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## Agent based simulation for the design of a mobility service in the Paris-Saclay area

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### Abstract

Autonomous vehicles promise an important opportunity for a complete paradigm shift for the design of transportation systems. These systems will become more flexible and efficient by adapting to the travelers' demand. On the other hand, multi agent systems offer an intuitive and powerful way to design complex distributed systems and agent based simulation has proved to be well suited for studying the performance of mobility services and their impact on the users and the traffic in general.

In this study, we use an Agent-Based modeling approach to design a mobility system based on a fleet of autonomous vehicles (robo-taxis and shuttles) and connected road side units, each of these elements represented by intelligent collaborative agents. In our model, the control is distributed among the agents and the global behaviour of the system emerges from local decisions. We then used a microsimulation tool to test the model on the real road network of the Paris-Saclay area. Since this area is planned to become a center for technology, innovation and education and is currently under constant development, it offers an opportunity for the design and the implementation of new models of transportation services.

We designed our mobility system in an incremental manner by introducing more components and more intelligent behaviour and testing its performance at each step.

Our results suggest that for our area of study, a mobility service that relies on autonomous vehicles aided by connected road side units that allow to retrieve information about the traffic would perform better than a regular service.

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*Keywords:* agent based simulation; shared mobility; robo-taxis

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## 1. Introduction

The area of Paris-Saclay, located at the south of the French capital city, is currently growing to become a center for technology, education and innovation. It is under constant development with new infrastructure being continuously delivered. This offers a challenging opportunity for the design and the implementation of new models of mobility services and local mobility stakeholders, along with academic institutions, are investigating this topic.

Autonomous vehicles will play a major role in these developments, they offer today a means for a complete shift in the paradigms of mobility systems. These new systems will be more flexible and efficient by relying on a wide range of data sources (including connected road side units) to assess, predict and react to changes in traffic and traveler's demand. On the other hand, multi agent systems offer an intuitive and powerful way to design complex distributed systems and agent based simulation has proved to be well suited for studying the performance of mobility services and their impact on the users and the traffic in general. Various agent based traffic simulation tools have been implemented, they offer medium to large scale simulation capabilities with varying levels of details.

In this paper, we aim to use the multi-agent paradigm to design and simulate mobility systems based on autonomous-shuttles and robo-taxis in the area of Paris-Saclay, the following sections describe some related work, the methodology that was followed in our study and the results of our simulations.

## 2. Literature review

Agent based approaches are very well suited for being used in the design, simulation and study of large complex systems where the control is not centralized and the environment is dynamic (Uhrmacher and Weyns (2009)). It is well established that the fields of transportation and road traffic are an obvious application area for such approaches given that: the control is geographically and functionally distributed; a high degree of autonomy and adaptation is expected from the different components of such systems and the phenomena studied in these domains (congestion, performance of mobility services, pollution...) emerge from local interactions between the agents. Burmeister et al. (1997) have been discussing the potential use of multi-agent systems in traffic and transportation as well as the interest that using agent based simulation tools can have. Some research focused on proposing multi-agent models with communication protocols and decentralized algorithms for traffic management. For example, Dresner and Stone (2004) present a reservation based intersection control mechanism. Numerous works also focused on the application of agent based approaches to model and simulate public transportation systems, Balbo and Pinson (2001) describes a decision support system (composed of two types of agents: buses and bus stops) meant to be used by human regulators to manage bus lines.

More recently, with the advent of new types of mobility systems such as shared autonomous vehicles, various investigations have been launched to study the the design of such systems and its implications on transport in cities in general. Martinez and Viegas (2017) simulated a combination of shared taxis and pre-booked mini-buses in the city of Lisbon, Portugal. Alazzawi et al. (2018) studies the impact of introducing a fleet of robo-taxi vehicles on the traffic in the city of Milan. Similarly, Vosoghi et al. (2019) performed simulations taking into account the how changes in mobility offers might affect the demand in the city of Rouen, France. Fagnant and Kockelman (2018) explores the use of autonomous vehicles with dynamic ride-sharing in Austin, Texas. Scheltes and de Almeida Correia (2017) investigates last mile connections of train trips using a fleet of automated vehicles in Delft, Netherlands.

Such studies rely on traffic simulation tools. Saidallah et al. (2016) present a comparative study of the mainly used ones in the literature.

## 3. Methodology

We use the SUMO simulation software (presented in Lopez et al. (2018)) for our experiment. Among other simulation tools, SUMO presents some advantages that are interesting for our study: (i) The tool is essentially microscopic. Each entity of the simulation (vehicle, pedestrian, traffic light...) is represented and tracked individually during the simulation, this allows us to implement a fine-grained multi-agent model. (ii) It allows to import and use real road networks, this is interesting to us since our objective is work on the real network of the Paris-Saclay area. (iii) It integrates a mathematical model for battery consumption and charging of electric vehicles (Kurczveil et al. (2014)),

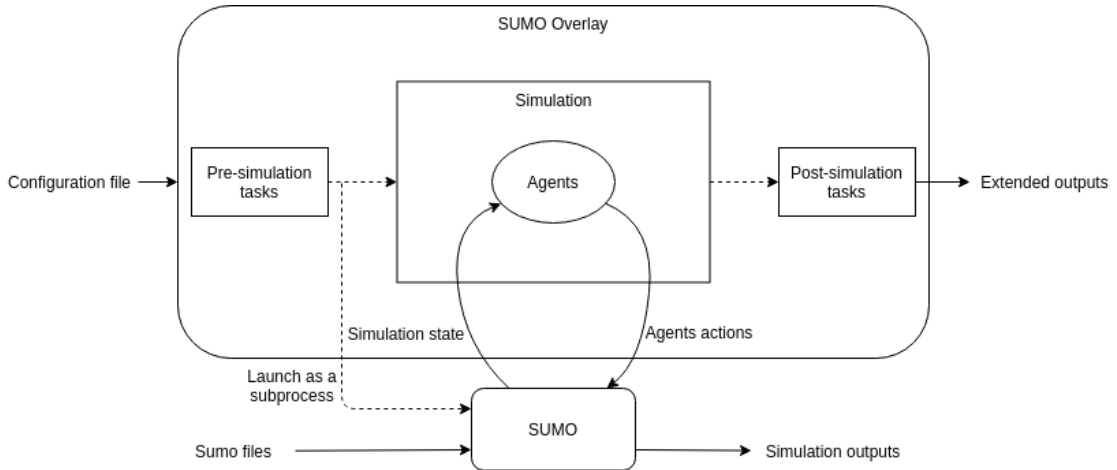


Fig. 1. SUMO Based software architecture for the implementation of our agent based model

which we can then rely on in the simulation of our mobility service. (iv) Finally, SUMO includes a Python API called TraCI (first described in Wegener et al. (2008)) that allows to influence the simulation and behavior of the different entities.

To ease the implementation of our multi-agent model and allow a greater flexibility during the setup of different simulation scenarios, we propose a software architecture described by figure 1. We use it to define our agents and their behavior and to affect the SUMO simulation.

In the same way SUMO takes some configuration files as input, our software architecture takes a configuration file indicating which simulation to run and the mobility services to be tested. The configuration also indicates some tasks to be performed before and after the simulation like generating a demand and using SUMO outputs to generate relevant plots. During the execution of SUMO, the simulation state is retrieved at each time step and the agents' information is updated. Then the communications between the agents occur and decisions of each agent are computed. The agents' actions are then sent to SUMO to be performed. These actions concern high level decisions of the agents as whether to stop at a bus stop or which robo-taxi vehicle to assign to a user while lower level decisions like itinerary computation are performed inside SUMO.

In the following sections we describe the agent based model we implemented in this software architecture and the preparation of the data used for the simulations.

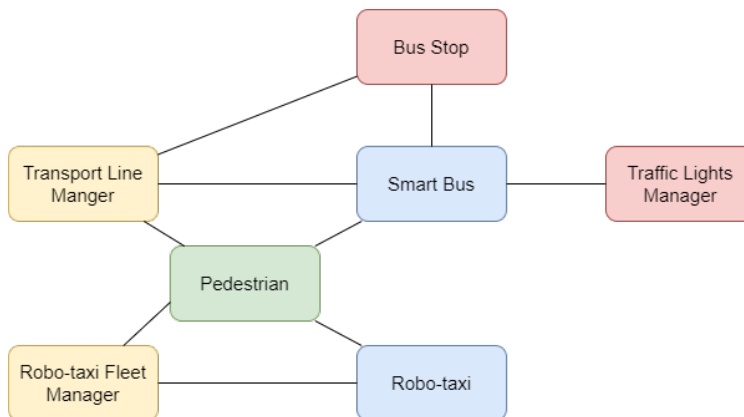


Fig. 2. Implemented agents

### 3.1. Multi-agent modeling

A multi-agent model is characterized by three components: the environment, the agents and the interactions between them. The former is provided to us by SUMO as the whole simulation state retrieved at each time step. The agents are grouped in four categories: Vehicles, Service Managers, Roadside Units and Pedestrians. Figure 2 summarizes the agents that we implemented, a line between two agents means that they interact with each other. The pedestrian agent sends ride requests to one of the service managers which then checks the corresponding vehicles and decides whether to send a bus (if it's a Transport Line Manager) or assigns a robo-taxi (if it's a Robo-Taxi fleet manager). In the first case, the manager checks all the pending queries and tries to achieve a trade-off between maximizing bus capacity usage and minimizing pedestrian waiting times as described in algorithm 2. On the other hand, the Robo-Taxi fleet manager forwards the queries to its available vehicles and each one of them estimates the expected arrival time for the pedestrian without delaying already planned trips (multiple pedestrians might be grouped if they share common departure and destination stops according the vehicle's capacity). The query is then assigned to the vehicle with the best offer (see algorithm 1). If no vehicle is currently available, the query remains pending. The pedestrians keep waiting in a bus stop for the vehicles that are assigned for them and then leave the network when they arrive at their destination stop.

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#### Algorithm 1 Robo-Taxi Fleet Manager Behavior

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**Require:**  $battery\_threshold \in [0, 1]$   
 $Q = \{\text{ordered pending queries}\}$   
 $V = \{\text{robo-taxi vehicles}\}$   
 $V_a \leftarrow \{v \in V / \neg charging(v) \wedge battery\_capacity(v) > battery\_threshold\}$   
**for all**  $q \in Q$  **do**  
      $Offers_q \leftarrow \{query(v, q) / v \in V\}$   
     **if**  $Offers_q \neq \emptyset$  **then**  
          $v^* \leftarrow \arg \min_{v \in V_a} Offers_q$   
          $assign(v^*, q)$   
          $Q \leftarrow Q / \{q\}$   
     **end if**  
**end for**

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#### Algorithm 2 Transport Line Manager Behavior

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**Require:**  $bus\_capacity > 0, time\_threshold > 0, capacity\_threshold \in [0, 1]$   
 $P = \{\text{pedestrians waiting for a bus on this line}\}$   
 $P_{considered} \leftarrow \{q \in Q / q \text{ will not be satisfied by an already running bus}\}$   
**if**  $|P_{considered}| > bus\_capacity * capacity\_threshold$  or  $\exists p \in P_{considered}, waiting\_time(p) \geq waiting\_threshold$  **then**  
      $send\_bus()$   
**end if**

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### 3.2. Data preparation

We imported the road network of the Paris-Saclay area and use it as the basis for our simulations. The network comprises 2800 junctions and 5700 edges and includes traffic lights, bus stops and dedicated bus lanes. We then defined an artificial user demand of 10000 users throughout the day from 7am to 7pm with two major rush hours at the beginning and at the end of the day and another smaller one around noon, as depicted in figure 3. The demands are uniformly distributed inside the time slots.

On the basis of this network and user demand, we set up 6 scenarios in an incremental manner, from a fixed schedule bus service to a complex one mixing demand responsive buses and robo-taxis. In all these scenarios, we do not consider conventional vehicles.

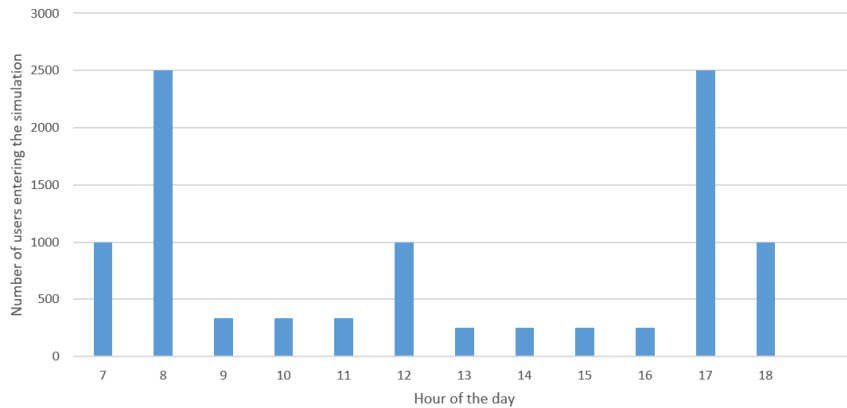


Fig. 3. Distribution of user demand throughout the day

**RegBuses** : In this first scenario, we simulate a real bus line with a fixed schedule. We chose the line 91.06 that serves as a primary bus access for students and workers in the area of Paris-Saclay. The buses of this line use dedicated lanes with very few intersections with other roads.

**SmartBuses** : Here, we simulate the same bus line with the same departure times for the buses except that the buses communicate with the traffic lights to ask for priority and with the bus stops to avoid unnecessary stopovers (no user is willing to take or go down from the bus at this stop).

**RespBuses** : The fixed schedule is replaced with a dynamic, demand responsive scheduled implemented by the TransportLine Manager agent defined in 3.1.

**RespBuses+RT** : A service of robo-taxis is operated during the day alongside the demand responsive bus line. A fixed share of 5% of the users are routed to use this service.

**RespBuses⊗RT** : Here the robo-taxis run only outside of peak times (from 9am to 12pm then from 1pm to 5pm) while the bus line is stopped on these time slots.

**RespBuses⊕RT** : In this last scenario, the bus line operates during all the simulation and the robo-taxis run only outside of peak times with 5% of the users redirected to them.

The robo-taxis are electric vehicles and so they were modeled with their battery characteristics. We also added a reserved parking area and 6 charging stations to the network.

#### 4. Experiments and results

In this section we discuss the simulations that we ran and compare the obtained results. The metrics that interest us the most in this study are the average waiting times and trip duration for the users in the simulations. The runs have been performed on a computer equipped with an AMD Ryzen 7 3800X CPU with 8 cores and 16 threads and 64Gb of RAM. The multiple cores feature was used by running up to 16 simulations in parallel. The time for each run was about 70 minutes.

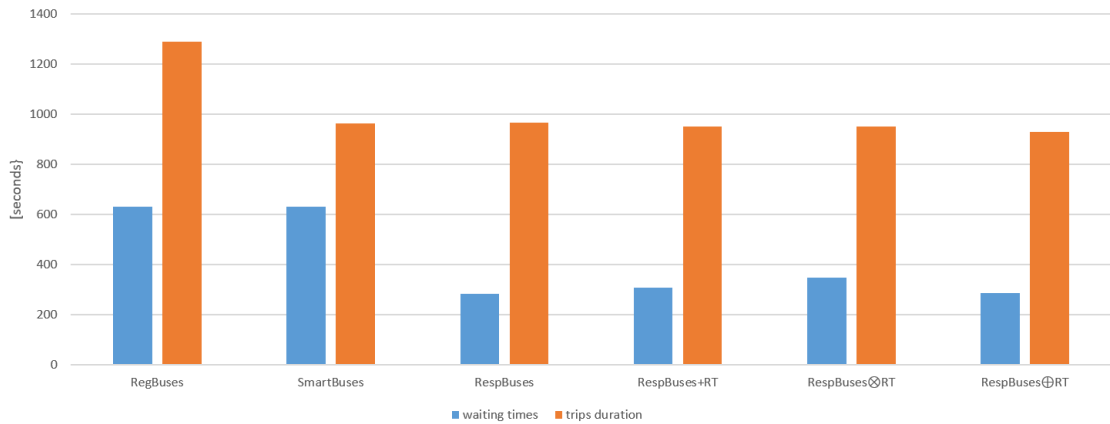


Fig. 4. Average users' waiting times resulting of each simulated scenario

Figure 4 depicts the average waiting times and trip duration for the users in our different simulated scenarios. By comparing the results of the first two scenarios, we conclude that introducing communications between the buses and the road side units (bus stops and traffic lights) allows a significant reduction in trip duration. This gain is also due to the fact that the buses run on dedicated lanes. We then note the advantage of having a demand responsive management of our bus line, it allows a gain of 50% in waiting times.

Introducing a fleet of 30 robo-taxis operating throughout the simulated day and redirecting 5% of the users to them have a negative effect on the waiting times compared to having only a demand responsive bus line. And the robo-taxis handling all the users outside of peak times does not perform better, this is due to the fact that in both cases, the fleet of robo-taxi vehicles with a 4 passengers capacity is not able to handle that number of users as well as the buses. In the simulations we ran, each robo-taxi went to to charge once during the simulated day.

Taken alone, the demand responsive bus service has been tested with various fleet sizes and values of the parameters involved in its control algorithm. Figure 5 shows that for all the values of **time\_threshold** that we tested, the service operates most effectively starting from a fleet of 15 vehicles and that increasing the fleet size without making any other change doesn't improve the results.

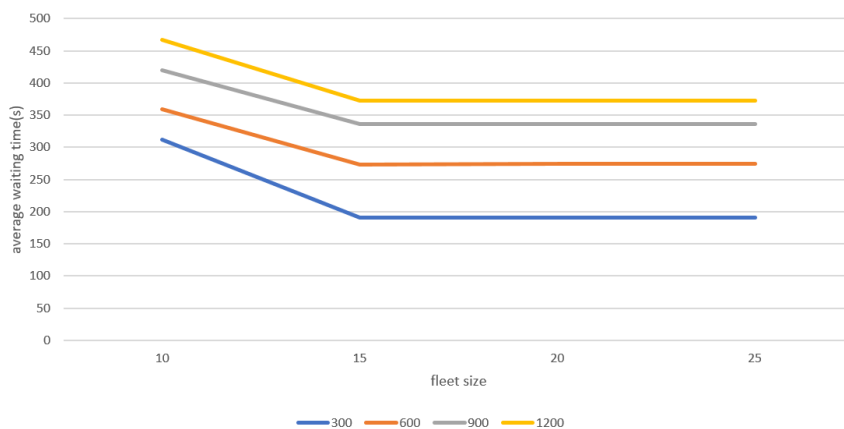


Fig. 5. Average users waiting times using increasing bus fleet sizes

## 5. Conclusion

In this study we developed a multi-agent model to simulate mobility services composed of demand responsive buses and on-demand robo-taxis. We developed a software architecture based on SUMO to implement our model and perform simulations on the area of Paris-Saclay with various configurations. Our results suggest that introducing demand responsiveness in a bus service, enabled by connected roadside units, and a fleet of robo-taxi vehicles would not surely benefit the users if it is not sized appropriately considering the demand. Our work shows how multi-agent simulations can be used to help the design of new transportation systems. In our future works, more realistic demand scenarios and as well as dynamic demand need to be taken into account.

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