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Demand modelling of autonomous shared taxis mixed with scheduled transit.

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ABSTRACT
Autonomous taxis (aTaxis) are promising to restructure the urban mobility universe: dispatching vehicles on roads to minimize congestion, reducing accidents and thus increasing savings of travel time, improving the transit level of service and reducing operating costs of public modes, thus limiting public subsidies. The simulation of demand and supply for on-demand services while considering the interaction with other modes has not yet been sufficiently investigated.
This paper proposes a framework for simulating on-demand aTaxi services, while considering interactions with scheduled transit. In particular, it is coupling an agent-based aTaxi model (VIPSIM) and the four-step model of VISUM. The framework is applied to a network in the Paris metropolitan area where aTaxis are implemented to replace a BRT service. Transfers between aTaxis and BRT are considered and a combined utility for public modes is calculated. The convergence between the two models is then performed. Results of the application case show that aTaxis improve the mobility performances of public transit. A supply management analysis proved that 20 aTaxis provides high service efficiency and increase the service profitability. Using 10 more vehicles attracts 15 more passengers. With 65 aTaxis, the demand is 10% higher with the same profit as the BRT.

Keywords: Autonomous taxis, on-demand service, demand simulation, mode choice, agent-based model
1. Introduction

1.1. Background

In recent years, a series of contributions has addressed issues of simulating autonomous vehicles (Berrada & Leurent, 2017), starting from vehicle dispatching (Wang, et al., 2013) to relocation strategies (Nourinejad & Roorda, 2014; Zhu & Kornhauser, 2017; Babicheva, et al., 2018), passing through vehicle electrification (Wang, et al., 2016), dynamic ridesharing (Fagnant & Kockelman, 2016; Zhang, et al., 2015) and integration into traffic planning models (Burghout, et al., 2015; Kloostra & Roorda, 2017; Auld, et al., 2017).

In regards to the representation of the road network, the majority of studies have considered a grid-based network as abstraction of the real network (Fagnant & Kockelman, 2014; Chen, et al., 2016; Zhang, et al., 2015). More advanced network representations include quasi-dynamic actual road networks with time-dependent, but deterministic travel times (ITF, 2015). Recent research employed dynamic traffic simulation tool such MATSIM (Bischoff & Maciejewski, 2016) or MITSIM (Adnan, et al., 2016; Azevedo, et al., 2016) and a cell-transmission model (Levin, et al., 2017) to model AVs in a congestible road network. In all of these studies, however, the demand is a fixed input, estimated based on a given penetration rate of AVs.

The consideration of demand by using a mode choice was explored by Levin et al. (2015a; 2015b). In fact, they proposed a four-step model dividing demand into different income groups. Mode choice is between parking, repositioning, and transit based on a nested logit model. A static and dynamic assignments showed that using AVs improves the capacity of the intersections, but does not reduce significantly the congestion. The disadvantage of this approach is that not everyone in a high-income group will own an AV and conversely in a low-income group. Yang (2017) integrated AVs into an existing four-step transportation model by modifying the model parameters. It divides the integration of the AV mode into four steps: car ownership model, trip generation, mode choice and traffic assignment. While Levin et al. (2015a; 2015b) assumed a 100% as a ratio of AVs penetration, Yang (2017) investigated six penetration rates and found that AV will increase the travel demand (longer travel distances) and bring better traffic conditions when the adoption rate becomes higher. Kroger et al. (2016) used a macroscopic model for the U.S. and Germany to assess the impact of AVs on the travel demand. The two case studies are differentiated by AV adoption rates and assumptions of user groups’ sensitivities. By focusing on the first three steps of the four step model, the authors showed that the introduction of AVs leads to moderate increase on travel distances and significant decrease of public transport trips. Even considering the mode choice, all of these studies, however, focused only on privately owned vehicles.

Studies dealing with the connection of AVs with public modes are very scarce. The study of the International Forum of Transport (ITF, 2015) found that the AV fleet size is influenced by the availability of public transport. In particular, around 18% more SAVs are needed in scenarios without high-capacity public transport, compared to scenarios where SAVs are deployed alongside high-capacity public transport. It follows that without public transport, 5000 additional cars are required and driven kilometers would increase by 13%. Vakayil et al. (2017) propose a spatially hub-based SAV network model that analyses transfers between AVs and mass transit. The model considers transit frequency, transfer costs and two rebalancing strategies. It proves that an integration between AV and mass transit services leads to reduction in congestion and vehicular emissions. Yu et al. (2017) assessed the potential of using on-demand SAV as the alternative to the low-demand buses to improve the first/last-mile connectivity in a study area in Singapore. The agent-based model is tested for a bus-only scenario and a series of scenarios integrating AV
with various fleet sizes. Criteria are defined for each actor. For users, the out-of-vehicle time is evaluated. For transportation services, it is the impact on road traffic. From AV operators’ perspective, the profitability is considered. Results are positive if all users accept to share the vehicle. Hörl (2018) explores the performance of four existing dispatching and rebalancing algorithms that have been used in literature to simulate SAVs. The attractiveness of the service is assessed according to the waiting time and the service fare. The operator influences the service level through dimensioning the fleet size and defining dispatching and rebalancing strategies. For all scenarios, the simulation for the Zurich area found almost the same values of waiting time. In addition, AV services appear to be cost-wise highly attractive for car and taxi users, while they are not able to compete with subsidized mass transit.

All of demand models have considered the case of private AVs that would replace conventional cars. On the other hand, major agent-based models focus on the supply operations and set-ups without detailing the demand side beyond statistical and spatial description in the form of an origin-destination matrix of trip-flows.

1.2. Objective

This paper proposes a modeling framework for the demand for autonomous taxis (aTaxis) while considering transit modes and private cars as well, in the same territory. Technical interactions and complementarities between these services (e.g. transfers, feeding…) and the impact on users’ mobility (e.g. accessibility, users’ costs, modal split…), are assessed by the framework. From the perspective of the operator (public or private), the fleet size impact is explored in order to increase demand and profit at the same time.

This paper brings about original contributions by:

(a) Proposing a novel modeling framework for the demand of taxi services,
(b) Considering aTaxis as a public mode and investigating the effect on the performance on the overall modal split
(c) Integrating interactions between aTaxis and public modes (transfers in particular)
(d) Applying the model for a real service, which will be deployed in next year.
(e) Considering in the model framework the results of a stated-preference survey that had been conducted in the same territory for the same service.

1.3. Method

The developed framework has the goal of integrating a dynamic supply model, which simulates performance of on-demand services, into a static demand model, which is dedicated exclusively to scheduled services. In particular, the framework relates VIPSIM (Babicheva, et al., 2018), an agent-based model developed by VEDECOM, and the VISUM four-step model (PTV Group, 2018). The convergence between these two models is proved through a real application case in the Paris Palaiseau area. Mobility impacts as well as economic performances of replacing a BRT (Bus Rapid Transit) service with autonomous vehicles are evaluated.

1.4. Paper structure

The paper starts by presenting the framework, with a brief description of VIPSIM, VISUM and the demand-supply connection scheme. A detailed description of the four-step model in VISUM and the convergence loop follows. The framework is then applied to a real case in order to investigate its performance, as well as the impact of autonomous taxis on users and the operator.
2. Demand-supply connection framework

The demand is modelled with VISUM, a static model that determines the impacts of existing or planned transport supply, which can encompass both the vehicle road network and the scheduled public modes. In particular, the demand can be modelled in VISUM using a four-step model: (1) Generation of trips, (2) Distribution to destinations, (3) Mode choice and (4) Route assignment. A separate agent-based simulation model VIPSIM was developed for the aTaxi system. It simulates movements of vehicles in interaction with passengers. The service performance in terms of passenger waiting time and travel time are among the key outputs generated. In the following, VIPSIM, an agent-based model for autonomous taxis, is presented. Then, the demand sub-model, the four-step model of VISUM, is presented while outlining main improvements to gather VIPSIM outputs. Finally, the connection between VIPSIM and VISUM is described and the corresponding mathematical problem is formulated.

2.1. Supply model: VIPSIM, an agent-based model for autonomous taxis

VIPSIM (Vedecom Integrated Passenger transport SIMulator) (Babicheva, et al., 2018) is an agent-based microscopic simulation model developed by the VEDECOM institute, which simulates the behavior and performance of a service of shared autonomous taxis. The vehicle and passenger movements are modeled in detail, as well as operations strategies such as the management of empty vehicles and ride-sharing assignment. An optimization interface allows the evaluation of optimization algorithms minimizing e.g. passenger waiting times, operator costs, empty vehicle mileage, etc. Empty taxis are redistributed to serve passengers or to anticipate demand, including the arrival of mass public transit vehicles at stations. Depending on the algorithm, they are reserved to nearest users in real-time through a first-come first served (FCFS) algorithm, or use more complicated algorithms that take into account deficits and surpluses of vehicles, based on current and predicted demand (Babicheva, et al., 2018).

When taxis are loaded, they consider ride-sharing passengers along their route with the objective to increase their loading efficiency. They accept passengers, who board and alight in dedicated stations. The stations are located within 400 meters from passengers’ origin/destination. Taxis are assumed to run according to a modified Intelligent Driver Model (IDM) (Kesting, et al., 2010) respecting speed limits and interactions with other vehicles.

The main inputs considered in VIPSIM are the passenger demand station-to-station for a given service period, the network infrastructure (roads, stations…) and the number of vehicles. The main outputs are the travel times of trips, passenger waiting times, the number of waiting passengers per station and the empty running times and mileage of vehicles.
FIGURE 1 Empty (green) and full (blue) vehicles destined to one of the stations

FIGURE 1 shows the main simulation model where aTaxis are moving towards a station to pick up waiting passengers. Empty vehicles are shown in green and (partially) loaded vehicles in blue. FIGURE 2 shows an example of the main VIPSIM outputs. The main KPIs (Key Performance Indices) are passenger waiting times (average and max), number of passengers served, average passenger and vehicle trip lengths, total kms of loaded and empty vehicle movements, energy consumption, station queue lengths, as well as ridesharing efficiency (number of passengers per loaded vehicle trip). Each output contributing to a KPI (e.g. average passenger waiting time) can be selected and its details displayed in a graph as well as on map.
2.2. Travel demand: Four-step model of VISUM

The demand model of VISUM is composed of four submodels in the following sequence: (1) Trip generation, (2) Distribution, (3) Mode choice and (4) Route assignment.

2.2.1. Trip generation

The trip generation model estimates for each Traffic Analysis Zone (TAZ) emitted and attracted trips. TAZ are areas of a radius of maximum 400 m around the station. Each train station is considered as an independent TAZ. The centroid of each TAZ is inserted near to the taxi station. Connectors are generated to link the centroid to transit stops and road nodes. Population and jobs for each TAZ are calculated by combining urban characteristics and job address data (INSEE, 2017).

The total amount of internal trips (noted \(Q_0\)) in the city is given by data of DRIEA (Regional and Interdepartmental Direction of Equipment and Planning). It is adjusted for the evolution of population and jobs in order to approximate actual internal trips. Trip generations and attractions are then obtained using the following equations:

\[
E = \frac{E_{tot} P_{TAZ}}{P_{tot}} \\
A = \frac{A_{tot} J_{TAZ}}{J_{tot}}
\]
Where $E_{tot}$ and $A_{tot}$ total generation and attraction respectively, given from surveys of DRIEA, $P_{TAZ}$ and $J_{TAZ}$ population and jobs respectively per TAZ and $P_{tot}$ and $J_{tot}$ population and jobs for all the study area.

2.2.2. Trip distribution

The gravity model computes the trip flows by OD pair zones. It is calculated based on vehicle travel time / transit travel time according to equation (1). In particular, the total distribution matrix is calculated as the sum of two distribution matrices: (1) for users of private cars and (2) for users of public modes.

$$F_{ij} = k_{ij}E_iA_j \exp (cU_{ij}) \quad (2)$$

Where: $k_{ij}$ is a normalization factor, $E_i$ generations by zone, $A_j$ attractions by zone, and $U_{ij}$ the utility between $i$ and $j$ (travel time here), $c$ is the utility sensitivity parameter.

In particular, we have: $\sum_j F_{ij} = E_i$ and $\sum_i F_{ij} = A_j$

2.2.3. Mode choice

Two modes are modeled: private cars and public transport. aTaxis are considered as a public transport mode. They are integrated with other transit modes (bus, train…) as an additional and complementary public service. In this step, the part of demand using each mode (private cars, public modes and autonomous taxis as well) is determined.

The mode choice multinomial logit model is a discrete logit model using a utility function of each mode. In general, the utility function is expressed as:

$$U_m = \psi^{(m)} - \tau^{(m)} - \tau^{(m)} = \psi^{(m)} - \tau^{(m)} + cR{\alpha}_R + cW{\alpha}_W$$

Wherein $U_m$ is the utility of the mode $m$, $\tau^{(m)}$ the tariff of using $m$, $\tau^{(m)}$ the generalized time, as a combination of $\beta^{(m)}_R$ and $\beta^{(m)}_W$, resp. the travel time and access time when using the mode $m$. $\alpha_R$, $\alpha_W$ are positive coefficients in Euro per unit time. $\psi^{(m)}$ is a coefficient of the $m$ mode preference, which reflects unknown impacts of other factors than times and cost (comfort, privacy, flexibility etc). Coefficients are determined by approximation or estimated from stated-preference surveys.

The utility of private cars includes running costs $\alpha_R\beta^{(c)}_R$. The utility of public transport is a combination of aTaxi utility and conventional public modes utility. In particular, the combined utility is constructed by making the distinction between common ODs and non-common ODs. 

**Non-common ODs.** Non-common ODs are ODs which are served only by one mode. In this case, the utility to go from O to D is equal to the utility of the used mode. For public modes, the generalized time is the perceived journey time, which combines travel times, waiting times, access and egress times and transfer times. For aTaxis, the generalized time combines travel time and waiting time.

**Common ODs.** Common ODs are trips served by combined modes (e.g. aTaxi and bus). The utility of these trips combines AVs utility (travel time and waiting time) until the transfer point, the transfer penalty and then public modes utility (perceived journey time) from the transfer point. Since aTaxis are considered as public transport modes, then the fare of the trip is integrated between AVs and conventional public modes. The preference of the combined mode, furthermore, could be different from the sum of AVs preference and public modes preference. Utility functions are provided later equations (8) and (9).
2.2.4. Assignment
The assignment of aTaxis is realized in VIPSIM. Consequently, the assignment of public modes is obtained outside of VISUM. Car assignment is then realized in VISUM. The car assignment impacts travel times which changes the overall trip distribution. Then two loops of assignment are applied in the model as presented in Figure 3(a): (1) for aTaxis, and (2) for private cars.

2.3. Convergence loop
In order to model the demand for aTaxis, VISUM requires the impedance of each mode. For conventional modes (private cars, bus, train...), the impedances are obtained directly from the network and timetables of public modes. For aTaxis (on-demand service), VIPSIM provides the impedance matrix, and thus the utility used for mode choice.

FIGURE 3 (a) shows the general assignment scheme, where VIPSIM is run in the inner loop for the aTaxi assignment (FIGURE 3(b)). The process stops when the mode choice and trip distribution converge.

The utility of aTaxis ($U_{aT}$), as a combination of travel times and waiting times equation (3), is given by VIPSIM model as a function of demand ($A$). The combined utility $U_{PuT}$ is then provided by (6) to (9) by making the distinction between common ODs and non-common ODs. Finally, the demand is calculated considering the combined utility based on a logit model (5). Hence, the overall system is a fixed point problem in Q or $U_{PuT}$, that could be summarized through the following equations:

\[ Q \]
\[ U_{aT} = f(Q) \]  

\[ Q(i,j) = Q_0 \exp(\mu_{P_{aT}}) / \sum_{i \in \{P_{aT}, Car\}} \exp(\mu_{U_m}) \]  

\[ U_{P_{aT}}(i,j) = U_{aT}(i,j) \quad \text{for} \quad (i,j) \in S^{(aT)} \]  

\[ U_{P_{aT}}(i,j) = U_{Bus}(i,j) \quad \text{for} \quad (i,j) \in S^{(Bus)} \]  

Where \( \Delta T \) is the transfer penalty. \( S^{(aT)}, S^{(Bus)} \) are respectively stations served by aTaxis and buses and \( \tilde{S} = S^{(aT)} \cap S^{(Bus)} \).

The problem is solved using the following program:

**Step0.** Set an initial value \( Q^{(z)} \). Let \( z = 0 \) and consider that \( Q^{(0)} \) is equal to the total demand resulting from the distribution step.

**Step1.** Calculate \( t_R^{(z)} \) and \( t_w^{(z)} \) by introducing \( Q^{(z)} \) in VIPSIM.

**Step2.** Update the demand volume in VISUM through running the third step of the model.

**Step3.** If \( Q^{(z+1)} - Q^{(z)} \leq \epsilon \), then stop where \( \epsilon \) is a predetermined convergence tolerance. Otherwise \( z = z + 1 \) and return to Step 1.

### 3. Simulation case study

#### 3.1. Case study description

**3.1.1. Territory**

The model framework is applied to Palaiseau, a French city located in the Paris metropolitan area, 17 km south from the center of Paris. It is home to about 32 000 inhabitants and provides about 22 000 jobs. The distribution of homes and jobs is heterogeneous. Palaiseau is becoming an area of interest because it is a part of a growing scientific cluster in France, which concentrates universities, graduate schools, research institutes and research labs of companies. The connection to the rest of the urbanized area is mainly ensured by the train line RER B, which traverses Palaiseau along a north-south axis and serves three stations. In particular, the Massy-Palaiseau station is a junction of RER B, RER C and a French high-speed rail line (TGV). It is furthermore a hub between train lines and several bus lines, including one BRT line.

**3.1.2. Taxi service**

A service of aTaxis in Palaiseau is planned to be implemented by 2020. The service is based on a fleet of taxis operating on a selected road network, connecting the Massy-Palaiseau station to
universities and research institutes. aTaxis aim to replace the existing service of BRT (Bus rapid transit line), the characteristics of which are provided by data of DRIEA and presented in TABLE 1.

**TABLE 1 BRT technical characteristics**

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel time</td>
<td>11min</td>
</tr>
<tr>
<td>Length</td>
<td>9.28km</td>
</tr>
<tr>
<td>Commercial speed</td>
<td>30km/h</td>
</tr>
<tr>
<td>Headway</td>
<td>5min (during Peak Hours)</td>
</tr>
<tr>
<td></td>
<td>15min (during Off-Peak Hours)</td>
</tr>
<tr>
<td>Number of vehicles</td>
<td>15 (during Peak Hours)</td>
</tr>
<tr>
<td>Number of stations</td>
<td>13</td>
</tr>
<tr>
<td>Vehicle.km travelled</td>
<td>230</td>
</tr>
</tbody>
</table>

The taxi network has a total length of 13 km and includes 21 stations. Each station is associated to one Traffic Analysis Zone (TAZ). The fleet is composed of 60 taxis. The average speed of taxis in the network is 50km/h, which is a function of link speed limits, interactions with other vehicles and entering/ exiting stations. The speed limits in the network vary from 30 to 70km/h. FIGURE 4 shows the overall aTaxi network by making the distinction between BRT network (in green) and additional roads used by aTaxis to improve the feeding service (in red).

**FIGURE 4 Palaiseau network for autonomous taxis**

3.1.3. Demand

The simulation is performed for one morning peak hour and focuses on home-to-work trips. Generations and attractions are generated by making the distinction between motorized persons, who are able to use private cars and public modes and non-motorized persons for whom public modes are the only option.

For private cars, the perceived travel time is in general over-estimated by more than 50% (Peer, et al., 2014) depending on the origin-destination length and driving conditions (congestion, traffic lights, intersections…). The mode preference against public modes is set up by default in VISUM to about 2 € for motorized persons. Non-motorized persons prefer using public modes whatever their impedance: they have been given a mode preference of -30 €.

For conventional public modes, the perceived time spent aboard vehicles is generally estimated accurately (Wardman, 2004). However, perceived passenger travel time can increase by as much
as 2.5 times in very crowded vehicles (6 standing passengers per m²). One waiting minute is perceived as 1.5 (Meunier & Quinet, 2015) to 2.5 (Wardman, 2004) travel minutes. Similarly, one walking minute is equivalent to two travel minutes (Meunier & Quinet, 2015). To sum up, consider factors of 2, 1.5 and 2 resp. for the bus travel time, the waiting time and the walking time.

For taxis, the travel time and waiting time seem to be the most important factors, even more important than fare (Wong, et al., 2015; Borja, et al., 2018). They are perceived resp. with a factor of 1.2 and 1.5 compared to actual spent time. The walking time is perceived as for bus. The mode preference coefficient is assumed to be closer to that of private cars than that of public modes since the service is on demand with guaranteed seating. We assume that it is equal to 1.5 €.

Finally, for public modes (aTaxis and conventional public modes), the fare is assumed of 1.2€ per trip. The transfer time between modes is slightly over-perceived by 20%.

Given the French estimated value of time of 12 €/h for commuting purposes (Quinet, 2013), the utility coefficients are summarized in

TABLE 2:

<table>
<thead>
<tr>
<th>Coefficients of the utility for modes</th>
<th>Notation</th>
<th>Car</th>
<th>Bus</th>
<th>aTaxis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel time</td>
<td>$\alpha_R^{(m)}$</td>
<td>0.3</td>
<td>0.4</td>
<td>0.24</td>
</tr>
<tr>
<td>Waiting time</td>
<td>$\alpha_W^{(m)}$</td>
<td>0</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>Walking time</td>
<td>$\alpha_A^{(m)}$</td>
<td>0</td>
<td>0.4</td>
<td>0.4</td>
</tr>
<tr>
<td>Transfer time</td>
<td>$\alpha_T^{(m)}$</td>
<td>0</td>
<td>0.24</td>
<td>0.24</td>
</tr>
<tr>
<td>Fare</td>
<td>$\tau^{(m)}$</td>
<td>0</td>
<td>1.2</td>
<td>1.2</td>
</tr>
<tr>
<td>Mode preference (non-motorized)</td>
<td>$\psi^{(m)}$</td>
<td>2</td>
<td>0</td>
<td>1.5</td>
</tr>
<tr>
<td>Mode preference (motorized)</td>
<td>$\psi^{(m)}$</td>
<td>-30</td>
<td>0</td>
<td>1.5</td>
</tr>
</tbody>
</table>

3.1.4. Equilibrium computation

FIGURE 5 shows convergence results between VIPSIM and VISUM. The first iteration corresponds to almost 100% of demand using public modes. In the next iteration, that passes to 40%. The convergence is then obtained for about 42% of the total demand, after three iterations.
3.2. Simulation results

3.2.1. Operational performance

The results presented here are those after reaching convergence (in 3 iterations). The fleet of 60 aTaxis attract 42% of the total demand, which corresponds to 594 users during the peak hour. The average passenger waiting time is 3 min, the maximum is 19 min and the 95% centile is 13 min. The average trip time is 3 min. The average passenger queue length is 1, but the maximum is 20 passengers. The average passenger trip distance is 4 km, indicating that the aTaxis is mostly attractive for relatively short trips. The total passenger km is 1350 km, which translates to 22.5 km per vehicle.

The ridesharing is moderately effective at 1.35 passengers per loaded trip, but the empty vehicle trips make up 70% of the total vehicle km, indicating that a large number of empty vehicles are circulating in the network in anticipation of potential passenger demand. The implemented algorithms do not take into account empty running costs, just minimization of current and anticipated passenger waiting times.

3.2.2. Mobility performance

Mobility performance include modal share and quality of service. TABLE 3 shows the situation of mode split between cars and public modes before and after introduction of aTaxis. Results show that replacing the BRT by aTaxis ensures about the same modal split, with an improvement of about 9.2% for public modes. Almost 21% of PuT trips are achieved entirely by aTaxis and about 70% of trips involve using aTaxis for part of the trip.

**TABLE 3 Mode split between private cars and public modes before and after introducing aTaxis**

<table>
<thead>
<tr>
<th></th>
<th>PUT modes</th>
<th>Motorized modes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>aTaxis</td>
<td>BUS</td>
</tr>
<tr>
<td>Before</td>
<td>0%</td>
<td>100%</td>
</tr>
</tbody>
</table>

FIGURE 5 Share of public transport demand by iteration number
An analysis of passenger costs of using BRT and aTaxis supports these findings (FIGURE 6). The focus is on all trips aiming to reach station 1, which corresponds to the Massy-Palaiseau station. Three main groups of ODs are emerging. 

(1) Origins that are directly served by the BRT and taxis: aTaxis seem to be more attractive in general. 

(2) Origins that are directly served by aTaxis but indirectly by BRT (involving usage of other bus lines or walking). The results show that for this group aTaxis significantly reduce user costs by an average factor 4. 

(3) Origins that are served by buses only. Trips from these origins involve transfers between BRT/ aTaxis and bus lines. Here, average generalized costs are similar and there is no clear predominance of one system over another.

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**FIGURE 6** Passenger generalized time for trips to station 1 (Massy-Palaiseau station), grouped by types of origin.

Focusing particularly on the area served by aTaxis (previously by BRT), the mode share is 28 % for BRT against 72 % for private cars. The introduction of aTaxis improves the service quality, inducing the evolution of the mode share to 38 % for aTaxis against 62 % for cars.

3.2.3. Costs performance

Costs of purchasing autonomous cars would be higher by 20 % (Bösch, et al., 2018) to 26 %
(Owens, 2018) compared to conventional cars. In addition, using autonomous cars would shorten vehicle lifespan to 1.5 to 3 years. Assuming a purchase cost of 36,000 € and a lifespan of 2 years, fixed costs would be, in the absence of drivers’ wages, about 50 €/day or 3€/h. Running costs are expected to decrease by 50 % for insurance (Litman, 2018), and would reduce the energy consumption by about 10 % (Bösch, et al., 2018). Considering the kilometric cost coefficient (PRK), running costs for medium-size vehicles are estimated to 0.4 €/km (Pelletier, 2018).

For the French BRT, the purchase cost of buses is about 220,000 € per bus (JDN, 2009) for a lifespan of about 7 years (Transbus, 2018). Depreciation costs are then about 100 €/day. Fixed costs include furthermore stations depreciation. We assume that total depreciation costs reach about 200 €/day. On the other hand, the median drivers’ wage is 2000 €/month (salairemoyen, 2018). Since the maximum work-week is 35 hours, at least three drivers are required for each bus. Considering furthermore an increase by 60 % due to taxes and by 25 % as average ratio of additional premiums (e.g. weekends, night, seniority, etc.), drivers wages would cost finally $2400 \times 3 \times 1.6 \times 1.25 = 480 \, €/$day. To sum up, the total fixed costs are then for conventional taxis about 680 €/day. Based on PRK of large-size vehicles, we estimate running costs at 3 €/km (Pelletier, 2018).

### 3.3. Application to supply management

For public modes, the main priority of the operator is probably the demand maximization, while ensuring the service profitability, or at least its viability. In general, the main factors influencing operator profit are the fleet size, vehicle capacity and pricing. We assume that the capacity of vehicles is fixed, that fares correspond to those of public modes, so 1.2 € per trip, and investigate the impact of fleet size on demand and profit.

FIGURE 7 shows the variations of demand and profit with respect to fleet size. Zero profit corresponds to the profit of BRT. For fleets inferior to 65 vehicles, aTaxis should generate more revenues than BRT, thus requiring less subsidies to ensure their financial viability. In particular, they are profitable for fleets inferior to 25 vehicles. Given the imbalanced distribution of demand (mostly generated in train station and with almost same destinations), then larger vehicle fleets induce more empty kilometers driven and in turn higher costs. On the other hand, the demand is barely affected by the fleet size (+1% for +10 vehicles). FIGURE 8 investigates the main reasons for this finding by evaluating ridesharing and empty vehicles traveled. It confirms that 20 vehicles leads to higher ridesharing efficiency (2 passengers per loaded vehicle), and thus higher operating efficiency.
3.4. Discussion

The demand modelling framework is capable of determining conditions of the traffic equilibrium for a given territory. It is based on a conventional four-step travel demand-forecasting model. The connection with an agent-based model (e.g. VIPSIM) allows modeling an on-demand service using a conventional macroscopic assignment tool (e.g. VISUM). The convergence between the two models is obtained after a limited number of iterations. The proposed framework assesses the impact of implementing new taxi services on the modal split depending on user sensitivities.
Further, it has the potential to investigate the efficiency of operational strategies (e.g. fleet size, ridesharing).

There are, however, some limitations to this demand simulation framework. Firstly, the four-step model suffers from a number of drawbacks that are related to the nature of these models (Mladenovic & Trifunovic, 2014). For instance, trips begin and end at a single point in a zone’s centroid, workers from households are matched to jobs based on travel time/distance and without considering income and trip purposes. A second issue concerns the data availability. Data is required for developing and calibrating the demand model. However, the most recent survey data that is published until 2018 is that of 2010. Moreover, data provided by DRIEA is by MODUS zones, which are not adapted to analyze station-to-station trips for a local feeding service (i.e. Palaiseau is composed of two MODUS zones, while we need at least 21 zones). In addition, it concerns only trips realized during morning peak hours. That prevents an analysis of complementarities between autonomous taxis and existing modes, which could alternate along the day depending on the demand volume. Finally, data related to on-demand service does not yet exist and has to be estimated.

Regarding the application case, the simulation was achieved for the case of Palaiseau city, a choice motivated by the EVAPS project led by VEDECOM, which aims to implement a service of autonomous taxis by year 2020. That will allow validation of our results and calibration of the simulation tool. The simulation scenario also has several limitations. The first limitation is related to the availability of data. Trip generations and attractions are based on old data and projected through observing the evolution of local population and jobs. Moreover, this data corresponds to the peak period and only home-to-work trips. Another limitation of our simulation scenario concerns the utility calculation. We include the mode preference in order to consider security, comfort, attractiveness, but the utility function does not include the access time and walkability, which would be expected to affect the trip cost and then the modal split.

4. Conclusion

This paper presents a framework for modeling demand and supply interactions for aTaxis mixed with scheduled transit. The framework couples a dynamic microscopic supply model for aTaxis (VIPSIM) with a static and macroscopic model for demand (VISUM). Consequently, it proposes a solution to model the demand for on-demand services and scheduled modes at the same time. It has in addition the potential to explore the effects of introducing locally (e.g. district level) an on-demand service on the global mode choice (e.g. city or regional level).

The application on a Paris Palaiseau case investigates the replacement of the BRT by 60 aTaxis, running at 50km/h and ensuring feeding shared trips. aTaxis would compete with the level of service of the BRT, specifically in areas that are served exclusively by aTaxis. It follows that the overall demand share for PuT is improved. A supply management analysis shows that increasing ridesharing ratios, and so the economic efficiency of the service, is achieved by reducing the fleet size, which affects in turn the volume of demand negatively. In particular, deploying ten more vehicles involve 1% more of users (+15 passengers). The study is focusing only on the peak conditions while aTaxis would likely be more efficient during off-peak times, where Bus offers less frequent service (longer waiting time). Improvements of mobility and economic performances could therefore be greater and more relevant for off-peak times.
Hence, future work should consolidate these findings by considering an analysis during off-peak periods. The supply management should be enlarged to include the fare optimization. That should consider a tariff by kilometer, as for conventional taxi services, and a dynamic pricing as for for-hiring services. In addition, such a service would be regulated in the future. An analysis of impacts of fleet and/or tariff regulation should be relevant. Finally, the estimation of the utility coefficients and mode preference of such services could be improved through stated-preferences surveys.

5. References


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**AUTHORS CONTRIBUTIONS**

**Jaâfar Berrada:** the demand model and the application case  
**Wilco Burghout:** the agent-based model VIPSIM  
**Ingmar Andreasson:** supervisor  
**Fabien Leurent:** supervisor