An attractiveness-based model for shopping trips in urban areas

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AN ATTRACTIVENESS-BASED MODEL FOR SHOPPING TRIPS IN URBAN AREAS

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ABSTRACT

This paper presents a modelling approach to characterise private car shopping trips in a city logistics point of view, in order to connect these movements with those belonging to urban freight distribution in the supply chain. The proposed modelling framework is a two-step procedure articulated as follows. First, an attraction model estimates the number of private car shopping trips arriving to each section of a given urban area. Second, a catchment area model relates the shopping trip destinations with the household locations. The model is calibrated using the data of both a database of the commercial activities and the recent household trip survey made in 2006 in Lyon urban area (France). We present the main results issued of the various simulations as well as several application examples and proposals, most of them made in a public policy perspective.
Keywords: urban goods movement, shopping trips, simulation, catchment area model, attractiveness.

INTRODUCTION

Shopping trips are an important component of urban traffic, since they are related to movements of people and goods: in France they represent about 50% of the total PCU km travelled by urban goods (including commercial vehicles). Moreover, travel patterns for shopping are subjected to important mutations, mainly because of the urban developments and trends on new retail and logistic distribution schemes.

Shopping trip estimation is usually made related to people, using the classical 4-steps modelling approach: it follows the hypothesis that these trips depend on the same factors as other trip purposes. However, several studies show that shopping trip generation rates are related to factors that are different from those of work trips for instance. Moreover, shopping trips are difficult to characterise due to the complexity and the variety of trip chains where at least one shopping activity takes place, and the available data sources have not been created for specific shopping trip generation.

We propose a new modelling approach that relates shopping trip flows to retailing supply. To do this, we calculate the catchment area of each zone i, in terms of number of households of each zone j that will make a journey that contains at least one shopping stop at i. The approach uses standard household travel survey data and available data about retail supply.

First, we present the main background issues to settle the context of our research. Then, the model is presented, focusing respectively on the definitions, assumptions and other hypothesis taken into account, the attraction phase and the catchment area phase. After presenting the two phases of the model, we present the calibration procedures and their main results. Finally, two examples of applications are proposed. More precisely, we show a simulation of extreme location and distribution scenarios in the urban area of Lyon (France) and an analysis of the impacts of e-commerce and teleshopping practices, in progressive usage increasing scenarios. The scenarios are compared on the criteria of total PCU km travelled by urban goods and total emissions of CO_2, taking into account the different types of vehicles used, i.e. private cars, light city freighters, urban trucks and semi-articulated vehicles.

BACKGROUND ISSUES

In the last decades, city logistics has been developed to deal with the main problems of urban freight distribution, studying freight movements in urban areas and proposing solutions to reduce congestion and pollution as main problematics. Recent studies have defined and characterised the different movements of urban goods (Patier, 2002; Ségalou et al., 2004; Russo and Comi, 2006). Two categories are predominant and represent about 90% of the overall urban goods movements: establishment supply movements, which are related to freight distribution between the different activities, and end-consumer commodity movements, where the purchased goods are moved by the consumer, related to shopping trips. The first group of urban freight movements, which corresponds to the exchange of goods between different establishments, has been one of the most studied subjects in city logistics research.

End-consumer movements, less studied in urban freight transport science, is an important component of urban freight transport, representing about 50% of the total km.PCUs (Passenger Car Units) of urban freight transportation, where establishment supply movements represent only 40 % (Patier, 2002). The remaining 10% contains the city maintenance and construction logistics movements, the waste distribution and a number of small particular activities such as postal services, among others In France, shopping trips represent 10% of the total person trips in working days, i.e. from Monday to Friday, and 25% in Saturday (Routhier et al., 2001). In terms of pollution, the urban transport of goods, including end-consumer movements, produces about 25% of the total CO2 emissions for transport, 35% of the NOx emissions and 40 to 50% of the particulate (Ségalou et al., 2004).

Moreover, mutations related to the development of new technologies and consumption trends have an important impact on the shopping behaviour, which influences the different travel habits, so the characteristics of the shopping trips (Routhier et al., 2009). Land use policies developed by public administrators will have also an influence on commercial activities location and the services they propose (Routhier et al., 2001). Moreover, the location of retail activity areas has an influence on freight flow generation, in both sides of the extended supply chain (traditional freight distribution and end-consumer movements). Although the contribution of end-consumer movements to the urban flows of motorised vehicles is important, they are rarely taken into account in city logistics, at both policy making support and transport planning and optimisation levels.

Shopping trip estimation is generally made by classical four-step models (Ortuzar and Willumsen, 2001; Hensher and Button, 2001) but in other fields non transportation-based models can also be found (Till and Timmermans, 1992; Bawa abd Ghioshi, 1999; Long-Lee and Pace, 2005; Kubis and Hartman, 2007).

Trip generation models relate trip generation rates to land-use and household characteristics. In general, the focus of research is the number of trips generated and their geographic distribution. Most of these models are integrated in other methods like the well-known family of classical four-steps models (Ortuzar and Willumsen, 2001), which is commonly used in general trip characterisation. The socio-economic characteristics of the trip makers are assumed to be significant determinants of travel behaviour because the factors determining the number of all types of trips are assumed to be the same as those for shopping trips (Cubukcu, 2001). These factors are, among others, income range, age, gender, employment status, car ownership, and household size. The physical and demographic characteristics of the area include: employment, population, and density. However, it is reasonable to believe that there are metropolitan area characteristics and trip maker characteristics which impact is significant only for shopping trip generation rates (Cubukcu, 2001). However, most of the studies dealing with shopping trips specifically are in general related to the regional or national level (Vickerman and Bramby, 1985; Badoe and Steuart, 1997; Cubucku, 2001; Simma et al., 2005); few models are proposed to characterise shopping trip generation factors in a urban context (Ségalou, 1999; Black et al., 2007). Most of the works deal with econometric and empirical approaches based on surveyed data, mainly collected to calibrate this type of models.

Shopping trip distribution is more heterogeneous. The main categories are the classical trip distribution methods (Ortuzar and Willumsen, 2001) based on gravitary and entropy-minimization approaches, and discret choice approaches (Thill and Timmermans, 1992). Moreover, in real estate research, catchment area models can also be used to estimate the main customer’s locations in order to estimate trip distances and household (or inhabitant) travel behaviour categories (Long-Lee and Pace, 2005; Kubis and Hartman, 2007). However, these models are built on specific surveys for one store or one retailing area and have not been conceived to be used with standard data on several urban contexts.

THE PROPOSED MODEL

Definitions and model description

The proposed model follows the definitions and principles enounced in Gonzalez-Feliu et al. (2010). In this work; the authors propose to model directly the private car shopping trips in order to compare them to establishment supply flows. According to several researches (Ségalou, 1999a; Dablanc et Pecheur, 2000; Toilier et al., 2005; Chambre de Commerce et d'Industrie de Lyon, 2008; Gonzalez-Feliu et al., 2010), we can observe than shopping trips are included in more complex trip chains. In all these chains, commercial activities are related to two connected shopping trips:

- An inbound trip, arriving at the considered commercial area. This is the part of the trip chain that is defined as shopping trip in classical passenger trip characterisation.
- An outbound trip, starting at the considered commercial area, where the goods that have been purchased are also travelling.

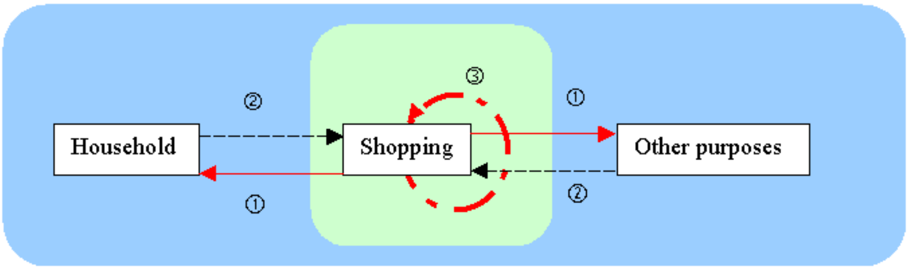

Figure 1: schema of the shopping-related trips

Although the end-consumer goods movements take place only when the outbound trip starts, they are closely related to inbound trips, as both types of shopping trips are always made consecutively one after the other (see Figure 1). A particular type of shopping-related trips is that of trips which purpose activity at the origin and the destination is related to shopping. The Shopping-Shopping trips can be considered as inbound trips for the arriving zone and outbound trips for the departing zone.

Trip generation (attraction)

In this phase the shopping trips attracted by each zone are generated. To do this, we built a model using the general trip rate generation modelling framework.The model will be able to generate the overall shopping trip rates (all modes) at each zone, for both emission and attraction. In a first time, we will characterise the shopping trips at the shopping destination, which represents both the inbound trip's destination and the outbound trip's origin. We will note the number of private car trips at a shopping destination *i* the private car shopping attractiveness of *i* and noted T_i.

Trips are the basic unit for zone-aggregation trip generation models, and the output variable is in general the number of trips which departure or arrival is located in a pre-identified zone i during a given time unit (Hobbs, 1979). As already said, the proposed model estimates the private car shopping trip attraction rates (Ortuzar and Willumsen, 2001). Following the general trip generation rate modelling framework (Hobbs, 1979; Cubucku, 2001; Ortuzar and Willumsen, 2001), the number of shopping trips *T* made by private car starting at or arriving to zone i can be formulated in the following way:

$$T_i = f\,(Ret_i, X_i, Tech_i)$$

where T_i is the total number of shopping trips generated in section i; Ret_i the set of retailing activity characteristics vector in section *i*; X_i the set of socio-economic characteristics of people and households belonging to section *i*; and $Tech_i$ the set of technology characteristics. This equation can be formulated as a vector function:

$$T = f\,(Ret, X, Tech) \qquad (1)$$

with $T = \begin{pmatrix} T_1 \\ T_2 \\ \\ T_i \\ \\ T_Z \end{pmatrix}$; $Ret = \begin{pmatrix} Ret_1 \\ Ret_2 \\ \\ Ret_i \\ \\ Ret_Z \end{pmatrix}$; $X = \begin{pmatrix} X_1 \\ X_2 \\ \\ X_i \\ \\ X_Z \end{pmatrix}$; $Tech = \begin{pmatrix} Tech_1 \\ Tech_2 \\ \\ Tech_i \\ \\ Tech_Z \end{pmatrix}$

Each vector contains a set of possible variables that can be included in the shopping trip generation model.

For this research the variables considered in the vector Ret_i are the following:

NrSMC : Number of small and medium stores;
NrBS : Number of supermarkets and big commercial surfaces;
NrVBS : Number of hypermarkets and similar stores;
Emp-SMC : Number of employees in the section's small and medium stores;
Emp-BS : Number of employees in the section's supermarkets and big commercial surfaces;
Emp-VBS : Number of employees in the section's hypermarkets and similar stores;
CC : Presence of an commercial centre (Ségalou, 1999), presented as a binary variable which takes the value 1 if at least one extra-urban commercial centre is located inside the section's perimeter and 0 otherwise.

These variables are obtained by aggregation of the SIRENE file data, for the considered city. The SIRENE databases is a set of French establishments information data files, which contains among others the retail activities' basic information (location, size category, commerce category, number of employees, etc.) for each city.

The population socio-economic characteristics vector *X* includes:

POP: Population of the considered section
NrH: Number of households of the considered section
DPOP: Population density;
DH: Household density;

These variables are extracted from INSEE[1] population census files. In France, each local administration has access to the population and household data of the national census. Other interesting databases are obtained from the household trip surveys, both local or national, or the Commerce and Industry Chamber national or regional surveys, although these data are less accessible and not available for all the medium urban areas.

The technology vector *Tech* is included in the framework only in a conceptual point of view. Current surveys do not have enough elements to well define tele-shopping usage trends, and other behavioural trends related to home delivery. Moreover, current data sources do not allow to characterise the relations between teleshopping trends and car usage behaviour (Beauvais, 2005). For these reasons we will not include in a first time the effects of teleshopping and home delivery services in our model, but only include them in a conceptual modelling framework.

The trip attraction function can be defined in different ways. We propose a multilinear function, defined as a pondered sum of the considered variables, and can be obtained by linear regression techniques applied directly on the available data. We can then define this function as follows:

$$T = \sum_e a_e Ret_e + \sum_f a_e X_f + \sum_g a_g Tech_g$$

We will estimate the coefficients by linear regression techniques, more precisely by the square minimum method.<Q

Classical approaches are applied to estimate the total number of shopping trips in a urban area (Vickerman and Bramby, 1984; Cubukcu, 2001) or those trips for each zone of a urban area (Ségalou, 1999; UK grocery trips). A different approach (Gonzalez-Feliu et al., 2010) proposes a modelling approach on three categories of urban space:

- The main *central urban area* contains the main city of the urban region and sometimes also other urban suburbs which can be assimilated to the main city, because of a continuity of the urban landscape.
- The *near periphery* includes the urban zones limiting with the central urban area first ring.

[1] French National Institute of Statistical Studies

- The rest of towns of the urban area belong to the *far periphery*.

The main problem of using this approach is that splitting the statistical population in three categories decreases the number of zones used to calibrate each of the three models, making these three sets of data not always enough accurate to ensure a quality econometrics analysis in the calibration phase of these models. For these reasons, we will test both approaches and compare them.

Catchment area distribution

Once the inbound shopping trips are generated at their destinations, we need to define the origin of these trips and the destination of the related outbound trip. From the household trip surveys results, we observe that households correspond to 80% of the inbound origins and to 85% of the outbound destinations. Therefore 70% of the shopping trips are included in household-shopping-household chains.

We propose to connect shopping destinations to households using a catchment area model. The proposed approach is a gravity probabilistic model. This model has a similar form than classic gravity distribution models (Ortuzar and Willumsen, 2001):

$$N_{hi} = A_i NrH_h T_i c_{hi}^{\beta}$$

where $A_i = \dfrac{1}{\sum_k NrH_h c_{hk}^{\beta}}$

In order to take into account the retailing supply of both household-related and destination zones, we introduce two other variables, one for each zone. The model can then be formulated as follows:

$$N_{hi} = A_i \frac{E_i^{\alpha_1}}{E_h^{\alpha_2}} NrH_h T_i c_{hi}^{\beta}$$

where $A_i = \dfrac{1}{\sum_k \dfrac{E_i^{\alpha_1}}{E_h^{\alpha_2}} NrH_h c_{hk}^{\beta}}$

MODEL CALIBRATION

The proposed framework is built and calibrated with the available standard data of the urban area of Lyon, which has about 2.000.000 inhabitants and 800.000 households. The main data sources are an extract of the register file of companies (SIRENE file) of the chosen area, the corresponding census database (INSEE file), and the 2006 personal trip survey, which follows a French standard (CERTU, 2008). In this survey, the urban community of

Lyon is divided into several small zones, grouped into macro zones. However, it is important that the methodology will be able to be applied to a chosen urban area or generalised into a model able to be used on any urban area without the need of a calibration and a testing phase. Shopping trip behaviours are heterogeneous and difficult to characterise using micro-simulation approaches, as the available data from surveys has not been collected for shopping trip characterisation and the high cost of these surveys made them adaptable to develop macro-simulation models, but not to micro-simulation ones.

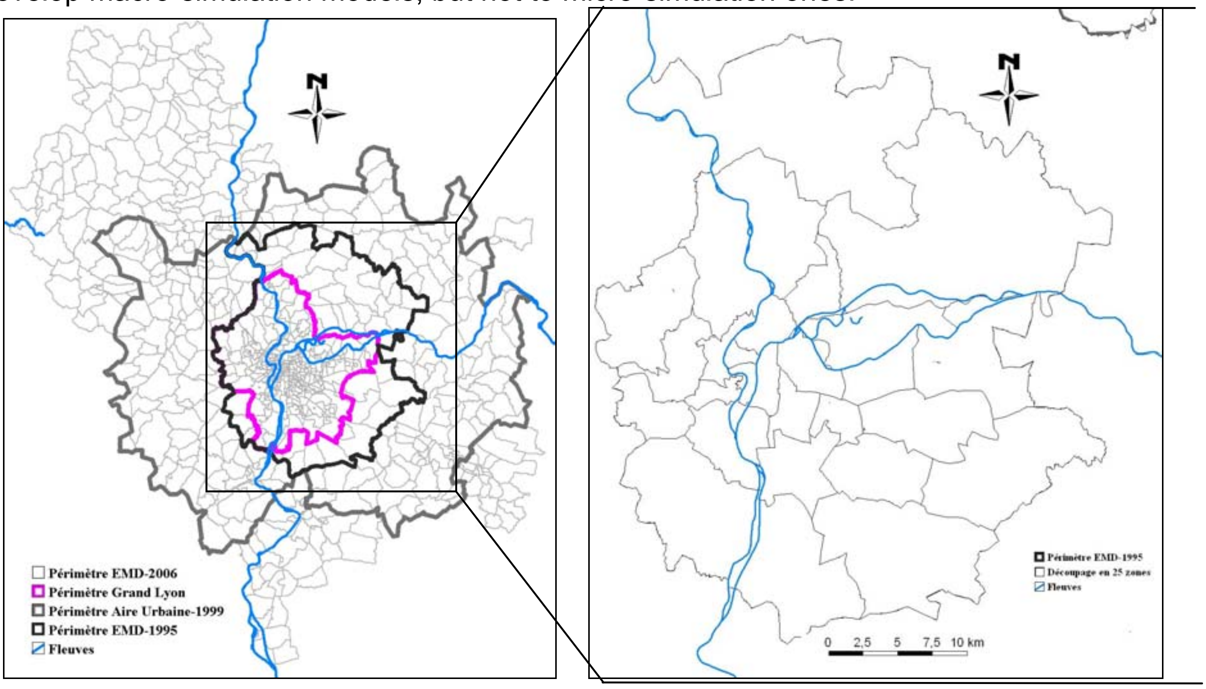

Figure 2: Maps of the Lyon urban area and the considered zones (source: L. Bouzouina, LET)

The model parameters are calibrated separately for each phase, following a mixed approach that combines an econometric analysis (using linear regression techniques) and the fitting method proposed by Hyman (1969). In the following subsections we describe the calibration methods and the main results of the calibration analysis.

Attraction phase

The attraction phase uses a multilinear function. To calibrate it, we define each coefficient by linear regression. We have implemented the model using R Commander (Fox, 2005), combining the different variables in order to obtain the most precise model. The model can be formulated as follows:

1C Model:

$$T_j = a_0 + a_1.POP_j + a_2.NrSMC_j + a_3.Emp-BS_j + a_4.Emp-VBS_j + a_5.MR_j$$

3C Model:

$$T_j^{CUA} = a_0^{CUA} + a_1^{CUA}.POP_j + a_2^{CUA}.NrSMC_j + a_3^{CUA}.Emp-BS_j + a_4^{CUA}.Emp-VBS_j + a_5^{CUA}.MR_j$$

$$T_j^{NP} = a_0^{NP} + a_1^{NP}.POP_j + a_2^{NP}.NrSMC_j + a_3^{NP}.Emp-BS_j + a_4^{NP}.Emp-VBS_j + a_5^{NP}.MR_j + a_5^{NP}.CC_j$$

$$T_j^{FP} = a_0^{FP} + a_1^{FP}.POP_j + a_2^{FP}.NrSMC_j + a_3^{FP}.Emp - BS_j + a_4^{FP}.Emp - VBS_j + a_5^{FP}.CC_j$$

We observe that the R² is close to 1 in all three categories of urban space. Moreover, the F test is close to 0 in two of the cases (see **Erreur! Source du renvoi introuvable.**). However, the one-category model is more robust, due to the highest number of individuals considered in the linear regression procedure.

Table 1 – Linear regression results for the best attraction analysis

Model	R²	F Test	Individuals
1C	0,82	1,28.10-9	33
3C - CUA	0,86	0,31	8
3C - NP	0,77	0,007	14
3C - FP	0,95	0,002	11

Catchment area phase

The catchment area phase presents various parameters that must be calibrated. We propose a calibration method that combines an econometric analysis (Kubis and Hartman, 2007) with a fitting procedure based on that of Hyman (1969). This calibration method is presented as a sequential procedure that can be resumed as follows:

1. Determination of the coefficients for both small and big stores by linear regression.
2. Revision of the model and final formulation
3. Determination of the coefficients to calibrate using the fitting procedure and iniziatilation of the procedure
4. Iterations for coefficient improvement using the fitting method

The linear regression analysis starts from the following formulation for the catchment area model:

$$N_{hi} = A_i \frac{E_i^{\alpha_1}}{E_h^{\alpha_2}} NrH_h^{\gamma} T_i c_{hi}^{\beta}$$

We approximate in a first time by excluding in the analysis the A_{ij} elements. Then, we can linearize the function using the logarithmic operator:

$$\log P(T_i) = \log K + \alpha_1 \log E_i - \alpha_2 \log E_h + \gamma NrH_h + \beta \log c_{hi}$$

Finally, using R Commander (Fox, 2005) we establish the form of the model as well as the variables and coefficients that are included in the final formulation. We found that the two best approximations are the following:

$$P(NrH_h;T_i)^{small} = \frac{E_i^{\alpha_{1S}}}{E_h^{\alpha_{2S}}} \frac{K^{small}}{NrH_h^{\gamma_S}} c_{hi}^{\beta_S}$$

and

$$P(NrH_h;T_i)^{big} = \frac{E_i^{\alpha_{1b}}}{E_h^{\alpha_{2b}}} \frac{K^{big}}{NrH_h^{\gamma_b}} c_{hi}^{\beta_b}$$

Table 2 – Linear regression results for the best catchment area model

Model	R²	F Test	Individuals
Small retailing activities	0,47	$1{,}04.10^{-23}$	179
Big stores	0,49	$3{,}98.10^{-25}$	176

The commercial supply for small stores in the residence zone can be supposed as a negligible variable, as in the different combinations that have been tested the coefficients were close to 0 and less influent than the commercial supply for small stores in the shopping zone. The number of households has an inverse effect as that we can intuitively hypothesise, but this can be seen in the following way: the influence of household is pondered by the distance. In fact, people trends are to go shopping close to the household zone when the commercial supply satisfies their needs, and the intra-zone distance is in general smaller than the inter-zone distance.

Then, the final model can be formulated. Taking into account the similarity of the distance coefficient, we propose the following catchment area model:

$$T_{hi} = \left(A_{hi}^{small} \frac{E_i^{\alpha_1 s}}{E_h^{\alpha_2 s}} \frac{K^{small}}{NrH_h^{\gamma s}} + A_{hi}^{big} \frac{E_i^{\alpha_1 b}}{E_h^{\alpha_2 b}} \frac{K^{big}}{NrH_h^{\gamma b}} \right) c_{hi}^{\beta}$$

with

$$A_i^{small} = \sum_{k \neq i} \frac{E_i^{\alpha_1 s}}{E_h^{\alpha_2 s}} \frac{K^{small}}{NrH_h^{\gamma s}} c_{hk}^{\beta}$$

and

$$A_{hi}^{big} = \sum_{k \neq i} \frac{E_k^{\alpha_1 b}}{E_h^{\alpha_2 b}} \frac{K^{small}}{NrH_h^{\gamma b}} c_{hk}^{\beta}$$

The third step is the fitting procedure. We start the procedure by initialising the algorithm. To do this, we first select the parameters that will be recalibrated. Alpha and gamma belong to the A_{ij} elements, and they should be calibrated using other approaches, such as that proposed by Ortuzar and Willumsen (2001), but they need complete O/D matrices where the total number of emission trips and the total number of attraction trips are the same quantity, which is not our case. For this reason, we keep the coefficients estimated by linear regression and make the calibration only on beta.

We define the following mean values of c (Hyman, 1969):

$$c^* = \frac{\sum_{hi} N_{hi}^R c_{ij}}{\sum_{hi} N_{hi}^R} \quad \text{and} \quad c^m = \frac{\sum_{hi} T_{hi}^m c_{ij}}{\sum_{hi} T_{hi}^m}$$

where N_{hi}^R is the number of measured trips arriving at *i* which households are located in *h.* *W*e also set $\beta_0 = average(\beta_0^{small}, \beta_0^{big})$.

The fitting procedure can the be defined, and is composed by several stages that are defined as follows:

0. Initialisation: Starting on β_0, a a better value of β is estimated in the following way:

$$\beta_m = \frac{\beta_0 c_0}{c^*}$$

1. Iteration phase:

   a. We make m=m+1. Using the latest value for β, noted β_{m-1}, we calculate the catchment area matrix using the model (3) and obtain the new mean modelled trip distance cost cm-1 using the following expression:

   $$c(\beta) = \frac{\sum_{hi} N_{hi}(\beta) c_{hi}}{\sum_{hi} N_{hi}(\beta)}$$

   We calculate $\delta(N_{ij}^{m-1}, N_{ij}^R)$. If this value is sufficiently close to accept the precision of the model, the iterations are stopped, otherwise we go to step b.

   b. We improve β in the following way:

   $$\beta_{m+1} = \frac{(c^* - c_{m-1})\beta_m - (c^* - c_m)\beta_{m-1}}{c_m - c_{m-1}}$$

The iteration phase is repeated until the precision of the model is accepted as good, i.e. when cm is supposed to be sufficiently close to c*. Moreover, if the parameter is not enough improved after I iterations, we also stop the calibration process. We report in Table 3 the main calibration results of the model.

Table 3 – Estimation results on the data of Lyon (2006)

	Surveyed	Estimated	Error
Number of trips per day	301629	296230	1,7%
Distance (Millions of km/day)	4,34	4,44	2,1%
Mean distance c (in km)	14,39	14,99	4,2%
Initialization value β_0	-	0,89	-
Best β value	-	0,91	-

After 50 iterations, we obtain an error on the mean distance lower than 5%. We observe that in a global perspective, the results are quite satisfactory. The distribution results are less performing but the estimation of the total distance due to private cars shopping trips can be estimated with a small error.

APPLICATION DOMAIN AN USAGE EXAMPLES

Possible uses of this can be related to both passenger and freight transportation, and also to marketing and real estate fields. For a public policy usage, different choices and applications can be proposed. For example, the proposed model can be used to simulate strategic planning scenarios to estimate the impact of urbanistics, legislation and other policy actions in both people and the global freight movement trends.

Another use can be to study the limits of several policies (Gonzalez-Feliu et al., 2010). It is important to note that the new distribution services (home delivery, proximity reception points, etc.) have a direct impact on shopping trips. In order to simulate the substitution of current practices by these new distribution services, the shopping trips by private car have to be characterised in order to define and simulate the substitution trends (from current shopping trips to the new distribution routes). Routhier et al. (2009) propose four extreme urban retailing supply scenarios:

1. concentrated shopping malls;
2. traditional medium level stores;
3. e-commerce plus home delivery;
4. e-commerce plus local pick up points.

To simulate, the inter-establishment movements (IEM) have been estimated using the LUTI model Freturb (Routhier and Toilier, 2007) and the end-consumer movements (ECM) using the proposed shopping trip model. The substitution of shopping trips for the teleshopping scenarios is made using the procedure proposed by Routhier et al. (2009). Moreover, the CO_2 emissions can also be estimated from the travelled distances and an estimation of the mean speed in each section using the commercial software Impact Ademe (ADEME, 2003).

	Km.PCU IEM	Km.PCU ECM	Km.PCU TOTAL	CO2 equivalent
Reference	2,7 Mkm/week	26 Mkm/week	28,7 Mkm/week	6150 t/week
All Hypermarkets	-87%	-3%	-11%	-16%
All proximity stores	+90%	-87%	-63%	-56%
All home deliveries	-87%	-85%	-85%	-86%
All pickup points	-87%	-95%	-93%	-92%

The “all hypermarkets” situation is a little better than the reference, in terms of freight flows for both types of movements. The establishment supply ones are drastically reduced because the logistics systems of the commercial centres allow a better rationalisation of freight distribution flows (about - 87% of the km.PCU respect to the reference situation). However, the end-consumer movements do not increase with respect to the reference(we observe a light decrease, near -3%), due to the need of using the private car to arrive to the peripheral commercial centres that a priori increases the length of private car shopping trips and the concentration of the activities in this form of commercial supply that reduces the number of trips. The global result is a reduction of a little more than 15% of the total km.PCU, which shows the importance of end-consumer movements in the overall logistics system of a urban community. The “all proximity stores” scenario has a higher impact. Although the establishment supply movements increase (+90% of the km.PCU), the end-consumer movements decrease because of the proximity that incentives the “on foot” shopping trips (about -87%). This is traduced by a reduction of the total km.PCU of 56% respect to the reference. The “all home delivery services” scenario has an impact on the end-consumer movements: although no shopping trips are observed, considering everybody is delivered home, the home-delivery trips (another component of end-consumer movements) present an important increasing trend, which is traduced by a reduction of -85% in the end-consumer km.PCU. The distribution to the logistic platforms for home delivery has been considered to be made in a similar way respect to the hypermarket distribution, in a very rationalised way (a collaborative situation is simulated), so the establishment supply movements are close to those obtained for the first scenario. The same hypothesis are made to the fourth scenario, but the reception points system has a better optimised distribution to the reception points. Moreover, we obtain a small number of private car shopping trips. This is derived from the current proximity shopping behaviour, considering than several households will use the car to take big quantities of goods from the reception points. The end-consumer movements in this situation have a similar trend respect to the “all small stores” one (-93%). These trips contain both the shopping and the reception points delivery movements. The overall freight flow trends for these two scenarios are respectively -86% and -92% respect to the reference situation. We see than the home delivery services are not the best solution, since the transportation system that replaces shopping trips is very rigid and its efficiency improvement is difficult (Alligier, 2007). The “all reception points” scenario seems to have a more positive impact, because a big reduction of the travelled distances can be made for both types of movements, which is not the case in the first family of scenarios. A combination of these four can be used by stakeholders to define urban commercial supply policies that integrate both types of movements in a city logistics point of view.

The catchment area approach can also be useful to simulate e-commerce policies and behavioural issues related to the new distribution forms. Although specific data about e-commerce behaviour in the zone of simulation is difficult to found, the findings of Rohm and Swaminathan (2004) can be applied to medium and big urban areas. These authors define 4 types of online shoppers on the basis of a specific survey for e-commerce behaviour on standard categories of population. We can state than although the store-oriented shoppers are only 15% of the sample, a catchment area approach including variables such as the commercial supply and the geographical distance (among others) represent the vehaviour of 3 categories, i.e. 89% of the population. For this reason, assuming the usage rates of e-commerce, the proposed model can distribute the related trips in order to reconstitute the delivery routes for several e-logistics schemas (Routhier et al., 2009; Durand et al., 2010).

We propose several results for studying the effects of e-commerce introduction. The usage-rate of these services is increased from 0% (assuming than in 2006 the e-commerce usage rates are negligible) to 100% with an increase of 10% for each scenario. The attractiveness model is used to estimate the potential demand of e-commerce distribution services for each zone and the remaining classical shopping trips. Following the simulation methodology of Durand et al. (2010) for route simulation, we can estimate the travelled distances of these forms of distribution. Then, the total distances (e-commerce distribution and classical shopping trips). The simulated data are the following:

Table 4 – Simulation results for progressive increase of e-commerce user rates

Scénario		Aval Livraison	Aval Achats	Total
0		0	25955939	25955939
LAD	10%	4%	-10%	-6%
	20%	8%	-20%	-12%
	30%	13%	-31%	-18%
	40%	17%	-42%	-25%
	50%	21%	-52%	-31%
	60%	25%	-63%	-38%
	70%	29%	-74%	-44%
	80%	33%	-84%	-51%
	90%	38%	-95%	-57%
	100%	40%	-100%	-60%
PR	10%	2%	-8%	-6%
	20%	4%	-17%	-13%
	30%	6%	-26%	-20%
	40%	7%	-34%	-27%
	50%	9%	-43%	-34%
	60%	11%	-52%	-41%
	70%	13%	-61%	-48%
	80%	15%	-70%	-55%
	90%	17%	-79%	-62%
	100%	18%	-82%	-65%

We observe that e-commerce competition scenarios are less performant that their analogous collaborative scenarios. Indeed, with an “all home delivery” scenario the total reduction of the number of km. PCU is near -60% whereas in a collaborative situation it is about 85%. The “all reception points” scenario presents similar results (-65% with respect to -92% for the collaborative scenario). We also observe than in a situation without important behavioural changes, a 50% reduction of the total number of Km.PCU is reached only with a 80% of usage rates for e-commerce.

CONCLUSION

In this paper we presented a new modelling approach for shopping trip simulation, in order to reproduce an estimation of end-consumer goods movements which would be able to be compared to freight distribution trips. Considering only the private car shopping trips, which are those that interact with freight distribution trips, we propose a two-step model. First, the attracted shopping trips are generated at each shopping destination section. Second, each shopping destination section is related to the possible household locations of the shoppers using a gravity catchment area model.

Another important element of shopping trips in urban areas is that each zone does not have the same characteristics. Following the administrative typology of rings to classify the urban community’s towns, we divided the considered zones into three categories for trip generation: the Central Urban Area (CUA), which is the main city’s area, the Near Periphery (NP), which represents the first ring, and the Far Periphery (FP), which contains all the other towns of the urban community. Similarly, we also propose a two-category model for the catchment area phase, in order to take into account the differences between shopping trips made for purchasing at small retailers and those related to big stores and hypermarkets.

The shopping trips at each retailing zone is well estimated, and similar results are obtained for the outbound trips. However, the inbound trips are less well estimated due to the influence of working activities (no information about the overall number of employees for all the economical activities is included). Moreover, two examples of modelling applications made with the proposed model are presented.

In order to improve the model, and to define an approach adaptable to each city, we have applied this methodology to a data file containing zones of two urban areas of different size. The main results are encouraging (similar regression coefficients and good approximations in both urban areas), and a deeper study is in process. Moreover, a better characterisation of the Commercial Centres, as for example defining them by their surface or their total revenue, have to be studied.

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