



Research article

Taxi services and the carsharing alternative: a case study of valencia city

Pasqual Martí^{1,*}, Jaume Jordán¹, Pablo Chamoso^{2,3} and Vicente Julian¹

¹ Valencian Research Institute for Artificial Intelligence (VRAIN), Universitat Politècnica de València, Camino de Vera s/n, Valencia 46022, Spain

² BISITE Research Group, University of Salamanca, Calle Espejo s/n, Edificio Multiusos I+D+i, Salamanca 37007, Spain

³ Air Institute, IoT Digital Innovation Hub, Plaza del Ayuntamiento 1, Carbajosa de la Sagrada Salamanca 37188, Spain

* **Correspondence:** Email: pasmargi@vrain.upv.es.

Abstract: The public's awareness of pollution in cities is growing. The decrease of carbon dioxide emissions from the use of fossil-fuel-powered cars stands out among the different viable alternatives. To this purpose, more sustainable options, such as carsharing fleets, could be used to replace private automobiles and other services such as taxis. This type of vehicle, which is usually electric, is becoming more common in cities, providing a green mobility option. In this research, we use multi-agent simulations to examine the efficiency of the current taxi fleet in Valencia. After that, we evaluate various carsharing fleet arrangements. Our findings demonstrate the possibility for a mix of the two types of fleets to meet present demand while also improving the city's sustainability.

Keywords: urban mobility; sustainability; carsharing; simulation; intelligent agents

1. Introduction

In recent years, both city administrators and the general public have become more conscious of the impact of pollution in metropolitan areas. As a result, there are an increasing number of projects aimed at improving sustainability and lowering cities' carbon footprint. Among its crucial targets, the European Union's 2030 climate and energy framework aims to lower the level of greenhouse gas emissions a 40% with respect to 1990*. Various municipal councils are advocating for legislation that places considerable limits on polluting automobiles, particularly in urban centres. With this, the inhabitant's quality of life would be generally improved thanks to an enhancement in air quality. Some localities have outright bans on personal petrol-powered vehicles. In contrast, others are more lenient

*2030 climate & energy framework: https://ec.europa.eu/clima/policies/strategies/2030_en

and the worst polluting vehicles (according to their technical datasheet, age or emissions) are the only ones prohibited.

Parallel to this, new mobility service models have emerged that are more suited to users' needs.

Among them, the widely used "ridesourcing service" stands out. This kind of services offer their customers on-demand rides that can be booked through a multitude of platforms (call-centre, mobile application, etc.).

As new mobility options are popularised, the research interest in measuring their urban transportation impact grows too. Authors publish in Reference [1] a study centred in San Francisco, California, that compares taxi services against ridesourcing solutions such as the ones offered by Lyft or Uber.

Despite the many similarities ridesourcing and taxi fleets may seem to have, their work reveals the two differ in the amount of satisfied requests and the customer waiting time. Furthermore, around 50% of ridesourcing usage was replacing public transportation and personal vehicle trips, having a deeper effect on urban mobility than if it were just substituting taxi rides.

New means of transportation do not just replace existing modes of transportation; they also produce new transportation trends among consumers. As a result, incorporating electric carsharing fleets [2] into city planning could help to reduce both excess pollution and traffic congestion. Passengers whose journey includes locations which are not served by the city's public transportation options may be able to fulfil their needs with carsharing. Carsharing customers can book a vehicle which is close enough to reach by foot and make a private use of it. At the end of their ride, the vehicle is available for another user. In turn, carsharing could bring a reduction in the amount of active private vehicles in the urban transportation system. The research published in Reference [3] reveals a decrease in the average number of vehicles owned per household in Vancouver, Canada, after the implementation of two separate carsharing services. Moreover, many users may no longer need to possess a vehicle in the future, which will substantially influence sustainability on multiple levels, including direct emissions from the active automobiles as well as indirect contaminating procedures for vehicle manufacturing.

In contrast with the stated above, authors in Reference [4] declare their data shows no significant relation between car ownership and free-floating car-sharing in Germany. This goes to show the complexity of urban mobility and how it is also affected by sociological factors. Nevertheless, the aforementioned study does not analyse impact on urban rides. Many taxi consumers would be eager to use carsharing services because they may be more cost-effective if the service is competitively priced. However, carsharing vehicles cannot meet all taxi demand. Some people are unable to drive or have special needs that this type of fleet can not meet. A taxi-like service will never be completely substituted.

Taxi and dial-a-ride fleets, among other conventional urban transportation services, may be partially substituted by carsharing services with potentially lower environmental impact. The carbon dioxide emissions of carsharing are reduced thanks to the nonexistence of empty movement (vehicle displacement without passenger) [5]. Furthermore, as hybrid and fully electric vehicles perform well in metropolitan settings, they may easily implement carsharing fleets. As a result, even if carsharing serves a small portion of the city's taxi demand, it will result in a cleaner environment. With this focus, a Beijing-centred work [6] investigates the features a carsharing fleet needs to outperform the existing taxi service with regard to travelling costs. A similar Research [7], also set in Beijing, assesses the efficiency of different arrangements carsharing services by means of simulation.

As can be inferred from above, many studies that look at the efficiency of urban transportation

alternatives focus on a specific town or urban area. This is a sensible choice because a critical aspect of an excellent urban fleet performance is its ability to adapt to citizens' mobility patterns and travel preferences. We pursue such a mindset by centring our research in the urban area of Valencia, Spain.

Valencia's government has been particularly engaged in developing the sustainable development goals (SDG) of the United Nations for the past few years. Among them, SDG 11: *Sustainable Cities and Communities* is specially relevant to our work. Authorities are implementing it through many policies such as the prohibition of petrol-powered vehicles in specific sections of the urban centre, pedestrianising roads and squares, developing additional parks and green spaces, and finally encouraging electric-powered vehicle usage.

Valencia had never had a carsharing service previously, and it was only recently that a small company named *Cargreen*[†] began offering it on May 9, 2021, with a fleet of 100 electric cars. The absence of this service means, in turn, the absence of GPS data belonging to carsharing trips. Nonetheless, we have data on the population, transportation, and social media activity that we utilise to recreate Valencian inhabitants' mobility patterns.

The findings of several of the research mentioned above are based on surveys and fleet data analysis. Instead, we employ agent-based modelling to simulate various mobility systems and their users, being able to define behaviours for each of them. In addition, our experimental setup allows us to simulate vehicle fleets directly in the city of Valencia. The multi-agent simulator SimFleet [8] is employed to run different scenarios and gather data that is later analysed to draw conclusions. The research questions of this article are first to assess Valencia's public taxi service efficiency from two viewpoints: sustainability, with focus on carbon dioxide emissions, and quality of service, mainly indicated by customer satisfaction. Then, we want to present the characteristics of a free-floating carsharing service so that is able to absorb a portion of the mobility demand in a sustainable manner while being a competitive alternative. Our results, supported by the experimental simulations, show there is potential to reduce part of the public taxi fleet in favour of a carsharing fleet. With both alternatives working together to serve the displacement demand, we could preserve a reasonable degree of customer satisfaction while improving the general sustainability of the urban mobility system. The present work is an extension of Reference [9].

The rest of the paper is structured as follows. Section 2 introduces the software and the data employed to build the simulation scenarios, as well as the system modelling and the experimental setup of this work. Then, Section 3 details the development of the various experiments, the metrics that evaluate fleet performance, and the collected results. Section 4 presents a general discussion on the results and findings of this work. Finally, in Section 5 we present our conclusions and future work.

2. Materials and methods

This section describes the software that was employed to build realistic simulation scenarios and the data used to this end. In addition, the simulator and its key features are introduced. Finally, the system modelling and our experimental setup are briefly described.

[†]<http://cargreen.es/>

2.1. Simulation environment: SimFleet

SimFleet [8] is a multi-agent based urban fleet simulator, initially intended for an easy implementation and experimentation of agent strategic behaviours. In this work, we carry out simulations with a modified SimFleet version. We the authors of the current work have actively contributed to SimFleet's development, which allows us to easily modify its operation to adjust the simulations to our research. It is implemented with SPADE [10], a Python agent development environment. This feature enables us to introduce to the simulations agents with behaviours and strategies defined by ourselves. In addition, SPADE provides scalability and more tools to develop complex mechanisms of communication among agents. For the current research, we have defined protocols for operating a taxi and a carsharing fleet. Moreover, we implemented separated customer strategies to make use of those services and a third one which enabled customers to use both. This was possible thanks to our experience with SimFleet and our access to its code on a lower level, which allowed us to alter its functionalities.

The urban mobility simulations are developed in SimFleet with three types of agents: FleetManager, Transport and Customer agents. Each fleet has a FleetManager, which generally acts as an intermediary between the users of such a fleet and its vehicles. In turn, each vehicle is represented by a Transport agent. Finally, Customer agents portray the actors that use the transportation system. We simulate three different transportation scenarios for this work: a taxi fleet, a carsharing fleet, and finally, a setting where both fleets operate over the same urban area. The specific behaviours and strategies of the three types of agents will vary for each scenario. However, the simulation goal is constant: all customers of the transportation service must get to their destination. Following, we briefly describe the particularities of the agent modelling of each fleet.

In taxi simulations, the FleetManager acts as a centralised entity that selects the taxi to which a particular customer request is sent. The followed strategy is to forward the request to the nearest available taxi. Transport agents act as a taxi, picking the customers up at their origin location and dropping them off at their destination. Lastly, Customer agents create a displacement request (from their current position to their destination) and send it to the FleetManager. Once they get assigned a vehicle, they wait for it to arrive.

To simulate carsharing fleets, in contrast, we employ an enhanced version of SimFleet, described in reference [11]. Such a version allows the three aforementioned agent types to simulate a *free-floating carsharing fleet*, implementing new behaviours for all of them.

The FleetManager now has to notify clients of any available (non-booked) car and its location. Transports play a more passive role, remaining parked at their origin locations and waiting for a booking request. On the other hand, customer agents can now choose the car they want to book based on their requirements. Furthermore, they must walk to their reserved vehicle to use it. A user-defined parameter limits the distance they can walk. Once in their transport location, they drive to their destination and finally park the car, leaving it available again. Ultimately, in scenarios where both fleets are present, the crucial difference appears in the Customer agent behaviour. The FleetManager and Transport agents of each fleet behave according to their fleet type (carsharing or taxi), as explained above. Regarding customers, these simulations accept taxi and carsharing customers and a new so-called hybrid customer. Hybrid customers will initially aim to book a carsharing vehicle. If unable, they will instead call for a taxi. Their behaviour, therefore, begins as a carsharing customer and transitions to a taxi customer if necessary to reach their destination.

2.2. Data generation

A simulation can recreate reality if the data on which it is based are accurate. Therefore, we decided to base our simulations on real data from Valencia, Spain, the location of our research. The regional[‡] and national[§] governments maintain open databases through which we have access to geolocated data: amount of inhabitants per area, average traffic intensity on each city road, and the positions of taxi stops, among others. Such data is fed to the *Load Generators*, presented in Rference [12].

These generators are used to allocate the elements of a simulation (customers, vehicles, resources, etc.) in the scenario in a way that reproduces the real city-data. Before the start of the allocation, the simulated area is split into multiple subareas. The *granularity* parameter determines the number of subareas. Then it computes a probability distribution for the entire area, attributing a selection probability to each subarea. This probability is calculated based on the population, traffic, and social activity in the subarea. The different factors are joined by Eq (2.1), where O_i indicates a subarea, p_i , t_i , and a_i the amounts of population, traffic, and social activity within O_i , respectively; and w_p , w_t and w_a are weights that regulate the influence of each type of data over the final probability value. The amount of data in a subarea is divided by the number of occurrences of the same type of data (P , T , and A , respectively) in the entire region.

$$\text{prob}(O_i) = w_p \cdot \frac{p_i}{\sum_{j=1}^P p_j} + w_t \cdot \frac{t_i}{\sum_{j=1}^T t_j} + w_a \cdot \frac{a_i}{\sum_{j=1}^A a_j}; \text{ with } w_p + w_t + w_a = 1 \quad (2.1)$$

For this work, the probabilistic map obtained by the *Load Generators* has been enhanced considering the main type of activity developed in each area of the city of Valencia. According to this, we find residential, primary, secondary and service industries, hospitals, and green areas, among others. By blending city and area data, we better characterise the movement patterns of citizens. Although we do not have data on specific GPS routes, we can define an origin-destination matrix. The paths of the agents are constructed as follows: Agents are assigned an origin point (contained in one of the sub-areas) in a semi-random way, according to the probabilities. Varying the values of the weights (w_p , w_t , w_a), we can increase the importance of the different factors, which is helpful to introduce different types of agents. For instance, in creating customer agents, more weight is given to population and social activity with respect to traffic. As for the destination of the journey, once the origin point has been selected, the map probabilities are recalculated, taking into account the activity type of each sub-area. For example, a journey departing from a residential area may be more likely to finish in an industrial sector and vice versa.

With our generators, we introduce individual citizens (customer agents) with their own displacement needs. Such needs can be satisfied with one of two options: taxi or carsharing services. The demand generation is transparent to the differences among concrete customer agents. Displacement requests are created as one-shot trips similar to those a taxi customer would demand. This trip model also fits the concrete type of carsharing mobility we study: free-floating carsharing, where, in general, once the customer reaches a destination, the vehicle will be available for any other user. With the described data generation setting, we improve the quality of our simulations with respect to those obtained with random agent movement.

[‡]*Govern Obert*. www.valencia.es/val/ajuntament/govern-obert

[§]*Instituto Nacional de Estadística (INE)*. www.ine.es/index.htm

2.3. System modelling

The simulations are performed in the city of Valencia, Spain. The data generators (Section 2.2) make use of geolocalized population, traffic and Twitter activity data to fill the scene with transport and customer agents, assigning realistic routes to the latter.

The scenario is loaded by SimFleet (Section 2.1) and the simulation executed. The system keeps track of different metrics regarding elapsed times and travelled distances throughout the simulation. These values will be collected once the simulation finishes to assess the performance. Following, we briefly describe the flow of each type of simulation.

In taxi simulations the fleet vehicles are allocated in various points within the city. Customers send travel requests to the fleet manager upon spawning. The fleet manager forwards each request to the closest available taxi to the customer. The taxi accepts the request, moves to the customer's position, picks them up and drives to their destination. Once at their destination, the customer agent completes its execution, and the taxi informs the fleet manager of its availability. When the fleet gets saturated and there are no free taxis, the customer waits a fixed amount of time before sends their request again. A customer can wait for a taxi as much as its maximum waiting time allows them. Once that time elapsed, if the customer could not get a taxi assigned, it will be marked as "unsatisfied" and leave the simulation.

Regarding carsharing simulations, the fleet vehicles are also allocated in various points within the city. Upon spawning, customer agents ask the fleet manager for the location of available vehicles. The customer can book a vehicle among those that are within its maximum walking distance. In general, it will aim to book the closest one to them. When the customer receives the booking confirmation it starts walking towards their vehicle. Once at the vehicle's location, the customer unlocks it and drives to their destination. Finally, the customer completes its execution and the vehicle informs the fleet manager of its new location and availability. If the customer is unable to book a transport after its maximum waiting time has expired it will be marked as "unsatisfied" and leave the simulation. This generally occurs when the customer does not have an available vehicle within walking distance at any point in time.

Finally, for hybrid simulations, those with both types of fleet, we have defined three types of customers: taxi, carsharing and hybrid customers. On the one hand, taxi customers can only travel by calling for a vehicle to the taxi fleet. Whether it is due to a lack of driving licence, a desire to avoid parking or simply not wanting to drive in the city centre, there will always be users who prefer a taxi service to one such as carsharing. On the other hand, carsharing customers will only use a carsharing vehicle. For these customers, we assume that they either prefer the lower price offered by the use of carsharing vehicles or that they have a strong environmental conscience, which pushes them to use more environmentally-friendly vehicles. Finally, hybrid customers have a utilitarian approach. They will first try to book a carsharing vehicle, knowing its use is cheaper and less polluting than a taxi ride. However, if they cannot book a vehicle after its maximum waiting time has elapsed, they will instead call for a taxi, as reaching their destination is what drives them the most. Because of that, the satisfaction dynamics are changed in hybrid-type customers: if a hybrid customer is unsatisfied, it means they have tried to book a carsharing vehicle for its maximum waiting time and failed and later tried to call a taxi and received no answer for another maximum waiting time. The other two types of customers preserve the original behaviour described above.

All types of simulation will stop once every customer is either at their destination or unsatisfied.

2.4. Experimental setup

Following, we present the system metrics and the simulations used to analyse Valencia's taxi and carsharing fleets. The experimentation consists on 15-hour simulations of transportation activity in the city with a variable demand generation that is higher at peak hours.

We defined metrics for customers' time and fleet vehicle distances and assignments, which are analysed to assess the performance of a fleet. Most metrics evaluate both carsharing and taxi fleets, although some are only meant for a concrete type or customers. All metrics are listed in Table 1.

Table 1. Description of the output metrics of the simulation. Customer and transport metrics describe individual factors relevant only to those types of agents. The overall simulation metrics provide indicators to estimate service quality and fleet performance.

Customer metrics	
Walked distance	Distance walked by the customer to its booked transport's location
Waiting time for a booking	Time a customer waited to get a confirmed booking
Waiting time for a pick up	Time a customer waited for a taxi to pick it up
Satisfaction	Boolean that indicates whether a customer has reached its destination
Transport metrics	
Assignments	Total number of served passengers
Empty distance	Distance travelled by a taxi without a passenger
Customer distance	Distance travelled by a vehicle while carrying a passenger
Simulation metrics	
Avg. customer booking time	Average of satisfied customers' waiting for booking times
Avg. customer waiting time	Average of satisfied customers' waiting for pick up times
Avg. customer walked dist.	Average of satisfied customers' walked distances
Satisfaction %	Percentage of satisfied customers (out of the total number of customers)
Total assignments	Number of assignments of a whole transport fleet
Avg. assignments	Average number of assignments per fleet vehicle
Avg. empty distance	Average empty distance travelled by the fleet vehicles
Avg. distance	Average distance travelled by the fleet vehicles
Unused vehicles	Number of vehicles with 0 assignments
CO ₂ emissions	Approximated amount of carbon dioxide emitted by the fleet

The performance of a fleet is evaluated from two different angles. On the one hand, from the customer viewpoint, lower waiting times and shorter walked distances boost satisfaction. On the other, when it comes to the fleet's economic efficiency and environmental sustainability, shorter empty distances and a higher number of assignments and occupied distances are good indicators. Finally, the universal simulation metrics are useful to measure the effect different number of vehicles and/or customers has in various scenarios.

The city of Valencia has a total of 2841 registered taxis[¶], but not all of them are active simultaneously. A maximum of 1044 taxis can be in service together, although the concrete number is highly variable according to weekday and time of the day. During concrete low demand periods, the city has had less than 200 active taxis. Regrettably, because of the absence of official data on the number of

[¶]Spanish National Statistics Institute <https://www.ine.es/jaxi/Datos.htm?tpx=32954>

active taxis each hour, we decided to portray it as a percentage of the overall number of taxis. Our baseline simulation experiment presents a taxi fleet of 840 vehicles, an 80% of the maximum number of active taxis. We hope that by doing so, we will be able to compensate for periods when taxi amounts are greater or lower.

Table 2. Mobility demand in terms of the number of customers per simulation hour.

Simulation hour	Customers	Demand intensity
7:00 – 8:00	500	Medium-Low
8:00 – 9:00	750	Medium-High
9:00 – 10:00	1000	High
10:00 – 11:00	750	Medium-High
11:00 – 12:00	250	Low
12:00 – 13:00	500	Medium-Low
13:00 – 14:00	750	Medium-High
14:00 – 15:00	1000	High
15:00 – 16:00	750	Medium-High
16:00 – 17:00	500	Medium-Low
17:00 – 18:00	750	Medium-High
18:00 – 19:00	1000	High
19:00 – 20:00	750	Medium-High
20:00 – 21:00	500	Medium-Low
21:00 – 22:00	250	Low
Total	10,000	

Regarding the demand modelling, we defined individual customers with a spawning time, location, and destination at least 2 km away from their origin. Our simulations reproduce 15 city activity hours, between 7:00 (AM) and 22:00 (10:00 PM). We have assigned to each one-hour interval a concrete demand intensity. Such intensity is related to the number of customers spawning within the hour. Specifically, we defined four intensities: Low, with 250 customers; Medium-Low, with 500 customers; Medium-High, with 750 customers; and High, with 1000 customers. We divided a total of 10,000 customers into one-hour intervals as shown in Table 2. The intervals between 9:00 and 10:00, 14:00 and 15:00 and 18:00 and 19:00 have been assigned a high demand. This reflects commuting to and from work and taking children to and from school or home.

The results of the baseline taxi simulation are compared with various configurations of carsharing fleets, aiming to assess their performance. In order to do so, another five simulation scenarios have been developed. The demand modelling described above was preserved, but the transportation service was implemented by means of a carsharing fleet. Each scenario has its own number of vehicles: *Cs-1000*, *Cs-840*, *Cs-560*, *Cs-280*, and *Cs-140*, which present fleets of 1000, 840, 560, 280 and 140 carsharing vehicles, respectively.

We can estimate how much different carsharing fleet designs can cover mobility demand by measuring the percentage of satisfied users. Furthermore, we may compare each fleet's greenhouse gas emissions as a function of the distance travelled by their vehicles.

The movement speed for vehicles is set to 40 km/h whereas for pedestrians (carsharing users) is of

4 km/h. With this, we average between the urban road speed limit of 50 km/h and the residential area speed limit of 30 km/h, as well as the time spent waiting in traffic lights. Regarding pedestrians, the average human walking speed of 5 km/h has been reduced by 1 to palliate our simulator's absence of traffic lights and the extra time they would incur. The maximum waiting time of all customers is set to 12 minutes (720 seconds). In addition, carsharing users can only book a vehicle which is within a 1000 meters walking distance. As a result, if a customer is unable to book a vehicle or has not been picked up by a taxi after 12 minutes elapse, it will be marked as unsatisfied and leave the simulation.

3. Results

This section presents the experiments carried out with the different types of fleet. First, the results for different carsharing fleet sizes to cover the demand in Valencia are shown. Then, we present the results for covering the same demand with different taxi fleet sizes. Finally, the results with combined hybrid fleets, i.e., a carsharing fleet and a taxi fleet, to cover the demand in the city are shown.

3.1. Carsharing fleets performance

In the first experiment, presented in Table 3, the performance of the carsharing fleet configurations is compared against the baseline configuration (Taxi-840). Time values in the table should be regarded as a guideline rather than an exact time measurement, as factors such as traffic congestion and traffic lights are not taken into account. In the taxi simulation, the customer booking time (Table 3, first row) shows the time required to call the taxi service provider and ask for a ride. The customer waiting time, on the other hand, indicates the average time elapsed between the call and the client pickup. These definitions vary for carsharing customers, for whom the booking time display the time spent on the app looking or waiting for an available vehicle to book. Therefore, the waiting time reflects the time it took the used to walk to the vehicle. All other metrics are common for the two types of services (please refer to Table 1 for a detailed explanation of each metric).

As can be seen, the fleet of 840 taxis achieves a high percentage of customer satisfaction. Its average booking and waiting times indicate that the fleet operated smoothly over most of the 15 hours. However, it got overloaded at some point, as 13 customers could not be served before their maximum waiting time elapsed. Each taxi made an average of 12.85 trips, an average of 6.13 Km long (including customer pickup). Still, 34 taxis were never given assigned to a customer. This is probably due to their original spawning location, making them unfit to serve any trip.

Before comparing the performance of the different carsharing fleets with the baseline, it is interesting to visualise how the demand evolved throughout the simulation. Figure 1 shows the evolution of the number of waiting and unsatisfied customers during the 15-hour period of the simulation. The number of waiting customers is indicated in the left vertical axis and represented by areas with a different shade of blue for each fleet configuration. Such a value is increased each time a customer enters the simulation. On the other hand, it decreases when a customer has booked a vehicle or its state changes to unsatisfied. The number of unsatisfied customers is indicated in the right vertical axis and represented by lines with different colours and patterns for each fleet configuration. This value is initially 0. As the simulation is carried out, the number increases each time a customer exceeds its maximum waiting time and is therefore marked as unsatisfied.

Observing the shape of the areas of Figure 1 change along the horizontal axis, we can visualise

Table 3. Simulation metrics comparison of the carsharing configurations (labelled as “Cs-” followed by the number of vehicles in their fleet) with the baseline taxi configuration of 840 transports.

	Taxi-840	Cs-1000	Cs-840	Cs-560	Cs-280	Cs-140
Avg. cust. booking time (min)	1	2.3	1.9	1.2	1	3
Avg. cust. waiting time (min)	2.5	7.6	7.1	7.2	8.3	11.6
Avg. cust. walked dist. (m)	0	518	522	554	611	655
Satisfaction %	99.87	90.77	89.57	82.86	61.59	38.21
Total assignments	9987	9077	8957	8286	6159	3821
Avg. assignments	12.85	9.57	10.95	14.85	22.15	27.49
Avg. dist. per assignment (Km)	6.13	5.44	5.47	5.47	5.43	5.41
Unused vehicles	34	52	22	2	2	1
Total empty distance (Km)	7423	0	0	0	0	0
Total distance (Km)	60,909	48,821	48,299	44,763	33,246	20,593
CO ₂ emissions (tonnes)						
Gasoline	6.68	5.35	5.30	4.91	3.65	2.26
Diesel	7.65	6.13	6.07	5.62	4.18	2.59

the demand peaks shown in Table 2. The amounts of waiting customers reach their maximum values between the 9:00–10:00, 14:00–15:00 and 18:00–20:00 time periods, reaching their absolute maximum in the evening for all configurations. Configurations cs-1000 and cs-840 behave similarly in terms of waiting and unsatisfied customers. This is clear as their areas and lines are almost overlapped, having cs-840 a slightly worse performance (higher values). The performance worsens as the fleet vehicles are reduced, as may be expected. The difference between unsatisfied customers of the cs-560 and cs-280 configurations is notable, as the latter significantly worsens the metric. The same can be observed for configuration cs-140.

Going back to Table 3, configuration taxi-840 outperforms all carsharing configurations in terms of customer satisfaction. The carsharing fleet cannot absorb the mobility demand with the restrictions we have introduced. However, we recognise that comparing taxi and carsharing fleets directly is not fair since they are so dissimilar. Taxis are most commonly utilised for brief, one-time trips. Carsharing services, on the other hand, may be used for a similar purpose or to replace private vehicles and even public transportation. Moreover, carsharing users must be willing to drive and park the transport on their own. Nonetheless, the findings suggest that a carsharing fleet may serve a portion of the taxi market (38.21% of customers with a carsharing fleet of only 140 vehicles, 61.59% with a fleet of 280 vehicles, and up to 82.86% with 560 vehicles), decreasing emissions by reducing the number of vehicles and the distance travelled.

From the standpoint of sustainability, it is noteworthy to observe how the average number of assignments per vehicle improves as the number of vacant vehicles decreases. Fewer transports have a lower environmental impact, both in terms of vehicle production and subsequent maintenance. Furthermore, it indicates a lower chance of traffic congestion, which reduces pollution and enhances the overall quality of life for all participants of the urban transportation system.

The use of carsharing vehicles has a simple but powerful benefit: it prevents empty vehicle move-

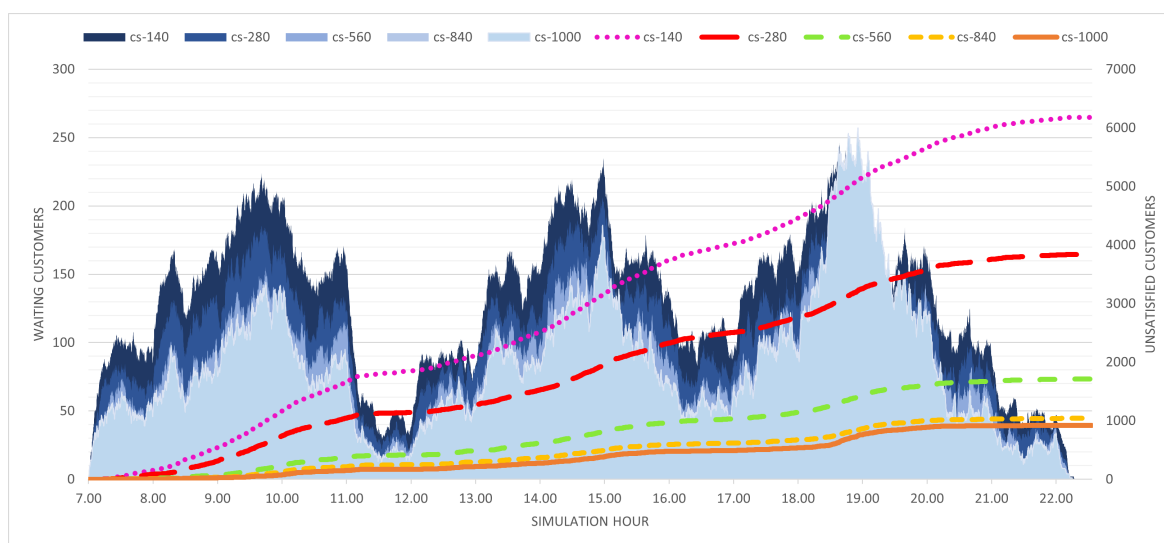


Figure 1. Visualisation of the evolution of the amounts of waiting clients (left vertical axis) and unsatisfied clients (right vertical axis) in the different carsharing simulations according to the simulation time (in hours). Simulations are labelled with “cs-” followed by the number of vehicles in their fleet.

ment. This is because our modelling disregards the relocation of vehicles, as this is a very complex problem which needs its own separate research, and thus is outside the scope of the current work. Table 3 presents carbon dioxide emissions for the different fleets assuming an average city consumption of 5 L/100km^{||} and presenting two values according to the type of fuel (diesel or gasoline). The results indicate that around 7423 km could be saved each 15 hours by avoiding empty journeys (with a fleet of 840 taxis). This represents a saving of around 0.81 to 0.93 tonnes of CO₂^{**}. Comparing simulations Taxi-840 and Cs-840, the reduction may reach around 1.38 to 1.58 tonnes. The savings would be significantly higher if the carsharing fleet was made up entirely of completely electric vehicles. The fleet in *Cs-140*, for example, covers 20,953 km every 15 hours. Travelling such a distance in a car with the mentioned consumption would result in around 2.26 to 2.59 tonnes of CO₂ emissions. All travelling emissions could be prevented if every car was electric.

3.2. Taxi fleet reduction

A different approach to increasing the sustainability of a transportation system is to reduce the number of vehicles in it. This rather drastic change must be carefully addressed to preserve an adequate level of service quality. In the following experimentation, we carried out various taxi fleet simulations, reducing the number of taxis in each fleet.

Figure 2 shows the evolution of the number of waiting and unsatisfied customers throughout the different simulations. This graph follows the format of Figure 1. Please refer to Section 3.1 for a detailed explanation of the graph. As it can be seen, the number of waiting customers reflects the three high-demand periods. In this case, configuration taxi-140 has a significantly higher number of waiting customers than the other configurations. Regarding the number of unsatisfied customers, the fleets of

^{||}Value obtained as an average of the gas consumption of vehicle models generally used for taxis in Valencia.

^{**}Computation made with <https://calculator.carbonfootprint.com/calculator.aspx?tab=4>

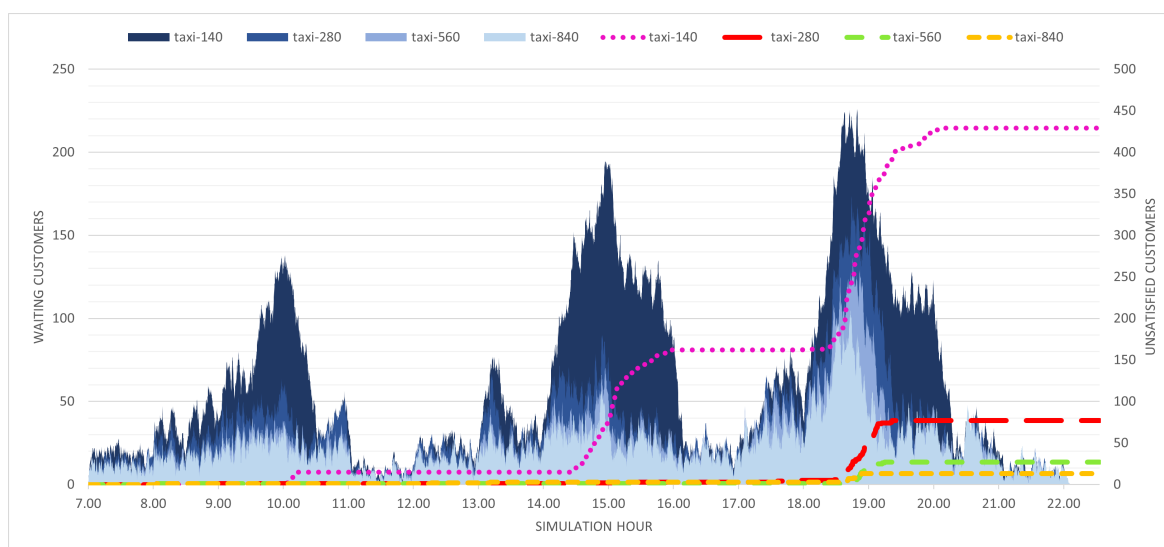


Figure 2. Visualisation of the evolution of the amounts of waiting clients (left vertical axis) and unsatisfied clients (right vertical axis) in the different taxi simulations according to the simulation time (in hours). Simulations are labelled with “taxi-” followed by the number of vehicles in their fleet.

configurations taxi-280, taxi-560 and the baseline taxi-840 only get overloaded during the third high-demand period (18:00–20:00). In configuration taxi-140, however, the fleet gets overloaded during each high-demand period, increasing its number of unsatisfied clients each time.

The simulation metrics of the different fleets, presented in Table 4, show good satisfaction percentages. It is especially remarkable the fleet’s operation in taxi-140, which only reduces satisfaction by a 4.07%, while its vehicles have been reduced an 83.33% with respect to the baseline.

Any conclusions drawn from our experimentation must be understood in the context of our simulation settings. Nevertheless, we see a potential for a reduction of Valencia’s taxi fleet (or the optimisation of its operation), aiming to lower its environmental impact. In this regard, we can see how the travelled distances, as well as the carbon dioxide emissions, increase as we reduce the number of vehicles. This is because the less taxis a fleet has, the more distance does each individual vehicle cover. Therefore, to correctly assess the sustainability in this case, we would need to compare the impact of producing and maintaining a vehicle against the impact of its usage emissions.

3.3. Hybrid mobility approach

The last set of simulations we performed present a hybrid approach to urban mobility. In our previous experimentation, the taxi fleet shows consistently better customer satisfaction. In contrast, the carsharing fleet presents the advantage of reducing the distances travelled by vehicle and consequently carbon dioxide emissions. This is, as mentioned before, because in carsharing the customer pickup is avoided. In turn, many clients may find themselves without a vehicle to book, as all of them parked are too far away. We combine a taxi and a carsharing fleet in the simulation scenario, aiming to balance both metrics.

We created five new simulation scenarios. The distribution of customers by type in these simulations

Table 4. Comparison of global simulation metrics of the different taxi fleets (labelled as “Taxi-” followed by the number of vehicles they contain) against the baseline taxi fleet of 840 vehicles.

	Taxi-840	Taxi-560	Taxi-280	Taxi-140
Avg. cust. booking time (min)	1	1	1	1
Avg. cust. waiting time (min)	2.5	2.8	3.5	6
Avg. cust. walked dist.	0	0	0	0
Satisfaction %	99.87	99.73	99.23	95.71
Total assignments	9987	9973	9923	9571
Avg. assignments	12.85	18.15	35.8	68.4
Avg. dist. per assignment (Km)	6.1	6.3	6.6	7.7
Unused vehicles	34	5	0	0
Total empty distance (Km)	7423	9154	12,331	21,972
Total distance (Km)	60,909	62,571	65,487	73,253
CO ₂ emissions (tonnes)				
Gasoline	6.68	6.86	7.18	8.03
Diesel	7.65	7.86	8.23	9.20

is 70% hybrid customers, 20% taxi customers and 10% carsharing customers (see Section 2.3 for a description of each customer type). The different instances vary in the number of vehicles for each fleet. Simulation (*cs-280, taxi-280*) has the highest number of transports, with a fleet of 280 carsharing vehicles and another with 280 taxis. Analogously, we defined simulations (*cs-280, taxi-140*), (*cs-140, taxi-140*), (*cs-140, taxi-70*) and (*cs-70, taxi-70*). As it can be seen, we intend to study the reduction of the number of vehicles, prioritising the taxi fleet.

The results of the simulations are collected in Table 5. We must take into account certain factors to analyse them. As hybrid customers can be served by the carsharing and the taxi fleets, some of their metrics are presented split by fleet type. In addition, the percentages of unsatisfied customers of a particular type are calculated over the total number of customers of that type (7000 hybrid, 2000 taxi, 1000 carsharing). Finally, please note that the increase in the customer waiting time for a taxi vehicle is partially due to the behaviour of hybrid customers, which exhaust their maximum waiting time (12 minutes) trying to book a carsharing vehicle before calling a taxi.

The results show that global customer satisfaction is relatively acceptable for every fleet combination tested. As expected, reducing the number of vehicles reduces the quality of service. Nevertheless, even with the smallest fleets (70 carsharing vehicles and 70 taxis), 74.06% of customers are satisfied. Among customers of different types, we can see how hybrid customers benefit from their freedom of choice, as they show lower dissatisfaction percentages for every simulation. In this regard, carsharing customers are more penalised, as they have more restrictions when it comes to booking a vehicle (maximum walking distance and the common maximum waiting time). Finally, it is interesting to see the evolution of the percentage of hybrid customers served by each type of fleet. In simulations (*cs-280, taxi-280*) and (*cs-280, taxi-140*) most of the hybrid customers are able to book a carsharing vehicle. However, when that fleet is reduced to 140 vehicles, the greatest part of hybrid customer demand is absorbed by the taxi fleet, as (*cs-140, taxi-140*) and (*cs-70, taxi-70*) show. Lastly, configuration (*cs-140,*

Table 5. Simulation metrics comparison of the hybrid simulations (labelled as “cs-” followed by the number of vehicles in the carsharing fleet and “taxi-” followed by the number of vehicles in the taxi fleet).

	Simulation				
	cs-280 taxi-280	cs-280 taxi-140	cs-140 taxi-140	cs-140 taxi-70	cs-70 taxi-70
Customer metrics					
Avg. taxi cust. waiting time (min)	11	11.4	12.8	15.1	16.2
Avg. cs cust. waiting time (min)	8.9	9.2	11	11	12.3
Avg. hybrid cust. waiting taxi (min)	17.2	17.4	17.1	19.7	19.8
Avg. hybrid cust. waiting cs (min)	8.9	9.2	11.1	11	12.3
Global satisfaction %	91.58	91.88	89.62	83.48	74.06
Hybrid cust. travelled by taxi %	31.11	31.34	53.91	45.34	55.69
Hybrid cust. travelled by cs %	64.46	64.35	41.83	43.71	24.46
Unsatisfied taxi customers %	8.70	7.70	7.00	16.20	22.60
Unsatisfied cs customers %	35.80	36.40	60.00	56.20	75.20
Unsatisfied hybrid customers %	4.43	4.20	4.26	10.94	19.86
Transport fleet metrics					
Total assignments	9158	9188	8962	8348	7406
Taxi fleet assignments	4043	4040	5641	4850	5446
Cs fleet assignments	5115	5148	3321	3498	1960
Avg. assignments (taxi)	14.43	28.86	40.29	69.29	77.80
Avg. assignments (cs)	18.27	18.37	23.72	24.99	28.00
Avg. dist. per assignment (taxi) (Km)	6.4	6.8	6.9	8.5	8.73
Avg. dist. per assignment (cs) (Km)	5.4	5.4	5.4	5.4	5.4
Unused vehicles (taxi)	21	2	0	0	0
Unused vehicles (cs)	3	4	1	1	1
Total empty distance (taxi) (Km)	4584	6712	8878	15132	18454
Total empty distance (cs) (Km)	0	0	0	0	0
Total distance (taxi) (Km)	26,106	27,742	39,122	40,964	47,570
Total distance (cs) (Km)	27,850	27,842	17,956	18,957	10,548
Carbon dioxide emissions					
CO ₂ emissions (taxi) (tonnes)					
Gasoline	2.86	3.04	4.29	4.49	5.22
Diesel	3.28	3.48	4.91	5.15	5.98
CO ₂ emissions (cs) (tonnes)					
Gasoline	3.05	3.05	1.97	2.08	1.16
Diesel	3.50	3.50	2.26	2.38	1.33
Avg. fleet CO ₂ emissions (tonnes)	6.35	6.54	6.73	7.05	6.84

taxi-70) presents a certain balance in this aspect.

Analysing the travelled distances of each fleet, we see that both (*cs-280, taxi-280*) and (*cs-280, taxi-140*) present similar total distances. Then, as the carsharing fleet is reduced and its usage decays,

the taxi service presents much higher distances. This is because as the number of taxis in the fleet is reduced, more distance has to be covered to pick each individual customer, as we commented in Section 3.2. Observing the number of unused vehicles it stands out a single carsharing transport which, as a result of its initial location, was not close enough to any of the customer to be used. Besides that, we want to remark the high distances of empty taxi journeys which are generally avoided with carsharing. Finally, the carbon dioxide emissions evolve in hand with travelled distances. Once again the trade-off among vehicle production pollution and vehicle usage pollution should be addressed. The number of vehicles in the fleet should be set at a level that increases its overall sustainability but is not so low as to increase the kilometres travelled by each vehicle further than a certain threshold.

4. Discussion

In this work, the experimentation has been performed through a multi-agent simulator. The combination of multi-agent modelling and simulation technologies seems appropriate to reproduce a system with a high degree of dynamism [13], such as the urban mobility one. Nevertheless, the data gathered from a simulation can be misleading if it is directly extrapolated to the actual system the simulation tried to reply to. Although we grounded all of our simulation scenarios on real data of Valencia, is it not possible to reproduce every detail, and thus concessions have been made. Because of that, any conclusions drawn from our results must be understood within our experimental settings. That said, our results show a series of trends worth discussing and from which concrete action could be derived to improve the sustainability of urban traffic systems.

The impact carsharing technology could have on our environment is substantial. On the one hand, it reduces the distance that a service vehicle travels empty (not carrying any customer). This implies a more energy-efficient trip, as more customers are displaced per energy unit spent. In addition, it can avoid direct carbon dioxide emissions by implementing the service with fully electric vehicles. Regarding the latter, one of the objectives of the Spanish government is to increase the number of hybrid and electric-powered vehicles in their public taxi fleets. A 2019 study^{††} indicates that the taxi fleet of Madrid, the capital of Spain, has a 26% of hybrid taxis meanwhile fully electrical vehicles account for only a 0.1%.

Our results show poor customer satisfaction with the carsharing services with respect to the taxi ones, although younger generations have positive perceptions on shared mobility [14]. The particularities of our free-floating carsharing proposal make it unfair to directly compare both types of fleet, as we commented above. Furthermore, we made strong assumptions with respect to the maximum walking distance and waiting time of our customers. Both magnitudes, while necessary to define the agents' behaviour in the simulation, in real life are likely to depend on many personal factors. Besides that, we believe a relocation service [15] for the carsharing fleet is essential to enable more users to make use of it. With accurate data of carsharing usage, the service provider could develop a relocation algorithm that allocates more cars in city areas where more demand is likely to be present according to the time of the day.

Besides the satisfaction, the type of user of each fleet must also be assessed. A dial-a-ride service such as taxis will always be needed, as some users will not drive a vehicle themselves. In addition,

^{††}“Movilidad urbana y metropolitana: un gran reto de las ciudades del siglo XXI”, Observatorio del transporte y la logística en España: https://observatoriodeltransporte.mitma.es/recursos_otle/monografico_otle_2019_movilidad_urbana_y_metropolitana_1.pdf

they might not be willing to, given the generally heavy traffic in cities and the lack of parking space in certain areas. Thus, potential users could be environmentally conscious people, tourists, users looking for savings, people with daily commutes that do not comfortably correspond to a direct public transport line, among others. In general, users would tend to have a young to middle-aged age profile. A reduction in prices is not enough for a carsharing system to be attractive enough to the general public [16] (with respect to the commodity of dial-a-ride services). Moreover, a certain infrastructure [17] must be ensured so that customers do not feel insecure making use of the service. On the one hand, parking facilities must be implemented, for instance, by allowing carsharing vehicles to park inside city centres or having enough reserved parking spaces for this type of vehicle. On the other hand, a reliable network of electric vehicle chargers would come in hand both for users and service providers.

From all our experimentation, we want to highlight the hybrid simulations of Section 3.3. A city is a complex set of systems that interact with each other. The urban mobility system is one of the most complexes, as it contains several actors. Because of this, the hybrid simulations, those where the demand is covered by both a taxi and a carsharing fleet, are the closest to a real city representation. Most users of the urban traffic system have freedom of choice over different displacement alternatives. Our results suggest that there is potential to improve the general sustainability of our cities. The public should be encouraged to use more environmentally friendly options considering the freedom of choice. Combining transportation services with a strong promotion of the most sustainable ones could be the best approach.

The analyses our work presents are relevant for the mobility options of today. Nevertheless, the situation may change in the near future with the introduction of autonomous mobility. Such a mode of transportation would effectively turn traditional taxi and carsharing vehicles into autonomous, demand-responsive taxis. In this regard, there are a number of studies that address the effects of autonomous transportation services. For instance, in [18] authors study the implementation of an autonomous demand-responsive service that communicates the rural and urban areas of Bremerhaven (Germany). The authors suggest that operational and environmental costs significantly decrease if the individual transportation vehicles are completely replaced with such a service. However, they remark how the fully autonomous operation of the vehicles is key for the economic sustainability of the service. Another study [19] shows through a Melbourne (Australia) case study how travel demand could be met with only a small part of the current fleet if the mobility followed an on-demand autonomous shared transportation model. However, their results also present that the reduction of the vehicle fleet would increase the travelled kilometres of each vehicle, thus having a negative impact on the environment. This finding is also present in our experimentation. Ultimately, we want to remark that mobility is a really complex subject and changes that would seem to report obvious benefits may end up worsening the overall system once implemented. That is why simulation is especially important when it comes to exploring and testing mobility solutions.

5. Conclusions

In this research, we looked at the implementation of a carsharing system in Valencia, Spain, intending to provide a more sustainable alternative to the city's current taxi fleet. We have created simulations based on real-world city data for agent movement and distribution. Our findings show that, while some form of taxi service will always be required, carsharing has a significant potential to cut carbon dioxide

emissions and traffic congestion in the city, albeit at the sacrifice of some consumer happiness.

With regard to the article's hypotheses, the experimentation shows a reduction in Valencia's taxi fleet is possible in terms of quality of service, which would be preserved. Nevertheless, this causes the sustainability of the fleet to worsen with respect to carbon dioxide emissions. On the other hand, after trying many configurations, we propose a fleet of 840 carsharing vehicles as a competitive alternative which presents a trade-off between customer satisfaction and sustainability. Finally, a hybrid solution that combines the usage of taxi fleets with green carsharing services is assessed. Such an option can meet all client demand while simultaneously reducing carbon emissions. This would be excellent for a transition to totally electric urban mobility, resulting in a more environmentally friendly city.

The urban mobility system of each city will have its own particularities. Many of them may heavily influence the usage of the different modes of transportation as well as their overall efficiency. Therefore, it is hard to state that our analyses of customer satisfaction can be transferred to other urban settlements. Nevertheless, we believe our general conclusions regarding the sustainability of reducing/replacing a taxi fleet with carsharing vehicles can be transferred to other cities of a similar size to Valencia. In any case, our experimental framework can be used to simulate carsharing fleets in any city, provided we have data to guide the demand generation, and thus we recommend experimenting before transferring any conclusions.

The current work paves the way for future research in various directions. On the one hand, we would like to look at more practical demand generation methods. This would involve a dependable data source and the subsequent choice of convenient features. On the other hand, we wish to add another mode of transportation to our simulations to examine the proportions of overall mobility demand that each system covers in greater detail. Vehicles from Valencia's public transportation system, such as buses, bikes, and metro lines, would be an excellent addition to improve simulations of city mobility. Finally, we will enhance the simulation regarding carsharing systems by adding vehicle relocation, a specially relevant feature for free-floating carsharing. Specifically, we want to develop a machine learning prediction solution, similar to the one presented in [20], that aids to determine the time of day when the relocation should take place as well as new vehicle locations.

Acknowledgments

This work is partially supported by grant RTI2018-095390-B-C31 funded by MCIN/AEI/10.13039/501100011033 and by "ERDF A way of making Europe". Pasqual Martí is supported by grant ACIF/2021/259 funded by the "Conselleria de Innovación, Universidades, Ciencia y Sociedad Digital de la Generalitat Valenciana". Jaume Jordán is supported by grant IJC2020-045683-I funded by MCIN/AEI/10.13039/501100011033 and by "European Union NextGenerationEU/PRTR". Pablo Chamoso is supported by grant CCTT3/20/SA/0002 (AIR-SCity project), funded by Institute for Business Competitiveness of Castilla y León, and the European Regional Development Fund.

Conflict of interest

The authors declare there is no conflict of interest.

References

1. L. Rayle, D. Dai, N. Chan, R. Cervero, S. Shaheen, Just a better taxi? a survey-based comparison of taxis, transit, and ridesourcing services in san francisco, *Transp. Policy*, **45** (2016), 168–178. <https://doi.org/10.1016/j.tranpol.2015.10.004>
2. R. Katzev, Car sharing: a new approach to urban transportation problems, *Anal. Soc. Issues Public Policy*, **3** (2003), 65–86. <https://doi.org/10.1111/j.1530-2415.2003.00015.x>
3. M. Namazu, H. Dowlatabadi, Vehicle ownership reduction: a comparison of one-way and two-way carsharing systems, *Transp. Policy*, **64** (2018), 38–50. <https://doi.org/10.1016/j.tranpol.2017.11.001>
4. A. Kolleck, Does car-sharing reduce car ownership? empirical evidence from Germany, *Sustainability*, **13** (2021), 7384. <https://doi.org/10.3390/su13137384>
5. J. Firnkorn, M. Müller, What will be the environmental effects of new free-floating car-sharing systems? the case of car2go in Ulm, *Ecol. Econ.*, **70** (2011), 1519–1528. <https://doi.org/10.1016/j.ecolecon.2011.03.014>
6. X. Dong, Y. Cai, J. Cheng, B. Hu, H. Sun, Understanding the competitive advantages of car sharing from the travel-cost perspective, *Int. J. Environ. Res. Public Health*, **17** (2020), 4666. <https://doi.org/10.3390/ijerph17134666>
7. T. Yoon, C. R. Cherry, M. S. Ryerson, J. E. Bell, Carsharing demand estimation and fleet simulation with EV adoption, *J. Cleaner Prod.*, **206** (2019), 1051–1058. <https://doi.org/10.1016/j.jclepro.2018.09.124>
8. J. Palanca, A. Terrasa, C. Carrascosa, V. Julián, Simfleet: a new transport fleet simulator based on MAS, in *International Conference on Practical Applications of Agents and Multi-Agent Systems*, (2019), 257–264. https://doi.org/10.1007/978-3-030-24299-2_22
9. P. Martí, J. Jordán, V. Julián, Carsharing in valencia: analysing an alternative to taxi fleets, in *Practical Applications of Agents and Multi-Agent Systems*, Springer, (2021), 270–282. https://doi.org/10.1007/978-3-030-85710-3_23
10. M. E. Gregori, J. P. Cámara, G. A. Bada, A jabber-based multi-agent system platform, in *Proceedings of the Fifth International Joint Conference on Autonomous Agents and Multiagent Systems*, (2006), 1282–1284. <https://doi.org/10.1145/1160633.1160866>
11. P. Martí, J. Jordán, J. Palanca, V. Julian, Free-floating carsharing in SimFleet, in *International Conference on Intelligent Data Engineering and Automated Learning*, Springer, (2020), 221–232. https://doi.org/10.1007/978-3-030-62362-3_20
12. P. Martí, J. Jordán, J. Palanca, V. Julian, Load generators for automatic simulation of urban fleets, in *International Conference on Practical Applications of Agents and Multi-Agent Systems*, Springer, (2020), 394–405. https://doi.org/10.1007/978-3-030-51999-5_33
13. N. Firdausiyah, E. Taniguchi, A. G. Qureshi, Modeling city logistics using adaptive dynamic programming based multi-agent simulation, *Transp. Res. Part E: Logist. Transp. Rev.*, **125** (2019), 74–96. <https://doi.org/10.1016/j.tre.2019.02.011>

14. C. Standing, F. Jie, T. Le, S. Standing, S. Biermann, Analysis of the use and perception of shared mobility: a case study in western Australia, *Sustainability*, **13** (2021), 8766. <https://doi.org/10.3390/su13168766>
15. H. Qin, E. Su, Y. Wang, J. Li, Branch-and-price-and-cut for the electric vehicle relocation problem in one-way carsharing systems, *Omega*, **109** (2022), 102609. <https://doi.org/10.1016/j.omega.2022.102609>
16. H. Habekotté, *Optimizing Carsharing Policies for a New Generation-A Quest on How to Upscale Carsharing as Part of Sustainable Mobility Systems in Dutch Urban Regions*, PhD thesis, University of Groningen, 2021.
17. A. Ciociola, D. Markudova, L. Vassio, D. Giordano, M. Mellia, M. Meo, Impact of charging infrastructure and policies on electric car sharing systems, in *2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*, IEEE, (2020), 1–6. <https://doi.org/10.1109/ITSC45102.2020.9294282>
18. J. Schlüter, A. Bossert, P. Rössy, M. Kersting, Impact assessment of autonomous demand responsive transport as a link between urban and rural areas, *Res. Trans. Bus. Manage.*, **39** (2021), 100613. <https://doi.org/10.1016/j.rtbm.2020.100613>
19. F. Javanshour, H. Dia, G. Duncan, R. Abduljabbar, S. Liyanage, Performance evaluation of station-based autonomous on-demand car-sharing systems, *IEEE Trans. Intell. Transp. Syst.*, **2021** (2021), 1–12. <https://doi.org/10.1109/TITS.2021.3071869>
20. P. Martí, J. Jordán, J. Palanca, V. Julian, Charging stations and mobility data generators for agent-based simulations, *Neurocomputing*, **484** (2022), 196–210. <https://doi.org/10.1016/j.neucom.2021.06.098>
21. D. I. Grozev, D. E. Topchu, D. I. Miteva, Assessment of CO2 emissions released from the taxi vehicle fleet in Ruse, in *Proceedings of the 2nd Virtual Multidisciplinary Conference*, (2014), 484–487.
22. J. Jordán, P. Martí, J. Palanca, V. Julian, V. Botti, Interurban electric vehicle charging stations through genetic algorithms, in *International Conference on Hybrid Artificial Intelligence Systems*, Springer, (2021), 101–112. https://doi.org/10.1007/978-3-030-86271-8_9
23. J. Jordán, J. Palanca, E. del Val, V. Julian, V. Botti, Localization of charging stations for electric vehicles using genetic algorithms, *Neurocomputing*, **452** (2021), 416–423. <https://doi.org/10.1016/j.neucom.2019.11.122>



AIMS Press

©2022 the Author(s), licensee AIMS Press. This is an open access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0>)