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Predicting Carsharing Station-Based Trip Generation Using a Growth Model

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Abstract

Carsharing is a service that allows members to rent cars for a limited time. In Montreal, Quebec, Canada, two types of services exist: a station-based and a free-floating service. This paper proposes a trip generation model for the station-based service of the Communauto carsharing operator for 2016. To better understand relations between space and time, a growth model is used, considering these factors at different levels. For example, some factors can impact all stations similarly, while other factors may impact each station differently. Thus, this model allows to consider both spatial and temporal variables allowing more precise estimations. The aim of this research is to estimate carsharing trip generation at the station level and provide insights into the impacts of implementing new stations on demand. A step-by-step approach was adopted to define the best predictive model for the use of carsharing stations. While more complex model formulations need to be tested to enhance the analysis, the final growth model obtained indicates that, in addition to the number of vehicles available at the stations, several exogenous factors have a significant impact on the trip generation rate of a carsharing station. For instance, the model shows that demographic factors, walkability level and number of bus stations have significant impacts on the use of carsharing stations.

Keywords: carsharing; station-based; trip generation; growth model; multilevel analysis; multivariate approach

1. Introduction

Carsharing is a phenomenon that has developed considerably in recent years (Shaheen and Cohen, 2007). It is a service provided by an organisation that allows individuals to rent a vehicle for a specified period. It is a good alternative to privately owned cars. In Montreal, the carsharing company Communauto offers two different services: a service for the provision of vehicles parked in stations with over 1030 hybrids and 20 electric cars among 413 stations, and a service based on a free-floating principle (where vehicles can be rented and parked anywhere within the service area), with 560 hybrids and 110 electric cars as of May 2017. This paper focuses on the use of the station-based service, but also considers data from the free-floating service to study its impact on the use of station-based cars.

This paper attempts to explain how exogenous factors, like the proximity to another transportation mode in a perimeter around stations or demographic features, affect the monthly use of station-based carsharing vehicles. The location of a carsharing station is an important factor for users and thus has an impact on the use rate of a station (Danielis et al., 2015). A description of the monthly use of stations-based carsharing vehicles is presented in the "case study" section. This study aims to provide carsharing operators with relevant insights regarding the factors influencing the use of stations and help them locate future stations.

The use of a growth model allows to account for many factors affecting the stations at different levels (factors identical to all stations vs. factors specific to each station, and factors that vary over time vs. factors that vary across space) and to make both a spatial and a temporal analysis. These models are often used in psychology and medicine but it seems that they are not yet much developed in transport.

The paper will begin with a literature review, followed by the description of the case study and the choice of candidate variables for the model. The methodology presents the model, the data structure and the step-by-step approach followed to obtain the model. Finally, the results are discussed.

2. Background

Even if research has bloomed on carsharing in the last decade or so, it is still a subject that has led to fewer modelling efforts in comparison with other transportation modes such as private cars or transit (Ciari et al., 2014). Several difficulties related to the modelling of carsharing demand are described by Jorge and Correia (2013): 'In classic transport systems, such as bus and underground services, the directional capacity is offered to clients irrespective of the existing demand; however, in one-way carsharing, demand can completely change the system's supply in ways that are hard to predict'. Many of the studies that have been carried out about carsharing deal with the typology of users (Kopp et al., 2013; Wielinski et al., 2015), origin-destination transactions (Becker et al., 2017) and the impact of carsharing on private cars (Martin et al., 2010; Le Vine and Polak, 2017). Its role in transportation transition is also examined in some studies (Russell, 2014). To optimise the fleet size, the price structure, the station or the free parking locations and to better understand general behaviours, operators need to understand the situation and to carry out predictive modelling (Lopes et al., 2014; Nourinejad and Roorda, 2015).

Multilevel models are sometimes applied to understand the impact of several factors. Contrary to other models, they make further analysis using micro and macro dimensions. Papers from Geels (2012) and Marx et al. (2015) deal with the advantages of this model to better understand the multidimensional interactions in transport.

Most of the time, studies are about spatial or temporal analysis as it is for instance the case in the longitudinal analysis of Heilig et al. (2017). However, to better understand the use of carsharing stations according to their location, a combined spatio-temporal analysis seems interesting. Growth models are adapted for such task that is why this work is focused on these models.

Growth models are often used in psychology, as for example in the paper by Schröder and Wolf (2016). In this paper, a social simulation was made to represent individual decisions according to external interactions. They are also used in medicine and in education to study the variation of test scores, to compare students of the same class, students from one school as well as students from many schools.

In transportation research both the temporal and spatial dimensions are critical to understand travel behaviours and growth models are hence well suited to look at complex phenomena such as carsharing usage. The aim of this paper is to provide insights into carsharing trip generation as stations and provide operators with knowledge in their decision-making about their station network. This paper also contributes to enhance the understanding of carsharing demand in a North American context. In a more simplistic way, there are many temporal or spatial analyses, but the two dimensions are rarely put together. This study is focused on Communauto data in a specific environment, but the developed methodology can be relevant for other contexts.

A similar analysis has been described in an article written by Lorimier and El-Geneidy (2013) with a multilevel model and 'using the case study of the Communauto carsharing based in Montreal'. Like this paper, the goal of their study is to better understand the influence of many factors affecting the use of stations. However, they approach their case study with a different dataset and by modelling the monthly vehicle-hours and cars' availability probability.

Stations' size, temporal features as seasonality, presence of big-box stores, transit access and vehicle age are reported as main predictors.

On other related studies, Celsor and Millard-Ball (2007) look at the carsharing market potential (another point of view for station location). Vehicle ownership, commute modal share and household composition seemed to have the best results to explain carsharing success. On a similar topic, discrete event simulations are used by El-Fassi et al. (2012) to assess carsharing system growth. On the Communauto case study, three main strategies were tested: increase current station capacity, merge multiple stations into a single one, or implement new stations. Metrics like the utilisation rate, the fidelity rate or demand pressure is used to better assign a potential strategy. Jian et al. (2016) on their side looked to model the vehicle selection behaviour of carsharing members in Australia with a spatial hazard based model. The vehicle selection may be deemed important to actually model a station utilisation rate. A station catchment area of two kilometres has been reported being preferable considering the users' home location and the station of use distances.

3. Case Study

3.1. Datasets

The dataset consists of several variables. The outcome variable is the use rate (defined below) for each station and for each month of the year 2016. First, this indicator is calculated for each hour and then aggregated by month. It is based on the number of reservations made and accounts for the number of vehicles available at the station at the time of booking. The calculation of this rate was allowed thanks to Communauto's data and is described by the following (eq.1).

$$Use\ rate_{ij} = \frac{Real\ use}{Maximum\ theorical\ use\ (use\ at\ 100\%)} \tag{1}$$

where i is the month and j the station.

A covariate used is the shortest distance to the free-floating area. It is set to 0 for stations located within the free-floating area. This variable is intended to observe the possible link between the use rate of carsharing stations and the presence of the free-floating area close to a station.

Other factors were studied, in particular demographic data from 2014, the last year available for the Montreal population. Using these variables in the model allows to better understand how demographic composition impacts the use of stations and which demographic factor has the greatest impact. The 2013 Origin-Destination survey of Montreal was also used to obtain the car access rate around stations and the amount of work trips with a destination in the surroundings of stations. This study also uses the "Pedestrian Index of the Environment" walkability index. This indicator was first defined by Singleton et al. (2014) and transferred to the Montreal context by Lefebvre-Ropars et al. (2017). It allows the determination of the extent to which an area is favourable to walking. The impact of other transportation modes has also been considered: the Montreal subway, rail and bus, thanks to 2016 GTFS data. These variables aim to explain how these transportation modes coexist.

Moreover, this paper only considers non-seasonal stations –i.e. stations opened all the year– because seasonal stations seem to generate different behaviours and, of course, are only observable for a part of the year. Stations that opened during 2016 also were not taken into account. For the few variables that fluctuate slightly by months, the yearly median was taken.

A correlation matrix was produced to identify highly correlated variables and select the most appropriate variables for the model. Table 1 describes all variables available to this study and those that have been kept for modelling after the correlation analysis.

Table 1. Descriptive analysis of all variables used in this study.

Variable	Min.	Max.	Standard deviation	Mean	Dispersion	Kept for the study
Output: Use rate	0.0013	0.812	0.130	0.347	0.375	True
Number of median vehicles per station	1.0	14.5	2.132	2.874	0.742	True
Shortest distance to a free-floating area (m)	0	14,640	1,541	647.4	2.381	True
Prop. of people between 25&34 y.o. living in this area*	0.087	0.335	0.058	0.237	0.245	
Prop. of people between 35&44 y.o. living in this area*	0.104	0.226	0.026	0.184	0.141	True
Prop. of people between 45&54 y.o. living in this area*	0.104	0.201	0.015	0.154	0.097	
Prop. of people between 55&64 y.o. living in this area*	0.108	0.189	0.018	0.141	0.128	
Prop. of males living in this area*	0.424	0.612	0.031	0.490	0.063	
Prop. of females living in this area*	0.389	0.576	0.031	0.510	0.061	True
Prop. of people with an annual income of CAD $35,000 (approx. USD $28,000) and up living in this area*	0.217	0.638	0.067	0.414	0.162	
Prop. of people with an annual income of CAD $50,000 (approx. USD $40,000) and up living in this area*	0.080	0.502	0.062	0.263	0.236	
Total population variation from last census*	1.461	35.92	8.168	17.29	0.472	
Prop. of households with 1 person*	0.198	0.623	0.073	0.470	0.155	
Prop. of households with 2 people*	0.250	0.392	0.019	0.307	0.062	True
Prop. of households with 3 people*	0.064	0.178	0.024	0.114	0.210	
Prop. of households with 4 people*	0.025	0.182	0.029	0.072	0.403	
Prop. of households with 5 people*	0.007	0.078	0.013	0.024	0.542	
Prop. of households with 6 people and more*	0.002	0.057	0.009	0.120	0.075	True
Average size of households*	1.300	2.799	0.244	1.903	0.128	
Average number of children in household*	0.365	1.446	0.185	0.871	0.212	
Prop. of people speaking French*	0.043	0.608	0.125	0.292	0.428	
Prop. of people speaking English*	0.005	0.389	0.081	0.090	0.900	True
Prop. of people speaking both languages*	0.376	0.746	0.073	0.597	0.122	
Prop. of Canadian citizen*	0.022	0.418	0.046	0.063	0.730	
Prop. of people with an undergrad diploma or higher*	0.073	0.605	0.122	0.363	0.336	
Prop. of unemployed people*	0.041	0.169	0.018	0.093	0.193	True
Car access rate inside a 400 m range from stations	0.398	0.917	0.265	0.573	0.462	True
Number of work trips with a destination inside a 400 m range from stations	153	87,864	8,576	3,839	2.234	True
Walkability index within 1200 m around stations	41.61	92.29	11.35	73.77	0.154	True
Distance to the nearest metro station up to 2500 m from stations (m)	10	2,360	539.4	667.5	0.808	True
Distance to the nearest train station up to 3000 m from stations (m)	60	2990	1011	1119	0.904	True
Number of bus passages per month within 500 m of stations	127,200	2,214,000	336,797	744,000	0.453	True

*Notes: *into a 1000 m range from the station; prop = proportion; y.o. = years old; only the Use rate variable is time and space dependent, all other variables are only space dependent.*

Each of the three variables "car access rate", "number of work trips" and "walkability index" were calculated in a perimeter of 400, 800 and 1200 metres around stations. Models have been tested with only one of these variables at a time and the best perimeter has been selected for the final model. Among these factors, the selected variables are therefore the car access rate within a 800 m range from the station, the number of work trips with a destination within a 400 m range from the station and the walkability index at 1200 m around stations.

4. METHODOLOGY

4.1. Multi-level and Growth Modelling

A multilevel analysis allows to link factors with different statistical units: micro and macro-units. Initially, these models were made for data with a hierarchical structure, i.e. with levels nested within each other. In this paper, the model aims to explain the variation of the use rate of carsharing stations. Because multilevels are part of a model class named "mixed", they allow the modelling of both fixed and random effects.

A growth model is an extension of a "classic" multilevel model. It is structured in the same way, but it also accounts for longitudinal data, whereas a "classic" multilevel model does not take them into account. Repeated measures are grouped in an additional level. Figure 1 describes the structure of the growth model developed in this paper.

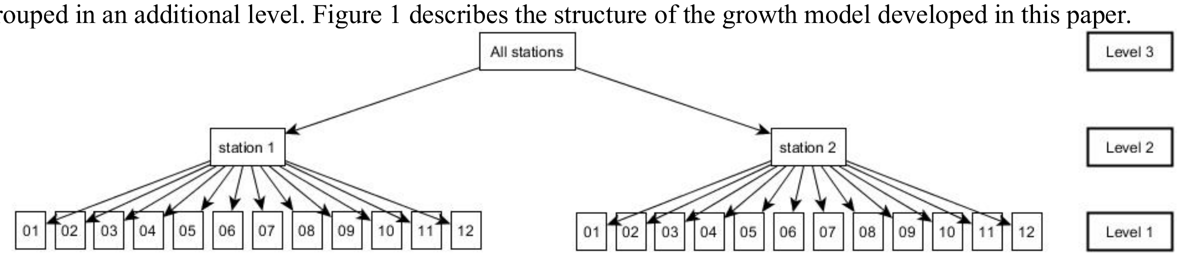

Fig. 1. Hierarchical structure of the growth model described in this paper

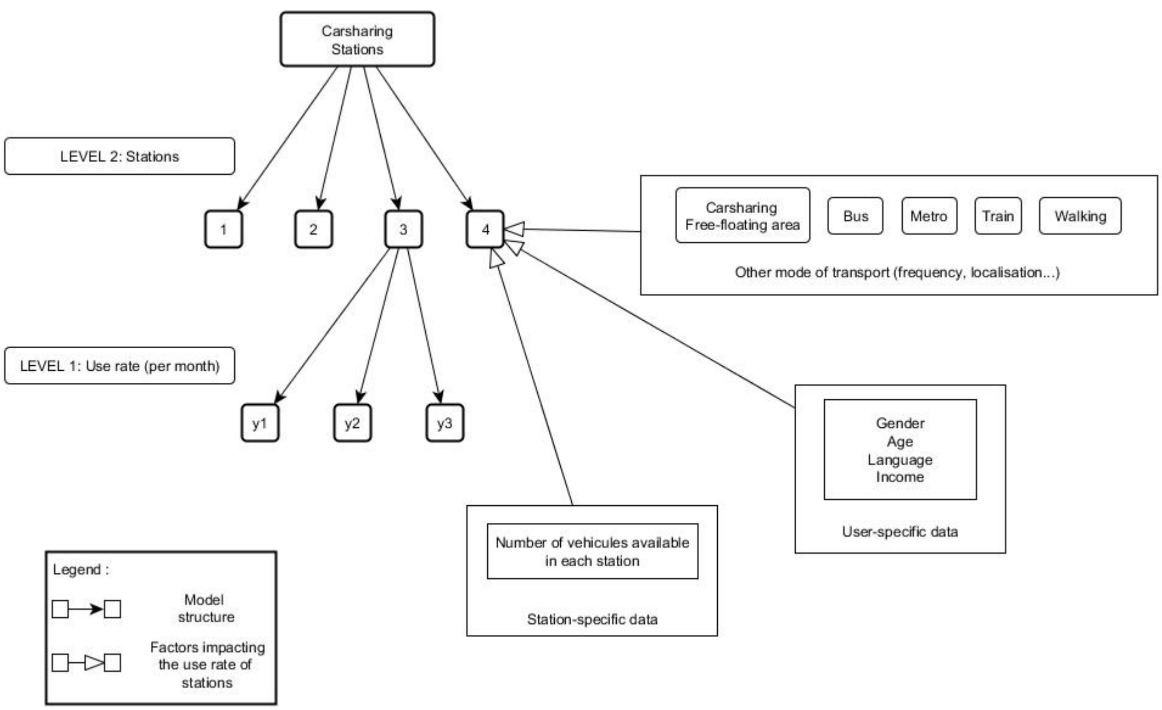

Fig. 2. Impact at different levels of many factors on the use rate.

4.2. Data Structure

The model described in this paper was estimated with the R programming language. The explanations related to the processing of the data and the methodology will therefore relate to this language. To make a growth model, data processing has been required for longitudinal data. A univariate form has therefore been used for the use rate. Because it varies by month, a new variable called "Time" was constructed to enumerate all months. They are numbered between 0 and 11 with January set to 0 to simplify the interpretation of the results. Then, because they affect the use rate differently, factors are considered differently accordingly to their spatial and temporal dimensions.

4.3. A Step-by-Step Approach

To make the best predictive model, a step-by-step approach has been used following the methodology described by Bliese *(2016),* which is also used in several other papers *(Bliese and Ployhart, 2002; Kwok et al., 2008).* A simple first model was made to be further complexified step-by-step; the best model is kept at each step.

First step: null model

The first model only considers the outcome variable: the use rate of carsharing stations, to serve as a baseline. In growth modelling, this very simple model allows to examine the properties of this variable. The equation used in this step is:

Level1: repeated-measures level

$$\text{Use rate}_{ij} = \beta_{0j} + e_{ij} \tag{2}$$

Level2: individual level

$$\beta_{0j} = \gamma_{00} + u_{0j} \tag{3}$$

where *i* represents the different measurement occasions and *j* represents the station, β_{0j} is the estimated average use rate score for the *j*-th station, e_{ij} is the within-individual random error and u_{0j} is the between-individual random effects.

Second step: time model

Because the outcome variable depends on time, this step adds the time dimension. This model enables to better understand the use rate behaviour throughout the 12 months of 2016. The equation used in this step is:

Level1:

$$\text{Use rate}_{ij} = \beta_{0j} + \beta_{1j} \times \text{Time}_{ij} + e_{ij} \tag{4}$$

Level2:

$$\beta_{0j} = \gamma_{00} + u_{0j} \tag{5}$$

$$\beta_{1j} = \gamma_{10} + u_{1j} \tag{6}$$

In this model, the possibility to have a different variation of the use rate between each station is considered.

Third step

This step allows to consider the impact of one station on another. For example, if one station no longer has vehicles, this model assumes that trips could be inferred to nearby stations.

Fourth Step

In this part, the model is made by adding to the previous model all factors that were presented in the "datasets" section. The variables having a significant impact on the use rate are then identified to build a final model: a significant predictive model with factors linked to station locations.

This last step allows to obtain the exogenous factors that emerge as factors affecting the use rate of the carsharing stations significantly. Predictive variables used in this research are "Time-Invariant Covariates" *(24)* i.e. they do not vary across months. Therefore, the equation used for this step is:

Level1

$$\text{Use rate}_{ij} = \beta_{0j} + \beta_{1j} \times \text{Time}_{ij} + e_{ij} \tag{7}$$

Level2

$$\beta_{0j} = \gamma_{00} + \gamma_{01} \times \sum Z_i + u_{0j} \tag{8}$$

$$\beta_{1j} = \gamma_{10} + u_{1j} \tag{9}$$

where $\sum Z_i$ are all variables accounted for in the model.

Then, variables are selected, thanks to the *stepAIC* R function, to find the best model. These variables are the only ones kept for the final model.

5. RESULTS

5.1. Descriptive Analysis

Figure 3 presents the variation of the monthly use rates throughout 2016 for 30 different stations. We clearly observe that the use rate varies and that this variation is not similar for all stations. Thus, a spatial-temporal analysis is relevant.

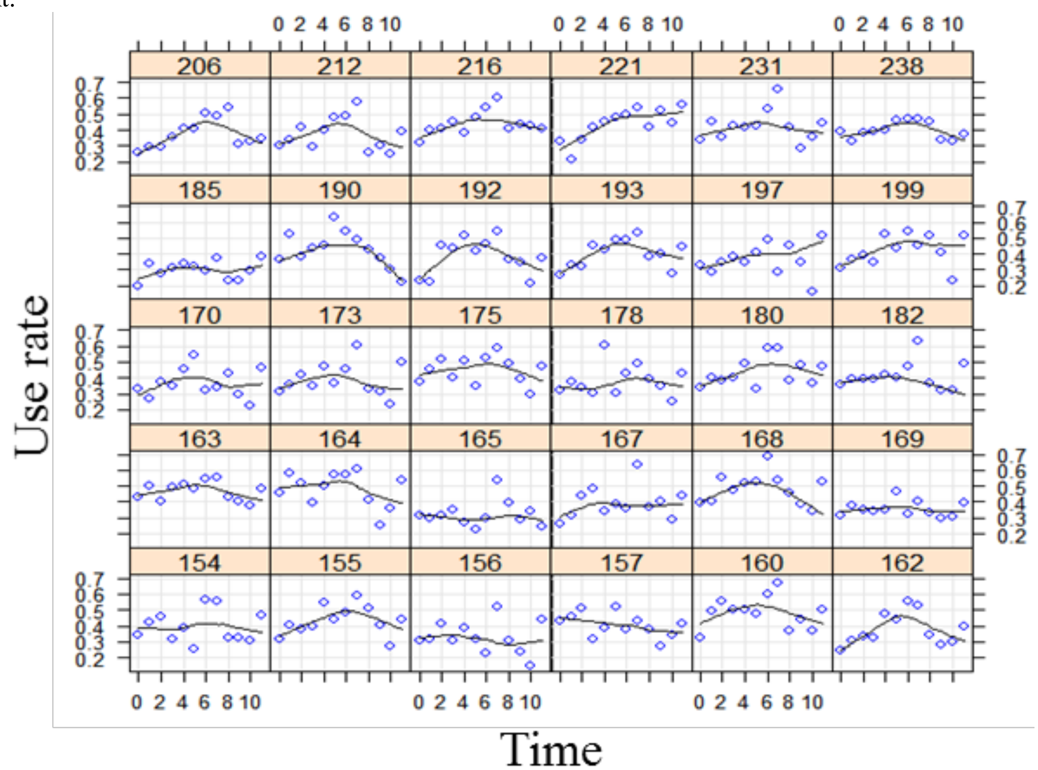

Fig. 3. Variation of the use rate according to months, examples of 30 stations numbered from 154 to 238 (standardised ID).

5.2. Model Formulation

The results obtained for the various models (using the steps described previously) are summarised in Table 2. The -2logLikelihood and AIC coefficients of each model are presented along. The best model is kept at each step and is complexified until the final model is identified.

Table 2. -2logLikelihood coefficients for each model tested.

Steps	Models		-2LL	AIC
Step 1: null model	M1	Basic model	-5,399.63	-5,393.63
Step 2: time model	M2	M1 with a linear time simulation and a different time variation for each station	-5,546.24	-5,534.24
	M3	M2 with a quadratic time simulation	-6,083.57	-6,069.57
	M4	M2 with a cubic time simulation	-6,067.75	-6,053.75
	M5	M3 with a cubic time simulation	-6,066.67	-6,050.67
Step 3:	M6	M3 with stations autocorrelation	-6,217.19	-6,201.19
Step 4:	M7	M6 with statistically significant variables	-6,396.57	-6,370.57

After grand-mean centring of all the data, a selection of variables was made to find the best model in the step 4. Table 3 presents the variables and coefficients obtained with this model. Step 3 results show an impact of stations autocorrelations indicating that what is observed at one station is not independent to what is observed at another station.

Table 3. Results obtained for the M7 model.

Independent variables	Coeff.	p-value
Intercept	2.42e-01	2.8e-230
Time	4.28e-02	2.7e-92
Time²	-3.24e-03	4.4e-71
Number of median vehicles per station	2.29e-03	1.4e-01
Walkability index within 1200 m around stations	2.02e-03	2.3e-10
Proportion of people between 35 and 44 years old living near the station within a 1000 m range	6.92e-01	9.7e-08
Proportion of unemployed people within 1000 m around stations	-5.85e-01	4.1e-04
Coefficient for 10,000 bus passages per month within a 500 m range from the station	2.11e-04	4.3e-02

Standardized within-Group Residuals				
Min.	Q1	Median	Q2	Max.
-3.53	-0.66	-0.080	0.52	6.15

Number of observations: 3,716	Number of Groups: 314
Random effects parameters:	**StdDev:**
(Intercept)	3.62e-02
Time	1.29e-06
Residual	1.02e-01

The summary of this growth model shows that in addition to time, the number of median vehicles per station has a significant impact on the station use rate as could be expected. It is interesting to note that the walkability index likewise emerges as a significant factor in the model. Furthermore, it positively impacts the use rate, indicating that members are more likely to use carsharing stations in areas suitable for walking. According to this result, the proportion of people between 35 and 44 years old living near the station at a 1000 m range and those who are unemployed also affect significantly the stations use rates. People between 35 and 44 years old seem to have a positive impact on the stations use rate as opposed to unemployed people. In addition, the number of monthly bus stop passages also seems to have a positive impact, indicating that areas better served by transit are favourable to the use of carsharing stations.

Thus, the final model equation is:

$$\mathrm{Use\ rate}_{ij} = \gamma_{00} + \gamma_{10} \times \mathrm{Time}_{ti} + \gamma_{01} \times \sum Z_i + (u_{0i} + u_{1i} \times \mathrm{Time}_{ti} + e_{ti}) \qquad (10)$$

where $\sum Z_i$ are all variables described in Table 3.

5.3. Residuals Analysis

Residuals are calculated for each station and for the first five months of 2017. Figures 4 and 5 show that their distribution approaches a Gaussian distribution while the normality does not confirm this assumption. Still, if we accept to remove the observations with the highest estimation errors, we now validate the normality of the residual distribution. It is worth noting that the network becomes highly saturated during the summer holidays when members borrow the cars for long periods for use during their long-distance travels and that the global activity level is quite low in early January when the temperature is usually very cold and snow storms frequent. These extraordinary behaviours surely affect the fitting of the model and are one reason why we punctually observe very high residuals.

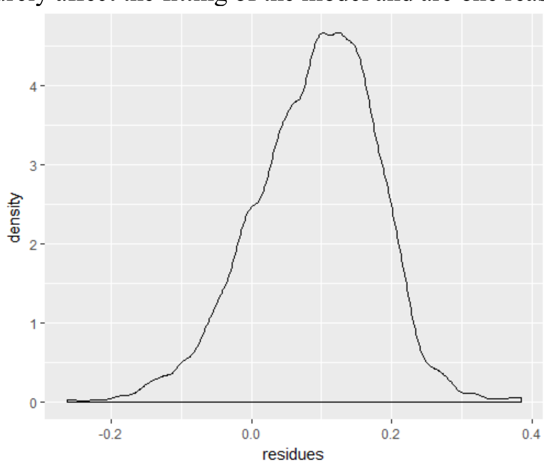

Fig. 4. Residuals distribution

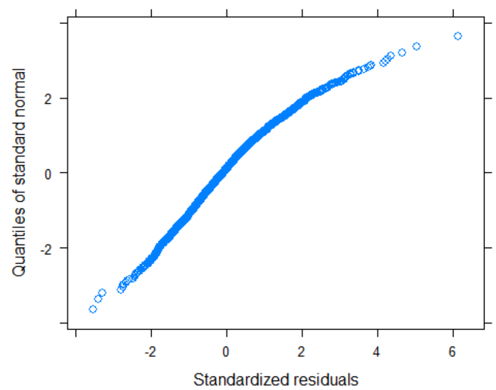

Fig. 5. Residuals normal quantile-quantile plot

Figure 6 allows to visualise the spatial distribution of these residuals. The objective is to determine if these residuals are spatially centralised or not and by analysing this figure, we see no clear spatial pattern of residuals which allows to validate the model.

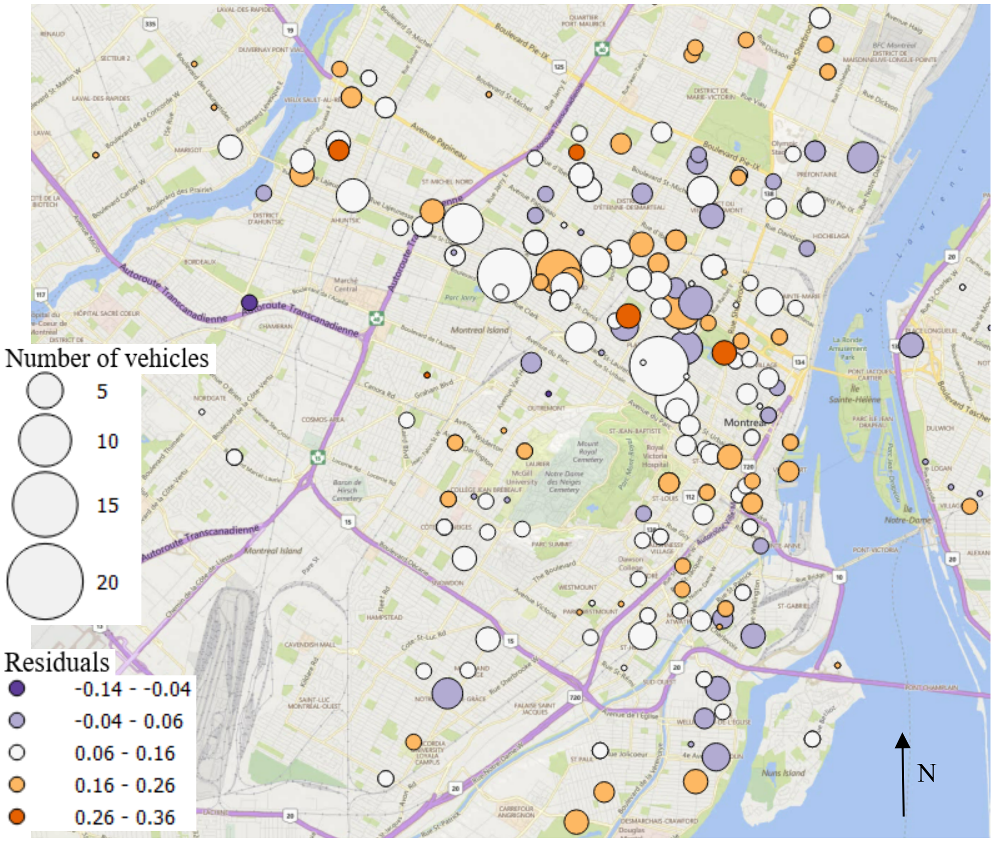

Fig. 6. Residuals spatial distribution for each station for May 2017

The main aim of this study is to help operators to predict the monthly use of stations thanks to a growth model. Thus, it will be interesting to discuss with operators to determine what error range are acceptable for strategic planning purposes. Moreover, to obtain a better predictive model, it would be useful to study the particularity of stations with an outlier predicted measure.

6. Conclusion

Carsharing is a relatively recent transportation mode. Different services were developed since the end of the 80's, beginning of the 90's, the most widespread carsharing solution being the station-based. The aim of this paper is to prove the relevance of growth models to better understand the impact of various factors namely the features of their surroundings on their use. Even though these models are complex, they seem to be relevant to understand the city context and can be adapted to transportation studies. They will help operators take decisions regarding the location of new stations by considering other modes of transportation and the city demography.

This research is focused on the carsharing stations' behaviour of the Communauto carsharing operator in Montreal, for the year of 2016. Nevertheless, the spatial-temporal study allowed by these models can be interesting for many other subjects in transport. In this paper, several factors emerged from this model as having a significant impact on the use of carsharing stations. For instance, it is interesting to note the impact of the walkability index on the use of stations.

Some perspectives arise from this study. More research is needed to better understand the interactions between station-based and free-floating services. The same apply to other transportation modes like bikesharing, public transit and private car; this would require availability of individualised data combining all available modes.

Models in this study were all represented by a linear representation of the use rate except for the time. Thus, a quadratic simulation or other regressions should be tested to improve the model. The variable selection can also be deepened and variables with other dimensions can be used such as meteorological data which is the same for all stations but which changes over time. Indeed, except the use rate, this study focused on spatial variables but temporal variables can also be used in a growth model.

7. Acknowledgments

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