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Transportation Research Procedia 00 (2021) 000–000

Transportation Research Procedia

www.elsevier.com/locate/procedia

24th EURO Working Group on Transportation Meeting, EWGT 2021, 8-10 September 2021, Aveiro, Portugal

Dynamic Modal Split Incorporating Trip Chaining: A Parsimonious Approach to Mode-Specific Demand Estimation

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Abstract

Dynamic mode choice is essential to understand the potential effectiveness of policies aiming to achieve desirable modal split targets or to manage the demand for resource-limited systems such as shared mobility services. In this paper, we propose an estimation of dynamic modal split for work-related trips, including mode- and time-specific costs, with activity participation based on utility maximization. In order to obtain an accurate profile while remaining at an aggregate level, three types of work activities are described (full time, morning and afternoon shift). The estimated modal split concerns motorized vehicles, soft modes but also train and urban public transport. Based on utility maximization principles, the accumulated utility is formulated within a departure time choice model. A Markov Chain Monte Carlo procedure is used to evaluate the marginal utility function parameters which are used in a joint departure time and mode choice evaluation. Mode specific travel speed for each time of the day is used to estimate also travelled distance distribution per mode. The methodology is applied and tested, using data collected in Ghent in 2008. 16.749 work-related trips have been considered in a simplified estimation where two successive trips are constrained to be done with the same mode. This methodology is characterized by low data requirements and the model is shown to be flexible to include all available type of information in order to refine or accelerate the estimation. The proposed method is easy to implement using only dynamic trip counts, without the need for simulation or traffic assignment.

Keywords: Mobility, Mode choice dynamics, Travel Demand, Work Trips, Markov Chain Monte Carlo

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1. Introduction

Making specific mode choices for an earlier trip influences following decisions, for example because of the consequent availability of transport alternatives at the origin or destination of the trips. To handle the aspects and correlation in mode choice, tour-based models seem to be the most relevant. When a tour-based mode choice modelling approach is adopted explicitly in activity-based models, the mode choice usually follows an activity scheduling model. For example, (Miller et al., 2005) consider the predicted schedule as an external input to the mode choice model. In many other cases only mode-specific tours are specified, based on the commute mode-choice only. This reduces the approach to unimodal tours and do not allow combinations of different modes within a single tour (Arentze and Timmermans, 2004; Bhat, 1997; Bowman and Ben-Akiva, 2001). More advanced models include a "main mode" for the tour as well as trip-based mode choice models, that are constrained by that choice (Bradley et al., 2010). Few models are able to handle all feasible mode combinations for tour-based choices (Vovsha et al., 2017).

DTA frameworks including mode choice under equilibrium conditions and including activity-related choices are an efficient way to represent full-day schedules of a whole population, considering feasibility constraints. Supernetwork representations allow to model multimodal travel choice problems in an integrated framework (Carlier et al., 2003). Although there is no essential difference between a supernetwork and a conventional traffic network, supernetworks are capable of representing the transition and interactions between multiple modes. Different choices are turned into path choice through the constructed network, offering a basis for activity-travel assignment. (Lam and Yin, 2001) were the first to present a conceptual activity-based and time-dependent traffic assignment model. Activity-travel patterns are input of particular networks that range from PT-only networks with mode choice (Fu and Lam, 2018), to multi-state supernetworks (Liao et al., 2013). However, all these models are constructed at the individual level, together with the scheduling and activity chain planning. Agent-based traffic simulators are another advanced approach for modelling complex choices and their interactions (Patwary et al., 2021). The creation of a synthetic population is commonly needed as input to estimate the aggregated demand emerging from these individual decisions and can be done in fitting or generation-based approaches (Saadi et al., 2018). On the contrary, in this work we believe that emerging behaviours at the aggregate level do not require advanced and complex user-based models to obtain a realistic dynamic modal split estimate, and able to be sensitive to testing policy and management solutions. Works focusing on the estimation of activity schedules based on aggregated OD matrices are very few, but recent works use those data to convert purpose-dependant demand into realistic activity schedules (Ballis and Dimitriou, 2020).

In the proposed work, we use a clock-based utility function to represent the positive part linked to the performance of the work activity and the parameters of the function are estimated through a Markov Chain Monte Carlo approach to infer modal split and working-type of population at a zonal level. The proposed methodology is presented in the following section and then a case study focusing on the estimation of work-related trips which count for more than 40% of the total daily trips described is presented with preliminary results. Extension to non-work related trips will be a next step in this research.

2. Methodology

In this work, we assume to have information, or a reliable estimation, of the total daily demand for work-related trips within a study area, D_{work}. Then, thanks to the proposed model, the time- and mode-dependent demand $D^{m}_{work}(t)$ is calculated according to departure time probabilities calculated based on utility maximization principles. Individuals are assumed to optimise their schedule to maximise their utility and the aggregated trips, resulting from a probability model which produces emerging traffic flows. We estimate their choices as a utility maximization problem with time-dependent travel times which are mode-specific but not function of the estimated flows.

Following the general framework proposed in (Yamamoto et al., 2000), we define the overall net utility accumulated during the reference time period $\boldsymbol{U}$ as the sum of the disutility/cost of travelling and the positive utility of performing one or more activities. We consider time of day discretized into time steps Δt. Utility varies with the type of activity and can be a function of activity start time, t_s; the marginal utility gained by individual i from doing activity of type a at time t is $u^i_a(t, t_s)$. The total accumulated utility for an individual i, $\boldsymbol{U^i}$, is the sum over the n activities comprising its activity sequence $A^i = [a^i_1, a^i_2, .. a^i_n]$. For readability, we omit that $n = n(i)$, and may simply denote activity using j rather than a^i_j. The j-th activity for individual i has (starting, ending) time denoted $(t^{i,j}_s, t^{i,j}_e)$; these partition the day. Each trip is included as an activity in the chain, and the associated u^i_j then represents the marginal (dis-)utility of travelling. We therefore have that individual i accrues total daily utility:

$$\boldsymbol{U}^i = \sum_{j=1}^{n} \sum_{t=t_s^{i,j}}^{t_e^{i,j}} u_j^i(t, t_s^{i,j})\, \Delta t \tag{1}$$

Equation (1) can easily be extended to capture zone-dependent marginal utilities simply by labelling activities in different zones as distinct activity types offering different marginal utilities. We believe anyhow that considering marginal utilities to be zone-independent is acceptable for this specific study, considering that the focus is on aggregate behaviour rather than estimating individual choices.

Additionally, in this study we focus on the work activity only, leaving the analysis of all activity types to future papers. In the following notation, w^- relates to all activities which took place before the trip to go to work and w^+ relates to all activities after leaving the work activity, including any trips made to access them. We formulate these two before/after blocks as singular activity types. We assume that the disutility of travelling has constant marginal cost, $c_t < 0$ per unit time. Travel time to the working activity, from zone y to zone z by mode m, $tt_{work}^{yz,m}(t_d)$, is OD- and mode-specific and depends on the departure time, t_d. Departure time is chosen to arrive at the desired start time: $t_d = t_s - tt_{work}^{yz,m}(t_d)$. Note that the trip components are assumed to be not individual specific. For individual i, commuting using mode m, with work starting and ending time (t_s, t_e) given a zone of origin y and destination z and hence travel time $tt_{work}^{yz,m}(t_d)$, the total daily utility gained is

$$\boldsymbol{U}_{work}^i(t_s, t_e, m|(y,z)) = \sum_{t=t_0}^{t_d-\Delta t} u_{w^-}^i(t, t_0)\, \Delta t \quad + \quad c_t tt_{work}^{yz,m}(t_d) \quad + \sum_{t=t_s}^{t_e} u_{work}^i(t, t_s)\, \Delta t \quad + \sum_{t=t_e+\Delta t}^{t_N} u_{w^+}^i(t, t_e + \Delta t)\, \Delta t \tag{2}$$

The total accumulated utility (2) includes four components. The first and last represent all trips and activities performed before and after work; the central components are the work activity and the trip to reach it. This formulation could easily be generalized to include dependence of the marginal utilities on the *location* where activities are performed. This would result in estimating OD-specific parameters. However, location choice is not explicitly studied in this paper and hence marginal utilities are considered zone-independent. Similarly, without information at the zonal level, travel time is approximated based on the type of activity (at the destination) and is mode-specific, i.e. $tt_{work}^{m}(t_d)$. These elements are the necessary components of the utility maximization process.

2.1. Marginal utility formulation

To estimate the total utility gain for each combination of departure times and modes, a time-dependent functional form is selected for the marginal utility (Ettema and Timmermans, 2003):

$$u_a(t, t_s) = \frac{\gamma_a \beta_a (U_a^{max})}{exp[\beta_a(t - (\alpha_a + t_s\tau_a))]\,.\,(1 + exp[-\beta_a(t - (\alpha_a + t_s\tau_a))])^{\gamma_a + 1}} \tag{3}$$

The model parameters are:

- α: if $\gamma = 1$ and $\tau = 1$ the saturation point is located at the α value and the function is symmetric.
- γ: if $\gamma > 1$, the saturation point is situated before α and the steepness of the left part is higher than the right part, $\gamma < 1$ represents instead a longer warm up phase.
- τ: controls whether saturation is reached at a fixed time of day or is relative to activity duration. When τ is close to 0, utility is determined by time of day (regardless of activity start time). Whereas $\tau = 1$ describes a fully duration-based utility function; the utility function is translated in time to follow the activity start time.
- U^{max} : the parameter U^{max} represents the maximal possible accumulated utility for a certain activity, it impacts the magnitude of the marginal utility function. This parameter controls the gain in performing one activity relative to any other alternative.
- β: determines the dispersion around the saturation point.

All marginal utilities follow this functional form, including those capturing the ‘activities’ w^- & w^+. In our model we use equation (3) to express the expected marginal utility at an aggregated level, i.e. at a zone level. Individual heterogeneity is captured by probability distributions of model parameters, which emerge from the parameters’ estimation process. For a given activity, this collection of model parameters across individuals is denoted $\boldsymbol{\theta}$.

2.2. Trip duration formulation

At the aggregate level, an assumption needs to be done in terms of experienced travel time. For each time of the day, various data sources can be used to get the expected travelling speed by mode $v_m(t_d)$. This value is considered as given and fixed while the travelled distance by mode is a distribution d_m, used to compute the expected travel time by mode and time of the day:

$$tt_{work}^{m}(t_d) = v_m(t_d) * E[d_m] \quad (4)$$

2.3. Estimation process

Based on formulations (2)-(4), the departure time is expressed as a discrete choice process using a multinomial logit model. The probability of choosing the pair of starting and ending times (t_s, t_e) and mode m is computed as follows:

$$P_{work}(t_s, t_e, m) = \frac{\exp\left(U(t_s, t_e, m) + c_t tt_{work}^{m}\right)}{\sum_m \sum_{t'_e > t_{s'}} \sum_{t_{s'}} \exp\left(U_a^i(t'_s, t'_e) + c_t tt_{work}^{m}\right)} \quad (5)$$

The time allocation probability is used to estimate the distribution of departure times of the complete population. The proposed framework is used to estimate all work-related trips inside a study area. This includes trips for which the activity at destination is work (6a) and the trips starting after the work activity (6b) which results in 2 trips for each worker (6c):

$$T_{\rightarrow work}(t) = D_{work} \sum_{m} \sum_{t_e > t_s} P_{work}(t_s = t + tt_{work}^{m}, t_e, m) \quad (6a)$$

$$T_{work\rightarrow}(t) = D_{work} \sum_{m} \sum_{t_s} P_{work}(t_s, t_e = t, m) \quad (6b)$$

$$T_{work}(t) = T_{\rightarrow work}(t) + T_{work\rightarrow}(t) \quad (6c)$$

A Bayesian approach based on Markov Chain Monte Carlo (MCMC) is used to estimate all parameters defining demand generated for each time of the day, given observations. This complete set of parameters denoted $\mathbf{\Theta}$ is composed of different components $\boldsymbol{\theta}$, related to aspects of the formulation such as utility- or distance-related parameters. The Metropolis algorithm (Metropolis et al., 1953) is used for estimating a plausible distribution of each parameter in an iterative process. Initial values and plausible prior distributions are selected for every element of $\mathbf{\Theta}$. In every iteration k, a new set of values Θ_k is sampled independently from a distribution defined by the previous value of each parameters Θ_{k-1}. These sampled values are included or not in the posterior distribution (output of the MCMC) according to the Metropolis rule, based on their "score". The score S_k at iteration k is reflecting both the plausibility with respect to the defined prior (i.e. the a priori knowledge available on parameter's values) and with respect to the observed data.

$$S_k = \sum_{\mathbf{\Theta}} \log\left(prior(\Theta_k)\right) + \mathcal{L}_k(T) + \mathcal{L}_k(D) \quad (7)$$

The sampled values for the marginal utility functions are used in order to generate trip distributions during the day with respect with choice probability (equation 5) and total demand D_{work} (equation 6). Thois output of trip generation model is compared to observed daily demand. In this application to mode choice estimation, the likelihood is made of two elements: $\mathcal{L}_k(T)$ relates to the observed total generated demand $T_{work}(t)$ for each time interval Δt calculated in equation (6) and $\mathcal{L}_k(D)$ relates to the known distribution of travelled distances for working purpose in the study area, regardless of the mode.

Given the aggregate nature of the estimation, this method is attractive because each variable is sampled without knowing its actual distribution but providing a posterior probability distribution as an output of this stochastic process. These distributions can represent better the heterogeneity of different users and the marginal utility of different activity types.

3. Case study

To test the methodology, we use a database from a multiday travel survey collected in the province of Ghent in 2008, including multiple users, days, and tour types (Castaigne, 2009). All trips to and from work are considered for this analysis. Since only substantial travel time differences will be influential, time resolution of 5 mins intervals for the observed demand is sufficient.

Modes are grouped into the following categories, based on their travel time distribution: motorized modes, train, urban public transport, and soft modes (figure 1a). For each of these modes, we estimated the travelled distances directly from survey data (for all kind of trip purposes) and fitted this distribution as starting point for the estimation. One of the goals of the estimation is to estimate those distributions for the work activities.

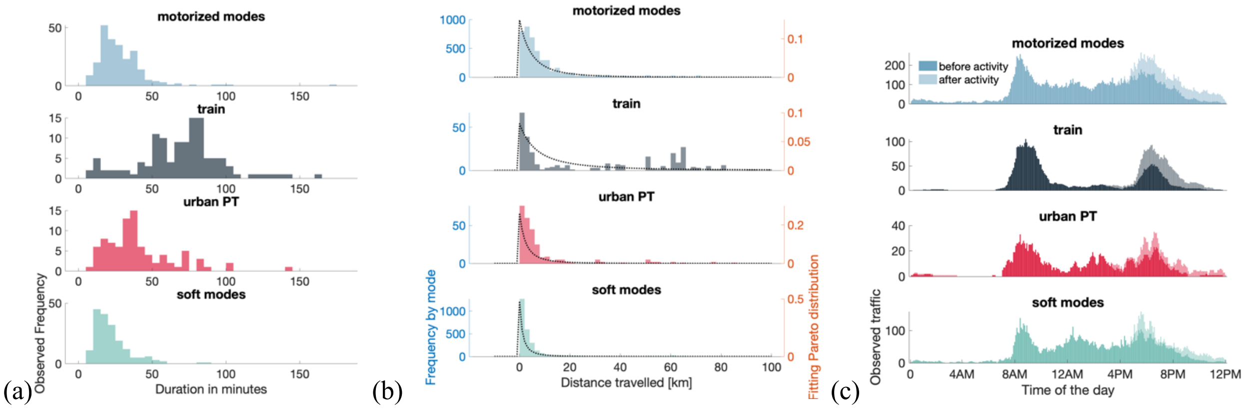

Figure 1 Observed (by mode) (a) trip duration frequency (b) travelled distance distribution (c) traffic by time of the day (5 minutes interval)

The input of the MCMC are i) the generated demand by time of the day, ii) the total travelled distance distribution, and iii) the modal speed by time of the day (figure 2). The first two are used for assessing the estimation quality and calibrate the parameters while the last is used inside the derived estimation of the travel time distribution. To estimate realistic travel times with respect to the observed traffic, we calculate a truncated average of observed travel speed using survey answers for each time period. Despite the large number of observations, there was not much data for every mode in every time interval. Missing data was added via linear interpolation of neighbouring data.

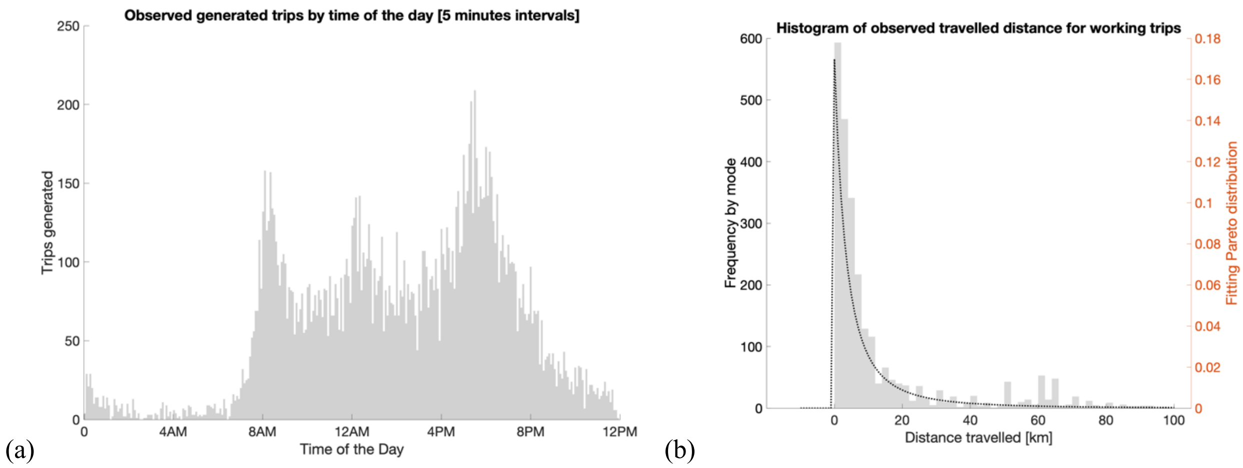

Figure 2 Input: (a) work-related generated demand by time of the day (b) Total travelled distance distribution

To reproduce daily dynamics, particularly the lunch-time peak, work activity has been separated into three sub-components: $w_{j=1}$ is “work in the morning”, $w_{j=2}$ is “work in the afternoon” and $w_{j=3}$ is “full-day work”. Each component has distinct marginal utilities for all three components of the estimation w_j^-, w_j, w_j^+.

The parameter τ_n is fixed to $\tau = 0$, meaning that all marginal utilities are fully clock-based. For each of these three activities, 13 parameters are thus estimated in the MCMC, corresponding to the parameters of equation (3) and the proportion of the whole demand corresponding to the given work-type. Two additional parameters are estimated for each mode in order to evaluate the distribution of travelled distance with a Pareto form:

- $\theta_{\text{utility}}^{(n=1:3)} = (U_n^{max}, \alpha_n, \beta_n, \tau_n, \gamma_n)$ for all work-activity subtype j
  with $n = 1$ $is\ w^-$, $n = 2$ $is\ work$ and $n = 3$ $is\ w^+$
- $\theta_{\text{share}}^{(j=1:3)} = P(w_j)$ with $\sum_{j=1:3} P(w_j) = 1$
  with $j = 1$ $work\ in\ the\ morning$, $j = 2$ $work\ in\ the\ afternoon$ and $j = 3$ $full-day\ work$
- $\theta_{distance}^{(m=1:4)} = (scale_m, shape_m)$
- $\mathbf{\Theta} = \sum_j (\theta^j + \sum_n \theta^{n,j}) + \sum_m \theta^m$

In total $\mathbf{\Theta}$ contains 48 elements to estimate. The total number of trips to be distributed is considered as fixed and known, since they represent the expected number of users working daily in a certain area, which is an information often available. Preliminary analysis showed that the number of successive trips performed by the same mode is higher than 80% and that this number is even higher for owned resources such as bike and car (Scheffer et al., 2021). For this reason and to accelerate the estimation procedure, we assume in the proposed case study that consecutive trips are done using the same mode.

4. Results

The estimation procedure has been run for 15.000 iterations. The resulting final demand profile is very accurate with respect to observed generated demand, with $r^2 = 0{,}82$. The main result of the estimation is the posterior distribution of estimated parameters. In order to estimate final marginal utilities, a burn-in period of 200 iterations is selected and all remaining values of the posteriors are used to compute the average of each parameter. Figure 3 shows the three estimated marginal utility functions. They are the primary component for the estimation of departure time distributions. The estimation of these three components is not correlated because the proportion is estimated independently. For this reason, the difference in the values of U^{max} is relevant within a sub-activity only.

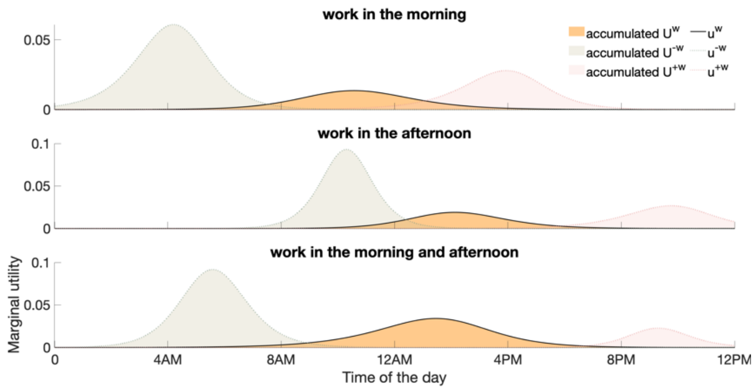

Figure 3 Estimated marginal utility functions of the three components

Figure 4(a) shows the final estimation for each time of the day. The separation of the work activity into three components makes it possible to better reproduce the mobility dynamics, with the three observed peaks which are well captured. The other derived output is the total travelled distance. In order to compare distance distributions, a number of distances values corresponding to the number of mode-specific trips is sampled from the estimated corresponding distribution. Figure 4(b) shows the frequency of all modes together and the comparison of share for each interval of 5km (the intensity of the color represents the length of the trip). Travelled distances are overall overestimated compared to the observed data. The relatively poorer fitting with respect to the demand is because the number of data points to fit and the order of magnitude is smaller, and also because the correlation between the estimated parameters and the output of each simulation is lower.

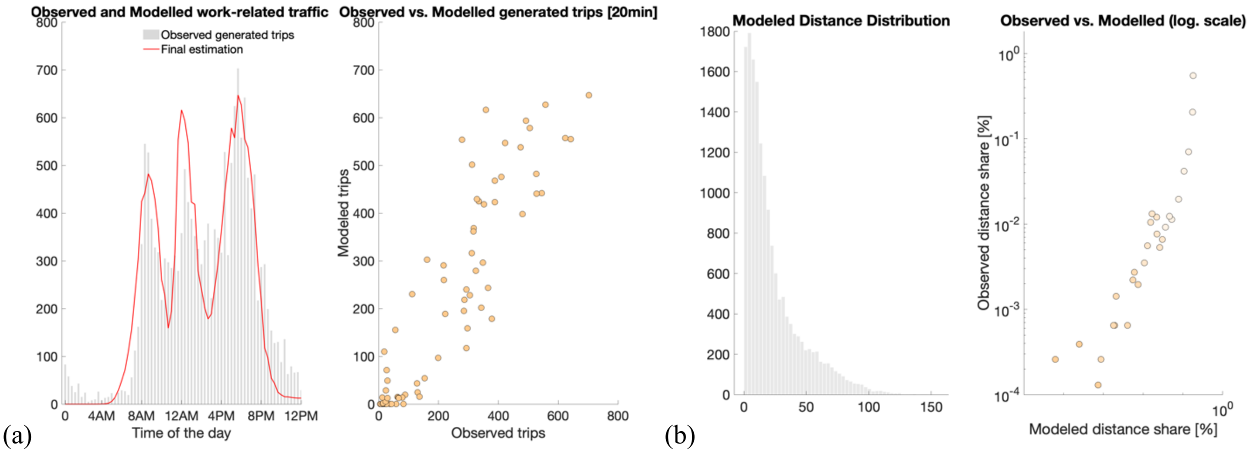

Figure 4 Estimated (a) traffic for each time of the day (b) travelled distance distribution

Including a mode component in the choice set results in a dynamic modal split estimation (figure 5a), which shows the ability of the model to produce such output even without resorting to advanced cost functions but only based on the positive component of the accumulated utility and a probability distribution of travelled distances. The estimation was done for a 5-minute interval, but the modal split results are shown for a 20-minute time interval. This avoids skewing the output with missing or outlying data, in terms of modal speed for example. The mode-specific departure time profiles (figure 5b) indicate a good representation of large-scale temporal dynamics. For example, around mid-day, the peak is more visible for soft modes and car users and almost no train users appear. The estimated work-related trips can be compared to figure (1c) that represent the real values for all kind of trip purpose.

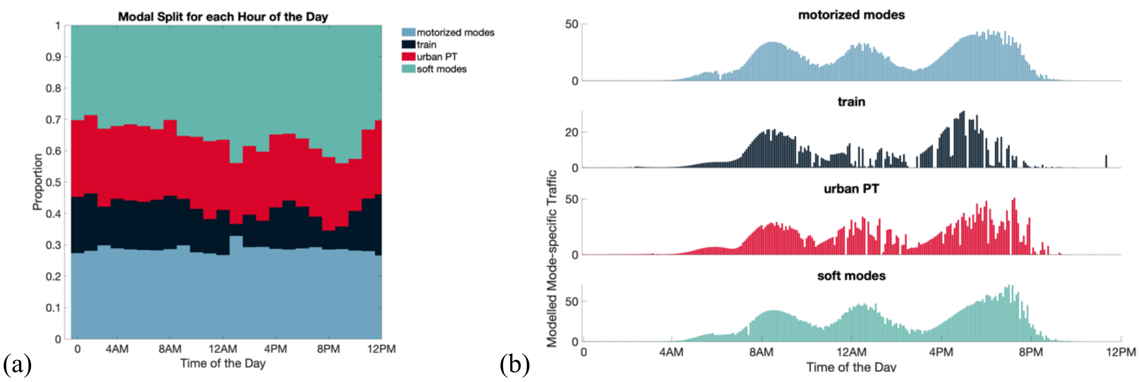

Figure 5 Estimated (a) dynamic modal split (b) mode specific demand profiles

However, the scale is slightly misrepresented because the total number of mode-specific users is not known or controlled in any manner, and there is no other component than the travel time, and the travelled distance distribution is not dependent on the time of the day. The peak of soft modes around 12AM can normally be explained by shorter trips associated to the shopping or eating activity. In general, there is an overrepresentation of modes for which trip duration is typically short, such as soft modes. The number of observed trips impacts also the quality of the estimation with a poorer estimation in night trips. In addition, the level of service is not included in the input information. This results in unrealistic modal split during that period when the train trips should theoretically result to a value close to 0 when the service is not available.

5. Conclusion

In this paper we proposed a Bayesian approach to estimate utility parameters of work-related marginal utility functions. The aspect of mode choice is estimated using dynamic speed and estimated distance travelled such that the total accumulated utility in a day, given mode choice and trip timings results in travel demand daily distributions. The application of the proposed methodology shows a relatively good estimation, in particular considering the low input data requirements. It also underlines the possibility to combine many information sources relating to diverse aspects of travel decisions. In the current state, the disutility of travelling results only in a halt of utility gain. Including a more detailed impact of mode-related decisions would also allow to obtain a better level of magnitude. Temporal dynamics are already emerging from the proposed model, relying only on time-specific speeds and the constraint of using the same mode for two successive trips. It is feasible with the proposed model to include the possibility of using different modes however this increases the computational time significantly and lacks to describe the strong existing correlation with the proposed, simplified choice model.

Acknowledgements

This research is supported by the EC-FEDER Programme Investissement pour la croissance et l'emploi of Luxembourg - Project MERLIN (2017-03-021-18).

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