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Disaggregate path flow estimation in an iterated DTA microsimulation

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Abstract

This text describes the first application of a novel path flow and origin/destination (OD) matrix estimator for iterated dynamic traffic assignment (DTA) microsimulations. The presented approach, which operates on a trip-based demand representation, is derived from an agent-based DTA calibration methodology that relies on an activity-based demand model (Flötteröd et al., 2011a). The objective of this work is to demonstrate the transferability of the agent-based approach to the more widely used OD matrix-based demand representation.

The calibration (i) operates at the same disaggregate level as the microsimulation and (ii) has drastic computational advantages over conventional OD matrix estimators in that the demand adjustments are conducted within the iterative loop of the DTA microsimulation, which results in a running time of the calibration that is in the same order of magnitude as a plain simulation. We describe an application of this methodology to the trip-based DRACULA microsimulation and present an illustrative example that clarifies its capabilities.

1 Introduction

This section introduces a novel path flow and origin/destination (OD) matrix estimator for iterated dynamic traffic assignment (DTA) microsimulations. The first part of this introduction describes the basic concepts of these simulations and reviews some of the existing implementations. The second part revisits existing OD matrix and path flow estimators. Based on this review, the new approach is then motivated.

Iterated DTA microsimulations are characterized by the following features. They are microscopic in that both travelers and vehicles are modeled at the disaggregate level. They are iterative in that the simulation runs typically according to the logic outlined in Algorithm 1, where a demand simulator and a supply simulator are alternately executed until a state of mutual consistency is reached. Finally, they are usually stochastic in that at least the simulated travel behavior is non-deterministic, whereas the traffic flow model may be either deterministic or stochastic. The foundations of the iterated simulation approach have been laid by Cascetta (1989) and Cascetta and Cantarella (1991), and their application to increasingly complex model systems is still the topic of ongoing research (Nagel et al., 1998; Nagel and Flötteröd, 2012).

Algorithm 1 Iterated DTA microsimulation

1. Initialization. Give every traveler an initial perception of the conditions in the network.
2. Iterations. Repeat the following until stationary conditions are reached.
   a. Demand simulation. Travelers select new mobility plans based on what they have observed during previous iterations.
   b. Supply simulation. The mobility plans of all travelers are simultaneously executed on the network.

Algorithm 1 leaves open which behavioral dimensions are represented by the demand simulation (e.g., route choice, departure time choice, destination choice, mode choice, ect), and, indeed, the iterative approach can in principle cope with any of these dimensions (Nagel and Flötteröd, 2012). However, only few existing DTA microsimulations go beyond route choice adjustments; amongst them are DynaMIT (Ben-Akiva et al., 1998; DynaMIT, accessed 2011), METROPOLIS (De Palma and Marchal, 2002), and DRACULA (Liu, 2005; DRACULA, accessed 2011) which also adjusts departure time choice for independent trips, and MATSim (Nagel et al., accessed 2011; Nagel and Flötteröd, 2012; Raney and Nagel, 2006) which in its current implementation adjusts route, departure time, and mode choice for complete trip chains and is continuously being extended towards further demand dimensions (Horni et al., 2008). Far more common are iterated microsimulations that constrain themselves to the equilibration of route choice (and a strictly trip-based demand representation). Amongst those are AIMSUN (TSS Transport Simulation Systems, 2006, accessed 2011), DYNAMEQ (INRO, accessed 2011), and PARAMICS (Quadstone Paramics Ltd., accessed 2011).

The usual representation of a trip-based demand is a (possibly time-dependent) OD matrix that describes the number of trips from every origin zone to every destination zone in a traffic network. The traditional OD matrix estimation problem is to estimate an OD matrix from traffic counts on network links and supplementary prior information. In lightly congested conditions, link flows are linear combinations of path flows, yielding a mathematically convenient setting, in which OD matrix estimation techniques such as entropy maximization and information minimization (van Zuylen and Willumsen, 1980), Bayesian estimation (Maher, 1983), generalized least squares (Bell, 1991; Bierlaire and Toint, 1995; Cascetta, 1984), and maximum likelihood estimation (Spiess, 1987) have been applied. These methods can be carried over at least approximately to congested networks (Maher et al., 2001; Yang, 1995; Yang et al., 1992; Bierlaire and Crittin, 2006; Cascetta and Posterino, 2001). The further addition of a time dimension, yielding various dynamic OD estimators, is also possible (Cascetta et al., 1993; Ashok, 1996; Bierlaire, 2002; Sherali and Park, 2001; Zhou, 2004).

All of the above-mentioned demand estimators adjust OD matrices subject to a given route choice model that is embedded in the traffic assignment procedure. Since route choice modeling is an intricate task (Frejinger, 2008), modeling errors are likely to introduce biases in the estimated OD matrices. This problem can be avoided through the use of path flow estimators (PFEs). The first PFE, introduced by Bell (1995) and Bell et al. (1997), estimates static path flows from link volume measurements based on a multinomial logit stochastic user equilibrium (SUE) modeling assumption. Further developments along these lines allow for multiple user classes and simplified traffic flow dynamics (Bell et al., 1996) as well as for the incorporation of a deterministic user equilibrium (UE) modeling assumption (Sherali et al., 2003, 1994; Nie and Lee, 2002; Nie et al., 2005). Summing up the path flows between an OD pair yields its OD flow, which means that PFEs also estimate OD flows.

The new path flow and OD matrix estimator described in this work operates on a trip-based demand representation, but it is derived from an agent-based DTA calibration methodology that relies on an activity-based demand model. The underlying agent-based approach is mathematically developed in Flötteröd et al. (2011a), and its applicability for large, real scenarios is demonstrated in Flötteröd et al. (2011b). The objective of this work is to demonstrate the transferability of the agent-based approach to the more widely used OD matrix-based demand representation. This complements previous presentations, where this possibility is stated but not made concrete. Here, it is shown in terms of an operational example how the new approach can be deployed for the estimation of OD matrices and path flows in a microsimulation context. The used calibration software is freely available on the Internet (Flötteröd, accessed 2011).

Transferring the originally agent-based approach to the OD/path flow domain also carries over its advantages to this domain. The new approach goes beyond existing methods in that it

- estimates the trip-making of individually simulated travelers without any aggregation;
- is compatible with almost arbitrary demand and supply simulators; and
- has a computational complexity that is in the order of a plain simulation.

The reduction of an activity-based approach into the trip-based approach described in this article is possible because a trip constitutes a subset of a trip chain, and a trip chain constitutes the mobility-related side of an all-day travel and activity plan. Since the activity-based calibration approach adjusts all-day travel plans to traffic counts, it is also applicable to the basic case of travel plans consisting only of a single trip. The essential difference to all other PFEs presented in the literature is that the presented approach does not aggregate travelers/trip-makers into continuous flows but treats them as integer entities, consistently with the individual representation of trip-makers in a microscopic DTA simulation.

This work is of particular relevance for Intelligent Transportation Systems (ITS). Agent-based simulations of activity-based models may be computationally too heavy to be deployed in real-time contexts, and hence the corresponding calibration methodology was so far applied only in planning applications (an exception, although only with synthetic data, is

Flötteröd (2008)). OD matrices and paths may be more suited for short-term and real-time demand estimation, such that an operation transferral of the activity-based methodology to these datastructures, as presented in this article, is likely to contribute to the real-time monitoring of traffic conditions in ITS applications.

The remainder of this article is organized as follows. Section 2 introduces the two software systems deployed in this study: the DRACULA microsimulation and the Cadyts calibration tool, which implements the proposed methodology. A case study that clarifies the workings of the new approach is given and discussed in Section 3. Finally, the article is concluded in Section 4, and ongoing and future research work is described.

2 Framework and system components

The work presented in this article involves two software systems: the DRACULA microsimulation and the Cadyts calibration tool. This section describes these systems and their interactions. DRACULA is outlined in Subsection 2.1, and Cadyts is introduced in Subsection 2.2. The interaction of both systems is described in Subsection 2.3.

2.1 DRACULA – a microscopic simulation DTA model

DRACULA ("Dynamic Route Assignment Combining User Learning and microsimulAtion") is a simulation tool to investigate the dynamics of demand and supply interactions in road networks. The emphasis is on the integrated microsimulation of individual trip-makers' decisions, travel experiences, and learning. DRACULA complies with the simulation structure given in Algorithm 1.

The system explicitly models individuals' day-to-day route and departure time choices, and how their past experience and knowledge of the network influence their future choices. Coupled with that is a detailed within-day traffic microsimulation based on car-following and lane-changing rules. The system evolves continuously from one day to the next until a pre-defined number of days or a broadly balanced state between the demand and supply is reached. Simulation results can be obtained throughout the evolution and on not just the means but also variances and probability distributions both within-day and between days. The full details of the DRACULA suite of models and their applications have been reported elsewhere (e.g., Hollander and Liu, 2008; Liu et al., 2006; Liu and Tate, 2004; Panis et al., 2006) and will therefore not be detailed herein.

For the purposes of this article, DRACULA's sophisticated supply simulator is coupled with a simple, externally implemented multinomial logit (MNL) route choice model (Ben-Akiva and Lerman, 1985), and departure time choice is neglected (in that fixed departure times are assumed). The limitations of MNL route choice models, in particular with respect to route overlap, are well understood and can to some extent be corrected for without abstaining from the MNL's convenient functional form (Ben-Akiva and Bierlaire, 2003; Cascetta et al., 1996). However, the synthetic study presented in this article is sufficiently served by a plain MNL model.

Formally, denote a single trip-maker by n and its choice set of available routes by $\mathrm{C_n}$. The probability $\mathrm{P_n(i)}$ that n chooses route $\mathrm{i} \in \mathrm{C_n}$ follows a multinomial logit model

$$\mathrm{P_n(i)} = \frac{\exp\left[\mu \mathrm{V_n(i)}\right]}{\sum_{\mathrm{j} \in \mathrm{C_n}} \exp\left[\mu \mathrm{V_n(j)}\right]} \tag{1}$$

where $\mathrm{V_n(i)}$ is the systematic utility of alternative i as perceived by n, and μ is a scale parameter. Letting $\mu = 0$ results in a choice model that is insensitive to utility and hence predicts a uniform choice distribution, whereas for $\mu \to \infty$ only the alternative of maximum systematic utility is selected with positive probability. In all experiments, $\mathrm{V_n(i)}$ is set to the negative travel time one would have experienced on the considered route in the previous iteration. That is, the more complex learning mechanisms provided by DRACULA (allowing for long-term driver memories with different weights on different days) are not exploited in this study. Further investigations with more complex modeling assumptions are left as a topic for future research.

The dynamics of the traffic assignment problem are comprised in this notation as follows:

- A time-dependent assignment problem requires to model path choice probabilities per time slice. In such a setting, the model (1) is applied per time slice, and the utility evaluated in this model is also computed time-dependently.

- Further choice dimensions can be incorporated in this notation by re-defining the elements in the choice sets as tuples of choices. For example, adding departure time would turn the elements of C_n into (route, departure time) tuples.

The simplicity of the used notation reflects the flexibility of the calibration approach. As long as there are trip-makers, (possibly time-dependent) utilities of alternatives, probabilistic choice models, and (possibly time-dependent) traffic counts, the presented approach is applicable.

Variability in the total demand levels is enabled by giving every replanning trip-maker an additional empty route that represents the alternative of not making a trip. Assuming a total number of N trip makers for a given OD pair (and departure time interval) and assuming that on average a fraction of $f \in (0,1)$ trip makers actually travels per day gives the no-travel route a choice probability of $1-f$ and requires to scale down the choice probabilities of all other routes by f. This turns the daily demand for the given OD pair into a binomial random variable with mean fN and variance $Nf(1-f)$. Although the stay-at-home alternative has (again for simplicity) a fixed probability to be chosen, it can be formally accounted for within (1) by solving $\frac{\exp[\mu V_n(\text{stay-at-home})]}{\exp[\mu V_n(\text{stay-at-home})]+\sum_{j\in C_n}\exp[\mu V_n(j)]}=1-f$ for $V_n(\text{stay-at-home})$:

$$V_n(\text{stay-at-home}) = \frac{1}{\mu}\ln\left(\frac{1-f}{f}\right) + \frac{1}{\mu}\ln\left(\sum_{j\in C_n}\exp[\mu V_n(j)]\right) \qquad (2)$$

where the logsum term is computed only over the true route choice alternatives. Whenever the following text speaks of route choice according to (1), this therefore comprises the additional no-trip alternative.

2.2 Cadyts – Calibration of dynamic traffic simulations

Cadyts ("Calibration of dynamic traffic simulations"; Flötteröd, 2009; accessed 2011) is a continuously developed software toolbox that allows to estimate activity based travel demand models from traffic counts and vehicle re-identification data. Cadyts has been originally developed for the calibration of agent-based DTA simulations, which do not use OD matrices. In this subsection, a more specific perspective is adopted on a trip-based demand representation with route choice and dropping a trip being the only choice dimensions.

For the sake of clarity, a somewhat simplified calibration setting is described in the following, which results in a particularly interpretable formulation of the estimation: (i) the network is assumed to be uncongested, (ii) the demand simulator is assumed to deploy an MNL route choice model, (iii) the traffic count sensors are assumed to have univariate normal error distributions, and (iv) the objective is to estimate the output (choice distribution) of the demand model, not its parameters. See Flötteröd et al. (2011b) for a straightforward derivation of these assumptions from the general approach; some explanation given in that reference are summarized in this subsection.

Denote by y_{ak} the traffic count obtained on link a in time interval k, by σ_{ak}^2 the respective sensor's error variance, and by A the set of all sensor-equipped links. The simulated counterpart of a measurement y_{ak} is denoted by q_{ak}. This quantity is straightforwardly obtained from DRACULA by counting the number of simulated vehicles crossing the sensor location per time interval. The basic calibration approach can be phrased in a Bayesian framework, where, essentially, the prior route choice distribution $P_n(i)$ of (1) is combined with the measurements' likelihood function into a posterior route choice distribution $P_n(i \mid \{y_{ak}\}_{a\in A,k})$ given the sensor data. Under the above assumptions, the following approximation of the posterior distribution can be obtained:

$$P_n(i \mid \{y_{ak}\}_{a\in A,k}) = \frac{\exp\left[\mu V_n(i) + \sum_{a\in A,k;ak\sim i} \frac{y_{ak} - q_{ak}}{\sigma_{ak}^2}\right]}{\sum_{j\in C_n} \exp\left[\mu V_n(j) + \sum_{a\in A,k;ak\sim j} \frac{y_{ak} - q_{ak}}{\sigma_{ak}^2}\right]} \tag{3}$$

where $ak \sim i$ indicates that the network travel times are such that following route i, for a given departure time, implies crossing the sensor on link a during simulation time step k. Equation (3) is obtained from a consistent mathematical derivation (Flötteröd et al., 2011a), but it also has a clear intuitive meaning.

The prior route choice probabilities are changed only through additive modifications of the utilities. That is, the only affected elements of the behavioral model are the alternative-specific constants (ASCs). This is plausible: the objective in the given setting is to adjust the choices and not the choice model coefficients, and an ASC captures all effects on a choice that are not reflected by the attributes of the alternatives (Ben-Akiva and Lerman, 1985).

Regarding the nature of the ASC modifications, consider a single addend $(y_{ak} - q_{ak}) / \sigma_{ak}^2$ in the utility correction. If more vehicles are counted in reality than are simulated ($y_{ak} > q_{ak}$), the addend is positive and the utility of routes that cross the sensor on link a in time interval k is increased. Hence, simulated drivers are encouraged to select routes that contribute to the simulated count, which results in a lower deviation between reality and simulation. If, on the other hand, the simulation generates a flow that is higher than the real count ($y_{ak} < q_{ak}$), the utility correction is negative and the simulated drivers are kept away from taking routes that contribute to q_{ak}. The scaling of the utility corrections by $1/\sigma_{ak}^2$ ensures that more reliable sensors take greater effect than unreliable ones. In summary, the calibration works like a controller that steers the simulated drivers towards a reasonable fulfillment of the sensor data. That is, the estimator (3) calibrates simulated behavior, but it does not calibrate the underlying choice model parameters, such as f or μ in (2) This is exactly the type of problem also tackled by an OD or path flow estimator, which does not explain why travelers select particular routes, destinations or departure times, but only estimates this behavior as such.

Like in the OD matrix estimation problem, the amount of information that can be extracted from (possibly time-dependent) traffic counts is limited, and supplementary information is needed in order to state a well-posed estimation problem. The present formulation solves this problem differently from traditional approaches in that the DTA simulator itself constitutes the prior information. Even in the extreme case of observing no traffic counts at all, the additive utility corrections in (3) become zero and the calibration falls back to a plain simulation. That is, the approach functions with arbitrarily small amounts of sensor data. However, it also needs to be acknowledged that using a limited amount of data also reveals only a limited amount of information, and hence one is just as dependent on, e.g., carefully selected sensor locations as in the traditional OD matrix estimation problem.

In the traditional OD matrix estimation problem, an over-fitting to the sensor data is avoided by carefully selecting the weights assigned to the sensor data and to the prior information, e.g., in terms of inverse covariance matrices (Cascetta, 1984). The estimator described here also incorporates such a balancing mechanism, where the "weighting parameters" are the sensor data's standard deviation σ in (3), the scale parameter μ in (1), and the traveling probability f in (2): The larger σ, the lower the utility correction in (3). The larger μ, the less the choice model (1) is spread out across alternatives, reflecting increasing certainty of the analyst about what the simulated travelers should be doing. The closer f is to one, the less attractive becomes the stay-at-home alternative in (2), meaning that the analyst is increasingly confident about the total demand level.

Cadyts can cope with more general settings than what is presented here. For example, the experiments described in Section 3 rely on some additional features of the calibration that enable its application in congested conditions (Flötteröd and Bierlaire, 2009).

2.3 Integration of DRACULA and Cadyts

This section describes how DRACULA and Cadyts are linked together. The next section then deploys the technology described here for a series of experiments.

The communication between DRACULA and Cadyts is based on exchanging data through files. The flow chart of Figure **Error! Reference source not found.** outlines the interactions between the two systems. The program logic is implemented in a Python script that calls both DRACULA, the route replanning module, and Cadyts in the necessary order.

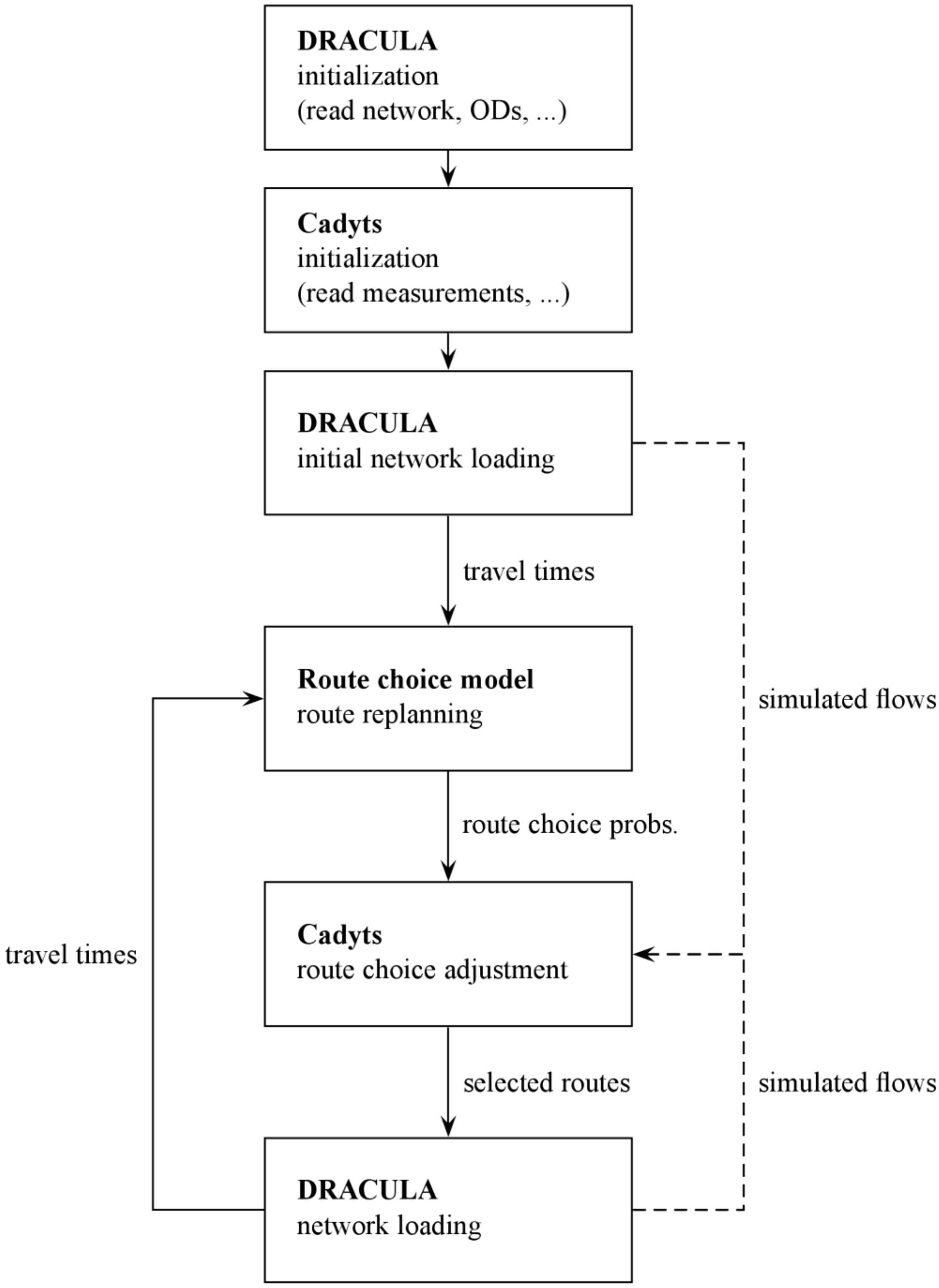

Figure 1: Interactions between DRACULA and Cadyts. The program flow is along the solid arrows. Dashed arrows represent additional data flows.

After an initialization of both systems, DRACULA is executed once with an arbitrarily selected route for each traveler. Hereafter, the iterations start. Given the most recent travel times, the route choice model is evaluated for every single traveler, and the resulting prior route choice probabilities are stored (recall that this includes the option of not making a trip). This corresponds to an evaluation of (1). Cadyts then internally adjusts the route choice probabilities according to (3), samples one route per trip-maker from the resulting posterior distribution, and saves this route as the chosen alternative. DRACULA then loads all chosen routes on the network. The resulting travel times are fed back to the route choice model, and the iterations start anew.

Cadyts operates at the fully disaggregate level in that it deals with individual travelers (trip makers) without associated OD pairs. The demand representation in DRACULA is based on OD matrices (possibly separated by time slice and/or user class). In order to interact these two approaches, DRACULA samples a population of trip-makers from the OD matrices in its initialization step. Every trip-maker in this population is then maintained as a uniquely identified entity throughout all following process steps, and its association to one particular OD pair is also stored. This allows to re-aggregate estimated path flows and OD matrices from the individually adjusted route choice behavior.

3 Experiments

We investigate the interactions of the Cadyts calibration with the DRACULA simulation in a synthetic scenario. The purpose of these experiments is to clarify the functioning and the capabilities of the approach. Experiments with real networks are the subject of future research. The computational feasibility of the calibration methodology for large-scale scenarios is demonstrated in Flötteröd et al. (2011b), where, however, a multi-agent simulation instead of a trip-based transport simulation is estimated.

The experiments are run in the network shown in Figure 2. Demand enters the network at the leftmost node, turns either left or goes straight at the diverge, and leaves the network at the rightmost node. A traffic light is located in the center of the straight route, serving as a bottleneck that generates congestion-dependent travel times. The link capacities and geometrical layouts are chosen such that the traffic light constitutes the only bottleneck in the system, and that free-flow travel is possible everywhere else. The two routes differ by 23 seconds under free-flow conditions (taking into account an average delay due to the signal) and by 1 km in length. One may think of a straight route going through a city-center and of a longer by-pass route. The difference in free-flow travel times corresponds to approximately 17 % of the free-flow travel time on the straight route.

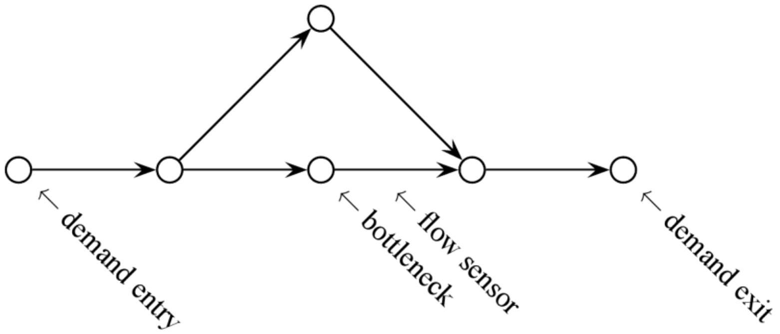

Figure 2: Test network

In this experiment, a population of 3000 drivers is considered. The stay-at-home probability $1-f$ is set to 1/3 in (2), which means that on average 2000 travelers decide to make a trip, with a standard deviation of approximately 26 travelers. The scale parameter μ of the utility function (negative travel time) in the logit choice model (1) is set to 0.01. Time is given in seconds. This results in the following overall form of the utility function:

$$V_n(i) = \begin{cases} -t_i & \text{if i is a route} \\ 100\ln(1/2) + 100\left(\exp[-0.01t_1] + \exp[-0.01t_2]\right) & \text{if i is stay-at-home} \end{cases} \qquad (4)$$

where the second row results form an insertion of the concrete parameter values for μ and f into (2). Considering both routes and the stay-at-home option, the choice set is hence three-dimensional. The length of the analysis period is one hour, an the demand is distributed uniformly over this time interval.

All calibration experiments follow the logic outlined in Figure 1. Plain simulations are conducted by taking Cadyts out of the loop, which is the same as running the calibration with an empty measurement file, i.e., with $A = \{\}$ in (3). All simulations and calibrations are run for 100 iterations, which appears sufficient to reach stationary conditions by visual inspection of the respective trajectories (see below).

Table 1: Test results. Time intervals are written as "hours:minutes", all other values are vehicles per hour (veh/h).

	simulation		calibration (σ=25 veh/h)			calibration (σ=10 veh/h)		
	inflow of entry link	inflow of sensor link	measured flow	inflow of entry link	inflow of sensor link	measured flow	inflow of entry link	inflow of sensor link
interval 1 0:00-0:15	1960.16 (47.21)	880.87 (39.53)	–	1938.51 (44.99)	880.39 (39.5)	–	1934.28 (44.74)	880.0 (39.88)
interval 2 0:15-0:30	2072.79 (53.26)	1069.96 (53.21)	700 (25)	1942.35 (52.8)	779.53 (57.67)	700 (10)	1920.16 (51.47)	716.55 (66.68)
interval 3 0:30-0:45	1960.0 (53.63)	1046.82 (52.61)	1300 (25)	2067.61 (55.35)	1231.69 (71.91)	1300 (10)	2102.04 (52.48)	1287.77 (89.32)
interval 4 0:45-1:00	1946.12 (51.41)	1024.31 (49.26)	–	1946.12 (51.41)	1028.71 (48.03)	–	1946.12 (51.41)	1032.63 (51.21)
interval 5 1:00-1:15	0.0 (0.0)	129.73 (20.63)	–	0.0 (0.0)	129.65 (19.39)	–	0.0 (0.0)	129.02 (19.31)

3.1 Plain simulation

A plain simulation in this setting results in the demand levels and simulated traffic counts indicated in the first wide column ("simulation") of Table 1. Every field of this table displays two values: a mean value and a standard deviation (in brackets). All statistics are obtained from the last 50 iterations of the respective runs.

The first simulation column displays the network entry flows. Their mean values are consistent with the demand profile. Their standard deviations are higher than the 26 veh/h one would expect from the binomial demand distribution, which is most likely a result of the link inflows being also randomly affected by traffic flow dynamics. No vehicles enter the system after one hour, which means that no demand is held back at the network entry because of congestion effects.

The second simulation column displays the simulated flows at the measurement location. Roughly half of the total network entries take the straight route (and hence pass the sensor location). Because it takes some time to reach the sensor link from the network entry, vehicles enter the sensor link even after one hour. This effect is compounded by the traffic light right upstream of the sensor link, which generates an additional delay for vehicles that take the straight route.

Figures Figure 3 and Figure 4 show the evolution of the network and sensor link inflows for two representative 15-min time interval over the iterations of the simulation. Since the initial route assignment is a 50/50 split, the system stabilizes almost immediately around a stationary distribution. The ongoing variability in the curves is due to (i) demand level fluctuations, (ii) route choice variations, and (iii) stochastic traffic flow dynamics.

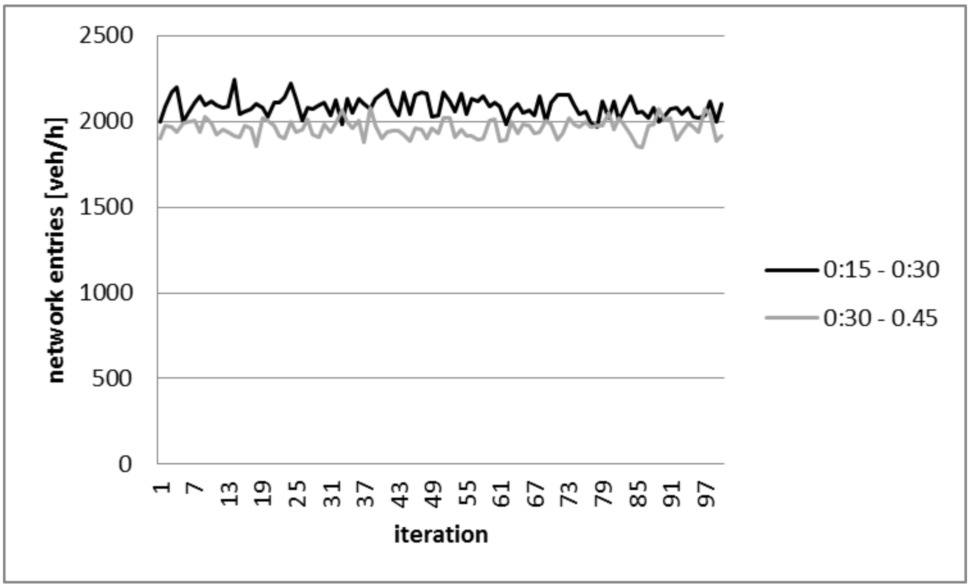

Figure 3: Network entries [veh/h] over iterations of plain simulation

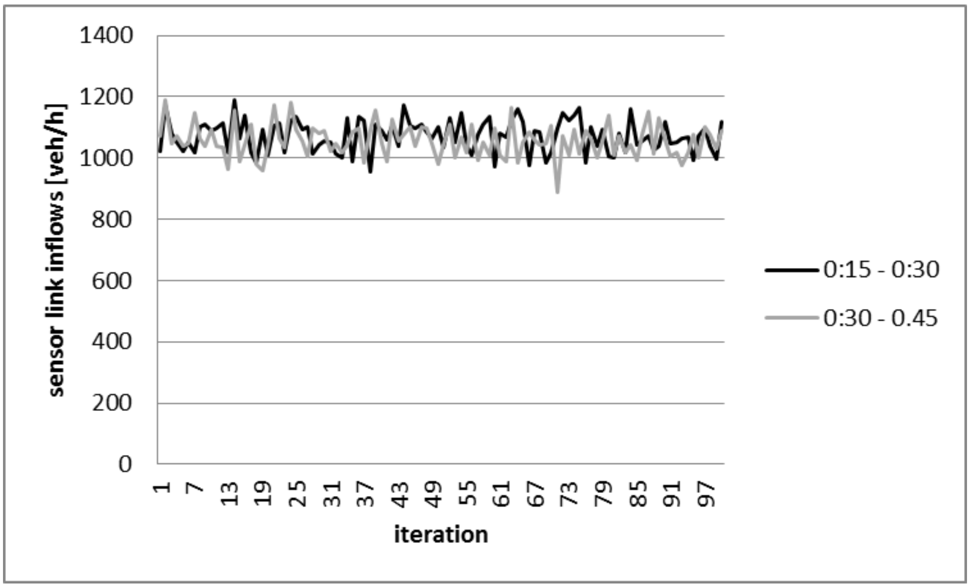

Figure 4: Sensor link inflows [veh/h] over iterations of plain simulation

3.2 Calibration

The same one-hour peak period as before is considered, where the traffic counts (which are arbitrarily constructed only in order to demonstrate the workings of the approach) are given in four 15 min time intervals. We investigate the exploitation of this sensor data to the adjustment of both the route choice and the total demand levels across all time slices. (Note that the estimation takes place jointly for all time slices.) In summary, the calibrated simulation adjusts to the measurements according to Algorithm 2 (which constitutes a technically straightforward generalization of Algorithm 1).

Algorithm 2 Iterated DTA microsimulation

1. Initialization. Give every traveler an initial perception of the conditions in the network.
2. Iterations. Repeat the following until stationary conditions are reached.
    a. Calibrated demand simulation. Trip-makers select new trips (or decide to stay at home) based on **Error! Reference source not found.**, using utilities as defined in **Error! Reference source not found.**.
    b. Supply simulation. The mobility plans of all travelers are simultaneously

The second and third main column of Table 1 show the results of two calibration experiments. In both experiments, the same measurement data is used: a measured flow that is roughly 300 veh/h lower than the plain simulation in the second time interval, and a measured flow that is roughly 300 veh/h higher than the plain simulation result in the third time interval. Through this, we investigate the ability of the calibration to both increase and decrease demand and path flow levels. No measurements are assumed to be available in the first and fourth time interval in order to underline that the method functions with arbitrarily few measurements. The two experiments differ in the standard deviation of the hypothetical sensor data, which is 25 veh/h in the first calibration experiment (second main column) and 10 veh/h in the second one (third main column).

In a nutshell, the calibration yields the effect one would expect from the sensor data: it modifies both the demand levels and the route choice in a way that improves the measurement reproduction, with the fit improving as the variance of the sensor data is reduced. This is plausible in that the calibration is designed to generate a statistically consistent combination of the prior information contained in the model system and the additional information contained in the sensor data.

Supplementary to Table 1, Figures Figure 5 and Figure 6 give the evolution of the calibrated network entry and sensor link entry flows over the iterations. Based on these figures and Table 1, three further observations can be made.

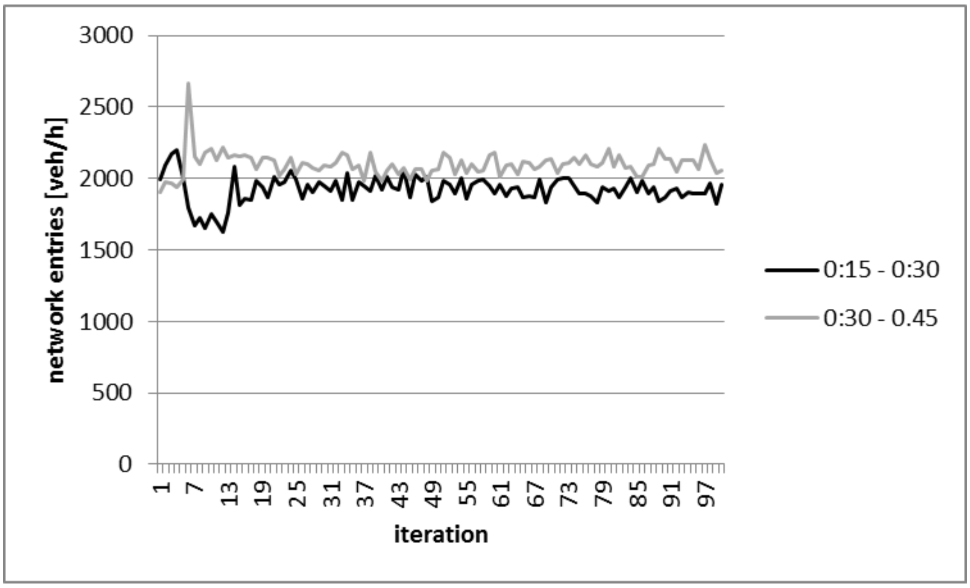

Figure 5: Network entries [veh/h] over iterations of calibration experiment 2 (σ=10 veh/h)

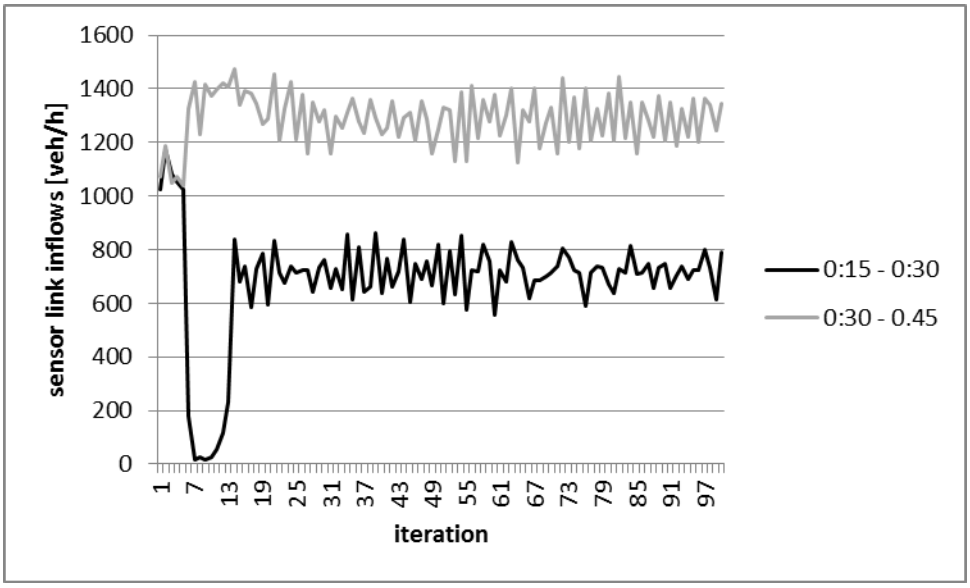

Figure 6: Sensor link inflows [veh/h] over iterations of calibration experiment 2 (σ=10 veh/h)

First, the adjustment of the demand levels is not as prominent as that of the route flows. This is due to the behavioral distribution generated by the simulation system (without any measurements): Figures Figure 3 and Figure 4 as well as the statistics in Table 1 reveal that the relative variability in the route flows is higher than the variability in the demand levels. Arguing in Bayesian terms (from which the calibration is indeed derived), this leaves greater freedom for adjustments of the prior route choice distribution than for adjustments of the prior demand level distribution, and hence the route flows are affected more strongly than the total demand levels by the sensor data.

Second, the variability in the sensor link entry flows increases as the fit to the measurements is increased. This is so because the measurements are selected to represent out-of-equilibrium conditions (they differ substantially from the flows resulting from a plain simulation): as the system is moved out of equilibrium, its sensitivity to the bottleneck-induced delay on the straight route increases, hence the reaction of the route choice model becomes stronger, and variability increases. This means that, although the calibration only compares mean simulated and measured flows, it implicitly also adjusts the system variability in a plausible way.

Third, the calibrated simulation attains quite rapidly a stationary state. Noting that the behavioral adjustment process implemented by the calibration is embedded within the iterative loop of the simulation, this indicates a vast computational advantage over usual approaches where the iterative simulation is embedded within an outer adjustment loop of the OD matrix. (The path flow estimator by Bell also is a one-step estimator, but it is yet to be transferred to a microsimulation setting.) In the presented approach, no outer loop is present, and the complexity of a calibration is in the order of a plain simulation: The computational overhead of the calibration is limited to (i) calculating one utility addend per traffic count and (ii) adding these numbers to the utilities of the alternatives each trip maker faces, cf. (3). The memory complexity of the calibration is limited to storing these utility addends. Other experiments with large-scale scenarios indicate that the computational overhead of the calibration is limited to a few percent of the total running time (Flötteröd et al., 2011a, 2011b).

Clearly, these results are conditional on the information obtainable with a single sensor. Given that two only loosely couple path flows are to be estimated, one would expect a supplementary sensor either on the detour link or at the network entry to provide more precise estimates. In general, any sensor location strategy applicable to standard OD matrix estimators can be deployed here as well.

4 Summary and outlook

This paper describes the first application of a novel OD matrix and path flow estimator for iterated DTA microsimulations. The presented approach is derived from an agent-based DTA calibration methodology that relies on an activity-based demand model. This work explains how to apply the calibration in the trip-based domain and presents illustrative examples that clarify its capabilities.

Summarizing, the following findings can be extracted from these experiments:

- the calibration interacts meaningfully with the simulation in that it improves the measurement fit in the proper direction;
- the calibration accounts for the uncertainty assigned to the sensor data;
- the calibration accounts for the uncertainty in the prior system states (demand levels, route choice) in that it adjusts such aspects more strongly that are represented a priori through a wider distribution in the uncalibrated simulation;
- although the calibration directly evaluates only the mean deviation between simulated and measured flows, the resulting shift of the system's working point can come along with a behaviorally and physically meaningful change in the variability of the system's states;

• the computational complexity of the calibration is in the order of a plain simulation.

Intelligent transportation systems are crucially dependent on efficient traffic monitoring techniques. The proposed path flow estimator contributes to this field. Our ongoing work focuses on the testing of the methodology for larger DRACULA networks that are based on real scenarios. Future work will comprise various extensions of the Cadyts methodology, including the incorporation of richer sensor data (vehicle re-identifications, smartphone data) and the joint calibration of further demand and supply parameters along with the demand estimation presented in this article.

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