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MODELLING THE USE OF ELECTRIC CARS IN A FREE-FLOATING CARSHARING SYSTEM

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Summary

The introduction of electric vehicles (EV) within a free-floating carsharing service lead to additional complexities that may lead to different user behaviors: smaller car range, charging stations and car fleet management. This paper looks over the impacts of the introduction of EVs on the customer behavior inside Communauto's Auto-mobile service in Montreal, where both EVs and hybrid vehicles (HV) are made available to the user.

Keywords: car-sharing, energy consumption, EV (electric vehicle), HEV (hybrid electric vehicle)

1 INTRODUCTION

In dense cities, carsharing systems have proven to be efficient and useful to urban mobility and sustainability. These systems provide access to cars without the burden of ownership, and they contribute to a reduction in the level of car ownership. Recently, free-floating carsharing systems have become increasingly popular because they provide access to cars wherever they are available across the street grid. The advent of smartphones facilitates the use of these services. Most free-floating systems have adopted fuel-efficient cars, e.g., Car2Go uses Smart cars. In Montreal, the Auto-mobile system is operated by Communauto, the oldest carsharing company in North America (since 1994). The Auto-mobile free-floating system offers two types of cars: the all-electric Nissan Leaf and the Toyota Prius hybrid.

Carsharing organizations and the general population mainly buy and use fuel-based vehicles. Interest in electric vehicles (EVs) has increased in recent years, but their market share is small: it is expected to be 2% of the global market in 2020 [1]. Many governments are promoting the introduction of sustainable energy sources, such as electricity, for transportation. They offer several incentives to encourage the use of EVs, such as access to HOV lanes [2], tax reductions or subsidies [3], and access to preferential parking [4]. Montreal has issued a request for proposals for the introduction of a one-way all-electric carsharing service [5], and the government of Quebec has launched a plan for the electrification of transportation in the province [6]. These developments motivated organizations such as Communauto to introduce EVs. However, such vehicles do not have, at this time, the profitability of fuel-based cars. This is because EVs must be moved to charging locations daily, which decreases their availability, and they have a higher initial cost [7], even though the electricity rates are very low in Quebec. The type of car may also influence the use of the service, and we need to explore the choice of car type: shorter-range EVs versus longer-range hybrid vehicles (HVs).

This paper is organized as follows. Section 2 presents the background about carsharing and electric vehicle studies. Section 3 presents the methodology and gives a descriptive analysis of the use of HVs and EVs based on data from Communauto. Section 4 presents a vehicle-type choice model and discusses the results, and Section 5 provides concluding remarks.

2 BACKGROUND

This section discusses various forms of carsharing and presents studies on EVs.

2.1 Definitions

There are three main types of carsharing. Station-based (or round-trip) carsharing is an early form (we will refer to it as regular carsharing): there is a network of stations where members reserve and take a car and return it to the same station [8]. This model is used by Zipcar, which operates in the USA, Canada, Austria, France, Spain, the UK, and Turkey. In Canada, Communauto also operates this type of service. The other types of carsharing do not require the car to be returned to its departure station. In one-way carsharing, the member books a car located at a specific station but can return it to any station in the network [8]; Autolib (Paris) is an example of such a service. Free-floating carsharing (third type) eliminates the stations and the need to book cars in advance [9]. Schaefers (2013) introduced the concept of the service area (SA) to replace the stations [10]. The user is free to bring the car outside the SA but must return it inside the SA to close the rental. In Montreal, Auto-mobile, operated by Communauto, and Car2Go services are free-floating schemes.

2.2 Electric Vehicles

While Montreal plans to gradually introduce an all-electric carsharing system, many other carsharing organizations have already introduced EVs into their fleets, and some use all-EV fleets. Yélobile introduced the first all-EV fleet in Europe in 1999. Based in La Rochelle, France, Yélobile offers a one-way carsharing service. Also in France, Auto Bleue in Nice and Autolib in Paris offer all-EV services. Auto Bleue is station-based (regular), and Autolib is one-way. In the United States, BlueIndy plans to introduce the largest all-EV service in Indianapolis with 500 “Bluecars,” 1,000 charging stations, and over 200 locations. In Colorado, Ethos operates the first all-EV service in America, a station-based system. Some mixed-fleet operators provide free-floating systems. Car2Go operates EV fleets in four of its 26 free-floating systems in North America and Europe [11].

There have been various EV studies. For example, Wappelhorst et al. (2014) carried out surveys in Berlin and in a small rural region in Germany to determine if the implementation of an e-carsharing scheme would be viable [12]. They compared attitudes toward innovative mobility supply (such as e-carsharing), built an attitude-

based typology, and looked at mobility behavior. They concluded that car dependency and car affinity limit the potential for new mobility services. New solutions would need to target new groups of customers to ensure economic viability. For many people, fuel-based cars are still important because of their long-range autonomy [13].

Some studies have explored the factors leading to the acquisition of EVs. Hidrue et al. (2011) state that socio-demographic factors such as youth, education level, and eco-oriented lifestyle increase the likelihood of EV acquisition [14]. On the economic side, people were focused on savings in fuel costs rather than environmental impact. Speculation about increases in gas prices was also a favorable factor to EV acquisition. Factors limiting EV acquisition included “range anxiety,” the higher initial cost, and the charging time. Other studies have also found that range anxiety is a primary concern [15][16]. However, a study of the first year of Autolib’s operation looked at the viability of EVs in urban areas [17]; the authors state that range autonomy does not seem to be an issue for the users. Research has also been conducted on consumer attitudes to the pricing of EVs. Using the van Westendorp price sensitivity method and a willingness-to-pay analysis, Larson et al. (2014) conclude that consumers are not ready to pay a net premium to acquire an EV [18]. They claim that the introduction of EVs has focused on technology rather than consumer preferences. To the best of our knowledge, there has been no study of the choice of car type within a carsharing program.

Firnkorn and Müller (2015) evaluate the private-car replacement potential in a free-floating system and policies that support carsharing systems [19]. They surveyed Car2Go users, asking if they would (a) forgo a car purchase/replace a currently owned car in the future or (b) dispose of a car that is currently shared with a friend or family member, if the Car2Go service were available permanently. Statement A received a positive response of 35% to 40%, and statement B received a positive response of 19% to 23%. The users who had driven an EV prior to the survey were more willing to replace their cars than the users who had never driven an EV. This seems to corroborate the results of Franke et al. (2012)[20], who found a positive relationship between EV experience and successful adaptation to cars with a limited range. Shaheen et al. (2013) carried out a similar study in a community of seniors in the San Francisco Bay Area [21]. Delang and Cheng (2012) surveyed the attitude of the Hong Kong population to the environmental impact of EVs [22]. The results showed that EVs were considered to have a limited positive impact; this could help to explain their slow rate of adoption in Hong Kong.

3 METHODOLOGY

3.1 Case study

Our study is conducted in collaboration with Communauto. Established in 1994, Communauto provides two distinct services:

- A traditional station-based service, in operation since 1994. This service operates in eight regions in Canada, with over 450 stations and 1,000 vehicles in the Montreal Metropolitan Area alone. We refer to this service as the regular service (REG).
- Auto-mobile, a free-floating service introduced in June 2013 in the Montreal area (and now available in Quebec City). This fleet is currently composed of 270 cars (+30 in Quebec City) with an SA of more than 76 km² (+ the area in Quebec City). We refer to this service as “AuM.”

We studied the Montreal service from June 2013 to April 2015. During this period, the number of vehicles increased from 24 to 165, and there were four expansions of the SA, from a total of 8 km² to today’s 76 km². Fig.1 shows the evolution of the SA (the subway lines are also shown).

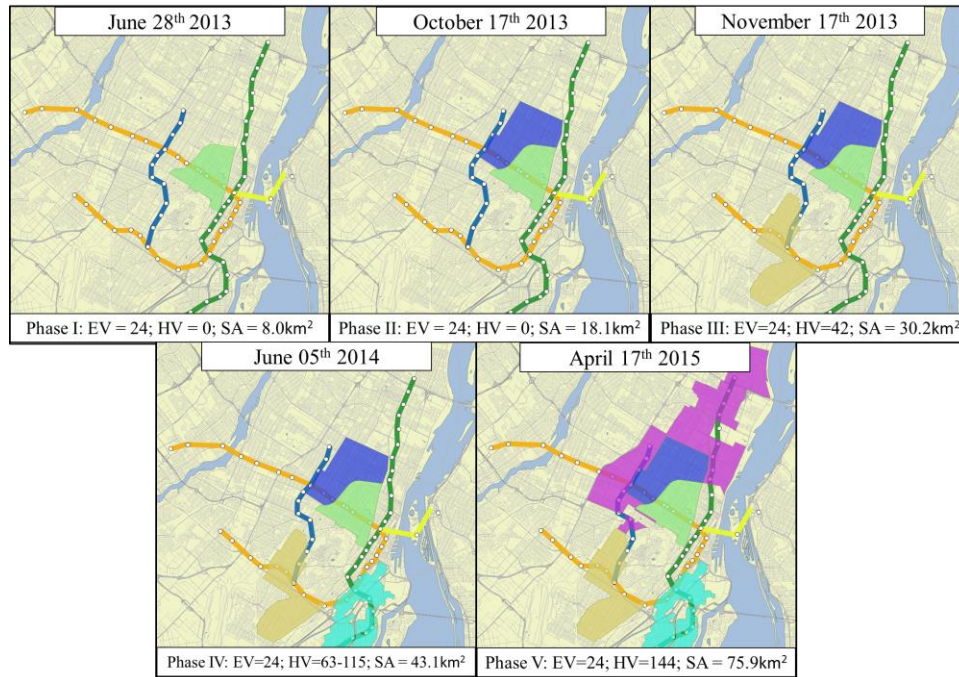


Figure 1: Evolution of Communauto's AuM service area from June 2013 to April 2015

To access a vehicle, users can proceed via the company's online services (app, website) or can do directly to a car in the street. The online services allow the user to locate available nearby cars, see the car type (EV or HV) and the energy (fuel / electricity charge) level. To access the cars, users swipe smart card through the car's terminal (the system is also compatible with OPUS transit smart card). The user can reserve a car for up to 30 minutes, free of charge, before taking possession of it. This gives the user confidence that the vehicle will be available when he/she reaches it. After accessing the car, the user is free to travel inside or outside the SA. The billing is on a pay-per-minute basis. Parking the car inside the SA will end the transaction (making the vehicle available to others) or it is possible to keep the car at the same per minute fare. The car's monitor indicates whether or not the vehicle is in the SA.

The refueling of HVs is usually performed by users, who receive free usage minutes as an incentive. At the end of an HV transaction, the tank must be at least half full. There is no obligation to charge an EV at the end of a transaction, but the remaining range must be at least 15 km. If the range of an available car falls below 20%, a Communauto employee will take the car to a charging station. Also, when necessary, the employees relocate both HVs and EVs to more desirable locations.

3.2 Information system

We used numerous data sources for this study. For the first part of this paper, the datasets contain the most up-to-date information as of April 24th 2015. For the second part where the vehicle's energy level is used, a complementary dataset of 7 months is used, with up-to-date information as of February 18th 2016.

The user dataset contains over 44,000 entries with information about the user's gender, age, subscription date, service package (rates), and home location (based on the Canadian postal code). This data is strictly anonymized. The vehicle dataset contains information about the make, model, and technology (fuel-based or electric).

The transaction dataset contains information on both the REG and AuM services. For REG, it contains every reservation (even if subsequently cancelled) from January 1st 2013 to April 24th 2015. For AuM, it records every time a car was borrowed, from June 28th 2013 to April 24th 2015. For AuM, a complementary dataset contains the geographical location of the vehicle (with a frequency of 3 to 4 GPS points per minute), but for a shorter time frame: June 28th 2013 to March 3rd 2014. This dataset also store the user ID and the vehicle ID.

The energy level dataset contains information about AuM vehicles and their energy level before and after a completed transaction. Also, the information about the reservation duration, distance and vehicle position is given. This dataset contains 52,099 reservations, from which 4,614 are made by EVs. With the car state of charge, we can deduct the amount of energy used for a trip, and consequently try to factor the influence of the charge on user behavior.

3.3 Data processing

We took several steps to validate data, create key figures, process the GPS traces, and integrate the datasets into a database management system.

3.3.1 Data cleaning and data integration

To ensure the reliability of the data, we first looked for inconsistencies (duplication, unexpected values, missing values). We removed the 4,807 employee-related transactions. Finally, we verified the distances provided. We evaluated the speeds, durations, and distances and removed records with excessive average speeds. We tagged the top and bottom 1% of the durations and the top 1% of the distances to eliminate biases. After these steps, 98,923 records were available for our study.

3.3.2 GPS processing

The AuM dataset contains car status and GPS traces (2,087,782 records). We used it to divide each reservation into trips. Thus, we can determine the distance, duration, start and end locations, activity duration, and location of each trip. Of the 22,993 reservations, we used 14,692 for our study. These reservations contained a total of 24,995 trips and 11,523 activities. This data was useful for our GIS-based study.

3.3.3 Client classification

For the clients, we developed a classification system with two levels. The first level, Type A, is the first Communauto service (AuM or REG) used by the client in its lifetime as a Communauto user. The second level, Type B, identifies clients who subsequently used the other service. For example, a “REG-AuM” is a client who used the regular system at first, then used the free-floating. A “AuM-AuM” is somebody who is using the free floating service exclusively.

3.3.4 Availability of other vehicles

Because we want to model the choice of the type of car, we need to know the availability of other cars near the selected pick-up location. We created eight binary variables to indicate whether or not there is an available nearby car. These variables are based on the vehicle type (EV or HV) and the radius of the search area (100 m, 200 m, 300 m, 400 m). We performed SQL queries for every transaction date and time to find the availability of every other car, and we processed the results to set the binary variables.

3.3.5 Energy level processing

The process used here is similar as the one presented in 3.3.1. The energy level range from 0% to 100% and represent the remaining car range, whether the state of the battery or the level of the fuel tank. When referenced, the energy level or state of charge variations are measured in unit of variation (e.g.: a decrease of 10 units from a charge level of 95% will drop the car charge level to 85%).

4 RESULTS

4.1 Vehicle type effect on distance

In this section we examine the differences of usage between HVs and EVs. We use the reservations made after the introduction of HVs to evaluate the usage rate (92,507 reservations). We define the usage rate to be the frequency of use of a specific car type. For a better understanding of the free-floating carsharing dynamics and a descriptive analysis of users' trips, please refer to Wielinski et al. [23].

We try to establish a distance break-point at which EV use would dramatically decrease. The hypothesis is that the EV battery is insufficient for longer trips (in reality or perceived by users), leading to a drop in the EV usage rate. Fig.2 shows the EV/HV usage rate in function of the distance travelled. The fleet sizes have been normalized.

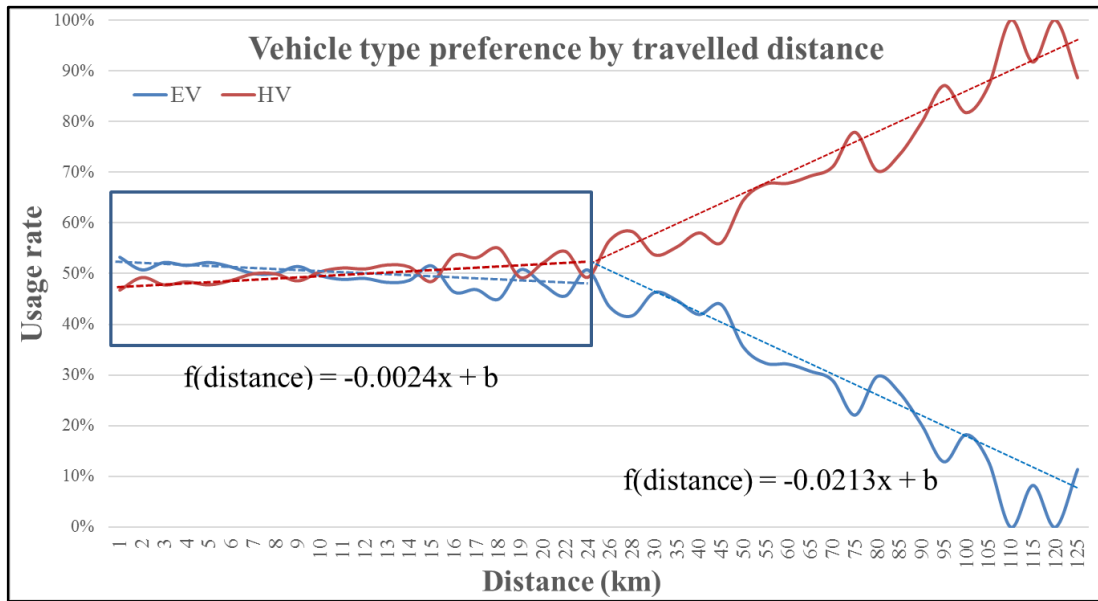


Figure 2: Usage rate of vehicle type by distance travelled (km)

HVs and EVs have similar usage rate for distances up to 24 km, ranging from 53.6% to 45.4% for EV. Above 24 km, the HV usage rate increases by 2.13% for every additional kilometer travelled. A clear preference for HVs is observed for longer distances. There is not really a clear explanation of this distance threshold: however, it represents approximately 2 to 3 times the size of the service area, this maybe a kind of “psychological” barrier for EV users.

4.2 Vehicle type effect on user activity

We used a GIS to evaluate the user activity by vehicle type. There is supposedly a user activity for each trip end identified from the GPS traces. Over an eight-month period, there were 5,287 EV activities and 6,236 HV activities. Our goal was to determine whether HV users are more willing to go outside the SA, and to what extent.

Of the 5,287 EV stops, 46.5% are inside the SA (note that the expansion of the SA over time has been taken into account), compared to 53.9% for HVs. This observation may seem counterintuitive, but it becomes clearer when we segment the data by month. Before the introduction of HVs, the proportion of EV stops outside the SA was between 55.6% and 66.3%. After November 15th 2013, the value has dropped between 34.5% and

41.8%, a reduction of 60%. For the HVs, in November the proportion is 48.2%, but it increases to a stable $54.7 \pm 1.1\%$ for December to February. Thus, the introduction of HVs changed user behavior.

Both EVs and HVs are used for trips outside the SA. To measure the extent, we use standard deviation ellipses (SDEs) to compare the two vehicle types. Fig.3 presents the SDEs for each vehicle type from November 2013 to February 2014. The SDE is an ellipse whose axes are the standard deviation of the x and y coordinates from the mean center. SDEs can illustrate changes that occur over time.

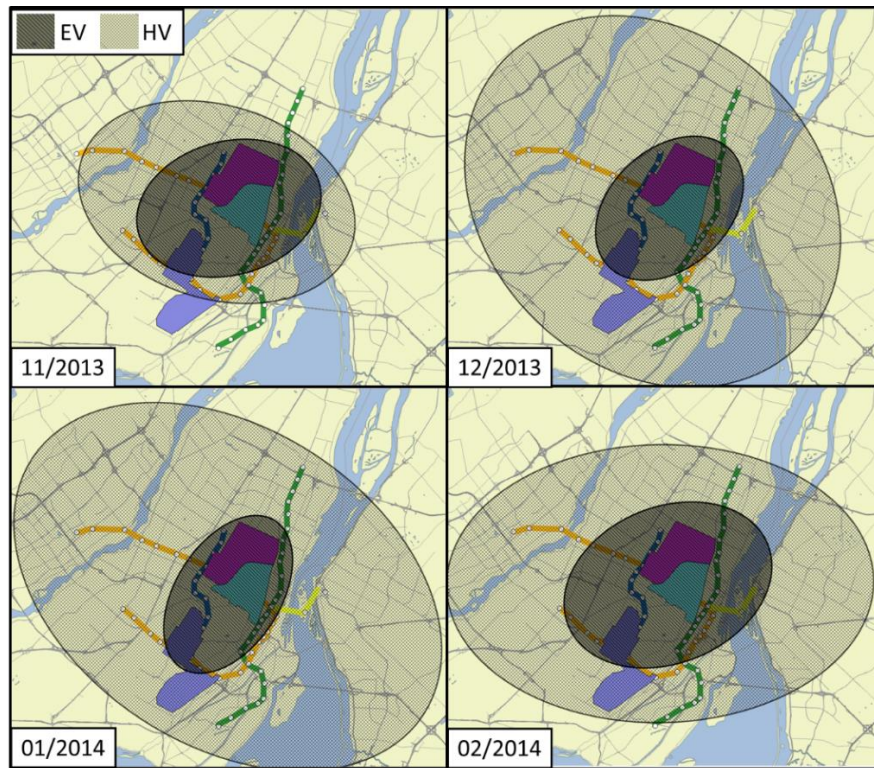


Figure 3: SDEs of user EV and HV activities (scale 1:100,000)

The HVs have larger SDEs, ranging from a 118.7% augmentation in November to 708.3% in January. In November, the difference between the two ellipses is relatively small. For HVs, the holiday period seems to have a noticeable impact. The EV SDE reduced after the introduction of HVs but nearly doubled in February. We need more data to confirm these findings, but there seems to be a significant difference between the HV and EV SDEs.

4.3 Consumption related factors for EVs

With the availability of the car state of charge, we can infer the total energy consumption used to complete the trip. Because fuel-based vehicles can be (in certain case they have to be) refuelled by the users, we can't deduct the energy used by them. Consequently, we only look these factors for EVs. The following factors were examined: the EV car age (newer 2015 models vs older 2011-2012 models), the time of the week (weekdays vs. weekend), the time of the day (AM, PM, evening, night), by origin-destination pairs, by month, by temperature (above or below the freezing point), by traveled distance and by initial energy level. The variable used to evaluate if a factor is significant or not is the distance traveled by energy level. This variable is thus greater if a vehicle travels a longer distance for the same amount of consummated energy.

An initial ANOVA analysis revealed only a significance difference for four factors; *EV car age*, *month/temperature*, and *traveled distance* (the latter only partially significant in a free-floating carsharing context). Because month and temperature are correlated, we consider them as one explanatory variable. The situation of the EV car age variable is particular because 1) newer models possess a more precise indicator of their state of charge than their older counterpart (where the energy level varies like a stepwise function), and 2) the batteries in newer cars are much more performant. Thus, the difference between those vehicle models is not surprising. Nevertheless, we ran a linear regression to evaluate the difference between the two generations of Nissan Leaf. The results show a decrease of -0.44 ± 0.06 km in car range for every energy percentage consummated by the older cars. On full charge, the newest generation can expect to accomplish ~ 31.0 more km than the previous generation before the vehicle reach the 30% mark. This represent ~ 3 to 5 more trips made by the users per cycle charge (the median trip distance being about 6 km). Regarding the temperature, when it is below the freezing point, the vehicle expected range by energy level decrease by -0.27 ± 0.03 km. It represents a reduction of ~ 18.9 km (~ 2 -3 regular trips) in a full recharge cycle (from 100% state to 30% state). About distance, there is a difference in energy consumption rates, but only between short trips (< 5 km) and really long trips (> 50 km). Longer trips offer the occasion to use the highway, increasing the vehicle range. Fig.4 presents the distributions of the main two factors in the difference of energy consumption: temperature and EV model (car age).

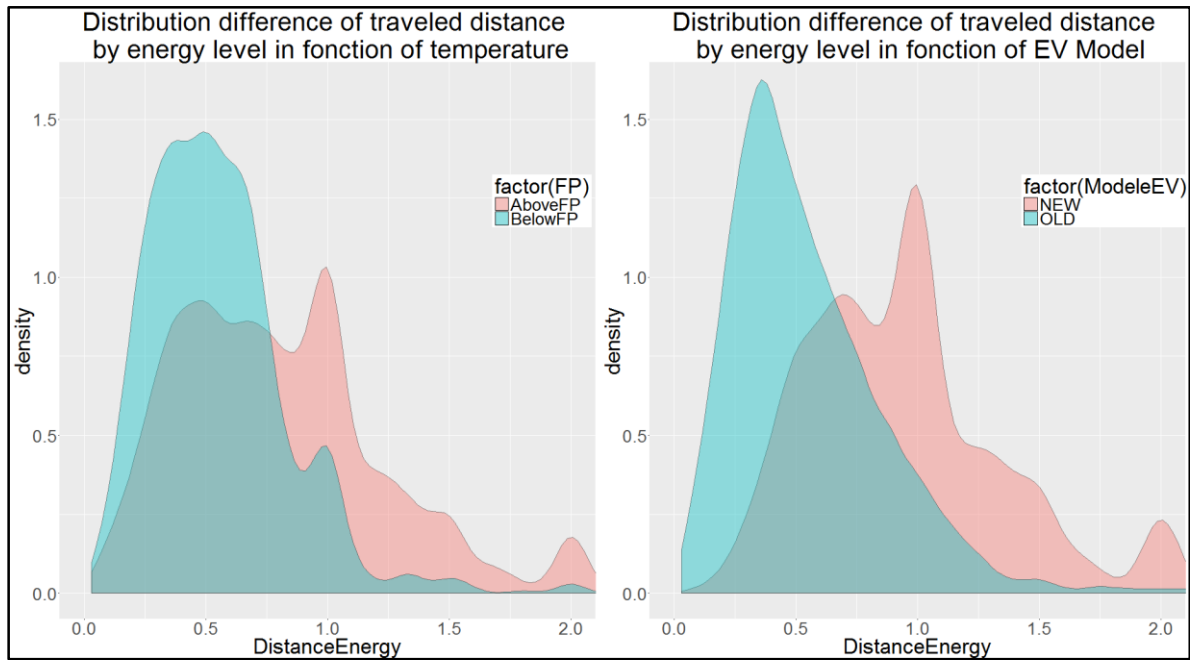


Figure 4: Distribution of car range by energy consumption while below and above the freezing point

4.4 Free-floating vehicle choice model

We now build a logistic regression to model vehicle choice (EV vs. HV). The model is estimated at the transaction level, and the outcome variable is the type of car chosen. The variables are listed in Table 1. The variables are user related (age, gender, subscription time, customer type), transaction related (energy level, distance travelled) and environmental related (proportion of EVs in the system, temperature, precipitations, snow on ground).

Some groups of variables (4 and 5; 7 and 8; 11, 12, 13, 14, 22, 23; 2 and 18; 19 and 20) are highly correlated. They cannot be simultaneously included in the model because this could bias the estimates. The

independent variable is the vehicle type. A success event occurs when a member borrows an EV (CarType = 1). To ensure that there is a real choice between the two types, we consider only situations where at least one vehicle of each type is available within a range of 100 m (see Section 3.3.4). This limits the dataset to 1,058 observations that meet these requirements.

4.4.1 Variables selection

We excluded variables 4, 7, 11, and 13 because of correlation. When we first fitted the model, several variables were not found to be significant: *Age_Cat*, *Gender*, *TypeA*, *TimeOfWeek*, *Service Subscription*, *Borough*, *EV_Prop*, *ABC*, *SnowOnGround*, *Snow(cm)*, *FP*, *MeanTemp*, *Hotx*, *DiffEnergyLevel*. They are excluded from the model. Multiple configurations of variables have been tested, each time evaluating variable significance and model performance. Finally, four variables have been selected for the final model, Table 2 shows the results from the logit model.

Table 1: Variables available for regression model

Id	Variable	Variable Type	Definition
1	<i>CarType</i>	Dichotomous	0 if HV, 1 if EV
2	<i>Distance</i>	Continuous	Travelled distance in km
3	<i>Gender</i>	Dichotomous	1 if Female, 2 if Male
4	<i>Age</i>	Continuous	Age of user
5	<i>Age_Cat</i>	Ordinal	Age by category (1 = 18–24, 2 = 25–39, 3 = 40–64, 4 = 65+)
6	<i>Service Sub.</i>	Continuous	Time (months) since user joined Communauto
7	<i>CurrentType</i>	Nominal	User type (1 = AuM–AuM; 2 = AuM–REG; 3 = REG–AuM)
8	<i>TypeA</i>	Dichotomous	Type of first Communauto transaction (1 = AuM; 2 = REG)
9	<i>TimeOfWeek</i>	Dichotomous	1 = Weekday; 2 = Weekend
11	<i>Snow (cm)</i>	Continuous	Quantity of snow on ground
12	<i>SnowOnGround</i>	Dichotomous	1 if no snow on ground, else 2
13	<i>Mean Temp</i>	Continuous	Mean temperature of day (°C)
14	<i>Freezing Point</i>	Dichotomous	1 if below freezing point, else 2
17	<i>EV_Prop</i>	Continuous	Proportion of EVs in fleet
18	<i>Dist_Threshold</i>	Dichotomous	If distance ≤ 24 km then 1; else 0
19	<i>EnergyLevelEV</i>	Continuous	Energy level at the start of the transaction
20	<i>EnergyLevelEVx</i>	Dichotomous	If EnergyLevelEV is above x%, where x = {50,60,70,80,90}
21	<i>DiffEnergyLevel</i>	Continuous	EV energy level – HV energy level
22	<i>Coldx</i>	Dichotomous	If the temperature is below x, where x = {-15, -10, -5}
23	<i>Hotx</i>	Dichotomous	If the temperature is above x, where x = {20, 25, 30}

Table 2: Final logit model output

Coefficient	Estimate	Std. Error	z value	Pr(> z)	Sig	Transf. coefficient
(Intercept)	-0.49250	0.20709	-2.37822	0.01739	*	0.611090
distanceKm	-0.03710	0.00958	-3.87048	0.00010	***	0.963577
Gender : Male	-0.73215	0.16729	-4.37631	1.21E-05	***	0.480871
EnergyLevelEV50	0.93323	0.20605	4.52897	5.93E-06	***	2.542721
Cold10	-1.06991	0.48026	-2.22776	0.02589	*	0.343038

4.4.2 Model interpretation and discussion

The model showed four different variables as significant. *DistanceKm*, representing the desired travel distance, affects negatively the odds to borrow an electric car. For every desired travel kilometer, the odds to borrow an electric vehicle decrease by a factor of 0.96 (for a 25 km trip, the odds decrease by a factor of 40%). The sociodemographic variable *Gender* affects negatively the odds when a male user is trying to locate a vehicle. In fact, they decrease the odds by a factor of 0.48. As a positive factor, the binary variable *EnergyLevelEV50*, that represent the situation where the level of charge of the EV is higher than 50%, increase by a factor of 2.54 the

odds of borrowing the EV. Finally, on really cold temperatures ($<-10^{\circ}\text{C}$), the odds to borrow an electric car decrease by a factor of 0.34.

This model only represents the state of charge of the EV because of two factors. Basically the energy level of HV is not a critical factor as the EV state of charge can be because users can manually refill HV, giving them, nearly, an unlimited range for mid-long range trips. Also, there is no clear interpretation or significance when plotting the HV energy level into the model. When trying to fit the difference in charge from both vehicle type (we could assume that users would prefer in certain occasions the vehicle with the most range), the variable doesn't stand out as significant. When looking over the distribution of the energy level of EV for both situations ($\text{CarType} = 0$ or 1), the distributions seem to indicate that to rent an EV, higher energy level increase odds (verified by the variable *EnergyLevelEV50*), but it is independent of the HV energy state. Extreme temperatures are known to decrease a vehicle range because of use of the car heater or the air conditioning. When fitting temperature, the variable doesn't stand out as significant, so we used several dummy variables for cold and hot temperatures. On one hand, hot temperatures were not as high as Montreal could get (data from September to February only), so these variables were not kept. On the other hand, even if this year's temperature has been milder than past years in the winter, temperatures colder than -10°C affected negatively the odds of choosing an EVs. This results is corroborated by the increase of nearly 50% of Communauto employee relocation trips during Winter.

We tested the model by predicting values on another dataset to see its performance. With a proportion of 58% of HV in the dataset, our model increase slightly the odds to an accuracy of 66% ($\pm 5.5\%$, $\text{CI} = 95\%$, p-value of 0.00341 for testing the model equality with a null model). The model could predict right 72.6% of HV occurrences, but only 57.3% of EV occurrences. This indicate that a variable is probably missing to increase the model performance. Reported AIC is at 938.9, while the log-likelihood from the fitted model is at -455.55, the McFadden's pseudo r-squared at 0.094 and the Cragg and Uhler's pseudo r-squared at 0.120. While this model hasn't been made to make critical on demand predictions, it gives us a good overview of the variables dynamic to a user mode choice in a free-floating carsharing setting.

5 CONCLUSION AND IMPACT ON THE OPERATOR

We have presented a comprehensive study of the differences in EV and HV use in a free-floating carsharing system. We first presented the usage rate in relation to the distance: there is a clear preference for HVs above a threshold of 24 km. Our spatial analysis confirmed this: HVs have a larger SDE and leave the SA more often. On energy consumption, the EV car age and the temperature showed a significant difference. Finally, a logit model indicated relationships between distance, user gender, temperature, initial energy state of charge, and the desirability of a vehicle. All three, traveled distance, male users, and cold temperatures reduce the odds of borrowing an EV, while a higher energy level increase the attractiveness of an electric car. These insights will serve as a starting point for further research on mode choice.

The choice model doesn't incorporate what may be the most important variable for a user: proximity. This could be done by capturing the position of the user when he is looking for a vehicle (via mobile or web-based), and then calculating the distance between each vehicles, but Communauto doesn't track users' requests. Another potential flaw of the model is the assumption that all users have a perfect knowledge of the positions of all vehicles surrounding him/her. In addition, the evolution of the service area and the car fleet may have distorted the results. To better understand the effect of changes in time, we project to perform a time-spatial analysis to understand the dynamic in the user behavior across time. In future studies, it will be interesting to explore a more qualitative analysis of the user decision choice pattern and influences, while also looking for strategies (policies and relocations) to help to increase the operator profitability for EVs.

The introduction of EVs can benefit to a carsharing operator, leading to a greener image and potential benefits related to the reduction of GHG emission. However, with our study, we showed that there is a significant difference of behavior between HV and EV users. This has to be taken into account by the carsharing operator,

given that EV cars are more expensive to buy and to manage (because of the recharge operations), and generate less revenues (because they cannot be available 24/24 hours), even though there is a gain in energy price.

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