USE OF SIMULATED ANNEALING TO ESTIMATE A PEAK-HOUR O-D MATRIX FOR URBAN FREIGHT DELIVERIES

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ABSTRACT

Urban freight transport has barely incited any modelling efforts when compared to passenger cars and public transport, which is mainly due to the lack of available data and the complexity of the delivery route patterns and the involved decision making. We present here a modelling approach consisting of a demand model followed by an entropy maximisation procedure to estimate an origin-destination matrix for urban freight transport vehicles, both for B2B and home deliveries, during the morning peak hour. This approach requires relatively few data inputs in comparison with other existing models, and represents an initial step towards the inclusion of freight delivery models in overall urban transport planning. The application of the model is illustrated with a case study in the city of Seville, with its efficiency proved by the validation of the results using actual traffic counts.

Keywords: transportation, city logistics, origin-destination matrix, urban freight, entropy maximisation.

INTRODUCTION

Urban passenger flow modelling often relies on the assumption of relatively simple displacement patterns, involving only work-related commuting or estimations of other habitual purpose trips. The results show that this assumption explains a high percentage of the observed vehicle flows, which is sufficient to use the resulting model for traffic planning purposes, perhaps after additional calibration using traffic counts. The data collection for these models is therefore based on origin-destination (O-D) surveys, which constitute the input for trip generation models, and additional trip distribution models are required to estimate the corresponding origin-destination matrices, which can be fed to commercial simulation packages.

In contrast with the above, the modelling of urban freight distribution is a completely different, and much more complex, process, with multiple stops in different parts of the city, routes changing from day to day and higher-level commercial and supply chain considerations involved (Ogden, 1989; Dablanc, 2007). Besides, commuters are usually willing to provide origin-destination information for administration-conducted surveys, whereas transport companies, operating in a very competitive environment, are normally much more reluctant to provide data on shipments, tours or timetables, which are viewed as commercially confidential (Morris et al, 1998). The collection of data to represent and model urban freight deliveries is an expensive and difficult task, far from being standardised or at least agreed upon (Patier and Routhier, 2008). As a result, decision makers in urban transport planning, when facing the need to include urban freight in their analyses, are often forced to proceed intuitively, without the appropriate set of data (Bryan, 1997). Given the fact that freight vehicle flows are small when compared to passenger traffic, they often tend to simplify the problem, dismiss the particularities linked to urban freight deliveries, assume that those flows correspond to a relatively small percentage of the total observed traffic (around 5-10% of vehicle flows on links, according to our observations) and rely on passenger models to provide the appropriate support for traffic management policies.

However, the consideration of urban freight flows in a joint but independent manner with passenger traffic is required given the different characteristics of both types of displacements. These characteristics include for example different contributions to congestion in terms of speed and schedules or different environmental impacts and energy consumptions. Urban freight traffic is also subject to different regulations in terms of accessibility or parking restrictions, and the introduction of innovative policies, like urban freight corridors or hub areas (Muñuzuri, 2005) requires precise knowledge of freight vehicle flows. The multiple objective of this type of models includes the quantification of accessibility and environmental problems and the evaluation of the effectiveness of new mobility policies and strategies in the city.

This is why the development of models which are simple and easy to implement, and which are able to extract as much information as possible to the available data sets, seems like a promising path. These models could at least provide a first step towards the inclusion of freight transport in the overall urban traffic planning process, in the usual cases where extensive, in-depth logistic surveys are not a possibility. We present here the modelling process to build a peak-hour O-D matrix for urban freight transport, making use of the available data sources and keeping the procedure simple enough to make it attractive for local authorities. The case-study application and validation will show that our model results in a reasonably close approximation of delivery vehicle flows, suitable for planning purposes. This work has been published in Muñuzuri (2010).

PREVIOUS MODELLING EFFORTS

Two different approaches, described by Ogden (1992) can be used to estimate urban freight transport: commodity-based and vehicle-based. The commodity-based approach is more economic or supply-chain oriented, and seeks to estimate the amounts of freight that move between different parts of the city. Several examples can be found in Hutchinson (1974), Ogden (1978), Russo and Comi (2001, 2004) and Wisetjindawat et al (2006). Our concern, nevertheless, lies rather with the vehicle-based approach, oriented towards traffic planning and transport policy-making, where the objective is to estimate delivery vehicle flows or the corresponding O-D matrices. Oppenheim (1993) formulates a nonlinear optimisation model to represent jointly the activity and transport system, thus estimating car and truck trips for a given urban area, while List and Turnquist (1994) use count data to derive origin-destination matrices for different types of trucks in an urban area by means of a large-scale linear programming model. The Freturb model (Routhier and Aubert, 1998) uses as input data the number of establishments and employees in each zone in order to estimate different indicators concerning urban freight movements, like the vehicle density and flows between traffic zones, the parking time for loading and unloading, freight volumes on roads and amounts of freight moved. Holguín-Veras and Patil (2008) formulate a multicommodity origin-destination synthesis model to estimate loaded truck trips, adding also an empty trip submodel and generating O-D matrices for the different commodities, assuming that the production and consumption of cargo in each zone is known.

Some models seek a higher level of detail, and concentrate on the estimation of individual delivery routes. For example, the Wiver model (Sonntag and Tullius, 1998) takes into account the complexity of trip chains, with multiple stops per route, for freight transport in a city. Origin-destination matrices are generated for different sectors, vehicle types and times of the day, considering either the volume of goods transported or the number of vehicles used. The GoodTrip approach (Boerkamps and van Binsbergen, 1999) estimates urban goods distribution using a supply chain approach. The volume of goods arriving to each zone is estimated based on consumer demand, and then combined in flows for each type of good. These combined goods flows are then assigned to vehicle tours. The result of the model is a set of origin-destination matrices and a list of tours per mode. Finally, Figliozzi (2007) analyzes tour configuration as dependent on the number of stops per tour, tour duration and time window constraints, deriving implications for the calibration of trip generation and distribution models.

More recently, agent-based simulation offers a new open field for researchers willing to represent the complex scenario of urban freight deliveries. For example, Zhang et al (2005) formulate a network flow equilibrium model combining different layers for automobiles and urban freight. A dynamic game structure is built considering infrastructure investments, and the resulting problem is solved using agent-based simulation. Hunt and Stefan (2007) provide agent-based microsimulations of individual vehicle movements, using a tour-based approach, built and calibrated to match the data collected in an extensive survey of urban freight movements in Calgary.

In the next sections we describe our estimation model for urban freight vehicle flows. In our research we have selected a typical 4-step approach, consisting of a specifically-designed trip generation model and a trip distribution model based on entropy maximization and simulated annealing techniques.

TRIP GENERATION MODEL

According to Cohen (1997), the different information sources used to build an urban freight model can be divided in two types, primary and secondary. Primary information sources (vehicle counts, logistic practice patterns, etc.) provide much better information for building the model, but are much more difficult and costly to access than secondary ones (aggregate statistics, census data, etc.). An adequate combination of the use of both types of sources is therefore required for improving the modelling process. However, even when lacking exact information, it can often be replaced by correlations that can work well in a broad scope, representing goods movements or delivery vehicle trips in terms of other indicators which are much easier to obtain (Hensher and Button, 2000). Authors like Adeogunsanya (1984) or Noortman (1984), for instance, apply linear regression models to relate the amount of goods produced or demanded by an urban zone to the available parameters (employment, socioeconomic level, number of inhabitants, …), as a sufficient means to estimate urban freight demand and supply.

Our objective here is to formulate a trip generation model that represents the number of vehicles entering and leaving each zone of the city during the morning peak-hour. Even though most freight-related trips are multi-stop, resulting in delivery tours with multiple origins and destinations for the same vehicle, the formulation of the model for the morning peak-hour period, when passenger traffic is high and shops are beginning to open, supports the assumption that the trips considered start at one zone and end at another, without the need to include multi-stop trips all around the city. This restriction, in any case, goes along with the interest of the local authorities in estimating the extent to which freight transport interacts with passenger transport (most freight-concerned local regulations, like access restrictions and time windows or parking policies are related to this issue), and it is during the peak hour when these interactions are most severe. The use of data in the formulation of the model will be mostly limited to secondary data, complemented with only a few small-scale surveys to freight receivers (shop owners) and vehicle counts. Note that shop owners do not have information about tours or loading factors, but they are often willing to provide data on delivery duration, frequencies, timetables, etc.

Two types of delivery trips are considered in our model. The first type corresponds to replenishment deliveries for retailers, and the trips are assumed to start at wholesalers' premises and end at retailers' premises. Premises identified as wholesalers in official statistics normally correspond to warehouses in the outskirts of the city which specialise in a given activity sector and supply goods to retailers in the city. The second type of delivery trips considered are home deliveries, which are assumed to start at retailers' premises and end at families' homes. Home deliveries not starting at the retailer's premises, but at some other external or subcontracted warehouse, are not considered in the analysis. In fact, the question often arises of determining what is and what is not urban freight transport. We think of urban freight transport as the ensemble of all the freight-related displacements that would be eliminated if the metropolitan region in question was geometrically reduced to a single point. Therefore, only those displacements originated and terminated inside the metropolitan area are included. Also, it is worth noting that this is a static model, which produces O-D matrices that are fixed as long as the location or delivery practices of wholesalers or retailers do not change significantly.

Deliveries from wholesalers to retailers

The number of trips attracted by each zone during the morning peak hour can be estimated using the data obtained from a limited number of demand surveys and vehicle counts. In each case, a given urban area (a street or a group of streets with a sufficient number of commercial premises to result significant) needs to be delimited. Then the number of vehicles entering the surveyed area to make deliveries can be counted, and compared to the theoretical number of deliveries to be received in the area, according to the frequency data gathered from the retailers. The result can be expressed with the calculation of the following coefficients, one for each activity sector k:

$$a^k = \frac{1}{S}\sum_{s=1}^{S}\frac{V_s^k}{\sum_{l\in k} d_s^l e^l} \quad \forall k = 1,...,K$$

Where:

S is the number of surveys carried out.

d_s^l is the number of freight-receiving retailers of type l, included in sector k, located in the surveyed area s.

e^l is the average number of deliveries received daily by a generic retailer of type l.

V_s^k is the number of delivery vehicles actually counted when entering the surveyed area s to make a delivery during the peak hour.

The calculation of these coefficients accounts for the fact that the number of deliveries made in each surveyed area during the peak hour, which is equal to $\sum_{l \in k} d_s^l e^l$, is not necessarily equal to the number of vehicles entering the area, V_s^k, given that the same vehicle often delivers to more than one retailer in the same trip. For each sector k and for each destination zone j the number of daily deliveries attracted during the peak hour can then be estimated as follows, where d_j^l is the number of freight-receiving retailers of type l, included in sector k, located in zone j:

$$D_j^k = a^k \sum_{l \in k} d_j^l e^l$$

Once the D_j^k values are known, it is possible to estimate the number of vehicles of each sector k with origin in each zone i, that is, the O^k_i for freight transport between wholesalers and retailers. The starting assumption states that the number of trips originated in the city for each sector O^k must equal the total number of destinations:

$$O^k = \sum_i O_i^k = \sum_j D_j^k = D^k$$

This is the total number of vehicles assigned to deliveries from wholesalers to retailers in each sector for the whole city. The amount of these vehicles that departs from each zone of the city during the peak hour can then be estimated as follows:

$$O_i^k = \frac{O^k \, o_i^k}{\sum_i o_i^k}$$

Where:

O_i^k is the number of freight vehicles of sector *k* which have their origin in zone *i*.

O^k is the total number of vehicles for sector *k*.

o_i^k is the number of wholesalers of sector *k* located in zone *i*.

Home deliveries

The number of trips with origin (Oi) and destination (Di) in each zone i can be calculated as a weighted average depending on the population of each zone, as follows:

$$O_i^k = \sum_{l \in k} v^l R_i^l \quad \text{and} \quad D_i^k = \frac{P_i \cdot \sum_i O_i^k}{\sum_i P_i} \text{, where:}$$

P_i is the population in zone *i*.
R_i^l is the number of retailers of type *l* doing home deliveries in zone *i.*

v^l is the average number of vehicles used for home deliveries by a retailer of type *l*.

TRIP DISTRIBUTION MODEL

The entropy maximisation approach

The objective of the distribution model is to calculate the values of , that is, the number of freight transport trips corresponding to sector k between zone i and zone j, for all (i,j) zone pairs in the city. These values are the elements of the freight origin-destination matrix. The procedure is based on the entropy-maximisation approach, which has been widely applied to the estimation of passenger O-D matrices (Van Aerde et al, 2003) but has never, to the authors' knowledge, been used to estimate urban freight flows. The input data for entropy maximisation uses the number of trips originated and terminated in each zone as inputs, and it calculates the elements of the matrix by maximising entropy or 'disorder', that is, by finding trips patterns that are as distributed as possible along the matrix. The entropy maximisation model is written as follows:

$$Max \quad W^k = \frac{\left(\sum_i \sum_j T_{ij}^k\right)!}{\prod_{ij}\left(T_{ij}^k\,!\right)} \qquad [1]$$

$$s.to: \quad \sum_j T_{ij}^k = O_i^k \quad \forall i,k \qquad [2]$$

$$\sum_i T_{ij}^k = D_j^k \quad \forall j,k \qquad [3]$$

$$T_{ij}^k \geq 0 \quad \forall i,j,k \qquad [4]$$

The same result is obtained by maximising the entropy function W^k or its logarithm. Besides, the sum of all the T_{ij}^k deliveries is constant, so it does not affect the optimisation process. As a result:

$$MaxW^k \equiv Max\left[\log\left((\sum_i \sum_j T_{ij}^k)\,!\right) - \sum_i \sum_j \log\,(T_{ij}^k)\,!\right] \equiv -Min \sum_i \sum_j \log\,(T_{ij}^k)\,!$$

Finally, the Stirling formula (log T!=T•logT–T) can be applied, and the objective function of the entropy maximisation model results:

$$-Min \sum_i \sum_j (T_{ij}^k \,\log T_{ij}^k - T_{ij}^k) \qquad [5]$$

This is a non-linear optimization problem with linear constraints, which can be formulated separately for each sector k and for B2B or home deliveries, and as a result the different sets of T_{ij}^k values (origin-destination matrices) can be estimated. This approach has been traditionally used in passenger transport analysis (see, for example, Wilson, 1974) to estimate trip distributions from a gravitational point of view, incorporating cost values to the distance covered by the displacements (Evans, 1973). This requires an additional cost restriction, namely:

$$\sum_i \sum_j c_{ij} T_{ij}^k = C^k \quad \forall i, j, k \qquad [6]$$

Where cij is the cost of travel between each pair (i,j) of zones and Ck is the total travel cost for sector k. Including this additional constraint, the resulting formulation is equivalent to the transportation gravity model, where the number of displacements between each pair of zones can be calculated as follows:

$$T_{ij} = A_i O_i B_j D_j f(c_{ij}) \qquad [7]$$

$$\textit{with:} \quad A_i = 1 \Big/ \sum_j B_j D_j f(c_{ij}) \qquad [8]$$

$$B_j = 1 \Big/ \sum_i A_i O_i f(c_{ij}) \qquad [9]$$

In these expressions, $f(c_{ij})$ is the deterrence function, which expresses a higher probability of occurrence for shorter trips, and which can be expressed as:

$$f(c_{ij}) = c_{ij}^a \cdot \exp(-b \cdot c_{ij}) \qquad [10]$$

Where *a* and *b* are parameters of the model.

In the case of urban deliveries, however, the organisation of delivery tours is due to commercial considerations, like customer locations or time windows, rather than on proximity. This implies that the cost restriction [5] is difficult to calibrate and has less justification in our case, with delivery routes less constrained in terms of length and duration than passenger commuting. With this in mind, and for means of comparison, we tested two different models in our analysis:

M1 Entropy maximisation model ([5], [2], [3] and [4])

M2 Gravitational approach ([7], [8], [9] and [10])

Solution techniques

To solve *M1*, we used Matlab to implement a simulated annealing procedure, described in the following pseudocode, thus improving the results obtained in Muñuzuri et al (2009):

```
Simulated annealing

Initialise T0; BestSolution=T0 ; BestEval=Evaluation(T0)
Initialise Temp, Niterexternal, Niterinternal, r

For external iterations = 1 to Niterexternal
      For internal iterations = 1 to  Niterinternal
            Find Tf in the neighbourhood of T0
            If Evaluation (Tf)<Evaluation (T0), then
                  T0=Tf,
                  If Evaluation (Tf)< BestEval, then
                  BestSolution=Tf, BestEval= Evaluation (Tf)
                  Else if rand(0,1) < exp((Evaluation(Tf) - Evaluation(T0)) / Temp),
            then T0=Tf
      End internal iteration
      Temp=r·Temp
End external iteration
```

In this procedure, the operation of finding neighbouring solutions was as follows (see Figure 1):

```
Find Tf in the neighbourhood of T0

Initialise Tf = T0
Let numzones be the number of rows and columns in the
O-D matrix
Random selection of i1, i2, j1 and j2, all different
and between 1 and numzones
Shiftvalue = unif (0, min(T0 (i1, j1), T0 (i2,j2)))
Update values:    Tf (i1, j1) = Tf (i1,j1) – Shiftvalue
            Tf (i1, j2) = Tf (i1,j2) + Shiftvalue
            Tf (i2, j1) = Tf (i2,j1) + Shiftvalue
            Tf (i2, j2) = Tf (i2,j2) – Shiftvalue
```

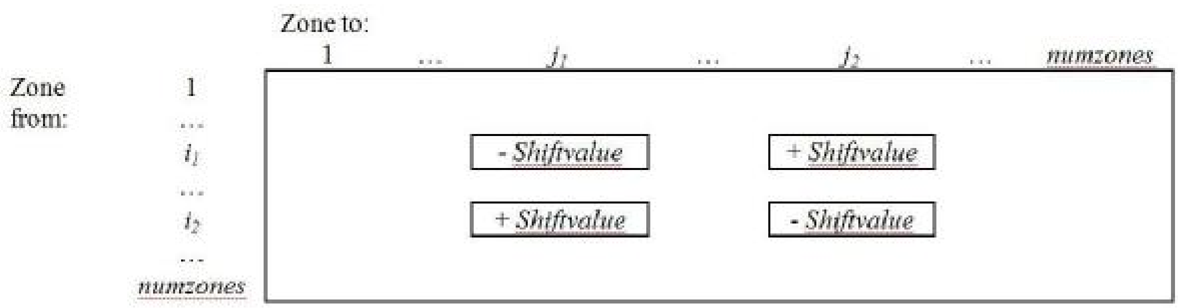

Figure 1 – Building of solution Tf in the neighbourhood of a given solution T0.

In *M2*, on the other hand, the expressions for Ai and Bj are recursive, in the sense that they depend on each other to be solved. However, they can easily be solved iteratively, starting with all the Bj values equal to 1 and calculating the Ai values. Then the new Bj values are calculated again, and the process continues until convergence is reached (Ortúzar and Willumsen, 1990).

CASE STUDY

The modelling procedure presented was applied for the estimation of delivery vehicle flows during peak hour in the city of Seville. The peak hour approach is appropriate here, as working hours begin between 8 and 9 a.m. and retailer shops open, depending on the type of business, between 8 and 10 a.m. Therefore, private traffic and goods traffic do interact in the morning, and the modelling process that we describe here represents the first step towards planning actions that help to alleviate this interaction. The remainder of the paper shows the data collection process, the results obtained and their validation through the comparison with actual delivery vehicle counts carried out expressly.

Data collection

The zoning of the Seville metropolitan area (provided by the local Mobility Agency) resulted in 181 zones, and the data available in the secondary sources of information was collected for each one of them. The clustering of businesses can have an effect on the results obtained, and in our case the analysis was divided into the five activity sectors identified by the Local Tax Agency of Seville according to the specific business practices: (1) transformation of mineral non-metallic products and chemicals (construction, pharmacies, glass products, paints, washing products, etc.); (2) transformation of metals (machinery, computers, electric equipment, vehicles, etc.); (3) other industries (textile products, shoes, furniture, paper products, financial institutions, etc.); (4) non-fresh food products, beverages and tobacco; and (5) fresh food products (fruit, vegetables, meat and fish). Allen et al (2000) state the need to also include transport related to services (inspections, customer service, installations, emergencies, etc.) and other commercial uses (sales representatives, company cars, etc.) in this type of analysis, and Holguín-Veras and Patil (2008) stress the importance of taking empty trips into account, but only the trips corresponding to vans or trucks moving freight were considered here due to the unavailability of additional data.

Four in-depth surveys were also carried out in different areas of the city, including the city centre and its surroundings. A total number of 290 retailers belonging to the five sectors were interviewed, thus obtaining data related to the average number of deliveries received daily by each type of retailer, the usual time of arrival of deliveries, the type of company making the delivery, and the type of vehicle used. This information is shown in Table I for one of the four surveys, and Table II shows the overall delivery frequency data which we used to build the model. Also, mainly five types of retailers happened to deliver their goods home to their final customers using vans or trucks: home appliances (sector 2), office appliances (sector 2), doors, windows and blinds (sector 2), food shops (sector 3) and furniture retailers (sector 4).

We also found that the average number of vehicles used for home deliveries is very close to one per retailer (for each one of the four types mentioned). Some of the retailers employ more than one vehicle for home deliveries, but many of them use the same vehicle for several stores.

Table I – Data collected and processed for one of the surveyed areas in Seville (Reyes Católicos).

SECTOR	TYPE OF ESTABLISHMENT	AVERAGE DAILY DELIVERIES	Nº OF ESTABLISHMENTS	UNLOADING TIME (min)	AVG DISPLACEMENT ITME (min)	TOTAL DELIVERY TIME (min)	DELIVERY SCHEDULE (h)	DELIVERIES PER HOUR	TYPE OF VEHICLE USED
1	PHARMACIES	2	3	4.0	7.0	11.0	6	5.5	VAN
1	FLOWERS	1	1	17.5	26.0	43.5	6	1.4	VAN
1	HAIR DRESSERS	0.2	1	2.5	23.0	25.5	8	2.4	VAN
1	PERFUMES/DRUGS	0.5	2	10.0	22.0	32.0	6	1.9	VAN & TRUCK
2	HOME APPLIANCES	1.5	2	6.0	31.0	37.0	8	1.6	VAN
2	DECORATION/GIFTS	0.4	2	17.5	24.0	41.5	8	1.4	VAN
2	HARDWARE	1	2	20.0	31.0	51.0	8	1.2	VAN
2	OPTICIANS	0.8	2	4.0	25.0	29.0	5	2.1	VAN
2	MULTIPRICE SHOPS	1	1	75.0	7.0	82.0	8	0.7	VAN
2	TELEPHONE SHOPS	1	1	4.0	14.0	18.0	5	3.3	VAN
3	BANKS	1	7	1.5	14.0	15.5	5	3.9	VAN
3	BARS/CAFETERIAS	3	13	10.0	3.0	13.0	8	4.6	VAN & TRUCK
3	TRAINING CENTERS	1.5	4	1.5	45.0	46.5	5	1.3	VAN
3	TOBACCO SHOPS	0.2	3	2.5	16.0	18.5	8	3.2	TRUCK
3	BAKERIES/ICE CREAM	3	2	12.5	18.0	30.5	8	2.0	VAN
3	PIZZA/BURGER	0.4	3	25.0	18.0	43.0	8	1.4	TRUCK
4	JEWELRY	1	5	2.5	36.0	38.5	8	1.6	VAN
4	TOY SHOPS	4	1	33.0	45.0	78.0	8	0.8	VAN & TRUCK
4	NEWSPAPER STALLS	4	3	2.5	9.0	11.5	5	5.2	VAN
4	FURNITURE	0.6	3	45.0	51.0	96.0	8	0.6	TRUCK
4	FUR/LEATHER	0.2	2	12.5	66.0	78.5	8	0.8	VAN & TRUCK
4	GIFTS/SOUVENIRS	0.2	2	6.0	27.0	33.0	8	1.8	VAN
4	PAINTINGS/ART SHOPS	0.6	1	6.0	54.0	60.0	5	1.0	VAN & TRUCK
4	SPORTS GOODS	1.5	3	3.5	36.0	39.5	8	1.5	VAN
4	LARGE CLOTHING SHOPS	1	11	4.0	27.0	31.0	8	1.9	VAN & TRUCK
4	SMALL CLOTHING SHOPS	0.2	6	7.5	27.0	34.5	8	1.7	VAN
4	LARGE SHOE SHOPS	1	4	5.0	39.0	44.0	8	1.4	VAN
4	SMALL SHOE SHOPS	0.4	5	5.0	39.0	44.0	8	1.4	VAN
5	SMALL FOOD SHOPS	1	2	20.0	7.0	27.0	5	2.2	VAN & TRUCK

Table II – Average number of deliveries per day for all the different types of premises considered within the five activity sectors.

Activity Sector	Business	Deliveries per day
Sector 1: Transformation of mineral non-metallic products and chemicals	Pharmacies	1
	Perfumes, druggists	0.2
	Plants	0.2
	Petrol stations	1
	Seeds	1
	Waste disposal premises	0.2
	Urban cleaning	0.2
	Cleaning services	0.2
	Dry cleaning of clothes	0.2
	Construction materials	1
Sector 2: Transformation of metals	Home appliances	0.4
	Domestic gear and hardware	1
	Doors, windows and blinds	1
	Home equipment	1
	Vehicles	0.2
	Spare parts for vehicles	1
	Boats and ships	0.2
	Machinery	0.4
	Tyres	1
	Office appliances	0.4
	Medical gear	0.4
	Other machinery	1
	Technical services for home appliances	1
	Mechanics for vehicles	0.4
	Technical services for consumer goods	0.4
	Mechanics for industrial machinery	0.4
	Other technical services	0.4
Sector 3: Other industries	Hotels, motels and boarding houses	1
	Home textiles	0.4
	Clothes	0.4
	Underwear	0.4
	Shoes	0.4
	Leather and furs	0.4
	Furniture (except office)	2
	Second-hand goods and furniture	1
	Music instruments and accesories	0.6
	Stamps, coins and medals	0.4
	Books, newspapers and magazines	3
	Jewelleries and watch shops	0.4
	Toys, weapons and sport items	0.6
	Other goods	1
	Textiles and clothes without premises	0.2
	Shoes without premises	0.2
	Other goods without premises	0.2
Sector 4: Non-fresh food products, beverages and tobacco	Confectioneries and pastries	2
	Bakeries	2
	Icecreams and sweets	1
	Fried food	1
	Food and beverages	3
	Food shops	11

	Food shops without premises	1
	Food and beverages on machines	1
	Department stores	2
	Restaurants	2
	Coffee and chocolate	2
	Bars and pubs	2
	Food and beverages without premises	1
	Other foods and beverages	2
Sector 5: Fresh food products	Fruits and vegetables	1
	Butcher's shops	1
	Eggs and farm products	1
	Fish	1

Finally, freight vehicle counts were carried out in the areas surveyed, and also in different streets of the city belonging to the first-level network. Vans and trucks, except those that appeared to be used for service provision, were counted every day for a week, and then average values were used for model building and validation. The primary data gathered in terms of frequency of deliveries, freight vehicle flows, etc., corresponded only to the four areas where the surveys were carried out. It was therefore necessary to average and then extrapolate the data to the rest of the city, thus neglecting any effect of socio-economic or network-related factors on the data.

The model does not include the size of the premises. It was therefore assumed that the effect of this factor on the number of deliveries received by retailers was negligible. This being a trip-based model, this assumption was somehow supported by the surveys carried out, which allowed to note that in most cases larger premises receive more amount of freight per delivery, but not necessarily more deliveries per day.

The above data was used for the estimation of movements related to all the premises corresponding to the first four activity sectors. Sector 5, however, was different, since the B2B movements all have the same origin, as explained in the next section.

The fifth sector: fresh food products

Calculations were carried out in a different manner for sector 5, dedicated to fresh food products. These products are distributed daily for the whole city from the Seville Fresh Food Wholesaler, MercaSevilla, which is located in a specific zone of the city (104 in the model network, see Figure 5). In order to operate from MercaSevilla distributing fresh food products to supermarkets and retailers around the city, vehicles require a specific licence. The number N of vehicles with a license for operating from MercaSevilla is known, and it was assumed to be equal to the number of vehicles departing from zone 104. The number of sector 5 vehicles departing from the other zones i in the city is therefore assumed to be equal to 0.

$$O_i^5 = \begin{cases} N, if\ i = 104 \\ 0\ otherwise \end{cases}$$

The number of sector 5 vehicles arriving to each zone j during the peak hour can then be estimated depending on the number of daily deliveries received by sector 5 in zone j

$$D_j^5 = N \frac{\sum_{l \in sector 5} d_j^l e^l}{\sum_j \sum_{l \in sector 5} d_j^l e^l}$$

Results and validation

Once the Oki and values had been calculated, we fed them to the models M1 and M2, in order to obtain the O-D matrices. The trip distribution models were formulated for each one of the five B2B sectors considered, and for overall home deliveries. The results obtained in each case were the six O-D matrices for freight transport in the city.

In M1, after testing different combinations, the parameters of the simulated annealing algorithm were fixed to the following values: Temp = 10; r = 0.95 (see the pseudocode above). The numbers of iterations were set to: Niterexternal = 100; Niterinternal = 10,000. This provided the best convergence performance of the algorithm, shown in Figure 2 for sector 3 (similar convergence curves were obtained for the other sectors and for home deliveries).

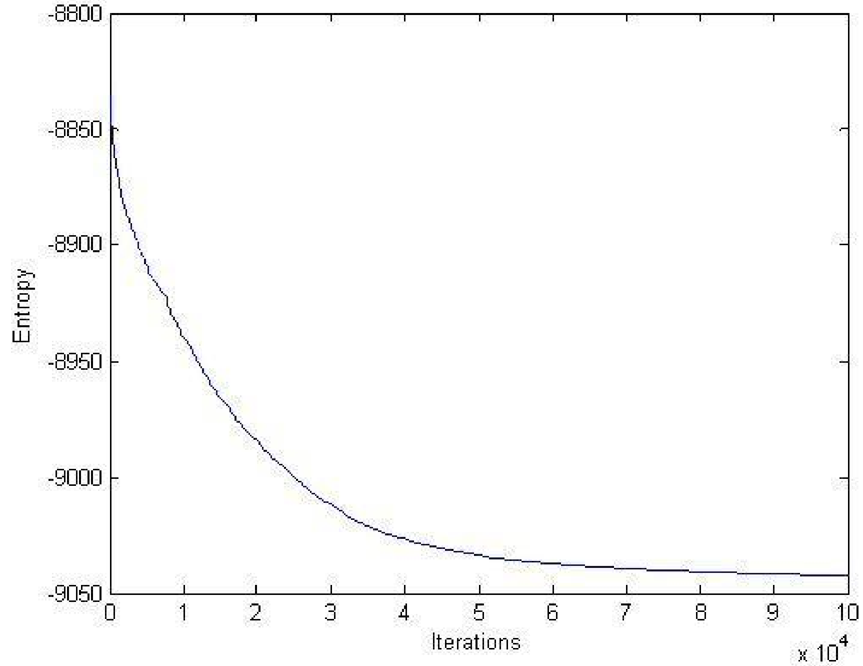

Figure 2 – Convergence process for the simulated annealing procedure when calculating the O-D matrix for sector 3.

With respect to M2, after testing different alternatives for the function expression, the one providing better convergence results (only two iterations needed) was:

$$f(c_{ij}) = c_{ij}^{0.5} \cdot \exp(-0.1c_{ij})$$

Where cij is the straight-line distance (Witlox, 2007) measured in minutes, assuming an average speed of 30 km/h, between the centroids of zones i and j. Note that this expression of the deterrence function also disincentives very short trips (see Figure 3), thus avoiding trips that start and end in the same centroid.

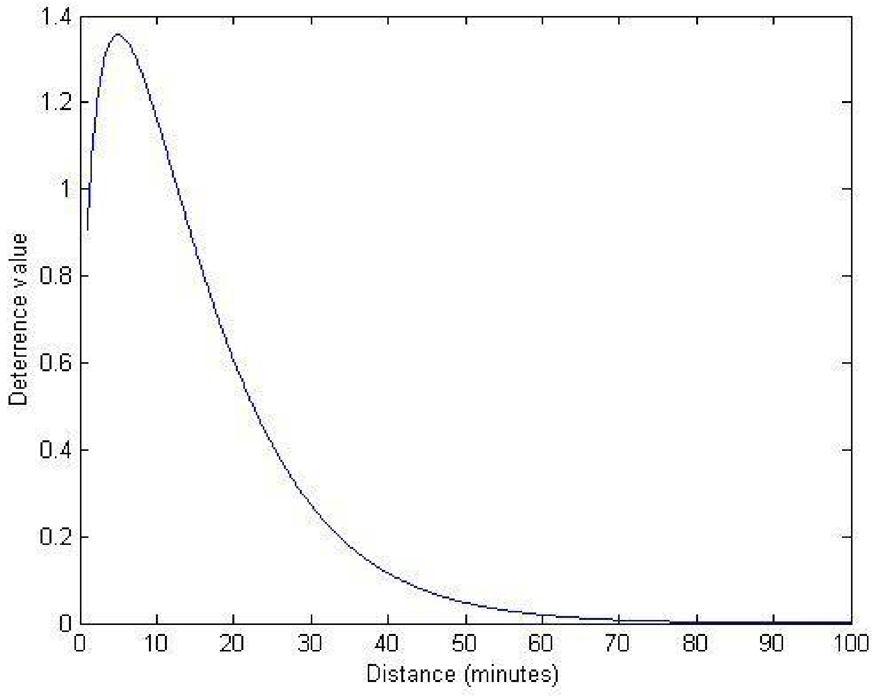

Figure 3 – Representation of the deterrence function used in the calculations for the gravity model.

The validation of the results obtained is one of the key issues that have to be faced by the developers of urban freight models, to the extent that we do not know of any urban freight model that has been validated with actual vehicle flow data. With passenger car models, automatic traffic counts, which are normally available for first-level links in most medium and large cities, are often placed in different parts of the city. However, automatic counts are not suitable to measure freight vehicle flows, as they do not identify the type of vehicle counted. It is important to note that only vehicles transporting freight are to be counted for model validation, and distinguishing between full and empty delivery vans or between freight-carrying vehicles and those dedicated to service providing or even passenger transport is a difficult and unreliable task itself.

In the application to Seville, once all the O-D matrices were estimated, the tool used for determining freight vehicle flows around the city was the commercial package EMME/2 , which performs equilibrium assignments (traffic flow calculations) using an urban network divided in zones and an origin-destination matrix. A matrix for passenger automobile traffic during the peak hour (8 to 9 a.m.) was already available, and we added the six matrices produced by M1 to obtain an overall freight O-D matrix for the city, and did the same with the six M2 matrices.

A joint assignment for passenger and delivery vehicles was then carried out using the software, and the results obtained from the simulation were passenger automobile traffic and freight vehicle flows for all the links in the street network of the city. Figure 4 shows a detail view corresponding to the surroundings of the Historical Centre, with both private cars and estimated freight vehicle flows depicted on it.

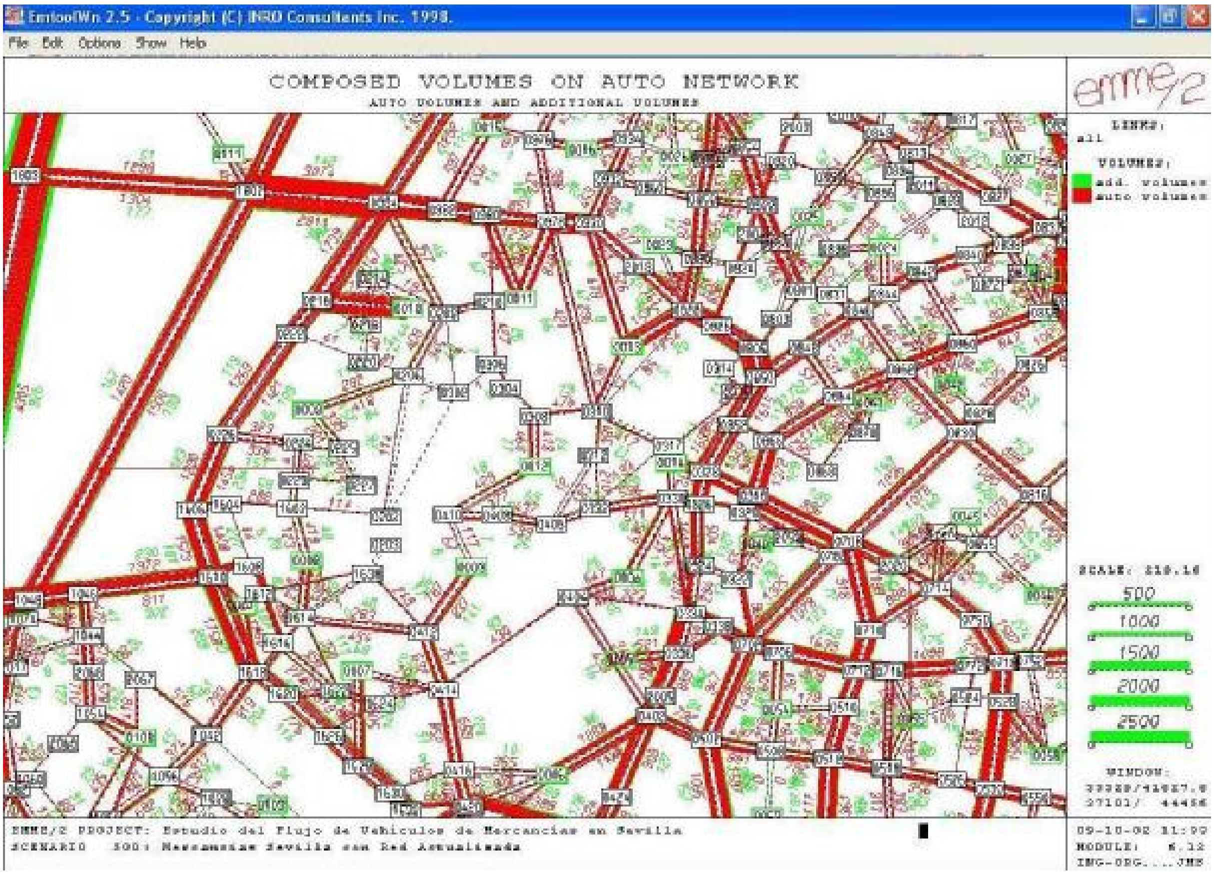

Figure 4 – Traffic volumes for passenger cars and freight vehicles obtained by EMME/2 for the surroundings of the Historical Centre of Seville.

All the points that were chosen for validation correspond to first-level streets or avenues, and are distributed along the city as shown in Figure 5. Actual delivery vehicle flows were counted for a week during the morning peak hour (the counts were carried out between 8.30 and 9.30 a.m.) and then averaged. Figure 6 shows a zoom into one of the links used for validation, and Table III contains the comparison between the estimated and actual freight vehicle flows for the selected locations of Figure 5.

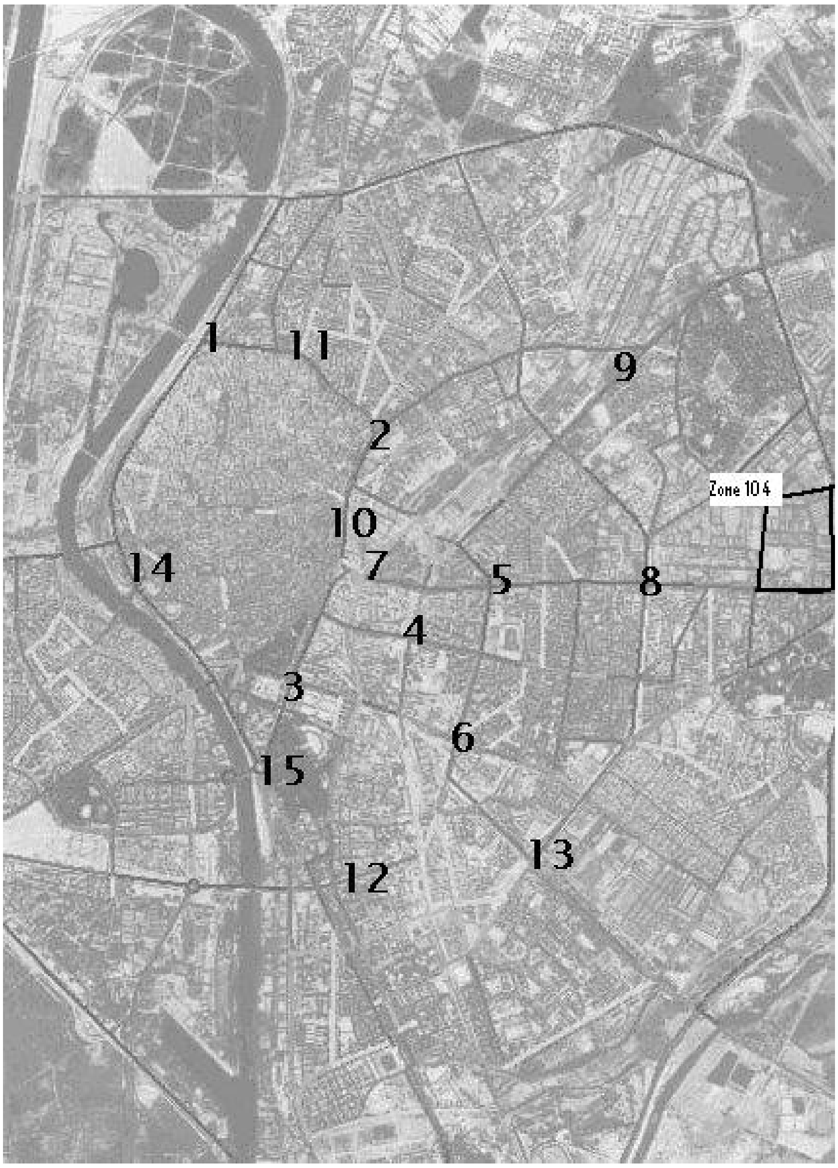

Figure 5 – Location of freight traffic counts distributed along the city of Seville, showing also the location of zone 104 (MercaSevilla).

The comparison presented in Table III and Figure 7 shows significantly better results for M1, using the entropy maximisation – simulated annealing procedure. Of the 29 vehicle counts used for validation, the model predicted 6 with an error smaller than 5%, and 15 with an error smaller than 20%. The overall weighted deviation, obtained by multiplying all the deviations by the flow ratio of the link and then adding all the numbers thus obtained, is also below 20%. The numbers show that the larger deviations are scattered around the city, with no observable corridors showing large differences. This might be due to the traffic counts not differentiating between through flows and parking search flows in the vicinity of the delivery destinations. The results also support the inclusion of the whole metropolitan area in the analysis, and incorporating the estimated freight-delivery interaction between the city and the surrounding commuting towns and industrial areas. Accepting the results as valid, for a network with a total link length of 1,907 km (including the whole city and the roads connecting it with the metropolitan area), the overall delivery vehicle flows during the morning peak hour add up to 276,500 vehicles•km (11.8% of the total in the metropolitan area), with an average speed of 30 km/h.

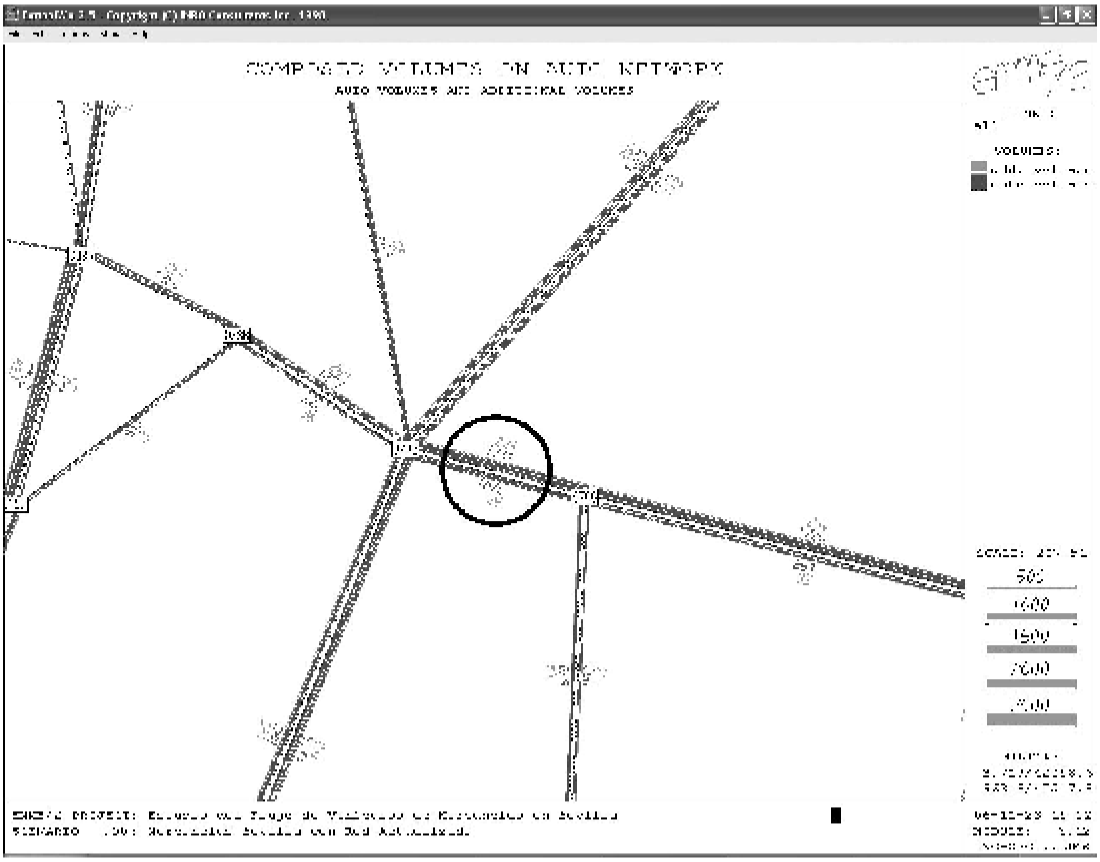

Figure 6 – Example of flow validation in the EMME/2 results. The circled link corresponds to Puerta de Carmona (nº 2 in Figure 5) and the numbers correspond to the passenger vehicle flow and the freight vehicle flow respectively.

Table III – Comparison between the results of models M1 and M2 with actual vehicle counts in different parts of the city..

Location	Street	Direction	Vehicle Counts	*M1* results	*M1* deviation	*M2* results	*M2* deviation
1	Torneo	Northbound	162	149	8%	380	135%
		Southbound	84	88	5%	137	63%
2	Puerta de Carmona	Southbound	132	113	14%	131	1%
3	Plaza D. Juan de Austria	Northbound	114	118	4%	195	71%
		Southbound	186	142	24%	139	25%
4	Eduardo Dato	Outbound	54	67	24%	145	169%
		Inbound	60	92	53%	58	3%
5	Luis de Morales	Northbound	135	125	7%	118	13%
		Southbound	162	181	12%	210	30%
6	Ramón y Cajal	Eastbound	102	53	48%	54	47%
		Westbound	222	215	3%	112	50%
7	Luis Montoto	Eastbound	54	53	2%	146	170%
		Westbound	204	246	21%	96	53%

8	Cruz del Campo	Eastbound	90	60	33%	138	53%
		Westbound	234	285	22%	158	32%
9	Kansas City	Inbound	168	180	7%	156	7%
		Outbound	114	135	18%	110	4%
10	María Auxiliadora	Clockwise	102	113	11%	125	23%
		Anti-clockwise	78	112	44%	164	110%
11	Arco de la Macarena	Clockwise	72	71	1%	192	167%
		Anti-clockwise	108	112	4%	76	30%
12	Bueno Monreal	Eastbound	180	234	30%	207	15%
		Westbound	120	153	28%	183	53%
13	Avenida de la Paz	Outbound	123	121	2%	381	210%
		Inbound	246	268	9%	100	59%
14	Paseo de Colón	Southbound	96	132	38%	133	39%
		Northbound	186	234	26%	229	23%
15	Paseo de las Delicias	Outbound	156	78	50%	155	1%
		Inbound	114	162	42%	56	51%
	Overall Weighted Deviation:				**19,23%**		**50,54%**

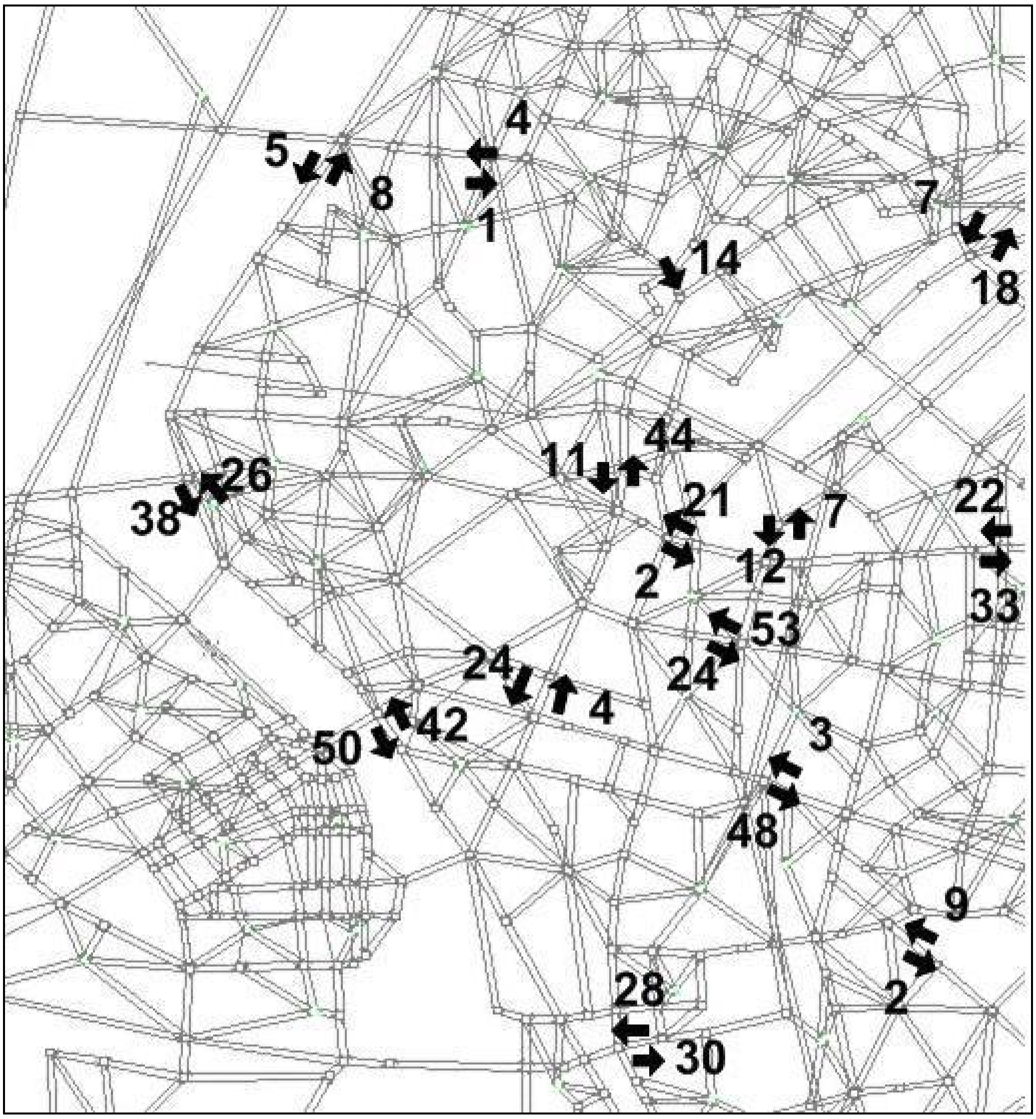

Figure 7 – Deviation percentages obtained in the different validation points distributed along the city of Seville.

CONCLUSIONS

With mathematical models being a representation of a complex reality, it is always possible to build more sophisticated urban freight models, introducing many more variables and parameters in the analysis. However, these additional variables and parameters may contribute to a better model fitting, but require much more data brought into the model. Keeping in mind that budget restrictions are often a definitive obstacle for primary data acquisition, while freight deliveries still need to be brought into the overall picture of urban traffic analysis, we have built a simple and feasible approach to estimate urban freight vehicle flows during the morning peak hour using a limited amount of available data. This model constitutes a first step along this line, appropriate for scenarios where the accuracy improvements obtained with more complex models would not pay off the additional costs in data provision.

Also, the application of the model to a real situation and its validation with traffic count data has confirmed its reasonable accuracy, always keeping in mind that the number of traffic counts used for validation would have to be much higher to guarantee sound statistical significance. Entropy maximisation seems to be appropriate to represent urban freight deliveries, and the simulated annealing algorithm ensures that we obtained the best solution in terms of entropy. But it is nevertheless true, as in any urban freight modelling effort, that the question of whether the delivery vehicles counted were really carrying freight remains unanswered. Further calibration of the O-D matrix could be undertaken using the traffic count data, but we have preferred to reproduce here the results of our model as they were produced by the trip generation and trip distribution models alone, to show their real accuracy and validity.

From an application-related perspective, the model described here is essentially oriented to urban policy evaluation, and among its possible uses stand the analysis of the effect of freight transport on peak-hour traffic, or its contribution to general pollution levels. It can also help to assess the way in which freight accesses commercial areas, identifying freight corridors in the city. Other possible applications include the evaluation from the point of view of freight deliveries of the introduction of new infrastructure in the network or new logistic policies, like consolidation or cooperation schemes. However, it is essential to stress the importance of systematic data collection on urban freight movements in order to further develop these modelling approaches. Also, the comparison between the results obtained by different models for different cities should be a future research objective, in order to determine to what extent the introduction of additional data and complexity produces an equivalent increase in the quality of the results.

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