COST, ENERGY AND ENVIRONMENTAL IMPACT OF AUTOMATED ELECTRIC TAXI FLEETS IN MANHATTAN

In press at *Environmental Science & Technology*

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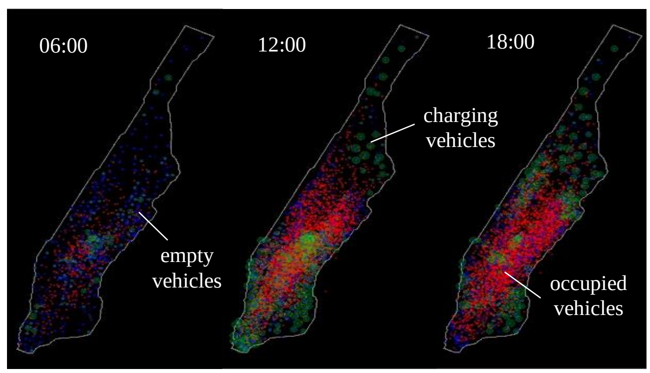
ABSTRACT

Shared automated electric vehicles (SAEVs) hold great promise to improve transportation access in urban centers while drastically reducing transportation-related energy consumption and air pollution. Using taxi trip data from New York City, we develop an agent-based model to predict the battery range and charging infrastructure requirements of a fleet of SAEVs operating on Manhattan Island. We also develop a model to estimate the cost and environmental impact of providing service, and perform extensive sensitivity analysis to test the robustness of our predictions. We 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. We 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 vehicle (ICEV). We 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.



INTRODUCTION

Transportation represents the fastest-growing segment of the world's greenhouse gas (GHG) emissions, with cars accounting for 8.7% of global energy-related carbon dioxide emissions in 2013, and car sales set to more than double by 2050.[1] Fortunately, battery electric vehicles (BEVs) have emerged as a market-ready technology with the potential to reduce the carbon intensity of private transportation.[2,3] Meeting the Paris Agreement's 2 °C and 1.5 °C targets will require massive deployment of electrified transportation. However, adoption of electric vehicles has been relatively slow for several reasons, including technological uncertainty, slow charging, range anxiety, and higher capital costs compared to other types of vehicles.[4,5] The convergence of electrification with two other emerging technologies—vehicle automation and smartphone-enabled shared mobility—could overcome the barriers described above and speed the transition to an electrified transportation system. Shared automated electric vehicles (SAEVs)[6] 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") and battery range for the trip requested, and charging can be split over many short periods in between trips, the shared mobility paradigm could enable the use of smaller cars with shorter battery range, overcoming the barriers of slow charging speed and high capital cost.[7,8]

Furthermore, because shared vehicles typically travel many more miles annually than privately-owned vehicles, deployment of SAEVs would increase the per-vehicle GHG reductions relative to private ownership, and spread the capital costs over more miles. SAEVs deployed in 2030 could reduce GHG emissions per mile by more than 90% relative to privately-owned conventional vehicles while substantially increasing cost-effectiveness.[7] A recent Rocky Mountain Institute report predicted that the marginal cost of SAEVs will quickly fall below that of conventional private vehicles so that SAEVs will dominate the mobility market by 2050.[9] 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.[10]

Several previous studies have employed agent-based modeling techniques to explore the feasibility of a fleet of automated taxis operating in an urban environment.[6,11–17] Building on these results, we 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,[18] compared with 1.9 in the U.S. as a whole.[19] As a result, taxi usage is relatively high—taxi trips currently represent about 8% of all daily trips taken by Manhattan residents.[20]

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 our 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, our 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, we 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 our model allows us 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.

METHODS

Taxi trip data

All trip data for our analysis were downloaded from the NYC OpenData 2015 database of yellow taxi trips. For most of our 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.

As with current pilot projects,[21] automated vehicles will likely need to remain within a defined geo-fenced area for the foreseeable future (i.e., level 4 automation),[22] 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.[23] Removing trips falling outside these boundaries on our representative day left us 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.

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 our estimates to be conservative (for details, see supporting information section 2).

Taxi routing model description

Using the R coding platform version 3.3.3, we developed an agent-based model to simulate the movement of taxis around Manhattan throughout the day. Agent-based modeling is well-suited to our 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.[24]

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,[25] and industry experts predict that automation will give further monopoly power to large fleets,[26] we assume that all trip assignments are managed by a single operator.

To assess a constant level of service across all model runs, we 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, we 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 we explore the impact of changing relocation algorithms in our sensitivity analysis (see supporting information section 7 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 we 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.

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. Our 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 our 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 we expect that increased empty miles are an artifact of the short average distance of Manhattan taxi trips (1.9 mi.; see supporting information section 2 for more details). Simulations of a fleet of ICEVs suggest that empty miles are almost the same as for an electric fleet, so we do not expect that electrifying Manhattan's taxi fleet would increase congestion.

Charger distribution model

To rationally populate our model with a network of chargers, we 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, we 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.

Simulation runs

Simulations were first performed using a single day of data, testing 10-mi. increments of battery ranges between 10 mi. and 200 mi., 250-count increments of the number of individual chargers between 1,000 and 4,000, and 100-count increments of the number of charging locations between 100 and 1,000, for a total of 2,600 simulations. All of these simulations were performed assuming a charging speed of 7 kW (Level 2 charging), or roughly 0.5 mi./min. assuming average energy consumption of 0.25 kWh/mi.[15] To measure the impact of not being able to fully recharge the fleet before the next day started, 84 parameter sets representing the range of values shown to be most influential were then used for simulations where the same day was repeated until the difference between the fleet's mean state of charge at the beginning and end of the day was less than five percent of battery range. Based on expected specifications for commercial wireless charging stations,[27, 28,29] these multi-day simulations were then repeated with charging speeds of 11 kW (0.75 mi./min.), 22 kW (1.5 mi./min.), and 50 kW (Level 3, 3.3 mi./min.), for a total of 336 simulations. Several hundred additional simulations were conducted to test the impact of varying different model assumptions (see supporting information section 7 for details).

Cost model

The taxi service's cost per mile was estimated using a model with the components summarized in Table 1. As shown in Equation 1, 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. We used a discount rate of 5% and a system time horizon of 20 years, assuming constant costs and demand throughout this period. In our sensitivity analysis, we varied the cost of each of these components to study the impact that different future cost trajectories would have on our 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 we expect electrification and automation will result in lower maintenance requirements, and because our simulated vehicles travel significantly fewer miles searching for passengers.

$$Cost\ of\ service = \frac{NPV_{cost}}{NPV_{miles}} = \frac{\sum_i C_i \cdot CRF}{\sum passenger\ miles \cdot CRF} \tag{1}$$

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

Table 1. Summary of cost model components

Component	***Value***	***Source***
Vehicle purchase	\$20,000/vehicle	*Based on* 16, 17
Vehicle lifetime	300,000 mi.	*Based on* 7, [20]
Automation	\$10,000/vehicle	13, [30]
Battery cost	\$200/kWh plus 30% fleet discount	[31], 17
Battery lifetime	Rate of degradation estimated using semi-empirical model (see supporting information section 4 for more details)	[32], [33], [34]
Charging infrastructure	\$700/charger/kW + \$15/charger/kW/year + \$10000/location	*Based on* [35], 9, 17
Electricity consumption	\$0.12/kWh	[36]
Vehicle efficiency	0.25 kWh/mi. + 0.0006 kWh/mi. per kWh battery capacity [a]	15, [37]
Parking	\$300/space-month [b]	*Based on* [38], [39]
Insurance	\$600/vehicle-year + \$0.05/mi.	[40], 13, [20]
Maintenance	\$0.04/mi.	[41], 9
Administrative overhead	\$2.50/vehicle-day	*Based on* [20], 9

a) When calculating the cost of electricity, we corrected vehicle efficiency for the additional weight of the battery.
b) Although we recognize that it is unclear who will pay for SAEV parking, we included the total cost to society of providing parking so that we 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.

RESULTS AND DISCUSSION

Fleet-sizing simulation results

As shown in Figure 1, we 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. For more simulation results, such as wait times and empty vehicle miles, see supporting information section 2.

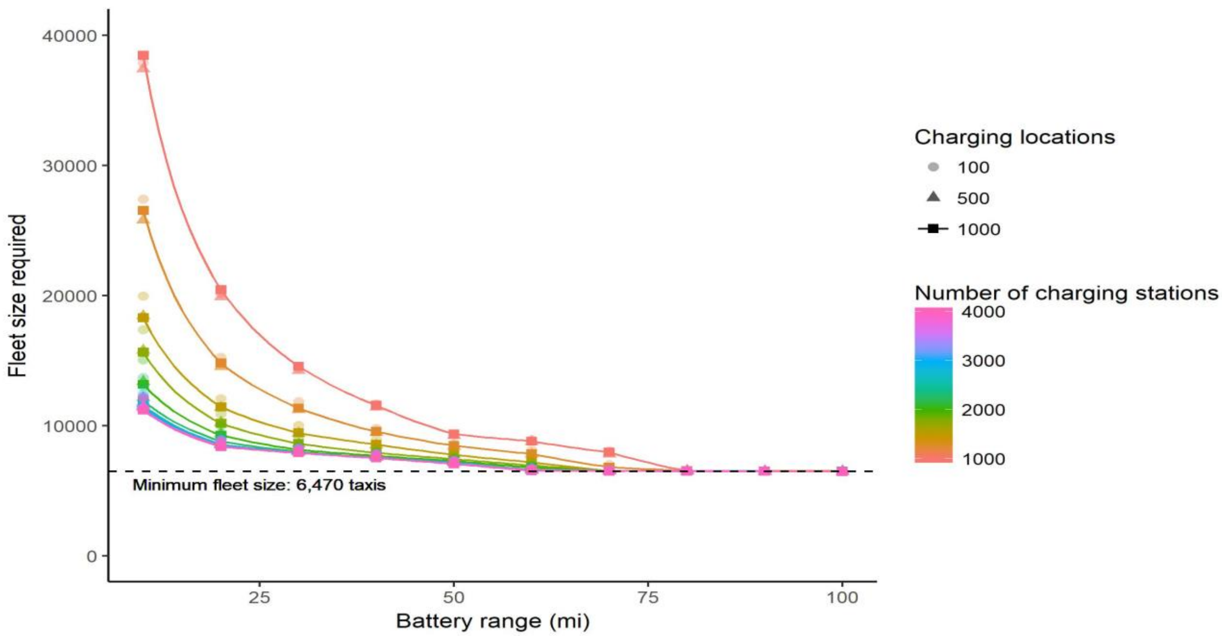


Figure 1. Required fleet size by battery range and charging network. Lines represent exponential fits for simulation results, which were collected at 10-mi. intervals in battery range.

In multi-day simulations, we 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. We 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.[42]

Cost model results

Given the results of the fleet-sizing simulation, we 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[35], and also increase battery degradation. As shown in Figure 2, taking all these trade-offs into account, we 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 3, 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, dynamic ride-sharing,[17] 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.,[20] 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.[13] (see supporting information section 1).

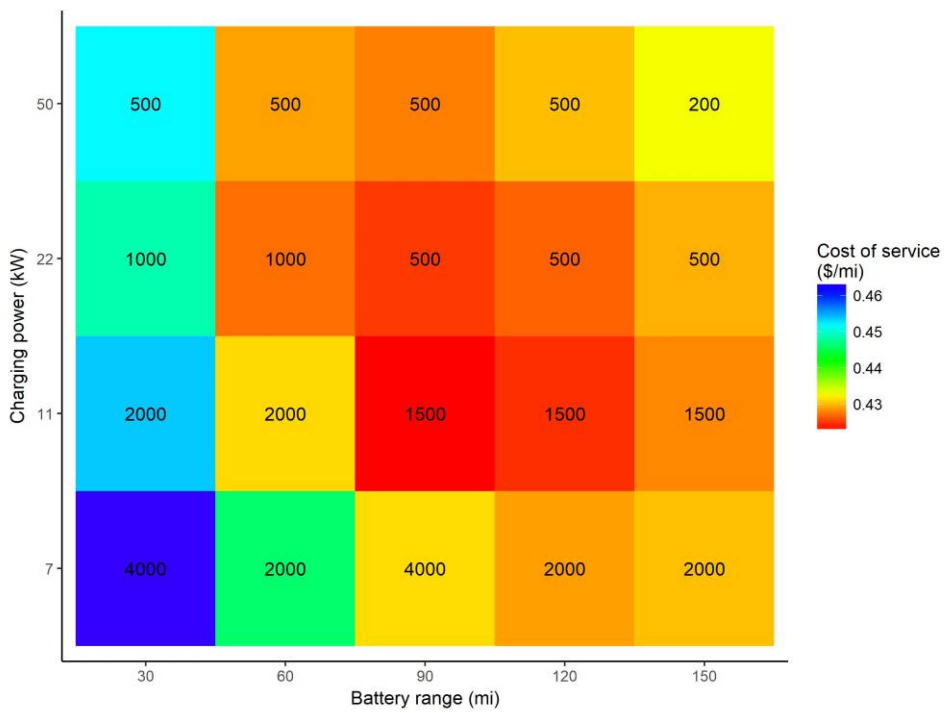


Figure 2. Estimated cost per mile of simulated taxi fleets with a given charging network and battery range. Numbers represent the number of chargers that returned the least cost for each combination of battery range and charging speed.

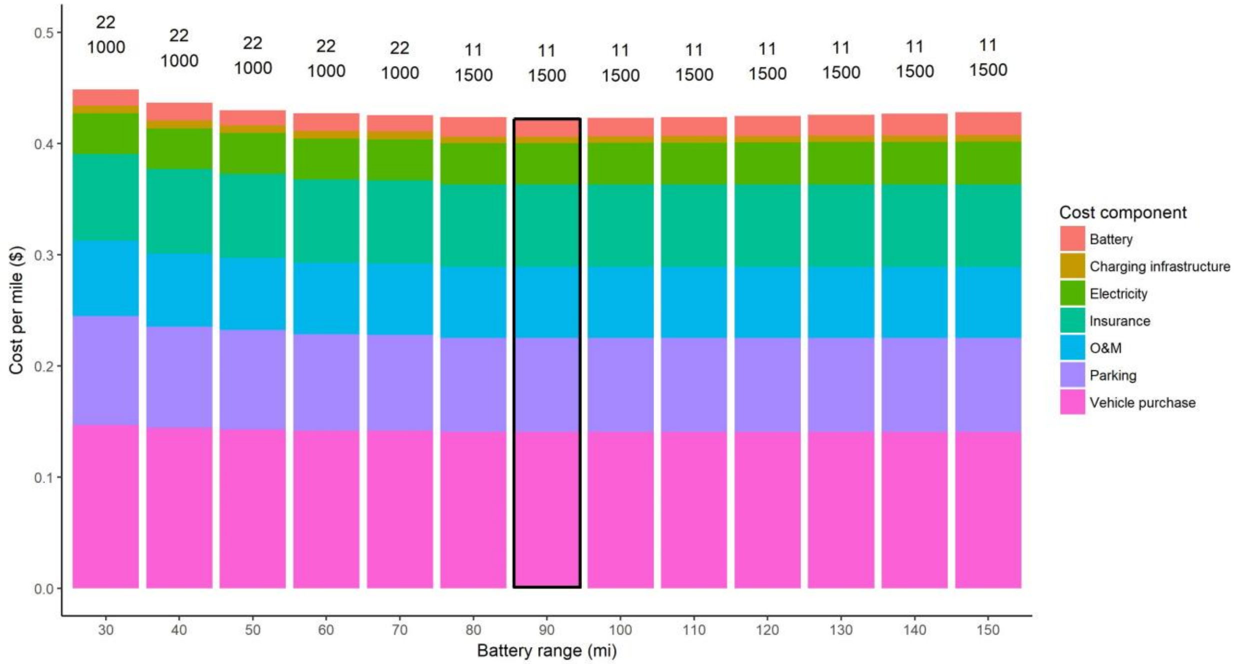


Figure 3. Breakdown of cost of service by component. The outlined column, representing results for a fleet with 90-mi. battery range, represents the lowest-cost configuration. Numbers represent the lowest-cost charging power (top), and number of chargers (bottom) for each battery range.

Looking at the breakdown of cost by component, we 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, our 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.

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, we 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 4, we 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 our earlier analysis, we 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[43]—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,[9] 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.

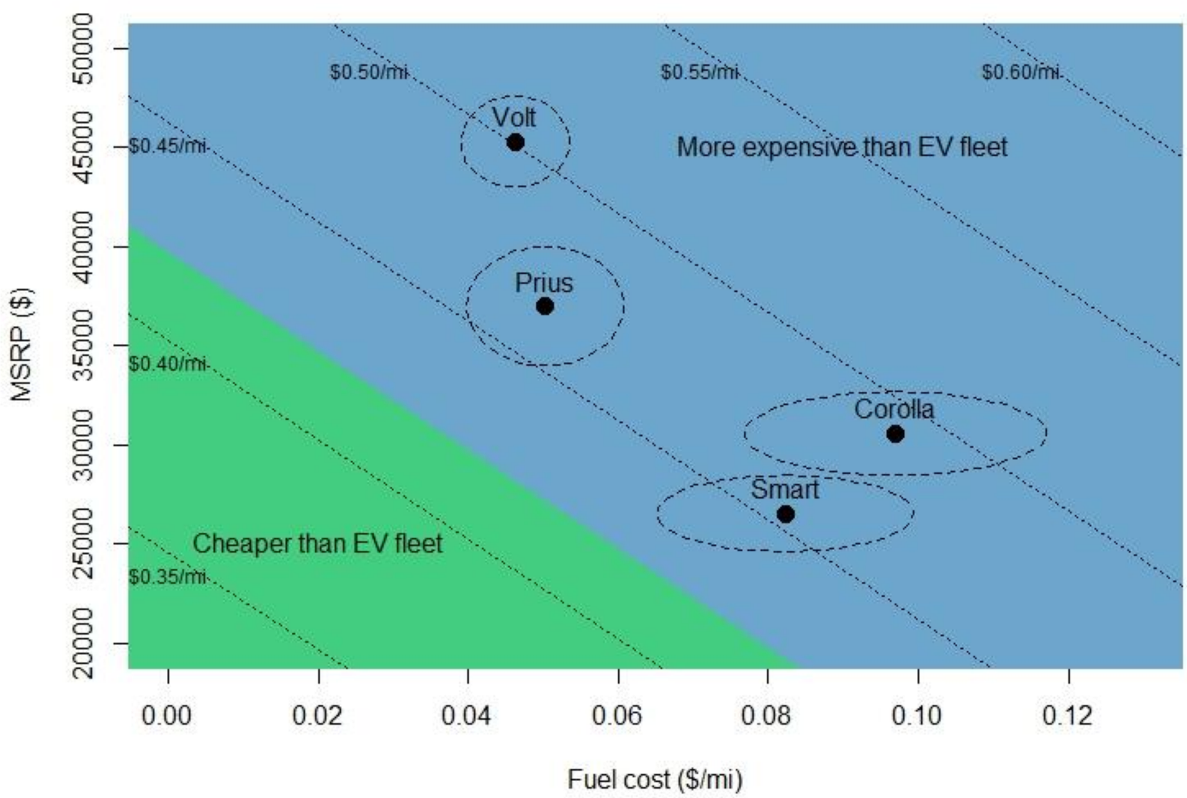


Figure 4. Comparison of estimated fleet costs for four different models of conventional vehicles. Ellipses represent ranges in manufacturer suggested retail prices and gas prices across the U.S. in June, 2017.

Using data cited elsewhere,[44–50] we can also project the energy, GHG and air pollution emission savings that would result from taxi fleet electrification (see supporting information sections 5 and 6 for details). As shown in Table 2, 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.[51,52] Meanwhile, NYC plans to reduce the carbon intensity of its electricity mix by half by 2030,[53] 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 2. 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)

Sensitivity analysis

To test the robustness of our results, we performed a variety of sensitivity analyses (see supporting information section 7 for details). First, we ran a subset of our 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 we do not expect that these results more accurately represent reality than those based on a single day of data.

Second, we conducted simulations with naïve relocation algorithms to test the impact of our assumption regarding perfect foresight. If taxis do not relocate until they are assigned a trip, we 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 our assumptions regarding the two relocation algorithms have counterbalancing effects, suggesting that our results are robust to inaccuracies in our 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 our result for battery range represents an upper bound, while that for cost of service represents a lower bound.

Next, we 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, we 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,[42] we expect the impact of constraints on charging locations to be minimal.

Finally, as summarized in Table 3, we tested the sensitivity of our 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 internal combustion engine vehicles, i.e., more than 300 mi. Our 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 3. 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[36] 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 [34]	$Loss > 0.4 - \frac{I_{charge}}{5} \Rightarrow$ $Loss_{cycle} \propto Ah^2$	$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

Limitations and directions for future research

The first limitation to our results arises from our assumption of exogenous demand—if costs fall as dramatically as projected in our 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, our results apply only to the densest area in the U.S., and it is difficult to generalize our 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 our 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 we have estimated in this study. On the other hand, we 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,[30] they might also enable significant reductions in weight, leading to substantial reductions in energy consumption, cost and GHG emissions.[7]

We also have not considered issues of equity in this paper, which deserve further analysis in future research. Our 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,[54] such that our simulation can still provide useful insights as to the future of shared mobility.

Acknowledgements

This report and the work described were sponsored by the U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO) under the Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Laboratory Consortium, an initiative of the Energy Efficient Mobility Systems (EEMS) Program. The authors acknowledge Eric Rask of Argonne National Laboratory for leading the Connected and Automated Vehicles Pillar of the SMART Mobility Laboratory Consortium. David Anderson and Sarah Olexsak from the DOE Office of Energy Efficiency and Renewable Energy (EERE) managers played important roles in establishing the project concept, advancing implementation, and providing ongoing guidance. Funding for this research came from DOE under Lawrence Berkeley National Laboratory (LBNL) Contract No. DE-AC02-05CH11231, and the University of California, Berkeley (UC Berkeley). Many thanks go to Wei Qi (McGill University), Colin Sheppard (LBNL), Donna T. Chen (University of Virginia), and Duncan Callaway (UC Berkeley) for providing advice and guidance during the research process. Dai Wang (LBNL), Scott Moura (UC Berkeley), and Vincent Battaglia (LBNL) provided guidance for developing the battery degradation model. Phillippe Phanivong (UC Berkeley) provided knowledge on the impact of charging infrastructure on the electric grid.

Supporting Information

More detailed literature review, taxi demand by hour and by day, link to animation of taxi simulation, correlation between taxi data and online maps predictions, growth in fleet size over time, maps of charging distributions, detailed description of battery degradation model, greenhouse gas emissions and air pollution calculations, results of sensitivity analysis, impact on electricity grid.

REFERENCES

(1) Hao, H.; Geng, Y.; Sarkis, J. Carbon footprint of global passenger cars: Scenarios through 2050. *Energy* **2016**, *101*, 121–131.

(2) 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.

(3) 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.

(4) 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.

(5) 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.

(6) 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.

(7) 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.

(8) 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.

(9) Johnson, C.; Walker, J. *Peak car ownership: the market opportunity of electric automated mobility services*; Boulder, Colorado, 2016.

(10) Greenblatt, J. B.; Shaheen, S. Automated Vehicles , On-Demand Mobility , and Environmental Impacts. *Curr. Sustain. Energy Reports* **2015**, *2*, 74–81.

(11) 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.

(12) 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.

(13) Chen, T. D. Management of a Shared, Autonomous, Electric Vehicle Fleet: Vehicle Choice, Charging Infrastructure & Pricing Strategies, University of Texas, Austin, 2015.

(14) Bischoff, J.; Maciejewski, M. Agent-based Simulation of Electric Taxicab Fleets. *Transp. Res. Procedia* **2014**, *4*, 191–198.

(15) 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.

(16) Bösch, P. M.; Becker, F.; Becker, H.; Axhausen, K. W. Cost-based analysis of autonomous mobility services. *Transp. Policy* **2017**, No. August, 1–16.

(17) Loeb, B. Shared autonomous electric vehicle (SAEV) operations across the Austin, Texas network with a focus on charging infrastructure decisions, 2016.

(18) 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.

(19) Schmitz, M. How many cars does the average American own?

(20) Burns, L. D.; Jordan, W. C.; Scarborough, B. A. *Transforming personal mobility*; New York, 2013.

(21) 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 May 1, 2018).

(22) NHTSA. *Federal Automated Vehicles Policy: Accelerating the next revolution in roadway safety*; Washington, D.C., 2016.

(23) NYC Taxi & Limousine Commission. Your guide to Boro Taxis http://www.nyc.gov/html/tlc/html/passenger/shl_passenger.shtml (accessed May 1, 2018).

(24) 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.

(25) 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 May 1, 2018).

(26) Lutz, B. Bob Lutz: Kiss the good times goodbye http://www.autonews.com/article/20171105/industry_redesigned/171109944/industry-redesigned-bob-lutz (accessed May 12, 2017).

(27) Clark, T. EV Charging Station Buying Guide http://www.evelectricity.com/charging/stations/ (accessed Jan 1, 2017).

(28) Tesla. Home charging installation https://www.tesla.com/support/home-charging-installation (accessed Jan 1, 2017).

(29) Qualcomm. Wireless Electric Vehicle Charging https://www.qualcomm.com/solutions/automotive/wevc.

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

(31) 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).

(32) 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.

(33) EPA. Dynanometer drive schedules https://www.epa.gov/vehicle-and-fuel-emissions-testing/dynamometer-drive-schedules.

(34) 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.

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

(36) NYDPS. *Monthly commercial bills including state GRT*; New York City, 2013.

(37) 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.

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

(39) SpotHero Inc. NYC Parking https://spothero.com/nyc-parking?monthly=true (accessed May 1, 2018).

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

(41) 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*; Los Angeles, California, 2012; p 10.

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

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

(44) 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), 54010.

(45) 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.

(46) Nansai, K.; Tohno, S.; Kono, M. Life-cycle analysis of charging infrastructure for electric vehicles. *Appl. Energy* **2001**, *70*, 251–265.

(47) 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.

(48) Pasion, C.; Oyenuga, C.; Gouin, K.; LLC, C. *Inventory of New York City greenhouse gas emissions in 2015*; New York City, 2017.

(49) 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).

(50) Spath, P. L.; Mann, M. K. *Life Cycle Assessment of a Natural Gas Combined Cycle Power Generation System*; Golden, CO, 2000.

(51) 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.

(52) 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.

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

(54) 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**.