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LINKING ACTIVITY-BASED MODELS WITH TRAFFIC COUNTS: A NUMERICAL EXAMPLE

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1. BACKGROUND

Although activity-based travel demand models have clear theoretical advantages over conventional aggregate four-step model – the most important ones are the fact that all basic travel decisions can be applied in a disaggregate fashion, the explicit linkages between the travel decisions of members of a single household, the consistent choices for a single person across all travel decisions and the disaggregate way of handling time of day travel decisions – conventional models still dominate the travel demand modeling paradigm (Vosha *et al.*, 2005; Walker, 2005). Davidson *et al.* (2007) highlighted several reasons that explain the acceptance of more sophisticated model frameworks. They can be broadly categorized as the degree of resistance to new modeling technology and the size of encouragement forces. The reasons include the size of the public agency, the size of the jurisdiction, the level of institutional history and the level of state support for travel demand forecasting. Davidson *et al.* (2007) also stressed that in order to reinforce the transition from conventional models towards activity-based models, it is imperative that the objective theoretical advantages of activity-based models are better explained to practitioners and communicated more actively.

This paper focuses on a concern that stems from misunderstanding and mistrust by practitioners. Many practitioners question the advantages of activity-based models over conventional four-step models in terms of replication of traffic counts, as it is in many respects easier to adjust a conventional travel demand model to fit base level traffic counts exactly than an activity-based micro-simulation model. In this regard, it is important to stress the distinction between static model accuracy in terms of the replication of the base-year observed data, and the responsive properties of the model that are related to the quality of the travel forecasts for future and changed conditions, as these two model properties do not necessarily coincide. In this paper, a framework is highlighted that actively links activity-based models with traffic counts in order to achieve the desired responsive properties – the model being sensitive to demographic changes and policy measures – of the activity-based models as well as the replication of traffic counts.

2. LINKAGES BETWEEN ACTIVITY-BASED MODELS AND TRAFFIC COUNTS

There are two possible approaches to link activity-based models with traffic counts, namely a direct and indirect approach. The first approach calibrates the model parameters of the activity-based model in such way that the model replicates the observed traffic counts (quasi-)perfectly. The second approach tries to incorporate findings, based on the analysis of traffic counts, into the model components of the activity-based models. The following subsections will elaborate and further clarify the two methods of linking activity-based models with traffic counts.

2.1. Indirect Linkage

The 'indirect linkage'-approach tries to identify events that affect travel behavior and resulting traffic patterns. Analysis of traffic counts for instance can be used to identify effects of holidays (Liu and Sharma, 2006; Cools *et al.*, 2007) and weather events (Cools *et al.*, 2008). These traffic swaying events then can be used to alter the impedance functions used in route choice modules. When events such as holidays and weather conditions are identified, their impact on travel behavior can even be further elucidated by analyzing activity diary data. Utility functions that express the propensity of performing certain activities – note that basically the utility functions of all elements of the activity-pattern generation can be modified in this way – can then explicitly incorporate explanatory variables to account for the events that were analyzed. In this regard, activity-diary collection tools that integrate geographical information logging, such as the PARROTS-tool (Kochan *et al.*, 2007) provide the required data to perform detailed analysis, for instance on route choice. It can be expected that the explicit incorporation of events that account for the variability in revealed traffic patterns and their underlying reasons, will result in both an improved responsiveness of the activity-based model and a better replication of traffic counts.

2.2. Direct Linkage

The 'direct linkage'-approach tries to fine-tune the model parameters of the activity-based model in such a way that the model replicates correspond maximally to the observed traffic counts on the network. Calibration opportunities exist at four levels (Figure 1): the data level, the model level, the OD-matrix level and the assignment level.

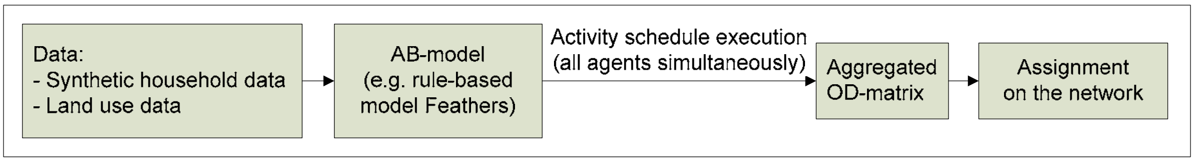

Figure 1: Four levels of calibration opportunities

Two approaches can be followed when considering calibration at the data level: a 'crude' approach, where the data is altered in order to achieve a better correspondence to the benchmark measures, and a 'fine' approach where agents (individuals or households) are weighted. The first approach immediately raises questions concerning the validity and the credibility: adjusting fields or adding or deleting records undermines the validity of the model and should be avoided. The latter approach attributes weights to the different agents. Note that the weights should be natural numbers (including zero) in order to have a logical meaning. The use of such weights can be defended by the fact that there exist groups of individuals with similar travel behavior that can be captured in representative activity patterns (RAPs). By using these RAPs, the complete activity-generation can be performed in a holistic manner (Kulkarni and McNally 2001). McNally (1999) and Wang (1996) have even further advocated the use of RAP's by showing that RAP's are relatively stable over conventional planning horizons (10 years). Weighting agents thus seems to be a worthwhile path to follow. Notwithstanding, the weighting procedure can become computationally very intensive as the number of possible weights increases with the number of simulated agents.

A second calibration possibility arises at the model level. The activity schedule generation could be altered in such a way that the obtained OD-matrix reproduces optimally the observed traffic counts. One solution to achieve this optimality is an 'updating'-process of the scheduling rules that are derived from the available travel survey data. Zone-specific rules can be introduced: for instance increasing the probability of certain destination choices, or increasing the probability of performing a certain activity. That way the production and attraction of these zones can be fine-tuned. 'Updating'-procedures have to be developed in order to benchmark the AB-model. When different forecasting scenarios are desired, it is necessary to keep the updated rules that were defined by the updating-process in the baseline year. That way the AB-model is constructed in a consistent way. Linking activity-based models with traffic counts by making behavioral adjustments (altering rules), thus might prove to be a valid way of overcoming practitioners mistrust.

The OD-matrix level is the third level where calibration opportunities arise. The OD-matrix is obtained by the simultaneous activity schedule execution of all agents. This OD-matrix can then be benchmarked in function of the screen-line counts. Different techniques exist to estimate OD-matrices from traffic counts. First, a distinction can be made between static OD-matrix estimation (count data only available for one time period) and dynamic OD-matrix estimation (count data available for a series of time periods). In practice, most models assume or require that a target OD-matrix is available. This target OD-matrix (the OD-matrix resulting from the activity-based model) is a crucial part of prior information. In statistical approaches, the target OD-matrix is typically assumed to stem from a sample survey and is regarded as an observation of the "true" OD-matrix. The observed set of traffic count data may also be assumed to be an observation of the "true" traffic count data, and therefore (small) deviations between estimated counts and observed counts may be accepted.

Thus, the purpose of the calibration process is to find an OD-matrix which produces “small” differences between the estimated link flows and the observed flows. Three modeling philosophies are postulated in the transportation literature (Abrahamsson, 1998): traffic modeling based approaches, statistical inference approaches and gradient based solution techniques.

The traffic assignment module is the last level where calibration is possible. Obviously the way of attributing origin-destination flows to the network plays a crucial role in how well the model-based traffic counts correspond to the benchmark measures. Ortúzar and Willumsen (2001) classify traffic assignment methods according to their treatment of congestion (inclusion of capacity restraints) and their treatment of differences in objectives and perceptions by agents (inclusion of stochastic effects).

3. NUMERICAL EXAMPLE

In this Section, a numerical example is provided to further illuminate the ‘direct linkage’-approach. Since the example is purely hypothetical and the goal is the explanation of the different calibration strategies, different assumptions are made to ensure the parsimony of the example. Figure 2 and Table 1display the basic information of the numerical example. The network assignment method that will be used is the ‘all-or-nothing’-assignment method (Ortúzar and Willumsen, 2001). This fixed choice implies that at traffic assignment level no more calibration is possible. Moreover, this choice procures the property that (in the described example) the counts on the different roads are an identity match to the origin-destination flows between two origin-destination pairs.

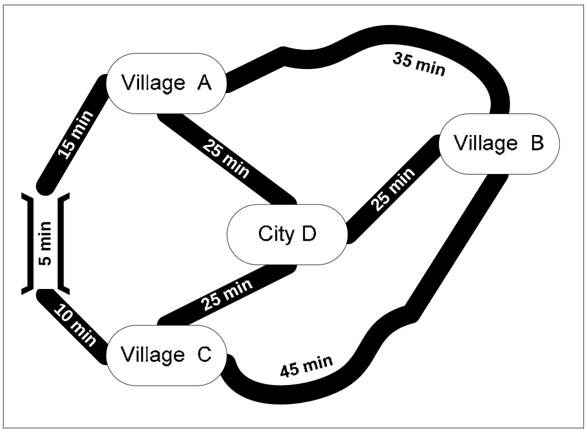

Figure 2: Visualization of the example

F = Female, M = Male		Number of households in			
HH-composition	HH-earners	Zone A	Zone B	Zone C	Zone D
2 adults (M & F)	2 (M & F)	70	70	55	80
2 adults (M & F)	1 (M)	30	30	20	30
2 adults (M & F)	1 (F)	10	15	15	26
2 adults (M & F)	0	10	10	10	24
1 adult (M)	1 (M)	35	30	45	92
1 adult (M)	0	5	5	5	28
1 adult (F)	1 (F)	30	30	41	92
1 adult (F)	0	10	10	9	28

Table 1: Population composition of the example

Concerning the activity-pattern generation, the following assumptions are made: workers in a village have a chance of 50% that they work in the city (Zone D), 25% chance that they work in their own village, and 12.5% chance that they work in one of the other villages. Conversely, workers living in a city have a 75% probability of working in their own city and a 8.33% probability of working in one of the surrounding villages. Concerning non-work activities it is assumed that males perform social activities and that females execute shopping trips. Half of the males living in a village fulfill their social needs in their own village, while one fourth travels to the city. The propensity of males traveling from their village to one of the neighboring villages is 12.5%. Half of the females living in a village prefer their own village as the favorite shopping location, one third prefers traveling to the city and 8.33% one of the other villages. By contrast, city people have a 75% propensity to stick to their own city to perform non-work activities and a 8.33% probability of travel to one of the villages to fulfill their needs. Furthermore, it is assumed that people performing their work and non-work activities at the same village/city immediately connect their work and non-work activities, while the others are expected to travel home first.

The representative activity patterns (RAPs) that can be observed for this numerical example are the following for the male population: Home-Work-Social-Home, Home-Work-Home-Social-Home and Home-Social-Home. For the females, the following RAPs can be identified: Home-Work-Shopping-Home, Home-Work-Home-Shopping-Home and Home-Shopping-Home. As complete information about all activity-patterns seldom is available, the starting point is a 20% random sample of the population. The following Table presents the OD-matrix obtained from this sample (scaled up to the population level for comparison purposes), and the one from the population. Note that the diagonal elements of the population OD-matrix are not observed on the road network and correspondingly can not be used for the calibration process.

Table 2: OD-matrices retrieved from the population (left) and survey (right)

	Population (* not observed)				Survey (Scaled up)			
	Zone A	Zone B	Zone C	Zone D	Zone A	Zone B	Zone C	Zone D
Zone A	*419	124	122	255	440	85	125	245
Zone B	124	*417	121	265	85	430	135	265
Zone C	122	121	*402	249	125	135	400	260
Zone D	255	265	249	*1317	245	265	260	1250

3.1. Calibration at the data-level

The goal of weighting agents is to procure the highest possible resemblance between the observed traffic counts on the network and the predicted traffic counts by the activity-based model. In the non-calibrated model all agents are equally weighted (weights equal to one). By iteratively altering the weights over the natural scale (0,1,2,…), an optimal correspondence can be found using meta-heuristics. Two different approaches can be distinguished when agents have to be weighted. The first approach weights the agents before their activity pattern is generated. Since agents are duplicated before the activity patterns are generated, the activity patterns of the replicated agents - created by the weights – can differ from the ones of the "true" agents. Thus, the convergence of the iterative process of weighting persons and calculating the activity patterns of the "agents" and their replicates is not necessarily satisfied. Nevertheless, it can be expected that in most cases a satisfactory result can be obtained after a reasonable amount of iterations.

The second approach weights the activity patterns of the agents. Take for example a male agent living in Village A, who works and performs his social activity in Village B. Doubling the weight of this person's activity pattern would result in improvement of the estimated OD-matrix, as the number of trips from A to B and from B to A would increase by one (from 85 to 86) and diminishes the gap with the flow observed on the network (86 is closer to 124 than 85). This example also illustrates the need for limiting the range of the weights. After all, one could see that weighting the agent with a factor 30 would boost the desired correspondence even further, yet it would seriously undermine the responsive properties of the model. Therefore, weights of the different agents should be increased separately, and one-by-one, ranging between predefined bounds.

3.2. Calibration at the model-level

At the model-level, the activity schedule generation could be altered by iteratively updating the probabilities of certain destination choices (related to their respective activity purposes). The updating process will attain a perfect match when the updated sample probabilities of the destination choices are equal to the unknown population probabilities. Table 3 shows the sample probabilities and the (unknown) perfect probabilities.

Table 3: Destination choice probabilities for work-related trips

Work / Habitat	Survey (non-calibrated)				Population (unknown)			
	Zone A	Zone B	Zone C	Zone D	Zone A	Zone B	Zone C	Zone D
Zone A	0.261	0.109	0.130	0.500	0.250	0.125	0.125	0.500
Zone B	0.021	0.234	0.234	0.596	0.125	0.250	0.249	0.500
Zone C	0.178	0.133	0.133	0.378	0.125	0.125	0.250	0.500
Zone D	0.091	0.078	0.078	0.701	0.083	0.083	0.083	0.750

If the updating process for example increases the likelihood of working in City D for workers residing in Zone C it is clear that an improved match is obtained between the estimated and observed traffic flows. Thus the goal of the updating process is to find the optimal parameters, which under normal conditions are unknown and only can be estimated.

3.3. Calibration at the OD-matrix-level

To illustrate the working of calibration methods at the OD-matrix level the reader is referred to Abrahamsson (1998), who gives a thorough literature review describing an extensive list of calibration options

4. CONCLUSIONS AND FURTHER RESEARCH

In this paper, different possibilities for linking activity-based models with traffic counts are highlighted. The discussed techniques provide the framework to overcome one of the main concerns by practitioners, namely the advantage of activity-based models over conventional four-step models in terms of the replication of traffic counts. In practice, a combination of the different proposed solutions can be recommended. Notwithstanding, it is important to recognize some open issues and avenues for further research. First, it is not always appropriate to assume that traffic counts are completely correct. Setting up some belief-structure might increase the responsiveness of the activity-based model. Second, the OD-matrix calibration that optimizes the correspondence between estimated and observed screen-line counts could negatively impact the correspondence to other measures such as vehicle miles traveled. Thus, formulation of a multi-objective calibration method is a key challenge. Finally, testing the calibration possibilities within a real environment such as the Feathers-framework would further provide empirical evidence of the proposed frameworks.

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