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A Multi-Agent Simulation Approach to Modelling a Free-Floating Carsharing Network

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Abstract. Alternative transportation services such as free-floating carsharing have gained significant amount of popularity throughout the years. Indeed, the trend is fueled by carsharing operators' vow to innovate in their offer for flexible and efficient means of transportation to their customers. This quest for flexibility can, however, raise operational questions such as network area and vehicle fleet optimal configurations. Research shows that when dealing with heterogeneous systems as the previously mentioned, its components would be best modeled by mixing simulation paradigms. Hence, for instance, entities such as the operator's planning center can be modeled as an agent that individually assesses the network and makes strategic decisions. However, the operator's internal procedures such as the reservation and charging processes can be modeled as process flowcharts, referencing to a discrete approach. This study focuses on Communauto's Montreal Free-Floating carsharing service (FFcs). Rather than estimating its demand, this study analyzes its operational performance and tracks how it is affected by several service usage policies. The developed multi-agent model was implemented on Anylogic simulation software. Experimentation shows an overall increase in service usage when customers are allowed to finish their trips out of the service area (Scenario 2) compared to when trip ends were restricted to the service area (Scenario 1). Tracking vehicle accessibility in Scenario 2 shows, however, an increase of latent demand during the week especially between 3:00 p.m. and 6:00 p.m., which could be countered with an effective relocation policy.

Keywords. Agent-based modeling, discrete event modeling, free- floating carsharing, system performance.

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INTRODUCTION

Smart phones' popularity and real-time data availability of transport network state are increasing the attractiveness of urban areas' populations to alternative modes of transportation, such as carsharing. First mentions of carsharing emerged in the late 1950s in Europe (Shaheen et al. 1999). Generally, carsharing is a service offered by a company that allows its members to access its fleet of vehicles scattered in a service area or grouped at specific stations for a fee (Schwieterman and Bieszczat 2017). Usually, carsharing systems are used for shorter distance journeys as an extension of the public transport network or personal vehicle usage (Li et al. 2017). Several types of carsharing were developed to satisfy the evolving market needs. The two main configurations adopted by Carsharing Service Operators (CSOs) are Station-Based and Free-Floating carsharing services (respectively referred in this text to as SBcs and FFcs). SBcs requires users to reserve a vehicle located in a station and drop it off in the same station after usage, creating round trips (Barnhart et al. 2012) (apart for some systems that permit one-way operations). This service is historically the most popular, with a market covering two thirds of the population in Europe (Shaheen et al. 2018). As to FFcs, it removes the need for stations by allowing users to pick up and return vehicles in any public parking spot within a service area defined by the CSO (Schaefers 2013). A mixture between those two configurations has also emerged. Indeed, one-way carsharing systems allow SBcs users to return a reserved vehicle in any desired station (Barnhart et al. 2012).

For this paper, our focus will be set on the FFcs configuration. What should the geographic boundaries of the service area be? How should vehicles be distributed to maximize their usage? Should vehicles be relocated within the service area? These questions are a prime example of the logistic challenges that CSOs face in the satisfaction of their demand. Simulation modeling can facilitate planning on a FFcs by unraveling the emerging phenomena of the system's evolution in time. For this reason, this paper proposes a multi-agent simulation model, based on real-world data, seeking to explore members' behavior in regard to several FFcs network policies, the ultimate goal being the assessment of service usage intensity. It is structured as follows. A background section presents previous works on FFcs and its ties to simulation modeling. After, the methodological approach and our case study (Communauto's FFCS) are presented, followed by a description of the developed model. The next section presents the results and discusses their significance. Lastly, this study's limitations and perspectives are outlined.

BACKGROUND

Free-floating Carsharing and its Users

In 2016, FFcs was operating in 34 medium-density cities across Europe and North America (Kortum et al. 2016). Authors pointed out that FFcs succeeds in moderate to heavily urbanized areas (Shaheen et al. 2005; Millard-Ball et al. 2005). Usually, FFcs is a popular mode of transportation around the morning peak, from 6:00 a.m. to 11:00 a.m. The service usage increases during the week, to reach its maximum during weekends (Costain et al. 2012; Wielinski et al. 2015). In the particular case of Communauto's Montreal FFcs, four categories of users were distinguished: low-frequency users (4 or less active days out of 90), average frequency users (10 active days or less out of 90), high frequency users (26 active days or less) and ultra-high frequency users (over 26 active days) (Wielinski et al. 2019).

As for the traveling habits, FFcs users differ from SBcs by their preference for shorter trips (Kortum et al. 2016 ; Wielinski et al. 2019). Moreover, the offered flexibility ensures that journeys made by a customer are not necessarily close to his home (or his favorite station). However, a trend towards commuting (vehicle usage to leave from or return home, usually after work hours) is discernible (Wielinski et al. 2019 ; Martin et al. 2010).

Simulation Modeling in the Carsharing Field

Many works showed the effectiveness of simulation approaches in the modeling of transportation flows. The main advantage outlined is the possibility to obtain both a spatial and behavioral representation of the decision-making process of simulated individuals (Ciari et al. 2014). Depending on the desired outcome (demand estimation, operational performance planning …), different simulation paradigms were used in the transportation field. First appeared in the 1960s, Discrete Event Simulation (DES) is one of them. Based on the sequential execution of operations on entities, DES is a very common way of modeling process-orientated models such as in our case the reservation process in a FFcs (Borshchev 2013).

In the early 2000s appeared Agent-Based Modeling, allowing researchers to focus on each transportation actor individual representation. In terms of SBcs' modeling, Ciari et al. (2014) used MATSim, an activity-based simulation software to evaluate its demand in the city of Berlin while considering the availability of different transportation modes and the dynamic routing of trips on a transportation network to simulate congestion. Recent study based on the tool improved the modeling of free-floating carsharing (Balac et al. 2019). Liping and Petering (2018) also developed a simulation model of a hypothetical reservation-based carsharing system but using a discrete event approach. Heilig et al. (2018) studied the integration of carsharing into an agent-oriented transport demand model simulating the behavior of the population of Stuttgart's region for one week. For the specific case of Communauto, a discrete-event model was previously developed to gage the impact of different network expansion strategies (Fassi et al. 2012). Several configurations have been tested to detect those that will maximize the level of customer satisfaction while minimizing vehicle fleet's size. The above-mentioned models either solely focus on SBcs or incorporate one-way carsharing.

Regarding FFcs, research focuses on several aspects. Barrios and Godier (2014) developed an agent-based simulation model to predict the level of service of car2go's FFcs in Austin, Texas and San Diego, California. Ciari et al. (2015) incorporated a FFcs network in MATSim to evaluate carsharing travel demand and its relation to pricing schemes. Qing et al. (2018) integrated FFcs into an activity-based dynamic user equilibrium model.

To our knowledge and in the case of Montreal, this model presented in this paper is one of the first to propose a multi-agent approach that analyzes the operational performance of a FFcs while including a street transportation network and animation of each trip on it, without considering any other transportation mode.

CASE STUDY

The subject of this study is Canada's oldest carsharing operator, Communauto. With approximately 3,000 cars in North America and Europe, this company has the biggest share of electric vehicles in Canada. Focus will be set on their FFcs network that has been operating since 2013. The service area covered by early 2018 around 104 km^2 and offered over 600 vehicles to its customers (Wielinski et al. 2019). 80% of those vehicles are hybrids, with the rest being electric.

METHODOLOGY

In this paper, we developed a multi-agent model to represent the daily operations on Communauto's FFcs network in the Montreal Island Area. Those operations involve customers who make trip reservations, CSO's staff who are responsible for charging electric vehicles as well as a planning center which synthesizes information on fleet availability and level of charge. Main interactions between those entities are represented on **Figure 1**.

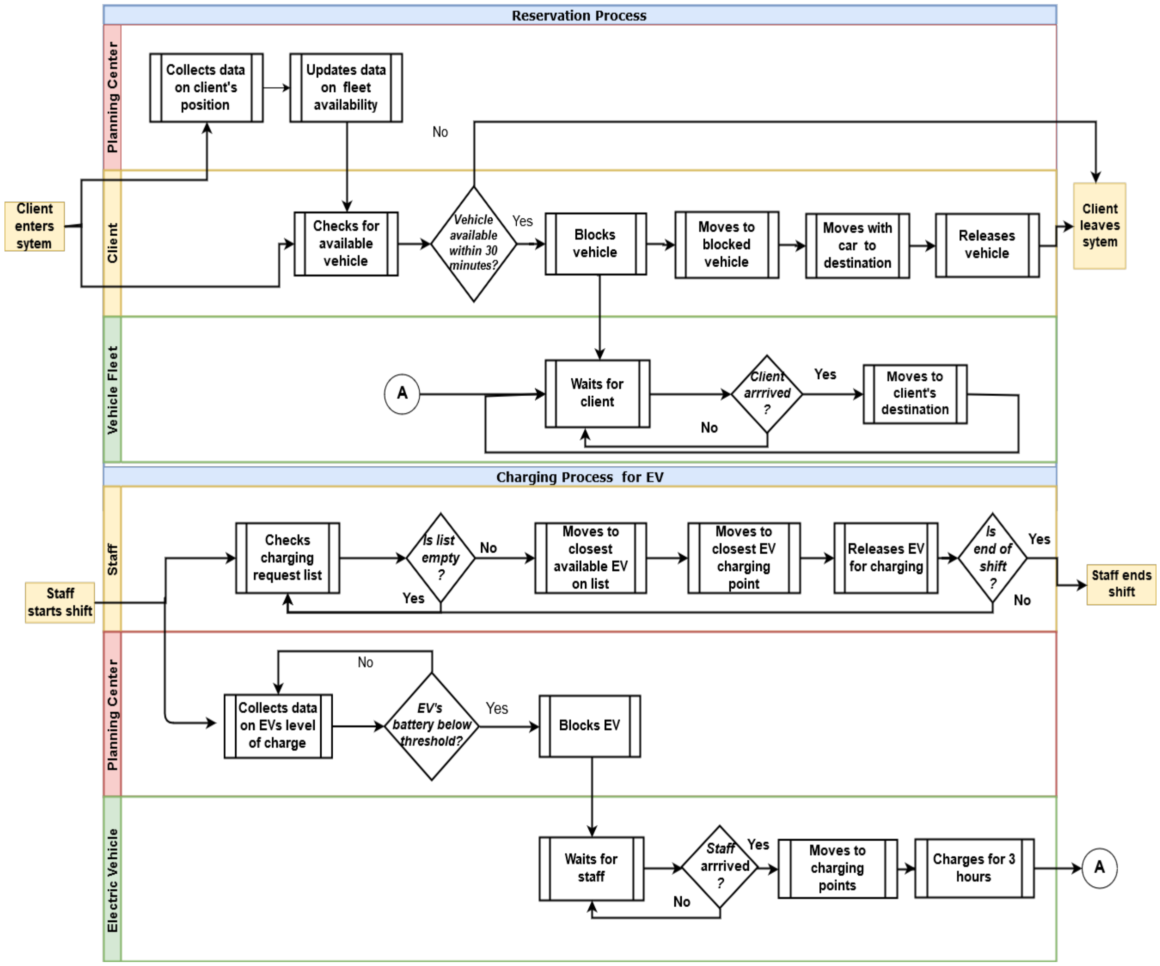

Figure 1. FFCS main processes

The model is a result of a junction between different components as generally found in most agent-based models. In this case, the three main components, presented in **Figure 2**, are a Multi-Agent Layer, a Trip Generator and a GIS Map. For clarity purposes, the trip generator will be presented first, followed by the Multi-Agent Layer and the GIS Map.

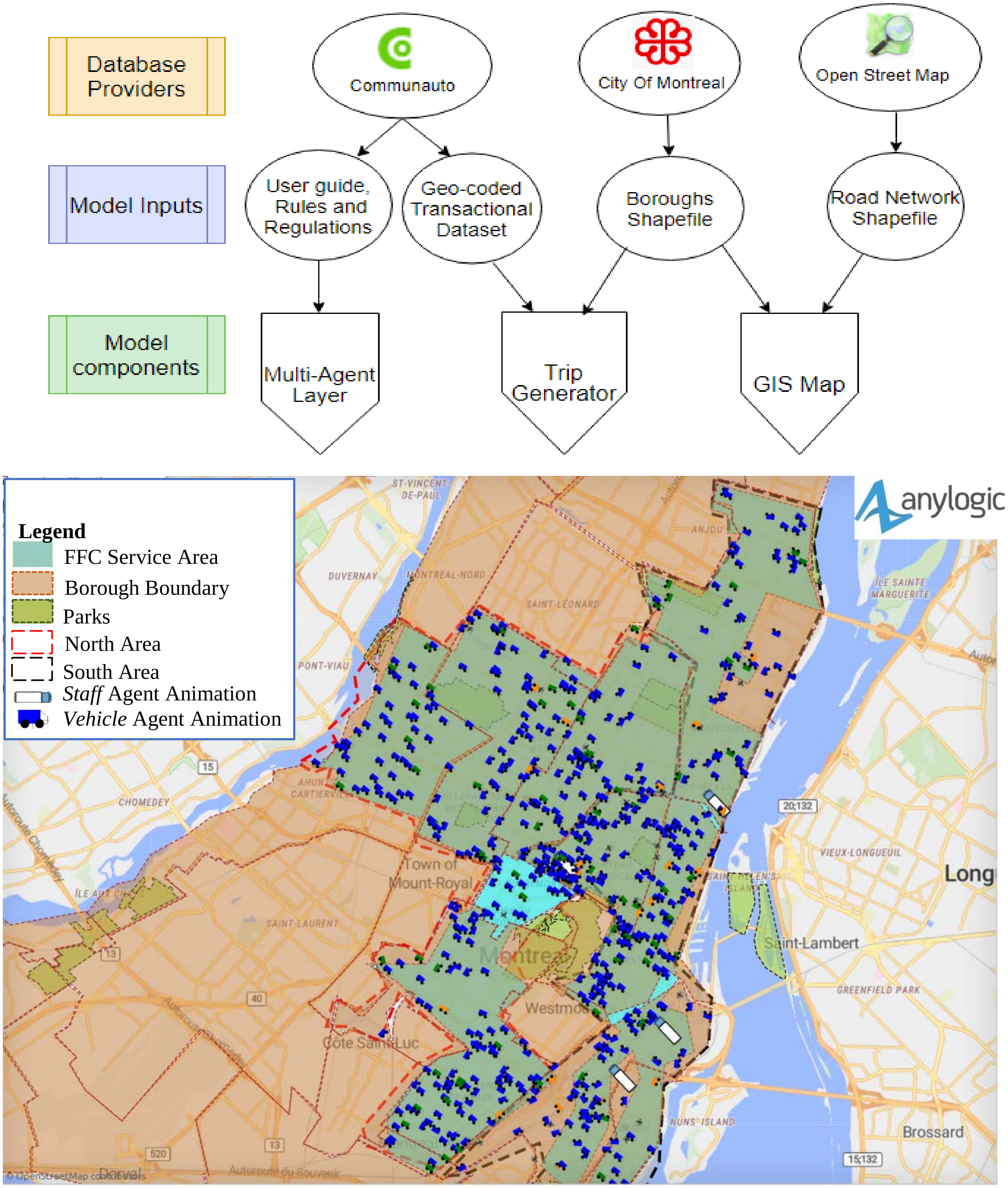

Figure 2. General methodological approach and service area

Trip Generator

Travel demand for a transportation mode is often based on behavioral models relying heavily on a population's revealed preferences (Ciari et al. 2014). This can for instance be acquired via an extensive mobility survey coupled to census data. Since the lack of extensive data on Communauto users' travel habits and the fact that travel demand estimation is not the focus of this study, our case directly generates the demand from the transactional dataset provided by the company. That dataset consists of geocoded trips for the month of September 2017, considered an average month in terms of trip intensity. Information on vehicle type and level of charge is also provided. All in all, for each trip, user identification, vehicle identification, start/end timestamps, trip distance are recorded. We cross-referenced this data with geocoded Montreal borough boundaries on a Geographic Information System software (QGIS). The number of trips occurring between two boroughs is calculated. From this we estimate the probability of OD pairs. Hence, this submodel will generate trip ends discretized in space (at the borough level) and time for a synthetic month (5 weeks).

Multi-Agent Layer

As introduced in Figure 1, different agents interact in the FFcs system.

Customer Agent

This agent instigates the reservation process. In our model, the customer agent is the physical representation of a generated trip. Hence:

- It will enter the network with an identification number, an origin and a desired destination (geocoded positions).
- It will look for the closest available vehicle.
- If it finds one, it will take it to fulfill its trip, else it will leave the system.
- After completing his trip, it will ultimately leave the system.

A set of rules will, however, need to be respected as per Communauto's FFcs Terms of Agreement (Communauto 2019). For instance:

- A vehicle cannot be blocked for more than 30 minutes prior to trip start.
- When using a hybrid car, the customer cannot release it without its tank being at least a quarter full.
- In case of fuel shortage of hybrid vehicles, customers handle the refueling at the CSO's charge.
- When using an electric car, the customer cannot release it with less than 15 km equivalent of battery charge (or there could be a fee penalty).

Ultimately, the customer agent wants to minimize his trip length by finding the fastest way to reach its destination.

Planning Center Agent

This agent represents the CSO's coordination platform. Hence:

- It collects data on the vehicles' location, which will be presented to the customers.
- It collects data on the vehicles' tank or battery level (respectively for hybrid or electric vehicles), which will be presented to the staff.

It also has to follow a set of rules such as:

- Automatically unblocking vehicles after more than 30 minutes of reservations without being picked up.
- Preventing car from moving around when they need to be charged.

Staff Agent

This agent is in charge of the electric vehicle charging process. Hence:

- It will check the electric fleet battery levels.
- It will bring vehicles with battery level under the threshold to the closest available charging point.

Also, staff operators only work during a specified timeframe at a specified capacity (4 operators covering 2 shifts of 8 hours, from Monday to Saturday).

Vehicle Agent

This vehicle ensures the transportation of customers to their destination. Two types of vehicles are provided in the fleet, with 86% being hybrid. Attributes such as fuel consumption for hybrids and autonomy for electric vehicles are randomly selected from a given probability distribution. This agent type has to send its level of charge and availability to the planning center. It has no decision role whatsoever.

GIS Map

Agents of this model interact on a tile map downloaded from Open Street Map (OSM), an online map service. This map is characterized by a thorough street network, which is segregated by road type (pedestrian and vehicle) to form a set of nodes and arcs. The network grids are defined by using the administrative boundaries of 19 Montreal Island's boroughs (**Figure 2**). The optimal path between two grids is defined using the shortest distance algorithm provided by OSM. Finally, the CSO's charging points are also geocoded on the map.

SIMULATION FRAMEWORK

Model Implementation

The model was implemented on Anylogic Simulation software (Anylogic 2019), which supports both agent-based and discrete-event models as well as system dynamics simulations. Since vehicles are uniformly distributed in the service area at the model startup, a warm-up period is necessary. The purpose is to allow them to position themselves as accurately as possible, in order to map out the real-life fleet configuration at the time that the transactional dataset was collected. Hence, the model is run for a total of 35 days, the first 7 days serving as a system warm-up period.

Model Validation

Validation is defined as being an important step to compare how precisely the conceptual model depicts the reality. Some authors argue that this step is similar to debugging a computer program (Li and Petering 2018). Hence, in our model, each branch of the process depicted in **Figure 1** is individually simulated on its own first, the purpose being to see if the desired output was reached. Furthermore, the animation process served as a visual guide to analyze if each process step happens in the order it is supposed to.

Trip Generator Performance

Since the transactions are discretized in time and space, it is important to assess how precisely trips are generated considering each stance.

Service usage

Figure 3 presents the evolution of the service usage of the simulated model broken down by the day of the week. Here, Sunday marks the first day of the calendar week.

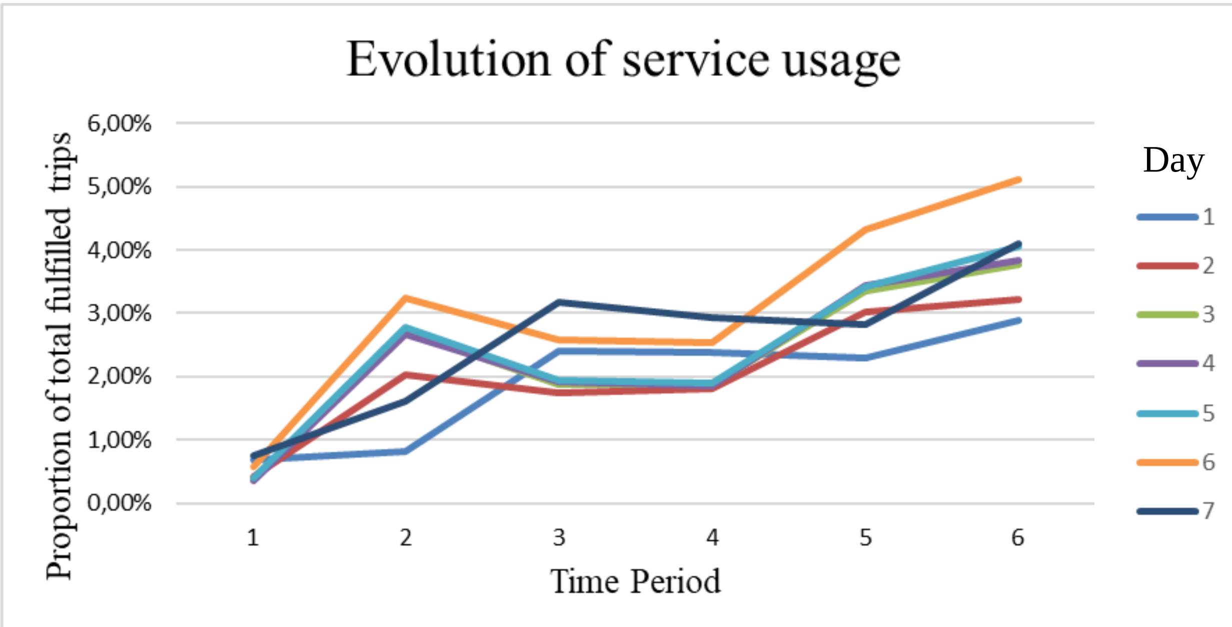

Figure 3: FFCS use by time of the day and day of the week

Timeframe	Time Period
< 6:00 AM	1
6:00 AM-8:59 AM	2
9:00 AM-11:59 AM	3
12:00 PM-2:59PM	4
3:00 PM-5:59 PM	5
> 6 :00 PM	6

TABLE 1. Time Period reference

Overall, almost a third of the trips were generated on the weekend with the peak being between 9:00 and 3:00p.m. and after 6:00 p.m. On weekdays, the peak is between 6:00 and 9:00 a.m. and after 3:00 p.m., though the service is more used on Fridays. Similar results were found by Wielinski et al.[12] for the same study object when analyzing service usage using passive data streams.

Relative Deviation in Simulated Trip Ends

A total of 70 854 client transactions were recorded in the dataset provided by the CSO for the reference month. The developed model generated 72 050 trips (warm-up period excluded). The validation process requires analyzing trip ends generation accuracy. Therefore, the relative deviation between the observed and simulated origin and destination borough trip ends was calculated as follows:

$$relative\ deviation = \frac{|observed\ value - simulated\ value|}{observed\ value} \times 100 \quad (1)$$

In **Equation 1,** the value refers to the number of trips generated between two boroughs. It is important to note that trips with less than 1% probability to happen in real-life between two grids were not taken into consideration in the trip generator development phase. We ultimately obtain the heat map in **Table 2** below.

	Destination Boroughs										
Origin Boroughs	CN	LR	ME	MH	OM	PM	RO	SO	VD	VM	VS
CN	0,588%	0,000%	0,003%	0,051%	0,058%	0,686%	0,252%	0,228%	0,014%	0,006%	0,102%
MH	0,031%	0,000%	0,016%	1,058%	0,017%	0,464%	0,177%	0,153%	0,071%	0,031%	0,098%
MR	0,064%	0,000%	0,000%	0,000%	0,001%	0,001%	0,064%	0,000%	0,001%	0,000%	0,017%
OM	0,042%	0,000%	0,000%	0,017%	0,057%	0,052%	0,066%	0,038%	0,010%	0,004%	0,028%
PM	0,549%	0,000%	0,001%	0,602%	0,079%	1,989%	1,011%	0,337%	0,024%	0,092%	0,344%
RO	0,044%	0,000%	0,000%	0,317%	0,034%	0,672%	0,112%	0,004%	0,031%	0,011%	0,182%
SO	0,358%	0,000%	0,001%	0,055%	0,013%	0,478%	0,107%	0,433%	0,156%	0,066%	0,040%
VD	0,047%	0,000%	0,001%	0,017%	0,003%	0,031%	0,027%	0,021%	0,083%	0,008%	0,028%
VM	0,086%	0,000%	0,000%	0,090%	0,006%	0,189%	0,069%	0,086%	0,023%	0,098%	0,071%
VS	0,013%	0,007%	0,001%	0,044%	0,018%	0,161%	0,103%	0,028%	0,025%	0,007%	0,245%

TABLE 2. Heat map of relative deviation of trip ends

The highest standard deviation noted was at approximately 2% for internal journeys in the Plateau Mont-Royal (PM) region. One probable cause can be that PM is the highest trip-generating region, with 28.3% of journeys departing from there. Therefore, we can confidently assume that the developed trip generator has an accurate level of prediction of the origin and destination boroughs of a trip.

RESULTS

Experimental setup

The purpose of the experimentation phase is to assess the application of two different service usage policies' impact on the fleet usage intensity. Two main scenarios were developed. Scenario 1 considers imposing a policy that prevents customers to end their trip out of the service area presented in **Figure 2** (FFCs Service Area). Scenario 2, however, wants to give more freedom to the customers, allowing them to end their trip out of the service area if desired, without leaving the Montreal Island boundary formed by the 19 boroughs on the GIS Map. In this scenario, customers can reserve a vehicle even if it is out of the service area.

Key Performance Indicators

The FFcs performance is assessed in both scenarios by measuring fleet usage intensity and vehicle accessibility. For the specific case of scenario 2 however, latent demand is thoroughly investigated.

Usage intensity cross comparison and evolution of service usage

For each car, the number of fulfilled trips per day for the 28-day study period was collected in order to track usage intensity per vehicle. It was compiled during the simulation when each policy was applied. When normalized, the scatter grams presented in **Figure 4** is obtained.

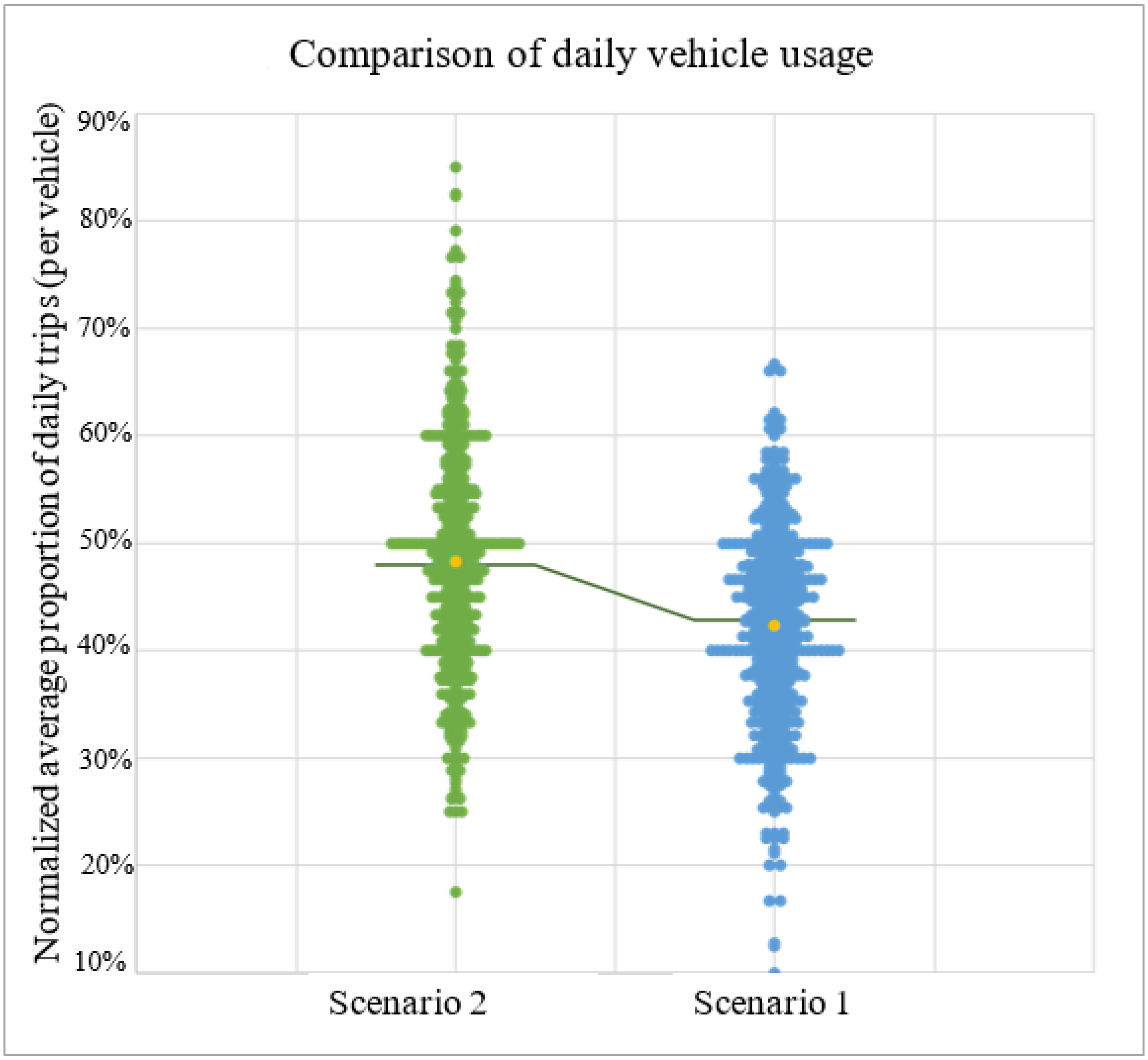

Figure 4: Comparison of vehicle usage in each scenario

Overall, Scenario 2 presents a higher vehicle mean utilization rate. However, the fleet is more uniformly used in Scenario 1. For the latter, almost 60% of the vehicle fleet accomplishes a similar number of trips on a daily basis. One probable cause stems from the fact that the CSO's service area was set up as to cover over 80% of their clients' home location, even though, customers don't always start their trips at their exact home location. However, in the areas where the service is most used such as Plateau Mont-Royal and Rosemont-La-Petite-Patrie (RO in **Table 2**), a high percentage of trips are symmetric in the sense that a customer will go from and go back to those boroughs with the same or a different vehicle (Wielinski et al. 2019). In consequence, if the CSO wishes for its vehicles to be used at similar rates, she/he would want to restrict vehicle usage inside a specific area. Similar tendencies were found in the city of Lisboa for one-way carsharing, also thanks to an agent-based approach (Lopes et al. 2014).

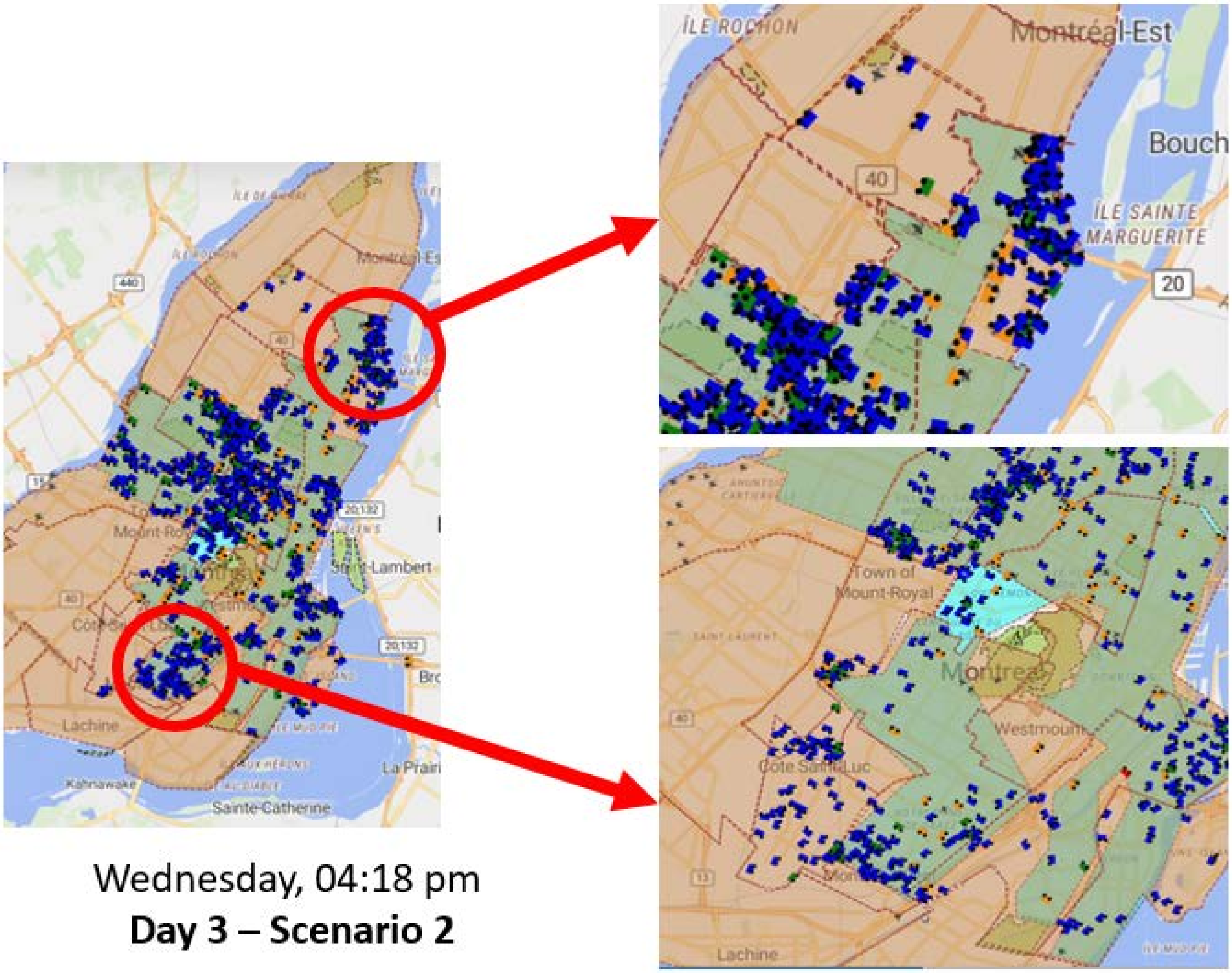

Figure 5 : Vehicle fleet repartition on the 3rd day of Scenario 2

When customers are not restricted to park the vehicle outside of the service area, the higher utilization rate noted for some vehicles could be caused by a decrease of the available fleet inside the zone. Trips who were previously missed due to the 30 minutes maximum vehicle reservation policy or to the parking inside service area restriction, can now be fulfilled, especially for customers located at the extremities of the zone. Some cars are therefore going to be situated outside of the service area and not be relocated when needed inside the service area, as depicted in **Figure 5**. Hence, the same vehicles located in high demand zones such as PM might be used more than they would have been in Scenario 1. However, since the service area was designed to cover 80% of the client's home location, vehicles parked outside of it after being used by a client could stay unused for a considerable amount of time due to lower demand in those areas.

Latent Demand

For the specific case of Scenario 2 and even though a higher vehicle average utilization rate was noted, the standard deviation noted in **Figure 4** alerts our attention to the importance of tracking vehicle fleet's availability over time.

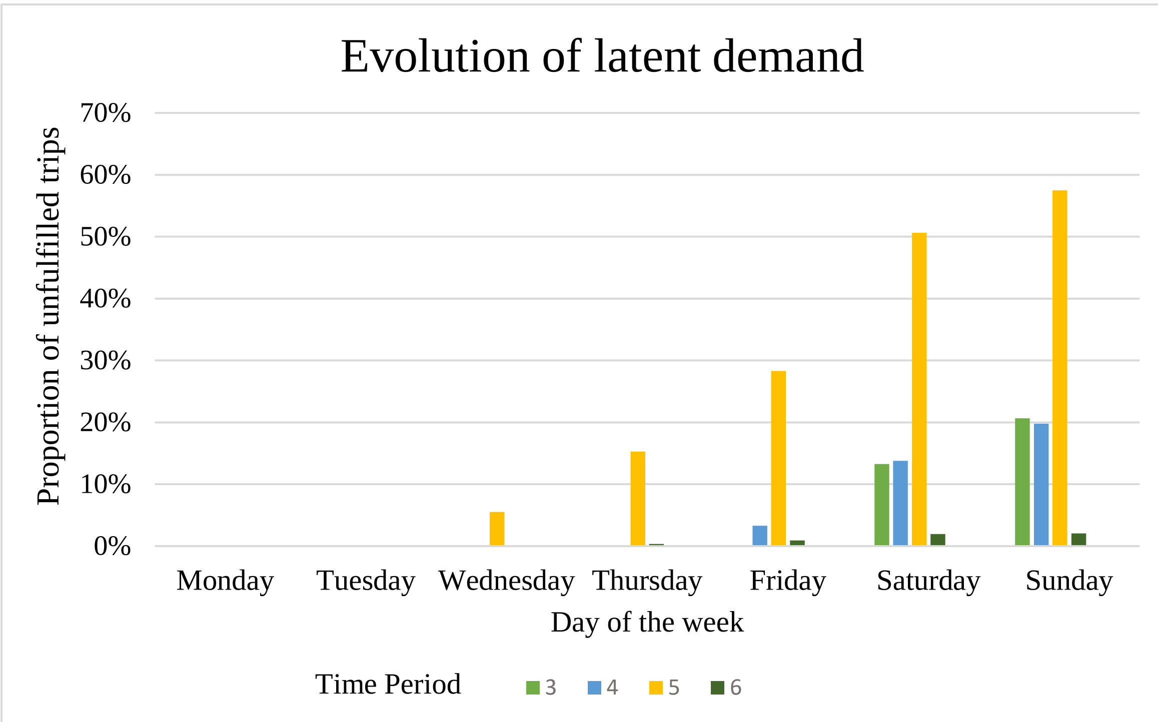

Figure 6 : Evolution of latent demand - Scenario 2

Latent demand is defined as being the number of customers' reservations that were approved by the planning center but were never fulfilled due to the vehicles' unavailability at the moment they were required. **Figure 6** tracks its evolution for the first synthetic week and the timeframes defined in **Table 1.**

Latent demand seems to increase over time to attain its peak by the end of the week, between 3:00 and 6:00 p.m. This increase could be caused by the scarcity of vehicles at strategic zones inside the service area (**Figure 5),** which further reinforces the need for an optimal vehicle redistribution system. If the CSO wishes to implement a configuration similar to Scenario 2, a relocation policy could help counteract that tendency.

Generally, scholars argue that one of the most effective ways to handle vehicle imbalance in carsharing systems may be to directly involve the customer in the relocation process, through price incentives for instance (Kek et al. 2009) (which was implemented in the past year by Communauto). However, this strategy seems to be more efficient with one-way SBcs. When dealing with FFcs users, who highly value convenience (Costain et al. 2012), it is recommended to allocate that task to the staff (Kek et al. 2009).

CONCLUSION

Contributions

Part of a growing body of research on carsharing networks, this paper aims to provide a multi-agent approach to studying operations happening on a FFcs over time. Several authors previously used passive data streams provided by Communauto to define the dynamics of its FFcs ecosystem. This paper attempts to add a spatiotemporal dynamic by integrating transactional data streams into a multi-agent simulation model.

Rather than estimating the travel demand, this project focuses on studying the operational performance of the FFcs. Therefore, a trip generator was developed in order to simulate as accurately as possible the network's solicitations, who were physically represented by customer agents. Experimentation has shown that not restricting trip ends to a service area would increase vehicle utilization rates inside of it but decrease it at the border regions. It may also cause an uneven distribution of the fleet who will ultimately affect the demand's satisfaction during peak periods. To counteract that tendency and if the operator doesn't wish to restrict its customers journeys, it would be beneficial to implement a relocation policy that would redistribute the vehicle inside the service area, in the specific boroughs where the demand is at its highest.

The major strength of our approach is its high visualization power, which helps in tracking the system's evolution over time. Moreover, the build, especially the GIS Map and its features allow the model to be easily scaled to incorporate other transportation modes such as personal vehicles, taxi and public transport to further study their ties to FFcs in urban areas.

Limitations

This model lays the foundation to further study FFcs' particularities in the grand scheme of transportation modes available to the public. While our model addresses the problem of spatial coverage, the demand was still derived from aggregated data. Therefore, additional information on customers' sociodemographic compositions, travel preferences and daily plans could help transform the model from a trip-based to a person-based approach (Lopes et al. 2014). Moreover, since FFcs' usage patterns generally shadows rather accurately the mobility patterns in urban areas, further information on the inhabitants' travel habits coupled with Census data could help in analyzing the complementarity between this transportation and mass transport modes. This approach would also allow naturally incorporating traffic in the customer's decision process.

Perspectives

Further developments of the model could incorporate geocoded public parking spaces, which were not available at the time of development. In the case of Communauto whose vehicles are only allowed to park at a public parking spot, taking into account the parking process would increase the system's behavior prediction accuracy. Vehicle imbalance could be further discussed by incorporating a relocation algorithm. The latter can be based on a mixed approach where customers could benefit of price incentives when they relocate vehicles inside the service area and staff would only relocate the vehicles in anticipation of peak demand periods.

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