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### Title

Cost, Energy, and Environmental Impact of Automated Electric Taxi Fleets in Manhattan

### Permalink

<https://escholarship.org/uc/item/6845z7qp>

### Journal

Environmental Science and Technology, 52(8)

### ISSN

0013-936X

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### Publication Date

2018-04-17

### DOI

10.1021/acs.est.7b04732

Peer reviewed

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

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4 In press at *Environmental Science & Technology*

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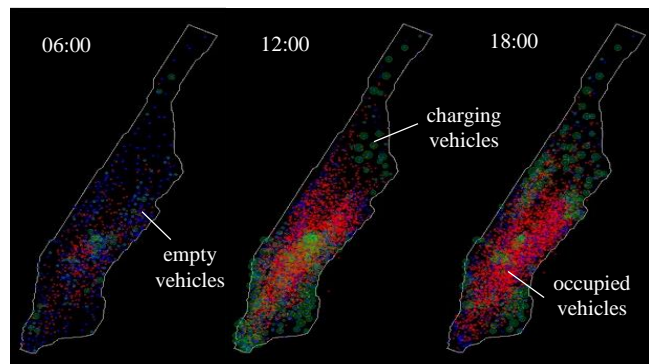
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22  
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24  
25 **ABSTRACT**

26 Shared automated electric vehicles (SAEVs)  
27 hold great promise to improve transportation  
28 access in urban centers while drastically  
29 reducing transportation-related energy  
30 consumption and air pollution. Using taxi trip  
31 data from New York City, we develop an  
32 agent-based model to predict the battery range  
33 and charging infrastructure requirements of a  
34 fleet of SAEVs operating on Manhattan  
35 Island. We also develop a model to estimate

36 the cost and environmental impact of providing service, and perform extensive sensitivity  
37 analysis to test the robustness of our predictions. We estimate that costs will be lowest with a  
38 battery range of 50-90 miles, with either 66 chargers per square mile rated at 11 kilowatts or 44  
39 chargers per square mile rated at 22 kilowatts. We estimate that the cost of service provided by  
40 such an SAEV fleet will be \$0.29-\$0.61 per revenue mile—an order of magnitude lower than the  
41 cost of service of present-day Manhattan taxis and \$0.05-\$0.08/mi. lower than that of an  
42 automated fleet composed of any currently available hybrid or internal combustion engine  
43 vehicle (ICEV). We estimate that such an SAEV fleet drawing power from the current NYC  
44 power grid would reduce GHG emissions by 73% and energy consumption by 58% compared to  
45 an automated fleet of ICEVs.



## 46 INTRODUCTION

47  
48 Transportation represents the fastest-growing segment of the world's greenhouse gas (GHG)  
49 emissions, with cars accounting for 8.7% of global energy-related carbon dioxide emissions in  
50 2013, and car sales set to more than double by 2050.<sup>1</sup> Fortunately, battery electric vehicles  
51 (BEVs) have emerged as a market-ready technology with the potential to reduce the carbon  
52 intensity of private transportation.<sup>2,3</sup> Meeting the Paris Agreement's 2 °C and 1.5 °C targets will  
53 require massive deployment of electrified transportation. However, adoption of electric vehicles  
54 has been relatively slow for several reasons, including technological uncertainty, slow charging,  
55 range anxiety, and higher capital costs compared to other types of vehicles.<sup>4,5</sup> The convergence  
56 of electrification with two other emerging technologies—vehicle automation and smartphone-  
57 enabled shared mobility—could overcome the barriers described above and speed the transition  
58 to an electrified transportation system. Shared automated electric vehicles (SAEVs)<sup>6</sup> would offer  
59 on-demand transportation in electric and self-driving cars similar to the service provided by  
60 current transportation network companies such as Uber and Lyft but likely at much lower cost  
61 and carbon intensity. Because each SAEV need only have enough seats (known as “right-  
62 sizing”) and battery range for the trip requested, and charging can be split over many short  
63 periods in between trips, the shared mobility paradigm could enable the use of smaller cars with  
64 shorter battery range, overcoming the barriers of slow charging speed and high capital cost.<sup>7,8</sup>

65 Furthermore, because shared vehicles typically travel many more miles annually than  
66 privately-owned vehicles, deployment of SAEVs would increase the per-vehicle GHG reductions  
67 relative to private ownership, and spread the capital costs over more miles. SAEVs deployed in  
68 2030 could reduce GHG emissions per mile by more than 90% relative to privately-owned  
69 conventional vehicles while substantially increasing cost-effectiveness.<sup>7</sup> A recent Rocky  
70 Mountain Institute report predicted that the marginal cost of SAEVs will quickly fall below that  
71 of conventional private vehicles so that SAEVs will dominate the mobility market by 2050.<sup>9</sup> It is  
72 possible that such cost savings will increase overall vehicle miles traveled as a result of induced  
73 demand, but some studies have predicted that the efficiency gains would outweigh any resulting  
74 potential increases in emissions.<sup>10</sup>

75 Several previous studies have employed agent-based modeling techniques to explore the  
76 feasibility of a fleet of automated taxis operating in an urban environment.<sup>6,11–17</sup> Building on  
77 these results, we develop an agent-based model to predict the system costs of a fleet of SAEVs  
78 operating in New York City (NYC). Manhattan is a good test case because it is likely one of the  
79 world's best-suited cities to implement an SAEV fleet. With 1.6 million people living in an area  
80 of 23 square miles, it is also the most densely populated region in the U.S. Car ownership in  
81 Manhattan is both challenging and expensive; average household vehicle ownership in  
82 Manhattan is about 0.3 vehicles,<sup>18</sup> compared with 1.9 in the U.S. as a whole.<sup>19</sup> As a result, taxi  
83 usage is relatively high—taxi trips currently represent about 8% of all daily trips taken by  
84 Manhattan residents.<sup>20</sup>

85 Previous studies have shown that electric taxi fleets are viable options under certain  
86 circumstances. However, those studies have chosen fixed values for various fleet parameters. To  
87 our knowledge, ours is the first study that explores a variety of vehicle, operational, and  
88 infrastructure parameters to identify the fleet configuration with lowest cost, and the  
89 corresponding environmental and energy impacts. In contrast to previous work, our analysis also  
90 assumes that taxis can relocate to charge whenever they are idle, which may reduce both the  
91 required battery range and overall cost as well as the impact of the vehicle fleet on the power

92 grid. Furthermore, instead of assuming that batteries will be replaced on a fixed schedule, we  
93 study the optimal battery replacement schedule by investigating the impact of battery  
94 degradation on the number of taxis required to serve demand. Including this flexibility in our  
95 model allows us to make substantive recommendations regarding how SAEV fleets should be  
96 designed, the greatest barriers facing implementation, and how the impact of this technology  
97 might differ from adoption of personal BEVs.

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99

## 100 **METHODS**

101

### 102 **Taxi trip data**

103 All trip data for our analysis were downloaded from the NYC OpenData 2015 database of yellow  
104 taxi trips. For most of our simulation runs, Wednesday, February 4, 2015 was used as a typical  
105 weekday (415,249 total trips) during the winter months when demand is at its highest. To test for  
106 stability over time as well as the impact of higher demand on two consecutive weekends, the  
107 simulation was also run with trip data for a 10-day period, February 6-15, 2015. To test the  
108 impact of fluctuations in seasonal demand (taxi demand is somewhat lower during summer  
109 months), this longer-period simulation was repeated using data from August 7-13, 2015.

110 As with current pilot projects,<sup>21</sup> automated vehicles will likely need to remain within a  
111 defined geo-fenced area for the foreseeable future (i.e., level 4 automation),<sup>22</sup> so, for both realism  
112 and computational simplicity, the data set was restricted to trips that both started and ended on  
113 Manhattan Island. Trips outside of Manhattan would presumably be served by a different fleet  
114 entity, as they largely are today by Green Cabs.<sup>23</sup> Removing trips falling outside these  
115 boundaries on our representative day left us with 349,026 trips or 84% of total demand. Other  
116 potential limitations of level 4 automation (inclement weather, accidents, road construction, etc.)  
117 fall outside the scope of this study.

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

128

### 129 **Taxi routing model description**

130 Using the R coding platform version 3.3.3, we developed an agent-based model to simulate the  
131 movement of taxis around Manhattan throughout the day. Agent-based modeling is well-suited  
132 to our research question because as compared to other analysis techniques, it allows for more  
133 realistic interaction between vehicles, passengers and charging stations, and easy modification of  
134 various assumptions such as strategies for charging, trip assignment, and vehicle relocation.<sup>24</sup>

135 The model proceeds chronologically, assigning taxis to trips in each minute throughout  
136 the day. Trip timestamps are used to represent the time when the trip was requested via a  
137 smartphone app, and priority is given to the first trip requested within the minute. The model

138 assigns to each trip the closest available taxi that has at least enough range to both serve the trip  
139 and then make it to the closest charging station. In cases where more than one taxi meets these  
140 criteria, the model assigns the taxi with the greatest battery range. Given that Uber has already  
141 become the single-largest taxi service in NYC,<sup>25</sup> and industry experts predict that automation  
142 will give further monopoly power to large fleets,<sup>26</sup> we assume that all trip assignments are  
143 managed by a single operator.

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

151 To manage vehicle relocation between trips, we assumed that the fleet operator would  
152 have a well-trained algorithm to predict the spatial distribution of future trip demand and  
153 efficiently route taxis between trips when necessary, to ensure vehicles are located within a 10-  
154 minute radius of trip requests whenever possible. Assuming perfect foresight, in cases where no  
155 taxi can reach a trip request within 10 minutes, the model allows taxis to start relocating as soon  
156 as they ended their previous trips. For example, a taxi that had been idling for five minutes could,  
157 within the 10-minute tolerance window, reach trips requests up to 15 minutes away. This  
158 assumption was verified with simulations that managed vehicle relocation based on historic trip  
159 data, and we explore the impact of changing relocation algorithms in our sensitivity analysis (see  
160 supporting information section 7 for details). In reality, relocation times will be stochastic, such  
161 that some trips will not be served within the 10-minute threshold. In this study we use 10 minutes  
162 merely as a benchmark for comparison between different fleets; real-world fleet operators must  
163 weigh the value of decreasing wait times against the cost of increasing fleet size.

164

### 165 **Charger routing simulation**

166 In between trips, taxis must also decide whether or not to drive to a charger. Again assuming  
167 accurate demand prediction, in each minute, each taxi identifies the charging locations where it  
168 could have driven and spent enough time charging to at least replenish the energy expended to  
169 get there. It is assumed that chargers are automated (either wireless or employing a robotic arm),  
170 such that vehicles begin to charge as soon as they arrive at a station. Each vacant charging point  
171 accepts the closest feasible taxi that has not already been assigned and is then designated as  
172 occupied until the taxi either accepts a trip request or its battery is fully charged. Note that this  
173 method differs significantly from previous models because it allows taxis to charge for very short  
174 periods in between trip requests instead of waiting to run out of charge and then remaining at a  
175 charger until the battery is fully charged. Our hypothesis is that this method allows for greater  
176 flexibility in charging, thus allowing the system to adjust to both shorter battery ranges and  
177 dynamic electricity pricing. In our simulations, the empty miles that taxis spent relocating to  
178 charge and to pick up passengers represented about 20-25% of passenger miles, or about 25  
179 miles per vehicle per day. While this is significantly more than that found by other studies, over  
180 half of trips are served by vehicles less than 0.1 mi. away, so we expect that increased empty  
181 miles are an artifact of the short average distance of Manhattan taxi trips (1.9 mi.; see supporting  
182 information section 2 for more details). Simulations of a fleet of ICEVs suggest that empty miles

183 are almost the same as for an electric fleet, so we do not expect that electrifying Manhattan's taxi  
 184 fleet would increase congestion.

185

### 186 **Charger distribution model**

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

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

204

### 205 **Simulation runs**

206 Simulations were first performed using a single day of data, testing 10-mi. increments of battery  
 207 ranges between 10 mi. and 200 mi., 250-count increments of the number of individual chargers  
 208 between 1,000 and 4,000, and 100-count increments of the number of charging locations  
 209 between 100 and 1,000, for a total of 2,600 simulations. All of these simulations were performed  
 210 assuming a charging speed of 7 kW (Level 2 charging), or roughly 0.5 mi./min. assuming  
 211 average energy consumption of 0.25 kWh/mi.<sup>15</sup> To measure the impact of not being able to fully  
 212 recharge the fleet before the next day started, 84 parameter sets representing the range of values  
 213 shown to be most influential were then used for simulations where the same day was repeated  
 214 until the difference between the fleet's mean state of charge at the beginning and end of the day  
 215 was less than five percent of battery range. Based on expected specifications for commercial  
 216 wireless charging stations,<sup>27, 28,29</sup> these multi-day simulations were then repeated with charging  
 217 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  
 218 total of 336 simulations. Several hundred additional simulations were conducted to test the  
 219 impact of varying different model assumptions (see supporting information section 7 for details).

220

### 221 **Cost model**

222 The taxi service's cost per mile was estimated using a model with the components summarized  
 223 in Table 1. As shown in Equation 1, where  $CRF$  represents the capital recovery factor and  $c_i$   
 224 represents the annual cost of the  $i$ th component in the cost model, levelized cost of service was  
 225 found by dividing total net present value (NPV) of costs by NPV of passenger miles. We used a  
 226 discount rate of 5% and a system time horizon of 20 years, assuming constant costs and demand  
 227 throughout this period. In our sensitivity analysis, we varied the cost of each of these  
 228 components to study the impact that different future cost trajectories would have on our

229 conclusions. Note that vehicle lifetimes were significantly shorter than the 20-year system time  
 230 horizon, about 8.2 years for the cost-optimal configuration. This life-span is longer than that of  
 231 current taxis because we expect electrification and automation will result in lower maintenance  
 232 requirements, and because our simulated vehicles travel significantly fewer miles searching for  
 233 passengers.  
 234

$$235 \quad \text{Cost of service} = \frac{NPV_{cost}}{NPV_{miles}} = \frac{\sum_i C_i \cdot CRF}{\sum \text{passenger miles} \cdot CRF} \quad (1)$$

$$236 \quad CRF = \frac{1 - 1.05^{-20}}{0.05} \approx 12.5$$

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 241 **Table 1. Summary of cost model components**

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

242 a) When calculating the cost of electricity, we corrected vehicle efficiency for the additional weight of the battery.

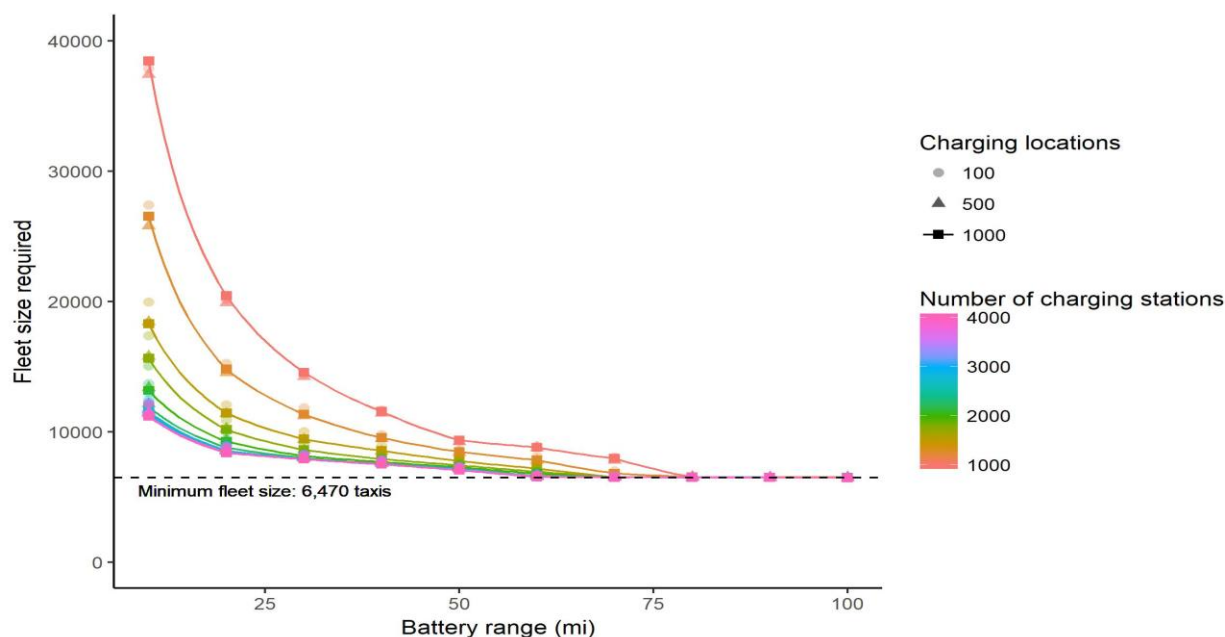
243 b) Although we recognize that it is unclear who will pay for SAEV parking, we included the total cost to society of  
 244 providing parking so that we could compare the total cost of various fleet configurations. It was assumed that the  
 245 operator would need to buy a parking space to store all idle vehicles at the point of lowest demand, or about 90% of  
 246 the total fleet size.  
 247  
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## 249 RESULTS AND DISCUSSION

250

### 251 Fleet-sizing simulation results

252 As shown in Figure 1, we found that the minimum fleet size required to serve all trips within 10  
 253 minutes of requests decreases asymptotically with increasing battery range and number of  
 254 chargers, ultimately falling to 6,470 vehicles at battery ranges of 70 mi. and greater. This  
 255 minimum fleet size requires at least 2,000 chargers rated at 7 kW (88 chargers per square mile,  
 256 or one for every 3.2 vehicles), but adding more chargers beyond this point has diminishing  
 257 returns, especially at higher battery ranges. Increasing the number of charging locations has a  
 258 much smaller effect than increasing battery range or number of chargers; this effect becomes  
 259 negligible once battery range exceeds 50 mi. For more simulation results, such as wait times and  
 260 empty vehicle miles, see supporting information section 2.  
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**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.

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

273 These results suggest that the main challenge to introducing SAEV fleets is not battery  
 274 range—currently available models like the Nissan Leaf more than suffice for meeting demand in  
 275 Manhattan. The greater challenge may be building out sufficient charging infrastructure. In  
 276 contrast with the scenarios of thousands of chargers considered above, according to the charger  
 277 database ChargePoint, there are currently only 456 chargers in Manhattan, including many  
 278 proprietary stations only accessible by Tesla owners.<sup>42</sup>



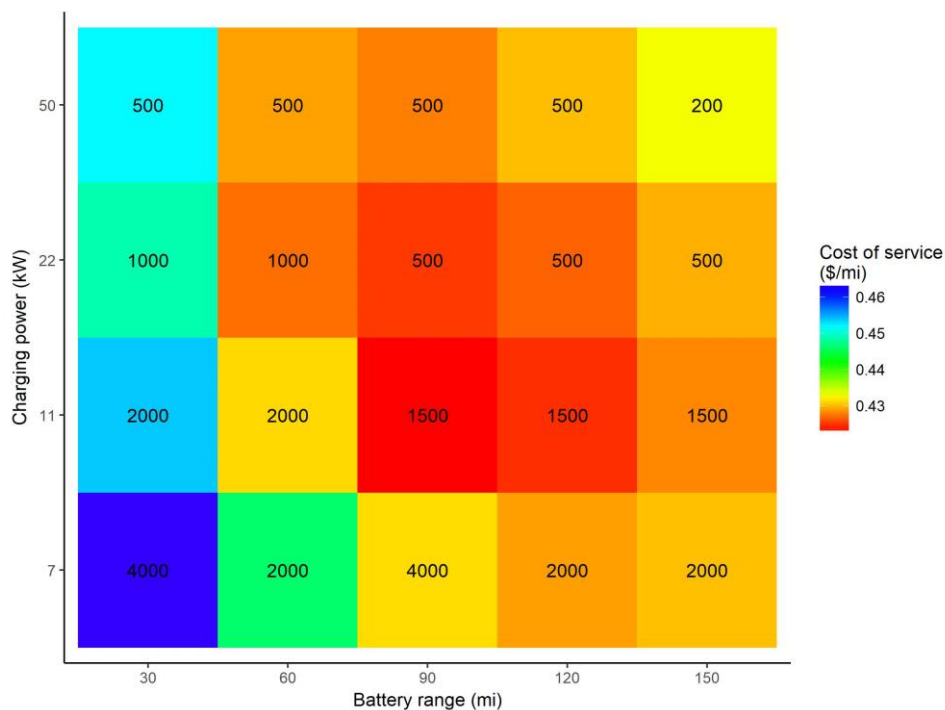
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280 **Cost model results**

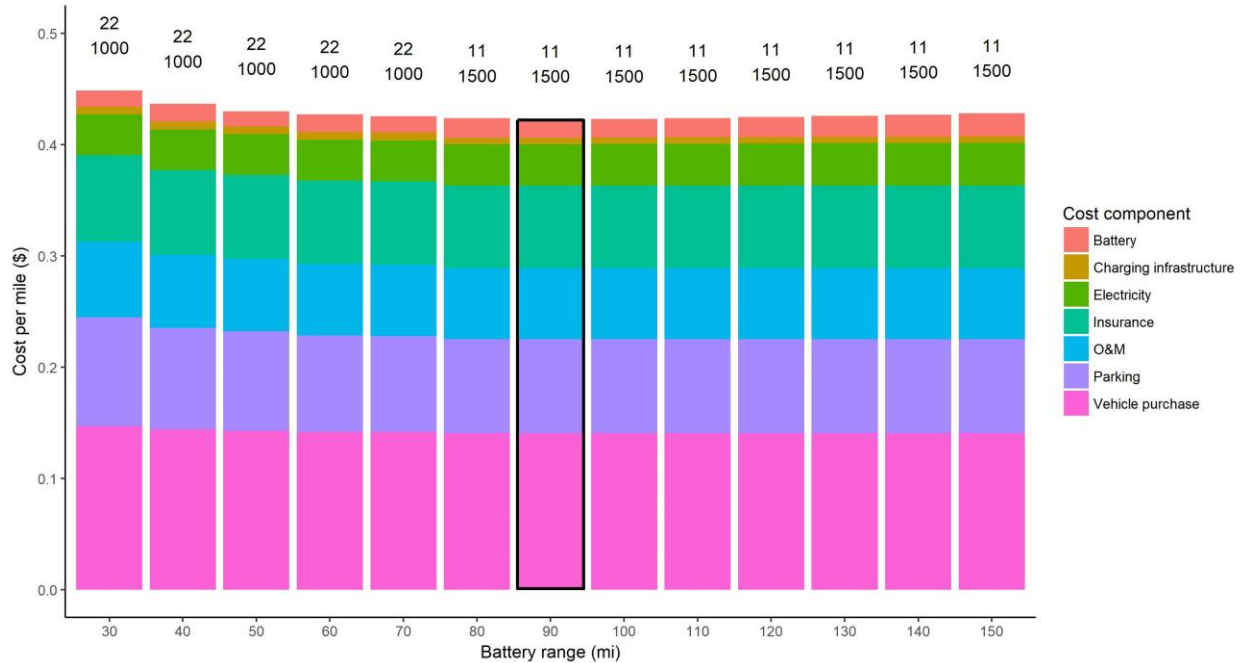
281 Given the results of the fleet-sizing simulation, we can see that there are several trade-  
 282 offs between different fleet parameters. Increasing battery range, charging speed, and the density  
 283 of chargers can decrease the number of vehicles required, but also increases other costs. For  
 284 example, Level 3 chargers reduce the number of chargers required, but cost on the order of ten  
 285 times as much as Level 2 chargers<sup>35</sup>, and also increase battery degradation. As shown in Figure  
 286 2, taking all these trade-offs into account, we identify a lowest-cost configuration at a battery  
 287 range of 90 mi., 1,500 chargers, and a charging power of 11 kW, with an estimated cost of  
 288 service of \$0.42 per revenue-mile. As shown in Figure 3, when paired with the appropriate  
 289 charging infrastructure, all battery ranges between 30 mi. and 150 mi. result in costs of less than  
 290 \$0.45/mi. As battery range increases beyond the point at which fleet size reaches a plateau, cost  
 291 continues to fall briefly because batteries can degrade further before being replaced. After battery  
 292 range surpasses 90 miles, however, the cost of battery purchase becomes the dominant factor,  
 293 and overall cost begins to rise again.

294 While these costs may seem optimistic, it should be noted that they do not include cost  
 295 reductions from improvements in battery technology or charging agreements, improvements in  
 296 BEV efficiency, right-sizing, dynamic ride-sharing,<sup>17</sup> bulk purchasing contracts, or optimal trip  
 297 assignment algorithms, and so could be considered conservative. These cost estimates are also  
 298 consistent with Burns et al.'s finding that a fleet of conventional SAVs could replace Yellow Cab  
 299 trips on Manhattan with a cost of \$0.50/mi.,<sup>20</sup> as well as Chen et al.'s estimate that an SAEV  
 300 fleet could serve taxi demand in Austin, Texas at a cost of \$0.40-\$0.50/mi.<sup>13</sup> (see supporting  
 301 information section 1).

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**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.

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

321

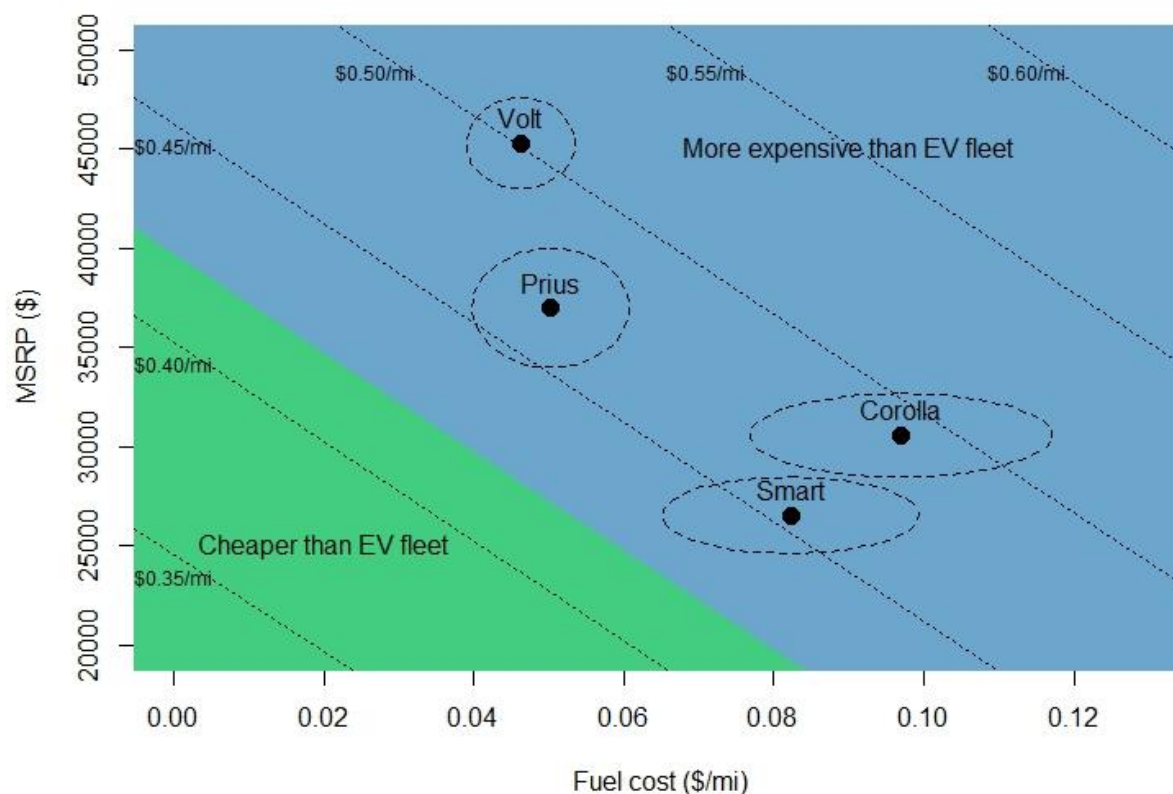
### 322 Comparison with conventional taxi fleets

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324 Comparison with a hypothetical fleet of conventional vehicles reveals that, unless both  
325 fuel prices and conventional vehicle purchase prices fall dramatically, a battery electric vehicle  
326 fleet will be cheaper. Simulation results show a minimum fleet size of 6,469 conventional  
327 vehicles, slightly less than the lowest result for a fleet of battery electric vehicles. The lack of  
328 relocation to chargers also reduces the total distance traveled by 1.4%. To determine the cost of  
329 service of this hypothetical fleet, we used a similar cost model to that for electric vehicles but  
330 with a maintenance cost of \$0.06/mi and no costs for electricity, batteries, or charging  
331 infrastructure. As shown in Figure 4, we then calculated the cost for a range of combinations of  
332 vehicle cost and fuel cost and compared them with estimates for four commercially available  
333 models: Toyota Prius, Chevrolet Volt, Smart Fortwo, and Toyota Corolla. As with the electric  
334 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

335 U.S. gasoline price (\$2.15 in June, 2017), all four of these models would cost significantly more  
 336 than a comparable fleet of electric vehicles. Using mean values, the cost increase ranges from  
 337 \$0.05/mi. for the Prius to \$0.08/mi. for the Volt.

338 Relative to the current cost of Manhattan taxis—median fare was \$5.42/mi. in August,  
 339 2015<sup>43</sup>—our estimated cost for the operation of an SAEV fleet represents roughly an order of  
 340 magnitude reduction (assuming about 10% profit margin). Aside from savings due to  
 341 electrification, the elimination of driver labor reduces cost by roughly \$1.30/mi,<sup>9</sup> with the  
 342 remainder of the savings coming from the increased efficiency of a single-operator, smartphone-  
 343 based system (fleet size is reduced by half), and the lack of medallion fees.



344 **Figure 4.** Comparison of estimated fleet costs for four different models of conventional vehicles. Ellipses represent ranges in manufacturer  
 345 suggested retail prices and gas prices across the U.S. in June, 2017.  
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348 Using data cited elsewhere,<sup>44–50</sup> we can also project the energy, GHG and air pollution  
 349 emission savings that would result from taxi fleet electrification (see supporting information  
 350 sections 5 and 6 for details). As shown in Table 2, SAEV fleets result in significantly lower  
 351 impact in every case except for sulfur dioxide emissions, which would increase by 10% due to  
 352 high emissions from battery production with the current power grid. Naturally, the air pollution  
 353 caused by electric vehicles comes from manufacturing facilities and power plants that tend to be  
 354 located in relatively rural areas, and so will likely result in much lower health impacts than  
 355 emissions from ICEVs.<sup>51,52</sup> Meanwhile, NYC plans to reduce the carbon intensity of its  
 356 electricity mix by half by 2030,<sup>53</sup> which would further reduce the GHG emissions of electric

357 vehicle fleets by a third, and substantially reduce air pollution as well. Serving the same trips  
 358 with personal electric vehicles driven 15,000 miles per year and 300 miles of battery range  
 359 would lead to 74,000 tons CO<sub>2</sub>-eq per year, meaning that replacing personal vehicles with short-  
 360 range SAEVs could reduce GHG emissions by more than half.

361

362 **Table 2. Comparison of energy, GHG, and air pollution emissions**

<i>tons/yr, unless noted otherwise</i>	<i>BEV</i>	<i>ICEV (BEV % savings)</i>	<i>HEV (BEV % savings)</i>
<i>Energy (GWh/yr)</i>	205	460 (55)	280 (27)
<i>GHG (ktCO<sub>2</sub>-eq/yr)</i>	33	122 (73)	76 (57)
<i>Carbon monoxide</i>	43	932 (95)	922 (95)
<i>Nitrogen oxides</i>	40	101 (60)	96 (58)
<i>Particulate matter</i>	11	20 (45)	20 (45)
<i>Volatile organic compounds</i>	70	132 (47)	104 (33)
<i>Sulfur dioxide</i>	78	71 (-10)	70 (-11)

363

364 **Sensitivity analysis**

365 To test the robustness of our results, we performed a variety of sensitivity analyses (see  
 366 supporting information section 7 for details). First, we ran a subset of our simulations for a full  
 367 10 days, and found that this increases the minimum required fleet size from 6,500 to 7,000, as  
 368 well as increasing the lowest-cost battery range by 10 miles. This result suggests that as demand  
 369 increases, if the taxi operator wishes to maintain the same level of service, costs must rise, and  
 370 battery range may need to increase moderately. Of course, if taxi fares were to actually fall by an  
 371 order of magnitude as predicted here, demand might shift dramatically, and so we do not expect  
 372 that these results more accurately represent reality than those based on a single day of data.

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

386 Next, we tested the effect of restricting chargers to a few locations, using the algorithm  
 387 described in the methods section. Given the challenges of obtaining permits and property, SAEV  
 388 charging might take place primarily in a few discrete parking garages that each have a large  
 389 number of chargers. However, we found that with an efficient charging algorithm, results for  
 390 fleet size and battery range do not change appreciably until the number of locations falls below  
 391 50. Given that there are already charging stations at over 100 locations in Manhattan,<sup>42</sup> we  
 392 expect the impact of constraints on charging locations to be minimal.

393           Finally, as summarized in Table 3, we tested the sensitivity of our results to a variety of  
394 changes in cost components, including cost of parking, vehicles, batteries, and electricity. These  
395 scenarios result in cost of service estimates ranging from \$0.29/mi. to \$0.61/mi. and a lowest-  
396 cost battery range of 50 - 90 mi. This result contrasts with current trends in electric vehicle  
397 development to expand battery range until it equals the travel range of internal combustion  
398 engine vehicles, i.e., more than 300 mi. Our study shows that battery range will not be the main  
399 obstacle for SAEV fleets. Currently available ranges more than suffice, and significant cost  
400 savings could result from reducing battery range from current levels.  
401  
402

403 **Table 3. Summary of results of cost model sensitivity analyses**

<i>Scenario</i>	<i>Explanation</i>	<i>Changes to cost model</i>	<i>Minimum cost of service (\$/mi.)</i>	<i>Lowest-cost fleet configuration</i>
<i>Baseline</i>	See methodology section	None	\$0.423	90 mi. battery 1500 chargers 11 kW
<i>Dynamic electricity rates</i>	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 <sup>36</sup>  No change in charging patterns	\$0.427	90 mi. battery 1500 chargers 11 kW
<i>Cheap batteries, expensive vehicles</i>	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
<i>Cheap vehicles, expensive batteries</i>	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
<i>No battery degradation</i>	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
<i>Nonlinear battery degradation</i>	Batteries degrade nonlinearly after reaching cut-off <sup>34</sup>	$Loss > 0.4 - \frac{I_{charge}}{5} \Rightarrow$ $Loss_{cycle} \propto Ah^2$	\$0.428	70 mi. battery 1500 chargers 11 kW
<i>No parking costs</i>	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

#### 404 **Limitations and directions for future research**

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

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

415 Accounting for higher demand and less dense geography would both likely require larger  
416 fleets, and so operating these fleets could cost more than we have estimated in this study. On the  
417 other hand, we did not consider the possibility of a heterogeneous fleet, in which some chargers  
418 have higher speeds than others, and some taxis have more or less battery capacity, or different  
419 numbers of seats. Because the average occupancy of NYC taxi trips is less than two people,<sup>40</sup> if  
420 there is no need to provide space for a driver, then most shared vehicles need have no more than  
421 two seats. Given that these vehicles will be smaller and rarely get into collisions,<sup>30</sup> they might  
422 also enable significant reductions in weight, leading to substantial reductions in energy  
423 consumption, cost and GHG emissions.<sup>7</sup>

424 We also have not considered issues of equity in this paper, which deserve further analysis  
425 in future research. Our simulated fleet can only serve customers with smartphones, and fleet  
426 rebalancing based on demand forecasting could lead to worse service in low income  
427 neighborhoods. However, these issues already exist with services like Uber and Lyft, and  
428 smartphone ownership is approaching ubiquity in urban areas,<sup>54</sup> such that our simulation can still  
429 provide useful insights as to the future of shared mobility.

#### 430 **Acknowledgements**

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

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450 **Supporting Information**

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

456

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