle state of charge could violate the independent contractor relationship, exposing service operators to legal action. Depending on the implementation strategy, there could be ways to circumvent these risks (e.g., only providing drivers with information on charger availability and forecasted demand), but such complications add another barrier to effective MODV electrification.

Policymakers should reform these policies to increase certainty in the relationship between MODV companies and their drivers. In September 2019, California passed a law[220] that requires TNC and taxi drivers to be treated as standard employees, thus eliminating any uncertainty. An under-appreciated consequence of the law (still under dispute) is that TNCs will now be allowed to direct drivers in between trips, as well as own and maintain vehicles in the same way as other fleet operators. While other strategies exist, this law could serve as a template for other governments around the world seeking to promote both labor equity and MODV decarbonization.

Once real-time MODV data become available, its value extends far beyond electrification itself. By shedding light on where people want to go, vehicle trajectory data can enable cities to start integrating MODV operations with innovative mobility services, such as bus rapid transit, bikesharing, and scooter sharing. Present-day public transit systems are designed to provide access to passengers arriving by foot or bike, making it challenging to integrate with vehicle fleets, but future systems could locate stations near highway on-ramps and parking lots to optimize such integration. Areas with a high density of on-demand trips may be better-served by vanpools, while areas with many short trips would be ideal for bike and scooter placement. Private companies have access to such data but have little incentive to reduce energy consumption or congestion. Figure 71 summarizes the linkages among policy levers, direct and indirect impacts, and outcomes.

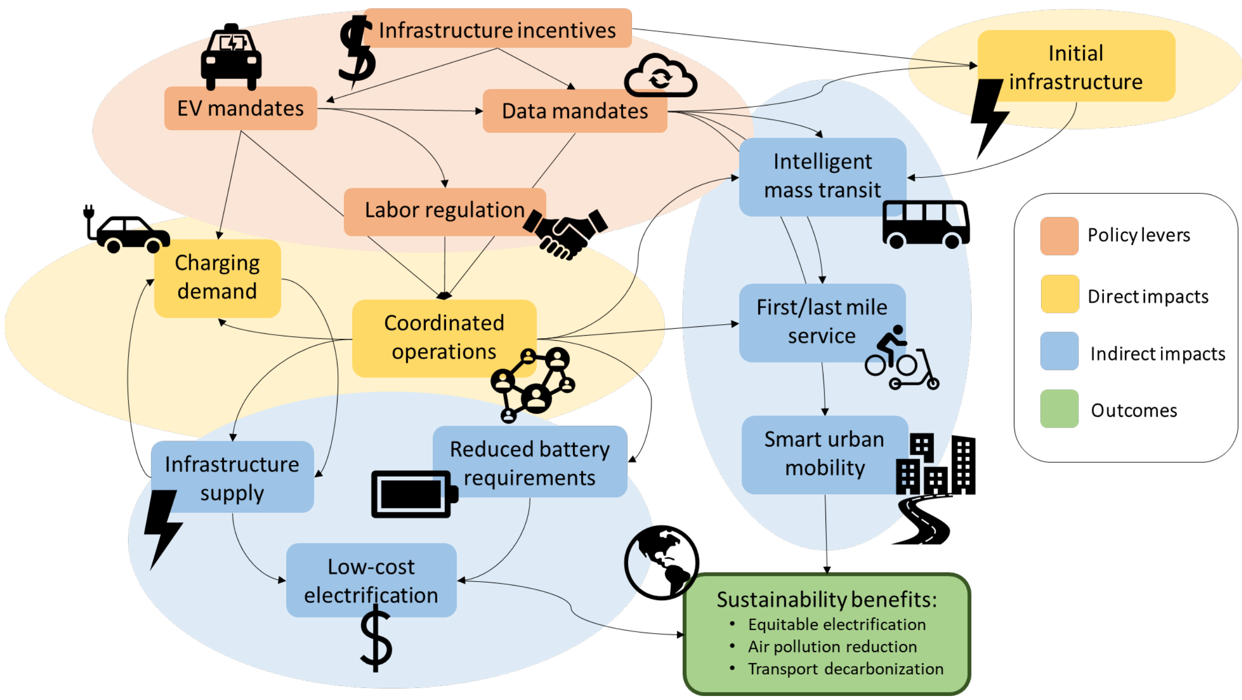


Figure 71. Flow chart depicting the impact of proposed policies to support fleet electrification.

More broadly, open data platforms with vehicle trajectory data encourage a wide swath of smart urban mobility strategies. For example, as more cities move to establish low-emissions zones (emulating London),[221] they will need to understand how much pollution and congestion is caused by each vehicle type across space and time. Data analysis could also inform policies designed to incentivize higher vehicle occupancy, for example through dynamic ride pooling. Ultimately with AVs, all these issues will become magnified, but much harder to regulate once a constituency becomes entrenched. Recently, cities have also started using taxi data to inform contact tracing and isolation efforts to help fight the COVID-19 pandemic; this public health feature will become increasingly important as the globe prepares for future waves of the novel coronavirus or other pandemics.[222]

Urban mobility has entered a period of rapid change, and MODV services may come to dominate the sector over the next several decades. This development carries the risk of increased congestion, pollution, unequal access, and increased carbon emissions. However, it also presents a massive opportunity for both decarbonization and smart urban mobility. When managed properly, BEVs can serve on-demand mobility at lower cost than fossil fuel vehicles with today's technology and provide grid benefits with coordinated charging. Strong political will targeted at MODV electrification can produce a cascade of positive spillover effects, but it will require carefully designed policies targeting both data and labor regulation to succeed.

Summary

In sum, this dissertation shows how MODV services are ripe for electrification. Not only does BEV technology lend itself to fleet services, but it is feasible with current technology. With small improvements in operations, current projects could eliminate revenue losses due to charging, while facilitating development of smart urban mobility and rapidly reducing transportation emissions and air pollution.

In particular, Chapter 1 shows that battery range will not be the main obstacle for SAEV fleets. Currently available ranges more than suffice, and significant cost savings could result from reducing battery range from current levels. Chapter 2 shows that the cost of charging infrastructure is a relatively small fraction of the total cost of an electric, ride-sourced trip, indicating that it might be prudent to slightly overbuild capacity to ensure high-quality service. It also shows that drivers have sufficient idle time to charge during their shift without losing revenue. Finally, in Chapter 3 I extend this result to current operations in China, showing that reduced revenue from BEVs results from irrational charging behavior that can be mitigated by simple software and policy interventions.

This dissertation also furthers theory and methodology in several ways. Chapter 1 describes the development of a new modeling technique with broad application, involving an abstraction of agent-based modeling to allow for retrospective optimization based on simple heuristics. In this chapter, I also develop a method to optimize fleet size to minimize total costs based on battery degradation and vehicle mileage. Chapter 2 shows how these models can be applied to a variety of real-world scenarios by integrating several different data sources and converting them to a uniform format that serve as inputs to the model, thus developing a general technique for planning MODV electrification. I also develop a theoretical approach to estimating charging infrastructure requirements based on wage rates and vehicle speeds, and a modeling approach to test the impact of different operational strategies. Finally, Chapter 3 shows the value of combining qualitative analysis from semi-structured interviews with quantitative results from machine learning and statistical analysis to produce insights that neither approach could have produced alone. This mixed-methods approach is relatively uncommon in the field of transportation engineering and my dissertation shows it is a promising avenue for future work.

These results suggest that goverments must act quickly to set firm electrification targets and establish citywide open data platforms to integrate real-time data on vehicle trajectory, battery charge, and charger availability. Regulators must also ensure that fleet operators provide drivers with training on best charging practices. In turn, digitization enabled by fleet electrification holds the potential to enable a host of smart urban mobility strategies, including integration of public transit with innovative transportation systems, emission-based pricing policies, and smart charging to facilitate uptake of renewable energy generation. As cities worldwide seek to fully electrify MODV services, this analysis has large-scale implications for decarbonized, cleaner urban areas.

Limitations and directions for future research

This dissertation has focused primarily on questions related to fleet operation, leaving several key areas for future research. First, while each chapter successively adds greater real-world detail related to driver behavior and operational barriers, future work should address these questions in more detail. For example, how do drivers decide where and when to relocate in between trips? How do they decide where and when to charge, including factors like amenities (e.g. food and rest areas), brand loyalty, and neighborhood location? Aside from conducting modeling based on data, it will be crucial to conduct pilot projects to study the real-world impact of various operational strategies and interventions.

Another important direction for future research is in the area of market dynamics. What are the bottlenecks in vehicle supply, and how does the fleet market intersect with the private BEV market? Finally, while my cost models largely assume amortized costs for newly purchased vehicles, the used vehicle market may provide opportunities for reduced costs and deserves further study. The same could be said of second-life applications for batteries after use in MODV services, as well as for alternative ownership models. For example, although short-range BEVs may not readily serve all of drivers' personal trips, leasing or renting vehicles for ridesourcing is already common, and deserves greater study. Finally, future work should incorporate dynamics of a fleet that changes over time with the introduction of both electric and automated vehicles.

While addressed in some detail, questions related to electricity infrastructure and markets also deserve further investigation. For example, it will be crucial to plan charging infrastructure in accordance with distribution grid capacity limitations, and operating fleets to simultaneously provide grid services could increase revenue while decreasing carbon emissions; future modeling should incorporate the trade-offs imposed by these factors. Meanwhile, other types of BEVs like private vehicles and logistics vans may compete for public charging resources, so future work should incorporate analysis of electric vehicles not involved in MODV services. Many of these issues could be addressed through obtaining and integrating additional sources of data, including real-time data from existing charging stations, more detailed analysis of driver shift change times and locations.

All of these questions relate to market supply, and future work should also include analysis of impacts on consumer demand for MODV services. For example, most of my analysis assumes exogenous demand, but if costs fall dramatically as projected with electrification and automation, demand for MODV services will likely skyrocket. If SAEVs then begin to replace other modes of travel, empty miles may lead to increased congestion, which also deserves further study. I have addressed these issues through conservative assumptions (e.g. including a 10-minute wait time buffer) and conducting a range of scenarios ranging from the island of Manhattan to entire cities in both China and the United States, to developing a model to extrapolate key parameters for the entire country. Nonetheless, all of these issues merit further study.

In turn, changes in VMT could have important implications for climate change, air pollution, and travel times. While my work focuses on the electrification of motorized transportation, future research must also include analysis of other transportation modes, including shared micromobility, active transportation, and mass transit. Future work should compare these various travel modes across a range of parameters – including carbon intensity, energy consumption and speed – and identify strategies for shifting demand to a more desirable mix of travel modes, while also reducing the need for mobility through reforms in housing and urban development policy.

More importantly, future work should study not just how many passengers MODVs will serve but whom. In particular, as discussed in the introduction, MODV services hold the potential to reduce structural inequality in the transportation system by reducing the dominance of private vehicles that leads to prohibitively high upfront costs. However, companies may not necessarily serve all customers equally, and future research should analyze the impact of different operational strategies on rider equity. For example, machine learning algorithms that account for users' names, neighborhood, gender, race, etc. can easily perpetuate existing inequalities. Especially in areas with high levels of segregation, fleets that prioritize wealthier areas will exclude marginalized groups, not only through the spatial distribution of vehicles but also by disproportionately serving times of day when wealthier users are travelling; disadvantaged groups that travel more at off-peak times may experience lower quality of service. In turn, the spatial distribution of mobility services will determine the impact electrification has on local air pollution, so future research should identify ways to ensure that operation serves areas with high levels of air pollution, especially those where pollution is a consequence of discriminatory governmental policy in need of legal remedies.

There are also a variety of barriers beyond fleet operation that have a disparate impact on already disadvantaged MODV users. People with limited or nonexistent access to banking services currently experience difficulties accessing MODV services, as do those without smartphones, or with a physical or cognitive disability. Meanwhile, users with fewer transportation options and educational resources are more vulnerable to a variety of forms of exploitation, including discriminatory pricing, predatory lending, and data privacy violations. Each of these issues deserve further study, including evaluation of possible policy interventions to ensure equal access.

Finally, while this dissertation focuses on vehicles and fleet operation, MODV services would not exist without drivers willing to provide their labor, and there are a number of issues regarding labor rights and equity that require further study. As the recent controversy surrounding TNC drivers' independent contractor status shows, all too often these drivers do not earn a living wage, and have little ability to negotiate the conditions of their employment. Given the complex costs of vehicle ownership and operation, it is unclear the extent to which new drivers accurately understand their total earnings, or the extent to which MODV companies take advantage of this lack of transparency when marketing to potential new drivers. Without careful implementation, MODV services also threaten incumbent technologies, including the taxi industry and public transit, both of which are important sources of stable employment. Future research should include holistic evaluations of MODV services' impact on equity, including both drivers and riders.

References

(1) Schneider, M. The Road Ahead for Electric Vehicles. *ICCG Reflect.* **2017**, *54*, 1–8.
(2) Hao, H.; Geng, Y.; Sarkis, J. Carbon Footprint of Global Passenger Cars: Scenarios through 2050. *Energy* **2016**, *101*, 121–131. https://doi.org/10.1016/j.energy.2016.01.089.
(3) Lah, O. Decarbonizing the Transportation Sector: Policy Options, Synergies, and Institutions to Deliver on a Low-Carbon Stabilization Pathway. *Wiley Interdiscip. Rev. Energy Environ.* **2017**, *6* (6), 1–13. https://doi.org/10.1002/wene.257.
(4) U.S. EPA. Inventory of U.S. Greenhouse Gas Emissions and Sinks (1990-2016). *United Stats Environ. Prot. Agency* **2018**. https://doi.org/EPA 430-T-18-003.
(5) Hawkins, T. R.; Gausen, O. M.; Strømman, A. H. Environmental Impacts of Hybrid and Electric Vehicles-a Review. *Int. J. Life Cycle Assess.* **2012**, *17* (8), 997–1014. https://doi.org/10.1007/s11367-012-0440-9.
(6) Cai, H.; Xu, M. Greenhouse Gas Implications of Fleet Electrification Based on Big Data-Informed Individual Travel Patterns. *Environ. Sci. Technol.* **2013**, *47* (16), 9035–9043. https://doi.org/10.1021/es401008f.
(7) Hawkins, T. R.; Singh, B.; Majeau-Bettez, G.; Strømman, A. H. Comparative Environmental Life Cycle Assessment of Conventional and Electric Vehicles. *J. Ind. Ecol.* **2013**, *17* (1), 53–64. https://doi.org/10.1111/j.1530-9290.2012.00532.x.
(8) Green, E. H.; Skerlos, S. J.; Winebrake, J. J. Increasing Electric Vehicle Policy Efficiency and Effectiveness by Reducing Mainstream Market Bias. *Energy Policy* **2014**, *65*, 562–566. https://doi.org/10.1016/j.enpol.2013.10.024.
(9) King, C.; Griggs, W.; Wirth, F.; Quinn, K.; Shorten, R. Alleviating a Form of Electric Vehicle Range Anxiety through On-Demand Vehicle Access. *Int. J. Control* **2015**, *88* (4), 717–728. https://doi.org/10.1080/00207179.2014.971521.
(10) Alternative Fuels Data Center. All-Electric Vehicles https://afdc.energy.gov/vehicles/electric_basics_ev.html (accessed Dec 4, 2018).
(11) Feng, W.; Figliozzi, M. An Economic and Technological Analysis of the Key Factors Affecting the Competitiveness of Electric Commercial Vehicles: A Case Study from the USA Market. *Transp. Res. Part C Emerg. Technol.* **2013**, *26*, 135–145. https://doi.org/10.1016/j.trc.2012.06.007.
(12) Wood, E.; Rames, C.; Muratori, M.; Raghavan, S.; Melaina, M. *National Plug-In Electric Vehicle Infrastructure Analysis*; Washington, D.C., 2017. https://doi.org/10.13140/RG.2.2.25881.93280.
(13) Alternative Fuels Data Center. Developing Infrastructure to Charge Plug-In Electric Vehicles https://afdc.energy.gov/fuels/electricity_infrastructure.html#level2 (accessed Dec 4, 2018).
(14) Schafer, A.; Victor, D. G. The Future Mobility of the World Population. *Transp. Res. Part A Policy Pract.* **2000**, *34* (3), 171–205. https://doi.org/10.1016/S0965-8564(98)00071-8.
(15) Bauer, G. The Impact of Battery Electric Vehicles on Vehicle Purchase and Driving Behavior in Norway. *Transp. Res. Part D Transp. Environ.* **2018**, *58*. https://doi.org/10.1016/j.trd.2017.12.011.
(16) US Federal Highway Administration. National Household Travel Survey https://nhts.ornl.gov/ (accessed Jul 7, 2020).
(17) Kelley Blue Book Co. Kelley Blue Book https://www.kbb.com/ (accessed Sep 28, 2018).
(18) US Bureau of Labor Statistics. Consumer Expenditure Surveys https://www.bls.gov/cex/ (accessed Jul 7, 2020).

(19) Alemi, F.; Circella, G.; Mokhtarian, P.; Handy, S. Exploring the Latent Constructs behind the Use of Ridehailing in California. *J. Choice Model.* **2018**, *29* (July 2017), 47–62. https://doi.org/10.1016/j.jocm.2018.08.003.
(20) Gehrke, S. R.; Felix, A.; Reardon, T. G. Substitution of Ride-Hailing Services for More Sustainable Travel Options in the Greater Boston Region. *Transp. Res. Rec.* **2019**. https://doi.org/10.1177/0361198118821903.
(21) Henao, A.; Marshall, W. E. The Impact of Ride-Hailing on Vehicle Miles Traveled. *Transportation (Amst).* **2018**, No. 0123456789. https://doi.org/10.1007/s11116-018-9923-2.
(22) Shaheen, S.; Cohen, A. Shared Ride Services in North America: Definitions, Impacts, and the Future of Pooling. *Transp. Rev.* **2019**, *39* (4), 427–442. https://doi.org/10.1080/01441647.2018.1497728.
(23) Rayle, L.; Dai, D.; Chan, N.; Cervero, R.; Shaheen, S. Just a Better Taxi? A Survey-Based Comparison of Taxis, Transit, and Ridesourcing Services in San Francisco. *Transp. Policy* **2016**, *45*, 168–178. https://doi.org/10.1016/j.tranpol.2015.10.004.
(24) Shaheen, S.; Cohen, A.; Yelchuru, B.; Sarkhili, S. *Mobility on Demand: Operational Concept Report*; Washington, D.C., 2017.
(25) Martin, E.; Shaheen, S. A. Greenhouse Gas Emissions Impacts of Carsharing in North America. *Trans. Intell. Transp. Syst.* **2011**, *12* (4), 1–114. https://doi.org/10.1109/TITS.2011.2158539.
(26) Shaheen, S. A.; Chan, N. D.; Gaynor, T. Casual Carpooling in the San Francisco Bay Area: Understanding User Characteristics, Behaviors, and Motivations. *Transp. Policy* **2016**, *51*, 165–173.
(27) Lucken, E.; Frick, K.; Shaheen, S. Microtransit Framework... **2020**.
(28) Shaheen, S.; Cohen, A. Mobility on Demand in the United States: From Operational Concepts and Definitions to Early Pilot Projects and Future Automation. *Anal. Shar. Econ. Math. Eng. Bus. Perspect.* **2020**, 227–254.
(29) Yvkoff, L. FedEx Sees Robots, Not Drones, As the Next Big Thing in Logistics - The Drive https://www.thedrive.com/tech/7430/fedex-sees-robots-not-drones-as-the-next-big-thing-in-logistics (accessed Jul 27, 2020).
(30) Conway, M.; Salon, D.; King, D. Trends in Taxi Use and the Advent of Ridehailing, 1995–2017: Evidence from the US National Household Travel Survey. *Urban Sci.* **2018**, *2* (3), 79. https://doi.org/10.3390/urbansci2030079.
(31) Burgstaller, S.; Flowers, D.; Tamberrino, D.; Terry, H. P.; Yang, Y. *Rethinking Mobility*; New York, 2017.
(32) Kammen, D. M.; Sunter, D. A. City-Integrated Renewable Energy for Urban Sustainability. *Science (80-.).* **2016**, *352* (6288), 922–928. https://doi.org/10.1126/science.aad9302.
(33) Porter, J. Uber launches new delivery services as demand for ride-hailing plummets https://www.theverge.com/2020/4/20/21227828/uber-connect-direct-deliveries-medication-pet-supplies (accessed Apr 29, 2020).
(34) Johnson, C.; Walker, J. *Peak Car Ownership: The Market Opportunity of Electric Automated Mobility Services*; Boulder, Colorado, 2016.
(35) Bansal, P.; Kockelman, K. M.; Singh, A. Assessing Public Opinions of and Interest in New Vehicle Technologies : An Austin Perspective. *Transp. Res. Part C* **2016**, *67*, 1–14. https://doi.org/10.1016/j.trc.2016.01.019.

(36) Taiebat, M.; Brown, A. L.; Safford, H. R.; Qu, S.; Xu, M. A Review on Energy, Environmental, and Sustainability Implications of Connected and Automated Vehicles. *Environ. Sci. Technol.* **2018**, *52* (20), 11449–11465. https://doi.org/10.1021/acs.est.8b00127.
(37) Zhang, J. Didi by the numbers https://www.scmp.com/tech/start-ups/article/2181542/didi-numbers-ride-hailing-firm-covered-more-miles-2018-5-earth (accessed Nov 22, 2019).
(38) China Financial News. The Ministry of Transport issued the "Statistical Bulletin on the Development of the Transportation Industry in 2018" http://www.financialnews.com.cn/sj_142/hysj/201904/t20190412_158127.html.
(39) Innovation Center for Energy and Transportation. *2018 New Data Analysis on Real-World Driving and Fuel Consumption for Passenger Cars in China*; 2018.
(40) Monika. China's automobile population totals 250 million units by June 2019 http://autonews.gasgoo.com/china_news/70016117.html.
(41) Shrivastava, A. Speed bump: Uber, Ola face sharp slowdown in growth of rides in 2018 https://economictimes.indiatimes.com/small-biz/startups/newsbuzz/uber-ola-enter-slow-lane-in-2018/articleshow/65927443.cms.
(42) Muralidhar, S. H. How Ola Disrupted Taxi Services in India? *Rev. Manag.* **2016**, *6* (3/4), 5–17.
(43) Allirajan, M. Drive 12,000km a year? Cheaper to call cab https://timesofindia.indiatimes.com/business/india-business/drive-12k-km-a-year-cheaper-to-call-cab/articleshow/59979877.cms.
(44) CEIC. India Motor Vehicle Registered https://www.ceicdata.com/en/indicator/india/motor-vehicle-registered.
(45) Staff. Here's how many taxis are now on South Africa's roads – and how much they earn https://businesstech.co.za/news/motoring/275265/heres-how-many-taxis-are-now-on-south-africas-roads-and-how-much-they-earn/.
(46) de Villiers, J. Almost a third of South African households now own their own cars - while 90% have electric stoves.
(47) Merven, B.; Stone, A.; Hughes, A.; Cohen, B. *Quantifying the Energy Needs of the Transport Sector for South Africa : A Bottom - up Model*; 2012.
(48) Bundesverband Taxi. Facts and figures http://taxipedia.info/zahlen-und-fakten/.
(49) Odyssee-Mure. Change in distance travelled by car https://www.odyssee-mure.eu/publications/efficiency-by-sector/transport/distance-travelled-by-car.html.
(50) Department for Transport. *Taxi and Private Hire Vehicle Statistics: England 2019*; 2019.
(51) Collinson, P. Average UK car mileage falls again on back of higher petrol prices https://www.theguardian.com/money/2019/jan/14/average-uk-car-mileage-falls-again-on-back-of-higher-petrol-prices.
(52) Correspondent. Number of taxis rises 86% in 2 years, buses reduce in Delhi https://www.hindustantimes.com/delhi-news/number-of-taxis-rises-86-in-2-years-buses-reduce-in-delhi/story-Fclx1TRJ4NMw60TXitB88I.html.
(53) Juan, D. Beijing takes aim at congestion, pollution with new car limits http://www.chinadaily.com.cn/a/201806/16/WS5b244a9fa310010f8f59d4a0.html (accessed Nov 22, 2019).
(54) Staff. Number of vehicles in 12 CDMX municipalities has soared 600% since 2000 https://mexiconewsdaily.com/news/number-of-vehicles-has-soared-600/ (accessed Nov 22, 2019).

(55) Pennington, J. Jams everywhere but Thailand's road network is anything but a picnic https://www.aseantoday.com/2017/03/jams-everywhere-but-thailands-road-network-is-anything-but-a-picnic/.
(56) Staff. CAPMAS: Egypt's licensed vehicles rose by 12% in 2014, reaching 7.9 million https://egyptindependent.com/capmas-egypt-s-licensed-vehicles-rose-12-2014-reaching-79-million/.
(57) Wenzel, T.; Rames, C.; Kontou, E.; Henao, A. Travel and Energy Implications of Ridesourcing Service in Austin, Texas. *Transp. Res. Part D Transp. Environ.* **2019**, *70* (March), 18–34. https://doi.org/10.1016/j.trd.2019.03.005.
(58) Erhardt, G. D.; Roy, S.; Cooper, D.; Sana, B.; Chen, M.; Castiglione, J. Do Transportation Network Companies Decrease or Increase Congestion? *Sci. Adv.* **2019**, *5* (5), eaau2670. https://doi.org/10.1126/sciadv.aau2670.
(59) Siddiqui, F. Falling transit ridership poses an 'emergency' for cities, experts fear https://www.washingtonpost.com/local/trafficandcommuting/falling-transit-ridership-poses-an-emergency-for-cities-experts-fear/2018/03/20/ffb67c28-2865-11e8-874b-d517e912f125_story.html?utm_term=.8a6b09394e54 (accessed Aug 31, 2018).
(60) California State Legislature. *California Clean Miles Standard and Incentive Program*; 2019.
(61) Shah, A. Exclusive: India plans to order taxi aggregators like Uber, Ola to go electric - documents https://in.reuters.com/article/india-electric-autos/exclusive-india-plans-to-order-taxi-aggregators-like-uber-ola-to-go-electric-documents-idINKCN1T805J (accessed Nov 21, 2019).
(62) California State Legislature. Senate Bill No. 1014 https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201720180SB1014 (accessed Oct 3, 2018).
(63) Walker, A. Uber's plan to get more electric cars on the road https://www.curbed.com/2018/6/19/17479086/uber-electric-vehicle-ride-sharing (accessed Sep 18, 2018).
(64) Etherington, D. Lyft sets goal of 1 billion autonomous electric rides per year by 2025 https://techcrunch.com/2017/06/15/lyft-sets-goal-of-1-billion-autonomous-electric-rides-per-year-by-2025/ (accessed Oct 1, 2018).
(65) SLoCaT. *E-Mobility Trends and Targets*; 2019; Vol. 2019.
(66) Statt, N. Norway will install the world's first wireless electric car charging stations for Oslo taxis https://www.theverge.com/2019/3/21/18276541/norway-oslo-wireless-charging-electric-taxis-car-zero-emissions-induction (accessed Nov 21, 2019).
(67) City of Amsterdam. *The Electric City: Plan Amsterdam*; 2016.
(68) Joselow, M. D.C.'s ballyhooed green cabs are a driver's "nightmare" https://www.eenews.net/stories/1060110833 (accessed Apr 30, 2019).
(69) Edelstein, S. NYC Issues Roadmap For Electrifying One Third Of Taxis By 2020 https://www.greencarreports.com/news/1089752_nyc-issues-roadmap-for-electrifying-one-third-of-taxis-by-2020 (accessed Apr 30, 2019).
(70) Shah, A. Ola's sputtering India electric vehicle trial a red flag for Modi plan https://www.reuters.com/article/us-india-autos-electric-insight/olas-sputtering-india-electric-vehicle-trial-a-red-flag-for-modi-plan-idUSKCN1GL0CL (accessed Nov 21, 2019).
(71) President of Costa Rica. Síntesis: Plan Nacional de Descarbonización 2018-2050

https://presidencia.go.cr/comunicados/2019/02/sintesis-plan-nacional-de-descarbonizacion-2018-2050/ (accessed Nov 21, 2019).
(72) Williams, D. First electric black cabs arrive in London https://www.standard.co.uk/news/london/first-electric-black-cabs-arrive-in-london-a3747246.html (accessed Nov 21, 2019).
(73) Alsema, A. Medellin to replace 1500 yellow cabs with electric taxis in attempt to curb pollution https://colombiareports.com/medellin-to-replace-yellow-1500-cabs-with-electric-taxis-in-attempt-to-curb-pollution/ (accessed Nov 21, 2019).
(74) Marchán, E.; Viscidi, L. *The Outlook for Electric Vehicles in Latin America*; 2015.
(75) Greenblatt, J. B.; Saxena, S. Autonomous Taxis Could Greatly Reduce Greenhouse-Gas Emissions of US Light-Duty Vehicles. *Nat. Clim. Chang.* **2015**, *5* (September), 860–865. https://doi.org/10.1038/nclimate2685.
(76) Li, R.; Fitzgerald, G. Ride-Hailing Drivers Are Ideal Candidates for Electric Vehicles https://rmi.org/ride-hailing-drivers-ideal-candidates-electric-vehicles/ (accessed Sep 18, 2018).
(77) Bauer, G. S.; Greenblatt, J. B.; Gerke, B. F. Cost, Energy, and Environmental Impact of Automated Electric Taxi Fleets in Manhattan. *Environ. Sci. Technol.* **2018**. https://doi.org/10.1021/acs.est.7b04732.
(78) Spangher, L.; Gorman, W.; Bauer, G.; Atkinson, C.; Xue, Y. Quantifying the Impact of U.S. Electric Vehicle Sales on Light-Duty Vehiclefleet CO2emissions Using a Novel Agent-Based Simulation. *Transp. Res. Part D* **2019**, *72*, 358–377.
(79) George, S. R.; Zafar, M. *Electrifying the Ride-Sourcing Sector in California*; San Francisco, 2018.
(80) Jenn, A.; Laberteaux, K.; Clewlow, R. New Mobility Service Users' Perceptions on Electric Vehicle Adoption. *Int. J. Sustain. Transp.* **2018**, *12* (7), 526–540. https://doi.org/10.1080/15568318.2017.1402973.
(81) Greenblatt, J. B.; Shaheen, S. Automated Vehicles , On-Demand Mobility , and Environmental Impacts. *Curr. Sustain. Energy Reports* **2015**, *2*, 74–81. https://doi.org/10.1007/s40518-015-0038-5.
(82) Pereirinha, P. G.; González, M.; Carrilero, I.; Anseán, D.; Alonso, J.; Viera, J. C. Main Trends and Challenges in Road Transportation Electrification. *Transp. Res. Procedia* **2018**, *33*, 235–242. https://doi.org/10.1016/j.trpro.2018.10.096.
(83) Blumenberg, E.; Agrawal, A. W. Getting Around When You're Just Getting By: Transportation Survival Strategies of the Poor. *J. Poverty* **2014**, *18* (4), 355–378. https://doi.org/10.1080/10875549.2014.951905.
(84) Dillahunt, T. R.; Veinot, T. C. Getting There: Barriers and Facilitators to Transportation Access in Underserved Communities. *ACM Trans. Comput. Interact.* **2018**, *25* (5), 29:1--29:39. https://doi.org/10.1145/3233985.
(85) Brown, A. Ridehail Revolution: Ridehail Travel and Equity in Los Angeles, University of California, Los Angeles, 2018.
(86) Spurlock, C. A.; Sears, J.; Wong-Parodi, G.; Walker, V.; Jin, L.; Taylor, M.; Duvall, A.; Gopal, A.; Todd, A. Describing the Users: Understanding Adoption of and Interest in Shared, Electrified, and Automated Transportation in the San Francisco Bay Area. *Transp. Res. Part D Transp. Environ.* **2019**, No. January, 1–19. https://doi.org/10.1016/j.trd.2019.01.014.
(87) Shaheen, S.; Bell, C.; Cohen, A.; Yelchuru, B. Travel Behaviour. Shared Mobility and

Transportation Equity. **2017**, 66.
(88) Steg, L. Car Use: Lust and Must. Instrumental, Symbolic and Affective Motives for Car Use. *Transp. Res. Part A Policy Pract.* **2005**, *39* (2-3 SPEC. ISS.), 147–162. https://doi.org/10.1016/j.tra.2004.07.001.
(89) Lamberton, C. P.; Rose, R. L. When Is Ours Better Than Mine? A Framework for Understanding and Altering Participation in Commercial Sharing Systems. *J. Mark.* **2012**, *76* (4), 109–125. https://doi.org/10.1509/jm.10.0368.
(90) Sperling, D. *Three Revolutions*; Island Press: Washington, D.C., 2018.
(91) Chen, T. D.; Kockelman, K. M. Management of a Shared Autonomous Electric Vehicle Fleet: Implications of Pricing Schemes. *Transp. Res. Rec. J. Transp. Res. Board* **2016**, *2572* (1), 37–46. https://doi.org/10.3141/2572-05.
(92) Chen, T. D.; Kockelman, K. M.; Hanna, J. P. Operations of a Shared , Autonomous , Electric Vehicle Fleet : Implications of Vehicle & Charging Infrastructure Decisions. *Transp. Res. Part A* **2016**, *94*, 243–254. https://doi.org/10.1016/j.tra.2016.08.020.
(93) Luk, J. M.; Kim, H. C.; Kleine, R. De; Wallington, T. J.; Maclean, H. L. Review of the Fuel Saving, Life Cycle GHG Emission, and Ownership Cost Impacts of Lightweighting Vehicles with Different Powertrains. *Environ. Sci. Technol.* **2017**, *51*, 8215–8228. https://doi.org/10.1021/acs.est.7b00909.
(94) Fagnant, D. J.; Kockelman, K. M. The Travel and Environmental Implications of Shared Autonomous Vehicles , Using Agent-Based Model Scenarios. *Transp. Res. Part C Emerg. Technol.* **2014**, *40*, 1–13. https://doi.org/10.1016/j.trc.2013.12.001.
(95) Fagnant, D. J.; Kockelman, K. M.; Bansal, P. Operations of Shared Autonomous Vehicle Fleet for Austin , Texas , Market. *Transp. Res. Rec.* **2015**, No. 2536, 98–106. https://doi.org/10.3141/2536-12.
(96) Chen, T. D. Management of a Shared, Autonomous, Electric Vehicle Fleet: Vehicle Choice, Charging Infrastructure & Pricing Strategies, University of Texas, Austin, 2015.
(97) Bischoff, J.; Maciejewski, M. Agent-Based Simulation of Electric Taxicab Fleets. *Transp. Res. Procedia* **2014**, *4*, 191–198. https://doi.org/10.1016/j.trpro.2014.11.015.
(98) Bischoff, J.; Maciejewski, M. Electric Taxis in Berlin – Analysis of the Feasibility of a Large-Scale Transition. In *Tools of Transport Telematics. Communications in Computer and Information Science*; Mikulski, J., Ed.; 2015; Vol. 531, pp 343–351. https://doi.org/10.1007/978-3-319-24577-5.
(99) Bösch, P. M.; Becker, F.; Becker, H.; Axhausen, K. W. Cost-Based Analysis of Autonomous Mobility Services. *Transp. Policy* **2017**, No. August, 1–16. https://doi.org/10.1016/j.tranpol.2017.09.005.
(100) Loeb, B. Shared Autonomous Electric Vehicle (SAEV) Operations across the Austin, Texas Network with a Focus on Charging Infrastructure Decisions, 2016.
(101) Shapiro, R. Staten Island has more cars per person than rest of city http://www.silive.com/news/2016/11/staten_island_has_more_cars_pe.html (accessed Jan 1, 2018).
(102) Schmitz, M. How many cars does the average American own? https://www.cars.com/articles/how-many-cars-does-the-average-american-own-1420694459157/ (accessed Dec 10, 2017).
(103) Burns, L. D.; Jordan, W. C.; Scarborough, B. A. *Transforming Personal Mobility*; New York, 2013.
(104) Said, C. Uber's new plan to woo drivers: It's electric

https://www.sfchronicle.com/business/article/Uber-s-new-plan-to-woo-drivers-It-s-electric-13005719.php (accessed Sep 18, 2018).
(105) Hagman, J.; Langbroek, J. H. M. Conditions for Electric Vehicle Taxi: A Case Study in the Greater Stockholm Region. *Int. J. Sustain. Transp.* **2018**, *0* (0), 1–10. https://doi.org/10.1080/15568318.2018.1481547.
(106) Baek, S.; Kim, H.; Chang, H. J. A Feasibility Test on Adopting Electric Vehicles to Serve as Taxis in Daejeon Metropolitan City of South Korea. *Sustain.* **2016**, *8* (9). https://doi.org/10.3390/su8090964.
(107) Yang, J.; Dong, J.; Zhang, Q.; Liu, Z.; Wang, W. An Investigation of Battery Electric Vehicle Driving and Charging Behaviors Using Vehicle Usage Data Collected in Shanghai, China. *Transp. Res. Rec.* **2018**. https://doi.org/10.1177/0361198118759015.
(108) Zou, Y.; Wei, S.; Sun, F.; Hu, X.; Shiao, Y. Large-Scale Deployment of Electric Taxis in Beijing: A Real-World Analysis. *Energy* **2016**, *100*, 25–39. https://doi.org/10.1016/j.energy.2016.01.062.
(109) Yang, W. H.; Wong, R. C. P.; Szeto, W. Y. Modeling the Acceptance of Taxi Owners and Drivers to Operate Premium Electric Taxis: Policy Insights into Improving Taxi Service Quality and Reducing Air Pollution. *Transp. Res. Part A Policy Pract.* **2018**, *118* (August), 581–593. https://doi.org/10.1016/j.tra.2018.10.011.
(110) Wood, E.; Rames, C.; Kontou, E.; Motoaki, Y.; Smart, J.; Zhou, Z. Analysis of Fast Charging Station Network for Electrified Ride-Hailing Services. **2018**, No. April, 10–12. https://doi.org/10.4271/2018-01-0667.
(111) Ke, J.; Cen, X.; Yang, H.; Chen, X.; Ye, J. Modelling Drivers' Working and Recharging Schedules in a Ride-Sourcing Market with Electric Vehicles and Gasoline Vehicles. *Transp. Res. Part E Logist. Transp. Rev.* **2019**, *125* (February), 160–180. https://doi.org/10.1016/j.tre.2019.03.010.
(112) Tu, W.; Santi, P.; Zhao, T.; He, X.; Li, Q.; Dong, L.; Wallington, T. J.; Ratti, C. Acceptability, Energy Consumption, and Costs of Electric Vehicle for Ride-Hailing Drivers in Beijing. *Appl. Energy* **2019**, *250* (April), 147–160. https://doi.org/10.1016/j.apenergy.2019.04.157.
(113) Hu, L.; Dong, J.; Lin, Z.; Yang, J. Analyzing Battery Electric Vehicle Feasibility from Taxi Travel Patterns: The Case Study of New York City, USA. *Transp. Res. Part C Emerg. Technol.* **2018**, *87* (December 2017), 91–104. https://doi.org/10.1016/j.trc.2017.12.017.
(114) Loeb, B.; Kockelman, K. M.; Liu, J. Shared Autonomous Electric Vehicle (SAEV) Operations across the Austin, Texas Network with Charging Infrastructure Decisions. *Transp. Res. Part C* **2018**, *89*, 222–233.
(115) Keskin, M.; Çatay, B. Partial Recharge Strategies for the Electric Vehicle Routing Problem with Time Windows. *Transp. Res. Part C Emerg. Technol.* **2016**, *65* (216), 111–127. https://doi.org/10.1016/j.trc.2016.01.013.
(116) Juanjuan, Y. How to solve the problem of charging thousands of electric taxis in Shenzhen?
(117) Saxena, S.; MacDonald, J.; Moura, S. Charging Ahead on the Transition to Electric Vehicles with Standard 120 v Wall Outlets. *Appl. Energy* **2015**, *157*, 720–728. https://doi.org/10.1016/j.apenergy.2015.05.005.
(118) Yang, J.; Dong, J.; Hu, L. A Data-Driven Optimization-Based Approach for Siting and Sizing of Electric Taxi Charging Stations. *Transp. Res. Part C Emerg. Technol.* **2017**, *77*

(2), 462–477. https://doi.org/10.1016/j.trc.2017.02.014.
(119) Jia, Y.; Zhao, Y.; Guo, Z.; Xin, Y.; Chen, H. Optimizing Electric Taxi Charging System: A Data-Driven Approach from Transport Energy Supply Chain Perspective. *2017 IEEE Electr. Power Energy Conf. EPEC 2017* **2018**, *2017-Octob*, 1–6. https://doi.org/10.1109/EPEC.2017.8286238.
(120) Lee, T. B. Waymo makes history testing on public roads with no one at the wheel https://arstechnica.com/cars/2017/11/fully-driverless-cars-are-here/ (accessed Jan 5, 2018).
(121) NHTSA. *Federal Automated Vehicles Policy: Accelerating the next Revolution in Roadway Safety*; Washington, D.C., 2016.
(122) NYC Taxi & Limousine Commission. Your guide to Boro Taxis http://www.nyc.gov/html/tlc/html/passenger/shl_passenger.shtml (accessed Jan 5, 2018).
(123) Van Dyke Parunak, H.; Savit, R.; Riolo, R. L. Agent-Based Modeling vs. Equation-Based Modeling: A Case Study and Users' Guide. In *Multi-Agent Systems and Agent-Based Simulation*; Springer: Paris, France, 1998. https://doi.org/10.1007/978-3-642-29066-4{_}11.
(124) Warerkar, T. Uber surpasses yellow cabs in average daily ridership in NYC https://ny.curbed.com/2017/10/13/16468716/uber-yellow-cab-nyc-surpass-ridership (accessed Jan 5, 2018).
(125) Lutz, B. Bob Lutz: Kiss the good times goodbye http://www.autonews.com/article/20171105/industry_redesigned/171109944/industry-redesigned-bob-lutz (accessed Dec 5, 2017).
(126) Wang, J.; Purewal, J.; Liu, P.; Hicks-Garner, J.; Soukiazian, S.; Sherman, E.; Sorensen, A.; Vu, L.; Tataria, H.; Verbrugge, M. W. Degradation of Lithium Ion Batteries Employing Graphite Negatives and Nickel-Cobalt-Manganese Oxide + Spinel Manganese Oxide Positives: Part 1, Aging Mechanisms and Life Estimation. *J. Power Sources* **2014**, *269*, 937–948. https://doi.org/10.1016/j.jpowsour.2014.07.028.
(127) EPA. Dynanometer drive schedules https://www.epa.gov/vehicle-and-fuel-emissions-testing/dynamometer-drive-schedules (accessed May 23, 2017).
(128) Schuster, S. F.; Bach, T.; Fleder, E.; M??ller, J.; Brand, M.; Sextl, G.; Jossen, A. Nonlinear Aging Characteristics of Lithium-Ion Cells under Different Operational Conditions. *J. Energy Storage* **2015**, *1* (1), 44–53. https://doi.org/10.1016/j.est.2015.05.003.
(129) Ellingsen, L. A.-W.; Singh, B.; Strømman, A. H. The Size and Range Effect: Lifecycle Greenhouse Gas Emissions of Electric Vehicles. *Environ. Res. Lett.* **2016**, *11* (5), 054010. https://doi.org/10.1088/1748-9326/11/5/054010.
(130) Peters, J. F.; Baumann, M.; Zimmermann, B.; Braun, J.; Weil, M. The Environmental Impact of Li-Ion Batteries and the Role of Key Parameters – A Review. *Renew. Sustain. Energy Rev.* **2017**, *67*, 491–506. https://doi.org/10.1016/j.rser.2016.08.039.
(131) Pasion, C.; Oyenuga, C.; Gouin, K.; LLC, C. *Inventory of New York City Greenhouse Gas Emissions in 2015*; New York City, 2017.
(132) Burnham, A.; Han, J.; Clark, C. E.; Wang, M.; Dunn, J. B.; Palou-Rivera, I. Life-Cycle Greenhouse Gas Emissions of Shale Gas, Natural Gas, Coal, and Petroleum. *Environ. Sci. Technol.* **2012**, *46* (2), 619–627. https://doi.org/10.1021/es201942m.
(133) Nansai, K.; Tohno, S.; Kono, M. Life-Cycle Analysis of Charging Infrastructure for Electric Vehicles. *Appl. Energy* **2001**, *70*, 251–265.

(134) Weis, A.; Jaramillo, P.; Michalek, J. Consequential Life Cycle Air Emissions Externalities for Plug-in Electric Vehicles in the PJM Interconnection. *Environ. Res. Lett.* **2016**, *11* (2). https://doi.org/10.1088/1748-9326/11/2/024009.

(135) Spath, P. L.; Mann, M. K. *Life Cycle Assessment of a Natural Gas Combined Cycle Power Generation System*; Golden, CO, 2000. https://doi.org/10.2172/776930.

(136) Litman, T. *Autonomous Vehicle Implementation Predictions: Implications for Transport Planning*; Victoria, Canada, 2016.

(137) Voelcker, J. Electric-car battery costs; Tesla $190 per kwh for pack, GM $145 for cells http://www.greencarreports.com/news/1103667_electric-car-battery-costs-tesla-190-per-kwh-for-pack-gm-145-for-cells (accessed Jan 1, 2017).

(138) Agenbroad, J. Pulling Back the Veil on EV Charging Station Costs https://rmi.org/news/pulling-back-veil-ev-charging-station-costs/ (accessed Jan 1, 2017).

(139) NYDPS. *Monthly Commercial Bills Including State GRT*; New York City, 2013.

(140) Litman, T.; Doherty, E. Parking Costs. In *Transportation Cost and Benefit Analysis*; Victoria Transport Policy Institute: Victoria, Canada, 2017; pp 1–27.

(141) SpotHero Inc. NYC Parking https://spothero.com/nyc-parking?monthly=true (accessed Jan 5, 2018).

(142) Metromile. Introducing pay-per-mile insurance https://www.metromile.com/.

(143) Propfe, B.; Redelbach, M.; Santini, D. J.; Friedrich, H. Cost Analysis of Plug-in Hybrid Electric Vehicles Including Maintenance & Repair Costs and Resale Values. In *EVS26 International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium*; World Electric Vehicle Association: Los Angeles, California, 2012; p 10.

(144) ChargePoint. ChargePoint: Find a charging location https://na.chargepoint.com/charge_point (accessed May 9, 2017).

(145) City, N. Y. 2015 Yellow Taxi Trip Data https://data.cityofnewyork.us/view/ba8s-jw6u.

(146) Nopmongcol, U.; Grant, J.; Knipping, E.; Alexander, M.; Schurhoff, R.; Young, D.; Jung, J.; Shah, T.; Yarwood, G. Air Quality Impacts of Electrifying Vehicles and Equipment Across the United States. *Environ. Sci. Technol.* **2017**, *51* (5), 2830–2837. https://doi.org/10.1021/acs.est.6b04868.

(147) Tessum, C. W.; Hill, J. D.; Marshall, J. D. Life Cycle Air Quality Impacts of Conventional and Alternative Light-Duty Transportation in the United States. *Proc. Natl. Acad. Sci.* **2014**, *111* (52), 18490–18495. https://doi.org/10.1073/pnas.1406853111.

(148) NYC Mayor's Office of Sustainability. *New York City's Roadmap to 80x50*; New York, 2016.

(149) Alternative Fuels Data Center. Alternative Fuels Data Center – Fuel Properties Comparison https://www.afdc.energy.gov/fuels/fuel_comparison_chart.pdf (accessed Aug 20, 2017).

(150) Granovskii, M.; Dincer, I.; Rosen, M. A. Life Cycle Assessment of Hydrogen Fuel Cell and Gasoline Vehicles. *Int. J. Hydrogen Energy* **2006**, *31* (3), 337–352. https://doi.org/10.1016/j.ijhydene.2005.10.004.

(151) Energy Information Agency. Table 8.1. Average Operating Heat Rate for Selected Energy Sources https://www.eia.gov/electricity/annual/html/epa_08_01.html (accessed Sep 17, 2017).

(152) Aaronson, L.; Boehm, G.; Delehanty, D.; Divelbliss, E. M.; Ernst, K.; Hoffman, K.; Kim, P.; Maurer, B.; Rieke, A.; Schmeiser Kathryn; et al. New York City Mobile Services Study Research Brief. **2015**.

(153) Sheppard, C.; Jenn, A.; Bauer, G.; Gerke, B.; Greenblatt, J.; Gopal, A. A Joint Optimization Scheme for the Planning and Operations of a Regional Electrified Fleets of Ride Hailing Vehicles Serving Mobility on Demand. *Transp. Res. Rec.* **2019**, 1–19. https://doi.org/10.1177/0361198119838270.

(154) Parrott, J. A.; Reich, M. *An Earnings Standard for New York City's App-Based Drivers Economic Analysis and Policy Assessment*; New York City, 2018.

(155) Uber. Uber fare estimator https://www.uber.com/fare-estimate/ (accessed Sep 18, 2018).

(156) Hall, J. V.; Krueger, A. B. An Analysis of the Labor Market for Uber's Driver-Partners in the United States. *ILR Rev.* **2018**, *71* (3), 705–732. https://doi.org/10.1177/0019793917717222.

(157) San Francisco County Transportation Authority. TNCs Today: A Profile of San Francisco Transportation Network Company Activity. **2017**.

(158) Wolbertus, R.; Hoed, R. van den; Maase, S. Benchmarking Charging Infrastructure Utilization. In *EVS29 International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium*; Montreal, Quebec, Canada, 2016; pp 1–18. https://doi.org/10.3390/wevj8040754.

(159) Idaho National Laboratory. *Plugged In: How Americans Charge Their Electric Vehicles*; Idaho Falls, Idaho, 2017.

(160) U.S. Department of Energy; U.S. EPA. fueleconomy.gov https://www.fueleconomy.gov/ (accessed Sep 18, 2018).

(161) Hyland, M.; Mahmassani, H. S. Dynamic Autonomous Vehicle Fleet Operations: Optimization-Based Strategies to Assign AVs to Immediate Traveler Demand Requests. *Transp. Res. Part C Emerg. Technol.* **2018**, *92* (April), 278–297. https://doi.org/10.1016/j.trc.2018.05.003.

(162) He, S. Y.; Kuo, Y. H.; Wu, D. Incorporating Institutional and Spatial Factors in the Selection of the Optimal Locations of Public Electric Vehicle Charging Facilities: A Case Study of Beijing, China. *Transp. Res. Part C Emerg. Technol.* **2016**, *67* (June), 131–148. https://doi.org/10.1016/j.trc.2016.02.003.

(163) San Francisco Treasurer & Tax Collector's Office. Registered Business Locations - San Francisco https://data.sfgov.org/Economy-and-Community/Registered-Business-Locations-San-Francisco/g8m3-pdis/data (accessed Sep 18, 2018).

(164) IWGSCG. *Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866*; Washington, D.C., 2016.

(165) MoneyChimp. Compound Annual Growth Rate of the Stock Market http://www.moneychimp.com/features/market_cagr.htm (accessed Apr 11, 2019).

(166) NYC Taxi & Limousine Commission. Taxicab specifications http://www.nyc.gov/html/tlc/downloads/pdf/specrules.pdf (accessed Sep 28, 2018).

(167) Union of Concerned Scientists. Going from Pump to Plug. **2017**.

(168) Nerdwallet. Rideshare Insurance for Drivers: Where to Buy, What It Covers https://www.nerdwallet.com/blog/insurance/best-ridesharing-insurance/ (accessed Sep 28, 2018).

(169) Pacific Gas and Electric Company. Electric schedule A-10 https://www.pge.com/tariffs/assets/pdf/tariffbook/ELEC_SCHEDS_A-10.pdf (accessed Sep 28, 2018).

(170) conEdison. Market Supply Charge Calculator https://apps.coned.com/CEMyAccount/csol/MSCcc.aspx (accessed Sep 28, 2018).

(171) Consolidated Edison Company of New York. Statement of Market Supply Charge - Capacity https://www.coned.com/_external/cerates/documents/elecPSC10/StatMSCCAP-40.pdf (accessed Sep 28, 2018).
(172) Energy Information Agency. Weekly Retail Gasoline and Diesel Prices https://www.eia.gov/dnav/pet/pet_pri_gnd_dcus_nus_a.htm (accessed Oct 10, 2018).
(173) Qualcomm. Wireless Electric Vehicle Charging https://www.qualcomm.com/solutions/automotive/wevc (accessed Jun 15, 2017).
(174) Tian, Z.; Jung, T.; Wang, Y.; Zhang, F.; Tu, L.; Xu, C.; Tian, C.; Li, X. Y. Real-Time Charging Station Recommendation System for Electric-Vehicle Taxis. *IEEE Trans. Intell. Transp. Syst.* **2016**, *17* (11), 3098–3109. https://doi.org/10.1109/TITS.2016.2539201.
(175) Dong, Z.; Liu, C.; Li, Y.; Bao, J.; Gu, Y.; He, T. REC: Predictable Charging Scheduling for Electric Taxi Fleets. *Proc. - Real-Time Syst. Symp.* **2018**, *2018-Janua*, 287–296. https://doi.org/10.1109/RTSS.2017.00034.
(176) Conway, T. On the Effects of a Routing and Reservation System on the Electric Vehicle Public Charging Network. *IEEE Trans. Intell. Transp. Syst.* **2017**, *18* (9), 2311–2318. https://doi.org/10.1109/TITS.2016.2641981.
(177) Google. Gas stations in San Francisco https://www.google.com/maps (accessed Oct 15, 2018).
(178) NYC City Hall. Leading the Charge: Mayor Announces Fast-Charging EV Hubs in All 5 Boroughs https://www1.nyc.gov/office-of-the-mayor/news/600-17/leading-charge-mayor-fast-charging-ev-hubs-all-5-boroughs (accessed Oct 1, 2018).
(179) PlugShare. PlugShare https://www.plugshare.com/ (accessed Oct 2, 2018).
(180) Avalos, G. PG&E launches electric vehicle charging network with 7,500 stations https://www.mercurynews.com/2018/01/17/pge-launches-electric-vehicle-charging-network-with-7500-stations/ (accessed Oct 2, 2018).
(181) Electric Vehicle Grant Programs. Charge Program: Apply for funding for electric vehicle, or EV, charging stations http://www.baaqmd.gov/grant-funding/businesses-and-fleets/charge (accessed Oct 2, 2018).
(182) Kontou, E.; Liu, C.; Xie, F.; Wu, X.; Lin, Z. Understanding the Linkage between Electric Vehicle Charging Network Coverage and Charging Opportunity Using GPS Travel Data. *Transp. Res. Part C Emerg. Technol.* **2019**, *98* (November 2017), 1–13. https://doi.org/10.1016/j.trc.2018.11.008.
(183) Lumb, D. New York approves surcharge for Uber and Lyft rides in Manhattan https://www.engadget.com/2018/04/02/new-york-surcharge-uber-lyft-manhattan/ (accessed Oct 10, 2018).
(184) Sabatini, J. SF's rideshare tax moves closer to ballot, proposed cannabis tax amended http://www.sfexaminer.com/sfs-rideshare-tax-moves-closer-ballot-proposed-cannabis-tax-amended/ (accessed Oct 10, 2018).
(185) Dong, Y.; Wang, S.; Li, L.; Zhang, Z. An Empirical Study on Travel Patterns of Internet Based Ride-Sharing. *Transp. Res. Part C Emerg. Technol.* **2018**, *86* (January), 1–22. https://doi.org/10.1016/j.trc.2017.10.022.
(186) Global Opportunity Explorer. Taiyuan: World's Fastest Electric Taxi Fleet Overhaul.
(187) Shenzhen Local Treasure. Since August, Shenzhen has added a electric car to use a pure electric vehicle.
(188) Xinhua News Agency. Guangzhou City promotes pure electric taxis.
(189) Xinhua. Electric taxis hit road in Sichuan.

(190) Galeon, D. 70,000 Beijing taxis are being converted to electric power https://www.weforum.org/agenda/2017/03/beijing-is-converting-its-fleet-of-70-000-taxis-to-electric-power.
(191) Tian, Z.; Wang, Y.; Tian, C.; Zhang, F.; Tu, L.; Xu, C. Understanding Operational and Charging Patterns of Electric Vehicle Taxis Using GPS Records. *2014 17th IEEE Int. Conf. Intell. Transp. Syst. ITSC 2014* **2014**, 2472–2479. https://doi.org/10.1109/ITSC.2014.6958086.
(192) Li, M.; Jia, Y.; Shen, Z.; He, F. Improving the Electrification Rate of the Vehicle Miles Traveled in Beijing: A Data-Driven Approach. *Transp. Res. Part A Policy Pract.* **2017**, *97*, 106–120. https://doi.org/10.1016/j.tra.2017.01.005.
(193) Sheppard, C. J. R.; Harris, A.; Gopal, A. R. Cost-Effective Siting of Electric Vehicle Charging Infrastructure With Agent-Based Modeling. **2016**, *2* (2), 174–189.
(194) Southern Metropolis Daily. Shenzhen: 80% of electric taxi drivers surveyed believe that charging affects daily operations.
(195) Lu, J. L.; Yeh, M. Y.; Hsu, Y. C.; Yang, S. N.; Gan, C. H.; Chen, M. S. Operating Electric Taxi Fleets: A New Dispatching Strategy with Charging Plans. *2012 IEEE Int. Electr. Veh. Conf. IEVC 2012* **2012**, 1–8. https://doi.org/10.1109/IEVC.2012.6183233.
(196) Tian, Z.; Tu, L.; Wang, Y.; Zhang, F.; Tian, C. Impact of Core Charging Station's Cease Operation in the Entire Charging Station System: A Case Study in Shenzhen. *Proc. - 3rd IEEE Int. Conf. Big Data Comput. Serv. Appl. BigDataService 2017* **2017**, 90–95. https://doi.org/10.1109/BigDataService.2017.12.
(197) Google. Google Vision AI.
(198) Crow, A.; Mullaney, D.; Liu, Y.; Wang, Z. *A New EV Horizon: Insights From Shenzhen's Path to Global Leadership in Electric Logistics Vehicles*; Boulder, Colorado, 2019.
(199) People's Network. From construction to operation, who is benefiting from the adjustment of the charging pile subsidy. http://auto.cnr.cn/gdzx/20190819/t20190819_524736953.shtml (accessed Sep 30, 2019).
(200) The Economist. China moves towards banning the internal combustion engine.
(201) Bauer, G. S.; Phadke, A.; Greenblatt, J. B.; Rajagopal, D. Electrifying Urban Ridesourcing Fleets at No Added Cost through Efficient Use of Charging Infrastructure. *Transp. Res. Part C Emerg. Technol.* **2019**, *105* (January), 385–404. https://doi.org/10.1016/j.trc.2019.05.041.
(202) Mahady, J. A.; Octaviano, C.; Araiza Bolaños, O. S.; López, E. R.; Kammen, D. M.; Castellanos, S. Mapping Opportunities for Transportation Electrification to Address Social Marginalization and Air Pollution Challenges in Greater Mexico City. *Environ. Sci. Technol.* **2020**. https://doi.org/10.1021/acs.est.9b06148.
(203) Nilsson, M.; Nykvist, B. Governing the Electric Vehicle Transition – Near Term Interventions to Support a Green Energy Economy. *Appl. Energy* **2016**, *179*, 1360–1371. https://doi.org/10.1016/j.apenergy.2016.03.056.
(204) Coignard, J.; Saxena, S.; Greenblatt, J.; Wang, D. Clean Vehicles as an Enabler for a Clean Electricity Grid. *Environ. Res. Lett.* **2018**, *13* (5), 0–8. https://doi.org/10.1088/1748-9326/aabe97.
(205) Bauer, G. S.; Zheng, C.; Shaheen, S.; Kammen, D. M. Leveraging Big Data and Coordinated Charging for Effective Taxi Fleet Electrification: The 100% EV Conversion of Shenzhen, China. *IEEE Trans. Intell. Transp. Syst.*
(206) Bauer, G. S.; Zheng, C.; Shaheen, S.; Kammen, D. M. Leveraging Big Data and Charging

Coordination for Effective Taxi Fleet Electrification: A Case Study of Shenzhen, China. In *Transportation Research Board 2020 Annual Meeting*; Transportation Research Board: Washington, D.C., 2020.
(207) GlobalPetrolPrices. Gasoline prices in Shenzhen, China https://www.globalpetrolprices.com/China/Shenzhen/gasoline_prices/ (accessed Apr 29, 2020).
(208) Wang, D.; Coignard, J.; Zeng, T.; Zhang, C.; Saxena, S. Quantifying Electric Vehicle Battery Degradation from Driving vs . Vehicle-to-Grid Services. *J. Power Sources* **2016**, *332*, 193–203. https://doi.org/10.1016/j.jpowsour.2016.09.116.
(209) Slowik, P.; Fedirko, L.; Lutsey, N. *Assessing Ride-Hailing Company Commitments to Electrification*; 2019.
(210) Eisenhardt, K. M. Agency Theory: An Assessment and Review. *Acad. Manag. Rev.* **1989**, *14* (1), 57–74.
(211) Allcott, H.; Wozny, N. Gasoline Prices, Fuel Economy, and the Energy Paradox. *Rev. Econ. Stat.* **2014**, *96* (5), 779–795.
(212) NYC Taxi and Limousine Commission. *2018 TLC Factbook*; New York City, 2018.
(213) Jenn, A.; Springel, K.; Gopal, A. R. Effectiveness of Electric Vehicle Incentives in the United States. *Energy Policy* **2018**, *119* (July 2017), 349–356. https://doi.org/10.1016/j.enpol.2018.04.065.
(214) Schmidt, B. World's largest charging station in Shenzhen powers all-electric taxi fleet https://thedriven.io/2019/05/24/worlds-largest-charging-station-in-shenzhen-powers-all-electric-taxi-fleet/ (accessed Mar 11, 2020).
(215) Bliss, L. Uber's Beef With L.A. Is Bigger Than Data https://www.citylab.com/transportation/2019/10/uber-lawsuit-data-privacy-scooter-tracking-los-angeles/600985/ (accessed Nov 21, 2019).
(216) California Air Resources Board. *Clean Miles Standard 2018 Base-Year Emissions Inventory Report*; 2019.
(217) European Commission. EU data protection rules https://ec.europa.eu/info/priorities/justice-and-fundamental-rights/data-protection/2018-reform-eu-data-protection-rules/eu-data-protection-rules_en (accessed Mar 2, 2020).
(218) Joshi, M.; Cowan, N.; Limone, O.; Mcguinness, K.; Rao, R. *E-Hail Regulation in Global Cities*; New York City, 2019.
(219) Internal Revenue Service. Independent Contractor Defined https://www.irs.gov/businesses/small-businesses-self-employed/independent-contractor-defined (accessed Mar 5, 2020).
(220) California State Legislature. AB-5 Worker status: employees and independent contractors https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201920200AB5 (accessed Mar 2, 2020).
(221) Edwards, T. ULEZ: The politics of London's air pollution https://www.bbc.com/news/uk-england-london-47814416 (accessed Mar 2, 2020).
(222) Vaswani, K. Coronavirus: The detectives racing to contain the virus in Singapore https://www.bbc.com/news/world-asia-51866102 (accessed Apr 29, 2020).