INTEGRATING CEMDAP AND MATSIM TO INCREASE THE TRANSFERABILITY OF TRANSPORT DEMAND MODELS

Dominik Ziemke, Corresponding Author
Technische Universität Berlin, Transport Systems Planning & Transport Telematics
Sekr. SG12, Salzufer 17-19, 10587 Berlin
Tel: +49-30-314-28383; Fax: +49-30-314-26269; Email: ziemke@vsp.tu-berlin.de

Kai Nagel
Technische Universität Berlin, Transport Systems Planning & Transport Telematics
Sekr. SG12, Salzufer 17-19, 10587 Berlin
Tel: +49-30-314-28308; Fax: +49-30-314-26269; Email: nagel@vsp.tu-berlin.de

Chandra Bhat
The University of Texas at Austin, Department of Civil, Architectural & Environmental Engineering
1 University Station, C1761, Austin, TX 78712
Phone: +1-512-471-4535; Fax: +1-512-475-8744; Email: bhat@mail.utexas.edu

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ABSTRACT
An activity-based approach to transport demand modeling is considered the most behaviorally sound procedure to assess the impacts of transport policies. In this paper, it is investigated whether it is possible to transfer an estimated model for activity generation from elsewhere (the estimation context) and use local area (application context) traffic counts to develop a local area activity-based transport demand representation. Here, the estimation context is the Dallas-Fort Worth area, and the application context is Berlin, Germany. Results in this paper suggest that such a transfer approach is feasible, based on comparison with a Berlin travel survey. Additional studies in the future need to be undertaken to examine the stability of the results obtained in this paper.

Keywords: Activity-based Demand Modeling, Agent-based Simulation, Transport Modeling, Model Transferability

1. INTRODUCTION

Traffic assignment models are useful tools to predict reactions of the transport system to policy measures. Traditional assignment models are static, taking constant OD flows as input, and producing static congestion patterns as output. In order to address dynamic policy measures such as a peak hour toll or changes of the opening times of workplaces and/or shops, *dynamic* traffic assignment (DTA) has emerged as a useful analysis approach *(1)*. Originally, DTA typically took time-dependent (hourly or day period) OD matrices as input; more recent approaches (e.g. TRANSIMS *(2)* or DynusT *(3)*) often take as input lists of trips where each trip is defined by the triplet of departure time, departure location, and destination location. It is clear that one can go one step further and take full daily plans as input. To the authors' knowledge, MATSim (Multi-Agent Transport Simulation *(4)*) is the only model system doing this at the large (regional) scale. The advantages of using complete daily activity-travel plans as DTA inputs include that all kinds of precedence constraints, such as the fact that a person cannot leave an activity location before having arrived, are automatically resolved. Also, such a model can accommodate more behavioral realism. For example, the time pressure relief during the remainder of the day, which may lead to additional activity participation, can be included as an element in the route choice between a tolled fast and a non-tolled slow route.

A question now is how the input to such an activity-chain-based traffic assignment model may be obtained? **Trip diaries** provide the necessary data – i.e. a sequence of departure times, mode choice decisions, and activity locations – directly. A disadvantage of using trip diaries is, however, that all information that is taken from the diaries is by definition not sensitive to policy measures. For example, if one wants to investigate departure time reactions to a policy measure, one cannot take the departure times from the trip diary. Instead, a model component needs to be built that endogenizes departure times in a meaningful way. Also, trip diaries are not available for the entire population in an area, but only for a very small fraction of the population.

Another drawback is that, in Germany and the U.S. (and many other parts of the world), the geo-coding of the activity location is considered sensitive information under privacy legislation, and thus often removed from scientific use files. Informal privacy standards suggest that it should not be possible to narrow down a search to less than seven persons from the data record, which, however, can be suspected to be possible when the street addresses of home and work locations are known. Since data owners often do not know how to sufficiently blur location data to satisfy the above "rule of seven", they prefer not to give out any location information at all.

Alternatively, publicly available commuting matrices may be used. These matrices do, however, not have a high enough spatial resolution for urban areas. For example, in the publicly available German data *(5)* all of the city of Berlin, with 3.4 million inhabitants, is represented by exactly one zone. In the U.S., commuting matrices are typically available only at a county-to-county level. Since such location aggregation based matrices may become the rule rather than the exception in privacy-sensitive societies, this motivates the search for alternative methods.

So, the question is whether high resolution origin-destination information can be generated in some other way? The standard solution would be to estimate an activity location choice model. This, however, is difficult if no trip data to estimate the model is available. OD matrix estimation studies *(6)* suggest that traffic counts may be used to make an initially rough OD matrix more appropriate for a region. As explained above, however, MATSim is not based on OD flows, but on full daily plans *(7)*. Thus, the issue becomes whether there could be a source for initial full daily plans for each individual in a region, and whether there is a procedure to update these initial full daily plans using traffic counts. The latter issue may be handled using a procedure proposed by Flötteröd et al. *(8)* and implemented in the software Cadyts (Calibration of Dynamic Traffic Simulations *(9)*). Cadyts (Section 2.3) is a procedure to update initial estimates of any arbitrary choice dimension of individual-level travel behavior based on real-world measurements. Cadyts has already been applied to update route choice predictions, both for car *(10)* and for public transit *(11)*. However, it has not been used to update daily full activity-travel plans, as it is done in this paper. The former issue – a means to generate initial complete daily plans for individuals in a region – is addressed in this paper using the Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns (CEMDAP *(12)*). In particular, the model parameters of CEMDAP, as estimated for the Dallas-Fort Worth region (the estimation context) are retained, and then used to generate the *initial* plans for individuals in Berlin (the application context in the current paper). Subsequently, Cadyts is used to update these initial plans using Berlin traffic count data. The main advantage of CEMDAP over other activity-based model (ABM) systems for the generation of the initial plans is that CEMDAP generates full daily activity-travel plans, which is exactly what MATSim expects as input. Similar attempts with other ABM systems would be considerably more difficult since, although possibly having daily plans internally, their output consists of hourly OD matrices *(13)* or of tours *(14)*. Also, they do often sample full individuals but rather provide activity chains with fractional weights *(14)*.

In summary, the objective of this study is to create an activity-plan-based MATSim transport model for Berlin that is policy-sensitive, but at the same time only based on CEMDAP predictions of initial activity plans combined with Berlin traffic count data. Essentially, it is investigated whether it is possible to transfer an estimated model for activity generation from elsewhere (the estimation context), and use local area (application context) traffic counts to develop a local area activity-based transport demand representation. At a broad level, this may be viewed as transferability with updating, except that the updating operates on the initial full daily activity plans rather than on specific model parameters as in traditional transfer updating. In more technical terms, the approach is the following:

- A synthetic population is generated in the application context, where each member has the attributes age, gender, employment status, being a student or retired. For the present study, only people of 18 years or older are considered.
- For each working/studying member of the synthetic population, a workplace/university location is randomly selected according to the coarse commuting matrix.
- If the large Berlin zone is designated as the workplace/school location, several possible workplaces/school locations are assigned to each person.
- Next, the ABM system CEMDAP *(12)* generates a full possible daily activity-travel pattern for *each* possible person-workplace/school combination. This means that the synthetic persons who are working/studying in the Berlin zone now have *multiple* activity-travel plans, which are quite different from each other because they all have different work/school locations.
- Finally, the MATSim transport simulation is run in connection with Cadyts in an iterative loop, where Cadyts is used to select plans which are consistent with traffic counts.

This approach is parallel to OD matrix estimation. However, instead of increasing and decreasing entries in the OD matrix to match traffic counts, the weights of multiple possible activity-travel plans of each synthetic person are increased or decreased to match traffic counts.

2. TOOLS

2.1. CEMDAP

Two major approaches to activity-based demand modeling can be distinguished *(15)*: (1) Models based on *random utility theory* that consist of systems of equations to capture relationships among activity and travel attributes and to predict the probability of decision outcomes *(15)* and (2) models based on *rule-based approaches* (also referred to as *computational process models*), which employ psychological decision rules in the form of condition-action pairs that specify how the solution to a given task is found *(15)*.

Here, the Comprehensive Econometric Microsimulator for Daily Activity-Travel Patterns (CEMDAP) is used, which is a software implementation of a system of random-utility-based models that represent the decision-making behavior of individuals *(12)(15)*. Since CEMDAP requires input information on individual level which is mostly only available at an aggregate level, usually, synthetic population generation (SPG) *(17)* needs to be applied as a pre-process. CEMDAP's output consists of the complete daily activity-travel patterns of each individual of the synthetic population *(15)(12)(16)* and outlines the sequence of activities (and corresponding travel) that a person undertakes during the day. This knowledge is the foundation for transport modeling. As in any market, however, demand is dependent on supply. So, the interaction of supply and demand needs to be modeled.

2.2. MATSim

In order to maintain the disaggregate view on the individual travelers throughout the whole modeling process a specific model is needed for the modeling of the interaction of supply and demand on the network. MATSim (Multi-Agent Transport Simulation *(4)*) is used for this task. MATSim constitutes an *agent-based* transport simulation consisting of two major components. First, the demand for transport is simulated on the physical network (*Physical simulation* in Figure 1; also referred to as *traffic (flow) simulation*, *mobility simulation (mobsim)*, *network loading* or *execution*). Second, the choice processes (decision making) that travelers undertake in reaction to what they experience while traveling are simulated (*Mental simulation* in Figure 1).

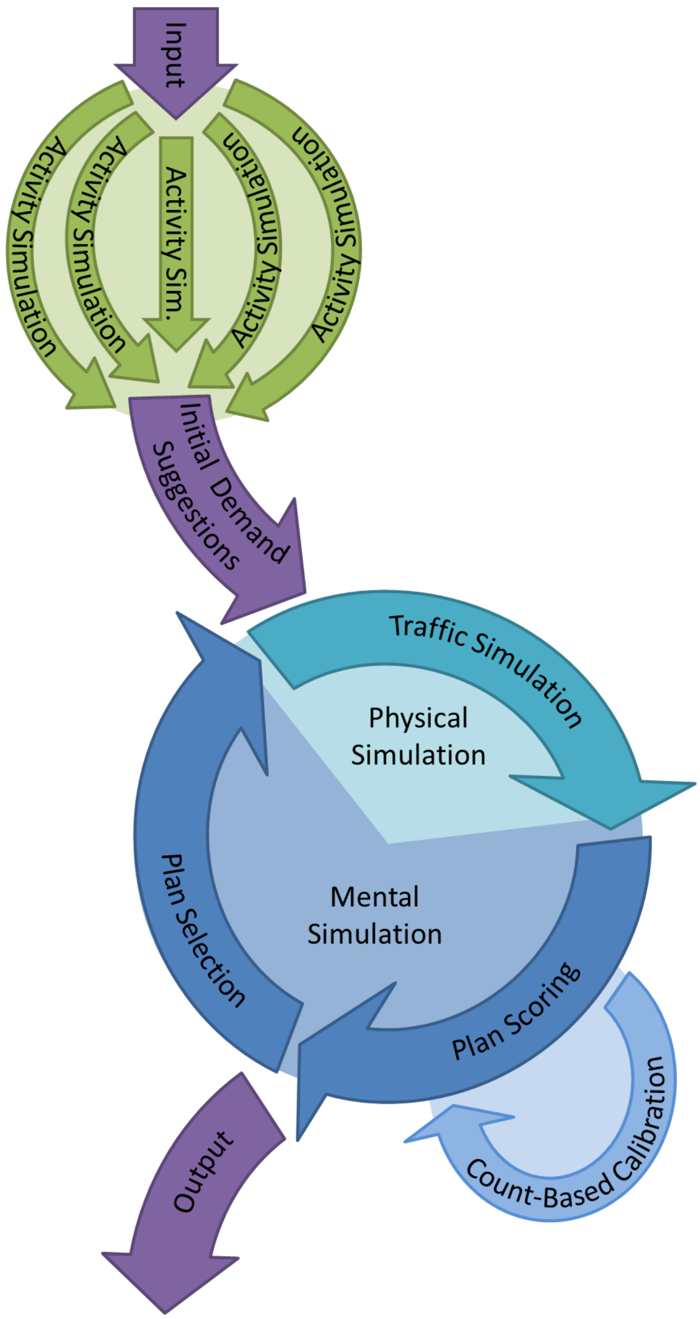

FIGURE 1 Methodology

Conforming with the microsimulation paradigm, the software objects representing travelers (*agents*) are retained during the whole simulation process. Each agent takes independent decisions and keeps a record of her/his decisions in a *plan*, which contains the agent's schedule of activities, including times and locations, along with the travel modes.

In the physical simulation, the selected plans of all agents are simulated simultaneously based on a queue model *(18)*. A directed graph is used, where every roadway segment (*link*) is modeled as a first-in-first-out (FIFO) queue and has the following attributes: Free-flow speed, link length, flow capacity, number of lanes, and allowed modes.

In every time step of the simulation, the state of each queue is updated. The agent at its head is put into the FIFO queue of the next link of her/his route and assigned with a time stamp, if the agent has spent at least the free-flow travel time on the link, the flow capacity has not been exceeded in this time step, and the next link on the agent's route has free storage capacity. In the next time step, this procedure is repeated.

Each plan is evaluated based on its performance, which is quantified by a score based on the notion of *utility*. The according *utility function (19)* encompasses the agents' activity participation and their travel performance:

$$V(i) = \sum_{act \in m} V_{perf,m} + \sum_{trav \in n} V_{trav,n} \tag{1}$$

where $V_{perf,m}$ is the utility of activity m and $V_{trav,n}$ is the utility of travel leg n. New scores are only calculated for the most recently selected plan.

Next, the agents decide which plan to execute in the traffic simulation of the next iteration. They may either generate a new plan by applying modifications to a copy of one randomly selected plan from their existing plans. Modifications may be done with respect to various choice dimensions (e.g. routing or time choice) through *(innovative) strategy modules*. If a new plan is created, this plan is marked as the agent's *selected plan* for the next iteration.

Alternatively, agents may select one of their already existing plans through *probabilistic selection* and execute it. To do so, a choice among their existing plans is performed by a multinomial logit model, where the selection probability $P(i)$ of a given plan i is related to the plan's score $V(i)$:

$$P(i) = \frac{e^{V(i)}}{\sum_j e^{V(j)}} \tag{2}$$

The optimization process in MATSim adheres to the concept of *evolutionary algorithms*. A plan may perform differently in different iterations as it is dependent on the behavior of other agents that steadily adapt their plans as well. This process may also be regarded as a *genetic algorithm* – an extremely flexible, though computationally inefficient optimization method inspired by biology *(19)*. In contrast to discrete choice models, which enumerate all possible alternatives, genetic algorithms do not find a globally optimal solution, but one *good* solution *(19)*.

In the genetic algorithm, transport demand adapts itself to transport supply over the course of iterations. It is, thus, possible to start the simulation procedure with little initial assumptions and have the evolutionary algorithm take care of adequate adaptation. Depending on how elaborate the representation of transport demand is at startup, MATSim itself can, thus, be regarded an (activity-based) demand generation module. Specifically, Balmer *(20)* shows how MATSim's iterative simulation process leads to an improvement in an agent's plans by including a module specific to each choice dimension that comprises an individual's daily plan. If these modules represent the corresponding behaviors correctly, the properties of the corresponding choice dimensions will converge to realistic values even if the original values are not appropriate. In this respect, it is fundamental to distinguish fixed from unfixed choice dimensions, because only those (fixed) choice dimensions whose properties do *not* undergo any modifications in MATSim's iterative procedure have to be initially correct *(20)*.

2.3. Cadyts

Microsimulations have become an important tool for transport modeling *(21)*. They offer a behaviorally more sound representation of the transport system than aggregate models. A drawback of microsimulation is, however, that they – in contrast to analytical models – do not have an explicit mathematical specification *(10)*.

Cadyts (Calibration of dynamic traffic simulations) overcomes this drawback through its calibration procedure in a Bayesian setting *(9)*. It updates estimates of arbitrary choice dimensions of individual-level travel behavior based on real-world measurements (e.g. traffic counts) *(9)(10)*.

As stated in section 2.2, the probability $P(i)$ of choosing plan i is determined in MATSim on the basis of the scores of the plans. Equation 2 can be called the *a priori choice probability* to choose plan i, indicating that this is the plan's choice probability *prior* to considering how the choice probability changes when, additionally, real-world observation data are taken into account. In order to update the plan selection of the synthetic persons, Cadyts combines this a priori choice distribution $P(i)$ with available traffic counts into an *a posteriori choice probability* $P(i|\mathbf{y})$ *(10)*.

As shown by Flötteröd *(22)*, the application of the *a posteriori* choice distribution requires nothing but adding a *plan-specific utility correction* (also referred to as *utility correction*, *utility offset*, or *linear plan effect*) to every considered plan of each synthetic person. Notably, Cadyts does not change the parameters of the choice model that generate the *a priori* choice probabilities $P(i)$.

The plan-specific utility corrections are composed of link- and time-additive correction terms $\Delta V_a(k)$. In case congestion can be assumed to be light and traffic counts are independently and normally distributed, these link- and time-additive correction terms become *(10)*

$$\Delta V_a(k) = \frac{y_a(k) - q_a(k)}{\sigma_a^2(k)} \tag{3}$$

where $y_a(k)$ is the real-world traffic count, $q_a(k)$ is the simulated traffic count, and $\sigma^2_a(k)$ is the variance of the traffic count at location a for time bin k. The utility correction of a given activity-travel plan of an agent is calculated as the sum of all $\Delta V_a(k)$ that are covered by the plan *(10)*. With this, the *a posteriori* choice probability of plan i of agent n becomes

$$P_n(i \mid y) \sim e^{V_n(i) + \sum_{ak \in i} \frac{y_a(k) - q_a(k)}{\sigma_a^2(k)}} \tag{4}$$

$$= P_n(i) \cdot e^{\sum_{ak \in i} \frac{y_a(k) - q_a(k)}{\sigma_a^2(k)}} \tag{5}$$

where $P_n(i)$ is the *a priori* choice probability of plan i of agent n, and $V_n(i)$ is the *a priory* score of a plan i of agent n as calculated with Equation 1. Intuitively, if the simulation value, $q_a(k)$, is smaller than the measurement from reality, $y_a(k)$, an increase in score and thus an increase in choice probability results. $\sigma_a(k)$ denotes how much one should trust that specific measurement – a large $\sigma_a(k)$ implying a large variance and thus a low trust level.

A discussed in section 2.2, the mental simulation of MATSim (Figure 1) consists of the two steps of *plan scoring* and *plan selection*. In the original version of Cadyts, the *utility correction* is used to modify the (*a priori*) plan *choice* probability by adding the utility correction to the considered plan's score in the logit model (Equation 4). Thus, plan selection becomes a function of real-world measurements (e.g. traffic counts) in addition to being dependent on plan scores. This has, however, the disadvantage that the utility correction is only temporarily calculated and applied once in the plan selection step.

An alternative approach is to embed the Cadyts utility offset as an extra component into the compound MATSim scoring function (Equation 1) next to activity scoring and travel leg scoring *(23)*. Equation 1 is, thus, modified to

$$V(i) = \sum_{act \in m} V_{perf,m} + \sum_{trav \in n} V_{trav,n} + w \cdot \sum_{ak \in i} \Delta V_a(k) \tag{6}$$

where w is the weight of Cadyts utility correction. This procedure constitutes a novel approach of coupling MATSim with Cadyts and is first presented and applied by Moyo Oliveros and Nagel *(11)*.

Conceptually and mathematically, Equation 4 stems from Bayesian statistics, i.e. it is a linearized version of the mathematically necessary correction of the behavioral choice probabilities once measurements are available. As one can see, the correction itself behaves as an agent-specific alternative-specific constant *(10)*.

3. INPUT DATA

3.1. Scenario and Network

The scenario considered in this study consists of the two German federal states of Berlin and Brandenburg. Transport supply consists of a roadway network, which was created based on data from OpenStreetMap *(24)(25)*. After simplification, the network consists of 11,345 nodes and 24,335 single-direction car-only links.

3.2. Synthetic Population

The synthetic population is based on commuter data provided by the German Federal Employment Agency *(5)*. These data yield the home and workplace municipalities of that part of the working population that is subject to social insurance contributions.[1]

Berlin consists of only one municipality, which accommodates 3,375,222 inhabitants *(26)* and hosts 1,105,037 socially-secured workers *(5)*. Because their home and workplace locations are not specified any more detailed than at the municipality level, inside Berlin so-called LORs[2] are used. Amongst other criteria, LORs are spatially defined so that one LOR's population does not fall below or exceed a certain minimum or maximum, respectively *(27)*. Thus, real-world settlement patterns can be approximated by selecting LORs randomly for each member of a synthetic population.

Scalings are used to account for the respective shares of socially-secured workers, adults, employment status, age, gender, and being retired or being a student *(28)*.[3] Based on this information, a 1%-sample of the relevant population is created.

[1] *Persons subject to social insurance contributions* (*sozialversicherungspflichtige Beschäftigte*) are working persons who are not self-employed and whose income exceeds a minimum threshold.
[2] *Lebensweltlich orientierte Räume*, a neighborhood-oriented zone system.
[3] In future studies, statistically more sophisticated approaches should be used, such as by Pendyala et al. *(17)*.

3.3. Counts

For updating the scoring of activity-travel plans, 8,304 hourly count values for 346 count station, collected by the *Berlin Traffic Management Center* (*Verkehrsmanagementzentrale*) are used.

4. METHODOLOGY

4.1. Approach

The main objective of this research is to connect the ABM system (CEMDAP, Section 2.1), the DTA system (MATSim, Section 2.2), and the calibration package (Cadyts, Section 2.3) in a novel approach to transfer an activity-based transport demand model. As pointed out in section 1, the main idea is to generate a set of *several possible* daily activity-travel plans for each agent using CEMDAP whose parameters have been estimated for another regional context (i.e. the Dallas-Fort Worth region). Then, Cadyts is used to update the scoring of daily activity-travel plans so that those plans are more frequently picked by the agents that are most consistent with measurements from the application context (i.e. the Berlin-Brandenburg region). This is achieved by running the following two steps multiple times:

1. First, for each member of the synthetic population, a workplace is selected with probabilities according to the commuting matrix. If the workplace falls into the Berlin zone, one of Berlin's LORs (Section 3.2) is selected randomly. The same is done for school locations (only persons of 18 years or older are considered).
2. Second, CEMDAP is run with the above input.

Thus, a set of several possible daily activity-travel plans for each agent is created. As CEMDAP's output is fully disaggregated to the individual-traveler level, it is a perfect match with the requirements of the input plans for MATSim. Only some data structural rearrangement is necessary to use the daily activity-travel patterns created by CEMDAP as input for MATSim *(28)*. Technically, all CEMDAP activity-travel output plans of a given synthetic person are combined into a set of multiple daily plan options of that same person for the MATSim simulation. From this point, MATSim's iterative simulation procedure (Central, circular part of Figure 1) is executed as described in section 2.2.

4.2. Discussion of Methodology

As pointed out in section 2.2, the consideration of choice dimensions is central to this process. Only those choice dimensions that cannot be modified during the simulation have to be represented correctly at the start of the simulation. Choice dimensions whose properties are subject to modification, by contrast, do not need to be initially correct.

Since only automobile traffic is considered in this study, **transport mode choice** is fixed. Accordingly, the number of motorists needs to be initially correct. **Route choice** is enabled as a choice dimension with a corresponding strategy module in the MATSim transport simulation, i.e. all agents are able to iteratively create and try out new routes. **Location choice** and **time choice** are regarded as fixed from the perspective of the transport simulation, i.e. agents cannot *create* new travel options in terms of timing or location choice during the transport simulation. The special feature of the approach in this study is, however, that agents are still able to *adjust* their timing or to *switch* locations among the alternatives they have been provided with by the initial demand suggestions generated by CEMDAP. This constitutes a novel compromise between fixed and unfixed choice dimensions. On the one hand, no innovative strategy modules of MATSim (Section

2.2) for these choice dimensions are used. On the other hand, the output of CEMDAP can be used as effectively as possible, since the decisions concerning these choice dimensions are already conducted by CEMDAP.

Via the mental simulation of the agents' decision making, the demand optimizes itself with respect to supply utilization. Cadyts (Section 2.3) ties in with the plan scoring process in the mental layer of the MATSim transport simulation and makes those options prevail that are both reasonable from a behavioral perspective (determined by the activity and leg scoring) and, at the same time, reproduce expected travel patterns (according to real-world measurements). As the influence which Cadyts can exert is obviously dependent on the variety of plans each agent possesses, CEMDAP is run multiple times and each output is considered one potential solution.

An analogous approach is employed by Moyo Oliveros and Nagel *(11)(23)* who generate randomized routes of public transport riders. Moyo Oliveros *(23)* argues that "random routes generation might seem inadequate from the classical assignment models perspective [and that] it would be impractical if it were implemented as a stand-alone module for route choice model". Since, however, "the search of candidate solutions is combined with a selection mechanism, […] where new alternatives for each agent are evaluated and the worst are discarded, this coupling constitutes a composite co-evolutionary algorithm that directs the choice distribution to a count match convergence" *(23)*. While the *suggested routes* may (just like the *suggested activity plans* in this study) not be regarded as correct solutions to the problem *initially*, the connection of the simulation with the updating procedure leads to the selection of those *potential solutions* which constitute *valid final solutions* to the problem of finding a transport demand representation.

5. RESULTS AND VALIDATION

As explained in section 1, the goal of this study is to find a demand representation with a model fit and validity as good as possible while adhering to the premise to use only easily available data as inputs. More than 100 simulation runs have been undertaken to find the best configuration to meet these criteria with the following results:

- Four *initial plans* seem to be sufficient.
- The *maximum number of plans* (a MATSim configuration parameter) should be about twice as high as the number of *initial* plans.
- Using *demand elasticity* (i.e. giving each agent an additional initial plan where the agent stays at home all day) is found beneficial to allow the calibration more freedom.
- A *flow capacity* of 0.02 (i.e. the double of the population scaling value) was found reasonable, based on indicators such as average trip duration (Table 1).
- For the setup of this study, a *Cadyts scoring weight* of *w=15.0* should be chosen. Lower values are detected to be not influential enough; higher values show first indications of overfitting.
- In contrast to the work of Flötteröd et al. *(10)*, where Cadyts was applied only for the hours between 6am and 8pm, in the present study Cadyts is applied to all 24 hours of the day. Setting the period to 6am through 8pm showed no discernible differences.

Table 1 depicts the settings and results of the preferred parameter combination (Column "With Cadyts") next to a respective run without Cadyts updating and reference values.

TABLE 1 Settings and Results of Simulation without/with Cadyts

Parameter	Without Cadyts	With Cadyts	Reference
Demand Elasticity	Yes	Yes	n/a
Number of Plans	10	10	n/a
Number of Initial Plans	4	4	n/a
Flow Capacity Factor	0.02	0.02	n/a
Cadyts Scoring Weight	0	15	n/a
Calibration Time	n/a	0 – 24h	n/a
Normalized Log-Likelihood	−219	−23	−10 *(22)*
Car Trips	3.98m	2.92m	3.2m *(28)*
Car Trips/Person	3.9	3.4	3.4 *(28)*
Avg. Trip Distance [km]	12.0	11.0	9.5 *(28)*
Avg. Trip Duration [min]	27.0	22.0	22.3 *(28)*

To assess the model fit, normalized log-likelihood values were compared to respective values from Flötteröd *(22)*. The log-likelihood L is computed as the average value over all counting stations a and time slots k as

$$L = -\frac{(y_a(k) - q_a(k))^2}{2\sigma_a^2(k)} \tag{7}$$

It is found that the fit to the counts (−23) is nearly as good as in the reference simulation (−10), and clearly much better than without calibration.

Figure 2 depicts the error graphs of the runs outlined in Table 1. It can be seen that the run with updating of plan scoring (Figure 2(b)) shows significantly lower mean relative errors (MRE; depicted in red with squares) with regard to real-world traffic counts. During daytime, the MREs are somewhat higher than 20%, which means that on average the amount of simulated traffic diverges from the amount of measured traffic by a bit more than 20% over all count stations. Mean absolute biases (depicted in blue with points) are significantly lower in the case with traffic-count-based updating (note the different scales).

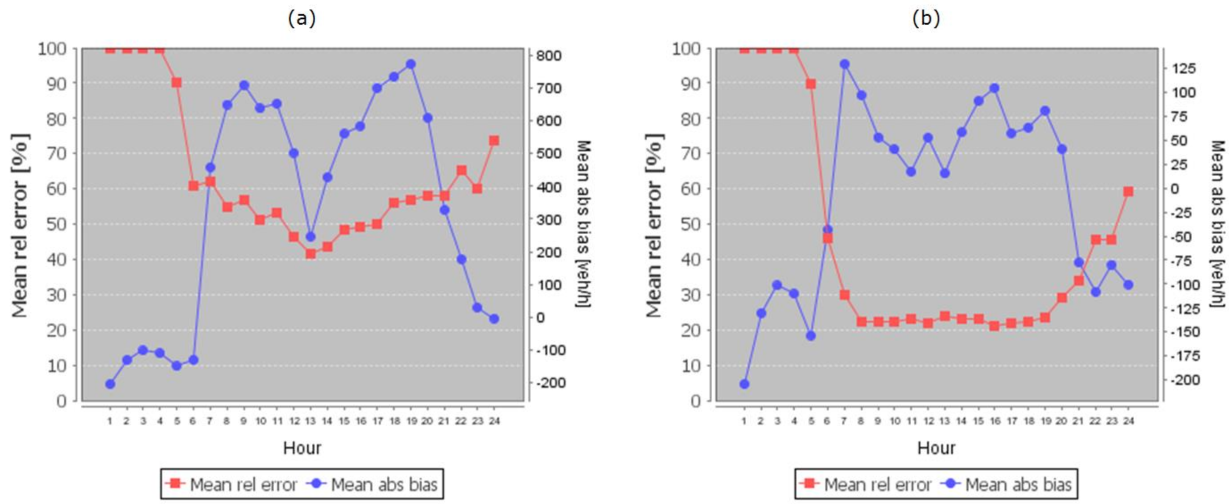

FIGURE 2 Error Graphs of Simulation without/with Cadyts: (a) Without Cadyts, (b) With Cadyts

A validation (based on data that have not been used to create the model) is particularly important to detect potential overfitting. Specifically, in case the weight of the Cadyts scoring component is overly high, the procedure may produce a good model fit, but override the behavioral components of the scoring function. To assess the characteristics of the generated travel patterns, the average values of table 1 were calculated from the travel survey *SrV 2008*[4] weekday travel survey for Berlin *(29)*, which encompasses 107,065 trips altogether. As most of the values used for validation are neither contained in the published report of the SrV travel survey nor in the public-use files, they were calculated with the SrV scientific-use files *(28)*. The distribution of trips by time of day and the distributions of trip distances, trip durations, average trip speeds, and activity participation at trip ends are depicted in Figure 3.

[4] *System of Representative Travel Surveys* (German: *System repräsentativer Verkehrsbefragungen*).

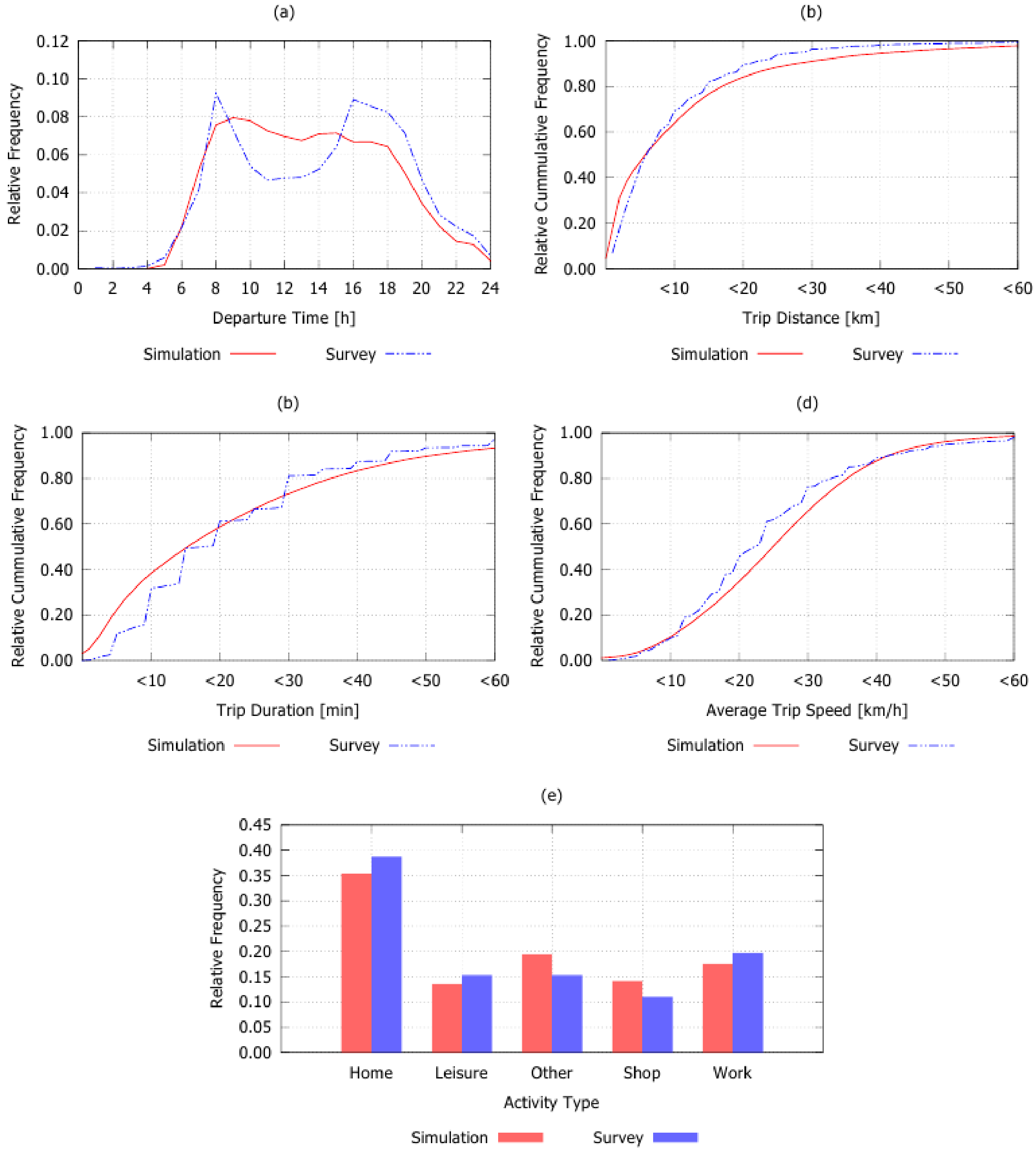

FIGURE 3 Comparison of Simulation and Survey: (a) Departure Times, (b) Trip Distances, (c) Trip Durations, (d) Average Trip Speeds, (e) Activity Types at Trip Ends

Figure 3(a) shows that the simulation has somewhat more traffic during daytime and a bit less traffic in the evening, which may be explained as follows:

- The mid-day drop in the survey data does not correspond to common wisdom from Berlin and is not contained in traffic counts – neither in those used for the present study nor in known others. Possibly, the survey population behaves differently from the full system.

For example, the important demand segment of commercial car traffic is not included in the survey. Presumably, the calibration procedure replaces that missing demand segment by plans that are as close as possible to the missing demand segment.

- The evening drip in the simulation results from the arguably lower number of evening activities between in Dallas/Fort Worth compared to Berlin. If this speculation is correct, the updating procedure does not have enough suitable plans to converge to observed traffic volumes.

Trip distances (Figure 3(b)) are very similar, with somewhat more medium-length trips in the survey and slightly more long trips in the simulation. Trip durations behave similarly (Figure 3(c)), where the steps result from survey participants tending to state "catchy" numbers. Similarly, figure 3(d) shows that speed are similar, with somewhat more medium-speed trips in the survey. The distribution of activities at trips ends is met quite well (Figure 3(e)). Notably, there is no specific mechanism in the simulation-calibration process that caters for the correct shares of activity types.

6. DISCUSSION

The flow capacity factor was set to 0.02 while the population was only a 1% sample. While the flow capacity factor and the population sample factor should normally be the same in MATSim, it may be necessary to balance adverse effects. Here, the generated demand may, in fact, be too large. Berlin employees probably have more vacation and possibly also more sick leave than their American counterparts. Also, a significant number of employees in Berlin work part-time, meaning that they might travel outside peak hours. Overall, this needs to be investigated in more detail. Preferably, a portable solution should be found rather than another solution that only works for the study area.

The approach currently selects a sub-zone (LOR) within the large Berlin zone randomly. It is, however, plausible to assume that there is in reality some gravity model, i.e. longer distances are less probable than shorter distances. Also, the destination-side supply constraints are currently not observed. Both issues could be addressed without having to resort to scenario-specific approaches.

The approach currently updates plan selection only against traffic counts; the updating against average trip time was done manually. It should be possible to include such aspects directly into the Cadyts calibration procedure, preferable not only as an average trip time but rather as a trip time distribution. An early version of this was done by Wagner and Nagel *(30)*.

In this study, no feedback from MATSim to CEMDAP is considered. So, location choice and time choice (according options being provided via CEMDAP initially) are not dependent on network conditions. This may be improved by the introduction of some feedback loop from MATSim to CEMDAP in potential follow-up studies.

7. CONCLUSION

The commuting matrix, either as input to the generation of an origin-destination matrix or as input to the generation of an activity-based demand, is often not available or not available without high enough spatial resolution. So, destination choice models are often used, which are, however, associated with problems like lack of suitable input data. In both cases (with or without a destination choice model) it is common to use traffic counts to further calibrate the OD matrices.

When assignment models are not driven by OD matrices, but by synthetic individual travelers with individual plans, the OD estimation technique is not directly useable. It is, however, possible to generate multiple plans per person, each having different activity locations, and then to use a Bayesian correction scheme in order to influence the plan choice probabilities towards measurement data. The procedure was developed and implemented by Flötteröd *(31)(8)*, but has so far only been applied to route choice, both for car *(10)* and for public transit *(11)*. In this paper, it is now for the first time applied to activity plan choice, which includes activity location choice.

To attain a set of possible activity-travel plans of each synthetic individual, CEMDAP (Section 2.1) was used in this study. Multiple CEMDAP outputs, generated by varying the workplace and school locations in the input files, are created and fed into the MATSim transport system simulation. To facilitate the application of CEMDAP, it is used with the minimally necessary input data, and on the basis of a readily estimated parameter set for the Dallas/Fort Worth region. The members of the set of activity-travel plans of each synthetic traveler are considered a set of *potential* solutions to the problem of finding a valid transport demand representation. A calibration algorithm (Cadyts, Section 2.3) is used to ensure that those initial suggestion of potential daily plans are selected that contribute to reproducing real-world traffic patterns. The procedure of feeding the output of a ABM model into a dynamic traffic simulation in interaction with a calibration algorithm that manages the adequate selection of initial suggestions is novel and increases the transferability of transport demand models from one region (the estimation context) to another region (the application context).

The model created in this study validated very well. MREs for volumes of traffic are around 20% during daytime hours (“With Cadyts” in Table 1 and Figure 2). The performance in terms of model fit is, thus, comparable to models based on travel diaries.

An independent validation, undertaken based on data from the Berlin 2008 SrV *(29)* travel survey, was successful concerning all considered properties. These properties encompass the total amount of car trips, the distributions of departure times, trip duration, trip distance, and average trips speeds as well the distribution of activity participation at trip ends.

To conclude, our results suggest that it may be possible for a model estimated for a different geographical region to be transferred to another region. On the basis of publicly available input data of the new region and in interaction with a traffic-count-based updating of activity-travel plan scoring (Cadyts), an evolutionary simulation (MATSim) may be able to generate a representative travel demand for the new region. Overall, the proposed approach appears quite encouraging in terms of developing policy-sensitive transport models for application contexts based on an estimated ABM model in an estimation context combined with traffic count data from the application context. Future studies need to investigate whether this holds true for other situations too, though it is important to point out that it is difficult to think of two contexts much more different than the Dallas-Fort Worth area in the U.S. and the Berlin area in Germany.

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REFERENCES

1. Chiu, Y.-C., J. Bottom, M. Mahut, A. Paz, R. Balakrishna, T. Waller, and J. Hicks. A primer for dynamic traffic assignment. *Transportation Research Circular E-C153*, Transportation Research Board, 2011.
2. *TRANSIMS*. http://code.google.com/p/transims/. Accessed March 26, 2013.
3. *DynusT*. http://dynust.net. Accessed Aug. 12, 2013.
4. *MATSim*. http://matsim.org. Accessed July 28, 2013.
5. Bundesagentur für Arbeit. Pendlerstatistik 2010. CD-ROM. 2010.
6. van Zuylen, H. and L. Willumsen. The most likely trip matrix estimated from traffic counts. *Transportation Research*, Vol. 14, 1980, pp. 281–293.
7. Nagel, K., and G. Flötteröd. Agent-based traffic assignment: Going from trips to behavioral travelers. In *R. Pendyala and C. Bhat, Travel Behaviour Research in an Evolving World – Selected papers from the 12th international conference on travel behaviour research*, International Association for Travel Behaviour Research, 2012, pp. 261–294.
8. Flötteröd, G., M. Bierlaire, and K. Nagel. Bayesian demand calibration for dynamic traffic simulations. *Transportation Science*, Vol. 45, 2011, pp. 541-561.
9. Flötteröd, G. *Cadyts – Calibration of dynamic traffic simulations – Version 1.1.0 Manual*. Transport and Mobility Laboratory, École Polytechnique Fédérale de Lausanne, 2010.
10. Flötteröd, G., Y. Chen, and K. Nagel. Behavioral calibration and analysis of a large-scale travel microsimulation. *Networks and Spatial Economics*, Vol. 12, 2011, pp. 481-502.
11. Moyo Oliveros, M. and K. Nagel. Automatic calibration of agent-based public transit assignment path choice to count data. In *Conference on Agent-Based Modeling in Transportation Planning and Operations*. Blacksburg, Virginia, 2013.
12. Bhat, C., J. Guo, S. Srinivasan, and A. Sivakumar. *CEMDAP User's Manual*. Center for Transportation Research, University of Texas, 2008.
13. Balmer, M., M. Rieser, A. Vogel, K. Axhausen, and K. Nagel. Generating day plans using hourly origin-destination matrices. In *T. Bieger, C. Laesser, and R. Maggi. Jahrbuch 2004/05 Schweizerische Verkehrswirtschaft*, Schweizer Verkehrswissenschaftliche Gesellschaft, 2005, pp. 5–36.
14. Rieser, M., K. Nagel, U. Beuck, M. Balmer, and J. Rümenapp. Truly agent-oriented coupling of an activity-based demand generation with a multi-agent traffic simulation. *Transportation Research Record, No. 2021*, Transportation Research Board, 2007, pp. 10-17.
15. Bhat, C., J. Guo, S. Srinivasan, and A. Sivakumar. A comprehensive econometric microsimulator for daily activity-travel patterns. *Transportation Research Record, No. 1894*, Transportation Research Board, 2004, pp. 57-66.
16. Bhat, C., K. Goulias, R. Pendyala, R. Paleti, R. Sidharthan, L. Schmitt, H.-H. Hu. A household-level activity pattern generation model with an application for Southern California. *Transportation*, Vol. 40, 2013, pp.1063-1086.
17. Pendyala, R., C. Bhat, K. Goulias, R. Paleti, K. Konduri, R. Sidharthan and K. Christian SimAGENT Population Synthesis. GeoTrans Laboratory, University of California. 2013.
18. Gawron, C. *Simulation-based traffic assignment*. Ph.D. thesis, University of Cologne, 1998.
19. Charypar, D. and K. Nagel. Generating complete all-day activity plans with genetic algorithms. *Transportation*, Vol. 32, 2005, pp. 369-397.

20. Balmer, M. *Travel demand modeling for multi-agent transport simulations: Algorithms and systems*. Ph.D. thesis, ETH Zürich, 2007.
21. Miller, E., J. Hunt, J. Abraham, and P. Salvini. Microsimulating urban systems. *Computers, Environment and Urban Systems*, Vol. 28, 2004, pp. 9-44.
22. Flötteröd, G. Cadyts - A free calibration tool for dynamic traffic simulations. In *Swiss Transport Research Conference*. Ascona, 2009.
23. Moyo Oliveros, M. *Calibration of Public Transit Routing for Multi-Agent Simulation*. Ph.D. thesis, Technische Universität Berlin, 2013.
24. *OpenStreetMap*. http://www.openstreetmap.org. Accessed July, 31 2014.
25. Zilske, M., A. Neumann, and K. Nagel. OpenStreetMap for traffic simulation. In *M. Schmidt and G. Gartner, Proceedings of the 1st European State of the Map – OpenStreetMap conference*, Vienna, 2011, pp. 126–134.
26. Amt für Statistik Berlin-Brandenburg. *Bevölkerungsstand in Berlin am 31. Dezember 2012 nach Bezirken*. https://www.statistik-berlin-brandenburg.de/Publikationen/OTab/2013/OT_A01-10-00_124_201212_BE.pdf, Accessed Nov., 4 2013.
27. Bömermann, H., S. Jahn, and K. Nelius. Lebensweltlich orientierte Räume im Regionalen Bezugssystem (Teil 1). *Berliner Statistik*, Vol. 8, 2006, pp. 366-371.
28. Ziemke, D. *Demand Generation for Multi-Agent Transport Simulations based on an Econometric Travel Behavior Model and a Traffic-Count-based Calibration Algorithm*. Master's thesis, Technische Universität Berlin, 2013.
29. Ahrens, G.-A. Endbericht zur Verkehrserhebung Mobilität in Städten - SrV 2008 in Berlin. Institut für Verkehrs- und Infrastrukturplanung, TU Dresden, 2009.
30. Wagner, P. and K. Nagel. Microscopic modeling of travel demand: Approaching the home-to-work problem. Annual Meeting Preprint 99-0919, Transportation Research Board, 1999.
31. Flötteröd, G. *Traffic state estimation with multi-agent simulations*. Ph.D. thesis, Technische Universität Berlin, 2008.