

# ANALYZING WEEKLY ACTIVITY-TRAVEL BEHAVIOUR FROM BEHAVIOURAL SURVEY AND TRAFFIC DATA

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## ABSTRACT

Trips are the necessary links between activities, involving the movement from one activity location to the next, and, as such, are strongly correlated with activity timing and the chosen mode of transport. With the aim of linking measured daily traffic with travellers' weekly activity patterns, in this study we work on two complementary views of weekly mobility: the longitudinal disaggregate behavioural aspects over the week and the transversal aggregate measure of traffic for each day of the week.

A sample of individuals had been selected within a study area around the city of Ghent, Belgium, and their activities and movements have been recorded and categorized with a behavioural survey. In parallel, traffic flows have been measured during the same weeks on the same area using loop detector and pneumatic tube data. By comparing the two datasets specific daily traffic patterns could be directly related to the weekly scheduling of individuals' activities, both on day-to-day and on a within-day basis.

It was found that, although home-work trips are the majority on workdays they represent only less than  $\frac{1}{4}$  of all daily trips. On weekends work-related trips are reduced to 5%; however, the total number of trips on Saturdays does not reduce considerably, which suggests that other purposes become much more important (e.g., shopping, sport activities). These trends are in line with the analysis of traffic flow data, where on Saturdays the total daily demand is comparable to a weekday, but the OD flow patterns

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are significantly different over the day. The joint collection of behavioural panel data and traffic data offers numerous possibilities for further theoretical research developments (i.e., for advanced behavioural models and dynamic traffic assignment). From the theoretical side, the proposed methodology can be adopted in models of travel demand to calibrate and validate behavioural model parameters, and vice versa activity-travel behaviour analysis can support and improve the results from OD estimation procedures. From the applied side, policy makers will benefit from the outcome of this study by having a more complete picture of weekly rhythms of daily life, habits and routine across a representative sample of households.

## **INTRODUCTION**

Mobility is an essential element in people's daily activity patterns. The scheduling and time dedicated to the different activities depend among others on the duration and the opportunity of travelling from one activity to the next. Nowadays, faster mobility options allow one to schedule more activities within a day and to travel longer distances with comparable journey times. However, despite the growing speed at which people can move from activity to activity, more and longer travels cause more congestion, safety and pollution issues. Therefore, understanding the relationship between daily activities and mobility is fundamental to identify the causes and the eventual remedies to guarantee a more sustainable mobility.

The view that the key to sustainability in this area lies in transport policies affecting the mobility behaviour (i.e., the daily transportation demand) is nowadays widely acknowledged. It is however remarkable that, so far, nearly all efforts have concentrated on the analysis of the demand on a daily basis, for instance focusing on activity-travel chains and durations, assuming that travel times and activity patterns would repeat every day, at least on an aggregate level. This emphasis on the daily horizon unfortunately contradicts the intuitive knowledge that a substantial fraction of activities are repeated from week to week, not from day to day. If one excludes work and schools trips, it is not hard to see that a number of trips follow a weekly cycle (shopping, sport or cultural activities, etc.). Nowadays, even work activities have partly lost their day-to-day repeatability, due to an increasing number of part-time jobs, teleworking or flexible work schedules, very often organized on a weekly basis [1]. Therefore the assumption that, although individuals' weekly activity-travel patterns may be clearly distinguished depending on the day of the week, differences may not be visible at an aggregate level (i.e., the well-known constant travel time, or travel time budget, principle, see e.g. [2]-[3]) is gradually weakening. This phenomenon is being observed particularly in countries like Belgium, where the above employment conditions are rather common. Furthermore, new management policies are expected to change travel behaviour beyond a single day, for

instance dynamic pricing is expected to yield a shift and bunching of non-work activities both during off-peak periods and during the weekend days.

On the basis of these considerations, this paper presents the preliminary results of a project aiming at performing a joint analysis of weekly activities and travel choices of individuals and the (resulting) daily traffic patterns: *Behaviour and Mobility within the Week (BMW)*. The main line of thought in this project is to view traffic not as a stand-alone phenomenon, obeying its own logic, but rather as a derived effect of activity patterns [4]. The main objectives of this project are therefore to:

- collect both behavioural and traffic flow data to prove that weekly cycles are important in the household mobility decisions;
- analyze weekly activity-travel patterns and their impact on day-to-day travel demand variations;
- reconcile these variations with observed traffic flow variations measured in the field through traffic flow data;
- acquire insight into the complementarity of the two approaches, in order to
- enrich activity-based demand models and dynamic origin-destination models to better deal with weekly cycles.

The joint collection of behavioural panel data and traffic data will offer numerous possibilities for further theoretical research developments (e.g., for developing, calibrating and validating advanced behavioural or dynamic traffic models). From the applied side, policy makers will benefit of the outcome of this study by having a more complete picture of weekly rhythms of daily life, habits and routine across a representative sample of households.

This paper is structured as follows. The next section gives an overview of the state-of-the-art on multi-day behavioural activity-travel surveys and will describe the traditional methods adopted in demand estimation from traffic data. Next, a description of the methodology adopted in this study is given, followed by a description of the study area and the data collection. Analysis of results is later provided, followed by a summary of the main conclusions and recommendations.

## LITERATURE REVIEW

### Activity-travel surveys

The principle of trip-based behavioural surveys is to collect trips of each individual from a sample of the population during a certain period. The information generally asked for each trip includes the departure and arrival times, the purpose, the transport modes, the distance and the destinations. These surveys are essential for mobility demand

modelling. However, most of these models are built on the paradigm that mobility is essentially linked to work and exhibits daily cycles. Such single-day analyses implicitly assume uniformity and/or behavioural independence in activity decisions from one day to the next [5]. On the other hand activity-travel models based on multiday data help identify rhythms or patterns in activity-travel behaviour over longer periods of time, thereby recognizing day-to-day variations and dependence in activity decisions across days [6]. For instance, multiday studies recognize that an individual's likelihood of participation in shopping on any given day will tend to increase the longer s/he has not participated yet in such an activity [7]. Multiday models can also better explain how individuals respond to a policy measure on a day-to-day basis. For example, an individual who has to drive a child to school on one day of the week while travelling to work may be reluctant to switch to other travel modes, in response to a policy action such as congestion pricing, even on days s/he is not dropping the child [8].

Therefore, the need for multiday activity-travel data analysis had been recognized already from the early '70s. It is however very difficult to find survey periods that are longer than a week due to the burden on the survey respondent, and typically they are between one to three days long [9]. An exception is a five-week travel survey conducted in Uppsala, Sweden, which was used to classify the day-to-day activity scheduling behaviour, its heterogeneity among individuals and the effect of habit in repetitive travels [10]-[12]. A seven-day activity diary survey was also conducted in England [13]-[14] and in the Netherlands [15] to study the impact of travellers' heterogeneity in the weekly scheduling of activities and travels. The importance of weekly activity scheduling behaviour is reinforced also by the increasing share of non-working trips observed every day. Hirsh et al. [16] used a one-week activity diary collected in Israel to examine the dependence among shopping activity participations of individuals across different days of the week. Distinct weekly rhythms in individuals' participation in social, recreation, and personal business activities can be clearly observed from these studies, and often it is spanned over more than a week time [17]. Moreover, some activities have been found to be related to specific days of the week, such as shopping [18], house cleaning, sport and cultural activities [19]-[20]. For instance, Schlich et al. [20] observed that leisure in Germany has become the most important weekly trip purpose with respect to travelled distance, as 41% of all person-kilometres travelled for leisure purposes (if one includes holiday trips, this share rises to 48%), which is twice the amount of commuting trips. Other studies confirmed using other survey data that non-work trips have been increasing to over one-half the total number of trips by adults [21]-[22].

Perhaps the most well-known and complete multi-week survey was collected in the cities of Halle/Saale and Karlsruhe, in Germany. The *Mobidrive* travel survey was conducted for six weeks and exploited in different studies (e.g., [1], [20], [23]-[26]). A total of 317 persons in 139 households participated in the survey. The use of multiple weeks for the data collection phase allowed a better understanding of weekly activity patterns and their

variability. The successful results of the *Mobidrive* survey and the opportunities offered by GPS technologies allowed more researches on the relationship between activity scheduling and travel behaviour on a multi-day basis in other countries, for instance in Switzerland [27] and Denmark [28].

All the above studies examined day-to-day (or more specifically weekly) variations in the context of both regular daily activities (such as work-commute patterns) as well as non-daily activities (such as shopping and leisure). These studies however do not link individual activity scheduling and patterns with aggregate measures such as the observed traffic flows. Analyzing the way activity-travel patterns reflect into traffic patterns observed on the roads can add extra insight into the way transportation users define their weekly activity schedules. Vice versa, a closer look at the way people plan their activities can be important information for enhancing and correcting traffic models and especially to estimate the demand for mobility derived from traffic data.

### **Demand estimation from traffic data**

Trip-based behavioural surveys are essential for relating trip characteristics, such as origin, destination, departure time and so forth, to trip purpose and to the main characteristics of individual travellers, e.g., their age, gender, social and economic status. Alternative way to analyze the demand for mobility in a road network is looking directly at traffic data, and to use this information to estimate the most likely origin-destination (OD) trips that may have generated this data. Key issue in the estimation of an OD matrix from traffic data is therefore the identification of the origin-destination pairs whose flow portions use a particular link in which traffic is observed. The common ground is the relationship between any origin-destination flow distributed on each (used) route alternative and each link flow in the network. This problem has been formulated in many ways, among which the most widely adopted is the bi-level optimization method, where a distance function is minimized at the upper level (e.g., [29]-[31]) and constraints are imposed at the lower level to guarantee consistency between network flows and costs. For an overview one can refer to e.g., [32]-[33].

Although this is a powerful methodology to obtain demand estimations with relatively low budget, this approach has also a number of shortcomings. First of all that the estimation results depend on the adopted models and the way the traffic network is simplified. Secondly, traffic data contain errors and variations that cannot be fully captured by any traffic model. And finally, there can be many combinations of demand patterns that result in the same observed link flow values, thus the problem is typically underdetermined, and the set of possible solutions usually grows with the size of the network, and the travel alternatives available for each OD pair, while it usually reduces by increasing the number of sensors. Generally speaking, the under-determinedness is expected in all cases where the information used to estimate the OD flows is insufficient to determine

them unambiguously, which is the most likely scenario in practice ([34]-[35]). Thus choosing the proper network simplifications and traffic models is not a straightforward task, and estimation results are very often difficult to be assessed. However, an assessment can be done by comparing the estimated OD matrices with the analysis of individuals' activity-travel patterns, as it is done in this study, or by using survey results to employ full-scale activity-based travel demand models. With this last approach OD matrices could be derived from starting from two different perspectives and direct comparison could be made. This approach is however beyond the scope and budget of this project and it be done hopefully in future studies.

## **DATA COLLECTION**

### **The study area**

The area around the city of Ghent was selected for our analysis for a number of practical reasons. Ghent is the capital and biggest city of the East Flanders province, and third biggest in Belgium, with a port and a university, and a number of companies situated in the central and southern part of the city. Moreover, the city is an important touristic attraction. Therefore, it is easy to understand that Ghent acts as an important attractor for daily activities for the whole province.

By car the city is accessible by two of the country's main roads, the E40/A10, which connects Ghent with Bruges and Ostend to the west, and with Brussels, Leuven and Liège to the east, and the E17/A14, which connects it with Antwerp and the Netherlands to the north, and with Kortrijk and Lille to the south. Other important aspects for choosing this site were that traffic data and models were readily available and the municipality was willing to collaborate and accepted both to select a sample of respondents for the survey from its records as well as to share both traffic data and models. Although the area is partly equipped with loop detectors, which cover most of the highways and the main provincial roads connecting Ghent with its surrounding cities, these were not sufficient to obtain a reliable estimate of OD trips, as large uncovered areas could be identified, especially on the secondary road network. Preliminary to the data collection phase, we therefore identified a number of locations where extra detectors were installed.

It should be pointed out that although the purpose of this study requires a common study area, the boundaries of this area are not necessarily the same for the two approaches (see Fig. 1). In fact, in the OD estimation from traffic counts, a consistent part of the estimation errors are due to network and modelling simplifications. In our particular case, the boundaries of this area suffer particularly of these errors. It was therefore necessary to study a broader area than for the survey case, to be sure that these errors were confined to an acceptable level in the common area. The zones within the city have

been chosen mainly based on the defined census zones, while outside of the city the main criterion used was to centre the zones on the main satellite cities. We obtained in this way a total of 32 zones. By doing so we could focus on estimating inter-city trips, and therefore exclude short trips that are likely to be done with slow transport modes (walking, bikes, etc.). For the same reason, concerning the simplification of the road network, we neglected all roads serving primarily local traffic.

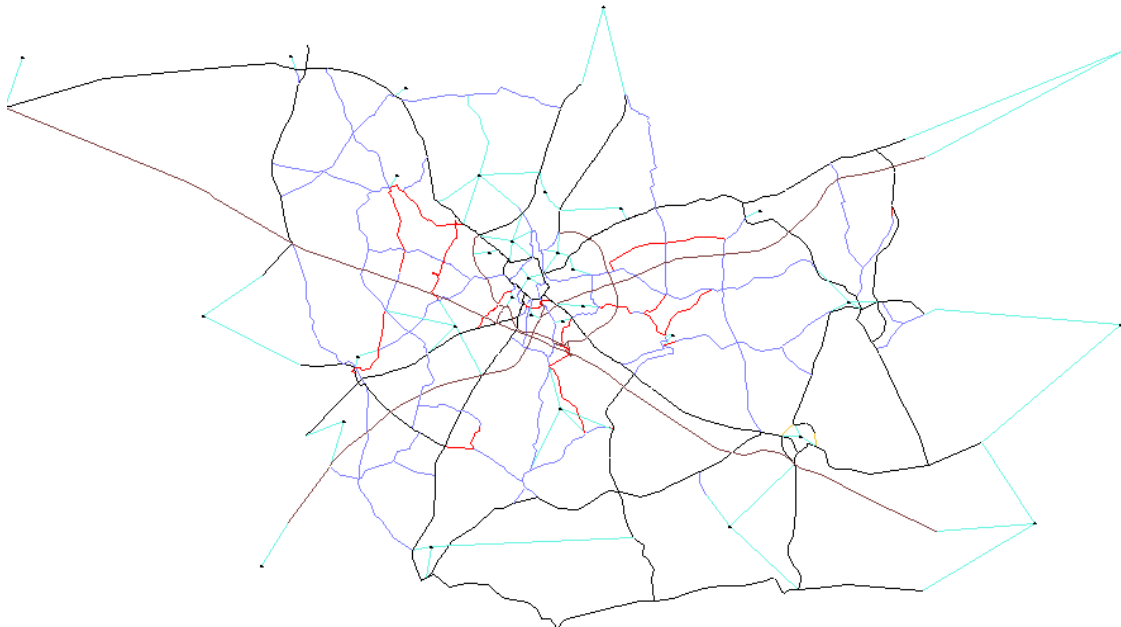


Fig. 1: Google Maps™ view of the study area (top picture) and network graph (bottom picture). The dotted ellipse identifies the perimeter of the area where surveys have been collected, while the dashed on shows the perimeter of the area used for OD estimation from traffic counts.

## **Behavioural data survey design**

As mentioned in the introduction, a deeper knowledge of mobility behaviours over a week needs conducting specific mobility survey. Such a survey requires an appropriate protocol. Regarding the sampling method, we decided that the surveyed sample would be drawn from individuals, since tracking for a week all household members would be a too heavy task and could have been a serious drawback for the success (response rate) of the survey. However, surveying only individuals does not allow us to take into account the household internal discussions and agreements on how the global household's activities patterns are spread not only over the days of the week but also among the household members. We agree that this is clearly a drawback but taking also this parameter into account would have meant a too large survey which could not fit within the time and budget constraints of this project.

First part of the survey questionnaire focused on the main socio-economic variables, which could partly explain differences in weekly trips patterns. This part was conducted through a phone call (recruitment call). In a second phase the respondents noted on a diary, either paper-based or through a dedicated web interface, information on their trips, e.g., destination, purpose, starting and ending times, used transport modes, trip distance and duration, and some other variables (accompaniment, parking fees, etc.). The use of paper-based diaries allowed us reaching some categories of people who do not have Internet access or are not comfortable with computers.

A random sample has been drawn from the Ghent population register using individuals from 12 to 75 years, with stratification according to the household size (single vs. other household types since it is well known that the response rate is quite lower for one-person households [38]), gender and age. The data collection phase began on September 1<sup>st</sup> and ended in December 2008.

The response rate and thus the recruitment of individuals always being a critical problem for such type of surveys, we decided to offer monetary incentives for respondents filling in a complete questionnaire for the whole week (10€). The planned goal on the basis of previous research (and particularly *Mobidrive*) and the available budget was to gather at least 500 valid questionnaires. Fortunately the response rate was much higher than expected so that we were able to receive 717 validated questionnaires for the available budget. This figure does not include questionnaires (76 respondents) from the pre-test conducted to assess the protocol and the questionnaire. The pre-test phase lasted two weeks and 500 individuals were contacted. The obtained response rate (14.6%) was over our expectations (10%). This positive response rate was also confirmed for the real data collection. From the pre-test phase, we also noticed unequal response rates according to age classes: we found that people born between 1975 and 1984 had a lower response rate than the others. Going deeper in the analysis, we could infer that such a situation is not really to be attributed to reluctance of these people to answer the



survey, but is mainly due to a greater difficulty in finding a phone number for people in this age class. According to these figures, we decided to modify the stratification scheme for the sample in order to obtain a set of respondents the closest possible to the real population: for example, we increased the amount of young people in our sample, in a way to also obtain, after finding of phone numbers, a good representativity of this part of the population in our sample.

Before starting the analysis, a data cleaning has been necessary. In the trips database we observed two kinds of errors, transcription errors and errors from the respondents due to, e.g., misunderstandings of the instructions. However most errors of this kind have been detected and corrected with the validation phone calls achieved after the test period. Some automatic corrections were undertaken when missing data or exact values of incorrect data can be guessed from other variables. For example if the arrival time is missing, we could compute it from the departure time and the trip duration. Finally the observations have been weighted according to the stratification variables: gender and taking into account the margins drawn from the National Register. On the other hand the addresses of all activities noted in the diary have been aggregated according to the zoning described in the previous section.

## **Dynamic OD estimation method**

In this study, we used traffic measurements in two ways: for estimating OD flows for each week day, and by reconstructing spatial traffic patterns using a (dynamic) traffic model to estimate traffic patterns where data was not available. We formulated the problem as bi-level according to traditional approaches. We chose Generalized Least Squares [30] as distance function in this study. For the optimization algorithm there are many different possibilities. Among these, the gradient search method was chosen, because it has the advantage that it is able to make full use of the output of the lower level, namely the assignment matrix. The lower level consists of a route choice and a dynamic network loading (DNL) models, jointly defining the Dynamic Traffic Assignment procedure. The input for this level is the OD matrix calculated at the upper level, while the output consists of link flows, the assignment matrix, travel times, etc.

For assigning the OD matrix onto the network the route proportions and a reference matrix have to be specified. We used the stochastic route choice model from the program INDY [36]. The DNL model loads the OD flows onto the network, resulting in path flows and link flows. In this study we adopt a macroscopic DNL model: the Link Transmission Model (LTM). LTM is a multi-commodity model, where each commodity corresponds to a specific (pre-defined) route. LTM has the property of being consistent with first-order Kinematic Wave theory, and to capture the dynamics of congestion realistically. Details on this model can be found in Yperman [37]. The municipality of Ghent provided two static OD matrices to use as reference, one for the morning peak

(between 8 and 9 AM), and the other one for the evening peak (between 5 and 6 PM), estimated from socio-demographic and socio-economic data, and calibrated using traffic count data in 2007. The static OD matrices cover a wider area than the one used in this study, and contain a considerably higher level of detail for the zoning and the graph representation with respect to our analysis. Therefore a preliminary operation for using this matrix was to further simplify it based on our aggregation criteria.

For this project three traffic count data sources were available. The first one consisted of data from the StartSitter system [39]. This system contains all real-time traffic data on all Belgian highways. Second, a number of fixed loop detectors are installed near the intersections between provincial roads. The third source consisted of data from tube detectors that were specifically installed for this project to obtain a more complete database. All of these data sources contain however missing and inaccurate data due to various reasons. For the tube detectors around 23.5% of the data was missing. For the fixed loop detectors on secondary roads this percentage was 5.5, while for the highway detectors it was 7.3. The large percentage of missing data for the tube detectors is due to the fact that many tube detectors were installed only during certain parts of the considered time period, and therefore no data were available for the remaining parts. Finally some traffic counts had to be deleted from the dataset for a number of reasons:

- data containing clear faulty values (e.g., zeros during the peak hours);
- traffic counts placed near the connectors, since, due to the aggregation, traffic flows in the model are usually higher than in reality;
- counts near the limits of the study area, as these counts also contain traffic that could originate and end both outside of the study area.

As final result of this cleaning process we could use data from 270 detector locations for around 3500 km of roads.

To derive an a priori daily OD matrix that partly describes the actual daily fluctuations of the demand we inferred the temporal patterns of the link flows to the OD flows assuming a linear relationship between these parameters. To account for different route flow patterns, we distinguished a number of temporal patterns in the link flows, and associated these with the OD flows. For details we refer to [40].

## DATA ANALYSIS

### Results from the behavioural survey

#### *Overview of socio-demographic characteristics*

We begin this analysis with a description of the survey respondents and their relevant characteristics for understanding their weekly activity-travel related choices.

Among all respondents, around 70% has a job or goes to school, and 85% has a fixed work or school place (7% declares to work or study at home, while 8% have no fixed place to work or study). Of all active respondents, 67% works or goes to school in Ghent city, 14% somewhere in the province, while 16% in another province (among which 8% declares to work in Brussels). For the workers only, 45% never needs to travel for work-related purposes, 39% needs to travel sometimes, and 16% has to do many trips for their job. 75% of workers are funded back (totally or partially) by the employer for their home-work trips.

Table 1 gives an overview of the employment characteristics observed in the surveyed population. Regarding the access to public transports, 40% of the population is entitled to a reduction on public transport. Almost 60% of the people have a seasonal ticket for public transport, of which 21% was freely distributed. Of all surveyed households we observed an average of 1.3 motorized vehicles, and 2.5 bikes.

Regarding household compositions, 18% of the population lives alone, 26% in a 2-persons household, 20% in a 3-persons household, 37% in a 4 or more persons household. Among these, 13% of the individuals live in a household having at least one child under 6, 14% in a household having at least one kid from 6 to 11, 21% in a household having at least one teenager from 12 to 17. Concerning the socio-professional status, we can mention that we have 56% of active people in the sampled population. If we consider the non weighted rate of working people in our sample, among the 15-65, this value rises to 65%, which is comparable to the figures of employment in the whole Flanders for 2008.

As one can see from the table, there is a significant number of people declaring to work at home at least one day a week. Furthermore the share of respondents declaring to have variable working hours is quite substantial (~32%) and there is about 1/5 of the population that has a part-time job. All these factors suggest that the traditional home-work commuting is gradually reducing its impact on the day-to-day and within day travel patterns. It is however more interesting to analyze how respondents distributed during the week their non-working related trips. This is presented in the next subsections.

Analyzing Weekly Activity-Travel Behaviour from Behavioural Survey and Traffic Data  
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Table 1: employment characteristics of the surveyed individuals

Teleworking	
No never	83.6%
Yes, at home, more than 90%	0.5%
Yes, at home, from 20 to 90%	4.6%
Yes, some times (less than 1 day/week)	10.2%
Yes, other	0.11%

Time of work	
Day work	84.5%
Night work	1.6%
Shifts, without night	3.8%
Shifts, with nights	5.5%
Other	4.6%

Work hours	
Fixed hours, imposed by employer	53.3%
Fixed hours, chosen by the worker	14.6%
Variable hours, imposed by the employer	21.0%
Variable hours, chosen by the worker	11.1%

Full time workers	77.5%
Part time workers	22.5%

Professional status	
Workman	10.1%
Employee	47.3%
Executive	1.9%
Freelance	6.5%
Liberal profession	2.9%
Teacher	9.8%
Civil servant	13.5%
Other	7.1%

*Results from the trips diary*

All respondents did at least one trip during the whole reporting week. During a working day the share of people not travelling at all ranges in between 4 and 6%, while it rises to 7% on Saturdays and 15% on Sundays. Fig. 2 shows the number of trips done by an average individual for each day of the week. It can be observed that around 50% of all

trips are done by car. This share rises to over 60% if intrazonal trips are excluded. It is interesting to observe that the number of trips per person on Tuesdays (3.7) is lower than on all other days, except from Sundays; this is surprising since Tuesday is often taken as a reference “working” day for a traffic model.

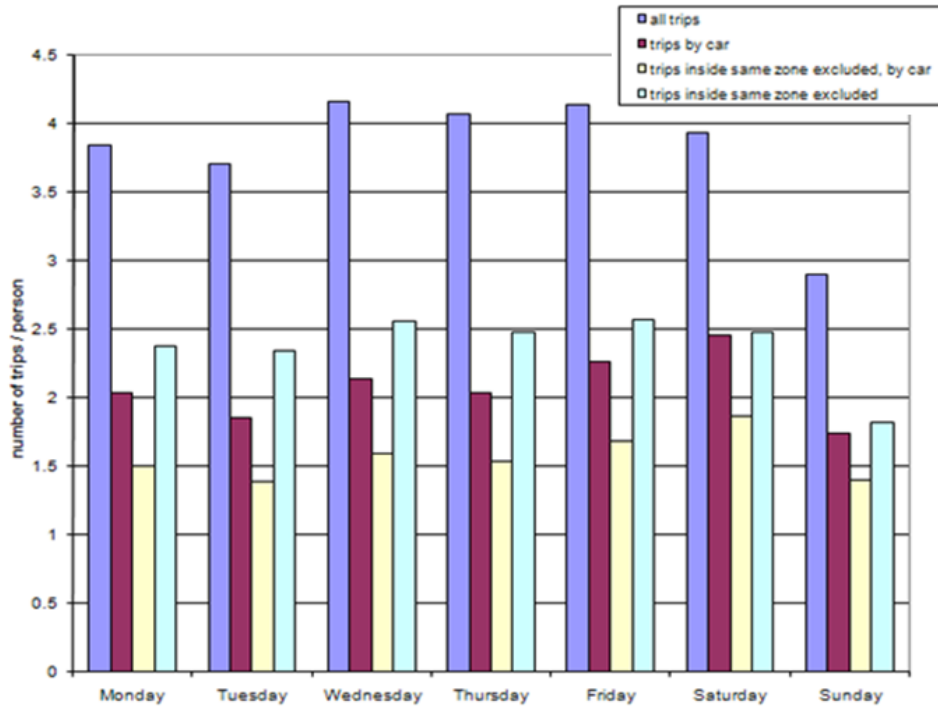


Fig. 2: number of trips per individual per day of the week

The time that individuals spend in travelling is around 9 hours per week, travelling about 280 km. On average, it means 1 hour and 18 minutes per day (around 40 km travelled), which seems consistent with past research but also in accordance with the well-known Zahavi’s conjecture<sup>†</sup> (see [43] for more details). Interestingly, there are no statistically significant differences amongst days of the week, even for Sunday. The time budgets we got for Monday and Tuesday are even shorter (but not significantly) than the one for Sunday. It means that if the number of trips is lower on Sunday, the trips are however longer (see below), so that the time budget amongst days is equal on average. This is confirmed by the survey: if we compute the average distance per trip, we can see that it is higher on Sunday with more than 13 km per trip versus slightly less than 10 km on weekdays and Saturday. This is somewhat in contrast with past research (e.g., [9], [41]).

<sup>†</sup> “Zahavi (1977) advanced the conjecture of constant travel time budgets (and constant travel expenditures as a percentage of income). Under the assumption of constant travel time budgets, an individual will allocate a fixed amount of time to travel; thus, if travel speed improves, then the time saved will be used to travel more or farther, while if congestion worsens, then people will make fewer trips, choose faster modes, and/or choose closer destinations. This controversial notion of constancy in travel time budgets is essentially the sole behavioural paradigm that has been applied to the issue of induced/suppressed demand.

### Trip purpose

Let us now analyze the travelling habits of the individuals in relation with the purpose of the trips. Table 2 and Fig. 3 show the share of activities for each day of the week respectively including or excluding the activity “going back home”.

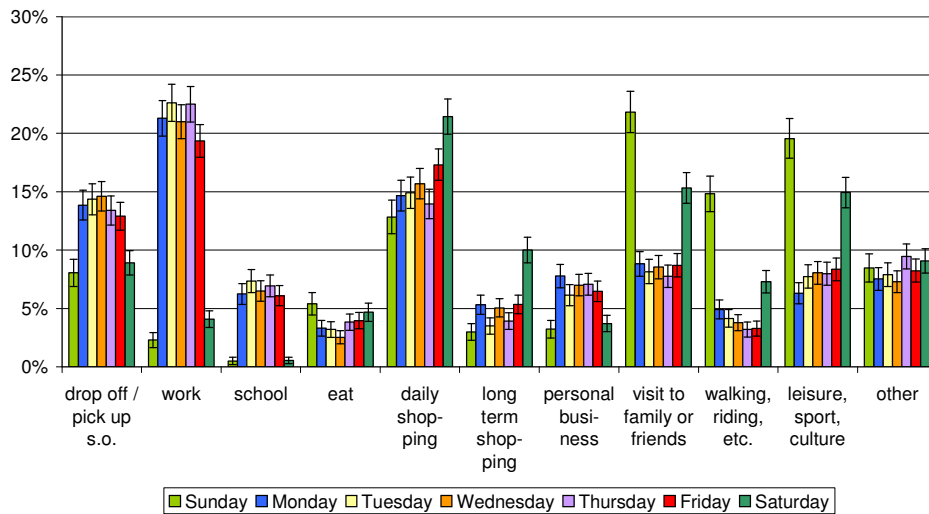


Fig. 3: share of activities for each day of the week excluding the trips to home

Table 2: share of trip purposes for each day of the week

	Mon	Tue	Wed	Thu	Fri	Sat	Sun
drop off / pick up someone	8.6 %	8.9 %	9 %	8.3 %	8.2 %	5.6 %	4.8 %
home	38 %	38 %	38.3 %	37.8 %	36.5 %	37 %	40.7 %
work	13.2 %	14 %	12.9 %	14 %	12.3 %	2.6 %	1.4 %
School	3.9 %	4.5 %	4 %	4.3 %	3.9 %	0.4 %	0.3 %
Eat	2 %	2 %	1.6 %	2.4 %	2.5 %	2.9 %	3.2 %
daily shopping	9.1 %	9.2 %	9.7 %	8.7 %	11 %	13.5 %	7.6 %
long-term shopping	3.3 %	2.2 %	3.1 %	2.4 %	3.4 %	6.3 %	1.8 %
personal business	4.8 %	3.8 %	4.3 %	4.4 %	4.1 %	2.3 %	1.9 %
visit to family or friends	5.5 %	5.1 %	5.3 %	4.8 %	5.5 %	9.7 %	12.9 %
walking, riding, etc.	3 %	2.6 %	2.3 %	2 %	2.1 %	4.6 %	8.8 %
leisure, sport, culture	3.9 %	4.8 %	5 %	5 %	5.3 %	9.4 %	11.6 %
Other	4.7 %	4.9 %	4.5 %	5.9 %	5.2 %	5.7 %	5 %

We can observe on working days that the share of trips to work range in between 12 and 14%. This statistic rises to around 23% if home trips are excluded, while they drop to 5% on weekends. Although on working days this purpose has straightforwardly the highest

share, it represents only less than 1/4 of all trips in a day. This reinforces the belief in this study that traffic models based on simply commuting traffic can have a rather erroneous pattern.

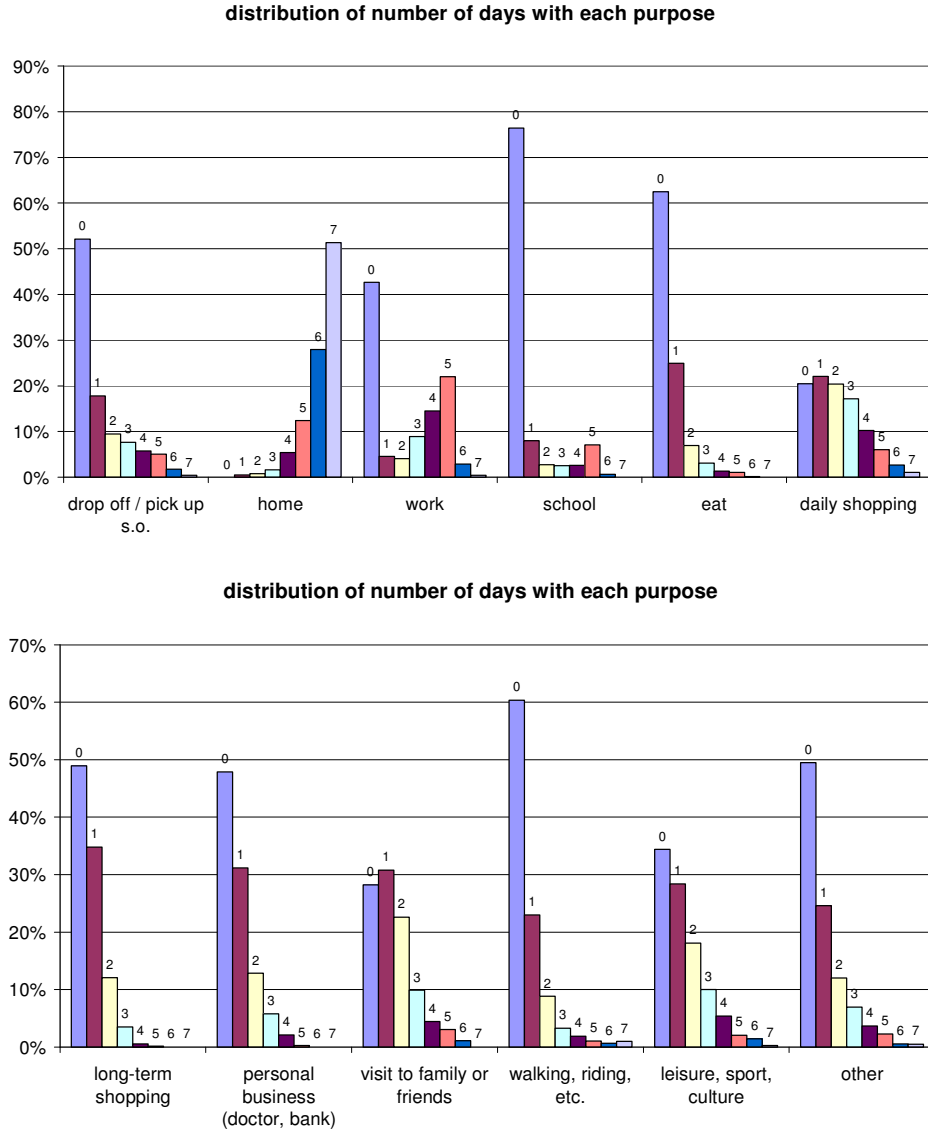


Fig. 4: number of days an average respondent travels during a week and for each purpose

The three purposes "visit", "walk, ride" and "leisure" of course increase during weekends, a little less than twice more trips on Saturday and more than twice on Sunday. Saturday is a special day for shopping (both daily and long-term) which pertains to more than 30% of the trips, while this purpose only reaches between 15 and 20% on weekdays and around 13% on Sundays. Interestingly, the purpose "drop off/pick up" purpose keeps still around 7% during the weekends, while it reaches 13% on weekdays.

A full-week survey allows going further in the analyses. Fig. 4 shows the number of days an average respondent travels each week for each purpose. On average, people go to work 2.3 days a week. More than 40% never goes to work; but it includes people who work at home, people on holidays, as well as non-workers. If we only consider working people, the mean goes up to 3.7 days. Similarly, if we only consider students, they go on average 3.7 days a week to an education establishment. Thus in an activity-based traffic model based on these figures it is more realistic to consider an average worker as working for 4 days a week rather than the more traditional five days a week.

Concerning the other trip purposes, the daily shopping is the purpose for which most respondents have realized at least one trip during their reporting week. This purpose occurs on average a little more than 2 days a week. As expected, the long-term shopping is less frequent for the respondents.

These figures allow us to highlight activities that are mainly performed once a week (long term shopping, personal business). However these analyses regarding the purposes would lead us to suggest that, methodologically, one-week is still a too short period for such survey. For example, if someone goes shopping or visit family every ten days, it is possible that such purposes do not appear in his agenda for the reporting week.

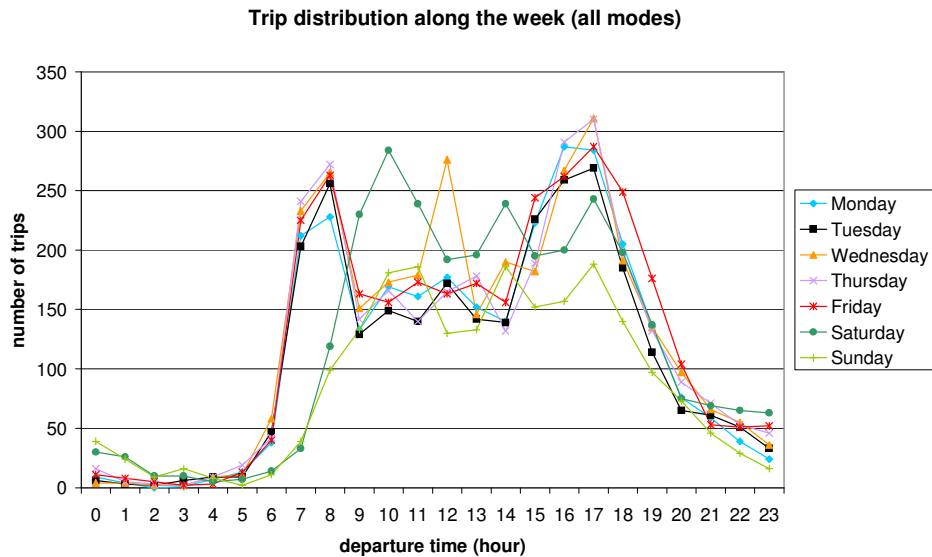


Fig. 5: departure times of respondents per day of the week for all purposes and all modes

Deeper insight into the daily habits of transportation users and their relation to daily traffic patterns can be achieved by looking at the departure times of the respondents (Fig. 5):

- The morning peak hour is quite similar for all weekdays, except for Monday where it is a bit weaker.
- The evening peak is wider, especially on Fridays.



- Wednesday is marked by a midday peak that can mainly be explained by the fact that schools close earlier on Wednesday afternoon in Belgium.
- Saturday and Sunday have specific hourly profiles:
  - Saturday has a rather significant morning peak but it occurs later than on weekdays (around 10 AM) but also two minor peaks at 2 PM and 5 PM. As we know, the number of trips on Saturday is at the same level as on weekdays but purposes are different.
  - People travel less on Sunday, which also presents three peaks but with equal trips densities: it is nevertheless larger in the morning (between 10 and 12 AM).

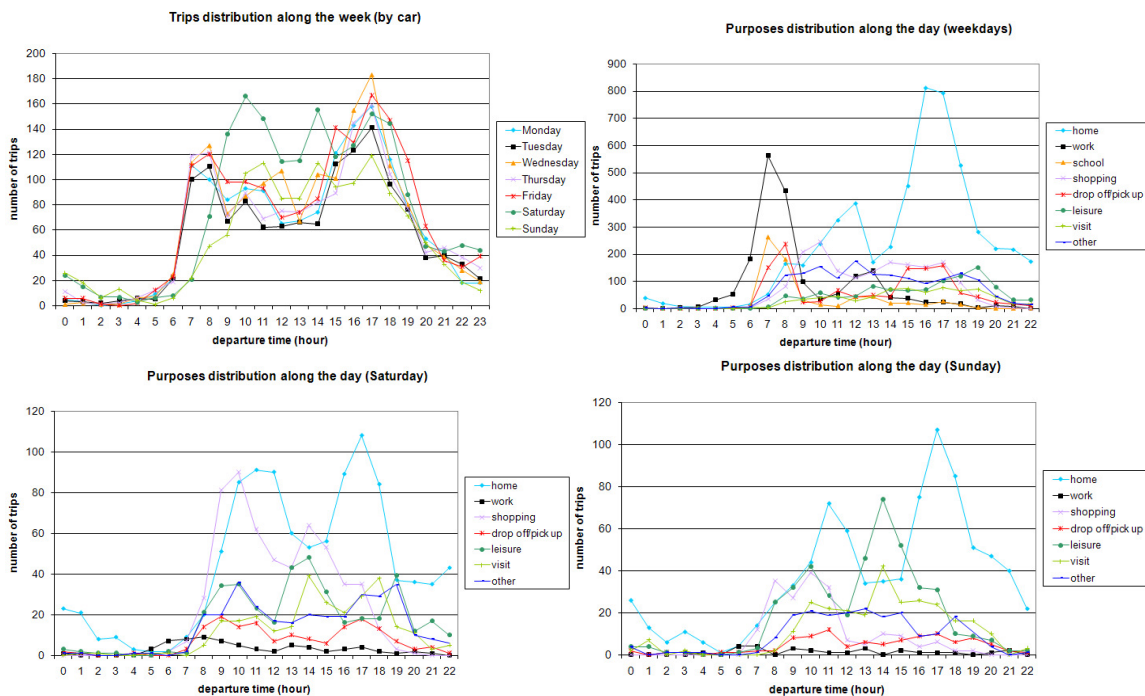


Fig. 6: departure times per day of the week by car (upper left), on working days (upper right), Saturdays (lower left) and Sundays (lower right)

If we only consider the car mode (both driver and passenger), the profiles are quite different (Fig. 6):

- The difference between morning and evening peaks on weekdays becomes more pronounced.
- The Wednesday midday peak has also considerably decreased, which could be expected if we suppose that it is mainly caused by trips by children and young people back from school (on foot, by bicycle).
- The morning and midday peaks of Saturday are really higher than on weekdays. This could perhaps be explained by the fact that most commuters do not travel

by car for their home-work trips but use their car for their less usual trips achieved on Saturday (shopping, leisure, visit, etc.).

## **Results from the OD estimation from traffic counts**

In order to test the aggregate results of the one-week survey we analyse the average traffic patterns, inferred from all available traffic counts, for each type of day. These patterns are reflected in Figure 7:

- As expected, Saturdays and Sundays show quite different patterns with respect to weekdays.
  - Both weekend days do not have a morning or afternoon peak, as expected, but experience a busy period from around noon till about 8 PM.
  - Saturday is on overall a busier day than Sunday, with the only exceptions from midnight till 5 AM and from 7 till 10 PM.
- On Wednesdays the morning peak is less intense than other days. There is increased traffic compared to the other days starting from 11 AM till 4 PM, with a peak between noon and 1 PM. This confirms the trends shown in Fig. 5.
- Thursday has the largest morning and evening peaks, and also during the rest of the day the traffic pattern remains at a high level, in line with the results of Fig. 5 and Fig. 6.
- On Friday there is much more traffic on overall, but only in the off-peak periods (between 9 AM and 5 PM). The morning peak seems to be the calmest of all workdays. Also on Friday evening and night there is a serious increase of traffic as compared to other days

From the above findings a number of general conclusions can be found in the same trend line with individuals' activity patterns:

- Work days show similar patterns. In particular Monday, Tuesday and Thursday do not seem to differ significantly, apart from a slightly lower demand on Mondays and a slightly higher demand on Thursdays;
- On Wednesdays around 40% more traffic than a typical working day is observed at noon while there is no significant change during morning and afternoon peaks. The peak is due to early closing of schools on Wednesdays, as shown also by the survey;
- On Fridays there is a wider demand during the afternoon peak. This is perhaps due to a significant portion of workers finishing their job earlier, and users going out on Friday evening;
- Weekend days show a completely different pattern with respect to work days, as they do not show the peaks typical of morning and evening commute.

Straightforwardly, they are also rather different from each other, since shops are mostly closed on Sundays; this is also in line with the results of Fig. 2.

- On Saturdays traffic flows seem to be rather stationary in between 10 AM and 7 PM, i.e. during the opening times of most of the shops.  
 On Sundays traffic gradually increases during the day, showing the highest peak at around 7 PM.

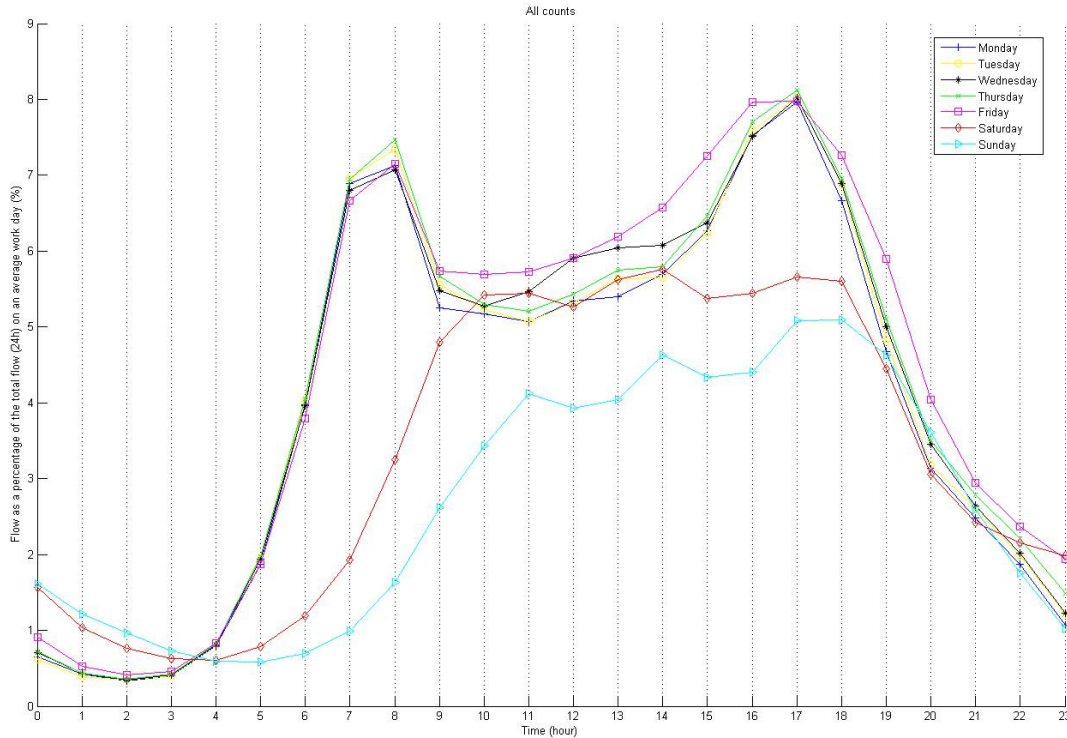


Figure 7 : Average traffic flow for each type of day

A comparison could be made between the traffic patterns resulting from the counts and the traffic patterns resulting from the OD matrix estimation. The traffic pattern within a zone is dependent on the production and attraction of that zone. We therefore calculate the average traffic pattern as the sum of the total production and the total attraction of a zone. To be able to make a comparison with the traffic pattern resulting from the counts, both patterns are normalized. There are 2 major differences between both approaches. The first is the fact that the pattern derived from the production and attraction of a zone does not take internal traffic into account. The second difference originates from the time lag between departure times of the demand and link flows. If we account for this time lag we get what is displayed in Figure 8.

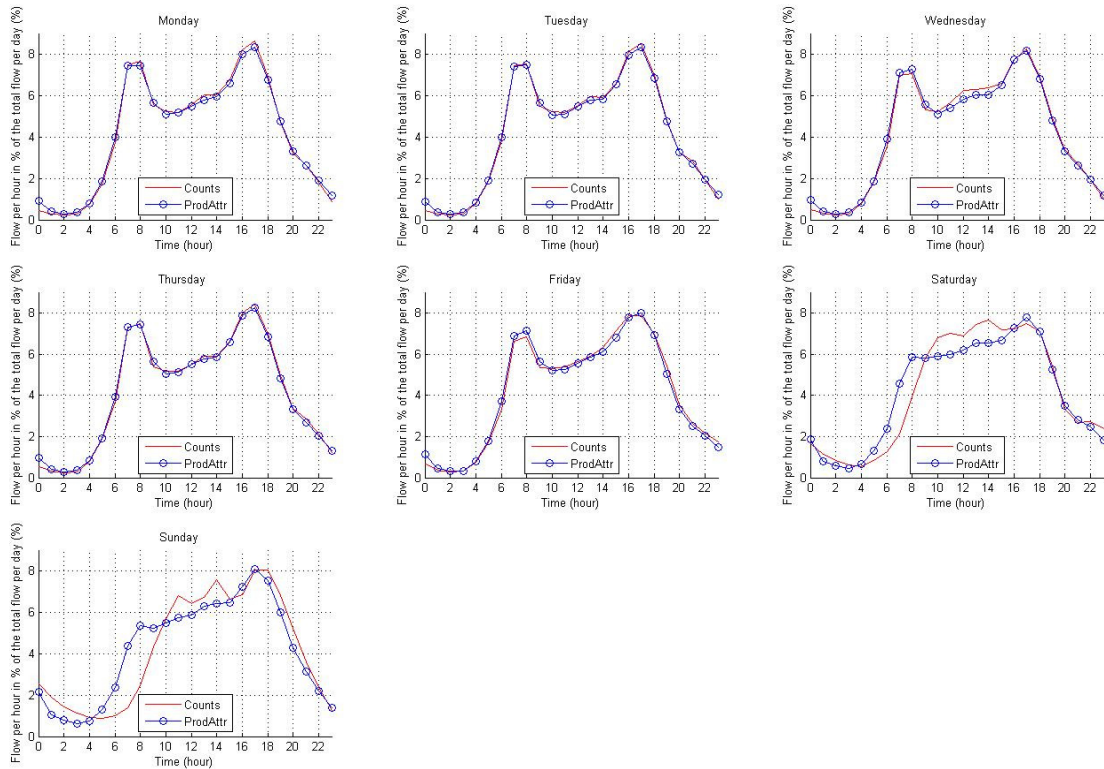


Figure 8 : Mean travel pattern resulting from counts and production/attraction

The magnitude of the difference is not so large as can be seen in Figure 8. This is because the curve the production and attraction curves not only represent highways, but also traffic on secondary roads. However on weekend days the differences on both figures do not match as well. This is presumably due to a worse result of the OD estimation process, which itself is a result of the use of a target matrix that did not reflect the correct travel pattern on weekend days since base on static OD matrices established for working days. Applying some correction factors to the target matrix using the results and the knowledge acquired from the behavioural survey may help at reducing this error. This problem will be explicitly addressed and tackled in a future study.

## CONCLUSIONS

Understanding the relationship between daily traffic and activity-travel patterns is fundamental for guaranteeing a sustainable transport system. To do so, a weekly horizon should be analyzed, as people show to schedule their daily activities on a weekly basis. This paper has presented the preliminary results of a project aiming at analyzing this relationship through two distinguished views, i.e. the longitudinal disaggregate behavioural choices over the week and the transversal aggregate traffic

measures for each day of the week. A sample of individuals has been selected within a study area, and their activities and movements are recorded. In parallel, traffic flows have been measured during the same weeks on the same area. By comparing the two datasets specific daily traffic patterns could be directly related to the scheduling of individuals' activities, both on day-to-day and on a within-day basis.

It was found that, although home-work trips are the majority on workdays it represents only less than ¼ of all daily trips. On weekends work-related trips drop down to 5%, however, the number of trips on Saturdays does not reduce considerably, which suggests that other purposes become much more important (e.g., shopping, sport activities). These trends are in line with the analysis of traffic flow data, where on Saturdays the total daily demand is comparable to a weekday, but the OD flow patterns are significantly different over the day. The next step in this research will be to use both sources of information for enhancing demand models exploiting the complementarity of the two approaches.

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