GENERATING THE UNIVERSE OF URBAN TRIPS FROM A MOBILITY SURVEY SAMPLE WITH MINIMUM RECOURSE TO BEHAVIOURAL ASSUMPTIONS

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ABSTRACT

For any kind of statistical analysis of trip matching algorithms, working on the samples of mobility surveys is hopeless as these typically cover not much more than 2% of travellers. The usual inference process works on a discrete representation of the territory (zones) and simply replace each trip in the sample by as many equal trips as the corresponding multiplicative coefficient N (inverse of the sampling coefficient). This paper presents an innovative application of the mobility surveys data (with geo-referenced information) as an alternative to Activity-based procedures using discrete choice models. We introduce some principles of fuzzy logic inference processes, which allow the production of a synthetic population of trips with a continuous representation of trips in space and in time. The proposed procedure uses a statistical approach to trip dispersion, using a Monte Carlo Simulation process, based on the survey data and the land use characteristics in order to preserve the mobility patterns observed in the survey. The procedure was applied to the Lisbon Metropolitan Area (LMA) and the results show a good match with the original data, but with a greater, more realistic space and time coverage. The results suggest a significant added value of this approach for the modelling of transport modes requiring space and time matching that cannot be correctly modelled with the traditional discrete representation of the territory as well as for estimation of traffic loads in low hierarchy arcs of the network.

Keywords: Mobility survey, Activity-based models.

INTRODUCTION

O/D matrices are a key ingredient of current travel analysis and planning studies. Although several complex algorithms to estimate O/D matrices from traffic counts have been developed in last decades (Gaudry and Lamarre, 1979; Kuwahara and Sullivan, 1987; Spiess, 1987; Cascetta and Nguyen, 1988; Doblas and Benitez, 2005; Ma et al., 2005), the traditional way of estimating O/D remains based on mobility surveys (Bierlaire and Toint, 1995), which is generally expensive. Commonly, O/D matrices estimates are based on small samples of home-interview data, which even in systematic data collection processes rarely go over sampling rates of 2%.

The geographical and statistical accuracy of this approach can really be a constraint to the modelling of some transport systems, mainly for transport systems with small mode shares (Ortúzar and Willusen, 2001).

In order to avoid these limitations as well as to allow representation of interdependencies among trips by the same person during a particular day, a new approach to travel demand modelling has emerged: activity-based models. These models build upon the set of activities developed by each interviewee an simulate his / her travel choices trying to reflect the strategies adopted by individuals and households when they are faced by restrictions imposed by transport supply and policies (Recker et al., 1985). These strategies could range from mode change, trip rescheduling, trip chaining and destination substitution, thus involving complex decision mechanisms.

The new generation of models based on the activity based approach include (Davidson et al., 2007):

- A tour based structure, being the tour a closed chain of trips starting and ending at the base location, (either home or workplace);
- An activity based platform implying that modelled travel is derived within the general framework of daily activities;
- Microsimulation techniques applied to the individual level converting activities and travel related choices in decisions among discrete choices.

This level of detail allows a better prediction of aggregate travel statistics, because they are ensured by more realistic and consistent representation of the underlying individual travel choices (Davidson et al., 2007).

The analysis of travel behaviour based on the activities performed by individuals has appeared in the beginning of the 1970s both in US and England. The activity based approach relies on individual activity programs and on its spatial and temporal restrictions. Basically travel behaviour is considered a demand derived from the activities that individuals want and need to do in different spatial locations (McNally, 2000; Handy, 2004). Thus in order to better understand travel behaviour one needs to know better the choices about the activities performed by the individuals. As a consequence the sequences and behavioural patterns replace trips as relevant analysis units (McNally, 2000).

Although the use of activity based models has increased significantly in the recent past these models are still a minority among the operational models. In the U.S. there are about 6 operational activity based models and 7 under development (Rossi et al., 2009). In Europe activity based models where developed for Stockholm (Algers et al., 2001), for Switzerland (Raney et al., 2003) and in the Rotterdam region (Arentze et al., 2000).

This paper presents an innovative approach to estimate O/D matrices and generate a universe of trips using data from a mobility survey sample instead of developing an activity-based model. This model allows modelling an entire population of trips considering trip chaining effects with the minimum recourse to the kind of behavioural assumptions and calibrations used in activity-based models. This approach allows a detailed statistical analysis of trip matching algorithms required for the assessment of intermediate transport modes that require matching between customers and between customers and vehicle (e.g. shared taxi, carsharing, carpool) without the recourse to complex models using ruled based activity models as ALBATROSS (Arentze et al., 2000) or discrete choice models as ILUTE (Salvini and Miller, 2005).

Three types of arguments support the use of this new modelling approach:

- Small sampling rates of current mobility surveys (rarely above 2%) that lead to many blank O/D matrix cells in conventional O/D estimation procedures, only solved with the use of larger zones;
    - Modelling of transport modes with low mode shares in real world, which may be misrepresented in the original survey for a large amount of O/D pairs;
- The need to evaluate the market potential of intermediate modes, involving some kind of sharing of vehicles and services by people with similar displacement needs, thus which depend on the proximity / overlap in space and in time of trips by different people, requires a micro-simulation approach (also made possible by the increasing computing power);
    - These models may dispense the concept of zones altogether, simulating each individual trip chain, but there are many locations not represented in the sample;
- Lack of finer data required for the calibration of conventional activity-based models.

The model presented in this paper uses a Fuzzy Theory methodology in order to extrapolate from conventional mobility surveys into a “virtual reality” where we represent the extreme points of all the trips in the population (origins and destination).

The developed methodology is based on the land uses of the study area with a rather fine territorial grain (some of them estimated in the case study shown here, due to poor statistical information at the time) as the “spreading” function around the available origins and destinations stated in the sample, considering different attachment to the original origin/destination depending on the distance among other variables.

Land uses are aggregated into the smallest statistical unit – a census tract, that in most cases are equivalent to a city block. Each census track centerpoint will then act as the origin and destination of the trips generated by the model.

The proposed procedure uses a statistical approach to trip dispersion, using a Monte Carlo Simulation process, based on the survey data and the land use characteristics in order to preserve the mobility patterns observed in the survey.

This procedure was applied to the Lisbon Metropolitan Area (LMA) using a mobility survey with a sample rate of 0.53%. This research is part of a more comprehensive project comprehensive project (SCUSSE, part of the MIT Portugal Program) that tries to evaluate the impact of innovative modes and services for urban transportation, including such concepts as urban road pricing with variable tariff levels and the CityCar, which should be considered in this project as part of the innovative solutions from the transportation sector.

METHODOLOGY

Introduction

Using a mobility survey, the model uses the available information from the original surveyed person to:

- Generate a set of persons similar to the interviewee (depending on the survey expansion multiplicative coefficient of the person);
- Model the trip chain of each new "virtual person" – preserving the array of trip purposes stated on the survey;
- Introduce (relatively small) variations in time and in space distance (keeping all the other attributes of each trip) – which depend of the origin and destination, the trip purpose and mode used for each trip;

The model uses statistical data from the survey to establish constraints and membership functions to determine "virtual origin and destination", attached to the land uses associated with the trip generation of each census track.

This model requires as input data:

- A mobility survey with geocoded trip ends and characterisation of the respondent and each trip that he performs;
- A detailed land use database used as seed for trip generation/attraction functions;
- A characterisation of the trip generation/attraction rates of land use activities for different times of the day and relation with the purpose of the trip (worker, visitor or other);
- A characterisation of the travel times in different transport modes and the number of transfers required in public transport between all the census tracts of the study area.

Framework

Figure II presents the logic framework of the trip generation model. Using the data available from a mobility survey, where all the trips from the same respondent are sorted, the model starts by building a person whose general attributes are the same as for the original respondent, but the origin and destination of his trips (residential, work and other activities location) is set by the land use patterns of the study area and the mobility and accessibility characteristics for the time of day that the trip was performed, and the trip start time can suffer some changes around the stated time of the trip.

Each respondent is then converted into a set of "siblings", the number of which depends of the expansion coefficient of the respondent in the survey, presenting the same attributes but some changes on their trip ends and trip scheduling. In spite of the changes introduced, the new set of travellers preserves the mobility patterns of the original respondent (e.g. trip production and chaining, transport modes, approximate travel time budget).

During the simulation, the model assesses the compatibility of the trip chain that is being generated with the travel time budget observed in the original respondent, and the time-space compatibility between anchor mobility points observed (residential and work or study place location).

For each trip end location the model calls a function (Census tract ownership function), which determines the trip end location using a Monte Carlo Simulation procedure. This ownership function is different for trip origins or destinations and is the core of the model.

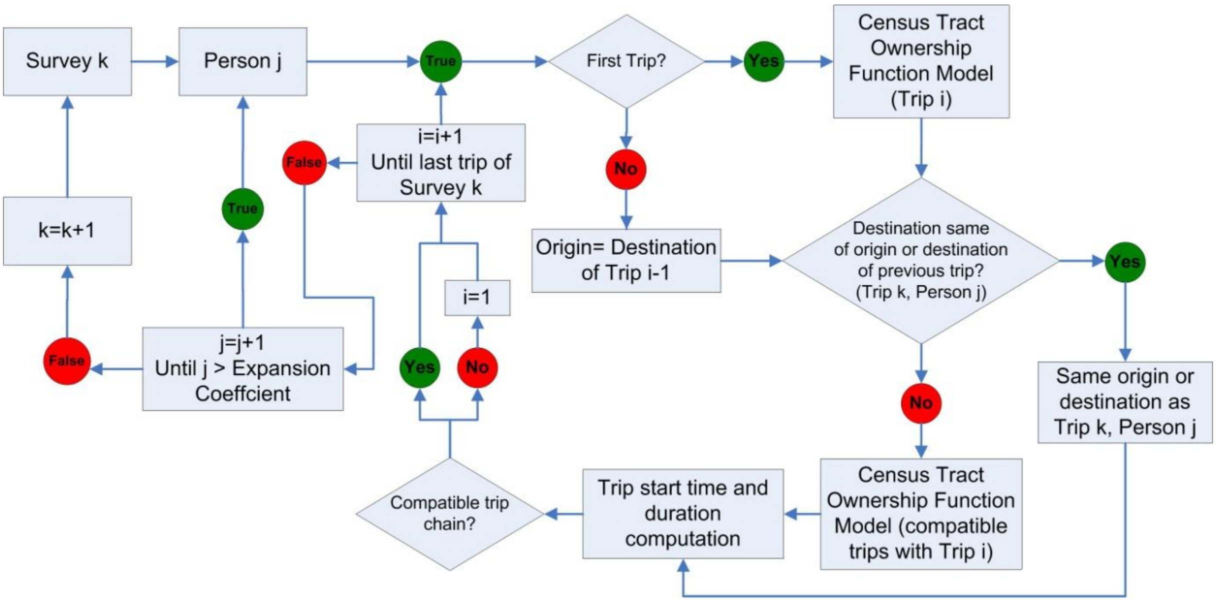

Figure I – Trip Generation Model Framework

Origin/Destination Ownership Analysis

The origin/destination ownership function is computed for each census tract of the modelling area for each trip. This model is based on a trip generation rate for each type of land use, linked to the trip purpose and the trip departure time.

The general framework of the function is presented in Figure II. Each type of land use presents a different trip generation rate for three different types of daily trip generation rates: workers, visitors and other (basically suppliers). Each type generation presents also different statistical distributions of trips along the days, where workers trips are normally more related with commuting peak hours during the morning and the afternoon, and visitors and other are more distributed along the day. Nevertheless, each land use type presents a different configuration of the statistical distribution along the day, where for example Restaurants and bars workers present a different time of the day for greater trip concentration than office workers.

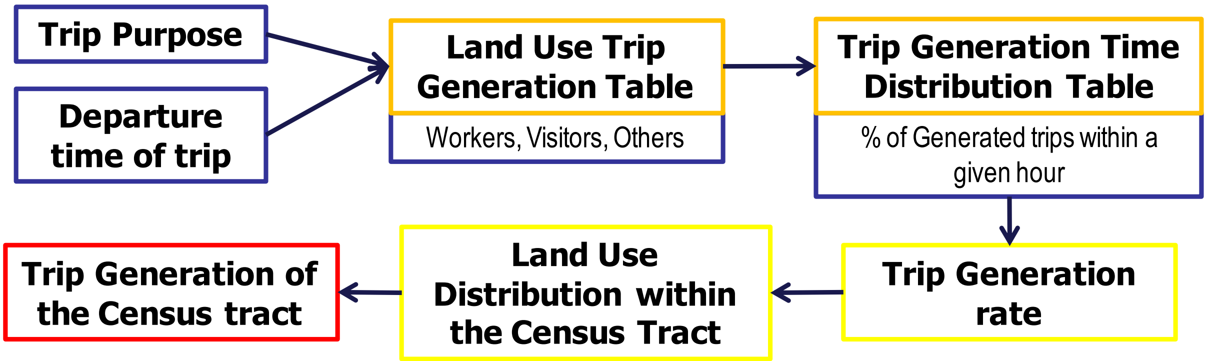

Figure II – Origin/Destination Ownership Function

Based on the land use distribution of each census tract, the model computes a trip generation rate. These generation rates are then corrected by some model correction factors and constraints.

Model Constraints and Correction Coefficients

The resulting trip generation for each census tract (BGRI) is "corrected" by a [0,1] factor related to its compatibility with the distance to the original point of the survey (just used for the first trip of the trip chain, normally linked to the residence), the declared transport mode (taken as fixed), and the travel time between census tracts for the stated transport mode.

The correction coefficient linked with the distance to the original points of the survey in the first origin of the trip chain, was developed using a parameterized "inverse logistic" function presented in Figure III. The correction parameter λ is an input parameter, which represents the distance in meters that produces a reduction of 10% of the coefficient (for each trip purpose this is the average highest distance that people consider as "near").

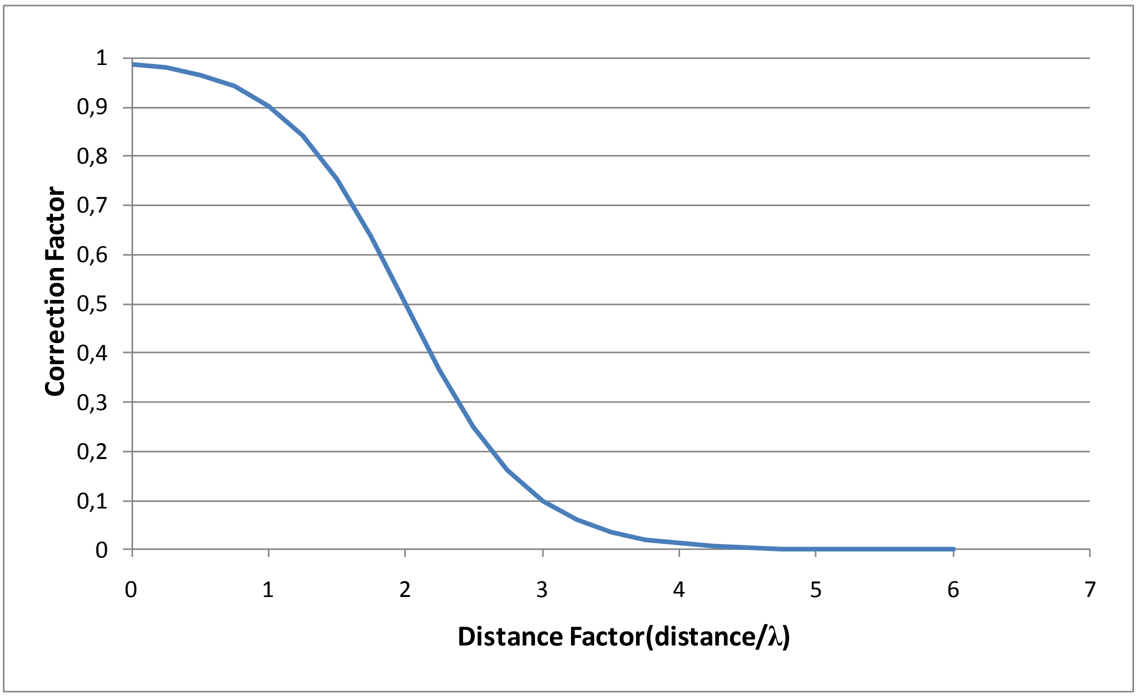

Figure III – Parameterized Inverse Logistic Function

The declared transport mode correction factor present following configuration for the different transport modes:

- For walking or biking the mode coefficient is 1 (all BGRIs are fully compatible)
- For private car (PC), the coefficient is computed based on the private car mode share of that BGRI and its neighbors, as declared in the survey.
- For public transport (PT) the coefficient presents a double layer:
    - Minimum number of transfers needed to connect the O/D BGRI pair (previously computed) – if this is higher than declared in the survey, the coefficient takes a value of 0, otherwise the value is 1.
    - An "inverted logistic" coefficient associated with the distance from that BGRI to the closest PT stop (pre-computed).

The last type of correction factor is a travel time compatibility assessment for a given O/D pair (origin and destination) between census tracts for the stated transport mode.

The expected travel times between all census tracts of the modelling area, for different transport modes, are previously computed in minutes. For a given O/D pair of census tracts, the travel time is compared with the travel time between the original survey census tracts of the survey. If this difference is greater in percentage or total value than the tolerance parameters the coefficient takes the value 0, otherwise it takes the value 1. The default tolerance parameters of the model are 25% in percentage or 15 minutes in absolute value.

After computing all the constraints and correction factors, they are multiplied by the trip generation of each census tract calculated by the origin/destination ownership function. Taking into consideration all the candidate census tracts for the origin or destination of the trip under analysis, the resulting corrected trip generation of each census tract is then converted into a probability of being the origin or destination of that trip.

APPLICATION OF THE MODEL: THE LISBON METROPOLITAN AREA (LMA)

Data Description

This new methodology was developed using the Lisbon Metropolitan Area (LMA) formed by other 18 municipalities as a case study, which has an area of approximately 320,000 ha, with approximately 2.8 million inhabitants, representing roughly 25% of Portugal population (Figure IV).

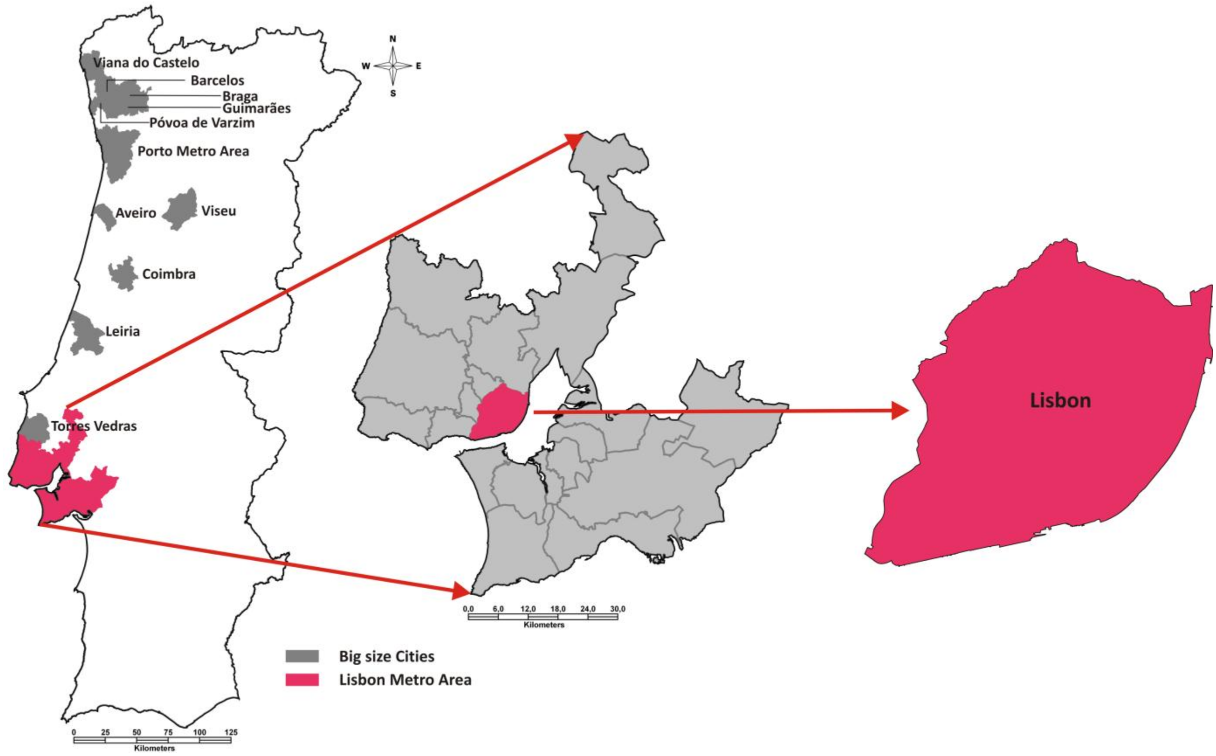

Figure IV – Lisbon location and metropolitan structure

The model uses a 1994 Mobility Survey of this metropolitan area as a data set. The Mobility Survey includes a sample of 30,681 respondents who describe their daily individual trips (only 21,954 respondents with trips performed that day), resulting in a total of 58,818 trips (46,106 trips during the week), all having their trip ends geocoded. After weighting, the survey estimate of daily trips in the LMA is 11,125,000 trips (4,826,389 trips during a regular week day).

The survey includes information on the household composition, with a detailed characterisation of all the members of the household (e.g. age, sex, profession, education level, driving license and car ownership) and a detailed description of the trips performed by the respondent the previous day.

This description of each trip includes

- The trip purpose classified in eight types: work/study, returning home, in service, shopping/leisure, meal, drop/take relative, personal matters and other;
- The trip departing and arrival time;
- The transport mode used and the number of transfers (with geocoded point of transfer)
- Information if the trip is home based and if it performed alone or accompanied;
- The coordinates of the origin and destination of the trip.

The aggregate mode share observed for the total number of registered trips is: 26% for soft modes (walking and biking), 32% for general public transport and 42% for private car. Analysing the trip length and the trip duration distributions for each aggregate transport mode presented in Table I, we can observe that private car trip while averagely longer in distance present smaller travel times than public transport. This fact shows that the travel time acceptance in the study area for a trip a similar across motorised modes, which leads to longer trips, normally with origins located in more disperse locations and with worse public transport coverage, being made by private car. Walking and biking trips present a considerable range of variation, the average walking or biking time being approximately 18 min.

Table I – Statistical distribution of trip length and duration for each transport mode

Mode	Average Trip length (km)	St. Dev. Trip length (km)	Average Travel time (min)	St. Dev. Travel time (min)
Walking and biking	1.37	4.27	17.81	17.14
Private car	14.42	34.50	31.55	34.73
Public transport	7.31	15.81	41.60	31.48
Airplane	231.97	39.95	307.50	286.38

Table II presents a similar analysis but classified by trip purpose. There is less variation observed within trip purposes than by transport modes. Nevertheless, we can observe smaller trip lengths for meal trips and larger lengths for trips in service, as expected.

Table II – Statistical distribution of trip length and duration for each trip purpose

Trip Purpose	Average Trip length (km)	St. Dev. Trip length (km)	Average Travel time (min)	St. Dev. Travel time (min)
Work/study	7.89	20.15	32.45	29.05
Returning home	9.96	27.42	33.46	34.01
In service	16.19	39.85	32.94	37.53

Trip Purpose	Average Trip length (km)	St. Dev. Trip length (km)	Average Travel time (min)	St. Dev. Travel time (min)
Shopping/leisure	9.38	28.07	25.46	29.50
Meal	4.66	15.59	19.42	17.56
Drop/take relative	5.26	13.45	20.81	18.71
Personal matters	9.69	25.95	31.87	30.27
Other	12.57	37.60	32.93	42.39

An assessment of the performed trip chains in the database revealed some interesting patterns. Table III presents the most significant trip chains observed in the database (approximately 81% of the sample), where we can see the percentage of each type of trip chain in the sample and the average travel time budget observed. The sample reveals that approximately 44% of the persons perform daily simple commuting trips, while commuting trip with intermediate stops just represent approximately 13%.

This value represents a database from 1994, when single purpose trips and simple trip chains remained as the main share of daily journeys. This figure has been evolving in more recent years towards more complex journeys and with a considerable decrease of the percentage of commuting trips.

Table III – Summary of the trip chain configurations observed in the database

Trip chain	Percentage	Average travel time budget (hours)
Work/study – Returning home	44.24%	1.36
Shopping/leisure – Retuning home	11.10%	0.87
Personal matters – Retuning home	9.38%	1.32
Work/study – Meal – Work/study – Returning home	4.91%	1.29
Work/study – Returning home – Work/study – Returning home	2.60%	1.46
Work/study – Returning home – Shopping/leisure – Returning home	2.46%	1.75
Other – Returning home	1.77%	1.26
Work/study – Shopping/leisure – Returning home	1.03%	1.61
Shopping/leisure – Returning home – Shopping/leisure – Returning home	0.91%	1.18
Work/study – In service – Returning home	0.85%	2.58
Work/study	0.82%	1.29
Work/study – Personal matters – Retuning home	0.81%	1.93

This assessment of the database allowed us to identify some patterns that identify more usual trip chains, the time and distance configurations also present in the database by transport mode and trip purpose. This information is relevant for the parameterisation of some tolerance values present in the model.

To model the census tract ownership functions a land use and activities database obtained from the Yellow pages web site (http://www.pai.pt) was used, which gathers an ample set of activities which have a fixed line phone number. These activities were clustered in 9 types of activities which are:

- Agriculture, which gathers all the agricultural and other related activities;
- Education, which encompasses all the types activities related to education, ranging from nursery and primary schools to universities;
- Health, which includes all the heath facilities within the study area, ranging from a small doctor's surgery to a hospital;
- Hotels, which cover all the accommodation facilities in the study area;
- Manufacturing, including all the manufacturing and related activities;
- Public entities, which include all the public entities and public offices;
- Private offices, which encompass all the private firms, ranging from a bank branch to a big consultancy firm;
- Restaurants, bars and leisure activities, which include all the food and beverage activities and other leisure activities (e.g. tennis courts or cinemas and theatres);
- Retail, which include all the retail shops in the study area.

The other land use type used apart from these 9 classes was dwelling units, which were obtained by the statistical data available at the census tract level.

Application to the LMA

The database of the mobility survey presents different spatial geocoding resolution for the Lisbon municipality, with very detailed geocoding to the door of the building of the origin or destination, and for the other municipalities of the LMA, with a very rough geocoding to the centroid of the Freguesia (parish). This variable geocoding detail forced us to consider an adaptation of the original model for the current database.

The process was simplified considering that trip ends located outside the municipality of Lisbon where re-assigned using no distance to origin corrections.

This paper only presents a sensitivity and O/D matrix compatibility assessment for the case study, where the sensitivity analysis was computed using 10 runs for several λ values (300, 600 or 900 meters), the travel time tolerance parameters remaining constant, and the O/D matrix compatibility using a reference zoning system with 66 zones, 40 of which inside the Lisbon municipality.

Assessment of the Results

Using a 66 zones discretisation of the study area, we computed a sensitivity analysis of the model estimated within the 10 models runs for each λ value. The results are presented in Table IV, where we can observe a small variability of the estimations for the 10 runs of λ value. There is no evident trend of increased variability with the increase of the λ value.

Table IV – Sensitivity analysis results within each λ value run

Indicator of Model Internal Variability	λ = **300 m**	λ = **600 m**	λ = **900 m**
Average VC[1] per across O/D matrix cells	0,0885	0,0912	0,0909
Average Dispersion[2] across O/D matrix cells	0,2737	0,2834	0,2815
Average VC[1] across Origins	0,0050	0,0049	0,0057
Average Dispersion[2] across Origins	0,0161	0,0158	0,0176
Average VC[1] across Destinations	0,0053	0,0049	0,0120
Average Dispersion[2] across Destinations	0,0167	0,0161	0,0407

Using a set of indicators for the assessment of the quality of zoning schemes defined in (Martínez et al., 2007; Martínez et al., 2009), we can compare the resulting O/D matrices for the different λ values and the raw survey data. These indicators are:

- Percentage of intra-zonal trips in the O/D matrix, which measures the percentage of trips on the O/D matrix main diagonal that represent trip inside the same zone.
- Percentage of 0 flow cells in the O/D matrix, which account the percentage of cells without any flow in the resulting O/D matrix.
- Percentage of cells with no statistically significant values, which measure the percentage of cells of the O/D matrix that have flow values lower than a reference value computed for a given significance level.
- Percentage of trips in non statistically significant O/D matrix cells, which measure the percentage of the O/D matrix trips in cells that have flow values lower than a reference value computed for a given significance level.
- Noise Level, which stands for the sum of the percentage of intra-zonal trips and the percentage of trips in non statistically significant O/D matrix cell for a given zoning system. This indicator excludes the overlapping of both components (subtraction to the sum of both percentages).

The results are presented in Table V, were we can denote that the λ parameter variation does not introduce a significant change in the estimates, with the exception of the noise level where we can see a decreasing trend with the increase of the λ value.

Comparing the results with the raw survey data O/D matrix, we can observe a small reduction of the percentage of intra-zonal trips and the percentage of zero flow cells in the O/D matrix. The percentage of cells with no statistically significant values does not present a clear tendency, while the percentage of trips in non statistically significant O/D matrix cells and the noise level, present more favourable values that the outputs of the trip generation model. This fact is mainly linked to a more balanced distribution of trips among the different O/D pairs, which might lead in some situations to non statistically significant situations. Nonetheless, this fact might lead to more accurate estimates for the trip assignment models, due to the more detailed representation of the O/D matrix flows.

[1] VC stands for variation coefficient .

[2] Dispersion stands for .

Table V – Summary of the O/D matrix analysis for the different λ values and raw survey data

O/D Matrix Estimation Process	Percentage of Intra-zonal trips in the O/D matrix	Percentage of 0 flow cells in the O/D matrix	Percentage of cells with no statistically significant values[3]	Percentage of trips in non statistically significant O/D matrix cells[3]	Noise Level
λ = 300 m	37,23%	4,36%	84,39%	23,28%	60,40%
λ = 600 m	37,13%	4,33%	84,41%	23,36%	60,38%
λ = 900 m	37,04%	4,34%	84,27%	23,27%	60,19%
Raw Survey Data	38,93%	29,50%	84,39%	19,37%	58,26%

We also performed an O/D matrix compatibility assessment. The results of this analysis are presented in Figure V and Figure VI, where we can observe a considerable fit of the number of trips hourly generated by the original and estimated survey.

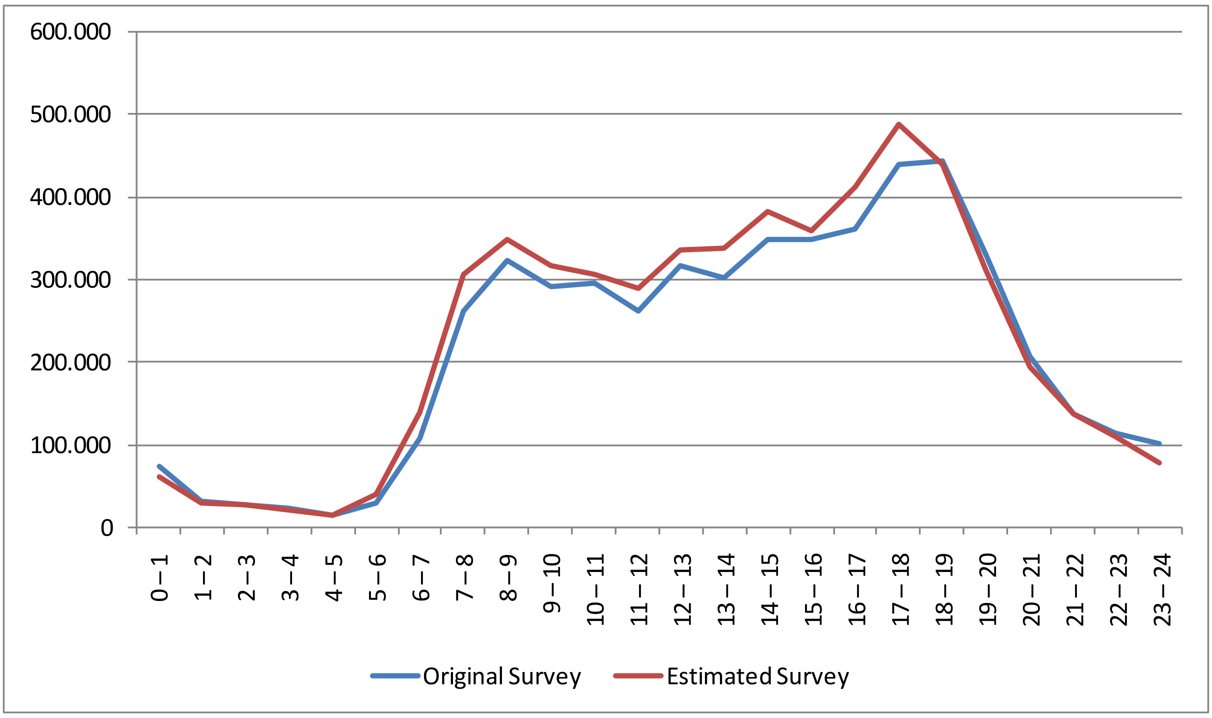

Figure V – Total number of trips generated per hour

[3] Defined as limit for statistical significance, relative error lower than 50%.

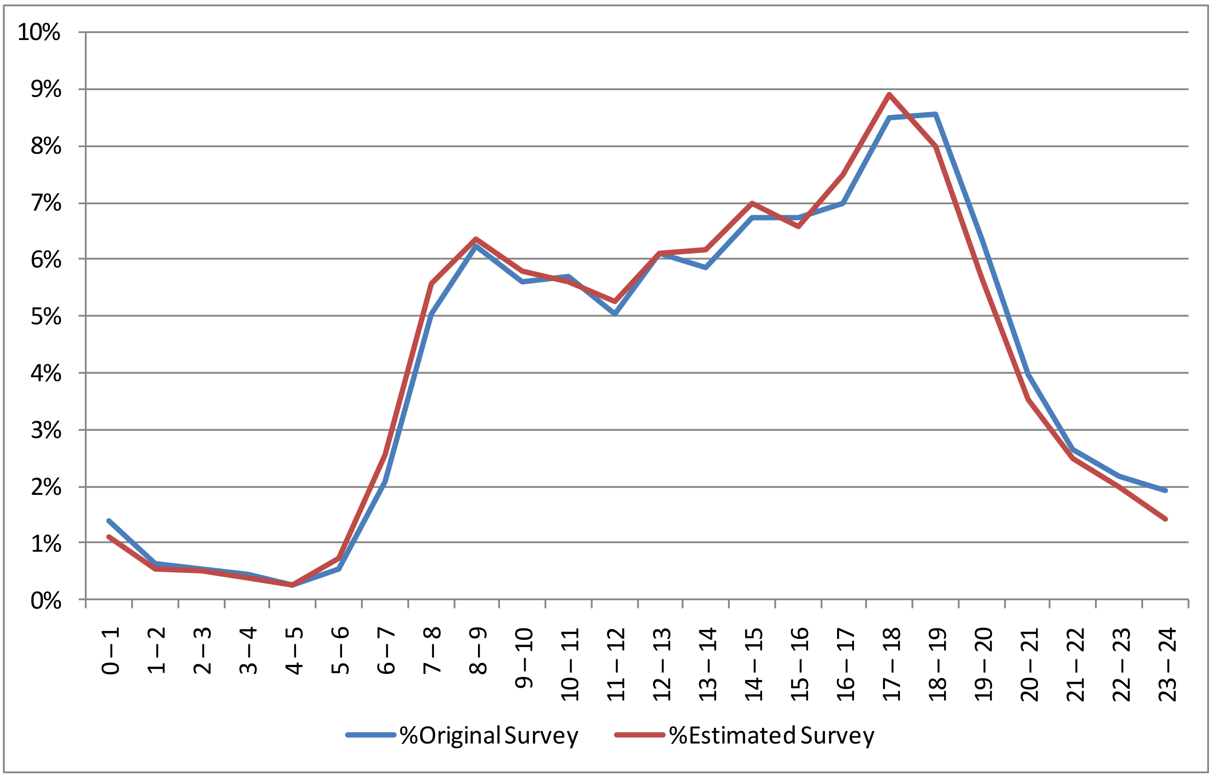

Figure VI – Percentage of number of trips generated per hour

CONCLUSIONS AND FURTHER DEVELOPMENTS

This paper presents an innovative travel and activity inference process, which introduces some principles of fuzzy logic inference processes, allowing the production of a synthetic population of trips with a continuous representation of trips in space and in time, using a current mobility survey, the transport network configuration and the land use and activities statistical and spatial distribution.

The methodology is currently under a validation process, using a LMA mobility survey and test bed. The results show a considerable robustness of the simulation parameters and a good overall fit with the original survey. And, as intended, the spatial dispersion of trip ends increases considerably, filling the space in a way that is much more coherent with the actual land-uses, allowing a more detailed spatial representation of the study area trip patterns and people concentration.

This is already allowing us to work with the current results as the basis for estimating the market potential for shared taxis and minibus express services, both of which are dependent on the availability of estimations of starting and ending points of trips with much better resolution than earlier available.

The next steps of our developments consist of checking the traffic flow estimates obtained with traffic allocation models based on these matrices (in successive simulation suns), and compare them with regular traffic counts obtained with automatic sensors, to see whether the variability we expect in the model results is similar or not with the variability existing in the real world, especially in links of low hierarchy. We hope to be able to develop a measure of dispersion of traffic values on links that should be considered for planning purposes, depending on the hierarchical level and on the expected value of that traffic flow.

REFERENCES

Algers, S., J. Eliasson and L.-G. Mattsson (2001). Activity-based model development to support transport planning in the Stockholm region. *5th Workshop of the TLE Network*, Nynäshamn.

Arentze, T., F. Hofman, H. van Mourik and H. Timmermans (2000). ALBATROSS - Multiagent, rule-based model of activity pattern decisions. *Transportation Planning, Public Participation, and Telecommuting*, No.1706, pp. 136-144.

Bierlaire, M. and P. L. Toint (1995). MEUSE - an Origin-Destination Matrix Estimator That Exploits Structure. *Transportation Research Part B-Methodological* Vol.29, No.1, pp. 47-60.

Cascetta, E. and S. Nguyen (1988). A Unified Framework for Estimating or Updating Origin Destination Matrices from Traffic Counts. *Transportation Research Part B-Methodological* Vol.22, No.6, pp. 437-455.

Davidson, W., R. Donnelly, P. Vovsha, J. Freedman, S. Ruegg, J. Hicks, J. Castiglione and R. Picado (2007). Synthesis of first practices and operational research approaches in activity-based travel demand modeling. *Transportation Research Part a-Policy and Practice* Vol.41, No.5, pp. 464-488.

Doblas, J. and F. G. Benitez (2005). An approach to estimating and updating origin-destination matrices based upon traffic counts preserving the prior structure of a survey matrix. *Transportation Research Part B-Methodological* Vol.39, No.7, pp. 565-591.

Gaudry, M. and L. Lamarre (1979). Estimating Origin-Destination Matrices from Traffic Counts - Simple Linear Inter-City Model for Quebec. *Logistics and Transportation Review* Vol.15, No.5, pp. 631-642.

Handy, S. (2004). Critical Assessment of the Literature on the Relationship among Transportation, Land Use and Physical Activity. Transportation Research Board and the Institute of Medicine Committee on Physical Activity, Health, Transportation and Land Use.

Kuwahara, M. and E. C. Sullivan (1987). Estimating Origin Destination Matrices from Roadside Survey Data. *Transportation Research Part B-Methodological* Vol.21, No.3, pp. 233-248.

Ma, G. Y., P. Li, Y. Wen and X. Y. Du (2005). Application of genetic algorithm in estimating origin-destination matrices of traffic network. *2005 IEEE International Conference on Granular Computing, Vols 1 and 2*, pp. 209-212

733.

Martínez, L., J. Viegas and E. Silva (2007). Zoning Decisions in Transport Planning and Their Impact on the Precision of Results. *Transportation Research Record* Vol.1994, No.1, pp. 58-65.

Martínez, L., J. Viegas and E. Silva (2009). A traffic analysis zone definition: a new methodology and algorithm. *Transportation* Vol.36, No.5, pp. 581-599.

McNally, M. G. (2000). The Activity-based Approach. *Handbook of Transport Modelling*. (D. A. H. e. K. J. Button, Eds.). Amsterdam: Pergamon.

Ortúzar, J. and L. Willusen (Eds.). (2001). *Modeling Transport*. New York: John Wiley and Sons Inc.

Raney, B., N. Cetin, A. Völlmy, M. Vrtic, K. Axhausen and K. Nagel (2003). An Agent-Based Microsimulation Model of Swiss Travel: First Results. *Networks and Spatial Economics* Vol.3, No.1, pp. 23-41.

Recker, W., M. M. G. and G. S. Root (1985). A Model of Complex Travel Behavior: Part I. A Theoretical Model. *UCI-ITS-AS-WP-85-2*. Institute of Transportation Studies, University of California Irvine 12.

Rossi, T., B. Winkler, T. Ryan, K. Faussett, Y. Li, D. Wittl and M. A. Zeid (2009). Deciding on Moving to Activity-Based Models. *88th Annual Meeting of the Transportation Research Board*, Washington D.C.

Salvini, P. and E. J. Miller (2005). ILUTE: An operational prototype of a comprehensive microsimulation model of urban systems. *Networks & Spatial Economics* Vol.5, No.2, pp. 217-234.

Spiess, H. (1987). A Maximum-Likelihood Model for Estimating Origin Destination Matrices. *Transportation Research Part B-Methodological* Vol.21, No.5, pp. 395-412.