Estimating Shared Autonomous Vehicle Fleet Size to Meet Urban Daily Travel Demand

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Abstract. Shared autonomous vehicles (SAVs) present the possibility of greatly reducing the number of cars in use, and consequently the required parking space. We present a methodology to estimate the required SAV fleet size to meet travel demand for a region, and develop a detailed synthetic population model where we model every individual in a city, along with typical weekday activity patterns to estimate the travel demand. We combine this with a simulation of SAV routing to determine the fleet size needed to satisfy all trips with small waiting times. Our results show significant reductions in both the number of vehicles on roads and parking demand in cities, which would result in substantial savings.

Keywords: Shared autonomous vehicles · synthetic populations · multiagent simulation · transportation · traffic

1 Introduction

Urban spaces and lifestyles are expected to be radically transformed in the near future with the availability and increasing use of Autonomous Vehicles (AVs). This will reduce congestion and increase safety, and potentially change travel behavior by reducing the need for vehicle ownership and promoting ride sharing. The benefits of AVs are expected to be more significant once the technology is combined with the shared economy. Shared Autonomous Vehicles (SAVs) are an envisioned new door-to-door mobility service, which is expected to be more affordable \cite{5}, reliable \cite{7} and environmentally friendly \cite{8} than conventional vehicles and privately-owned AVs.

Therefore, in the present work, we focus specifically on the possibility of using a fleet of shared autonomous vehicles to serve the entire daily travel demand of a region. We use the city of Richmond, VA, USA as a case study, though our methodology is broadly applicable. We develop a system that combines a detailed discrete event simulation methodology for modeling the use of shared autonomous vehicles with a data-driven synthetic population model of Richmond where every person is represented along with typical weekday activity patterns.
The simulation allows us to come up with a realistic estimate of the size of the fleet required as well as the parking demand for the SAV fleet.

2 Shared autonomous vehicle management

We used an agent-based SAV model, which we call the SAV management model, to estimate SAV fleet size and curbside parking footprint for the city of Richmond. The model inputs include (1) synthetic trips, with origin, destination and departure time, and (2) Origin-Destination (OD) travel time matrix. The synthetic trips and travel time matrix are obtained using the synthetic population model and routing algorithm discussed in the next section. The design of the SAV model is elaborated below.

There are three types of entities in the simulation model: (1) client entity, (2) vehicle entity, and (3) queue entity. Clients generate call events, once they decide to move from one place to another. When handling the call events, the SAV system will assign empty vehicle entities within a 2-mile travel distance to fulfill the trip, which leads to pick up and drop off events. After dropping off the last client entity, if the vehicle entity is not assigned for other services, the system will initiate a relocating event to determine whether the vehicle is in an SAV surplus area and needs to relocate to under-served areas. The vehicle will eventually park if it is in an under-served area and is not assigned to service. The simulation starts with no vehicles in the system and keeps adding vehicles into the system once the client has waited for more than 10 minutes. This allows us to estimate the number of vehicles needed to satisfy the travel demand with a maximum waiting time of 10 minutes (or any other chosen threshold).

3 Travel Demand and Routing

We use a detailed, data-driven modeling approach to generate the estimated travel demand for the city of Richmond, VA, known as a synthetic population model [1]. The steps in this process are:

- **Baseline population synthesis**: We begin by creating a set of disaggregated agents with multiple demographic variables attached to them, using the methodology of Beckman et al. [4]. The demographic data are drawn from the 2015 American Community Survey (ACS) for the state of Virginia.
- **Activity assignment**: In this step we use data from the National Household Travel Survey (NHTS)\(^4\) to assign a daily activity sequence to each agent in the synthetic population constructed in the previous step [9].
- **Location choice**: In this step we assign a location for each activity for each agent. Road network data are used to create home locations. Locations for other activities are then assigned using business and school location data, using a gravity model.

\(^4\) [http://nhts.ornl.gov/](http://nhts.ornl.gov/)
Routing

For the routing work described in this paper, we used a regular-expression constrained variant of the Dijkstra’s shortest path algorithm developed in [3] with optimization and parallelization implemented in [2].

Network description. The transportation network covered the Richmond Urban Area and was extracted from the HERE StreetMap Premium data set for the U.S., version 2017 (Q2).

Routing. The study included over 2.8 million trip requests, extracted from the synthetic population. The computations were split onto 360 cores on a computational cluster, finishing in roughly 22 compute days.

Figure 1 shows the distribution of travel distances and the distribution of travel times. For the purpose of visualization, travel distances are rounded to the nearest tenth of a kilometer and travel times are rounded to the nearest minute. Both distributions have exponential tails, as shown by the log-linear insets. Our travel demand does not include long-distance travel, since this is not assumed to be serviced by the city’s SAV fleet.

4 Results

We applied the models to the City of Richmond, Virginia, USA. The SAV model was implemented with SAV market penetration rates of 1%, 10%, and 100% to explore the impact of market size on the fleet requirement and correspondingly the parking footprint. The results are tabulated in Table 1. The results suggest that the larger the market size, the more efficient the SAV system, as the number of trips served per SAV increases from 19 trips per SAV per day in the 1% market penetration scenario to 22 trips per SAV per day in the 100% scenario. Additionally, the results show that the parking demand is linearly correlated with the number of SAVs in the system. Despite the fleet size of the system, the parking demand is, on average, approximately 5-6 spaces per SAV running in the system.

The vehicle replacement rate of the SAV system is approximately 5.4. The Richmond synthetic population includes a total of 370,130 households and 671,165
adults, who generate 2.9 million trip requests on a daily basis. In the U.S., the average vehicle ownership per adult is approximately 0.99 [10]. The metropolitan area of Richmond approximately owns 664,453 private vehicles. Our results show that 169,882 vehicles are sufficient to serve the region to ensure that all clients can be picked up within the 10-minute waiting window. In other words, the replacement ratio is approximately 5.4 (i.e., 664453/126710).

The parking demand in the study area also declines dramatically after the introduction of SAVs. In the U.S., approximately four parking spaces are needed to accommodate the parking demand of one privately owned vehicle [6]. Therefore, at the 100% market penetration level, the SAV system holds the potential to reduce over 85% of the existing parking spaces. The reduction in parking space would translate into significant savings in city expenditures.

Acknowledgments: HSM and SS were supported in part by DTRA CNIMS Fund HDTRA1-17-0118 and NSF Grant CNS-1737492.

References