MGSC 662
Decision Analytics

Fleet Relocation for Communauto Free-Floating Car-Sharing System

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1. Introduction

1.1. About Communauto

Communauto is a Canadian car-sharing company headquartered in Montreal operating in 5 provinces and 16 cities in Canada and in Paris, France. It was founded in 1994 and is the oldest in North America, and the third largest car-sharing operator in Canada. The company generates CAD15M annual sales revenue and offers over 2,000 vehicles in Montreal and Quebec City.

"Communauto was born out of the necessity of using cars differently. From this individual need, we created a solution for the future" says Benoit Robert, Communauto's President and Founder. Its vision of offering a practical and economical alternative to possession of an automobile, integrating carsharing with public transportation and reducing impacts to the environment has led the company to smart mobility - a cleaner, safer and more efficient way for people to get around.

Communauto differentiates from its competitors by offering two distinct services to maximise efficiency and coverage to its customers: (1) the one-way Flex service, which does not require a reservation and allows drivers to park within a Flex Zone, and (2) the traditional round-trip reservation service requiring returning of car in limited specific stations. Of its 2,000 cars, a third are in the free-floating service (one way) and two-thirds in the station-based service (round trip). Montrealers were the first to benefit from this dual offer.

1.2. Car-sharing Industry in Canada

Presently the car-rental industry worldwide as well as in Canada is facing supply chain issues leading to an unbalanced demand and supply. During the pandemic, due to a steep decrease in demand, rental operators across Canada sold off 30-40% percent of their fleets on average. However, as the pandemic restriction eased in 2020-21, there has been a surge in demand and shortage of vehicles. So much so that it has been named the "Car-pocalypse" of 2021 by Forbes Magazine. However, despite the supply chain issues, the car-sharing industry is projected to grow over the next few years with Statista predicting an annual growth rate of 15% and total industry revenue generation of 703 million CAD by 2025. User penetration has increased by 1.9% in 2021 and is further projected to rise up to 2.5% by 2025.

2. Problem Description

2.1. Pain Points

Due to the unbalanced industry demand and supply, Communauto is primarily facing hindrances in rebalancing flex-cars to meet demand. The issue was analysed from both the customer and company perspective. According to the reviews from customers, the flex cars were available but usually not in their respective regions. Moreover, in regions that did indicate availability, it was unreliable and often appeared to be a flex 'ghost' car. That is, when a customer arrived at the specific location of the car, it could not be located. Likewise, the company's main challenge is idleness of flex-cars in low demand areas and unavailability in areas of intensive use resulting in overall unmet demand and hence, dissatisfied customers.

Presently, Communauto does not have a proactive strategy for dealing with the unbalanced demand and supply and employs a minimal incentive approach to avoid idleness of cars. The customers are being offered a reward of 30 minutes' credit for returning vehicles marked with a gift icon to a fixed area of intensive use. However, as this approach does not take into account the shifting demand and the area specified with the incentive remains unchanged, the eligible audience remains limited and movement of these cars are infrequent.

2.2. Solution and Scope

The proposed solution to Communauto's current demand and supply challenge is optimized relocation of flex-cars, which can be implemented through three stages.

Short-Term Solution:

Within the initial stage, the pressing need of free-floating service would be addressed by deploying traffic agents from a centralized point to move vehicles from low demand to high demand. This will be a base model whose objective is to fulfil a minimum level of demand while minimizing costs associated with fuel, wage and distance to relocate vehicles based on demand.

Scope

The scope of this project will consist of the initial stage model where demand and availability of the Montreal region will be focused upon.

Assumptions

There are a few underlying assumptions of this base model concerning demand, availability, employees and relocation incentive for customers. The aim will be to meet 20% of total demand per region and allow a 1-hour relocation lead time for staff who will be deployed from Communauto headquarters in Montreal and will relocate vehicles only once. Moreover, the relocation incentive offered to consumers is assumed to not incur direct costs but it's take-up and revenue impact is considered.

In addition, as the data on the exact location of the cars is currently unavailable, Montreal will be divided into regions using postal codes and region centroids will be used for distance calculations. The process of determining availability, demand, regions and distances will be further elaborated in section 3 Data Pre-processing.

Medium-Term Solution:

Following the first stage, the second will focus on operationalizing multiple relocation of vehicles by staff members to meet demand threshold and take in account real-time locations of flex cars.

The base model will be enhanced into one that improves accuracy by integrating real-time internal company data into previous assumptions. Correspondingly, vehicle regions will be replaced by exact locations and staff would be assigned based on their present/specified locations. Furthermore, statistics on the availability of Communauto flex-cars will be acquired through real-time data received by the company from their application.

End-State:

The end state of the relocation optimization solution will realize the company's mission of smart mobility which entails a transformation into a flexible reward system that encourages stakeholders in the ecosystem to create and fulfil demands. It would incorporate the idea of interchangeability in the roles of users and relocators resulting in a wider ecosystem of the company.

The model aims to enhance practicability for the company by diminishing the staff-customer boundary into mover-driver with dynamic freelancer rewards being offered for all. Demand statistics employed will be specific to Communauto region and forecasted through predictive analysis on past data trends. Customer incentives will be varied to bridge demand and supply gap, potentially with separate UX/UI for mover and driver.

3. Parameters and Data Preprocessing

3.1. Approach and Complications

The main focus in data collection is to leverage available public reports and data to estimate hourly demand per Montreal Flex region, compared with Flex cars availability, regional location and demographic information. A major constraint for data collection is Flex vehicles availability, due to lack of Communauto internal data on vehicle locations and a complete picture on Flex vehicles parking accessibility. Current best effort to count availability in each FRA region is based on a snapshot of Flex vehicles locations at 7pm on Nov 26th, 2021, then count how many cars sitting in each FRA. The target hour for optimization in order to match demand is 8pm on the same day.

3.2. Data and Estimation Methods

3.2.1. National Usage

To properly estimate how many users Communauto has accumulated across Canada, Canadian-wise shared car usage data is needed. According to Statista's report on the car-sharing industry in Canada, the projection shows that there will be around 800,000 shared car users within Canada in 2022. Combined with the most up-to-date market share of Communauto in Canada (10%), the number of Communauto users is projected to be around 80,000 users in 2022. This will be the basis for Montreal Communauto Usage Estimation.

Note that the shared car industry has been growing in recent years, but was heavily influenced by COVID-19 pandemic as people reduced travel plans due to quarantine, which caused a potential mismatch between supply and demand in the market as related policies became looser along with reduced number of cases across Canada.

3.2.2. Communauto Usage in Montreal

Out of all cities where Communauto has been providing businesses in Canada, Montreal has taken a significantly important role. However due to data limitation and user privacy reasons, we did not have any access to the real distribution of Communauto users' demographic information. In this case, we used the population within each city/region proportional to the total population of these cities/regions to estimate how many unique users existed within the Flex service region.

According to Communauto websites, there are currently 14 cities/regions where it provides shared car services, totalling around 10.56 million population. Montreal Flex region population is 10.82% of total population for all 14 cities/regions. Using this information, we can estimate the number of unique users located in the Montreal Flex region is 10.82% of total Communauto 2022 projection calculated previously, which is around 8,656 users.

$$Montreal\ Users = Canadian\ Users \times \frac{Montreal\ Flex\ Region\ Population}{Canada\ Population}$$

3.2.3. Daily Regional Demand

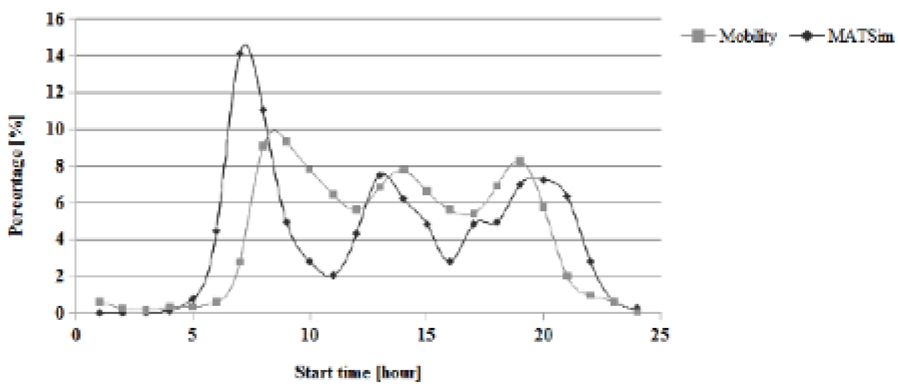
According to the carsharing demand estimation research conducted in Zurich, Switzerland, daily demand of carsharing (shared cars usage) in a region has approximately one-to-one relationship with the number of unique users located within the region. With previous projection on Montreal Communauto users, for each of the FRA region, the number of users located in one region could imply how much daily demand occurred in that specific region. Thus for each region i:

$$Daily\ Region\ Demand_i = Users\ in\ that\ region = Montreal\ Users \times Population\ Proportion_i$$

3.2.4. Hourly Regional Demand

There are many ways to estimate hourly demand in each region. The most straight-forward approach is learning this from historical Flex car transactions that occurred in that region. With time series prediction, demand could be estimated within a high confidence level. However, since the real transactions from Communauto are confidential, we have to consider other possible approaches to obtain hourly demand level.

The approach that was conducted here at this tier is to use Montreal overall traffic flow data. The pain point here is even though we have access to weekly average traffic conjunction levels in Montreal, we still have trouble correctly mapping this information to shared cars demand. Note that the weekly average of Montreal traffic level is reasonably similar to that of Zurich, thus we can apply findings from the Zurich Car Sharing research to estimate hourly demand in Montreal. Hourly demand is demonstrated as follows.



According to the plot, for around 8pm, it's reasonable to assume that the hourly demand is 8% of daily demand. With hourly demand percentage, we apply this to daily demand we estimated for each region, thus we have the following to calculate hourly demand, targeted at 8pm:

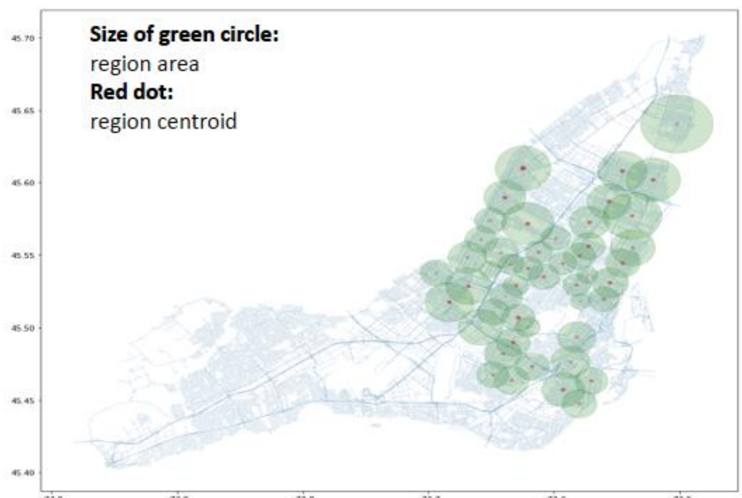
$$Demand\ of\ region_i\ at\ 8\ pm = Region\ Demand_i \times\ Hourly\ demanad\ projection$$

Combining the availability of Flex cars in each region in Montreal at 7pm, we can compare this availability with hourly demand at 8pm, then shuffle the cars between regions so that it could meet the demand for the next hour better.

On an extensive basis, demand could vary regions from regions along with time. For instance, there might be more demands going towards city centres or places where offices clustered in the morning as this is the time slot when people go to work. Similarly, we might see more demand at around 5pm or 8pm as during these time frames people would head back to housing areas. Weather also has a significant impact on car usage as well. Demand estimation could be further extended to a more complicated predictive model with weather and population flow within each region given all related information including historical demand is accessible.

3.2.5. Montreal FRA Regional Data

The primary reasons we choose FRA as regions instead of all other information include (i) FRA (postal code regions) is on an adequate level of scale, with around 48 FRAs in Flex service region, (ii) FRA regions mapped well with the Flex service region's shape, and (iii) public information (including area, centroid location and population information) could be easily accessed. The following is the demonstration of regions covered in the Communauto Flex region.



Communauto Flex Service Regions by FRA

3.2.6. Average Fuel Cost

Fuel cost was conducted from the CAA website. At the time the data was collected (Nov 27, 2021), the rolling monthly average for gas price per litre is $1.55. According to Statistics Canada, the average consumption of gas in Canada is 8.9L/100km. This gives us an estimation for average fuel cost per meter, which is the product of fuel cost per litre and average gas consumption.

3.2.7. Wage Information

Wage per travelling agency is conducted from Communauto hiring website. Each of these agents is compensated with $15/h.

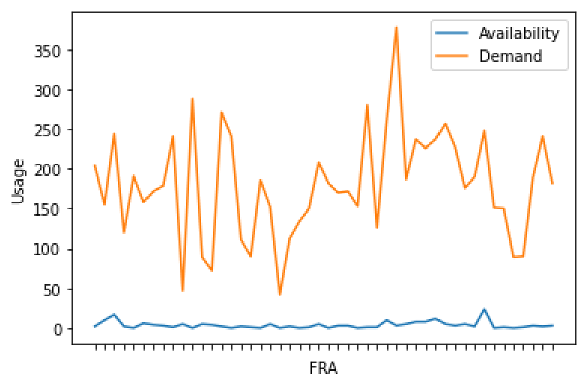
3.3. Converting RFA to Centroid

Obtaining and adapting region boundary data is another pain point. Since full and real time public parking information is not available and Communauto automobiles are heavily relying on street parking due to its collaboration with the Montreal government. Its Flex vehicles enjoy privileges for street parking, which is extremely limited in quantifying parking meters in eligible parking spots. Thus in current scope, we excluded parking as a constraint for Communauto Flex vehicles. However in future extension, parking availability and locations should be considered in the model. Flex vehicles are recorded as counts within each of FRA, here to calculate the distance between each region in order to rearrange cars according to demand, FRA region centroids are used as substitution for distance required to move Flex vehicles between the regions. Similarly, the distance between the Communauto Montreal headquarter and each region is calculated based on region centroid as well.

3.4. Visualizing Demand and Supply

The plot in Appendix 8.3 shows the availability of Flex vehicles in each region versus size of the demand. Plotting method we used here is based on the GeoPandas package in python. Centroids of each region are the centers of each circle in the plots. The size of each circle represents the size of the demand, and the colour density represents the relative ratio of how much percentage of demand has been fulfilled by Flex vehicles availability. We noticed that: (i) Flex cars are concentrated in certain regions, and (ii) some regions are showing high demand for the next hour, but low availability within that region.

The line chart below demonstrates the difference between demand and supply in each region. This shows us that there is a significant mismatch between demand and supply, shuffling Flex vehicles would ultimately help Communauto meet with customers' demand, thus potentially generating more sales.



4. Optimization Model Formulation

4.1. Decision Variables

In formulating the basic model, we considered four decision variables, which are:

$X_{i,j}$: *Number of cars moved from region i to region j*
$S_{i,j}$: *Number of staff who will move the cars from region i to region j*
$C_{i,j}$: *Number of customers who will move the cars from region i to region j*
Y: *Dummy binary variable*

S_T: *Total number of staff available*
$Availibility_i$: *Initial availability in region i*
$Demand_j$: *Demand in region j*
$postal\_code$: *List of postal codes where Communauto operates*

4.2. Objective Function

Our objective function focuses only on minimizing the costs associated with Communauto fleet relocation. The reason why we are not incorporating revenue for this model is due to unavailability of revenue data. The total costs is as follows:

$$\sum_i \sum_j Distance_{i,j} * fuel\_cost * X_{i,j} + \sum_i \sum_j wage/person/hour * S_{i,j} + \sum_i \sum_j distance\_hq_i * fuel\_cost * S_{i,j}$$

The objective function consists of three components, in which each component refers to cost breakdown of fleet relocation expenses. The first component is the total fuel cost to move cars from regions with excess fleet to regions with demands to meet. The second term of the objective value refers to the total wage expenses for the traffic agents, in which staff are paid per hour no matter if the task takes less than one hour. The third component is the fuel cost to transport the traffic agents to areas that need cars to be moved out from.

4.3. Constraints

$$\sum_i X_{i,j} \geq 20\% * Demand_j, for\ all\ j\ \epsilon\ postal\_code$$

$$C_{i,j} + S_{i,j} = X_{i,j}, for\ all\ i,j\ \epsilon\ postal\_code, i \neq j$$

$$\sum_j X_{i,j} = Availibility_i, for\ all\ i\ \epsilon\ postal\_code$$

$$\sum_i \sum_j S_{i,j} \leq S_T$$

$$S_T - \sum_i \sum_j S_{i,j} \leq M * Y$$

$$M * (1 - Y) \geq \sum_i \sum_j C_{i,j}$$

$$X_{i,j}, S_{i,j}, C_{i,j} \geq 0, for\ all\ i,j\ \epsilon\ postal\_code, Y\ \epsilon\ \{0,1\}$$

To begin with, constraint (1) imposes that all areas must be able to fulfil at least 20% threshold of the demand in that area. Constraint (2) ensures that either customer or staff will be assigned to move the car from region i to region j. Note that this constraint excludes the case when i = j since cars are not needed to move from region i, and there is no need to assign drivers for those cars.

Furthermore, constraint (3) imposes that the number of cars that remained in region i and the cars moved from region i will equal to the initial availability in that specific area. Constraint (4) ensures that the number of staff assigned to relocate the cars does not exceed the number of staff available.

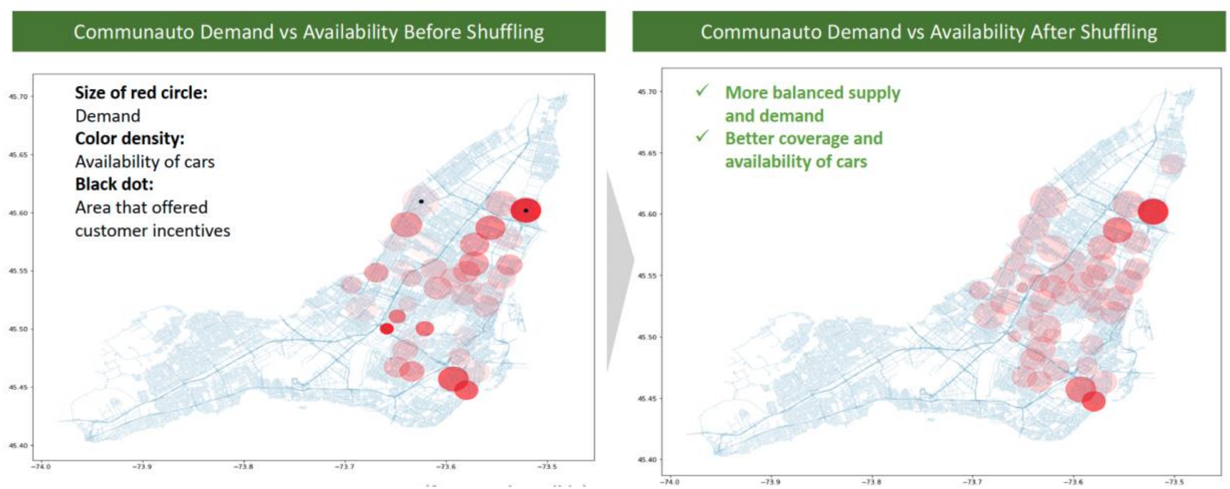
Constraints (5-6) are a set of logical if-then constraints, utilizing the big M concept to enforce the model to use all the staff the company has before starting to offer incentives to the customer. The way the constraints work is, if the company has not used all the staff, Y will be equal to one and forces all Ci,j to be zero. Inversely, if the company used all the staff, Y will be equal to zero and allows the total number of Ci,j to be less or equal than M. Here, M is an arbitrarily big number that does not limit both Si,j and Ci,j. For this model, we set the value of M = 10000.

The last constraint, constraint (7), forces decision variables $X_{i,j}$, $S_{i,j}$, and $C_{i,j}$ to be positive integers and dummy variable Y to be binary.

5. Modelling Results

5.1. Baseline Model Results

After optimization execution in Gurobi, more balanced supply and demand and better coverage and availability of cars can be observed. Visually, the availability of cars represented by the intensity of red was disproportionate to the demand denoted by the size of circles before shuffling. Now, the simulated distribution is more balanced with comparable color intensity and size. To Communauto, this means improved efficiency serving customers with limited cars and generating revenue. The overall coverage of cars availability has also been improved considering the evenness of red illustrating fulfilled supply-and-demand and the smaller gaps between circles where cars are neither available nor in demand. To customers, this enhances the accessibility of Flex vehicles when getting around from anywhere in the city.

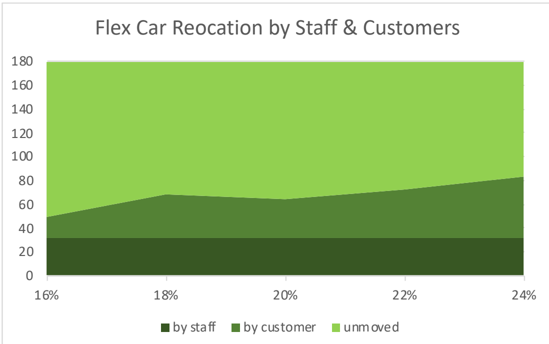


Numerically, 64 Flex cars will be moved between regions by 32 staff members and 32 customers, for 50.6km and 84.7km total distance covered by staff and customers respectively. Cost-wise, the total cost incurred is CAD $516.6, with $18.0 additional cost incurred for staff than customers, including wage and fuel cost for customers to get to region i from the headquarter.

5.2. Sensitivity Analysis

5.2.1. Demand Fulfilment Levels

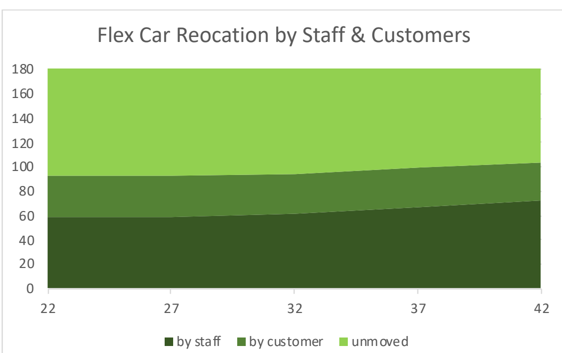
20% demand fulfilment per region is assumed in the baseline model. In practice, Communauto can adjust the percentage of demand fulfilment based on its target to address the pressing need of free-floating service. Generally, the higher the demand fulfilment, the lower the total additional cost for staff (more cost-effective), yet the more the customer movers are needed to realize the benefit. 20% is the threshold in which the ratio of number of staff and customers used ties and minimizes the total cost incurred - a local minimum for a non-linear optimization problem if cost-effectiveness is desired and no specific demand fulfilment level is assumed. It is also worth to note that even lower total cost and additional cost for staff can be obtained for fulfilment levels below 18%, those scenarios would deviate from the objective of centralized staff deployment to increase free-floating service availability and might not create as much impact compared to today's minimal incentives to avoid idleness.



Demand Fulfilment Level	16%	18%	20%	22%	24%
Total cars moved between regions	49	60	64	73	83
Number of staff used	32	32	32	32	32
Total cost incurred	$510.6	$514.1	$516.6	$526.6	$538.8
Total additional cost incurred for staff than customers	$17.8	$18.1	$18.0	$17.8	$17.7

5.2.2. Traffic Agents Capacity

32 traffic agents are assumed in the baseline model. Similarly, Communauto can vary the number of staff members to employ based on the operation cost and risk appetite it can afford. Since it is assumed that relocation incentive for customers does not incur direct cost and revenue impact is yet to be considered, the total cost and additional cost for staff is more impacted by the number of staff used than the number of customers expected to move the cars. In general, the fewer the staff used, the lower the additional cost for staff (more cost-effective), yet the more the customer movers are needed to realize the benefit. Communauto can employ a certain number of traffic agents to meet the demand fulfilment in the initial stage and then reduce the number of hires with learnings on revenue impact and confidence of customers take-up to achieve the same fulfilment level.



Number of staff used	22	27	32	37	42
Total cars moved between regions	57	61	64	69	74
Number of customers expected	35	34	32	32	32
Total cost incurred	$359.3	$437.9	$516.6	$595.5	$674.5
Total additional cost incurred for staff than customers	$11.1	$14.3	$18.0	$21.7	$25.2

5.3. Insights and Learnings

From the above analysis, we can summarize three key insights and learnings which tie back to the other business priorities on revenue, service level and customer experience in section 2.2 strategy formulation. Firstly, Communauto meets the maximum demand possible for minimal relocation costs through the deterministic relocations from staff and the rest will be carried by the customers. Revenue can be further optimized with percentage fulfilment of dynamic regional demand. Secondly, allocation is done in a way that staff cater the relocations which are closer to the headquarters and the customer incentives are promoted for relocations which are further. This is constrained by the staff number assumption in this proof-of-concept, yet service level can be optimized with dynamic staff and customer mover capacity. Last but not least, the maximum customer incentive value we could set would be the average additional cost incurred for staff compared to customers, which is calculated by (wage + total cost) / number of staff = $15.6 per move. The concept can be carried forward to the formulation of reward strategy through mover take-up optimization with credit or cash rewards.

6. Problem Extensions

In this section, we will explore the possibilities of extending our base model through adding multiple components assuming access to the necessary data. It acts as a way forward to add to our proof-of-concept built above and be used to showcase the potential and values of the solution if given proper data access.

Vehicles' Locations – we can improve the accuracy of our model and solution if we use vehicles' live locations at the time we want to run our model. This data is readily available to the company.

Agents' Locations – we can improve the accuracy of our model and solution if we use our travel agents' live locations at the time we run our model. Each day before running the model, the agents could come online and provide their location (the company can set some simple rules to ensure they have enough online agents in different regions of the city each day as needed).

Multiple Relocations – we can improve the solution efficiency if we assign each agent to relocate multiple vehicles. Time constraints must be taken into account here and there will be a trade-off between one person doing many relocations and meeting the demand at a certain time in day.

Parking Locations – if we could access the status of parking spaces which Flex cars are allowed to park, we could directly point out the slot vehicles have to be moved to. Accessing this data is challenging. There are some apps that offer something similar, but none of them are perfect and/or free. Communauto can possibly access this data and gather and collect it to be used in the analysis.

6.1. Proposed Formulation

Parameters:

$X_{i,j}$: 1 if car i has to be moved to region j, 0 otherwise
$S_{i,j,k}$: 1 if car i has to be moved to region j by staff k, 0 otherwise
$C_{i,j}$: 1 if car i has to be moved to region j by customers, 0 otherwise
$SU_k: 1\ if\ staff\ k\ assigned\ to\ move\ cars$
$Y: Dummy\ binary\ variable$

Decision Variables:

$CPD_{i,j}$: Distance between car i location and parking space j location
$ACD_{i,j,k}$: Distance between $staff$ i location and car location j
$S_T: Total\ number\ of\ staff\ available$
$car\_id: Set\ containing\ list\ of\ unique\ identifaction\ number\ for\ each\ car$
$region: Set\ containing\ list\ of\ regions$
$Demand_j: List\ containing\ demand\ in\ region\ j \in region$

Objective Function:

$$\sum_i \sum_j CPD_{i,j} * fuel\_cost * X_{i,j} + \sum_i \sum_j \sum_k wage/person/hour * S_{i,j,k} + \sum_i \sum_j \sum_k ACD_{i,j,k} * fuel\_cost * S_{i,j,k}$$

Constraints:

Fulfil 20% of the demand of each region

$$\sum_i X_{i,j} \geq 20\% * Demand_j, for\ all\ j\ \epsilon\ region$$

Each car can be moved by either staff or customers

$$C_{i,j} + \sum_k S_{i,j,k} = X_{i,j}, for\ all\ i\ \epsilon\ car\_id, j\ \epsilon\ region, i \neq j$$

Utilize staff before employing customers incentive approach to relocate the cars

$$\sum_i \sum_j S_{i,j,k} \leq M * SU_k$$

$$S_T - \sum_k SU_k \leq M * \mathrm{Y}$$

$$M * (1 - Y) \geq \sum_i \sum_j C_{i,j}$$

Non-negativity and binary constraints

$$X_{i,j}, S_{i,j,k}, C_{i,j}, SU_k \geq\ 0, for\ all\ i\ \epsilon\ car\_id, j\ \epsilon\ region, k\ \epsilon\ staff\_id\ Y\ \epsilon\ \{0,1\}$$

Additional Constraints:

$$\sum_k \sum_i S_{i,j,k} = 1, for\ all\ j\ \epsilon\ region$$

$$\sum_k \sum_j S_{i,j,k} = 1, for\ all\ i\ \epsilon\ car\_id$$

$$\sum_k \sum_i S_{i,0,k} = S_T$$

$$\sum_k \sum_j S_{0,j,k} = S_T$$

$$\sum_i \sum_j S_{i,j,k} \geq 1, for\ all\ k\ \epsilon\ staff\_id, i \neq j$$

6.2. External Data and Flexible Rewards

We could also expand the problem so that the model is used for a different purpose using external data. For instance, in extreme weather conditions in winter, we could solve the model to make sure Communauto vehicles are not left on the street to prevent vehicle damage. This time, we would input locations of cars on the street into our model and input parking spaces which are safe (e.g. located inside a building). This could potentially save a lot of maintenance cost for the cars and also decrease down time of Communauto vehicles after storms.

We could also generate flexible customer incentives instead of a fixed amount based on the urgency of the demand in certain locations in which we need cars to be available. The incentive could go up as much as the cost incurred if an agent was sent to do the job.

7. Conclusion

This report presents a mathematical model to solve the problem of fleet relocation for the Communauto free-floating car-sharing system. Since the industry demand and supply is unbalanced and Flex cars have great potential to be utilized, we proposed a strategy to optimize the reallocation of Flex in 3 phases – centralized staff deployment, multiple relocation by staff and smart mobility & flexible reward. As a proof-of-concept for the first phase, we focused on the business priority to minimize relocation costs and have built a model to address the pressing need of free-floating service by deploying traffic agents from a centralized point to move vehicles from low demand to high demand regions. The model has solved for the minimal relocation cost to meet 20% demand fulfilment level in each FRA region in Montreal where Communauto Flex is operating, and demonstrated more balanced supply and demand as well as better coverage and availability of Flex cars after relocation. Carrying forward, Commuauto can extend the supply-demand based optimization for reducing revenue loss due to unmet demands, enhancing service level with dynamic staff and customer movers capacity and improving user experience with an optimal reward strategy. Internal vehicle data and real-time traffic data will play an important role in Communauto’s free-floating services and the full potential of smart mobility is yet to unlock.

8. Appendix

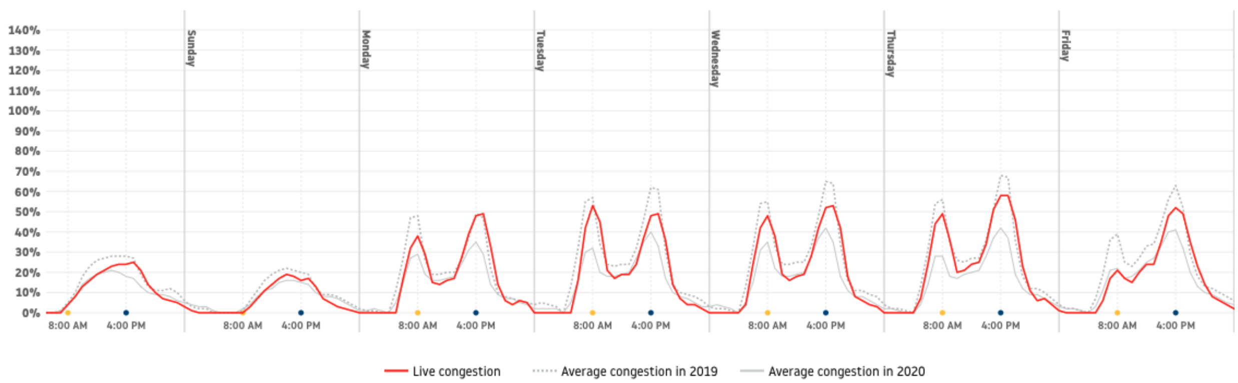
8.1. Demand and Number of Users

Relationship between daily number of car usage in service and number of unique users in the region.

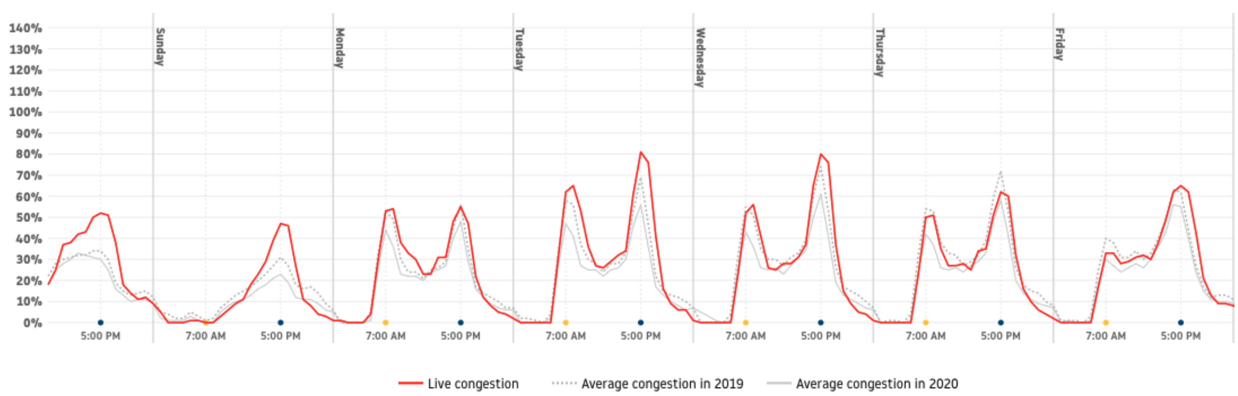
TABLE 2 Round-trip carsharing simulation statistics with different fleet sizes for a constant membership.

Variable	Original	2x fleet	3x fleet	4x fleet	5x fleet
Number of cars:	911	1,822	2.733	3,644	4,555
Number of rentals/work day:	830	1,597	1,906	2,077	2,081
Rentals increase over original[%]:	-	192	229	250	250
Number of trips:	2,157	4,088	4,993	5,409	5,414
Trips increase over original[%]:	-	189	231	250	250
Average trip distance[km]:	6.9	7.0	6.9	6.6	7.0
Number of used cars:	604	1,183	1,541	1,824	1,873
Number of unique users:	814	1,553	1,856	2,013	2,029

8.2. Hourly Conjunction Level

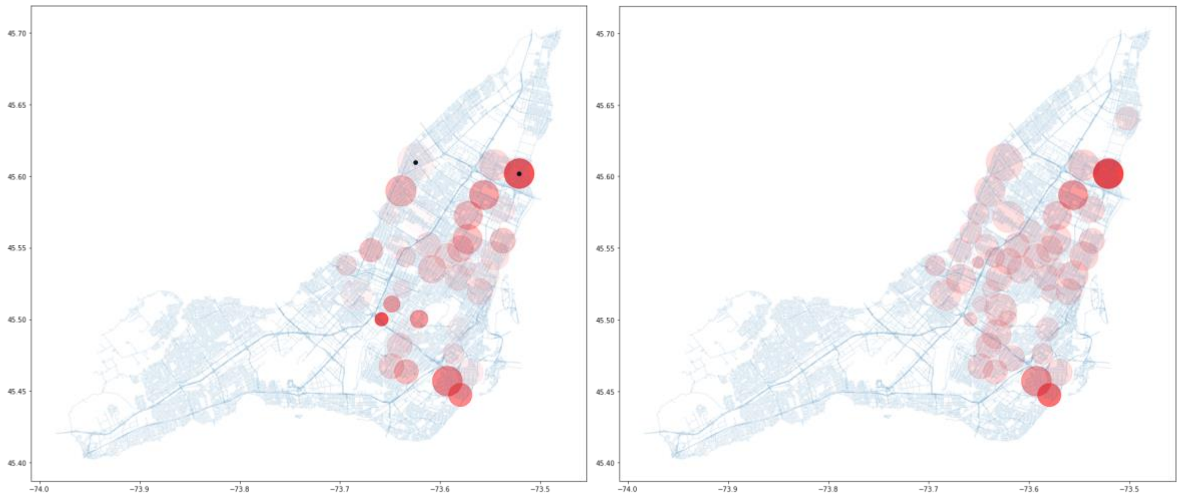


Montreal Hourly Conjunction Level (Nov 27 - Dec 3, 2021)



Zurich Hourly Conjunction Level (Nov 27 - Dec 3, 2021)

8.3. Communauto Flex Vehicles before and after Shuffling



8.4. Communauto Service Cities/Regions and their Population

City	Population
Toronto	2731571
Cambridge	129920
Guelph	131794
Hamilton	536917
Kingston	123798
Kitchener	233222
London	383822
Ottawa	934243
Waterloo	104986
Gatineau	276245
Montreal	1704694

Quebec City	531902
Sherbrooke	161323
Calgary	1239220
Edmonton	932546
Halifax	403131

8.5. FRA Region Centroid Location, Population, Area Availability at 7pm and Demand at 8pm

FRA	Availability 7pm	Gift Icon Count 7pm	Region Centroid Latitude	Region Centroid Longitude	Population	Population %	Users	Demand at 8pm
H4G	2	0	45.4630778	-73.570371	26868	0.0235173	204	16
H4H	10	0	45.4473077	-73.579942	20395	0.01785155	155	12
H4E	17	0	45.4569642	-73.592825	32159	0.02814846	244	20
H4C	2	0	45.4761361	-73.586952	15854	0.01387685	120	10
H4A	0	0	45.4730267	-73.617348	25257	0.02210721	191	15
H4B	6	0	45.4634615	-73.633739	20830	0.0182323	158	13
H4V	4	0	45.4672704	-73.64877	22681	0.01985246	172	14
H3X	3	0	45.4817226	-73.640538	23675	0.0207225	179	14
H3W	1	0	45.4897205	-73.632522	31872	0.02789725	241	19
H4P	5	0	45.5000609	-73.658539	6228	0.00545131	47	4
H3S	0	0	45.5067556	-73.628552	38042	0.0332978	288	23
H3T	5	0	45.5002185	-73.621059	11744	0.01027941	89	7
H3R	4	0	45.5106794	-73.648169	9531	0.00834239	72	6
H4L	2	0	45.5173998	-73.68328	35802	0.03133715	271	22
H4N	0	0	45.5284396	-73.668056	31772	0.02780973	241	19

H3M	2	0	45.5375736	-73.693675	14614	0.01279149	111	9
H3P	1	0	45.5212843	-73.638233	11905	0.01042033	90	7
H3N	0	0	45.5289241	-73.630224	24500	0.02144461	186	15
H3L	5	0	45.5481998	-73.668938	20027	0.01752944	152	12
H2N	0	0	45.5398436	-73.650905	5602	0.00490338	42	3
H2P	2	0	45.5434341	-73.634179	14839	0.01298843	112	9
H2C	0	0	45.56058	-73.658045	17713	0.01550402	134	11
H2M	1	0	45.5514113	-73.64238	19774	0.01730799	150	12
H2S	5	0	45.5349567	-73.608025	27406	0.02398821	208	17
H2R	0	0	45.5406166	-73.620531	24063	0.02106211	182	15
H2G	3	0	45.5441403	-73.593028	22501	0.01969491	170	14
H2E	3	0	45.5518486	-73.612205	22696	0.01986559	172	14
H2A	0	0	45.5614254	-73.598657	20131	0.01762047	153	12
H1Z	1	0	45.5715602	-73.62089	36900	0.03229821	280	22
H2B	1	0	45.5738248	-73.650563	16694	0.0146121	126	10
H1H	10	0	45.5895898	-73.639132	34471	0.03017213	261	21
H1G	3	3	45.6097698	-73.624683	49857	0.04363935	378	30
H1Y	5	0	45.5492759	-73.579702	24704	0.02162317	187	15
H1X	8	0	45.5559897	-73.572694	31317	0.02741147	237	19
H1T	8	0	45.5724898	-73.571818	29871	0.0261458	226	18
H1M	12	0	45.5868054	-73.556258	31264	0.02736508	237	19
H1K	5	0	45.6077348	-73.54573	33861	0.02963821	257	21
H1W	3	0	45.5443029	-73.545472	30021	0.02627709	227	18
H1V	5	0	45.554931	-73.537425	23211	0.02031636	176	14

H1N	2	0	45.5768956	-73.537681	25117	0.02198467	190	15
H1L	24	2	45.6017641	-73.52117	32709	0.02862987	248	20
H1B	0	0	45.6403709	-73.502294	19884	0.01740427	151	12
H3H	1	0	45.4932081	-73.582067	19756	0.01729224	150	12
H2W	0	0	45.5179701	-73.578883	11685	0.01022777	89	7
H2H	1	0	45.5364022	-73.573532	11843	0.01036606	90	7
H2J	3	0	45.5291818	-73.582128	24896	0.02179123	189	15
H2K	2	0	45.5308669	-73.555572	31859	0.02788588	241	19
H2L	3	0	45.519425	-73.560388	24077	0.02107437	182	15