On the link between activity patterns and traffic within-day demand profiles: empirical analysis and application to demand estimation

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Context and motivation:

Determining the demand for a transportation network has been a classical topic for researchers and practitioners in the past decades. The most classical methodology to generate this demand is the so-called *four step model*. This model is based on aggregate demographic data and provides an origin-destination (OD) matrix, which is a good approximation of the demand of commuters for a specific network. Since its demand is based only on socio-demographic information, this model is useful for planning and forecasting applications, on the basis of statistical trends for a specific area. This representation of the demand is normally *macroscopic,* since the demand is represented aggregated level. One of the main limitations of this approach, is that demographic variables are normally assumed *static*, which means that they are not suited to capture *within-day* traffic dynamics (congestion dynamics, spillback,…). *Dynamic Traffic Assignment (DTA)* tools can potentially overcome these limitations ([1]–[3]). However, to reproduce realistic traffic conditions, DTA models need as input a *dynamic* OD matrix rather than a static one. In addition, the four-step model is trip based, i.e. it represents traffic demand and flows for a specific time period and hence does not consider the eventual trip sequences done by the road travellers during a day. For this reason, these classes of models have been usually adopted to represent the commuting demand in the busiest peak hour.

A cheaper way to estimate a *dynamic* OD matrix is to correct/calibrate an available old (static or dynamic) OD matrix in order to reproduce the observed traffic conditions [4], [5]. This approach may partly solve the problem of obtaining socio-demographic information, usually expensive to collect and relatively quickly outdated, and can be combined with DTA tools. However, this method is also disregarding trip sequences, correlations between trip schedules of individuals, constraints due to the duration of daily activities, etc.

A third, alternative, approach may be to use *Activity Based Models* and, specifically, *Activity-Based demand generation models* [6]–[8], to represent the daily demand. In this case a synthetic population is generated by e.g. census data, or daily activity travel diaries from a sample of the population, generating A*ctivity Plans*, which describe the entire daily activity pattern for each user on the network. The advantage is twofold. First, since the *Activity Plan* includes departing/arrival times at the destination, it is a *dynamic* information, which is a desirable property for dynamic demand estimation models. Furthermore, this plan includes different activities, which allow the model to consider other purposes rather than the basic home-work commuting. While the relevance of the trip chain has been already investigated in literature [9], assessing its potential contribution to represent the demand is still missing in macroscopic models.

If research on *Activity-Based* models is attracting more and more interests, this branch of the research mainly focuses on the *single-user* point of view. Rather than producing an OD matrix, A*ctivity Plans* are generally used as input for *microscopic agent-based DTA.* In these models, like Albatross (Arentze and Timmermans [10]) and MATSim (Feil et al. [11], Balmer et al. [12]), each user is modelled as a single user, maximizing his own utility, which, according to economic theory

[13] is function (at least) of the departing time, the number of scheduled activities, the duration of the activities and the travel time.

We believe that building a bridge between an aggregated representation of the demand and its behavioral, user-specific, component is needed in order to use macroscopic DTA models in a more efficient and reliable way. Specifically, we investigate the aggregate relation between *Demand Activity Patterns* and traffic states. The classic demand matrix is in our approach assumed to be a convolution of different activity patterns. Some of them are defined as *rigid*, like the home-work activity, and they are more difficult to be modified or rescheduled, while others are more *flexible*. It is intuitive to realize that *rigid* activities determine the network condition, while the *flexible* ones are influenced by the given state, since user can change plans of leisure activities if the cost to reach the destination is too high. To support these assumptions, in this study we perform an empirical analysis of activity-travel patterns from a multi-day travel survey, and later we present a new modeling framework based on the above-mentioned analysis.

Methodology and Results

The goal is to exploit the Travel Diary in order to reproduce *aggregate Activity Patterns*, rather than *disaggregate* Activity Plans. We first focus on identifying *Demand Activity Patterns*, which are broadly defined as *rigid* and *flexible* demand patterns. Travel diaries and traffic counts for the city of Ghent have been used to relate these distributions with the observed traffic flows. The database has been collected in the BMW Project (Behaviour and Mobility within the Week, Viti et al., 2010), which was carried on by KU Leuven and the University of Namur. 500 participants provided information for six weeks, including purpose of their trips, departure times and locations. As first step, we identify at least three groups of activities (*Activity Components*):

I. *Within-Day-Systematic Activities (DSA):* These are *rigid* activities, in which arrival and/or departing time is not flexible (i.e. going to work, returning home), and they are likely to be observed every day or at least for multiple days a week;
II. *Within-Week-Systematic Activities (WSA):* These are *flexible* activities, which are not systematic within the day, but are likely recur every week (i.e. swimming pool, weekly shopping) at least once;
III. *Non-Systematic Activities (NSA):* These *flexible* activities represent extraordinary events with respect to the usual user activity scheduling (i.e. visiting the doctor is an example); their occurrence is not likely every week but they are observed on longer time periods (e.g. a month).

All the activities are classified in the data according to the above three groups through a cluster analysis. The authors identify that the demand can be sufficiently represented through four/five distinct *Activity Demand Components*. Under these assumptions, the *Home-Work Activity Patterns*, which is the main rigid component, represents a relatively small share of the total daily demand (12%). If we further focus on rigid trip sequences with no more than two trips during the day (i.e. the loop *Home-Work-Home* – the percentage rises up to 35%. These percentages are similar to other reported in literature [14], and show how considering more complex trip chains and daily patterns is fundamental to capture the total demand, as trip sequences with non-work related trips still remain the largest majority in a day. To evaluate at aggregate level the *Activity Patterns*, three of the most important characteristics of the daily activity tour have been evaluated: Travel Time distribution, Departing Time Distribution and Activity Duration. In Figure 1 departing time and activity duration for WSA-Home (*flexible)* and Work-Home (*rigid*) tours are presented. The *flexible* component of the demand enters into the network after the morning peak when the *rigid* component leaves the system, and the typical duration is shorter with respect to the *rigid* component (9 hours on average for the *rigid* component and 2 hours for the *flexible* one).

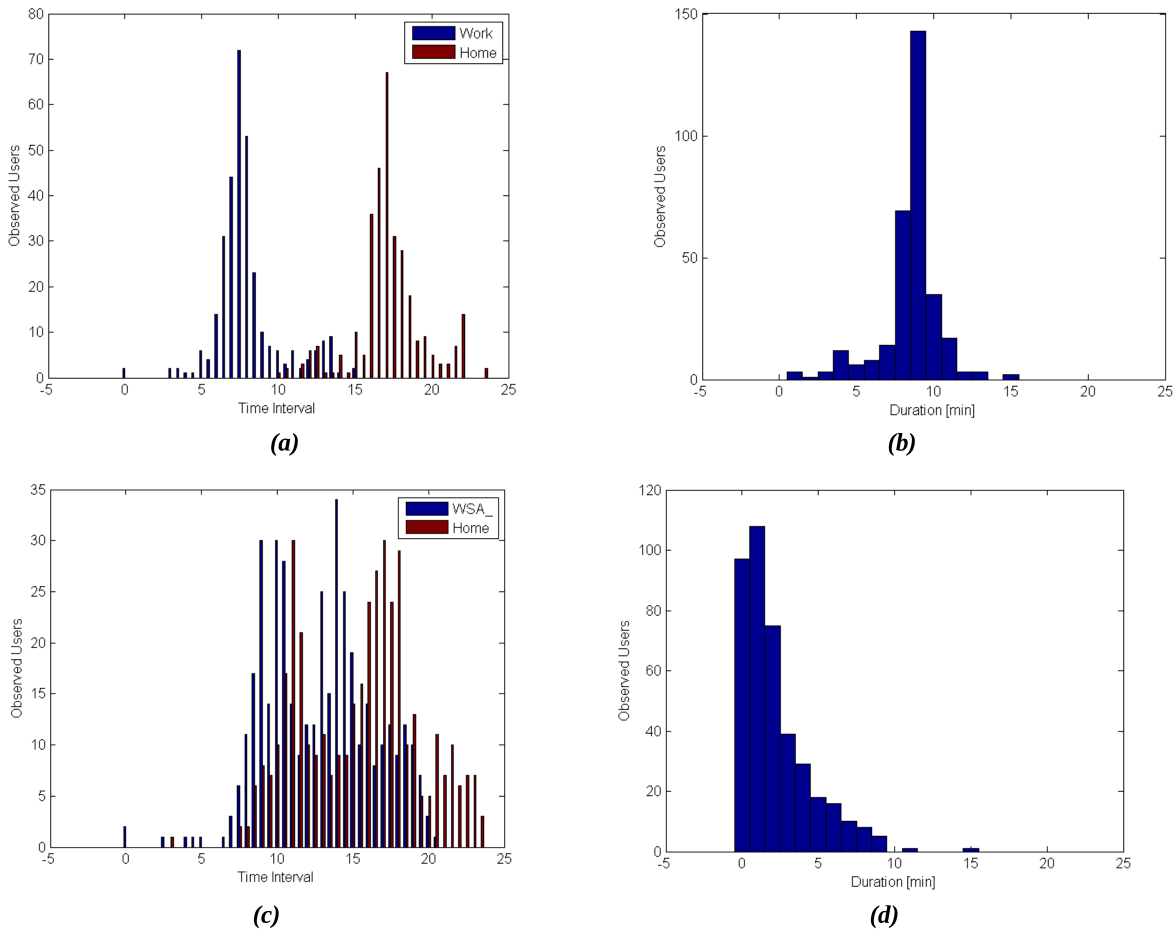


Figure 1: (a) Departing Time Work-Home tour (b) Duration distribution Work-Home Activity (c) Departing Time WSA-Home tour (d) Duration distribution WSA-Home Activity

Both duration of the activity and the departing time to reach that activity can be represented through a probability distribution. We can therefore define *Activity Function* as the probability function, which describes a certain *Activity Pattern* in an aggregated way. These functions can be identified by fitting an opportune parametric function to the observations, which can be very sharp in cases like *Home-Work* and *Work-Home* activities (Figure 1a), or more dispersed over a day as the case of *Within-Week-Systematic Activities* (Figure 1c). The identified *Activity Function* for each activity transfers information derived from the microscopic population directly to the aggregate demand flow. Specifically, the *mean value* of this distribution is the average departing time for users within one *Activity Pattern*, while the *covariance* term shows the dispersion of the departing time with respect to this value. It is relevant to point out that this information can be obtained not only through microscopic information, but also exploiting other source of data containing individual movements, e.g. *floating car data*, or GSM/GPS data. Activity duration distributions (Figures 1b and 1d) can on the other hand be used to further constrain the demand between two sequential activities.

It should be further pointed out that the discrepancy between what we observe in terms of link flows and the real demand flows depends on the travel time between the origin node and the observed link. This is dealt with in the conventional demand estimation problem from traffic data.

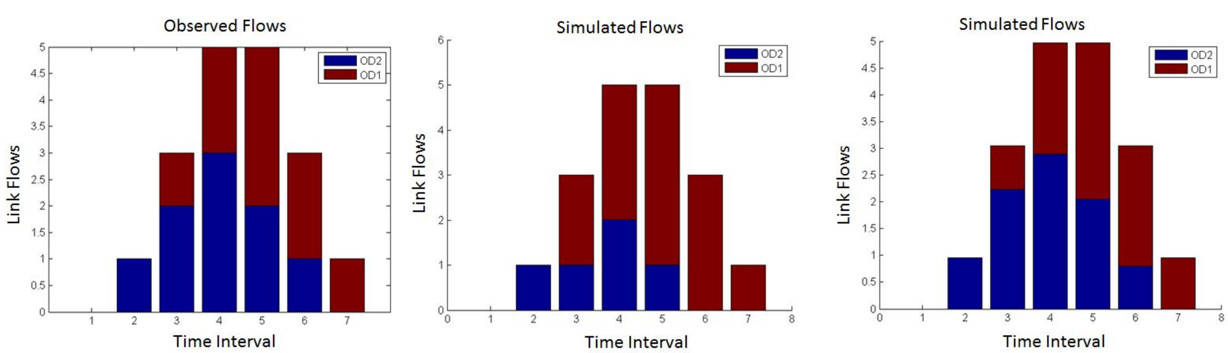
Nevertheless, the component of the flow related to specific origin will derive from the original Activity Function.

To illustrate the concept, an experiment has been performed on a toy network to show how including activity scheduling and duration can improve the quality of demand estimation. In the experiment, a *rigid* demand from two different origins moves to one common destination, only one route is available for each origin-destination pair, but having a different travel time. Both the real and the starting demand for performing OD estimation are not generated according to a probability function, so when the shape is representable through this function a small error between the matrices is observable. An *Activity Function* is generated by fitting the starting matrix shape. This simulates the fact that the starting matrix is derived by observations, which are a sample or an approximation of the real demand. If the shape of the demand is modelled through an *Activity Function*, and the parameters of the function are corrected rather than the disaggregated demand flows, the proper demand can be reproduced, independently by the traffic condition (congested or uncongested).

		Constant Link Cost		Uncongested DNL		Congested DNL	
	Start	Classic OD estimation	Imposing Activity Probability	Classic GLS estimation	Imposing Activity Probability	Classic GLS estimation	Imposing Activity Probability
Error OD Flows	55%	44%	7%	38%	6.5%	47%	19%
Abs Error Link Flows	2	0	0.25	0.0021	0.25	0.00019	69.75

Table 1:Proof of concept results

The experiment has been performed using constant link costs, i.e. not considering congestion dynamics, and a more realistic *Dynamic Network Loading* (i.e. the Link Transmission Model developed by Yperman [15]), both in congested and non-congested conditions. In all the conditions, when the demand profile is constrained though the *Activity Function*, the travel time to reach the detector is indirectly considered since the average value of the departing time is an explicit coefficient of the demand. Only few combinations of demand flows exist, which can properly reproduce the observed traffic regime according to the imposed Activity Function (Table 1 and Figure 2).



(a) (b) (c)

Figure 2: Constant Link Costs - Flow composition for the (a) Observed flows on the network: (b) Estimated according to the classic OD estimation procedure; (c) Estimated considering a correct Activity Function;

The difference between the results showed in table two should not to be considered surprising. The low improvement obtained using the standard approach is related to the fact that the algorithm ends in a local optimum very close to the starting point. In this specific proof of concept, by exploiting

the *Activity Function* the solution space becomes convex. However, this represent an extreme case, while in general we expect a smoother shape is expected in more complex networks.
In the presentation of this work more details will be given on an empirical analysis upon the correlation between activity data and traffic state is performed. We will also generalize the new demand estimation methodology presented here in form of the illustrative example. In this general methodology, the demand is assumed to be composed by different demand patterns, which influence and are influenced by the network states, and their functional parameters can be estimated from traffic data using an extension of the classical dynamic demand estimation problem. Since departing time, activity duration and travel time are found to be important determinants to be considered in order to evaluate the correlation between traffic state and activity patterns, this information is transferred to the Mobility Demand through an *Activity Distribution,* which is able to capture the existing correlation between traffic and demand flow. The derived distribution then works as constraint on the generated flow between an origin destination zone transferring the observed behavior to the demand in term of average statistics. If this element is considered within a demand estimation problem, local solutions related to unrealistic demand patterns are less likely to occur as the simple illustrative example showed. This means that the objective function used to identify the demand is smoother and more reflecting observed activity-travel patterns.

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