The impact of on-demand service schemes provided by a fleet of shared autonomous vehicles

Wang, Senlei; Homem de Almeida Correia, Goncalo; Lin, Hai Xiang

Publication date
2018

Document Version
Final published version

Published in
hEART 2018: 7th Symposium of the European Association for Research in Transportation, 5-7 September, Athens, Greece

Citation (APA)
Wang, S., Homem de Almeida Correia, G., & Lin, H. X. (2018). The impact of on-demand service schemes provided by a fleet of shared autonomous vehicles. In *hEART 2018: 7th Symposium of the European Association for Research in Transportation, 5-7 September, Athens, Greece* (pp. 1-8)

The impact of on-demand service schemes provided by a fleet of shared autonomous vehicles

Senlei Wang[1], Gonçalo Correia[2], and Hai xiang Lin[1]

[1]Delft Institute of Applied mathematics, Delft University of Technology

[2]Department of Transport and Planning, Delft University of Technology

March 28, 2018

Abstract

The introduction of the concept of a fleet of shared autonomous vehicle (SAVs) which function as a centralized taxi service system presents an innovative way in transport modes. A fleet of SAVs can provide tailored on-demand services via a centralized operation to serve travel demand over time. In our study, An agent-based model (ABM) is developed to simulate tailored time-varying service (TVS) provided by a fleet of SAVs in a demand-responsive fashion. The proposed system can switch the service scheme between the door-to-door service (DDS) and station-to-station service (SSS) automatically based on the time of day; In peak hours, the SAV system aims to serve as many trips as possible with predesignated stations as a SSS by providing an on-demand service. In off-peak hours, a DDS in a demand-responsive fashion is provided by a fleet of SAVs which can benefit the travelers with great convenience. Also, DDS and SSS provided by SAVs in a demand responsive fashion are simulated separately. The potential benefits of TVS provided by SAVs are investigated and then compare it with DDS and SSS. The simulation results indicate that the tailored TVS can increase the utilization of SAVs by 2.5% and number of passengers transported per days by 2.9%. Compared with DDS in peak hours, there are reductions of averaging waiting time and energy consumption up to 25.5 % and 3.7% respectively. In off-peak hour, the TVS can be easily employed to eliminate the avearge 9-minute walking time of the SSS. In addition, we find out that there is a significant increase of trips by empty SAVs at around 82% for all service schemes. It is an important issue for further investigation.

Keywords : Shared autonomous vehicles; on-demand service; quality of service; agent-based model

1 Introduction and Background

We are now at the dawn of the next revolution with the introduction of automated driving vehicles. There are aspects of the automated cars that still need to be refined, and there are many legal, regulatory and technical problem that delay the deployment of autonomous vehicles (AVs). The real potential of AVs is that it makes possible the implementation of an entirely new transportation system. In other words, AVs will have the power to fundamentally transform transportation mobility and revolutionize the transport system (Krueger et al., 2016; Zakharenko, 2016). Since AVs seems to improve road safety, reduce the fatal accidents, improve the operational efficiency of roads with higher speeds and increased capacity, and reduce the local emission of pollutant and the parking demand (Correia and van Arem, 2016; van den Berg and Verhoef, 2016).

Several studies have explored the impact of shared autonomous vehicle as a alternative mode in a demand-responsive fashion to serve travelers. The most related works are that a fleet of SAVs replace the conventional taxis or buses service. Earlier works (Fagnant and Kockelman (2014),Fagnant et al. (2015)) investigate benefits and environmental implications of shared autonomous vehicles(SAV) using agent-based simulation. Spieser et al. (2014) examines the problem of fleet sizing and financial benefits of Automated Mobility-on-Demand Systems (AMoD) using the actual transportation data in Singapore. Several study focus on investigate how an SAV system perform and how much benefits when considering the dynamic ride-sharing (Fagnant and Kockelman, 2016; Zhang et al., 2015). Other works concern multi-mode of transport in analysis of SAVs system. Martinez and Viegas (2017) investigates the new shared mobility alternative in the city of Lisbon, Portugal for both all private mobility and bus services. Zachariah et al. (2014) investigates a fleet of autonomous taxi (aTaxi) that provide on-demand service among taxi stands in conjunction with the service of New Jersey Transit Train in New Jersey. The autonomous vehicles as a feeder service have been explored (Liang et al., 2016; Scheltes and Correia, 2017).

AV prototype released by Google with its cute and compact shape resembling the podcars in PRT system. AVs as conceptual cousins with podcars in personal rapid transit (PRT) systems, are capable of roaming on the open roads instead of being confined to dedicated tracks. A fleet of SAVs can function as PRT system to provide the direct service in a demand-responsive fashion to serve the travel demand in the similar scenarios, such as airport, business and industrial parks, downtown districts, campuses or theme parks.

One of ideal implementations is that a fleet of shared autonomous vehicles (SAVs) via a centralized operation functions both as rail-less PRT system and a taxi system to provide demand-responsive service to serve the time-varying travel demand during the course of a day. That is to say, SAVs system would function much like a PRT systems providing station-to-station service (SSS) during peak hours, but it will operate on the public road rather than on dedicated guide-ways. For the rest of the day, especially when the demand is light, SAVs provide the convenience of the door-to-door service (DDS)in a demand-responsive fashion.

little was known about the impact of time-varying service (TVS) scheme on demand provided by a fleet of SAVs. Note that the two service modes do not operate in parallel. In simple terms, the on-demand service modes provided by

SAVs can switch between peak hours and off-peak hours in order to maximize the usage of SAVs to serve travel demand. To fulfill the research gap, exploration of the potential benefits of this SAVs system is implemented by developing an agent-based model (ABM) in Anylogic software to simulate the time-varying service scheme provided by SAVs, and then compare it with door-to-door service provided by SAVs system.

The assessment of operations and strategies in this work will be done through ABM. ABM is a relatively new paradigm that describes a system from the perspective of its constituent units. Unlike to "top-down" modeling approach, ABM is an efficient method to simulate complex adaptive systems in a bottom-up manner. In other words, ABM is a simulation approach to modeling systems comprised of individual, autonomous, and decision-making entities called agents. The main characteristics of ABM are that agents can individually assess its situation and make decisions on the basis of a set of rules. Agents may execute various behaviors appropriate for the system they represent (Bonabeau, 2002).

2 Model Specification and Operations

Our model simulates the operation and interactions of SAVs and traveler's requests within a hypothetical city area and a synthetic population of trips. We need to estimate the average demand by O-D pairs. The aggregate O-D matrix is hypothetical. Demand matrix involves the probability of daily trip triggered between traffic analysis zones, and the distribution of occurrence time of trips is also customized. O-D matrix (travelers' requests in each zones) is a square array in which the i-th row and j-th column indicates the probability that the passenger at the zone i selects the j-th zone as a trip destination. The main diagonal of the matrix is composed of zeros, and the sum of the values in each row must be 1. We define the intensity of demand in each hour to mimic the morning and afternoon peak hours and off-peak hours.

Services provided by SAVs are on demand. we considered three service schemes. Specially, in the tailored TVS simulation model, we formulate the operation in peak hours and offpeak hours respectively. In the peak hours, travelers who send a request ahead of time need walk to the nearest pickup station to wait for a SAV, and then the system will assign a idle SAV to serve the traveler. The SAVs will find the shortest path by means of Dijkstra algorithm without considering the traffic delays in the networks. After that, travelers are dropped off at predesignated station where is closet to their destinations. The passengers may give up and disappears from the network for a time-out period in term of the cancellation of the on-demand service. In off-peak hours, travelers who request the on-demand service can be picked up at their origins, and dropped off at their destinations directly.

We use the first come first serve (FCFS) principle to assign idle SAVs to serve the travelers. When a vehicle send a request, the matching algorithms will check the request lists. Then, the traveler who waiting for a long time will have a priority to be assigned a SAV. A key to the design of SAVs system is how to designate precise location of SAVs' service stations to serve as many trips as possible in peak hours. It is acceptable by examining trip densities in each traffic analysis zones. It is reasonable to assume that people will accept a five or ten minute walk to and from fixed stations equivalent to a distance of about a quarter mile or a half mile. Compared with the optimal design, fixed stations are uniformly distributed among the traffic analysis zones in our study.

The vehicle speed is predetermined in baseline scenarios in peak hours and off-peak hours respectively. Based on the research conducted by Wang et al. (2016) in terms of speeds during the different time periods, the reduction of the speed in peak hours ranges approximately from 10% to 30%. So we assume that the speed of SAVs is 20% less than that of SAVs in off-peak hours. The speed in off-peak hours is constrained by the free flow speed and maximum safe speed of SAVs. In our model, we assume the vehicle speed in off-peak hours is 10 meters per second (36 kilometer per hour).

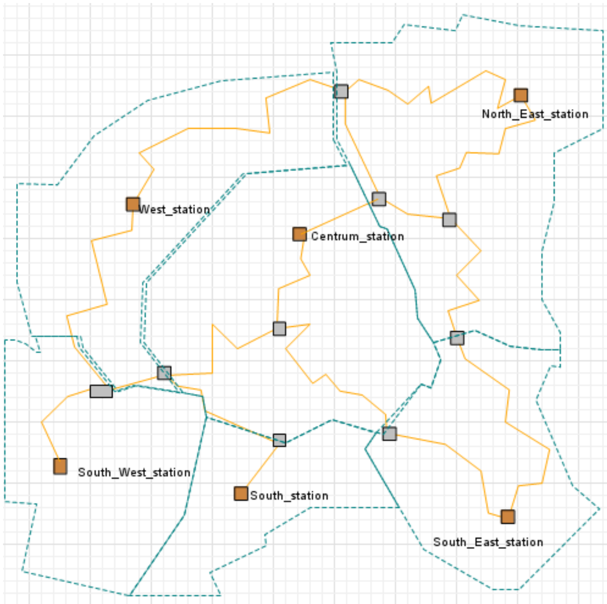

Figure 1: City topology

3 Experiment

The simulation model coded in Java language was developed in Anylogic proprietary ABM platform. The city scale is 5 Km* 5 Km. The city landscape topology consists 6 traffic analysis zone, 78 links and 77 nodes (see in figure 1). For the station-to-station service, SAVs operate among 6 zone station providing an on-demand service. For energy consumption, we adopt the distance-based relation. The manufacturer has announced an electricity consumption of 1 kWh per 7 km (`https://www.tesla.com/efficiency/well_to_wheel.php`).

The system capacity refers to the total number of trips the SAVs served for one simulated day. we specify that the SAS can provide an door-to-door service on demand in off-peak hours, and fixed station service are implemented in a demand-responsive fashion at the rest of the day.

Table1 shows basic input parameters for SAVs system via a centralized operation, and Table2 is the simulated result for the operation of SAVs in three scenarios.

Table 1: Input parameters

Category	Value
City scale	5km*5km
Road link	78
Road nodes	77
Traffic zones	6
Demand size	1250
Vehicle maximum speed	40 kph
Vehicle peak-hour speed factor	0.8
Vehicle off-peak speed	36 kph
Vehicle capacity	2 person
Operating hours	Around the Clock
Fleet size	70
Timeout for PT	20 minute
Walking speed	1.4 meters per second
AM peak	7 AM-9 AM
PM peak	4 PM-6 PM

4 Results and Discussion

We have analyzed SAV's service schemes. Three scenarios are simulated: door-to-door service, station-to-station service, and time-varying service. Simulated results for three scenarios are stated in table 2. Simulated results indicate that door-to-door service increases the travelers' average waiting time by 25.5% in off-peak hours. Compared with DDS, the average waiting is reduced by 25% and 11.5% respectively in SSS and TVS. This is because that the SAVs only provide services between stations on demand. SAVs spatial service length are shortened, thereby improving the utilization of SAVs. The average vehicle trip lengths are 11.2 km, 9.5 km, and 10.5 km for DDS, FSS and TVS respectively, which confirm the fact that vehicle trip lengths can be saved when the SAVs operate within stations.

The remarkable difference among three scenarios is the waiting time in peak hours. Both the SSS and TVS reduce the average waiting time in peak hour by 10.8%. That is, the SSS and TVS could improve the quality service. At the same time, they can increase the system capacity by 2.4% and 2.9% respectively. What's more, the SSS and TVS can reduce energy consumption and VKT by 13.3%, 3.7% respectively. But inconvenience resulting from the walking in a full-day SSS and peak-hour TVS is a obvious side effect which will impede the adoption of SAVs.

Compared to the average travel time, the average waiting time is larger in the simulated results. One of reasons is that fleet size of SAVs is too small to serve the whole travel demand. We still need to investigate the impact of the fleet sizes on people's traveling in SAVs system, and obtain the near optimum fleet size.

Also, we assume that travelers can give the on-demand service up with a given time out(20 minutes) to choose other Public transportation (PT)(See Figure 2). This time limitation will make more travelers choose this on-demand

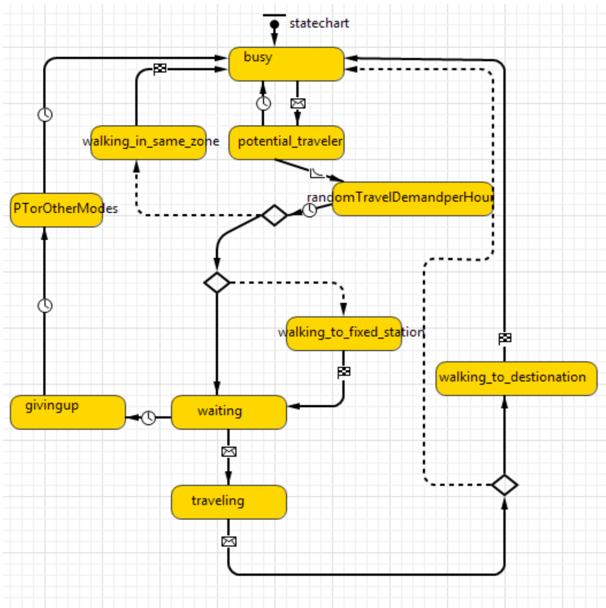

Figure 2: Person state chart

service. If we change the specific time interval with a smaller value, more travelers will leave. Consequently, the value of the average waiting time may diminish.

The simulated results indicate that the travelers' walking time in peak hours is around 9 minutes that is relatively long. This is because we only designate one fixed station in each zone in our model. In our model, we assume the vehicle speed in peak hours and off-peak hours. we did not take into account the realistic traffic condition. In fact, the empty SAVs reposition for pickup appears to generate more trips which have the potential to cause traffic delay. There is a significant increase of trips by empty SAVs at around 82% for all service schemes in our simulation. So it is necessary to take into the realistic traffic condition into account to explore the impact of SAV's operation in the future study.

A system which encompass all the benefits does not exist. The tailored TVS which can maximize the usage of SAV in heavy demand profile with acceptable quality of service and convenience in light demand profile is full of promise. We promote the tailored TVS scheme as an alternative to taxi service. However, there are many aspects need to be further considered. We did not simulate the scenario that the two service scheme operate in parallel. In other words, a door-to-door service or a station-to-station service are available for travelers at the same time. Also, the price variations for respective service scheme are need to be investigated. Travelers can choose different service scheme based the price they can afford.

Table 2: Simulation results

Category	DDS	SSS	TVS
Average waiting time	10.4 min	7.8 min	9.2 min
Average waiting time in peak hour	11.6 min	8.6 min	8.8 min
Average waiting time in off-peak hour	9.8 min	7.3 min	9.2 min
Average traveling time	11.8 min	9.8 min	10.7 min
Maximum traveling time	21.8 min	15.7 min	18.7 min
Average vehicle trips length	11.2 km	9.5 km	10.5 km
Average walking time before pickup	0	9.3 min	9.4 min(peakhours)
Average walking time after drop-off	0	9.4 min	9.3 min(peakhours)
Energy consumption	2974 Kwh	2579 Kwh	2862 Kwh
System capacity(time-out 20)	1854 trips	1899 trips	1908 trips
Passengers transported in peak hours	757 persons	788 persons	776 persons
Additional trips due to empty SAVs	1538 trips per day	1574 trips per day	1581 trips per day
Total VMT	20821 km	18055 km	20040 km

References

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. 99.

Correia, G. H. d. A. and van Arem, B. (2016). Solving the user optimum privately owned automated vehicles assignment problem (uo-poavap): A model to explore the impacts of self-driving vehicles on urban mobility. *Transportation Research Part B: Methodological*, 87:64 – 88.

Fagnant, D. J. and Kockelman, K. M. (2014). The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. *Transportation Research Part C: Emerging Technologies*, 40:1 – 13.

Fagnant, D. J. and Kockelman, K. M. (2016). Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in austin, texas. *Transportation.*

Fagnant, D. J., Kockelman, K. M., and Bansal, P. (2015). Operations of shared autonomous vehicle fleet for austin, texas, market. *Transportation Research Record: Journal of the Transportation Research Board*, (2536):98–106.

Krueger, R., Rashidi, T. H., and Rose, J. M. (2016). Preferences for shared autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, 69:343 – 355.

Liang, X., Correia, G. H. d. A., and Van Arem, B. (2016). Optimizing the service area and trip selection of an electric automated taxi system used for the last mile of train trips. *Transportation Research Part E: Logistics and Transportation Review*, 93:115–129.

Martinez, L. M. and Viegas, J. M. (2017). Assessing the impacts of deploying a shared self-driving urban mobility system: An agent-based model applied to the city of lisbon, portugal. *International Journal of Transportation Science* *and Technology*, 6(1):13 – 27. Connected and Automated Vehicles: Effects on Traffic, Mobility and Urban Design.

Scheltes, A. and Correia, G. H. d. A. (2017). Exploring the use of automated vehicles as last mile connection of train trips through an agent-based simulation model: An application to delft, netherlands. *International Journal of Transportation Science and Technology*, 6(1):28 – 41. Connected and Automated Vehicles: Effects on Traffic, Mobility and Urban Design.

Spieser, K., Treleaven, K., Zhang, R., Frazzoli, E., Morton, D., and Pavone, M. (2014). Toward a systematic approach to the design and evaluation of automated mobility-on-demand systems: A case study in singapore. In *Road Vehicle Automation*, pages 229–245. Springer.

van den Berg, V. A. and Verhoef, E. T. (2016). Autonomous cars and dynamic bottleneck congestion: The effects on capacity, value of time and preference heterogeneity. *Transportation Research Part B: Methodological*, 94(Supplement C):43 – 60.

Wang, X., Fan, T., Li, W., Yu, R., Bullock, D., Wu, B., and Tremont, P. (2016). Speed variation during peak and off-peak hours on urban arterials in shanghai. *Transportation Research Part C: Emerging Technologies*, 67:84 – 94.

Zachariah, J., Gao, J., Kornhauser, A., and Mufti, T. (2014). Uncongested mobility for all: A proposal for an area wide autonomous taxi system in new jersey. In *Transportation Research Board 93rd Annual Meeting*, number 14-2373.

Zakharenko, R. (2016). Self-driving cars will change cities. *Regional Science and Urban Economics*, 61(Supplement C):26 – 37.

Zhang, W., Guhathakurta, S., Fang, J., and Zhang, G. (2015). Exploring the impact of shared autonomous vehicles on urban parking demand: An agent-based simulation approach. *Sustainable Cities and Society*, 19:34–45.