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Shared Autonomous Vehicle Simulation and Service Design

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ABSTRACT

Driverless cars are on the way. This technology, allowing more accessible, dynamic and intelligent form of Shared Mobility, is expected to revolutionize urban transportation. One of the conceivable mobility services based on driverless cars are shared autonomous vehicles (SAVs). This service could merge taxis, carsharing and ridesharing systems into a singular transportation mode. However, the success and competitiveness of future SAV services depend on its operational models, which are linked intrinsically to the service configuration and fleet specification. On the other hand, any change on operational models will result in a different demand. Using a comprehensive framework of SAV simulation in a multi-modal dynamic demand system with integrated SAV user taste variation, this study evaluates the performance of various SAV fleets and vehicle capacities serving travelers across the Rouen Normandie metropolitan area in France. The impact of ridesharing and rebalancing strategies on service performance is furthermore investigated.

Research results suggest that the performance of SAV is strongly correlated to the fleet size and the strategy of individual or shared rides. Further analysis indicates that for the proposed pricing scheme (20% lower for ridesharing scenario), the standard 4-seats car with shared ride remains the best option among all scenarios. The results underline also that enabling vehicle-rebalancing strategies may have an important effect on both user and service related metrics. The estimated SAV average and maximum driven distance prove the importance of vehicle range and charging station deployment.

KEYWORDS: Shared autonomous vehicle; Multi-agent simulation; Demand modeling; Service performance

1. Introduction

Driverless cars or autonomous vehicles (AVs) represent a transformative technology that could have important implications for society, urban mobility, economy, and environment (Fagnant and Kockelman, 2015, 2014; Greenblatt and Shaheen, 2015). The fact that this technology is driverless and accordingly available every time and everywhere yields in considerations that it might be rather shared and consequently easily accessible and affordable for all (Fagnant et al., 2015; Harper et al., 2016; Meyer et al., 2017). After several years of growing interest in AVs by car manufacturers investing millions of dollars to develop driverless cars, gaining expertise of operation of future shared autonomous vehicles (SAVs) is a major concern. Their goal is to play the role of an operator of vehicle sharing systems with new business models capturing profit per kilometer or per trip (Burns et al., 2013; Firmkorn and Müller, 2012; Stocker and Shaheen, 2018). A multitude of SAV services is conceivable and yet it is largely unclear which ones will prevail in term of efficiency and effectiveness.

Today's mostly experimental SAV services are modified versions of ordinary electric cars with four or five seats inside. However, it is still uncertain how the most efficient design of these vehicles would look like. In addition to the vehicle characteristics and features, operational aspects of this new service could intensely influence its success. Some configurational characteristics such as fleet size, allocation and relocation strategies, service area and infrastructures have a direct impact on parameters, which are important for travelers for their mode choice decision. Obviously, travel time and cost are the main ones, but in the case of a shared system, some other parameters such as wait times and detour times (in the ride share mode) gain importance. Moreover, the variation of individual feelings towards using this system might significantly affect the service performance. In particular, the absence of a driver in SAV could cause an important concern for travelers

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and consequently result in lower demand. Thus, all of these parameters are to be considered in the upstream planning in order to have an accurate estimation of service performance measures.

Due to recently developed approaches, and especially multi-agent simulation, those aforementioned parameters can be reflected at a fine-grained level. Potentially, earlier multi-agent activity-based simulations are able to consider the complex supply-demand relationships of the multi-modal transportation system. Various aspects of operating future SAVs are the subject of current research efforts based upon this approach. Especially some in-depth investigations have been recently carried out on SAV fleet optimization, rebalancing, and cost structures of operational models (Bösch et al., 2018; Hörl et al., 2019; Loeb and Kockelman, 2019). In several studies, the human-related side of driverless cars and their impacts on service demand have been assessed (Kamel et al., 2018; Vosooghi et al., 2019). The impact of ridesharing on operational efficiency of SAV has also been the subject of few investigations (Farhan and Chen, 2018; Hörl, 2017). However, to the best of our knowledge, none of these studies considers all affecting aspects of SAV operation at the same time. The present research addresses this gap by conducting comprehensive dynamic demand simulations in a multimodal network. The analysis of given simulation outputs allows to investigate the effects of different operational components and vehicle specification (specifically vehicle capacity) on the efficiency of the offered service, considering dynamic demand responsive to the network and the level-of-service (LoS) with incorporated user taste variations and value of travel time (VTT). The further contribution of the present research is the SAV service design upon a real world case study and its performance evaluation using more relevant metrics. To respond the existing needs in the simulation and analysis, some features on traveler behavior and vehicle allocation and relocation strategies have been beforehand modified or developed. Simulation experiments are based upon the real data for the transportation system of the Rouen Normandie metropolitan area in France using the multi-agent transport simulation platform (MATSim).

The remainder of this paper is structured as follows. In section 2, we first present a review of the relevant literature on this topic. This is followed in section 3 by presenting the model specification and setup process. In section 4, overall results as well as detailed analysis categorized by each service aspect are presented. Finally, in section 5, insights gained through this research are discussed and suggestions for further work are given.

2. Prior research

Large investigations are carried out on SAV demand modeling and simulation particularly in the last 5 years. Several approaches have been developed to anticipate the demand of future SAV services. These approaches fall into two main categories: (i) survey and analysis, and (ii) agent-based simulation. The first approach is mainly used to produce rough estimations of potential demand based on stated preferences surveys (Bansal et al., 2016; Haboucha et al., 2017; Krueger et al., 2016). The second approach is widely employed for various study purposes and particularly those related to the supply side of SAV services in the context of dynamic demand simulation. The simulations based on the latter approach involve two different multidimensional decision processes: (i) discrete choice modelling that is based on the assumption of random utility maximization, and (ii) co-evolutionary algorithm, which is more relied on finding stochastically the maximized utility for various choice sets including not only travelers' route and mode choice decisions, but also a set of activity decisions. The second group of simulations is known as activity-based multi-agent simulation. Given the purpose of this study conducting comprehensive simulations considering all affecting factors in order to design the SAV services, only multi-modal simulations incorporating dynamic demand that is responsive to the network and traffic are reviewed.

In major studies, SAVs are integrated into the area where private cars are not allowed or they are all replaced by the new service. Azevedo et al. (2016) proposed an integrated agent-based traffic simulator built on disaggregated behavior models in both demand and supply (SimMobility) to study the potential impacts of introducing an autonomous mobility on demand (AMoD) service in a car-restricted zone of Singapore. In their work, individual preferences to use autonomous vehicles were kept unchanged and only cost of the service was assumed as 40% less than the regular taxi service in Singapore. The studied AMoD system uses autonomous mid-size sedans without sharing rides. Their simulation takes advantage of some optimization processes in terms of facility location, vehicle assignment and routing and vehicle rebalancing. Their results suggest that rebalancing results in higher demand. In addition, the passenger waiting time is strongly correlated to the fleet size and number of parking stations. However, further growth of those variables have no more impacts once an optimal demand is reached. Heilig et al. (2017) used an agent-based travel demand model with macroscopic traffic simulation to evaluate the transportation system of Stuttgart region where all the private cars are replaced by an AMoD service. In their study, the simulation is done for more than one day (one week) and the changes in overall transportation system performance are analyzed. Furthermore, the fleet required to fulfil the demand is investigated. In their simulation, the cost per mile of a proposed service is assumed 70% less compared to the private cars and the user preferences kept unchanged. The simulation encompasses the relocation strategy during nighttime, and it is shown that total vehicle mileage decreases up to 20% after the introduction of a new AMoD service. Martinez and Viegas (2017) tried to explore the potential outcomes of so-called radical change in urban mobility configuration of Lisbon city after introducing Shared Mobility services based upon a

spatially aggregated agent-based simulation. In the simulated scenarios, all private mobility and conventional buses are replaced by Autonomous Shared Taxis and Taxi-Buses. Their simulation incorporates several optimization models in order to assign dynamically the vehicles or generate them if needed along the day. Their results suggest that congestion and emissions would strongly decrease by introducing those shared services. Chen and Kockelman (2016) employed a multinomial logit mode choice model in an agent-based framework to assess various dynamic pricing strategies on mode shares estimate of electric SAV in Austin, Texas. Due to the spatial aggregation, the mentioned study ignores trips under one mile and non-motorized modes. Since SAV travelers can use their in-vehicle time to do other activities, the value of travel time (VTT) for this mode in the mentioned study is considered variable and dissimilar to transit. The simulation includes private cars, transit and electric SAV; and the analysis suggests that electric SAV modal share changes significantly by variations of VTT and service fares. Besides, it is shown that some service operational metrics can be improved via targeted pricing strategies. Wen et al. (2018) investigated in a comprehensive study the deployment of AV and SAV services as the last-mile solution focusing on operation design. They employed a detailed nested logit structure for the mode choice model. In their study, an agent-based simulation is used to estimate the LoSs. It is shown that there is an important trade-off between fleet size, vehicle occupancy and traveler experience in terms of service availability and response time. Although the mentioned research incorporates SAV user preferences, but the latter is carried out by varying the alternative specific constant in the mode choice model, which includes only the unobserved (undetected) parameters of mode choice decision and neglects user specific attributes.

All of the above-mentioned studies incorporate discrete choice modeling as a traveler decision choice mechanism. In some other studies, however, utility scoring is used instead. Hörl (2017) utilized MATSim to evaluate the dynamic demand response of an autonomous taxi service. In his study, two service operators are integrated into the simulation and system performance as well as operational indicators are compared. A fleet of 1000 AVs is introduced to the transportation system of the city of Sioux Falls in all the scenarios. The simulation results reveal that the service with ridesharing attracts a larger number of travelers at off-peak hours. The user taste variation in the mentioned study is kept unchanged. In our previous work we used the same framework (MATSim) to explore the impact of user trust and willingness-to-use on fleet sizing of SAV service integrating to the transportation system of Rouen Normandie metropolitan area (Vosooghi et al., 2019). The simulation is performed using the categorized scoring utility according to the individual sociodemographic attributes of users. Our previous work incorporates the first dynamic demand simulation of SAV service considering the user taste variation. It is shown in the mentioned study the significant importance of traveler trust and willingness-to-use varying the SAV service use and the required fleet size. That work benefits of several optimization models in order to assign dynamically the vehicles. However, the study incorporates SAV services without ridesharing and rebalancing strategy. A summary of the aforementioned studies is presented in Table 1 stating the objectives and the main features.

Table 1

Summary of the selected literature on SAV demand modeling and service simulation.

Author(s), year	Demand estimation approach / Mode choice mechanism	Vehicle characteristics	SAV user preferences	Assessment purposes
Azevedo et al., (2016)	Activity-based multi-agent simulation / Hierarchical discrete choice modelling	Mid-size sedans w/o ridesharing	Unvaried	Impact assessment, determine the fleet size and parking stations requirements
Chen and Kockelman, (2016)	Activity-based multi-agent simulation / Multinomial logit mode choice modelling	NM	Variable (willingness to pay, value of travel time)	Sensitivity assessment of pricing strategies E-SAVs mode shares
Heilig et al., (2017)	Activity-based multi-agent simulation / Discrete choice modelling	Standard 4-seats w/ ridesharing	Unvaried	Impact assessment, determine the fleet size
Martinez and Viegas, (2017)	Trip-based agent-based simulation / Discrete choice modelling	6-seats minivan w/ ridesharing	Variable (car ownership, public transport pass)	Impact assessment, impacts on car fleet size, volume of travel and parking requirements, CO ₂ emissions
Hörl, (2017)	Activity-based multi-agent simulation / Utility scoring	Standard 4-seats w/ and w/o ridesharing	Unvaried	Dynamic demand response simulation of AVs and SAVs
Wen et al., (2018)	Trip-based multi-agent simulation / Nested logit mode choice modelling	Standard 4-seats w/ and w/o ridesharing	Variable (intrinsic preference)	Design of last-mile AV and SAV services integrated to public transit
Vosooghi et al., (2019)	Activity-based multi-agent simulation / Categorized utility scoring	Standard 4-seats w/o ridesharing	Variable (age, gender and household income)	Impact assessment of user preferences on individual-ride SAV fleet sizing

Some other studies investigate the use of SAV services in a multi-modal system incorporating various dispatching strategies or pricing schemes. However, the demand of the proposed services in these simulations is not necessarily dynamic (Auld et al., 2017; Farhan and Chen, 2018; Hörl et al., 2019) or responsive to the traffic states (Chen et al., 2016; Fagnant and Kockelman, 2018, 2014). Many other studies include static or predefined demands (Boesch et al., 2016; Fagnant and

Kockelman, 2014; Levin et al., 2017) or simulate only one mode (Bischoff and Maciejewski, 2016; Loeb and Kockelman, 2019; Zhang et al., 2015a). There are also large in-depth investigations on AV dynamic assignment (Hyland and Mahmassani, 2018), ride-share matching optimization problem (Agatz et al., 2011; Alonso-Mora et al., 2017) and SAV rebalancing and ridesharing (Spieser et al., 2014; Zhang et al., 2015b). These studies being focused rather on optimization problems ignore mode choice mechanism in a multi-modal context or time-dependency in travel time caused by congestion.

As seen in Table 1, most of earlier comprehensive simulations to investigate the operation of SAV service are based on the homogeneous structure of behavior in terms of sociodemographic attributes, with exception of our previous work (Vosooghi et al., 2019) which incorporated only individual ride service. The vehicle characteristics and specifically vehicle capacity and its impacts on SAV service performance has also remained a missing component in all of the prior studies. Service cost and the need for enabling rebalancing strategy have similarly gained little attention. Considering all above-mentioned SAV simulation features, this study is to the best of our knowledge, the first comprehensive investigation of a real-world scenario that could provide a new insight into the design of such service.

3. Model specification and set up

3.1. Simulation framework

In this work, the multi-agent transport simulation MATSim (Horni et al., 2016) and its Dynamic Vehicle Routing Problem (DVRP) extension (including the Demand Responsive Transport (DRT) application) (Bischoff et al., 2017; Maciejewski et al., 2017) are used. The main idea behind MATSim is the simulation of an artificial population, represented by agents, who perform their respective plans including activities and movements between activity locations throughout a day. The movements are simulated within a dynamic queue-based model in which all agents interact dynamically with each other in a network (traffic simulation). At the end of the simulation day, which usually exceed 24 hours due to the longest activity chain, all agents evaluate the performance of the executed plan by measuring and scoring the deviations from the initial plan and the utility of using a mode. This process is called “utility scoring”. In next iterations, agents try to maximize their scores by modifying their plans. This “re-planning” process is performed rather by using another mode and route or by ending an activity sooner than at its planned end time. The more agents explore potential alternatives, the more they learn about their optimal plans. Once the convergence on the total score is reached, agents stop to innovate their plans and they try to select one plan from their memorized set of plans and to find out the plan with the best score. This is repeated until a systematic relaxation is reached.

Re-planning is usually done after the plan execution and traffic simulation. However, for the simulation of new transportation systems and specifically those that need a cyclic re-computation of vehicle tasks and routes (e.g. SAV, on-demand services with multiple requests), instant decisions must be made while the traffic simulation is running. This is possible with dynamic agent module included in DVRP-DRT extension (Maciejewski, 2016), which directly interacts with the traffic simulation of MATSim.

3.2. Ridesharing and rebalancing

In the present study, we used the dispatch algorithm of ridesharing that is developed by Bischoff et al. (2017) and performs a centralized on-the-fly assignment of vehicles to on-demand requests. This optimizer returns a list of requests and vehicle paths between pick up and drop off points. In order to route SAVs dynamically, an insertion heuristic that aims to minimizing the total SAVs workload is employed. The latter is measured as the total time spent on handling requests. This leads to a lower detour for each user. The optimization process seeks also to the lower vehicle usage for more requests, which results in more service availability and consequently greater demand. During the simulation, when a new request is submitted, the algorithm searches the routes of all vehicles for optimal insertions. An insertion is feasible when it satisfies the following conditions: first, the overall travel time constraints (including waiting and in-vehicle times) are satisfied for already inserted requests (passenger(s) on board), and second, the expected boarding times for the awaiting and upcoming requests need to remain within a defined time frame. All feasible insertions are then evaluated and the first insertion that offers the smallest increase of vehicle work time will be selected. If no feasible insertion is found, the request is rejected. A request can be rejected (e.g. due to constraints violation) only immediately after submission, and already accepted requests cannot be rejected or re-scheduled.

We employed the rebalancing strategy that is included in DRT extension of MATSim. This is based on Minimum Cost Flows problem. In this problem, one seeks to “optimize” the time varying flows on each arc between aggregated demand hubs and idle vehicles, taking into account congestion effects along arcs and at nodes. Idle vehicles are relocated in regular intervals according to the estimated demand of the previous iteration. The expected demand for the next 60 minutes is considered in the optimization process.

It should be mentioned that the selected dispatch and rebalancing algorithm may have a strong impact on service performance indicators (Hörl et al., 2019; Hyland and Mahmassani, 2018). Particularly, when the demand for SAV service is relatively high, applying simplified assignments (e.g. FIFO) can lead to a worst service efficiency (Hyland and Mahmassani, 2018). However, we found that the employed strategies of vehicle assignment and relocation are accurate enough for our purpose. It is worth mentioning that the multi-agent simulation already adopts heuristic rules in feedback loops to achieve approximate convergence and consistency between multidimensional decisions and network loading. Thus, it may require even more computational resources to achieve equilibrium when very sophisticated heuristic rules are applied to find good assignment and relocation of vehicles.

3.3. Inputs and model setup

As stated before, the main goal of the present study is to design an SAV service considering all affecting operational and user related aspects. For this purpose, the simulation inputs are based on real activity chains replicating the traveler patterns and schedules derived from the transport survey and census. Fig. 1 illustrates the overall framework. A synthetic population for the case study area is generated using an open source generator developed in our work (Kamel et al., 2018) which applies fitness-based synthesizing with multilevel controls. Some major attributes such as age, gender, income level and socio-professional category have been used for controls. These are the attributes, which have been found to have an important impact on SAV mode choice (Al-Maghraoui, 2019) or are used as the joint attributes of synthetic population and activity models. The activity chains are then allocated to each synthetic individual according to its socio-professional attributes. In fact, based on transport survey analysis conducted for two French case study areas (Paris and Rouen Metropolitan area), we found that the activity chains are significantly correlated to those attributes (Kamel et al., 2019; Vosoghi et al., 2019). The socio-professional category consists of six groups of persons: employed, unemployed, students, people under 14 years, retired and homemakers. The generated synthetic population has been evaluated by comparing relative errors of synthetic and real population in each zone for estimated and given marginal data of each attribute.

For two main trip purposes (work and study), the fine-grained geographical zones of activity are given in the census data. For other trip purposes, an origin-destination matrix based on the transport survey is estimated. Both of these data are employed in the process of activity chain allocation. In the latter case, for each trip origin in each zone, a destination zone according to the probability of trip purpose by socio-professional category is allocated. Then, the activity's precise locations are randomly appointed along the zone in keeping with existing activity types and land-use category.

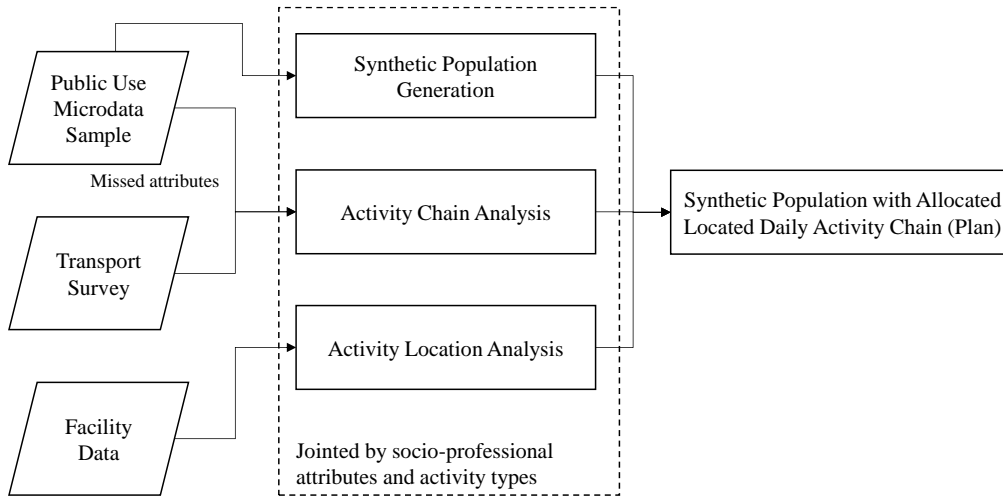


Fig. 1. Synthetic population generation and activity chaining framework.

In MATSim the utility scoring is based on the Charypar-Nagel scoring method (Charypar and Nagel, 2005). The function includes both activity and leg scores. In conducted simulations, only legs' scoring utilities are set according to the utility functions estimated from the recent local transport survey (EMD Métropole Rouen Normandie 2017) by employing logit model. In addition to travel time (including waiting time) and travel cost, user's car ownership as well as parking availability at destination have been found to be significant parameters in the mode choice model. Thus, they are incorporated into the utility scoring. The detailed list of parameters as well as the estimations are available in Vosoghi et al. (2019).

In the ridesharing algorithm, we set the detours up as the ride times can be extended up to 30% of direct distance. Bigger detour times for passengers are allowed only if their waiting times do not surpass 15 min. However, in that case the SAV ride

is more penalized in terms of utility (scoring). During simulation, the idle SAVs are rebalanced every 5 min. The size of square cells used for demand aggregation is assumed to be 1 kilometer.

3.4. *User taste variation*

User taste variations were integrated into the model based on the methodology proposed in our previous work (Vosooghi et al., 2019). In order to set up the model according to the travelers' perception and tendency towards using SAVs, an online survey has been made (Al-Maghraoui, 2019). User trust as well as their subjective criteria behind their willingness-to-use were identified. We found that socio-professional category as well as three other sociodemographic attributes are significant to SAV taste variations among individuals: income, age and gender. The marginal time- and cost-varying parameters in the scoring function are multiplied by the factors of user trust and willingness-to-use. These factors have been estimated according to the analysis of the conducted survey and utilities of actual modes.

3.5. *Simulated scenarios*

In order to apply our simulation to design an SAV service for a real-world scenario, we chose to consider Rouen Normandie metropolitan area (France) as a case study. Rouen was a fitting venue for at least three reasons. First, we had access to a most recent transport survey (EMD Métropole Rouen Normandie 2017). Second, the population (about 500,000 inhabitants) and the metropolitan area network sizes allow us to perform the simulation with an acceptable downscaling rate (10%) which results in quite accurate outputs compared to the full scale model (Bischoff and Maciejewski, 2016). Actually, in some studies relying on agent-based simulation and utility scoring, the population of case study areas is highly downscaled (1%) due to the high computational time (Hörl et al., 2019; Kamel et al., 2019). This extensive downscaling could potentially affect the service performance evaluations considering the spatiotemporal interaction of supply and demand in large study areas. The third reason for choosing this area is that some experiments on self-driving cars are being conducted for a few years, hence opening a possibility to get data on traveler behavior in a near future and to integrate it to the extended simulations. Furthermore, Rouen Normandie metropolitan area is a promising candidate for replacing existing private modes with an SAV service especially in the Rouen old town.

To support the simulation of such a scenario, the synthetic population from the Public Use Microdata Sample (INSEE 2014) was generated. Based on the local survey including 5,059 households and 11,107 individuals, 929 activity chains including eight trip purposes were found. As mentioned before, the activity chains and time profiles were allocated to the synthetic individuals according to their socio-professional category.

The simulations were run for several fleet-size and fleet-capacity scenarios with and without considering ridesharing or rebalancing strategies to appreciate system performance metrics. Regarding SAV, prices of 0.5 Euro per kilometer for individual ride and 0.4 Euro per kilometer (direct distance) for ridesharing services are assumed. These service prices are slightly more expensive than private car ride costs in France (0.3 Euro per kilometer - DG Trésor (2018)) and they are almost similar to the values that have been estimated or concluded in other investigations; for instance, Chen et al. (2016) estimated the price for electric SAV from \$0.42 to \$0.49 per person-trip-mile and Bösch et al. (2018) 0.43 CHF per passenger kilometer. In our study, the SAV service waiting time is integrated to the utility scoring and the value of waiting time is considered 1.5 times larger than the value of in-vehicle travel time (Wardman et al., 2016). The SAV fleet is initially distributed from four fixed points inside the city and out of old town, and therefore no "warm-start" as in Fagnant and Kockelman (2014) or random distribution are considered.

3.6. *Performance metrics*

Unlike the limited number of studies in which an SAV service and its demand are dynamically simulated, significant investigations are present on the performance evaluation of such system. A long list of performance metrics are as well used. These metrics are not necessarily having the same consequences. For instance Fagnant and Kockelman (2014) used traveler wait times in order to estimate required fleet sizes to serve various predefined demands. Since the demand in their study is considered static, the wait times could be a relevant indicator to evaluate the service performance. However, as shown in a more recent work of the same authors, the lower in-vehicle and wait times in a simulation enabling dynamic ridesharing result in higher excess vehicle kilometer travelled (VKT) (Fagnant and Kockelman, 2018) and therefore cannot be the only relevant indicators for the fleet sizing. Actually, traveler wait times have been used as a key indicator to define the optimum scenario in some other dynamic demand simulations (e.g. in Azevedo et al. (2016) or Chen and Kockelman (2016)). However, in the current research, in particular, for the fleet sizing we use the term of "fleet in-service rate". This indicator is defined as the number of occupied or in-service vehicles (including going to pick up a client) over all vehicles. The other metric representing the proportion of extra VKT (due to the unoccupied or rebalancing mileage) over total VKT will be used in

parallel in order to evaluate empty vehicle traveling distances and to find the balanced trade-off between these two indicators. The detour distance would be among the main traveler-related indicators representing extra travel distances due to the shared rides. The traveler wait times here will be used as the LoS evaluation; the lower the wait time, the higher the service level is. In fact, due to the dynamic decision mechanism between available alternatives for each traveler, higher wait times result in lower SAV demand and consequently service usage. Therefore, this parameter implicitly affects the main performance indicators. With the aim of comparing the service revenues for different scenarios, the in-vehicle passenger kilometer traveled (PKT) is defined. This indicator presents the sum of trip distances that each traveler performed being on-board SAVs. In order to investigate the usage pattern of SAV service in the case of ridesharing, the “on-board occupancy rates by number of passengers” is proposed. Other metrics used in the dynamic demand simulations to evaluate the performance of proposed service are number of persons or vehicle trips (Chen and Kockelman, 2016; Heilig et al., 2017) and average in-vehicle times (Hörl, 2017; Martinez and Viegas, 2017). However, these performance indicators being descriptive rather than consequential will not be used for the fleet sizing and vehicle capacity determination.

To evaluate the overall performance of the transportation system, mode share indicator as in the majority of other studies will be compared. Although this research does not incorporate environmental impact measurements, the total driven distances (car and SAV) for all scenarios are estimated and compared in order to give an illustration of how the congestion would change after the introduction of different SAV services. It should be mentioned that due to high uncertainty of future SAV service and infrastructure costs, in the present study only transport related indicators are evaluated and analyzed.

4. Case study results

4.1. Overview

A base-case scenario (S0) simulation run was conducted without integrating SAV and calibrated using the actual modal shares of the case study area. Next, the SAV service for various fleet sizes (2k to 6k) with individual rides (S1) as well as for those with ridesharing strategy were simulated. In the case of ridesharing, three different vehicle capacities were suggested for the simulation: small car with two seats (S2), standard 4-seats car (S3), and 6-seats minivan (S4). Table 2 illustrates the modal splits for all scenarios. It should be mentioned that given the low modal share of bike (less than 0.1%) and related changes, this mode has not been simulated.

Table 2
Modal splits estimated for all scenarios and fleet sizes*.

Scenario	Fleet size Mode	2000	2500	3000	3500	4000	4500	5000	5500	6000
S1- non-ridesharing										
	Car	59.3	58.8	58.5	58.3	58.0	57.7	57.6	57.4	57.5
	Walk	28.3	28.3	28.2	28.2	28.2	28.2	28.2	28.1	28.1
	SAV	3.1	4.4	5.3	6.0	6.5	6.9	7.2	7.5	7.6
	PT	9.2	8.4	8.0	7.6	7.3	7.1	7.1	6.9	6.8
S2- ridesharing (2-seats small car)										
	Car	59.1	58.8	58.5	58.3	58.1	57.8	57.7	57.8	57.7
	Walk	28.3	28.3	28.3	28.2	28.2	28.3	28.3	28.2	28.2
	SAV	3.8	4.6	5.2	5.9	6.3	6.5	6.7	6.9	7.0
	PT	8.8	8.3	8.0	7.6	7.5	7.3	7.2	7.1	7.1
S3- ridesharing (standard 4-seats car)										
	Car	58.9	58.7	58.3	58.1	58.0	57.9	57.8	57.7	57.7
	Walk	28.3	28.3	28.3	28.3	28.3	28.3	28.3	28.3	28.3
	SAV	4.0	4.6	5.3	5.9	6.0	6.4	6.6	6.8	6.8
	PT	8.7	8.3	8.0	7.7	7.6	7.4	7.3	7.2	7.2
S4- ridesharing (6-seats minivan)										
	Car	59.1	58.8	58.4	58.2	58.0	57.9	57.8	57.8	57.7
	Walk	28.2	28.3	28.3	28.3	28.3	28.3	28.3	28.2	28.2
	SAV	4.1	4.6	5.4	5.9	6.1	6.4	6.8	6.7	6.9
	PT	8.6	8.3	7.9	7.6	7.5	7.4	7.3	7.2	7.1

* Due to the rounding process for each modal share, the sum could exceed or be less than 100%.

As shown in Table 2, the modal shifts towards an SAV service come from both public transport and car modes. This is actually consistent with findings in the literature (Chen and Kockelman, 2016; Hörl, 2017; Martinez and Viegas, 2017; Wen et al., 2018). However, in the case of big SAV fleet sizes, the public transport mode share decreases significantly relative to

car. This is due to the utility of the proposed service, which is rather similar to the public transport mode. The service cost is also an important factor that encourages public transport users to choose a service that costs a bit more but is more appealing due to the lower travel time. Table 2 illustrates an interesting result regarding SAV modal share evolution. As it is expected, by increasing the fleet size, SAV modal shares increase accordingly. However, this growth does not follow the same trend for all scenarios. While SAV modal share in scenario 1 (individual ride) is the lowest one among all scenarios in the case of the smallest fleet size, this metric is conversely the highest for the fleet size of 6k vehicles. This is because there is a balanced trade-off between service cost, demand (which affects waiting time) and extra in-vehicle time due to detour distances. In fact, when the waiting time is more important compared to in-vehicle times, which is the case for small fleet sizes, the time-based cost of service could surpass the service cost for users. Therefore, the SAV demand and consequently its modal share decreases. However, in the case of big fleet sizes, as the waiting time is not as important as in the case of small fleet sizes, the in-vehicle time (including detour time) becomes an important factor for the decision-making.

Table 3 illustrates the evolution of total driven distance including private car and SAVs. By deploying SAV services, this indicator increases in all scenarios. Clearly, having bigger fleet size in each scenario results in more usage of vehicles. However, scenarios with ridesharing strategy have lower total driven distance compared to individual ride (except for the scenario with 2.0 k SAVs). This is because of the higher SAVs' occupancy rates in ridesharing scenarios. Comparison of vehicle capacities shows that in the scenarios with the fleets of 4-seats and 6-seats SAVs, the total driven distance is slightly lower than when 2-seats small SAVs are simulated (except for the scenario with 2.0 k SAVs). Meanwhile, for some fleet sizes, this indicator has the lowest value when 4-seats standard cars are used. The shorter total driven distance of individual ride service and smaller vehicles in ridesharing scenarios when 2.0 k SAVs are simulated is due to the relatively much lower service demand that is due to the low LoS provided in that fleet size.

Table 3
Total driven distance including car and SAV modes (million kilometer).

Fleet size	S0- base-case scenario	S1- non-ridesharing	S2- ridesharing (2-seats small car)	S3- ridesharing (standard 4-seats car)	S4- ridesharing (6-seats minivan)
-	8.88	-	-	-	-
2000	-	10.05	10.06	10.14	10.17
2500	-	10.50	10.33	10.31	10.30
3000	-	10.77	10.43	10.43	10.45
3500	-	10.95	10.61	10.50	10.53
4000	-	11.12	10.62	10.48	10.53
4500	-	11.20	10.66	10.55	10.53
5000	-	11.26	10.60	10.53	10.56
5500	-	11.31	10.73	10.60	10.59
6000	-	11.32	10.69	10.58	10.63

In Table 4 a summary of the average number of rides per SAV for all scenarios is presented. As seen here, in the case of small fleet sizes, the SAVs with bigger capacity satisfy more requests. This is because in that case, the expected waiting time is relatively high enough to play a major role in the mechanism of SAV mode choice decision. In the scenarios of SAVs with ridesharing and bigger vehicle capacity, the expected waiting time is lower compared to the scenarios of individual ride, thus more rides are satisfied. However, by increasing the number of vehicles, the detour distance become a more important parameter and therefore in the scenarios with more places in the vehicles, slightly less requests are observed. It should be noted that the expected waiting and detour times are the parameters that are estimated for each synthetic individual (agent) during the simulation. Agents learn about their plans (including trips and activities) and final decisions are made in the last iteration when a convergence is reached. Thus, the real and expected waiting and detour times have different values. We present only real values in this paper since the number of expected values is huge and we cannot visualize them all.

Table 4
Average number of rides per SAV.

Fleet size	S1- non-ridesharing	S2- ridesharing (2-seats small car)	S3- ridesharing (standard 4-seats car)	S4- ridesharing (6-seats minivan)
2000	11	16	17	17
2500	16	17	17	17
3000	17	17	18	18
3500	17	17	17	17
4000	17	16	16	16
4500	17	16	15	15
5000	16	14	14	14
5500	15	14	13	13
6000	14	13	13	13

As it is shown in Fig. 2, the average detour time fluctuates between 4 and 7 minutes in all scenarios. Likewise, the average in-vehicle time varies from 37 to 48 minutes. However, the variation of waiting time (excluding smallest fleet size) for each fleet size remains minor. It should be mentioned that since the simulations are dynamic-demand, low average waiting times for small fleet sizes are due to the low SAV demand especially during peak hours (particularly in S1 and S2). In fact, for fleet size below a certain size, the expected waiting time increases importantly. This makes SAV less competitive to other available alternatives in terms of generalized cost (except in the morning peak hour when the LoS of other alternatives are as low as SAV, see Fig. 3). Thus, the demand of SAV service and consequently estimated waiting time decrease. By increasing the number of vehicles, the expected waiting time declines. However, as its value is smaller than a critical waiting time (a value that make SAV non-competitive in terms of utility), its impact on SAV mode choice becomes minor. As a result, the estimated waiting time follows a very slight decreasing trend particularly in ridesharing scenarios. In non-ridesharing scenario, the estimated average waiting time falls faster for big fleet sizes. This occurs since by increasing the number of vehicles, for each request an available SAV can be found in lower direct access distance, however, in the ridesharing scenario, this SAV may not necessarily be without passenger and therefore a relatively higher waiting time is required. Thus, the decrease of average waiting time by enlarging fleet size in ridesharing scenarios goes slighter.

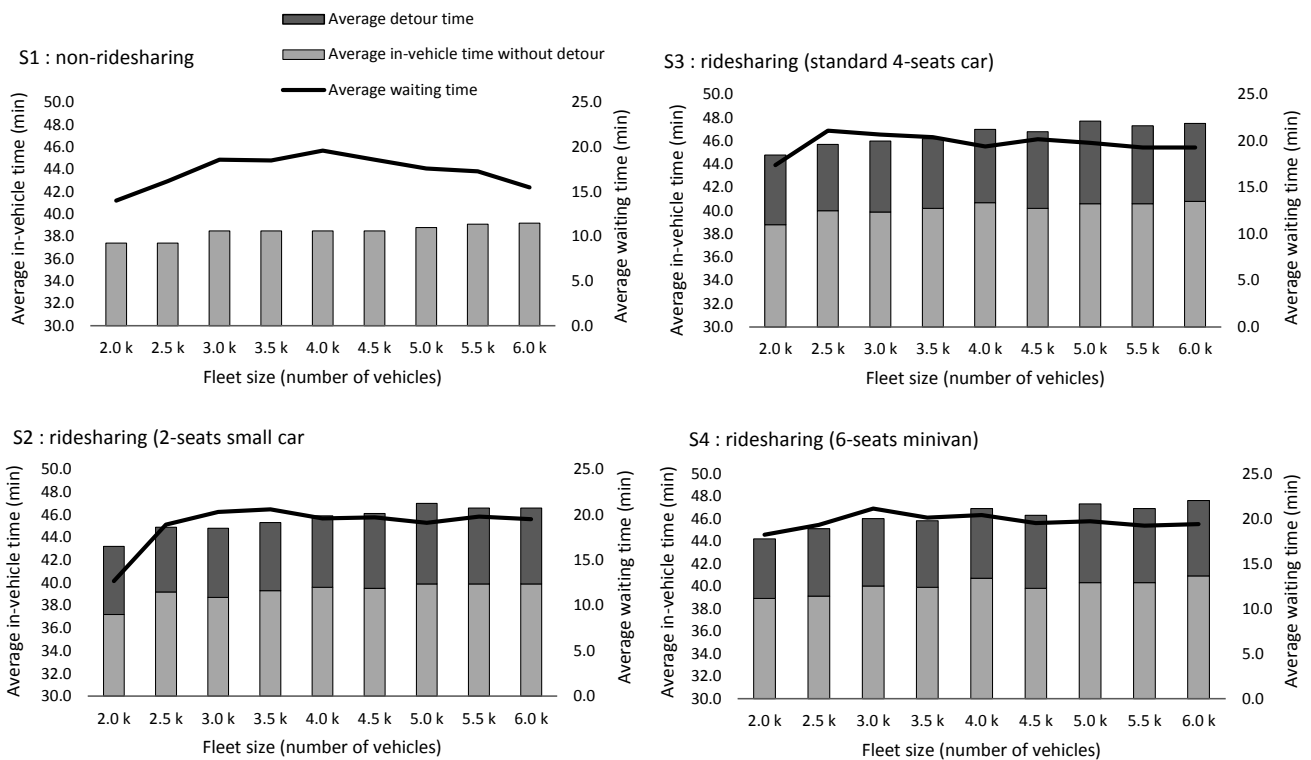


Fig. 2. SAV service time variables for all scenarios and fleet sizes.

4.2. Fleet size

The bigger fleet size and accordingly the higher SAV modal share does not necessarily lead to a better-optimized operation. In fact, a trade-off between overall expenses and revenues has to be balanced. Service costs include capital expenditure (CAPEX) and operating expenses (OPEX). Since this research does not incorporate infrastructures of SAV service, CAPEX can be assumed to be directly correlated to the fleet size. OPEX is however associated to fleet usages and mileage. Fig. 3 illustrates the hourly fleet in-service rates for all scenarios and various fleet sizes. As shown in this figure, consistent with daily trip patterns, two peak service usages for morning and evening peak hours occur. However, unlike the SAV modal share, the service usage is decreased for big fleet sizes. In fact, by increasing the fleet size, once the fleet usage becomes no longer saturated in the morning peak hour, the latter decreases quickly. This occurs as by improving the LoS indicators (waiting time or accessibility in this case), the demand rises, however, this demand is somehow limited to the number of people who are already likely to choose this service comparing to other alternatives that they have, even if the waiting time is very low. Similarly, if the fleet size is small and the LoS is accordingly low, users try to find a more appropriated mode. As a result, as seen in Fig. 3, for the small fleet sizes and especially in scenario 1 (individual ride), the fleet usage decreases abruptly. This actually can also be seen in the real behavior of travelers regarding the use of any other shared service (Al-Maghraoui, 2019). Again, we emphasize that the simulation results present the indicators when the

interaction of service demand and supply is iteratively relaxed. This means that users have already experienced the SAV service for various level of demands. As a result, the expected waiting time specifically in the case of small fleet sizes is already memorized and supposed to be high for many travelers. Consequently, they do not choose this mode in the case of small fleet sizes.

As seen in Fig. 3, in individual ride scenario (S1), SAV service reaches the maximum fleet usage at least for one hour in some fleet sizes. This is not however the case for ridesharing scenarios. This is due to two main reasons. First, in ridesharing scenarios in peak hours there are always SAVs with available seats in acceptable distance for any requests. Second, since there is no rebalancing strategy in those scenarios (SAVs stay at same place where the last passenger is dropped off), some SAVs that dropped off a passenger(s) far from demand hubs remain in idle mode at that location and thus the fleet usage does not reach the maximum value. This shows the importance of enabling rebalancing strategy especially when rides are shared among travelers.

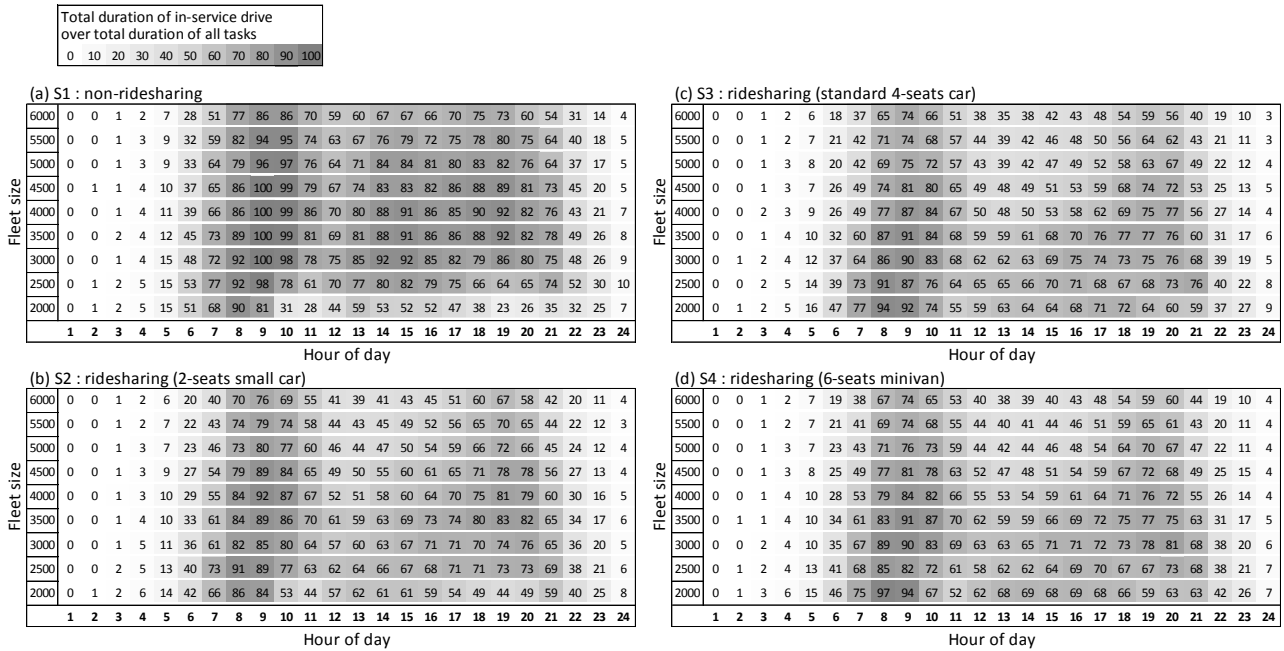


Fig. 3. SAV fleet hourly in-service rates.

Empty traveling distance is also part of fleet usage. A high-performance fleet size is characterized by a greater use and a lower empty distance. Fig. 4 shows the comparison of average daily in-vehicle service rates (fleet usage ratio) and empty VKT over total VKT (empty distance ratio) for all scenarios and fleet sizes. As seen in this figure, the fleet usage is fluctuating more than the empty distance ratio. In fact, by increasing fleet sizes, the empty distance ratio changes only by maximum 3%, meanwhile the fleet usage drops dramatically (up to 16%). This may occur because there is no rebalancing strategy incorporated in those scenarios and the pick-up ride distances remain approximately within the same range of values (with lower usage and consequently more available vehicles, the pick-up ride distance becomes slightly shorter). In order to identify the best performing fleet size, two aforementioned indicators are used. Actually, regardless of any estimations about service operational cost and benefits, the fleet usage indicator can be used as the measure of effectiveness concerning CAPEX. Similarly, the empty distance ratio may be enough indicative for the changes on OPEX term. Since the latter indicator stays rather constant for all fleet sizes, the best fleet sizes are identified according to the fleet usage ratio. For individual ride service, the fleet of 3.5k SAVs, in the case of small cars with two seats, 2.5k vehicles and for the other scenarios, approximately 3k vehicles are the best performing size of fleet.

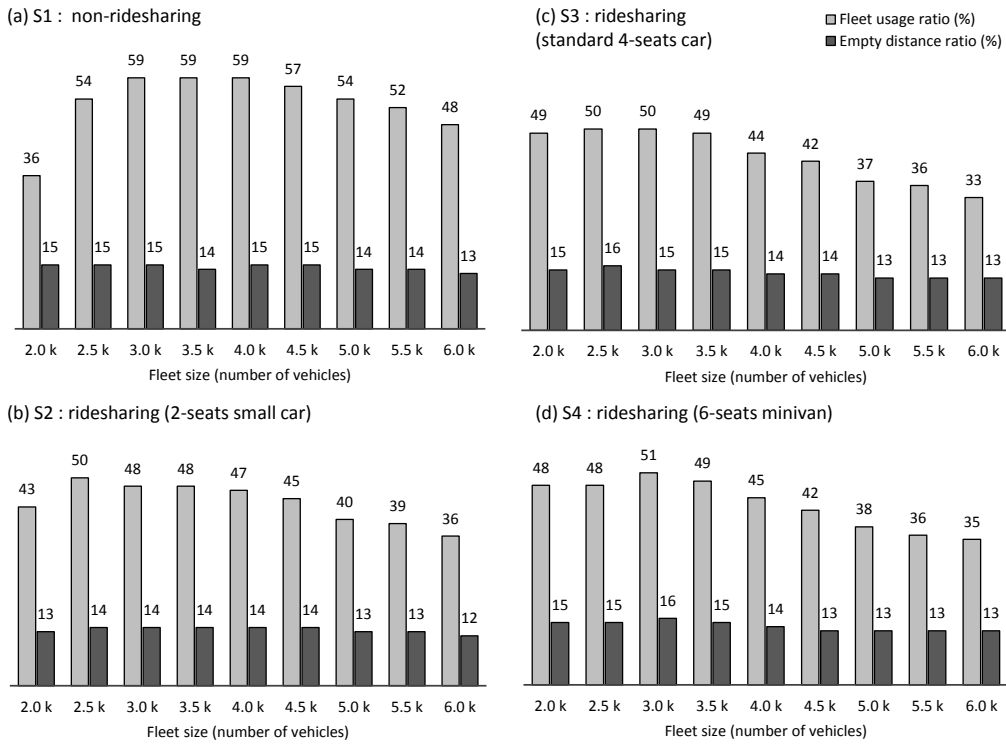


Fig. 4. Comparison of fleet usage and empty distance ratios for different scenarios and fleet sizes.

Another interesting observation in Fig. 3 is the shift of the morning peak-hour service usage from 7-9 am for small fleet sizes to 8-10 am for big fleet sizes. This is actually due to two main reasons. First, in the simulation, agents with different socio-professional category have different utility scoring. This means that for instance for some groups of people the marginal utility of traveling or the value of travel time (VoT) is bigger than for other groups. Second, user taste variation among different category of travelers are affecting SAV mode choice. As a result, by improving the LoS (travel time, including wait time), the SAV service for the users with different socio-professional categories and accordingly different trip purposes become more attractive (in terms of utility). Since each activity at destination has a dissimilar model of start-time and duration, hourly usage pattern of SAV service by considering different group of users changes. Fig. 5 illustrates the evolution of SAV service users by their socio-professional categories for different fleet sizes. As seen here, by increasing fleet sizes, the ratio of employed people in all scenarios decreases. For students and people under 14 years old, this ratio fluctuates and does not follow an increasing or decreasing trend. Meanwhile, the changes on the ratio of unemployed people remain minor. However, there is a relatively significant growth in the use of SAV service by retired people and homemakers when the fleet size is large (especially in the case of individual ride). By comparing scenarios of each fleet size, it can be seen that the SAV service with individual ride is less attractive for employed and unemployed users. This occurs since the cost-related parameters of mode choice decision are more important than time-related parameters for those groups of users. The above analysis shows the importance of considering users' profile in estimating fleet hourly usage, which can potentially affect the fleet sizing.

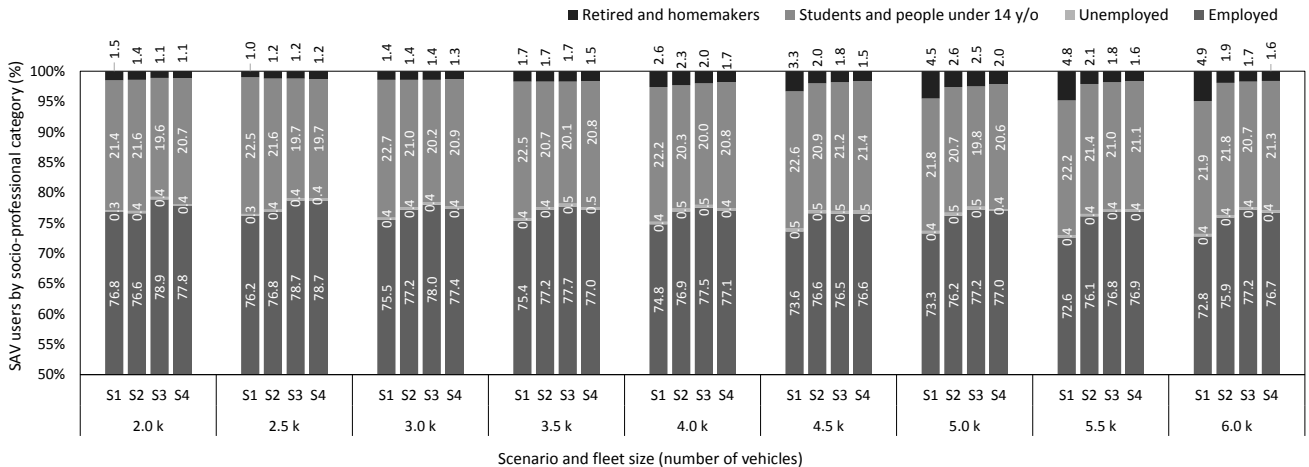
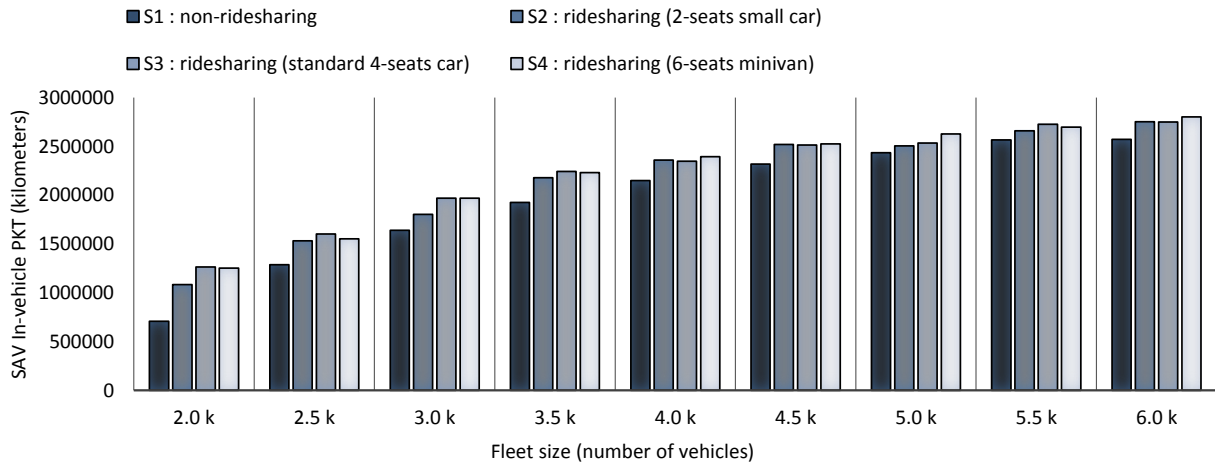


Fig. 5. SAV service users by socio-professional category.

4.3. Sharing strategy of ride

As seen in Fig. 3, in the scenarios with ridesharing, the fleets are never 100% in-service for the time slices of one hour. This may occur when rides are shared but empty vehicles are not rebalanced. When a request is registered, the nearest occupied vehicle with an available seat and acceptable detour time is assigned. As a result, there are always some vehicles quite far from the demand hubs that are not consequently used for a while. In fact, ridesharing results in relatively lower fleet usage for almost all fleet sizes (except for the fleet size of 2.0 k, see Fig. 4). The more rides are shared, the less the fleet is used. However, each user pays for the provided services and traveled kilometers. In this case, the indicator of in-vehicle passenger kilometer traveled (PKT) may be more relevant. This indicator presents the sum of trip distances that each traveler performed being on-board SAVs. Fig. 6 illustrates the comparison of SAV overall PKT for all scenarios and fleet sizes. As shown in the figure, the overall PKT of the individual ride scenario is minimum for all fleet sizes. This indicator is however almost similar for all ridesharing scenarios in the case of medium fleet sizes (3.5 k to 4.5k). By increasing the number of vehicles, the relative difference of PKT between individual ride and ridesharing scenarios decreases. This is actually due to the high LoS provided in the case of large fleet sizes. In fact, the potential requests for the SAV service are limited. Thus, when the fleet is accessible enough for a major part of potential users, the greater service availability (occurring when the rides are shared) does not necessarily result in an important increase in demand and PKT accordingly. As a result, the growth of PKT and its differences between individual ride and ridesharing scenarios decrease.

**Fig. 6.** Comparison of SAV overall PKT for all scenarios and fleet sizes.

4.4. Vehicle capacity

As shown before, the best performing fleet size in the case of ridesharing scenarios according to the fleet usage and empty ratios is between 2.5 k and 3.5 k vehicles. Comparing the PKT for those fleet sizes, it seems that the fleet of standard 4-seats car may be the best performing option for ridesharing. As seen in Fig. 6, for small fleet sizes, the overall PKT of standard 4-seats car is greater. In fact, for those fleet sizes, the fleet usage is almost saturated during peak hours (see Fig. 3). As a result, services are less accessible especially when the vehicle is smaller and the number of available seats are lower. It could seem that the service with bigger capacity vehicles would be more used by travelers in that case, however, due to extra detour time (expected), the PKT of 6-seats SAVs is slightly less than 4-seats SAVs. This means that for the same SAV service price, users prefer to choose a medium capacity car that has relatively lower waiting and in-vehicle times compared to 6-seats minivan. By increasing fleet size, as there is enough SAVs to satisfy the demand, the differences between PKTs for those scenarios become relatively minor. However, since in that case more demand are satisfied, the probability of pooling rides with an acceptable detour time becomes higher. Thus, some especially big size vehicles handle many requests in high demand areas. Meanwhile, the idle vehicles that have already dropped-off a passenger far from the demand hubs stay at the same place for a while. This non-homogeneous spatial distribution of idle and high workload SAVs results in a different PKT for ridesharing scenarios with big fleet sizes. This is happen when the rebalancing strategy is not enabled. It should be mentioned that in the small and medium fleet sizes, the fleet usage is relatively high, therefore SAVs are somehow rebalanced across the high demand hubs and dispersed better within the region. This shows again the importance of considering rebalancing strategy.

In order to explore the use of vehicle capacities, on-board occupancy rates by number of passengers (PAX occupancy ratio) are compared for ridesharing scenarios. As seen in Fig. 7, for all ridesharing scenarios by increasing the fleet size, the 1 PAX ratio decreases slightly while the other ones increase. In fact, when more vehicles are available, the demand is greater; thus the probability of finding further trip requests in an acceptable time or distance buffer from actual ride(s) becomes higher. Therefore, the rides are more shared in the big fleet sizes and more seats are occupied. As illustrated in the Fig. 7, 3 PAX ratio varies from five to eight percent in the case of standard 4-seats car and 6-seats minivan. However, the ratio of 4 PAX is less than 1%. Furthermore, the sixth seat of minivan is almost never used. Actually, by comparing the other metrics one can observe that the differences between standard 4-seats car and 6-seats minivan are very small. In fact, given the amount of initial investment and operational costs of the bigger vehicles, the extra capacity may not necessarily be profitable. Therefore, it seems that standard 4-seats are more adopted to the proposed service rather than 6-seats minivan. Nevertheless, we have to keep in mind that the extra capacity could have an important impact on the SAV’s LoS. 6-seats minivan can also be used for special requirements such as larger groups and families.

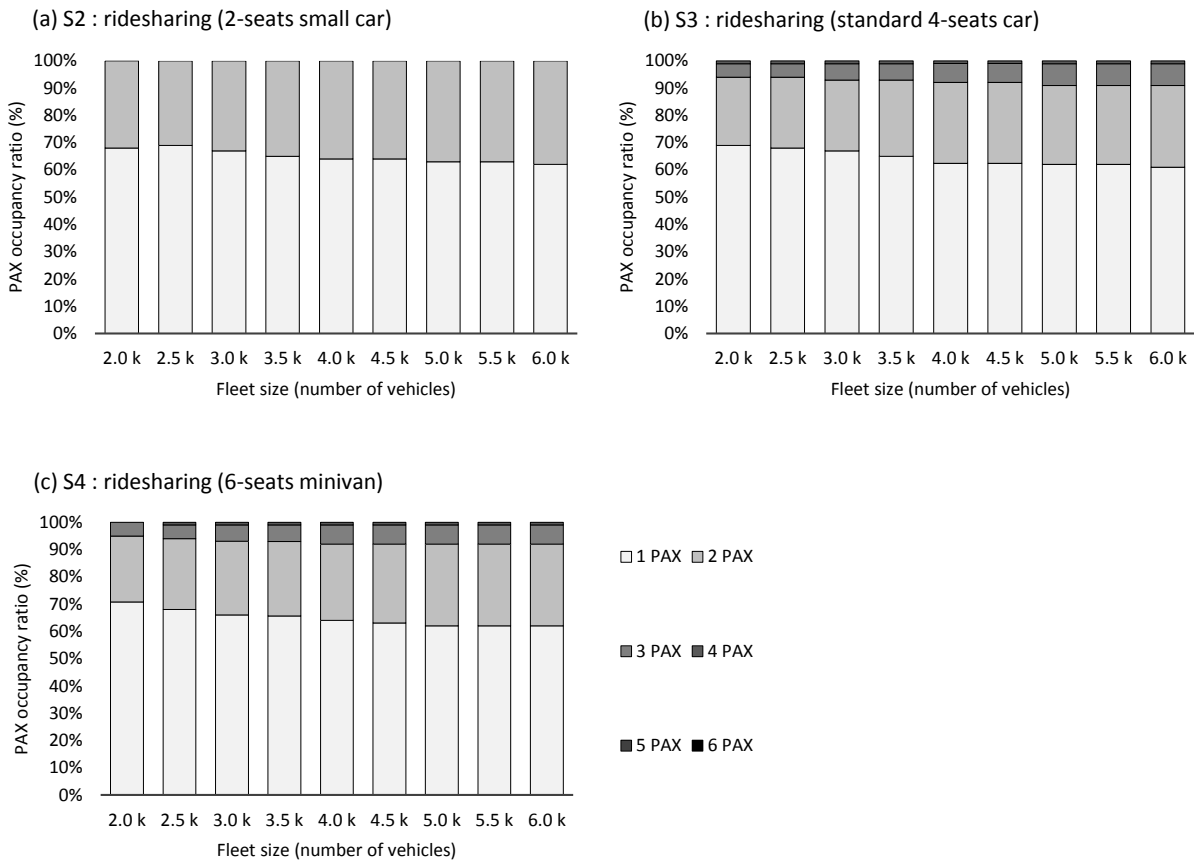


Fig. 7. On-board occupancy rates by number of passenger for ridesharing scenarios.

The analysis on the origin and destination activities of trips performed by a fleet of 3.0 k standard 4-seats SAVs (see Fig. 8) illustrates that almost half of all trips start or end at users’ homes. For the total of 9% of trips, the purpose at origin or destination is shopping or accompanying (escort), that shows the importance of extra vehicle capacities in terms of number of seats or luggage space. Also, given an important share of work and study activities at origin and destination (about 40%), it is likely that providing extra space and additional services for business, entertainment and education purposes may provide a better customer experience while using SAV service.

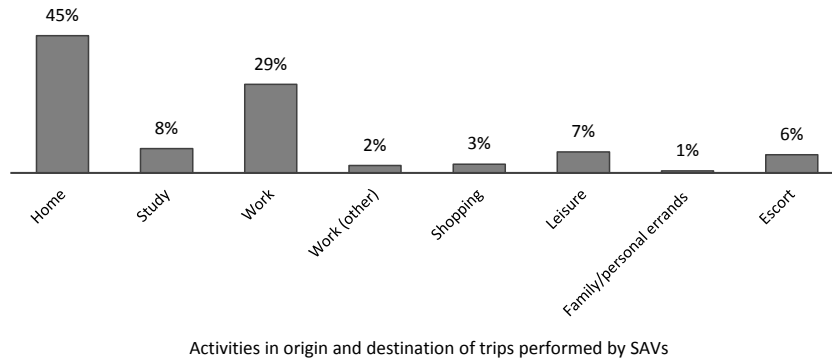


Fig. 8. The share of activities in origin and destination of trips performed by a fleet of 3.0 k standard 4-seats SAVs (percentage).

4.5. Vehicle range

The future SAVs are likely to be electric. In electric vehicles, the range is limited according to the battery capacity and specifications (e.g. weight, life cycle, etc.). In fact, given the important cost of battery among vehicles parts, its capacity may strongly affect the capital expenditure and operational expenses. According to the analysis on the SAV range for different scenarios and fleet sizes (see Table 5), it is shown that the average driven distance of SAVs may intensely vary (from 361 to 647 kilometers). Furthermore, the vehicles do not have the same driven distance and for some, the latter could be very large (even 975 kilometers). This occurs when the demand is saturated, and the vehicles are occupied for a long time during the day. By comparing the outputs, one can observe that the average driven distance is correlated to the fleet usage ratio (see Fig. 4) and the average number of rides per SAV (see Table 4). In all fleet sizes except when 2.0 k vehicles are simulated, the average driven distance of non-ridesharing SAVs is the largest compared to other scenarios. This is because by sharing the ride, SAV driven distances are lower than when the ride is dedicated just to one passenger. However, in the case of the smallest fleet size, as seen in Fig. 3, the fleet usage is dramatically lower compared to other fleet sizes due to the high expected waiting time and lower service request. Thus, the average driven distance of non-ridesharing SAVs remains the lowest among all scenarios. The aforementioned distances could further increase by considering vehicle rebalancing, showing that vehicle ranges and possibly charging infrastructure need to be taken into account in future research.

Table 5

Summary of vehicle driven distances for all scenarios and fleet sizes.

Scenario	Fleet size	2000	2500	3000	3500	4000	4500	5000	5500	6000
S1- non-ridesharing	Average driven distance (km)	414	610	645	647	631	606	566	543	495
	Maximum driven distance (km)	652	975	907	894	895	866	925	822	884
S2- ridesharing (2-seats small car)	Average driven distance (km)	469	549	528	543	503	477	422	408	377
	Maximum driven distance (km)	779	880	923	869	820	817	791	778	807
S3- ridesharing (standard 4-seats car)	Average driven distance (km)	546	553	546	524	463	445	392	386	354
	Maximum driven distance (km)	820	919	866	900	825	866	799	797	691
S4- ridesharing (6-seats minivan)	Average driven distance (km)	541	528	552	526	479	444	408	383	361
	Maximum driven distance (km)	861	847	888	870	779	883	761	841	714

4.6. Ride sharing service cost

The aforementioned results are given when the cost of the ridesharing service is assumed to be 20% less than individual rides (0.4 Euro per kilometer compared to 0.5 Euro per kilometer for individual ride). This price is encouraging enough for the travelers to prefer the ridesharing service to individual rides within the same fleet size (according to the PKTs - see Fig. 6). Although reducing service price and sharing rides leads to a higher PKT, the former may not be interesting for the operators as the service benefits for each kilometer of ride decrease (if we assume that by increasing PKT, the fix cost of operation per kilometer remains unchanged). Thus, it is important to compare the benefit that an operator could gain due to

the growth of PKT with the loss that occurs due to the reduction of profit per kilometer. In order to explore the evolution of service performance indicators, two lower prices for ridesharing services are assumed (30% and 40% less than individual ride price) and the impacts on PKT and empty vehicle traveling distance in kilometer (EVK) are compared. As seen in Fig. 9, reducing service price results in 4-10% higher PKT compared to the initial ridesharing scenario, with the maximum value for 3.0 k SAVs in the second and third scenarios and 2.5 k SAVs in the fourth scenario. However, the EVK changes vary between -4% and 18% with the maximum values at the same fleet sizes in each scenario. As illustrated here, the reduction of service price does not cause proportionate improvements on the operational performance indicators of the major scenarios and fleet sizes. In fact, the increase of PKT as the main indicator of service profits, which is lower than 10% in the best case, is not enough to cover the loss of direct income occurred due to the lower service price (30-40%). In fact, the latter is certainly higher than 10% since the operational costs are included in the service price. Moreover, in the cases when an important growth of PKT is occurred, the EVK increases and therefore the cost of service for operator grows as well. Therefore, for the fleet of 2.5k to 3.5k SAVs, the scenarios with initial service price remain more advantageous.

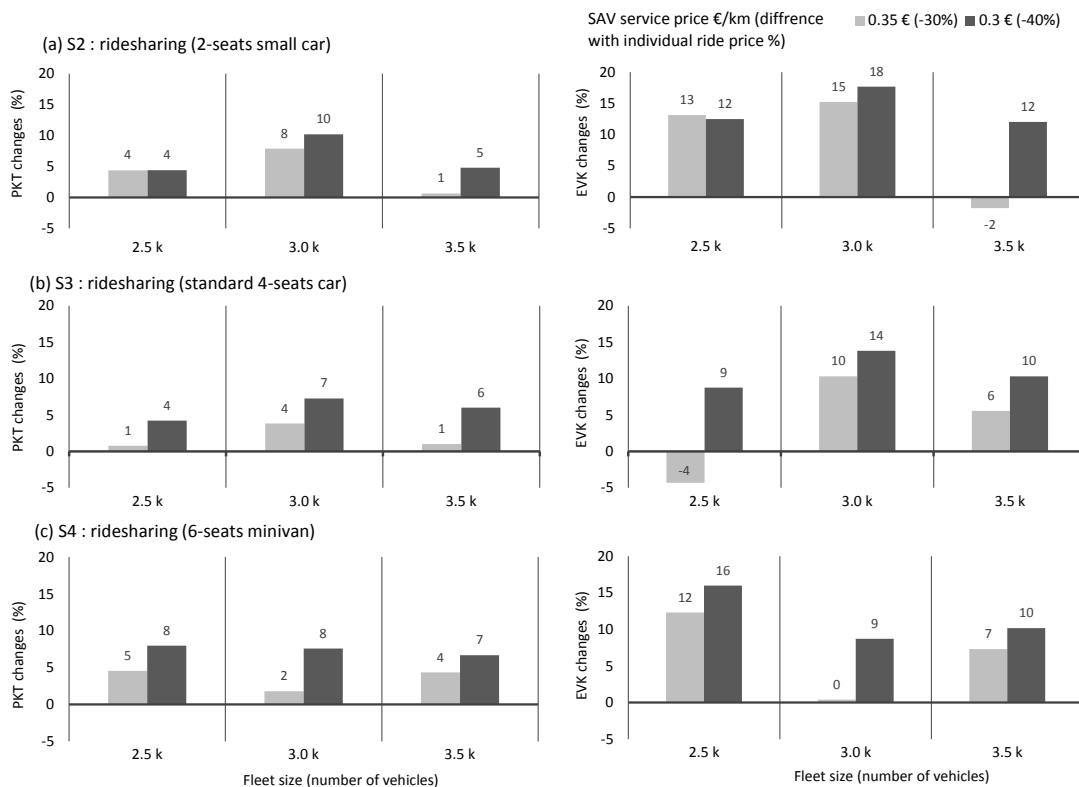


Fig. 9. The changes on PKT and EVK in the case of lower prices for ridesharing SAV services of 2.5 k to 3.5 k vehicles.

4.7. Rebalancing strategy

The fleet usage ratio and PKT may be improved by rebalancing SAVs. Although, this strategy can result in higher EVK. In order to explore the impacts on SAV service performances, optimum fleet size of each scenario is re-simulated with rebalancing enabled. During these simulations, vehicles are reallocated to different cells of 1 square kilometer (used for demand aggregation) according to the cost flow minimization of idle vehicles and scattered requests. Empty vehicles are considered idle when there is no request after 10 minutes of staying. The reallocation process is done every 5 minutes. The cost of single ride and ridesharing services assumed to be as initial values (0.5 €/km for single ride and 0.4 €/km for ridesharing). Table 6 illustrates the changes on performance metrics. As demonstrated here, modal share, fleet usage ratio and in-vehicle PKT increase for all scenarios when SAVs are rebalanced. However, the empty distance ratio increases significantly. In fact, the growth of service benefits correlated to fleet usage and in-vehicle PKT, occurs at the expense of extra operational costs due to empty traveling distance. Consequently, the decision on using a rebalancing strategy has to be made according to the cost and benefits that the operator of such services is expecting for each kilometer traveled by empty vehicles and passengers. Some other important changes occur in terms of the SAV's LoS. As seen in Table 6, the average waiting time has meaningfully decreased for the ridesharing scenarios after introducing rebalancing. This occurs when the empty vehicles, which are far from the demand hubs, are reallocated to those zones. As a result, there are more vehicles available within lower wait times. Nevertheless, in-vehicle and detour times remain almost unchanged. Regarding in-vehicle time, the changes before and after introducing rebalancing strategy are minor since the trip patterns do not change

significantly. Consequently, this indicator varies in the same order that has been observed for various fleet sizes of the same scenario (see Fig. 2). However, given the greater number of available vehicles and accordingly lower wait times, it seems that the detour time should similarly decrease. This did not occur due to the higher demand as well as lower 1 PAX and bigger 2 and 3 PAX ratios. In fact, after enabling rebalancing more rides are shared. Therefore, the average detour time remains almost unchanged. In the case of the individual ride scenario, since the service is saturated during morning and evening peak hours, the rebalancing strategy does not necessarily result in significant waiting time changes.

Similar to fleet usage and in-vehicle PKT, average and maximum driven distances increase for all scenarios. This means that by introducing a rebalancing strategy the vehicles need to have larger batteries or need to recharge more frequently.

Table 6

Performance metrics' changes before and after enabling rebalancing strategy.

Scenario	Non-ridesharing (3.5 k)		Ridesharing 2-seats small car (2.5 k)		Ridesharing standard 4-seats car (3.0 k)		Ridesharing 6-seats minivan (3.0 k)	
	no rebalancing	with rebalancing	no rebalancing	with rebalancing	no rebalancing	with rebalancing	no rebalancing	with rebalancing
SAV modal share (%)	6.0	6.3	4.6	5.2	5.3	6.4	5.4	6.4
Average waiting time (min)	18.5	18.4	18.9	13.9	20.7	13.1	21.1	14.8
Average in-vehicle time (min)	38.5	38.7	43.9	44.1	46.0	45.2	46.0	44.8
Average detour time (min)	N/A	N/A	4.7	5.2	6.1	5.8	6.0	5.9
Fleet usage ratio (%)	59	68	50	66	50	66	51	67
Empty distance ratio (%)	14	20	14	26	15	24	16	24
In-vehicle PKT (km)	1.93 M	2.08 M	1.53 M	1.81 M	1.97 M	2.40 M	1.97 M	2.41 M
1 PAX ratio (%)	100	100	69	63	67	59	66	61
2 PAX ratio (%)	N/A	N/A	31	37	26	33	27	31
3 PAX ratio (%)	N/A	N/A	N/A	N/A	6	7	6	7
4 PAX ratio (%)	N/A	N/A	N/A	N/A	1	1	1	1
5 PAX ratio (%)	N/A	N/A	N/A	N/A	N/A	N/A	<1	<1
6 PAX ratio (%)	N/A	N/A	N/A	N/A	N/A	N/A	0	0
Average driven distance (km)	647	746	549	715	546	707	552	723
Max. driven distance (km)	894	978	880	964	866	896	888	939

5. Discussion and conclusion

The rising popularity of carsharing and technological advancements on electric and autonomous vehicles are leading to the emergence of new shared mobility systems. Some car manufactures and transportation network companies (e.g. Uber and Lyft) have already announced their plans for deploying SAVs in the future. Understanding dynamic tradeoffs between service configuration and demand is an important prerequisite for delivering such services. This study sought to investigate the design of an SAV service considering its demands responsive to the network, user taste variations and traffic in a multi-modal context. Simulations of various SAV fleet sizes and capacities considering ridesharing and rebalancing strategies across the Rouen Normandie metropolitan area in France provide initial insights. As suggested by these simulations, the SAVs performance is strongly correlated to the fleet size, specifically in the case of individual ride service. The results show that the SAV modal shares vary from 3.1% to 7.6% for different fleet sizes of 2.0 k to 6.0 k vehicles. While the SAV modal share of small fleet size for individual ride is the minimum among all scenarios including ridesharing with various vehicle capacities, this term is the greatest for the medium and big fleet sizes. The latter actually occurs when the fleet of individual ride service exceeds a critical size (2.5 k), from which the smaller fleet size results in a significant decline of fleet usage (34% compared to 8% that is observed from 3.0 k to 2.5 k vehicles). In fact, for fleet sizes this small, the expected wait times increase meaningfully and lead to very low service utility compared to other alternatives; thus, the demand decreases accordingly. On the contrary, once the peak hour demand is satisfied in acceptable wait times, the service performance decreases slightly by increasing fleet size. This variation is not as significant as in ridesharing scenarios since in those cases the change of fleet size has less important impacts on the LoS. The results also suggest that the average waiting time, which is estimated when the interaction of demand and supply is relaxed (and therefore it is different from the aforementioned expected waiting time), decreases meaningfully for the smallest fleet sizes. This is actually contrary to what is usually suggested when the SAV simulation with predefined or static demand is performed and shows the importance of considering dynamic demand in the simulation of on-demand services.

Further analysis reveals that in the case of ridesharing services without vehicle rebalancing, the changes of average waiting time remain insignificant for the medium and big fleet sizes. Nevertheless, this indicator decreases in the individual ride service for the big fleet sizes. In fact, in ridesharing scenarios since the service is never saturated in the case of medium and big fleet sizes, when an upcoming request is registered, the nearest vehicle with available seats is allocated to it. However, in individual ride services, the nearest empty vehicle has to be allocated to that request. Bigger fleet sizes result in more available

vehicles in individual ride services and the waiting time decreases accordingly. Increase of fleet size similarly results in more available seats in ridesharing scenarios (up to 5%). However, this change is not significant since the fleets are not as occupied as in individual ride scenario and the increase of seats availability does not have an important impact on the availability of service. It is also shown that average in-vehicle and detour times vary slightly according to the fleet size. These changes being relatively minor (less than four minutes) follow almost the same trend.

By comparing the fleet usages and empty distance ratios of different scenarios, we found that the optimum fleet sizes for individual ride and ridesharing cases are different. Those results suggest that while the best fleet size of individual rides is 3.5 k, in the case of small car with two seats, 2.5k vehicles and for standard 4-seats car and 6-seats minivan, 3k vehicles are the best performing fleet sizes. The indicators show that considering transport related service performance, there are no big differences between standard 4-seats car and 6-seats minivan. Since the bigger capacity vehicle may be financially less efficient due to the higher vehicle and operational costs, it seems that 6-seats minivan cannot be a performant alternative. However, we have to keep in mind that the extra capacity and seats may potentially affect the user comfort perception and consequently their choice in the real world. Further comparison of four suggested fleet sizes illustrates that given the relatively high in-vehicle PKT and low empty distance ratio of the 3.0 k vehicles with share rides, this scenario is the best option among all the considered scenarios. Furthermore, taking into account the trade-off between waiting and detour times and service cost, we consider that the proposed pricing scheme for SAV ridesharing service (20% less compared to individual ride) is enough attractive for users. In addition, the results show that decreasing of ridesharing service prices up to 40% of individual ride does not cause proportionate improvements on the operational performance indicators and would not be beneficial for the operator.

Importantly, enabling vehicle rebalancing is found to have a profound effect on both user and service related metrics. For optimum fleet sizes of ridesharing scenarios, rebalancing results in lower average waiting times (25-35%). Nevertheless, in individual ride scenario, this indicator remains unchanged since the service is already saturated in peak hours without enabling rebalancing. In-vehicle PKT and empty distance ratio increase for all scenarios, however, the change of the latter indicator is relatively more important (42-85% against 7-17%). Besides, the detour times remain almost unchanged. Given these indicators, the decision on enabling rebalancing strategy should be made according to the financial analysis based on the cost and benefits that operator of such services is expecting for each kilometer traveled by passengers and empty vehicles.

The average driven distances for optimum scenarios without rebalancing varies from 546 to 647 kilometers. Given the relatively lower range of today's electric vehicles, it will be required that the majority of SAVs recharge during the day. Furthermore, enabling rebalancing results in higher average driven distance (707 to 746 kilometers). Considering maximum driven distance exceeding even 900 kilometers, these indicators suggest that future SAVs with today's range specifications will necessarily require some recharging infrastructure.

The employed agent-based simulations incorporate user taste variation developed previously by the authors. The detailed service usage indicator estimated for time slices of one hour illustrates a shift of the morning peak-hour service usage from 7-9 am for the small fleet sizes to 8-10 am for big fleet sizes. This shows the effect that different SAV users with different trip patterns may have on the service usage and prove the importance of considering user taste variation in SAV demand modeling and simulation.

While these investigations and results offer a broad and new understanding of SAV service performance and design, there are several opportunities for improvement. For example, rather than having the same pricing scheme for all rides, future efforts should examine dynamic pricing (e.g. time-based or demand-based). In addition, an improved rebalancing strategy may be proposed and evaluated within this simulation framework. The authors further plan to integrate electric SAV (ESAV) into the simulation and investigate the evolution of service performance indicators according to various charging station positioning and vehicle ranges.

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