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# Impact of ridesharing on operational efficiency of shared autonomous electric vehicle fleet

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## 1. Introduction

The convergence of self-driving and electric vehicle technology holds great promise for transforming urban land use (in an on-demand carsharing platform with decreased parking infrastructure) and alleviating congestion (in a ridesharing platform with increased vehicle occupancy). Carsharing provides access to automobiles without incurring capital and maintenance expenses associated with vehicle ownership. For low-mileage travelers, carsharing provides a lower-cost alternative to owning a private vehicle but provides more flexibility than transit service. However, carsharing operations are likely to induce imbalances in the spatial and temporal vehicle distribution that requires relocation operations to maximize vehicle availability (Jorge et al., 2014). Hence, the management of such operations becomes complicated due to demand characteristics, imbalance issues, operational constraints, and the need to maximize the use of carsharing systems (Repoux et al., 2015). An effective relocation strategy is an essential component for sustainable carsharing operations (Bruglieri et al., 2014; Kek et al., 2006), which can be implemented without significant driver labor costs once self-driving technology is introduced to the vehicle fleet. Simultaneously, with location information available via smart phones, ridesharing systems have received increased attention given their mobility and environmental benefits. The goal of these systems is to match travelers with similar itineraries to available vehicles, thereby reducing the number of vehicles required to meet the travel demand. Ridesharing services, such as UberPOOL and Lyft Line, have shown great potential in improving mobility services in terms of accessibility and sustainability. With the average occupancy rate per vehicle-mile at 1.63 for all trips in the United States (Santos et al., 2011), increasing vehicle occupancy through ridesharing can also be considered an effective strategy to manage urban traffic congestion. Integrating the carsharing mode with ridesharing holds great potential to decrease private vehicle ownership, vehicle miles traveled (VMT), urban greenhouse gas emissions, and energy use. However, current macroscopic transportation planning models lack the ability to properly incorporate emerging transportation modes (e.g., carsharing and ridesharing services). In this paper, a stand-alone agent-based simulation model is used to evaluate a fleet of shared autonomous electric vehicles (SAEVs) with ridesharing. First, the literature review synthesizes existing work in areas of ridesharing matching and shared autonomous fleet operations. Then, a three step methodology is presented to analyze the ridesharing potential of SAEVs, taking into consideration vehicle type and charging infrastructure characteristics. A subsequent case study, based on the population density patterns of Austin,

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Texas, is presented and analyzed to reveal impacts of vehicle and charging infrastructure type on fleet service metrics and operational costs. Finally, broad conclusions from the analytical framework and case study results are presented, along with limitations of the study.

## 2. Literature review

This section overviews two bodies of previous research relevant to this work: ridesharing matching and operations of shared automated fleets. In the context of assessing ridesharing opportunities, much of the prior literature focuses on taxi services. Ma et al. (2015) proposed a real-time taxi-sharing model to measure the efficiency of a conventionally fueled non-autonomous taxi ride sharing service in Beijing by using pick-up and drop-off points determined through GPS trajectories of 33,000 taxis over a period 87 days. The goal is to minimize the increase in travel distance associated with each taxi, while satisfying travel requests. However, this approach does not guarantee that the system-wide vehicle miles traveled (VMT) would minimized. The developed simulator showed that ridesharing could potentially increase the number of travelers served by three times as compared to a ride-hailing service while saving 11% in total VMT given a study area of 1280 $km^2$. Alonso-Mora et al. (2017) simulated a fleet of taxis in New York and demonstrated that a vehicle fleet of capacity equivalent to 10 and 4 passengers will require 2000 and 3000 vehicles to serve 98% of New York taxi demand, respectively. The average wait time and trip delay was estimated to be 2.8 min and 3.5 min, respectively. A recent work by Santi et al. (2014) quantifies the benefits of taxi-sharing using taxi ride GPS dataset in New York City. It was observed that a 5-min arrival time window, over 90% of sharing opportunities can be exploited with 32% travel time savings. Other studies examining ridesharing opportunities extend beyond taxi fleets to look at commute trips or overall travel within a region. Agatz et al. (2011) proposed an optimization model to match riders and drivers based on data from the Atlanta regional travel demand model, and demonstrated a matching rate of 70% with low participation rate and time flexibility of 2% and 20 min, respectively. Similarly, a discrete event, pickup and delivery model was proposed to optimally match riders and drivers with a matching rate of 85% in Italy (Di Febbraro et al., 2013). In another study (Cici et al., 2014), smart-phone data and social network data were used to estimate the benefits of ridesharing on the daily home-work commute. This type of data are easier to collect than GPS traces, and considered to have a higher penetration to provide an adequate sample of citywide travel patterns. The benefits of meeting points in ridesharing systems are explored in a study by Stiglic et al. (2015), and it was demonstrated that this increased flexibility results in additional feasible matches between drivers and riders. For a meeting point within a certain distance from true origin or destination, a vehicle is matched with multiple riders without increasing the number of stops it needs to make. Alexander and Gonzalez (2015) explore the impact of rideshare adoption on congestion using smart-phone data in Boston. However, the study follows an aggregate modeling approach, and tries to determine static long-term definitive travel patterns without considering dynamic fluctuations.

Another body of relevant research focuses on the operations of shared autonomous vehicles, with and without ridesharing. Fagnant and Kockelman (2015) proposed a discrete-time agent-based model to simulate shared autonomous vehicles (SAVs) using trip data from Austin's regional travel demand model in Texas. The results from the study suggest that dynamic ridesharing greatly reduce wait times from 9.0 min to 4.5 min during the heaviest peak hour given the total number of trips to be 56,324. This model restricted ridesharing to instances where adding a partner would not increase travel time of existing riders by more than 40%. The percentage of shared trips in this instance came out to be 20.8% of total trips. Zhang et al. (2015) also simulated SAVs with dynamic ridesharing, within a limited 10 mile by 10 mile grid based city at a one minute time step interval. The paper assumes a 50% willingness to share rides, and found that only 6.7% of vehicle-trips were shared. However, despite the low sharing rates, dynamic ridesharing shortens the average delay per trip up to 37% during peak hours, providing faster and more reliable rides than a fleet without ridesharing. Martinez and Viegas (2017) presented a study to evaluate the impacts of automated shared taxis with ride-sharing in Lisbon, Portugal. The authors developed an agent-based simulation model to simulate 1.2 million trips and scenarios reflecting a situation where private car, taxi and bus trips are replaced by automated taxis. The study indicates a decrease in cost by 55%, highly increased transportation accessibility in the city, and carbon emission reductions of almost 40%. Brownell and Kornhauser (2014) evaluated the necessary autonomous vehicle fleet size for personal rapid transit, and smart paratransit. The model predicts a fleet size of 1.6 to 2.8 million six-passenger vehicles to serve state-wide demand in New Jersey. The models did not account for rebalancing, but they do estimate upper and lower bounds of the fleet size. Ma et al. (2017) proposed a computationally efficient linear programming model to solve the SAV Pickup and Delivery Problem with Time Windows (PDPTW) using space-time network to optimize operations. The case study shows that allowing travelers to request vehicles in advance (via a reservation system) can significantly increase vehicle use rate, leading to a vehicle replacement rate of one shared autonomous vehicle per 13 private vehicles. Ridesharing is not accounted for in this study.

These previous shared autonomous vehicle studies either assume gasoline powered vehicles or do not explicitly consider vehicle refueling, thus ignoring the impact of electric vehicle range on fleet operations and the charging infrastructure needs associated with such fleets. In terms of accounting for electric vehicle technology, Scheltes and Correia (2017) developed a model to simulate automated last mile connection services using electric vehicle technology. The study showed the proposed system was only able to compete with walking mode, in terms of total travel time on the last mile, unless the speed of vehicles is increased and pre-booking is allowed. However, the model does not allow ridesharing, and is implemented on a small scale to only serve trips to and from a transit station. The variation in vehicle capacity and charging configuration, and their impact on the performance of such a system is not studied. Loeb et al. (2018) proposed a model simulating performance characteristics of SAEV fleets that focuses on charging station and charging time requirements, using realistic vehicle speeds, allowing flexible charging strategies, and requiring all demand for trips under 47 miles to be met. The study concluded that reducing charge times lowers fleet response times, however fleet size increase offers significant improvement in response times in Austin, Texas. Similarly, increasing vehicle range beyond 109 miles has