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Research Article

Agent-Based Simulation to Improve Policy Sensitivity of Trip-Based Models

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The most common travel demand model type is the trip-based model, despite major shortcomings due to its aggregate nature. Activity-based models overcome many of the limitations of the trip-based model, but implementing and calibrating an activity-based model is labor-intensive and running an activity-based model often takes long runtimes. This paper proposes a hybrid called MITO (Microsimulation Transport Orchestrator) that overcomes some of the limitations of trip-based models, yet is easier to implement than an activity-based model. MITO uses microsimulation to simulate each household and person individually. After trip generation, the travel time budget in minutes is calculated for every household. This budget influences destination choice; i.e., people who spent a lot of time commuting are less likely to do much other travel, while people who telecommute might compensate by additional discretionary travel. Mode choice uses a nested logit model, and time-of-day choice schedules trips in 1-minute intervals. Three case studies demonstrate how individuals may be traced through the entire model system from trip generation to the assignment.

1. Introduction

The most common travel demand modeling approach is the trip-based model, sometimes called the four-step model, which is essentially based on the concept proposed by Manheim [1]. But the conventional trip-based model has significant limitations, such as static definition of travel market segments across all modeling steps, independent trips that ignore activity schedules over the entire day, lack of intrahousehold coordination, or coarse representation of time of day. Activity-based models [2] were introduced in the 1970s to model travel behavior explicitly, overcoming many of these limitations of the trip-based model. However, it took two decades before activity-based models leaped from academia into application [3]. Even today, the vast majority of transport agencies continues to use trip-based models, despite their well-known shortcomings.

Major challenges to move from a trip-based model to an activity-based model include longer model runtimes, more sophisticated hardware requirements, larger efforts to calibrate the model, lack of experience with activity-based models, and lack of established software packages, among others. There is a need of methodology that overcomes some of the limitations of the trip-based model mentioned above. At the same time, models need to be agile enough to be prepared to analyze a large range of scenarios (including unanticipated scenarios) and fast enough to allow for multiple model runs (particularly if stochastic variation leads to nondeterministic model results).

In this paper, a microsimulation model is presented that creates travel demand for individual synthetic households and persons. The agent-based design makes the model very flexible. Every module may use a different set of households or person attributes. While household size is important in trip generation, it is irrelevant in destination choice. Microsimulation also allows adding attributes. For example, if three different levels of transit pass ownership (such as no pass, daily pass, and monthly pass) shall be distinguished,

this attribute can be added to the synthetic population and be used by those modules where transit pass ownership might be relevant (such as mode choice). In the traditional four-step model, the market segmentation would be tripled by adding transit pass ownership, which would seriously affect runtime, calibration, and memory requirements. The agent-based approach also allows tracing of individual travelers. If travel demand is simulated for individuals, it would be trivial to identify travel demand of, for example, five-person households with 2 cars, no transit pass, and low income. Such a detailed analysis is possible with an activity-based model but almost impossible in traditional trip-based models.

The methodology described here microsimulates travel demand but simplifies the construction of activity schedules. To compensate for this shortcoming, travel time budgets are modeled explicitly for every household. Thereby, longer work trips will, in tendency, reduce discretionary travel, and vice versa.

The paper reviews the state of the art in microscopic travel demand modeling in Section 2, followed by a detailed description of the proposed methodology in Section 3. Section 4 provides a case study application, and the paper provides some conclusions in Section 5.

2. State of the Art

By far, the most common approach for travel demand modeling is the aggregate trip-based model, first applied for Chicago in 1955 [4]. The form of this model used nowadays is largely based on the framework proposed by Manheim [1]. Even though the fifth-step time-of-day choice was added later [5], the term "four-step model" was kept due to its popularity. The terms four-step, five-step, and trip-based models are used synonymously today. McNally [6] provided a comprehensive overview of the individual steps of the trip-based model.

The limitations of the trip-based model were identified early by Horowitz [7]. While this modeling approach showed practical usefulness to model transportation systems, it only models the result (travel) but not the motivation (activities at different places). Activity-based models, in contrast, model activities for which travel needs to occur [8, 9]. As such, the motivation for travel is modeled rather than the traveling itself.

Adler and Ben-Akiva [2] introduced the concept of modeling activities throughout an entire day (travel pattern), where several purposes (sojourn) may be combined on one tour and each travel segment between activities is called a trip. They also pointed out the necessity to model joint activities of household members of the same household and provided econometric solutions to estimate activity patterns from a household travel survey. Damm and Lerman [10] expanded the approach by modeling discretionary activities around the work activity, recognizing that much of the daily activity pattern is driven by the need to be at work. Kitamura [11] further refined the simulation on nonwork activities and provided estimation guidelines that strictly followed utility maximization theories.

Bhat and Koppelman [12] point out that trip chaining, such as going from home to work to shopping to home (H-W-S-H), is a major limitation of the trip-based model. It represents this trip chain as one home-based work trip (H-W-H) and one non-home-based other trip (Other-Other). Schultz and Allen [13] estimated that non-home-based trips account for 25 to 30 percent of all trips. In trip-based models, home-based and non-home-based trips are handled independently. A change of the home-based trip (such as a delay due to congestion) does not affect the non-home-based trip in a trip-based model.

Applications of activity-based models remained mostly academic through the end of the 20th century. An exception is the Portland Metro model that was briefly used in 1998 and later abandoned [14]. Limitations in data and lack of confidence in this new modeling paradigm prevented widespread use [15]. A breakthrough in the application of microsimulation for modeling activities was provided by Kitamura et al. [16]. For the first time, it was possible to estimate (relatively simple) models that generate travel demand at the microscopic level.

The San Francisco County Model followed the design of the Portland Oregon Model and became operational in 2001 [3] and shortly thereafter followed New York City and Columbus, Ohio, using the CT-RAMP model design [17]. Several model developments in academia are worth mentioning as well. The ALBATROSS model was developed as an activity-based framework to model travel demand [18]. TASHA was developed by Miller and Roorda [19] for the Greater Toronto Area. The CEMDAP model was developed by Bhat et al. [20] for Dallas/Fort-Worth Area in Texas. mobiTopp [21] was developed by the Karlsruhe Institute of Technology and is currently applied to the Stuttgart metropolitan area. mobiTopp simulates activities over the course of an entire week, which allows for a more reasonable scheduling of occasional activities, such as shopping or going out to eat. This weekly simulation of activities was later enhanced by Arentze and Timmermans [22] with the explicit negotiation of activities among household members.

A hybrid model has been developed by Bernardin and Conger [23]. Auto-ownership, tour generation, and tour mode choice were built as disaggregate models, while the remaining tour stops and departure times were modeled in an aggregate model. The hybrid approach reduces the computational burden at least by a factor of six [23].

Thus far, there have been few studies that explicitly compare the trip-based model with the activity-based model. At a theoretical level, Rasouli and Timmermans [24] analyzed four commonly cited limitations of the trip-based model (including (1) insufficient spatial and temporal resolution, (2) lack of behavioral foundation, (3) lack of integration in model estimations, and (4) interdependency of trip generation, destination choice, mode choice, and route choice) and concluded that the activity-based model has only partly overcome these shortcomings. Erhardt et al. [25] compared the trip-based model with the activity-based model for the San Francisco Bay Area and found that both models perform similarly, but the activity-based model offers additional scenario capabilities. Lemp and McWethy

et al. [26] implemented a trip-based model and an activity-based model for Austin, Texas. They point out that the activity-based model is more difficult to calibrate and the creation of a synthetic population may be time consuming. On the other hand, they commended the enhanced scenario capabilities of activity-based models.

A comprehensive analysis of benefits and limitations of activity-based models is given in the NCHRP Synthesis Report 406 [27]. They conclude that the activity-based model needs to validate at least as well as the trip-based model. They further argue that agencies that make use of the added scenario capabilities of activity-based models should upgrade to this model type. At the same time, however, they discourage agencies to move to an activity-based model if the added scenario capabilities are not exploited, as the trip-based model may work reasonably well for many simpler scenario analyses.

Challenges with model calibration and runtime are often cited as major concerns for using a full scale activity-based model [26, 28]. For many applications, the scenario capabilities are not utilized, and a simpler model would perform just as well. This paper attempts to fill this gap by proposing a model that overcomes some of the limitations of the trip-based model yet runs significantly faster and is easier to calibrate than activity-based models.

3. Model Overview

The Microsimulation Transport Orchestrator (MITO) has been developed as a microsimulation for travel demand. A synthetic population was generated [29] and travel demand is simulated for every household and person individually. As shown in Figure 1, mandatory trips (home-based work (HBW) and home-based education (HBE)) are distinguished from discretionary trips (home-based shop (HBS), home-based other (HBO), non-home-based work (NHBW), and non-home-based other (NHBO)). For mandatory trips, the trip destination is already set in the synthetic population (as work place or school place). For discretionary trips, the model calculates a travel time budget, which is calculated for each household individually. Based on theory of constant travel time budgets [30], longer work trips will lead to shorter discretionary trips, while telework may lead to more time spent on discretionary trips. In line with Zahavi's theory, the travel time budget is not a hard constraint for an individual household but rather used to influence the probabilities to choose different destinations. On the average, however, travel time budgets are modeled to remain constant over time. Destination and mode choice are built as logit models, and the time-of-day choice is simulated by a Markov model. The assignment is currently conducted in MATSim [31], but any other assignment model can be linked to MITO.

The model can be set up with a traditional household travel survey. For the application presented below, the German survey "Mobilität in Deutschland" from 2008 [32] was used to estimate and calibrate each modeling step. Highway traffic counts were used for model validation. MITO is written in Java. It is open source and can be accessed at https://github.com/msmobility/mito. A sample setup with all required input can be provided by the authors. The following five sections describe the MITO step by step.

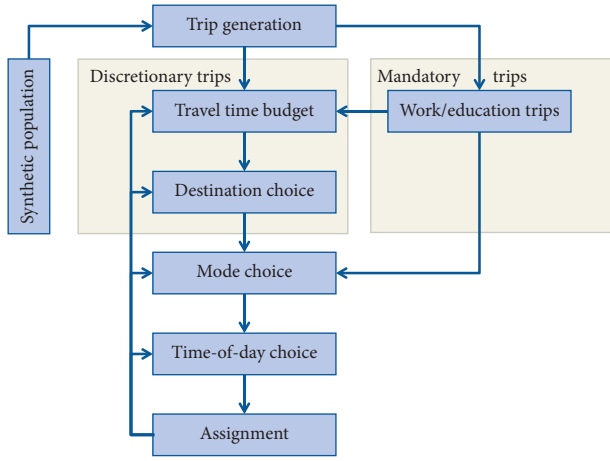

Figure 1: Model flow chart of MITO.

3.1. Trip Generation. Traditionally, average trip generation rates are applied to the number of households segmented by predefined household types. Every household of a given type will be assigned the same (real) number of trips, such as 1.26 work trips for a given household type. In reality, however, trip generation is more heterogeneous, with some households making no trips and other households making more than a dozen trips, even if they are of the same household type. For MITO, a microsimulation trip generation model was built [33] to simulate the full diversity of trip making.

Using the observed trip frequencies of a household travel survey, this method uses sample enumeration to select the number of trips individually for every household. Household types were defined inductively by testing over 67 million possible household-type definitions and selecting for every purpose the one household-type definition that best described the observed differences in trip making. As an example, Table 1 shows the distribution of number of trips generated by 24 household types for the trip purpose home-based work.

Number of workers and economic status (Economic status was defined by the survey as a relationship between number of adults, number of children, and net income of a given household [32]. Thereby, the survey attempts to represent an "equivalent income," where a one-person household tends to have a higher economic status than a two-person household with the same net household income.) were found to be most descriptive to explain the number of work trips. Other demographic attributes (namely, household size, car ownership, and urban area type) were not found to be as explanatory to describe the number of work trips [33]. As expected, the data show a tendency of more work trips for households with more workers and higher economic status.

In application, sample enumeration is used to select the number of trips generated for every household for each trip

Table 1: Number of work trips by household type.

HH type	Workers from	Workers to	Economic status	0 trips	1 trips	2 trips	3 trips	4 trips	5 trips	6 trips	7 trips	8 trips
A	0	0	1	1,056	35	4	2	0	0	0	0	0
B	0	0	2	636	14	5	0	0	0	0	0	0
C	0	0	3	3,601	47	2	1	0	0	0	0	0
D	0	0	4	1,474	18	2	0	0	0	0	0	0
E	0	0	5	330	4	0	0	0	0	0	0	0
F	1	1	1	351	266	30	3	0	0	0	0	0
G	1	1	2	362	291	45	3	1	0	0	0	0
H	1	1	3	1,234	1,198	104	11	1	0	0	0	0
I	1	1	4	954	833	79	4	1	0	0	0	0
J	1	1	5	295	252	19	0	0	0	0	0	0
K	2	2	1	122	90	63	13	1	0	0	0	0
L	2	2	2	243	223	140	28	8	0	0	0	0
M	2	2	3	995	898	716	87	9	0	0	0	0
N	2	2	4	1,015	897	715	65	6	1	0	0	0
O	2	2	5	467	325	272	32	4	1	0	0	0
P	3	4	1	25	24	19	12	5	1	0	0	0
Q	3	4	2	66	65	79	40	13	2	1	0	0
R	3	4	3	150	157	146	81	21	3	1	0	0
S	3	4	4	191	125	146	104	26	7	2	0	0
T	3	4	5	61	45	30	32	4	2	1	0	1

Data source: German household travel survey "Mobilität in Deutschland."

purpose. As a result, some households will make dozens of trips, while other households do not make a single trip.

3.2. Travel Time Budgets. Based on the number of trips, this module estimates the total time by purpose that households allocate to travel within a day. Travel time budget (TTB) is a concept which postulates that only a certain and quite stable amount of time will be allocated to travel to move between activities during an average day [30]. All over the world and in different decades, people in most countries travel between 60 and 75 min per day [34, 35]. The results may indicate that there is an unobserved desired travel time budget and that the variations that can be found in individual TTB are balanced out at the aggregated level [34, 36].

Despite empirical evidence, TTBs have not been considered in most travel demand models. While activity-based models recognize that the day has no more than 24 hours and allows only for activities that fit into one day; time budgets for travel time are commonly ignored.

Common approaches in a traditional trip-based model will attempt to select closer destinations when congestion worsens. This behavior does not match observed work-trips destination choice. To respect the total TTB, the model needs to select shorter trips of non-work trip purposes if congestion worsens, while work and school trips should be kept unchanged. If congestion worsens significantly, work and school (and housing) locations should change in the long run, which can be handled in a land use model. The transport model should not change origins and destinations of mandatory trips instantaneously. This is accomplished in MITO by calculating household TTB for every trip purpose.

Seven models were estimated using the household travel survey [37] for six trip purposes and the total TTB. At the household level, the explanatory variables for the household's TTB depend on its sociodemographic characteristics, its location, and its travel behavior. The number of trips for each trip purpose, which were microscopically simulated in trip generation, was used as an inverse proxy for the remaining time for other activities that the household would perform.

Survival analysis was selected to account for duration dependence effects [38]. In survival analyses, the dependent variable is the time until an event occurs and is commonly used in clinical studies to model the time in remission of a disease or time until death. In transportation analysis, the survival time can be referred as the travel time and the event is to travel. The survivor function $S(t)$ gives the probability that the time traveling (t) is longer than the specified time T. Parametric survival models are more consistent with the theoretical survivor function and simpler, and the calculation of the quantiles (i.e., median travel time) is defined. Therefore, if the underlying distribution assumption is met, parametric survival models are preferred over semi-parametric models (also called Cox proportional hazards model).

Assuming a Weibull distribution, the survivor function can be expressed by using equation (1), while the median travel time can be calculated using equation (2):

$$S(t) = e^{-\lambda t^p}, \tag{1}$$

$$t_{50} = (-\ln 0.5)^{1/p} \cdot e^{\beta_0 + \sum \beta_i \cdot x_i}, \tag{2}$$

where $\lambda = e^{\beta_0 + \sum \beta_i \cdot x_i}$, $1/p$ is the scale of the Weibull model, t_{50} is the median TTB, β_0 is the intercept of the Weibull model, β_i are the coefficients of the Weibull model, and x_i are the explanatory variables.

The scale and coefficients of the model were fitted using the package Survival from the free software environment *R* for statistical computing [39]. The best model was selected

for each trip purpose based on the AIC (Akaike Information Criterion) with a backwards stepwise approach.

The number of trips by purpose and selected socio-demographic attributes were statistically significant to explain the TTB. The estimation results published in [37] suggest that trip purposes compete for travel time budget among each other. In other words, households distribute their total travel time among the different purposes and an increase in number of trips for one purpose will reduce the travel time allocated for other trip purposes.

3.3. Destination Choice. The trip distribution module selects destinations for the generated trips at a microlocation level. Trips generated at the household level are assigned to persons within the household using a rule-based approach. HBW and NHBW trips are assigned to workers, HBE trips are assigned to students and other trips are assigned plausibly to all household members depending on their age. Trip destinations are selected as zones at first. In a subsequent step, microscopic coordinates are assigned inside the selected zone. A multinomial logit choice model is used to select destinations from a given origin.

To speed up computation time, a matrix containing the exponentiated utilities of each origin-destination relation is precalculated for every trip purpose :

$$e^{U_{i|j}} = e^{\beta * \mathrm{imp}_{i|j} + \ln(\mathrm{attraction})} = e^{\beta * \mathrm{imp}_{i|j}} * \mathrm{attraction}, \quad (3)$$

where $e^{U_{i|j}}$ is the exponentiated utility for choosing the destination j for trip purpose p, starting from origin i and $\mathrm{imp}_{i|j|p}$ is the impedance for this trip. The attraction variable reflects the number of opportunities in the destination zone for the given purpose and is estimated in the trip generation phase. The weight of the impedance is defined by the purpose-specific parameter β. Impedance is calculated by

$$\mathrm{imp}_{i|j} = e^{\left(\mathrm{td}_{i|j} * \gamma_p\right)}, \quad (4)$$

where, $\mathrm{td}_{i|j}$ is the travel distance between i and j and γ_p is a (negative) parameter that is calibrated for each trip purpose p separately. Travel distances are used for the impedance. However, travel times are accounted for by a travel time budget constraint. The parameters β and γ_p are calibrated to match the distribution and the average reported trip distances for each purpose in the household travel survey.

In trip distribution, all home-based trips are processed first, as the origin is already fixed at the home location of the person. In a second step, origins and destinations for the non-home-based trips are assigned and connected to trip ends of home-based trips.

For the mandatory trips HBW and HBE, no destination choice is modeled here, as school or work places are already defined in the synthetic population. For the nonmandatory trip purposes shopping and other, destinations are chosen constrained by the overall TTB distribution. Origins are again set as the home location. The model attempts to select destinations within the TTB calculated for this household and trip purpose. The budget constraint is not considered to be a hard constraint for a given household. Rather, the model adjusts probabilities for all destinations to achieve that the TTB is met on the average, though some households may exceed or underuse their TTB. After one household is completed, the TTB for the following households is adjusted up or down ($\mathrm{ttb}_{\mathrm{adjusted}}$) to match the TTB across all households on the average.

For each trip of the next household, the choice probabilities for every destination are multiplied by an adjustment factor μ_j. This factor is taken from a normal distribution with a mean of $\mathrm{ttb}_{\mathrm{adjusted}}$ and a standard deviation of ten minutes to allow for some deviation from the ideal travel time budget. If previous households have exceeded their TTB, this normal distribution is shifted to the left to encourage shorter destinations for subsequent households, and vice versa. Over time, the model will select destinations that best fit both the observed trip length frequency distribution and the average TTB.

In a last step, the non-home-based trips are distributed. As neither origin nor home is known for these, a reference zone has to be selected first. The model looks for the destinations of previous assigned home-based trips in an attempt to spatially relate non-home-based trips with home-based trips. For non-home-based work trip, the workplace provided by the synthetic population is used as the origin, while previous home-based shop and other trips are used as origins for non-home-based other trips. If there were several home-based trips, the reference zone is randomly selected among those candidates. When no fitting trip was found, the work zone of the assigned person will be used as a reference zone for non-home-based trips, if applicable.

3.4. Mode Choice. MITO employs mode-choice models based on data from the national household travel survey. We estimated individual models for trips by purpose, as modal utilities differ across purposes. For example, individuals tend to accept longer travel times for leisure trips as opposed to shopping trips. The models simulate the choice among the modes—Auto driver, Auto passenger, Bicycle, Bus, Train (suburban and regional), Tram or Metro, and Walk. Modal utilities are computed as a function of the following attributes:

(1) Characteristics of the individual making the trip—age, sex, and possession of driver's license

(2) Characteristics of the household the individual belongs to—household size, number of autos owned, number of children, number of employed persons, residential area type, and distance to the nearest transit stop

(3) Characteristics of the trip—trip length and generalized cost (travel time plus travel cost converted to equivalent time using value of time)

The coefficients of modal attributes were estimated in a logit-modeling framework using Biogeme [40], an open-source freeware designed for maximum likelihood estimations of discrete-choice models. As some modes are more similar than others, we adopted a nested logit structure which accounts for correlation within nests. After examining

different nested structures, the most appropriate structure was found to be one with Auto driver and Auto passenger in an Auto nest, the three transit modes in a Transit nest, and Bicycle and Walk as independent modes alongside Auto and Transit, as shown in Figure 2(a) the left. The nested logit models were then estimated in an incremental manner to ensure a minimum 95% confidence level while avoiding significant correlations of independent variables. Sample estimation results for the mode choice model were published by Rayaprolu et al. [41].

MITO is also equipped to predict mode choice in an impending scenario with autonomous vehicles (AVs) or self-driving cars. To model the impact of AVs on mode choice, we extended the choices by including AVs in the choice set. We distinguish the modes privately owned AVs and AVs offered as a shared service, assuming their impact on travel behavior and choice to be different. Given that little is known about their characteristics, we adopted an incremental logit approach [42] considering AV Private as an improved version of Auto driver and AV Shared as an improved version of the transit service bus. We assume that the value of time (VOT) for AV Private will be the lowest. In the estimated mode choice model (without AVs), Auto driver had the lowest VOT. It was also assumed that other unincluded attributes between AV Private and Auto driver are similar, such as the ability to use air conditioning or the privacy of the personal vehicle. We chose bus as the base for shared AVs assuming they would be offered as a service with vehicles shared by multiple passengers. The modified model structure is shown in Figure 2(b). The main benefit of the incremental logit model is that assumptions need to be made explicit. The user can set the benefits of AVs in comparison with the existing modes Auto driver and Bus. Given the lack of observed data and the challenges of stated-preference surveys about choices, the respondent has not experienced yet; these assumptions are rather arbitrary for the time being. The incremental mode choice model forces at least the model user to make those assumptions explicit.

3.5. Time-of-Day Choice. MITO simulates a departure time for each trip. Time-of-day choice is based on the observed departure times in the national household travel survey.

The survey data are used to obtain empirical distributions of arrival times and duration of the activity for each travel purpose. Based on these distributions, the times are selected by means of a probabilistic choice. Arrival time distributions are selected instead of the departure time for two main reasons: first, we had more confidence in self-reported arrival times (start of the activity) rather than self-reported departure times (start of the trip). Secondly, departure times are subject to the selected destination and mode, while arrival times are mostly dependent on the start of an activity. These two hypotheses are particularly relevant for mandatory trip purposes, where the starting time of the activity is defined, but they are also compatible with non-mandatory trips. By choosing arrival times, we reduce the amount of required data input to single distributions by purpose, independent of mode or destination of the trip.

The following steps are carried out for every trip:

(i) Select an arrival time by randomly sampling the corresponding arrival time distribution

(ii) Calculate the departure time by subtracting the travel time by the selected mode from the arrival time

Up to this step, all trips are stored in production-attraction (P-A) format. To convert trips into origins-destination (O-D) format, a return trip is added to all home-based trips. Therefore, a departure time for the return trip is generated for all home-based trip purposes:

(i) Select an activity duration by randomly sampling the corresponding duration activity distribution of the given trip purpose

(ii) Calculate the departure time of the return trip by adding the duration to the arrival time

(iii) Reverse origin and destination to account for the return travel direction

Departure times before or after midnight are transformed by adding or subtracting 24 hours. The time resolution of the time-of-day choice model is 1 minute.

3.6. Traffic Assignment. MITO trips can be fed into any traffic assignment model. Individual trips can be either aggregated to origin/destination matrices to perform a static user equilibrium traffic assignment or used by an agent-based assignment, such as a Dynamic Traffic Assignment (DTA) or microscopic traffic assignment models. Using an agent-based traffic assignment model allows tracing individuals all the way from trip generation to the assignment.

For the application of MITO presented below, the agent-based transport simulation framework MATSim [31] was used for traffic assignment. MATSim can be used as a Dynamic Traffic Assignment (DTA) model that simulates individual vehicles on the road network. In contrast to microsimulation models, overtaking of vehicles is not modeled, but the first-in-first-out assumption is applied for every link. A major benefit of a DTA model like MATSim is that the number of vehicles on a link can never be larger than the link capacity, which is a common shortcoming of static user equilibrium assignment methods.

While MATSim is able to adjust mode, departure time, route, and even supress single trips in response to congestion, all adjustments except route choice were turned off in the simulations presented below. The travel demand presented below is the original travel demand by MITO. MATSim is merely used to select routes for all trips. Travel times and distances are fed back to MITO.

3.7. Model Validation. MITO was applied to the metropolitan area of Munich (Germany). All modules described in Sections 3.1 to 3.6 were calibrated to match observed data of the German national household travel survey. Figure 3 shows the traffic volumes that were assigned to the network.

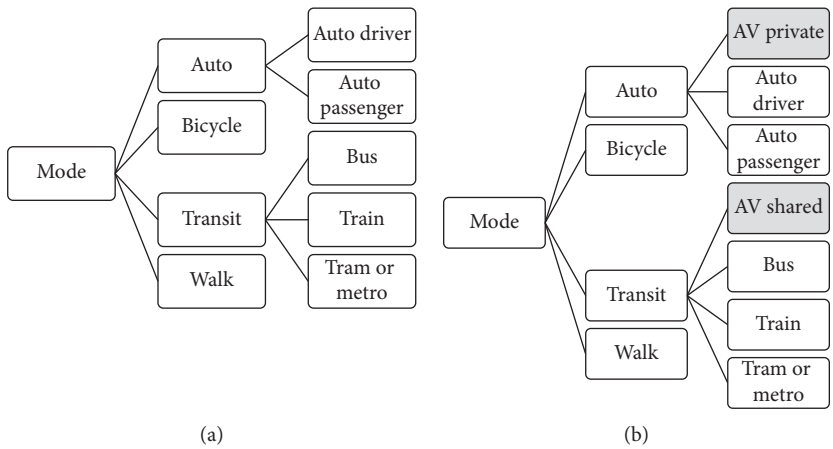

Figure 2: Mode choice nesting structure without (a) and with (b) autonomous vehicles.

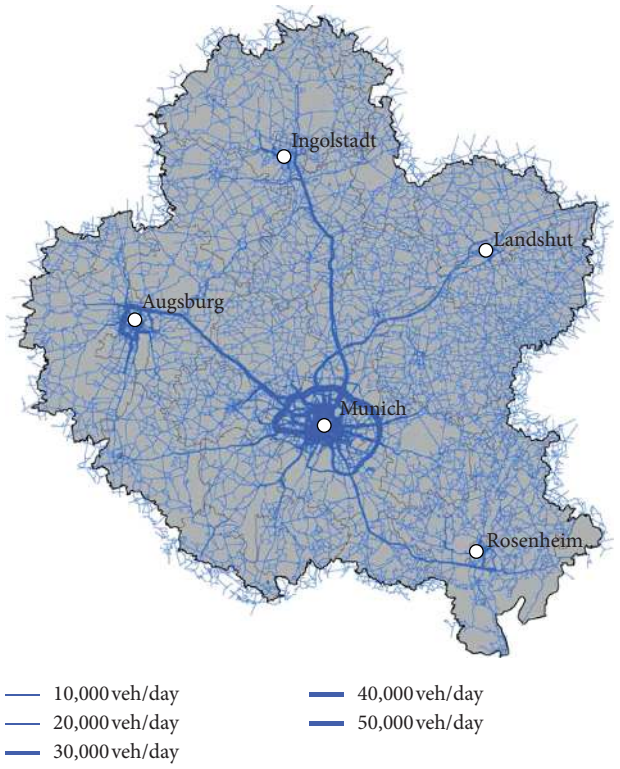

Figure 3: Traffic volumes assigned to the network.

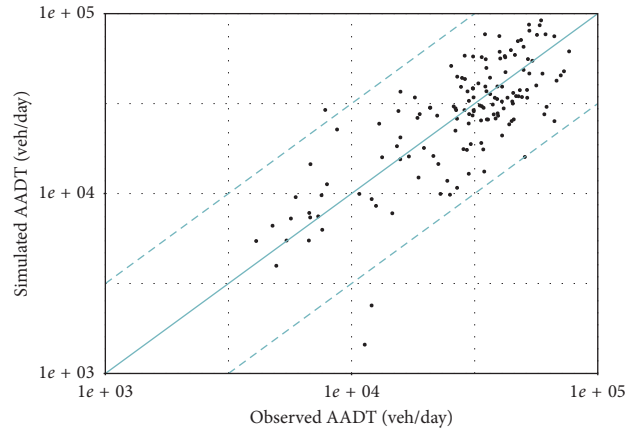

Figure 4: Simulated vs. observed traffic volumes (AADT : average annual daily traffic). The solid blue line is the line $y = x$, and dashed lines delimitate the +50% and −50% error band.

The model was validated by comparing the output of the traffic assignment (road traffic only) with traffic counts. Figure 4 compares traffic counts on motorways with simulated volumes. The Root Mean Squared Error (RMSE) was 14,769 veh/day, and the Percent Root Mean Square (% RMSE) error was 45%.

4. Case Studies

MITO was applied to three case studies to demonstrate its ability to analyze changing travel demand of individuals.

4.1. Refugee Group Arrival. The first case study covers the integration of a larger group of refugees. The goal of this case study was to analyze alternative ways of allocating such incoming population. Specifically, the effects on travel demand of the implementation of a refugee camp and the equal distribution of refugees across an entire city were compared. MITO was applied to the metropolitan area of Munich (Germany), and 20,000 refugees were allocated in the city of Munich. The base year model was used that did not include autonomous vehicles.

The sociodemographic characteristics of refugees are likely to differ from residents. In absence of observed data, we assumed that all refugees belong to single-person households are 25 years old, have a small income, and own a driver's license but have no car. For travel time budgets, the lowest economic status was assumed, and for mode choice, the lowest income category was assigned to refugees.

With these specifications, three MITO runs are compared: the base scenario (no refugees), the refugee camp scenario, and the scenario with distributed refugees. Figure 5 shows the average number of trips per household by trip purpose. As the impact of refugees on trip generation and trip distribution of residents is minimal (20,000 refugees against 4.4 million residents), average values per household

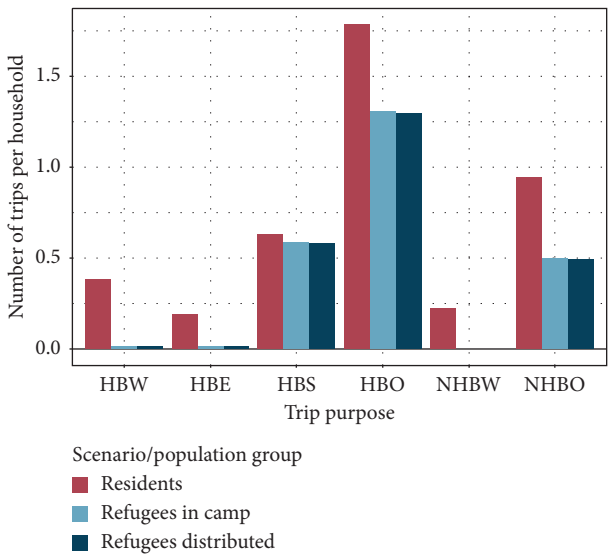

Figure 5: Average number of trips per household by population group and scenario.

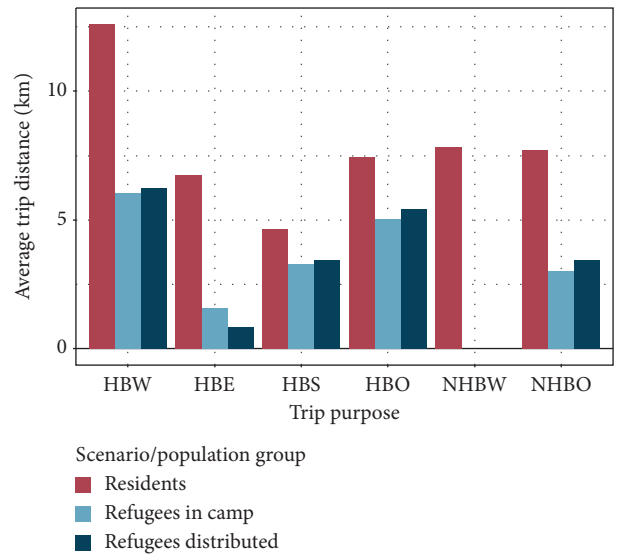

Figure 6: Average distance travelled by population group and scenario.

by trip purpose are presented. The number of trips of refugees is, on average, smaller than the number of trips of residents. As the refugees do not have a work or education place, yet the number of home-based work (HBW) and home-based education (HBE) trips is very small (yet a few may go for a job interview). They do not make any non-home-based work (NHBW) trips. The number of home-based shopping trips is almost equal between residents and refugees, as everyone needs to buy groceries. As expected, there were almost no differences found in trip generation between the two refugee allocation scenarios.

Figure 6 shows the average travel distance of the trips by purpose. The distance travelled by refugees is smaller than the distance travelled by residents due to smaller travel time budgets of refugees that were caused by lower income levels. Figure 7 shows the number of trips (using all transport modes) that end in each model zone for the two scenarios that include refugees. As expected, Figure 7(a) shows a high concentration of trips with destination in the vicinity of the refugee camp, while the number of trips is spread out over a larger area when the refugees are allocated across the entire city.

Lastly, Figure 8 shows the traffic assignment in MATSim. The plots show the additional daily traffic volume caused by trips made by car by refugees under the two allocation scenarios. The number of car trip legs was around 15,000 in both scenarios (each home-based trip has two car trip legs and each non-home-based trip only one). Refugees' car modal share is around 30%, in contrast to residents' car share of 40%. The spatial distribution of these traffic volumes is very different between Figures 8(a) and 8(b), showing that significant congestion increases are expected when a large number of refugees are allocated in one camp. With a refugee camp, the added volumes exceed 1,600 veh/day on selected arterial roads close to the camp. When the refugees are allocated across the entire city, the affected area is larger but the additional traffic volumes are below 400 veh/day.

As expected, the impacts of added population are stronger when the new residents are concentrated in a small area like a refugee camp. This case study showed that MITO is able to simulate changes in the input data at the resolution of individuals. MITO can trace the resulting travel demand of individuals that share a common attribute (such as being a refugee). The information can be traced through every modeling step, from the trip generation all the way to the traffic assignment.

4.2. People with Disability. For the second case study, we added a variable to categorize if a person has a severe physical or mental disability. The German Statistical Office collects and publishes data on people who own a disability pass. In 2018, 9.4% of the population had a severe disability (7.6 million). The goal of this case study was to evaluate how modal split may vary within a region if it is taken into account how people with disabilities experience different modes, as well as which policies could be more effective to increase transit share of people with disabilities.

Disability was added as an attribute to the synthetic population based on the distribution of severe disability by age, gender, and type of disability. A base scenario was generated with some service assumptions (Table 2). Specifically, persons with disabilities experience restrictions to certain modes and also have an increased disutility for walking. The disutility for walking was modeled as a reduction of walking speed (from 5.0 to 2.5 km/h) and as an increased perception of walking distance (by 50%).

Figure 9 shows the modal shares for the base scenario by disability type. Even though the auto travel time is increased for people with disabilities, auto modes have a higher share than people without disabilities (72.4% and 75.8% compared to 65.2%). The higher share of private motorized modes is caused by the unavailability of cycling and the increased disutility for walking. Although transit travel times increased

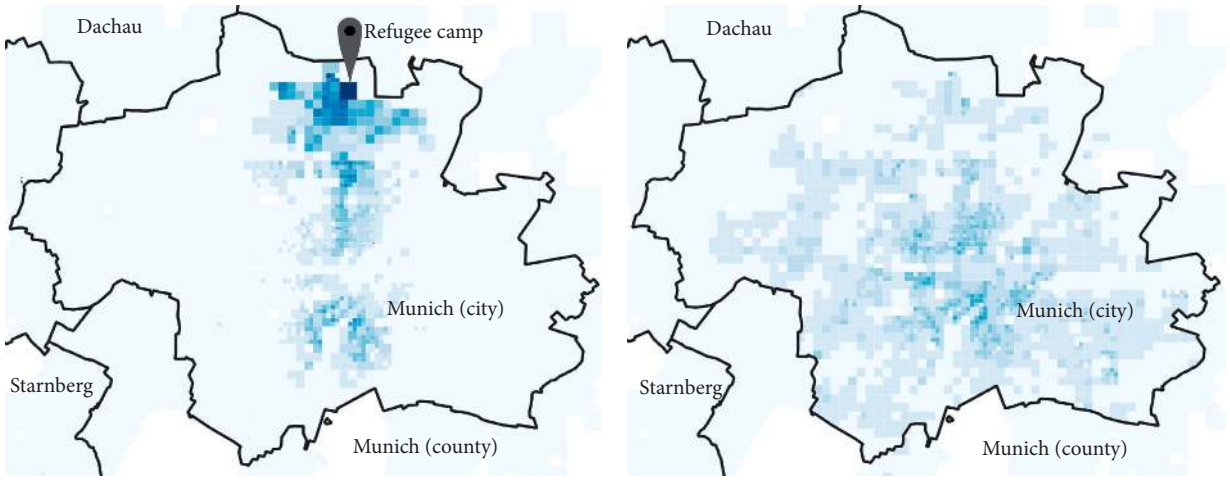

Figure 7: Number of trips by destination zone made by refugees. (a) Refugees located in one camp. (b) Refugees distributed (the refugees' home locations are randomly distributed within the Munich city boundaries).

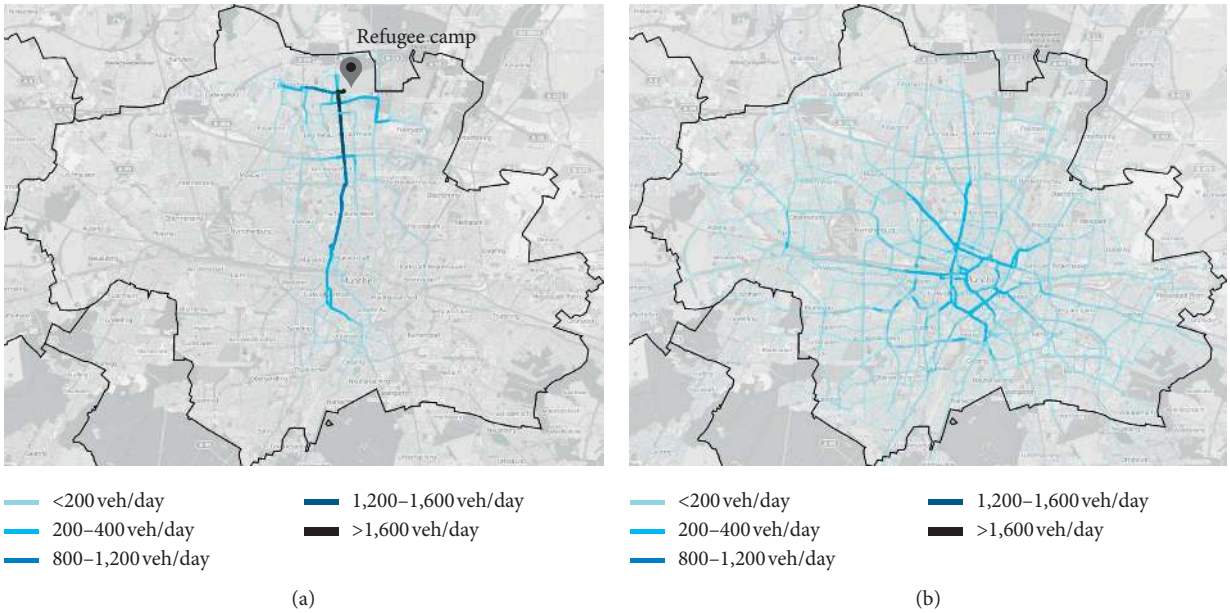

Figure 8: Increase of traffic volume due to trips made by refugees (base map source: openstreetmaps.org). (a) Refugees located in one camp. (b) Refugees distributed.

Table 2: Assumptions by modes in the base scenario.

Mode	Persons without disability	Persons with mental disability	Persons with physical disability
Auto driver	Auto travel time	Not available	Auto travel time + 4 minutes (access/egress)
Auto passenger	Auto travel time	Auto travel time + 4 minutes (access/egress)	
Bicycle	Distance by bicycle	Not available	
Walk	Distance by walk	Increased disutility for walking (distance +50%)	
Transit	In vehicle, travel time + access/egress at 5 km/h + transit fare at 0.12 EUR/km	In vehicle, travel time + access/egress at 2.5 km/h + 1.5 extra minutes per transfer + transit fare at 0.12 EUR/km	

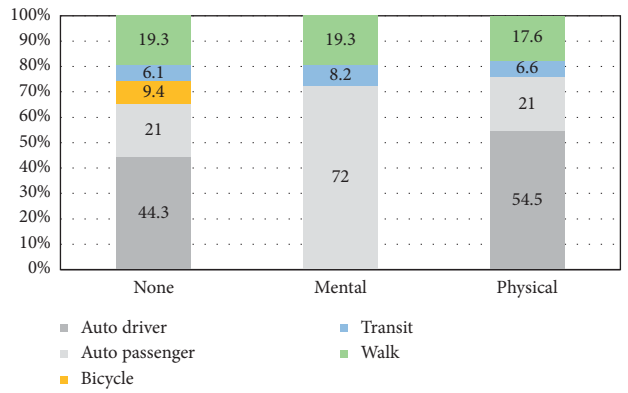

Figure 9: Modal share at the base scenario.

Table 3: Transit service assumptions for persons with disability by scenario.

Scenario	People with mental or physical disability
Base	In vehicle, travel time + access/egress at 2.5 km/h + 1.5 extra minutes per transfer + transit fare at 0.12 EUR/km
Policy A "faster transit"	In vehicle travel time + access/egress at 5 km/h + transit fare at 0.12 EUR/km
Policy B "free transit"	In vehicle, travel time + access/egress at 2.5 km/h + 1.5 extra minutes per transfer + free transit fare
Policy C "faster and free transit"	In vehicle travel time + access/egress at 5 km/h + free transit fare

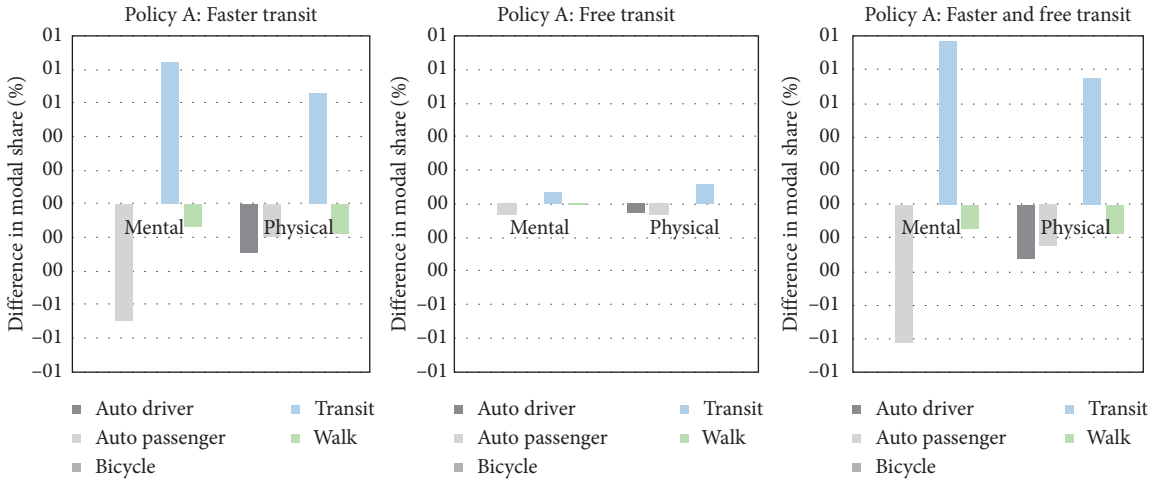

Figure 10: Differences in modal share by policy scenario for persons with mental and physical disabilities.

for people with disabilities, their transit share is higher due to the limitation of other modes.

To test policies that intend to increase the transit share of people with disabilities, three policy scenarios were generated: policy A "faster transit"; policy B "free transit"; and policy C "faster and free transit" (all apply to people with disability only). Table 3 summarizes the transit service assumptions by policy scenario.

The results indicate that people with disabilities are more sensitive to travel time than cost (Figure 10). Providing free transit increased the transit share by 0.1%, while a faster access and egress travel time increased transit by 0.8%. The combination of both measures increased the transit share by 1% for persons with mental disabilities and by 0.7% for persons with physical disabilities. The majority of travelers with mental disabilities shifted from the auto passenger mode; while travelers with physical disabilities shifted from both auto driver and auto passenger. The case study showed how MITO can incorporate new attributes in mode choice and simulate the service for a certain group of travelers.

4.3. Flexible Work Start Hours. In a third case study, we tested the effects of assigning work starting times with the goal to alleviate peak hour congestion in dense urban areas and their access roads.

For demonstration purposes, we assumed a policy that realizes a uniform distribution of work start times between 6 and 9. We reassigned the arrival time for trips from home to work for all workers in the city of Munich (the return trips

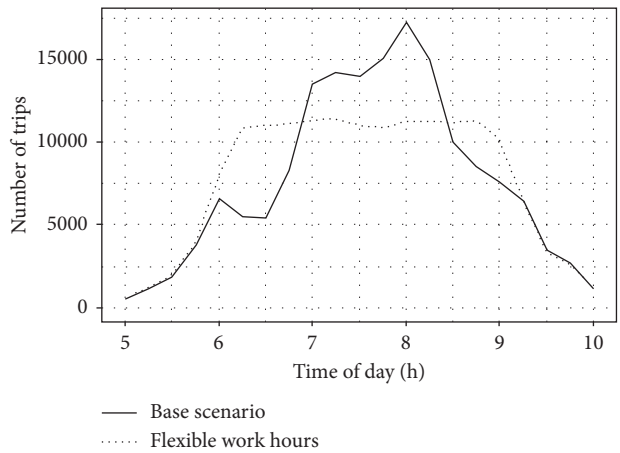

Figure 11: Distributions of departure time to work.

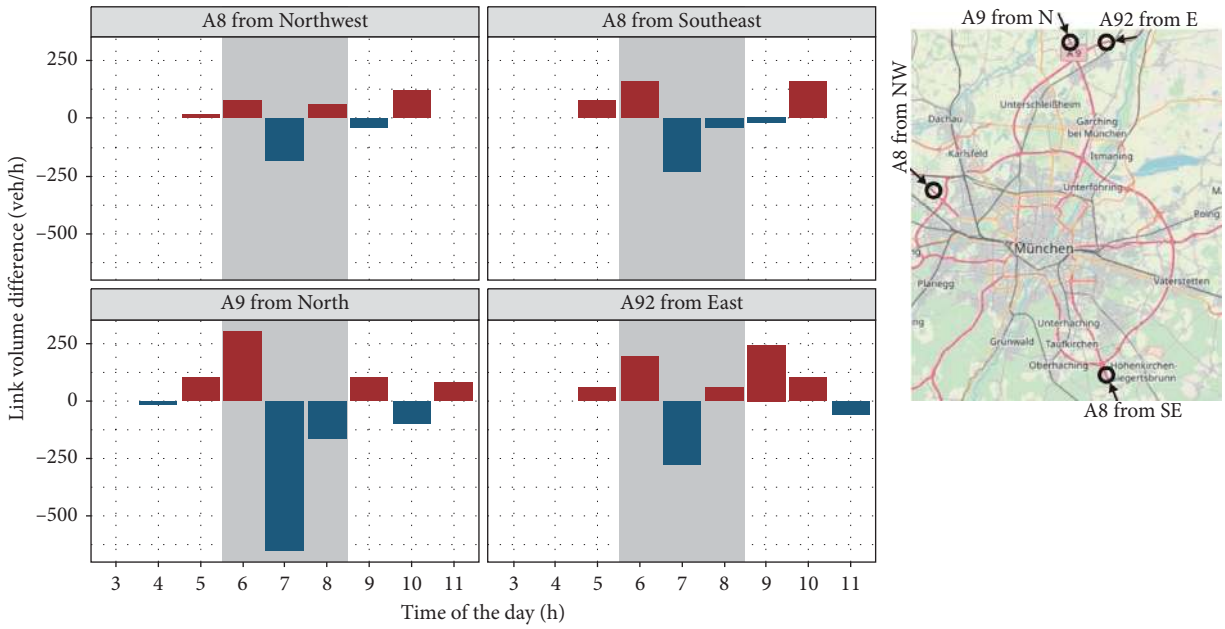

Figure 12: Link volume differences (volume with flexible work hours minus volume of base scenario) at selected roads in the direction of the Munich city center. The gray area is the peak-hour period from 6:00 to 9:00. Blue colors represent a reduction of link volumes, and red colors represent an increase after the introduction of assigned work start times. The map shows the locations of these volumes on the network (base map source: openstreetmaps.org).

are shifted consistently). Figure 11 shows the original and modified departure time distribution for these trips. The results were evaluated by comparing traffic counts between the scenario with shifted working hours and the base scenario.

Figure 12 shows that assigned work starting hours increase the traffic volumes between 5:00 and 6:00 AM. On the contrary, they mostly reduce the traffic volumes during the most congested hours. The differences in link volumes before and after the adjusted period (6–9 AM) and the adjacent hours are due to random variations between model runs. Because the scenario helped to slightly reduce congestion during the morning peak hour, the average travel time to work by car was reduced by 6%, or from 18.1 minutes to 16.9 minutes. Traditional aggregate models commonly are limited to a few time-of-day periods (often defined as AM Peak, Midday, PM Peak, and Night). Every time-of-day period is assigned separately in static user equilibrium assignments, and the network is assumed to be cleared by the end of each period. In contrast, MITO can easily simulate the time-of-day choice of selected agents and MATSim is able to assign flows continuously over the course of the day without the need to define static time-of-day periods.

5. Conclusions

The presented model is capable to present travel demand of individuals using a disaggregate trip-based design that was enhanced by simulating travel time budgets (TTB) and time-

of-day choice. The TTB module accounts for the fact that people who have to commute longer tend to do less other travel. Vice versa, the model will create more other travel for someone who telecommutes and does not travel to a work place.

The microscopic nature of the model made it possible to analyze travel demand by detailed travel market segmentations, as shown with the refugee scenarios in the previous section. While traditional trip-based models generate non-home-based trips that are entirely disconnected from home-based trips of this households, the presented model can allocate, for example, non-home-based-work trips starting from the person's work location. Furthermore, microsimulation also allowed each modeling step to select socio-demographic attributes that are relevant for the modeling step at hand. Trip generation of discretionary trips, for example, is segmented among others by area type (which is not used anywhere else), while mode choice uses driver's license ownership (which is not used anywhere else). The microscopic structure of the model makes the model design much more flexible than traditional trip-based models.

However, microsimulation comes at a price. Due to its stochastic nature, every model run is slightly different. On the average, these differences balance out and produce practically identical results for the entire study area. When small subareas are investigated, however, each model run may show noteworthy different results. The user needs to apply caution to not interpret scenario differences that are as small as the expected stochastic variation [43]. Sometimes, various random seeds are set purposefully to analyze the range of plausible outcomes [44, 45]. This is a useful approach to handle stochastic variation, yet it requires multiple model runs, and therefore, more runtime.

During model development, great emphasis was put on fast model runtimes. The resulting model runs even faster than many traditional trip-based models. On a workstation with 16 processors with 2.6 Ghz and 64 MB RAM, this model generates the complete travel demand for 4.5 million people and 4,924 zones in 11 minutes. The assignment, however, required much more runtime. For this study area, a coarse network that excludes local roads with 138,080 links was used. MATSim ran with a sampling rate of 5 percent and iterated 50 times to approximate an equilibrium. In total, the assignment runtime required 2 h 45 min on a regular workstation. If multiple years and many scenarios need to be simulated, this may be an obstacle. A static user equilibrium assignment algorithm would run much faster, and could be the preferred approach when runtime is a concern.

The developed model has overcome some significant shortcomings of conventional trip-based models. However, it does not provide the full capacity of activity-based models. Shortcomings of MITO include the lack of intra-household coordination or the lack of feedback that a delayed activity should delay subsequent activities. For applications where such model capabilities are of relevance, an activity-based model is still the best choice. For many other applications, however, this level of detail may not be relevant. In those cases, MITO provides a simpler approach that is behaviorally richer than the trip-based model but less complex than activity-based models.

Data Availability

The model developed is open-source, a link to download the model is provided in the manuscript. Input data can be provided for various study areas upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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