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2 **OPERATIONS OF A SHARED, AUTONOMOUS, ELECTRIC VEHICLE FLEET:**
3 **IMPLICATIONS OF VEHICLE & CHARGING INFRASTRUCTURE DECISIONS**
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25 **ABSTRACT**
26

27 There are natural synergies between shared autonomous vehicle (AV) fleets and electric vehicle
28 (EV) technology, since fleets of AVs resolve the practical limitations of today’s non-autonomous
29 EVs, including traveler range anxiety, access to charging infrastructure, and charging time
30 management. Fleet-managed AVs relieve such concerns, managing range and charging activities
31 based on real-time trip demand and established charging-station locations, as demonstrated in
32 this paper. This work explores the management of a fleet of shared autonomous (battery-only)
33 electric vehicles (SAEVs) in a regional discrete-time, agent-based model. The simulation
34 examines the operation of SAEVs under various vehicle range and charging infrastructure
35 scenarios in a gridded city modeled roughly after the densities of Austin, Texas.

36 Results based on 2009 NHTS trip distance and time-of-day distributions indicate that fleet size is
37 sensitive to battery recharge time and vehicle range, with each 80-mile range SAEV replacing
38 3.7 privately owned vehicles and each 200-mile range SAEV replacing 5.5 privately owned
39 vehicles, under Level II (240-volt AC) charging. With Level III 480-volt DC fast-charging
40 infrastructure in place, these ratios rise to 5.4 vehicles for the 80-mile range SAEV and 6.8
41 vehicles for the 200-mile range SAEV. SAEVs can serve 96 to 98% of trip requests with average
42 wait times between 7 and 10 minutes per trip. However, due to the need to travel while
43 “empty” for charging and passenger pick-up, SAEV fleets are predicted to generate an
44 additional 7.1 to 14.0% of travel miles. Financial analysis suggests that the combined cost of
45 charging infrastructure, vehicle capital and maintenance, electricity, insurance, and registration
for a fleet of SAEVs ranges from \$0.42 to \$0.49 per occupied mile traveled, which implies
SAEV service can be offered at the equivalent¹per-mile cost of private vehicle ownership for
low mileage households, and thus be competitive

46 with current manually-driven carsharing services and significantly cheaper than on-demand driver-
47 operated transportation services. When Austin-specific trip patterns (with more concentrated trip
48 origins and destinations) are introduced in an additional case study, the simulation predicts a
49 decrease in fleet “empty” vehicle-miles (down to 3 to 4 percent of all SAEV travel) and average
50 wait times (ranging from 2 to 4 minutes per trip), with each SAEV replacing 5 to 9 privately owned
51 vehicles.

52 **KEYWORDS**

53 Agent-based modeling, carsharing, electric vehicles, autonomous vehicles.

54 **INTRODUCTION**

55 Recent transportation trends in increasing electric vehicle (EV) sales and growing carsharing
56 membership have important impacts on greenhouse gas emissions and energy use. Incentivizing
57 plug-in EV adoption and shared-vehicle use may be key strategies for helping regions achieve
58 national- and state-level air quality standards for ozone and particulate matter, and ultimately
59 carbon-emissions standards. At the same time, with the rise of the shared-use economy, carsharing
60 is emerging as an alternative mode that is more flexible than transit but less expensive than
61 traditional private-vehicle ownership. However, the growth of EVs and carsharing are both
62 hindered by technological and social factors. For EVs, the most significant hindrance may be
63 “range anxiety,” a user’s concern for being stranded with a fully discharged battery and no
64 reasonable recharge option (Bartlett 2012). Meanwhile, as EVs penetrate the private and
65 commercial vehicle fleets, they are also gaining ground in the carsharing world. EVs are a natural
66 match for carsharing operations as existing members of carsharing operations tend to drive smaller
67 and more fuel efficient vehicles than non-carshare members (Martin and Shaheen 2011). Cutting
68 edge carsharing operators (CSOs) are already employing EVs in their fleets (such as Daimler’s
69 Car2Go and BMW’s DriveNow operations), but the manual relocation of fleets in one-way
70 carsharing systems continues to present profitability challenges to CSOs. The introduction of
71 autonomous driving technology would remove the challenge of manual vehicle relocation and
72 presents a driver-free method for shared EVs to reach travelers’ origins and destinations as well as
73 charging stations. In a carsharing setting, a fleet of shared autonomous electric vehicles (SAEVs)
74 would automate the battery management and charging process, and take range anxiety out of the
75 equation for growth of EVs. With the recent popularity of on-demand transportation services
76 through transportation network companies, it is possible to imagine a future travel system where
77 autonomous vehicle (AV) technologies merges with carsharing and EVs in a SAEV fleet. But can
78 self-driving vehicles be shared, self-charged, and right (battery-) sized for the trip lengths that
79 travelers desire?

80 This study attempts to answer this question through the simulation of a SAEV fleet in a discrete-
81 time agent-based model, examining fleet operations in a 100-mile by 100-mile gridded
82 metropolitan area. Scenarios combine short-range and long-range electric vehicles with Level II
83 and Level III charging infrastructure to look at the impacts of vehicle range and charging time on
84 fleet size, charging station sites, ability to meet trip demand, user wait times, and induced vehicle
85 miles traveled (VMT). Following the discussion of the simulation results, a financial analysis
86 highlights the tradeoffs between capital investment in vehicles and charging infrastructure and user
87 benefits.

88 PRIOR RESEARCH

89 There is a wealth of literature examining carsharing, electric vehicles and charging infrastructure
90 planning, and autonomous vehicles as separate topics. Studies looking at gasoline-propelled and
91 (especially) electric AVs in a shared setting are more limited. Wang et al. (2006) proposed a
92 dynamic fleet management algorithm for shared fully automated vehicles based on queuing theory.
93 In a simulative environment with five stations and five vehicles, the average passenger waiting
94 time was 3.37 minutes with average vehicle usage rate of 4.3 vehicles, compared to a fixed dispatch
95 algorithm where average passenger wait time was 4.89 minutes and vehicle usage rate 3.7 vehicles.
96 Spieser et al. (2014) modeled a fleet of shared self-driving vehicles in Singapore in the absence of
97 any private vehicles, and found that each shared vehicle can replace three privately owned vehicles
98 and serve 12.3 households. In Kornhauser et al. (2013), aTaxiStands (autonomous taxi stands) are
99 placed in every half mile by half mile pixel across New Jersey, and passengers walk to taxi stands
100 rather than allowing AVs to relocate. Douglas (2015) uses the base model proposed in Kornhauser
101 et al. (2013) to size the fleet of an autonomous taxi system in a 5-mile by 5-mile subset of the New
102 Jersey model and found a minimum of 550 vehicles was needed to serve the trip demand. Burns
103 et al. (2013) examined the performance of a shared autonomous fleet in three distinct city
104 environments: a mid-sized city (Ann Arbor, Michigan), a low-density suburban development
105 (Babcock Ranch, Florida), and a large densely-populated urban area (Manhattan, New York). The
106 study found that in mid-sized urban and suburban settings, each shared vehicle could replace 6.7
107 privately owned vehicles. Meanwhile, in the dense urban setting, the current taxi fleet could be
108 downsized by 30% with the introduction of autonomous driving technology with average wait
109 times at less than one minute. The International Transport Forum (2015) looked at the application
110 of shared and self-driving vehicles in Lisbon, Portugal, and found that with ride-sharing enabled,
111 each shared vehicle can replace approximately 10 privately owned vehicles and induces 6% more
112 VMT than the current baseline. Without ride-sharing, each sequentially shared vehicle can replace
113 6 privately owned vehicles but induces 44% more travel distance. This study also looked at the
114 impact of electrifying shared self-driving vehicles, assuming an electric range of 175 kilometers
115 (108 miles) and a recharge time of 30 minutes, and found that the fleet would need to be 2% larger.
116 Fagnant and Kockelman (2014) presented an agent-based model for Shared Autonomous Vehicles
117 (SAVs) which simulated environmental benefits of such a fleet as compared to conventional
118 vehicle ownership and use in a dense urban core area. Simulation results indicated that each SAV
119 can replace 11 conventional private owned vehicles, but generates up to 10% more travel distances.
120 When the simulation was extended to a case study of low market penetration (1.3% of trips) in
121 Austin, Texas, each SAV was found to be able to replace 9 conventional vehicles and on average,
122 generated 8% more VMT due to unoccupied travel (Fagnant et al. 2015).

123
124 Charging/refueling in a fleet of shared self-driving vehicles has remained a missing component in
125 all of the prior studies mentioned here except ITF (2015) and Fagnant and Kockelman (2014), both
126 of which model the refueling process rather simplistically. Fagnant and Kockelman (2014)
127 modeled the logistics of refueling by assuming the 400-mile range SAVs could refuel at any
128 location within the grid with a fixed service lag time. In ITF (2015), recharging of EVs is only
129 looked at in terms of equivalent fleet sizing compared to longer-range and shorter-recharge-time,
130 gasoline-propelled vehicles. No study has examined the operations of shared autonomous vehicles
131 looking specifically at the vehicle propulsion system and charging infrastructure, both of which
132 have direct impacts on the vehicle's ability to travel to passengers as well as fueling/charging
133 stations. The work described here builds from the framework in Fagnant and Kockelman (2014)

134 and analyzes the operations of a SAEV fleet under different vehicle range and charging
135 infrastructure assumptions. There are natural synergies between AVs and EVs, as the “smart”
136 nature of AVs resolve the practical limitations of the non-autonomous EV in the market today.
137 These limitations include the previously discussed all electric range, charging station density, and
138 charging time management. Fleet managed “smart” AVs relieve such concerns from the individual
139 traveler, managing range and charging activities based on predicted trip demand and established
140 locations of charging stations, as demonstrated in the work here.

141

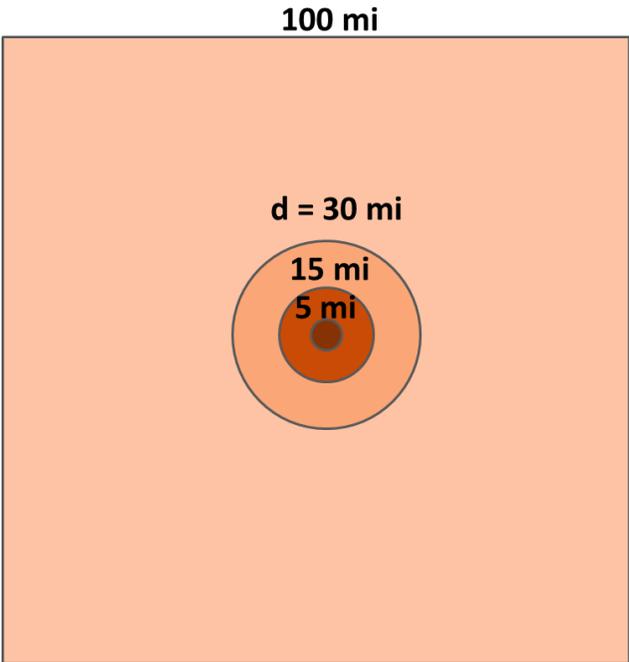
142 **METHODOLOGY**

143

144 **Model Setup**

145 The discrete-time agent based model used here is an expansion of the 10-mile by 10-mile model
146 proposed by Fagnant and Kockelman (2014). In its setup, the model generates a square 100-mile
147 by 100-mile gridded metropolitan area, divided into 160,000 quarter-mile by quarter-mile cells.
148 The gridded city (roughly modeled after the population density pattern of Austin, Texas) is divided
149 into four zones as shown in Figure 2-1: downtown (the innermost 2.5-mile radius), urban (the next
150 ring 7.5-mile radius), suburban (the next ring 15-mile radius), and exurban (the remainder area).
151 Zone population densities and trip rates are determined with data from the Austin travel demand
152 model segmented by population density (see Table 1). Each zone has its own unique average trip
153 generation rate (representing approximately 10% of all trips in the Austin region inclusive of return
154 trips, reflecting what Shaheen et al. [2006] estimates as market potential for carsharing in a
155 manually-driven setting) and average peak and off-peak travel speeds (derived from sample peak
156 and off-peak trips from the Austin travel demand model), as shown in Table 1.

157



158

159

Figure 1. City Zones and Zone Limits

160

Table 1. Zone Trip Generation Rates & Travel Speeds

	Population Density (persons/mi ²)	Avg Trip Gen. Rate (trips/cell/day)	Travel Speed (mi/hr)	
			Peak	Off-Peak
Downtown	7500-50,000	129	15	15
Urban	2000-7499	39	24	24
Suburban	500-1999	11	30	33
Exurban	<499	1	33	36

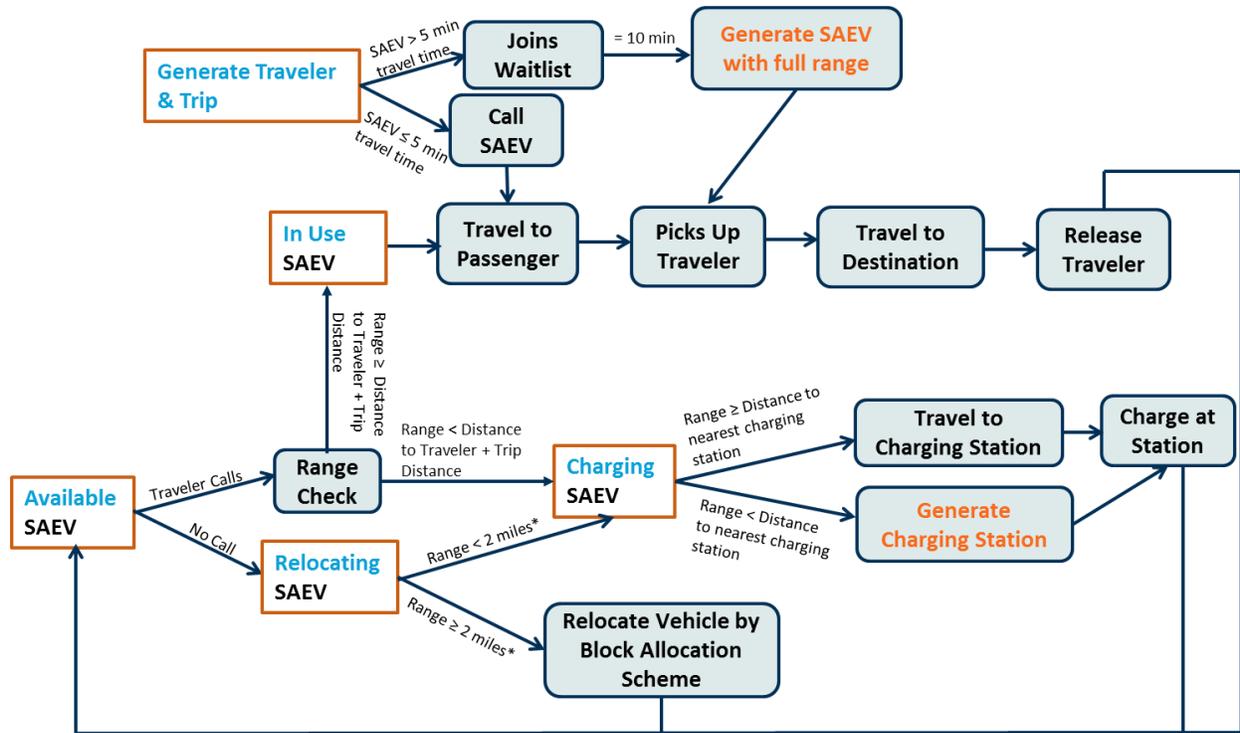
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162 The actual trip generation rate in each cell is drawn from a Poisson distribution with Table 1’s
 163 value used as the average rate for each 5-minute time step within a 24-hour temporal distribution
 164 following the 2009 National Household Travel Survey (FHWA 2009). The destination cells for
 165 each trip generated are assigned as a function of the trip length (drawn from the 2009 NHTS trip
 166 length distribution) and proportional to the share of cells to the north, south, east, and west of the
 167 origin cells. In other words, the trip generation methodology used here favors higher attraction
 168 levels towards the city center. In the simulation, roughly 680,000 SAEV trips are generated per
 169 day (representing roughly 10% of trips in a simulated 2.9 million people region). For detailed
 170 information on the step-by-step trip generation methodology used here, please refer to Fagnant
 171 and Kockelman (2014).

172 The model first runs through a two-phase warm start, during which the number of charging stations
 173 and the size of the SAEV fleet is determined. After the warm start completes, the model then runs
 174 for 50 consecutive days with the predetermined fleet size and charging station layout to output
 175 fleet operation performance metrics. Each phase of the model is discussed in detail in the following
 176 sections.

177 Charging Stations Generation

178 In Phase 1 of the warm start, consecutive 24-hour days are modeled to determine the number of
 179 charging stations needed for full service of the SAEV fleet. Figure 2 demonstrates the process of
 180 how and where charging stations are generated in the warm start.



181

182

Figure 2. Agent Based Model Algorithm: Charging Station Generation

183 Once a trip is generated by the process discussed in the Model Setup section, a traveler looks for
 184 the closest *available* status SAEV within a 5-minute travel time radius through a greedy search
 185 algorithm (searching at increasing distances starting from its own origin cell). If an available
 186 SAEV is located within a 5-minute travel-time radius, the traveler claims the SAEV and the SAEV
 187 falls under *in use* mode for the subsequent time periods to pick up the traveler, complete the
 188 assigned trip, and release traveler. If a SAEV is not available within a 5-minute travel-time radius,
 189 the traveler joins a waitlist. In the following 5-minute time step, travelers on the wait list are
 190 prioritized and served first, before new trips generated during the current time step are served by
 191 SAEVs. When a traveler has been on the waitlist for 10 minutes (or two time steps), a new SAEV
 192 is generated with full charge in the traveler’s origin cell.

193 Once a SAEV releases a traveler at the destination cell, the vehicle changes from *in use* to *available*
 194 status, and awaits for a traveler call in the subsequent 5-minute time step. If the vehicle is not
 195 called in the time step, the SAEV changes from *available* to *relocating* status, and its subsequent
 196 actions are discussed in the Strategic Vehicle Relocation section. If a traveler calls, the SAEV
 197 checks to ensure that its remaining range is greater than the distance to the traveler plus the distance
 198 of the requested trip before accepting the call. If the range is insufficient, the call is rejected and
 199 the SAEV changes from *available* to *charging* status. In *charging* status, the SAEV looks for the
 200 nearest charging station (by the same greedy algorithm used in trip matching), and if one does not
 201 exist within its remaining range, a charging station is generated in the SAEV’s current cell. The
 202 SAEV then stays in *charging* status at the charging station for the number of time steps
 203 proportional to its remaining range to achieve full charge status, as shown in Equation 1:

$$T_{charge} = \left\lceil \frac{Range_{full} - Range_{current}}{Range_{full}} \right\rceil T_{full} \quad (1)$$

where T_{charge} is the number of time steps a SAEV remains at the charging station in *charging* status before becoming *available* for the next traveler, $Range_{full}$ is the number of grid cells a SAEV can travel when fully charged, $Range_{current}$ is the SAEV's current remaining range, and T_{full} is the number of time steps required for a fully depleted SAEV battery to fully charge. Phase 1 continues until the number of charging stations on consecutive days converges to within 1%.

SAEV Fleet Generation

When Phase 1 is complete, the charging station layout is set and no more charging stations can be added to the city. The SAEV fleet is cleared to start Phase 2, which determines the size of the SAEV fleet. The two phases of the warm start operate independently of each other since the number of SAEVs required in the fleet depends on the number of charging stations available. During the generation of the charging stations, the corresponding SAEV fleet is (temporarily) oversized. The overall algorithm for Phase 2 is similar to that of Phase 1. However, because no charging stations are generated in Phase 2, in order to accept a traveler's call, the SAEV must have sufficient range to travel to the traveler, complete the requested trip, and travel to the nearest charging station from the destination cell. Phase 2 is run for 20 days, with vehicles cleared at the end of each day. The average number of SAEVs generated from the 20 days is taken as the fleet size for the full run.

Waitlist

Once the charging station locations and SAEV fleet size is determined from the two-phase warm start, the program runs through 50 consecutive days when vehicles are in continuous operation (no vehicle clearing). The full run's model structure is identical to that of Phase 2, except no new SAEVs are generated and travelers remain on the waitlist. If a traveler's trip request is rejected in 6 consecutive time steps (equivalent to 30 minutes on the waitlist), that trip is considered unserved and is removed from the waitlist.

Strategic Vehicle Relocation

During each step of the model (warm start and full run), available SAEVs that are not called by travelers are assigned to *relocating* status for that time step. The relocation strategy used in this model first attempts to balance the available SAEVs in the current time step with the expected demand in a 2-mile by 2-mile block in the subsequent time step, then uses two additional strategies to efficiently distribute SAEVs amongst bordering blocks with a large vehicle supply gap. This combination of relocation strategies was deemed the most effective out of several that were tested in Fagnant and Kockelman (2014), which also describes the relocation process in detail. To ensure that vehicles in *relocating* status have sufficient range for relocation, a check ensures that the SAEV has sufficient range to travel a distance equivalent to 5 minutes of travel time from its original cell (roughly equivalent to 2 miles but varies slightly with zone) plus the distance to the nearest charging station to the relocation destination.

241

MODEL SCENARIO RESULTS

243 The agent-based model described here is run for several scenarios to examine the sensitivity of
 244 various fleet operation metrics to model inputs, as shown in Table 2. A non-electric SAV scenario
 245 (assuming 400-mile range and 15 minute refueling time) is run as a reference case for comparison
 246 to the results in Fagnant and Kockelman (2014). Next, the SAEV scenario assumes the vehicle has
 247 an 80-mile range (similar to current models of the Nissan Leaf, Chevrolet Spark, Honda Fit EV,
 248 and BMW i3) and 4 hour recharge time, corresponding to charging times of current market BEVs
 249 with a 240-volt AC Level II charger. A SAEV Fast Charge scenario combines the same 80-mile
 250 vehicle with a recharge time of 30 minutes, mimicking the specifications of current market BEVs
 251 with a Level III 480-volt DC high-current charger. Following fast charging guidelines, the SAEVs
 252 in the fast charge scenarios will only be charged to 80% full to protect the batteries from losing
 253 capacity with repeat fast charging, which effectively reduces the range to 64 miles. The last two
 254 scenarios looks at various types of charging in combination with long-range BEVs (LR SAEV)
 255 matching the 200-mile range specification of the upcoming Chevrolet Bolt and Tesla Model 3
 256 (both with 2017 planned release dates). The LR SAEV scenario combines a 200-mile range with
 257 a 4-hour recharge time while the LR SAEV Fast Charge scenario combines a 160-mile effective
 258 range with a 30 minute fast charge time.

259

Table 2. Scenario Results

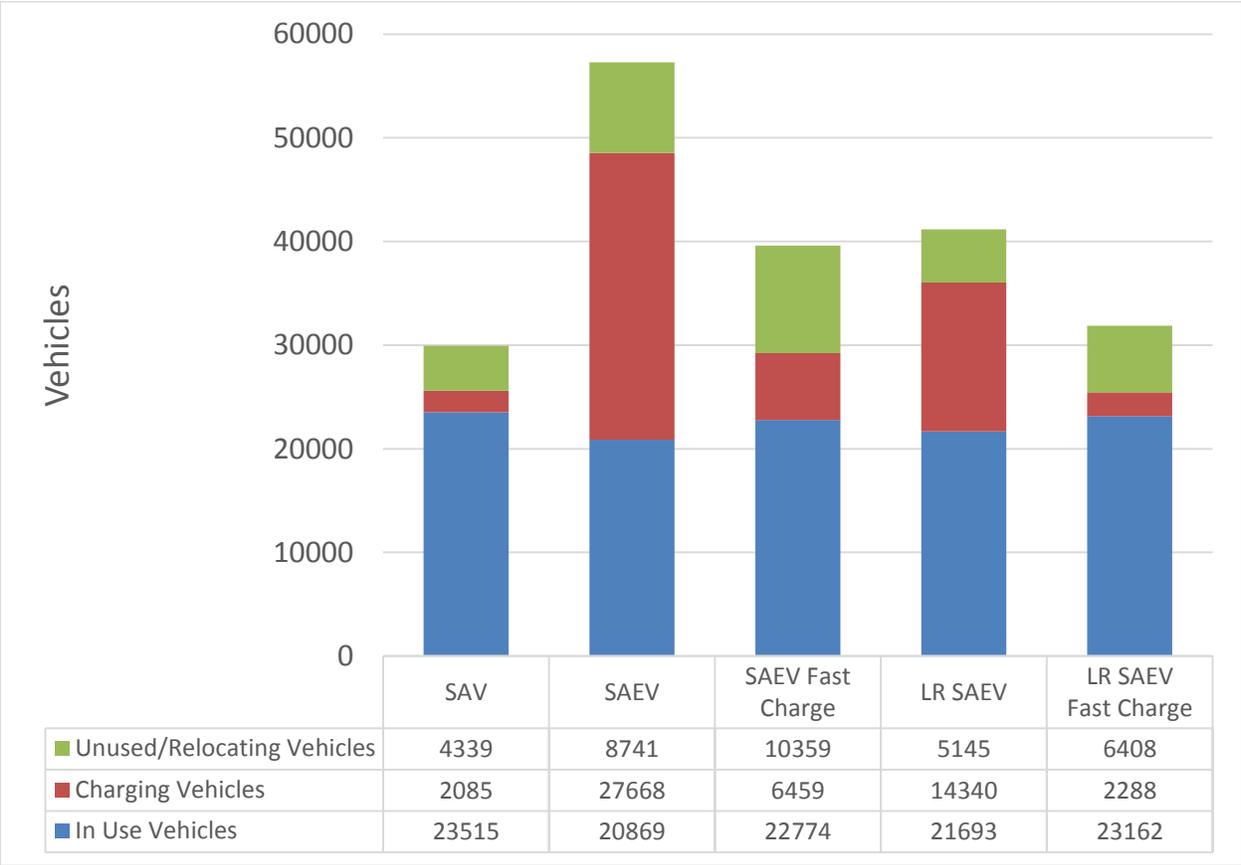
Scenario	SAV	SAEV	SAEV Fast Charge	LR SAEV	LR SAEV Fast Charge
Range (mi)	400	80	64	200	160
Refuel/Recharge Time (min)	15	240	30	240	30
# of Charging/Fueling Station Sites	1062	1562	1573	1555	1517
# of Chargers/Fuel Pumps*	2245	30,129	16,510	16,554	2389
Fleet Size	29,939	57,279	39,593	41,179	31,859
Avg Daily Miles per Vehicle	259	131	197	190	241
Avg Daily Trips per Vehicle	22.3	11.4	16.9	16.3	20.8
Private Veh Replacement Rate	7.32	3.73	5.53	5.33	6.82
% Trips Unserved	2.13%	3.94%	4.36%	2.29%	2.73%
Avg Trip Distance (mi)	10.1	9.41	9.08	10.0	10.0
Avg Wait Time Per Trip (min)	9.3	8.1	7.7	8.4	9.5
Avg Range Remain. at Recharge (mi)	1.6	43.1	40.7	5.4	2.5
% Total Unoccupied Travel Distance	6.6%	10.7%	14.0%	7.1%	7.1%
% Unoccupied Travel for Trips	5.2%	4.1%	3.0%	4.7%	4.9%
% Unoccupied Travel for Charging	0.3%	2.5%	5.0%	0.6%	0.7%
% Unoccupied Travel for Relocation	1.1%	4.1%	6.1%	1.9%	1.4%
Max % Concurrently Charging Vehicles	7.5%	52.6%	41.7%	40.2%	7.5%

260

*As proxied by the maximum number of concurrent charging/refueling vehicles in the day.

261 Simulation results show that the number of vehicles needed in a fleet is highly sensitive to charge
 262 time and, to a slightly lesser degree, vehicle range. Substituting Level III in place of Level II
 263 chargers for SAEV and LR SAEV fleets reduced the required fleet size by 30.9 and 23.3%,
 264 respectively. On the other hand, increasing the electric range of vehicles from 80 to 200 miles

265 reduced the fleet size by 28.1 and 19.5% respectively for Level II and Level III charging schemes.
 266 Combining these effects, the necessary fleet for the SAEV scenario is almost double the size of
 267 that for the LR SAEV Fast Charge scenario. Using 2009 NHTS rates for 3.02 private car trips per
 268 licensed U.S. driver and 0.99 household vehicles per licensed driver (Santos et al. 2011), the
 269 private vehicle replacement rate is highest at one shared vehicle for every 7.3 private vehicles in
 270 the SAV scenario, in line with the results from the mid-sized urban and suburban models in Burns
 271 et. al (2013) and the regional model in Fagnant and Kockelman (2015). However, once the fleet is
 272 electrified, the private vehicle replacement rate ranges from a comparable 1:6.8 vehicle ratio in the
 273 LR SAEV Fast Charge scenario to a much lower 1:3.7 vehicle ratio in the SAEV scenario. Non-
 274 electric SAV fleet requires the fewest number of vehicles (29,939) for full service, and the closest
 275 competitive EV scenario (LR SAEV Fast Charge) increases that fleet size by 6.6%, a slightly larger
 276 difference than estimated in ITF (2015) despite longer EV range assumption. As seen in Figure 3,
 277 a snap shot of each vehicle’s activity during the peak 5-minute period (defined as the time step
 278 with the most *in use* vehicles) demonstrates that with longer charging times and shorter ranges,
 279 vehicles are simply tied up at charging stations not able to service trip demand. While the number
 280 of *in use* vehicles is relatively consistent across all scenarios, the number of *charging* vehicles
 281 increases significantly with longer vehicle charge times and shorter electric range.
 282



283
 284 **Figure 3. Peak (5-Minute) Period Vehicle Use**

285 As seen in the results in Table 2, for full service, all EV scenarios produced similar numbers of
 286 charging station sites. This result suggests that the number of charging station sites (cells with

287 charging stations) necessary for full service has an inelastic relationship with the vehicle’s electric
288 range, but is more determined by the geography of the city (or size of the service geo-fence).
289 Conversely, the total number of chargers needed (as proxied by the average number of charging
290 vehicles in the time step with the most concurrent charging across 50 days) is highly sensitive to
291 charge time and vehicle range. Using Level III chargers cuts the charge time for SAEV and LR
292 SAEV fleets by 87.5%, and correspondingly, the number of needed chargers by 45.2 and 85.6%.
293 Holding charging infrastructure constant, substituting LR SAEVs for SAEVs in the fleet (and
294 increasing vehicle range by 150%), the number of chargers needed decreases 45.0 and 85.6%.
295 Generally speaking, high trip demand periods coincide with high charging activity periods.
296 Simulation results suggest that the LR SAEV Fast Charge scenario is best at spreading out charging
297 demand across the day, with a maximum of 7.46% of vehicles in the fleet concurrently charging
298 during any time step. On the other hand, in the base SAEV scenario, as many as 52.6% of the
299 vehicle fleet charge concurrently during the peak charge time period of the day (defined as the 5-
300 minute period with the largest percentage of charging vehicles).

301 Simulation results show that longer vehicle range translates into higher percentages of trips served,
302 as vehicles simply cannot serve trips longer than its maximum range. In the 2009 NHTS, 1.05%
303 of the trips are over 80 miles long. In the simulation results, the difference between trips served
304 between the 200-mile LR SAEV and the 80-mile SAEV is 1.65%. However, longer vehicle range
305 is generally associated with longer wait times in the simulation results, primarily due to the
306 inefficiency of serving trips originating in low-demand suburban and exurban areas a shared
307 setting. As seen in Table 2, longer-range vehicles spend more of their “empty” VMT for passenger
308 pick-up while shorter-range vehicles spend more of their “empty” VMT for relocation.

309 Each autonomous driving scenario produced an additional 7.1 to 14.0% of unoccupied VMT, in
310 line with estimates in ITF (2015) and Fagnant et al. (2015). As seen in Table 2, for vehicles with
311 longer range (SAVs and LR SAEVs), the greatest portion (65.6 to 78.4%) of that induced travel
312 can be attributed to unoccupied vehicles traveling to pick up passengers. Unoccupied travel to
313 charging/refueling stations played a relatively minor role in inducing additional VMT, summing
314 to 0.5 to 0.7% of total VMT (or 4.5 to 10.0% of “empty” miles traveled) for longer range vehicles,
315 as seen in Figure 4. Due to the more frequent need to recharge, induced miles traveled for
316 recharging is greater for scenarios with shorter range vehicles. SAEVs registered an additional 2.5
317 to 5.0% miles for charging activity, consisting of 23.6 to 35.4% of their total “empty” miles
318 traveled.

319 Not only do shorter range vehicles charge more frequently, simulation results in Table 2 also show
320 that they utilize a smaller percent of their range before a charging event. The phenomenon of
321 shorter-range vehicles recharging with higher baseline remaining range can be attributed to the
322 demand-based charging strategy employed here, where a vehicle is assigned to charging status
323 after rejecting a trip request due to insufficient range. With shorter ranges, the SAEVs are more
324 frequently assigned to charging status due to increased probability of having insufficient range for
325 trips. To explore whether charging less frequently would improve the fleet performance of the
326 shorter range SAEV scenarios, scenarios incorporating both demand- (trip rejection) and distance-
327 (maximum remaining range) based charging strategies were also run. Table 3 displays simulation
328 results where SAEVs are assigned to charging status after the vehicle has rejected a trip due to
329 insufficient range and met a maximum remaining range threshold. Results show that combining
330 demand-based charging with a 75% (60-mile) maximum remaining range criteria yielded the best

331 fleet performance metrics from a user perspective. Average wait times reduced to 7.37 minutes
 332 per trip and percent of trips unserved decreased to 1.70%, competitive with the SAV scenario
 333 results in Table 2. From the operator perspective, applying this charging strategy increases the
 334 necessary fleet size slightly (by 0.1%) and decreases induced travel by 12.7%. Increasingly
 335 stringent recharging distance criteria continually decreases induced VMT, primarily from
 336 reduction in relocation miles. However, as relocation miles decrease, induced miles to pick up
 337 travelers increase (and subsequently increases wait times), demonstrating the inherent tradeoffs
 338 between reducing extra VMT and enhancing user experience (as measured by wait times and
 339 percent of trips served). Scenarios with distance-only thresholds for charging were also examined,
 340 but those scenarios all yielded longer wait times than charging strategies that incorporated demand.

341 **Table 3. Demand- and Distanced-Based Charging (SAEV with Level II Charging)**

Charging Strategy:	Recharge Upon Trip Rejection, Max Remaining Range=80 mi	Recharge Upon Trip Rejection, Max Remaining Range=60 mi	Recharge Upon Trip Rejection, Max Remaining Range=40 mi	Recharge Upon Trip Rejection, Max Remaining Range=20 mi
Fleet Size	57,279	57,354	57,278	57,174
% Trips Unserved	3.9%	1.7%	3.0%	3.4%
Avg Wait Time (min)	8.1	7.4	8.2	8.5
Avg Range Remaining at Recharge (mi)	43.0	22.2	13.2	6.4
Avg Trip Distance (mi)	9.5	9.5	9.5	9.5
% Total New Induced Travel	10.7%	9.3%	9.1%	9.0%
% New Induced Travel for Charging	2.5%	3.3%	3.1%	3.1%
% New Induced Travel for Relocation	4.1%	1.9%	1.6%	1.5%
% New Induced Travel for Trips	4.1%	4.1%	4.4%	4.5%

342

343 **FINANCIAL ANALYSIS**

344 Simulation results offer some insight into how combinations of vehicles and charging
 345 infrastructure impact fleet operations, but a financial analysis is necessary to truly grasp the
 346 tradeoff between additional capital investment (into vehicles with bigger batteries or more
 347 expensive fast charging stations) and user benefits (measured in additional trips served or
 348 decreased wait times). For each vehicle and charging station type, analysis was conducted for three
 349 cost levels: low-, medium-, and high-cost scenarios, as shown in Table 4.

350 **Table 4. Vehicle & Charging Infrastructure Cost Assumptions**

	Low Cost	Mid Cost	High Cost
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Vehicle Capital			
SAEV (per vehicle)	\$35,000	\$40,000	\$55,000
LR SAEV (per vehicle)	\$45,000	\$50,000	\$80,000
Replacement battery (per kWh)	\$240	\$405	\$570
Vehicle Operations			
Maintenance (per mile)	\$0.055	\$0.061	\$0.066
Insurance & Registration (per vehicle-year)	\$1,280	\$1,600	\$1,920
Electricity (per kWh)	\$0.11	\$0.13	\$0.26
Charging Infrastructure			
Level II Charging (per charger)	\$8,000	\$12,000	\$18,000
Level II Annual Maintenance (per charger)	\$25	\$40	\$50
Level III Charging (per charger)	\$10,000	\$45,000	\$100,000
Level III Annual Maintenance (per charger)	\$1,000	\$1,500	\$2,000

351

352 For vehicle capital costs, the non-autonomous SAEVs are assumed to cost from \$25,000 (similar
353 to Mitsubishi i-Miev and Smart Fortwo Electric Drive BEVs) to \$45,000 per vehicle (approximate
354 retail cost of BMW i3 BEV), with a most likely price of \$30,000 (comparable to Nissan LEAF and
355 Ford Focus Electric BEVs). The non-autonomous LR SAEVs are assumed to cost between \$35,000
356 (projected price of the future 2017 Tesla Model 3 and Chevrolet Bolt) and \$70,000 (retail price for
357 the current model Tesla Model S), with a most likely price of \$40,000 per vehicle as critics believe
358 the projected pricing for LR BEVs is too optimistic (see, e.g. Anderman 2014). These vehicle costs
359 do not consider government rebates and incentives for EV purchases. AV technology is assumed
360 to add \$10,000 to the cost of each vehicle around the time AV technology first hits the commercial
361 market in 2025, per estimates from IHS (2014) and Schultz (2014). To convert vehicle capital
362 costs to a per-mile basis, each SAEV is assumed to be in operation for 231,000 miles before
363 replacement, equivalent to the average life span of a New York City taxicab (New York City Taxi
364 & Limousine Commission 2014). The battery is assumed to be replaced once during the SAEV's
365 service span (or per 115,500 miles), in line with most BEVs' 100,000-mile battery warranties and
366 evaluations of EV batteries (see, e.g., Knipe et al. 2003). Cost for replacement batteries (24 kWh
367 for SAEVs and 60 kWh for LR SAEVs) are assumed to cost between \$380 to \$570 per kWh, per
368 estimates from Plotkin and Singh (2009).

369 For vehicle operation costs, maintenance (including tires) is assumed to cost between 5.5 and 6.6
370 cents per mile, similar to non-autonomous vehicles (AAA 2014). Insurance and registration are
371 assumed to be on the order of two to three times the cost of privately owned vehicles, similar to
372 assumptions in Burns et al. (2013), which translates to \$1,280 to \$1,920 annually (AAA 2014).
373 Per-mile fuel costs assume electricity ranges 11 to 26 cents per kWh, with a mid-range cost of 13
374 cents per kWh, the US national residential electricity average (EIA 2015). The high cost scenario
375 allows flexibility in accommodating future variable priced electricity, a growing possibility with
376 the introduction of smart metering technology.

377 For charging infrastructure, Level II chargers are assumed to cost between \$8,000 and \$18,000
378 each, including costs for installation, hardware, materials, labor, and administration (Chang et al.
379 2012, USDOE 2012). Annual maintenance cost for Level II chargers are assumed to be minimal

380 at \$25 to \$50 per year (USDOE 2012). Level III chargers are assumed to range from \$10,000 to
 381 \$100,000, with average cost at \$45,000 per station (USDOE 2012, New York City Taxi &
 382 Limousine Commission 2013). This cost includes installation, hardware, materials, labor,
 383 administration, and transformer upgrades. Annual maintenance cost for Level III chargers are
 384 assumed to range from \$1000 to \$2000 (New York City Taxi & Limousine Commission 2013).
 385 To convert charging infrastructure to a per-mile basis, the service life span of charging stations is
 386 assumed to be 10 years (Chang et al. 2012). Table 5 breaks down the cost per occupied mile of
 387 travel (costs are incurred for total miles of travel but allocated to each occupied mile of travel) for
 388 each vehicle and charging infrastructure combination in the mid-cost scenario.

389 **Table 5. Equivalent Cost Per Occupied Mile Traveled (Mid-Cost Scenario)**

	SAEV	SAEV Fast Charge	LR SAEV	LR SAEV Fast Charge
Vehicle & Battery	\$0.249	\$0.250	\$0.346	\$0.346
Vehicle Maintenance	\$0.071	\$0.071	\$0.066	\$0.066
Insurance & Registration	\$0.038	\$0.026	\$0.025	\$0.020
Electricity	\$0.045	\$0.045	\$0.042	\$0.042
Charging Station Capital	\$0.015	\$0.030	\$0.007	\$0.004
Charging Station Maintenance	\$0.000	\$0.010	\$0.000	\$0.001
TOTAL	\$0.417	\$0.433	\$0.486	\$0.479

390
 391 Under the most likely mid-cost scenario, a fleet of SAEVs or LR SAEVs can be operated at an
 392 equivalent per-occupied-mile-traveled cost of \$0.42 to \$0.49. The most uncertain component of
 393 this operating cost estimate is the AV technology. While \$10,000 per vehicle is assumed in the
 394 base results in Table 5, the range of cost estimates of market-ready AV technology is large. Various
 395 sources report the cost of the retrofitted AV technology on current Google self-driving cars to
 396 range from \$75,000 to \$250,000 (Rogers 2015, Tannert 2014). Once the technology is mature, IHS
 397 (2014) estimates AV technology will cost between \$3500 to \$5000 per vehicle after 5 to 10 years
 398 on the market. Incorporating the Table 4's mid-cost figures for all other cost components, SAEV
 399 operation costs range from \$0.392 per mile when AV technology costs are \$5000 per vehicle to
 400 \$0.867 per mile when AV technology costs are \$100,000 per vehicle.

401
 402 Using APTA (2013) statistics, for a transit system that serves 2.4 billion annual passenger-miles,
 403 general administration expenses (including facilities and salaries) add approximately \$0.184 to
 404 per-mile operational costs. Assuming operating margins of 10% (similar to the transportation
 405 industry average) and using mid-cost estimates from Table 4, SAEV service can be offered at
 406 roughly \$0.66 to \$0.74 per occupied mile of travel. These costs are on the low end of current
 407 manually-driven free-float carsharing services such as Car2Go, which charges roughly \$0.70 to
 408 \$1.23 per mile in Austin, Texas (assuming trips are between 2 to 10 miles and travel speeds are
 409 between 15 to 35 mph). Under this pricing assumption, SAEV users would pay roughly 21 to 49%
 410 of what is currently charged by transportation network companies like Uber and Lyft (whose
 411 equivalent per-mile pricing is \$1.50 to \$3.18 in Austin). In fact, these costs are competitive with
 412 AAA (2014) estimates of average costs of private vehicle ownership, which ranges from \$0.40 to
 413 \$0.95 cents per mile depending on annual mileage and vehicle type, suggesting that availability of

414 a SAEV fleet can have significant impacts on private vehicle use (and ownership), particularly for
415 low-mileage households.

416 Cost estimates in Table 5 are derived from fleet size and induced VMT estimates with a demand-
417 based charging strategy with no maximum range restriction (Table 2). Adding a 75% maximum
418 range restriction (Table 3) on the SAEV base scenario reduces the cost by \$0.020 per mile, yielding
419 the most cost efficient scenario at \$0.397 per mile. It is worth noting that cost estimates are based
420 on traditional, wired charging infrastructure. Currently, a residential Level II wireless (inductive)
421 charger can deliver similar charge times as traditional corded units while costing approximately
422 \$2500 more per unit (Evatran n.d.). This translates to a minimal \$0.002 to \$0.003 increase in
423 equivalent per-mile costs for the SAEV fleets modeled here. Level III inductive chargers are not
424 currently commercially available. If wireless charging is not available for the SAEV fleets, an
425 alternative would be to install traditional corded charging infrastructure and hire charging station
426 attendants at each of the 1500 some odd charging station sites. Assuming one \$15-per-hour-wage
427 attendant per charging station site, per-occupied-mile-traveled costs in Table 5 would increase
428 \$0.077 to \$0.085.

429 While these per-mile costs are lower than current carsharing services and competitive with private
430 car ownership, their ability to compete with a fleet of non-electric SAVs depends on the availability
431 of wireless recharging infrastructure and government tax incentives on EV purchase prices.
432 Assuming SAVs utilize existing gasoline stations with no additional infrastructure investment, a
433 fleet of SAVs can be operated for \$0.400 per mile with a 231,000-mile vehicle life span, \$30,000
434 per SAV purchase cost (\$20,000 for vehicle, \$10,000 for AV technology), 30 mpg fuel economy,
435 \$3.50 per gallon gasoline price, \$15 per hour wage per service attendant per gasoline station, and
436 the same AAA-based costs for maintenance, insurance, and registration prescribed to SAEVs. Of
437 course, this per-mile cost is highly sensitive to gasoline prices. With EVs purchased at full price,
438 SAEVs with wireless recharging are competitive with SAVs on a per mile basis when gasoline is
439 at \$3.50 per gallon. With current federal tax incentives of \$7500 per EV, SAEVs become price-
440 competitive with SAVs when gasoline is at \$2.50 per gallon. Without wireless recharging
441 infrastructure (and using station attendants at charging sites), SAEVs purchased with the \$7500
442 federal tax rebate are not price-competitive with SAVs until gasoline reaches \$4.69 per gallon.
443 Without the federal rebate, this increases to \$5.70 per gallon.

444 **AUSTIN, TEXAS CASE STUDY**

445 While the Poisson-based trip generation process modeled in the simulated monocentric city
446 provides some variation in each cell's trip generation rate, actual trip rates in real-city geographies
447 are significantly less "smooth." In exurban areas, an overall low population density is often
448 reflected by pockets of relatively dense residential development among much larger areas of very
449 sparse population. To offer more realism here, a case study using Austinites' year-2010 trip
450 patterns with U.S. departure time choices (varying every 5 minutes) was performed. The 5-county
451 region's 1413 traffic analysis zones (TAZs) and personal trip tables (by origin versus destination
452 zone) were used to appreciate the effects of real-world (spatially and demographically
453 heterogeneous) trip-making behaviors.

454 Austin's 1413 TAZs were mapped onto the 400-cell by 400-cell gridded region with each TAZ's
455 trip ends assigned to one quarter-mile by quarter-mile cells. The TAZ closest to the geographic

456 centroid of the Austin region (as determined by the mid-point value of all TAZ centroids' longitude
 457 and latitude coordinates) was identified as the simulated region's center (cell [200, 200]). Then,
 458 each of the remaining 1412 TAZs corresponded to a cell in the simulated region by indexing the
 459 TAZ centroids' latitude and longitude coordinates relative to the city center. This process creates
 460 a "spiky" trip generation pattern, where only 1413 out of the 160,000 cells (less than 0.9%) in the
 461 simulated region served as trip origins and destinations, rather than permitting every cell to
 462 generate (and attract trips). In reality, the 1413 TAZs in the 5-county region span across 3918
 463 square miles, or 39.2% of the 100-mile by 100-mile simulated region. The charging strategy of
 464 trip rejection plus a maximum 75% remaining range was employed here, since this strategy
 465 improved fleet performance metrics (in Table 3), as compared to a charging strategy based solely
 466 on trip rejection.

467 Table 6 shows scenario results from the Austin case study. Despite the significantly more
 468 concentrated (spatial and temporal) patterns of trip generation in these Austin data, the average
 469 daily miles per vehicle are very close to Table 2's results, which used much smoother, simulated-
 470 trip generation rates. However, because the average trip distance (across all ground modes, not just
 471 those by automobile, as used earlier in this paper) in the Austin case study is only 5 miles (as
 472 opposed to the 9 to 10 mile average trip distances in Table 2's NHTS-based results, which exclude
 473 all non-auto trips and all trips under 1 mile in distance), the daily trips per vehicle (and
 474 corresponding private vehicle replacement rates) are higher. SAEVs with Level II charging
 475 infrastructure are estimated to replace 5 private vehicles in this Austin scenario, while LR SAEVs
 476 with Level III charging infrastructure replace 9 private vehicles. Intrazonal trips are modeled as
 477 zero distance trips here, and are thus excluded from the model. This is an important result: working
 478 with trips that average almost twice as long (using the NHTS trips, which can end far outside the
 479 origin region, unlike MPO-based trip tables which end at the boundary of a region) keeps the
 480 vehicles almost twice as "busy", resulting in roughly 50 percent higher vehicle replacement rates.

481 **Table 6. Fleet Performance Metrics from Austin Case Study Scenario**

Austin Scenario	SAV	SAEV	SAEV Fast Charge	LR SAEV	LR SAEV Fast Charge
Range (mi)	400	80	64	200	160
Refuel/Recharge Time (min)	15	240	30	240	30
# of Charging/Fueling Station Sites	21	25	26	23	25
# of Chargers/Fuel Pumps*	1053	16,334	9889	8852	1080
Fleet Size	14,802	26,758	16,772	21,859	14,750
Avg Daily Miles per Vehicle	253	137	216	171	253
Avg Daily Trips per Vehicle	27.4	15.2	24.2	18.6	27.5
Vehicle Replacement Rate	8.98	5.00	7.95	6.09	9.02
% Trips Unserved	0.52%	0.44%	0.25%	0.48%	0.41%
Avg Trip Distance (mi)	5.15	5.13	5.14	5.14	5.15
Avg Wait Time Per Trip (min)	3.49	2.86	3.01	3.15	3.25
% Total Unoccupied Travel Distance	3.15%	4.03%	4.19%	3.25%	3.38%
Max % Concurrent Charging Vehicles	7.11%	61.04%	58.96%	40.50%	7.32%

482 *As proxied by the maximum number of concurrent charging/refueling vehicles in the day.

483

484 While the Austin trips cannot go past the 5-county regional edge or border, trips under 1 mile are
485 included here (as long as their origin and destination zones differ). Restricting trip origins and
486 destinations to less than 1 percent of the 100-mile by 100-mile region means higher concentrations
487 of SAEVs in select, trip-active cells, which reduces the number of unserved trips (to less than 1%
488 across all Austin scenarios), average wait times (to between 2 and 4 minutes), and “empty” VMT
489 (to between 3.1 to 4.2%). Those results are partly due to vehicles needing to travel less for next-
490 passenger pickup, due to the heavy concentrations of trip origins and destinations.

491 Restricting all trips to travel between these 1413 cells also drastically reduces the number of
492 charging station sites necessary, from 1500 some charging sites down to just 23 to 25 cells with
493 charging stations. These charging station sites are estimated to have as many as 653 charging pads
494 per station in the 80-mile SAEV with Level II infrastructure scenario, down to 43 charging pads
495 per station in the LR SAEV with Level III infrastructure scenario (in order to meet the charging
496 demand of the 5-minute period with the highest number of concurrently charging vehicles per day),
497 and their locations represent just 1.8% of the 1413 trip-active cells, or just 0.0002% of the 100-
498 mile by 100-mile region’s 160,000 cells. The total number of actual chargers (charging spaces)
499 needed are approximately 50% of what was simulated in the NHTS-based trip generation
500 simulation. Such results underscore the fact that charging station locations are a function of both
501 the geography of the service geo-fence and travelers’ trip-making patterns.

502 Finally, a financial analysis of the Austin SAEV scenarios yields operating costs of \$0.386 to
503 \$0.472 per occupied-mile traveled, with the 80-mile range SAEVs and Level II charging
504 infrastructure scenario providing the lowest operating costs, which is consistent with findings from
505 the simulated-region’s scenarios (as shown in Table 5).

506 CONCLUSIONS

507 Motivated by natural synergies between autonomous driving technology and EVs in a shared
508 setting, this paper employs an agent-based model to simulate the operations of a fleet of SAEVs
509 serving 10% of all trip demand in a medium-sized metropolitan area under various vehicle and
510 infrastructure scenarios. Simulation results show that fleet size is highly dependent on charging
511 infrastructure and vehicle range. For the non-electric SAV scenario, each shared vehicle can
512 replace 7.3 private vehicles. For a fleet of 80-mile range SAEVs with a 4 hour full recharge time,
513 this replacement rate drops to one shared vehicle for every 3.7 private vehicles, since more than
514 half of the fleet is tied up in charging activities during any time period. Simulation results also
515 suggest these shared fleets can serve 95.6 to 97.9% of all trips with average wait times between 7
516 and 10 minutes per trip, while producing an additional 7 to 14% of “empty” VMT for traveling to
517 passengers, strategic repositioning, and accessing charging stations. While this induced travel can
518 be reduced slightly with strategic charging, model results also reveal the inherent tradeoffs
519 between reduction of induced “empty” travel and improvement of user experience (as measured
520 by wait times and percent of trips served). These tradeoffs highlight the need for a dynamic pricing
521 scheme for SAEVs which penalizes trips that incur more relocation miles (and thereby increase
522 subsequent trip wait times) and incentivize trips that coincide with strategic relocation (and thereby
523 decrease subsequent trip wait times). A case study using Austin, Texas trip patterns also was used
524 here, to examine the impact of higher concentrations of trips across fewer zones on the service

525 metrics of the SAEV fleet. With more concentrated trip demand, SAEVs traveled similar daily
526 miles, but were able to serve a larger share of trips (over 99%) with shorter average wait times,
527 ranging from just 2 to 4 minutes. In the Austin case study, “empty” vehicle-miles constitute only
528 3 to 4 percent of all SAEV travel, and each SAEV could replace 5 to 9 privately owned vehicles,
529 due to somewhat shorter trip distances, as compared to the original simulation.

530 Financial analysis reveals that despite requiring the largest fleet and the most charging stations,
531 the base 80-mile range SAEV fleet with Level II charging stations is the cheapest to operate on a
532 per-mile basis of all the EV scenarios. This is primarily due to the high sensitivity of per-mile
533 operating costs to vehicle purchase price (with SAEVs assumed to cost \$10,000 less per vehicle
534 compared to LR SAEVs in the mid-cost scenarios). While SAEVs with Level II charging
535 infrastructure is cost effective, the scenario is ineffective in spreading out charge demand, with as
536 much as 53% of the fleet concurrently charging during the peak charging period of the day. If
537 SAEVs become a widely adopted mode, this type of fleet can create significant demand on the
538 electric grid and necessitate large parking areas (stations) while charging during peak hours. LR
539 SAEVs with Level III fast charging infrastructure, while costing 14.9% more per mile compared
540 to SAEVs with Level II charging stations, is very effective at demand spreading, with only 7.6%
541 of the fleet concurrently charging during the peak charging period.

542 Financial analysis reveals that under the most likely scenario, a fleet of SAEVs can be operated at
543 \$0.41 to \$0.47 per occupied mile traveled. The competitiveness of SAEVs compared to non-
544 electric SAVs hinges almost singly on the availability of automated wireless charging. With
545 wireless automated charging, SAEVs can be price-competitive with SAVs when gasoline is priced
546 at \$3.50 per gallon or less. But with attendant serviced charging, SAEVs are only price competitive
547 with SAVs when gasoline reaches \$4.35 to \$5.70 per gallon.

548 The agent-based model presented here has limitations that merit improvement in future
549 applications of this type. First, the charging-station generation process mimics the objective of a
550 coverage model (see, e.g., Toregas et al., 1971), thereby ensuring full coverage of all charging
551 demand, but it does not consider budgetary constraints and allows for an unlimited number of
552 charging stations. Additionally, the scenarios modeled here assume that SAEVs will serve 10% of
553 a region’s trip demand and that the temporal and spatial distributions of SAEV trips are the same
554 as the region’s overall trip-making patterns. In reality, an SAEV’s fleet metrics should be sensitive
555 to trip demand density, over space and time. Additionally, SAEV mode may be more attractive to
556 specific types of trips, rather than be equally appealing for all trips. Chen and Kockelman (2016)
557 explores pricing and operations of a SAEV fleet when competing against other modes (privately-
558 owned manually-driven cars and city bus service) and find that with higher SAEV shares, fleet
559 performance improves. When SAEV mode shares lies between 14 and 39% (as predicted in the
560 study), private vehicle replacement rates increase to one SAEV for every 10 to 26 vehicles with
561 “empty” VMT constituting 7 to 9 percent of all SAEV travel. That is to say, trips that are more
562 efficiently served by SAEVs are more likely to choose the SAEV mode, which in turn also
563 contributes to improved fleet performance metrics.

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