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Spatial disaggregation to generate city-scale travel demand models

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Abstract

Many activity based models specify locations at the traffic analysis zone (TAZ) resolution. In city scale travel models and for MaaS predictions, a finer grained spatial resolution may be required. An artificial neural network was used to classify predicted daily schedules based on the total travel duration using a household travel survey. We propose a TAZ to street address based disaggregator that first generates a choice set of schedule variants and then selects the final candidate according to the schedule specific probability weight function delivered by the classifier coefficients. This paper describes how the technique has been applied to The Netherlands. It shows that realistic schedules are produced using a zoning having a large variety in TAZ size.

Keywords: simulation; agent based modelling; travel plan; activity location disaggregation

1. Introduction - Problem statement - Proposed solution

Many activity based models specify locations at the traffic analysis zone (TAZ) resolution. In city scale travel models and especially when investigating slow and station-based *shared* modes (e.g. in a MaaS context) or *co-traveling* (e.g. carpooling), a finer grained spatial resolution is required. Spatially uniform and independent sampling of addresses for activity locations may lead to overestimation of travel duration/distance in large TAZs. We propose a *TAZ to street address based disaggregator* that first generates a choice set of schedule variants and then selects the final candidate according to a user specified criterion. Activity addresses are not sampled independently but in the context of the predicted schedule. The proposed tool does support several choice *generators* and *selectors*. This paper describes how the technique has been applied to The Netherlands using a zoning having a large variety in TAZ size. The schedule *selector* is based on a neural network based classifier trained on daily travel duration reported in a household travel survey.

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2. Literature overview

Few models predict travel at street address (facility) level. Most papers operating at TAZ level do not discuss the properties of the zoning in terms of geographical area, number of inhabitants or economic and mobility parameters. This may be due to the availability of only a single dataset at a particular level of spatial detail (e.g. statistical sectors). On the other hand, many papers use spatially uniform sampling for TAZ to address disaggregation.

2.1. Street address based travel predictors

SACSIM [7, 8] is an activity based model using a temporal resolution of 30[min] and spatial resolution of parcel level for the predicted episodes. Work and school location are simulated for each individual. Hence, persons are assigned a parcel (street address) *before* the travel prediction starts. For work, school and primary tour destination locations, first the TAZ is sampled and then the parcel. Intermediate destinations are sampled in a similar way but more contextual constraints do apply in that case.

Schedule prediction (including adaptation) and schedule execution are simulated in an integrated way by ADAPTS and TRANSIMS [**?** 10]; this requires position information to be exchanged between the tools.

SimMobility consists of a long term (LT) simulator, a mid term (MT) simulator which contains a *pre-day* activity based predictor of daily schedules and a short term (ST) simulator which simulates actual movements on the road [2]. The SimMobilityST model receives trip-chains and activity-schedules from SimMobilityMT as inputs and can alter these by rerouting and activity timing adaptation. The spatial resolution for activity locations is the building postcode [13]. This is a 6-digit postal code made up of the sector code (two digits) and the delivery point (4 digits). [1]

Setup of a MATSim model for Baoding (China) is discussed in [22]. The modeled universe is very small. All locations for shopping, leisure, work, education and home are modeled individually in an activity-based schedule predictor which directly exports street addresses. However, the experiment covers an unrealistically small toy model and the design may suffer from combinatorial explosion.

[19] discusses the creation of travel plans to feed a MATSim model for São Paulo, Brazil. The eqasim pipeline [9] is used to create travel demand. Prototype plans extracted from household travel surveys are assigned to individuals by hot-deck-matching [9]. Travel demand is given in origin destination commute matrices. Primary locations (home, work) are determined together based on the OD matrix and sampled from the address databases. Locations for other activities are sampled in a next stage.

[15] builds a MATSim model for Vienna and focuses on multi-modal trips. Activity locations are specified by coordinates (as opposed to zones). The authors mention the problem of finding skewed distributions for travel distance by randomly selecting locations in districts. The authors developed a spatial disaggregation algorithm to overcome that problem.

2.2. TAZ based travel predictors

[17] uses the *Kutter model* (Berliner PersonenverkehrsModell) to generate MATSim plans. The Kutter model provides activity chains defining tours in which locations are TAZs and where activity type and mode are specified.

[16] discusses travel demand modeling for Berlin using both a macroscopic model (VISUM) and a microscopic model (MATSim). Data are extracted from an household travel survey (HTS) specifying the home location at statistical zone level along with an activity chain including location, travel start/end times, mode and personal attributes. In order to generate daily travel plans for MATSim, activity locations need to be determined. Home locations are distributed inside the zones according to additional land use information on block level detail. The paper does not mention details about disaggregation.

[24] describes an experiment that uses daily activity plans generated by CEMDAP based on parameters estimated for Los Angeles (the '*estimation context*'), transforms these into plans for Berlin inhabitants ('*application context*') and calibrates the model using CADYTS and traffic counts for the Berlin region. The experiment aims to show that parameters for the entire daily plan can be determined in this way. The synthetic population is generated starting from

[1] https://en.wikipedia.org/wiki/Postal_codes_in_Singapore

Berlin data. Each working and/or studying agent is assigned several potential work/university locations based on a given OD matrix. As a consequence, each such agent can select between plans having different locations. CADYTS is used to force agents to select plans consistent with the given traffic counts. The neighbourhood where the work/school is located in the zone (extracted from the OD matrix) is sampled at random. CEMDAP is executed: it predicts the TAZ for other activities (i.e. different from home, work, school). A random location again is sampled in the TAZ. The papers do not mention details about position sampling.

[14] describes a travel demand and MATSim based assignment model. Home and mandatory activities locations are assigned first. Locations for discretionary activities are assigned at TAZ level based on travel impedance (distance) and attraction. In a subsequent step microscopic coordinates in the TAZ are assigned; details about position sampling are not provided.

Albatross [3] (covering The Netherlands) and the decision tree based FEATHERS_0 described in [6] (covering Flanders, Belgium) predict travel between TAZs. FEATHERS_0 has been applied to the Flemish area of $13,625[km^2]$ using a statistical sectors (approximately 10000) [4, 5] and at a more coarse level using nearly 2400 zones. The recent FEATHERS_4 version predicts travel demand between TAZs using discrete choice modeling. It has been applied to The Netherlands using 7700 TAZs [12]. Both models use impedance matrices for trip distance and duration between TAZs. The matrices have been pre-computed on a loaded network by skimming after traffic assignment.

[1] builds a MATSim model for Flanders starting from FEATHERS_0 predictions and using the CRAB database of Flemish addresses[2]. Each apartment in a building has its own address. The building type (purpose, function) however is not specified in the CRAB database. First, each household is assigned an address drawn from the set of addresses in the TAZ containing the household home location. This is done by means of sampling from a uniform distribution. Addresses that have not been assigned as home addresses are used as '*reusable*' (shared) addresses for shops, schools, companies, etc.

[23] focuses on methodological aspects that need attention when integrating the daily schedule predictor FEATHERS_0 with MATSim. Address disaggregation is done by sampling from the CRAB database using a uniform distribution. The following problems need attention. First, information is lost when the tools are used in an iterative loop because of the different levels of spatial resolution used and because agent identities are not transferred between both tools. Second, the objective functions (i) *RUM* (random utility maximization) in FEATHERS_0 on one hand and (ii) *scoring* in MATSim on the other hand should be verified to be compatible in order to avoid MATSim to converge to a state that is not compatible with the FEATHERS_0 prediction.

TASHA is an activity based model of the *computational process* type. It is able to handle ride sharing among members of a household. One of the development objectives for TASHA is to not require more data than classical 4-step models. [18] states that the activity generation model is based on random draws of activity attributes from 262 observed joint probability distribution functions of frequency, start time and duration. Persons have given home, work and school locations. The locations of *home* and the usual places of *work/school* are given as model inputs. The activity location choice for other activities is based on a series of entropy models. In TASHA an activity location is specified only to the level of a zone (TAZ). TASHA uses euclidean distance between TAZ centroids [21] as trip distance.

Our paper contributes to the travel demand modeling research by proposing a technique that samples addresses in the context of a travel plan and not independently.

3. Principle of Operation

The method presented in this research replaces the one reported in [11]. The disaggregation technique consists of two steps: (i) travel duration classifier (travDurClassifier) and (ii) TAZ-to-address disaggregation (tazToAddrDisAggr).

3.1. Travel Duration Classifier

The proposed method is based on travel duration (as opposed to travel distance) because the time budget for travel is historically more stable than the distance driven (*BREVER*-law) [20]. Hence, we assume that it is less sensitive to travel management policies. Sensitivity of travel demand to policies constitutes the core of our research.

[2] https://overheid.vlaanderen.be/informatie-vlaanderen/producten-diensten/centraal-referentieadressenbestand-crab

Using an household travel survey (HTS) we construct a classifier that predicts the 15[min] bin that contains the total daily travel time reported by the respondents (ODiN, in The Netherlands, OVG in Flanders). The classifier is a simple multilayer perceptron (artificial neural network, ANN). It is trained on observations available from the HTS.

Attributes extracted from the HTS as predictors are: *gender*, *age*, *educationLevel*, *carAvailable* (boolean indicator), *holiday* (reported in HTS), *nTrips* (number of trips), *travelDur* (discretized total travel duration, 24 bins of 15[min] each). Values for these properties are available in the FEATHERS predictions too.

The ANN has 6 input features, 4 hidden layers of width=5 with a ReLU and a softmax output layer. The hyperparameters have been determined experimentally. The model is trained on 94208 observations and ran for 200 epochs. The test accuracy is only 14.60% and obviously a consequence of the deliberately chosen small bin size.

The coefficients of the softmax layer are interpreted as the probability for the schedule to have a total daily travel duration belonging to that bin. It provides a probability weight function (PWF) for the total travel duration (which is independent of the prediction models used in FEATHERS).

Each TAZ based schedule generated by FEATHERS is submitted to the ANN in prediction mode. Instead of retaining a single value (the predicted travel duration bin), we associate the vector of coefficients of the softmax layer as a PWF to the schedule. Figure 2a shows the PWF for a particular schedule.

3.2. Addresses

A set of addresses each having one or more purpose labels (e.g. *residence*, *industry*, *office*, ...) is used. Each address belongs to exactly one TAZ used by FEATHERS. Each building purpose label is mapped to zero or more activity types known by the schedule predictor. This results in a general relation specifying which addresses in each TAZare available for each activity type.

Address use is either *exclusive* (e.g. for *home*) or *shared* (e.g. for *shopping*) for a given activity type. Addresses for exclusive use are assigned first.

Address-purpose pairs are subdivided into two subsets: *stable* and *volatile*. Stable addresses do not change while considering different schedule variants. For a given individual, all *stable* addresses are fixed in the initialisation stage (e.g. *school* address). *Volatile* addresses may change during the course of the address reassignment stage.

3.3. TAZ to Address Disaggregator

The tazToAddrDisAggr operates by combining a schedule *variant generator* with a *variant selector*. Several generators and selectors are available to the tazToAddrDisAggr user.

A schedule predicted by a TAZ based predictor specifies activity locations as TAZs (zones, hence collections of addresses). A variant generator in tazToAddrDisAggr creates specific schedule variants by sampling an address for each *volatile* location. The resulting disaggregated schedule variants are used to populate a choice set of N (typically 100) schedules. For each schedule in the choice set, the total travel duration is computed.

In this paper we discuss the combination of

- a *generator* for which the total number of sampled addresses over all variants is given. In order to create a variant, the generator first samples the TAZs in the schedule for which to find a new address using the number of candidate addresses in the respective TAZs as a weight. Only in the selected TAZs new addresses are sampled. This avoids frequent resampling the same addresses in TAZs having few candidates.
- a *selector* that uses the PWF defined in Section 3.1.

The disaggregator has no complete freedom since the predictor specified the TAZs where the activities will take place. The prediction induces constraints on travel distance (between TAZs) and hence on travel duration. This means that not the complete domain of the PWF is available to the *selector*. After the required number N of schedule variants have been generated, it is known which bins in the classifier domain have not been used. An adjusted PWF is created by re normalisation of the used bins only.

The PWF can be modulated by a temperature concept (same as used in large language models). The PWF is raised to the power $1/T$ where T is a non-negative temperature value and then renormalized. The lower the chosen temperature, the lower the entropy. Near zero temperature corresponds to the case where the value having the largest

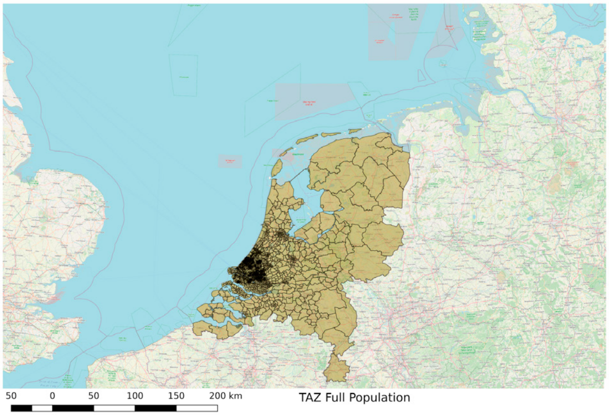


Fig. 1: Heterogeneous zoning for The Netherlands.

probability will be chosen. Near infinite temperature is equivalent to uniform sampling from the choice set. The effect of temperature is shown in Figure 2.

4. Datasets for Location (TAZ) to position (address) disaggregation

For the Dutch model the BAG dataset is used. It specifies for each address in the country (i) the coordinates, (ii) a set of building function (purpose) labels along with (iii) municipality and other administrative data. Multiple addresses may be assigned to the same building (apartments).

5. Results discussion for the Dutch model

Results for the Dutch model are discussed below.

A map showing the heterogeneous zoning is shown in Figure 1. Such zoning allows to assess to evaluate effects of address TAZ to address disaggregation.

In order to evaluate results, we explicitly distinguish **intra**Zonal end **inter**Zonal trips. The origin and destination of an **intra**Zonal (**inter**Zonal) trip belong to the same (different) TAZs.

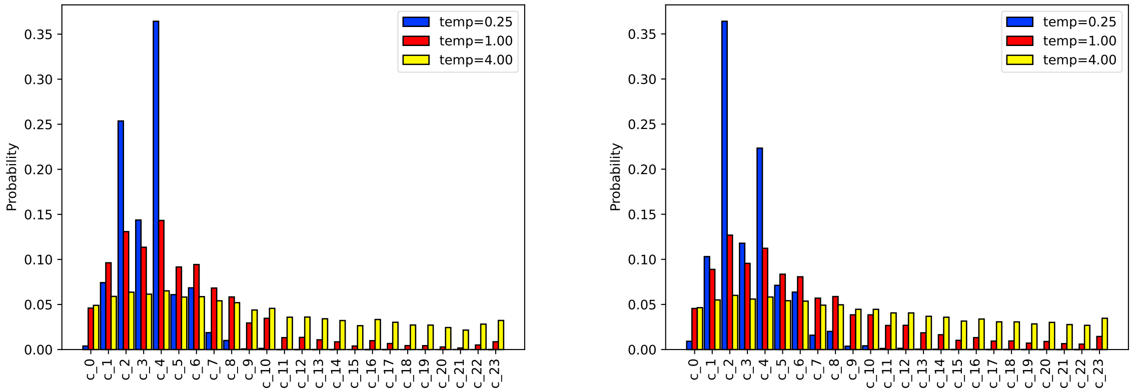
In the TAZ based travel demand prediction we define a zone to be *large* if and only if more than $1/3$ of the predicted trips is **intra**Zonal as explained in [11]. All other zones are called *regular* zones. The UTN2 project contains *regular* zones covering the study area and *large* zones (surrounding the study area). A pure **intra**Zonal (**inter**Zonal) travel plan contains **intra**Zonal (**inter**Zonal) trips only.

Two models are combined: FEATHERS (TAZ based travel demand predictor) and tazToAddrDisAggr (spatial disaggregator). Hence most results depend on properties of both tools. It is worth noting that the travel distance and duration for *pure* **intra**Zonal trips (which occur mostly in large TAZs) the chosen addresses are independent of FEATHERS sub-models. Therefore, the travel related properties of pure **intra**Zonal *schedules* depend on the tazToAddrDisAggr only.

The tazToAddrDisAggr was used to generate a 10% population fraction to feed the countrywide MATSim model. No spatial filtering (used to generate data for city scale models) was applied. The population fraction contains 1.4 million individuals.

Figure 2b shows the average of the PWFs computed over all schedules (individuals) for three different values of the *temperature*. The red bars show values for *temperature* = 1. The blue bars correspond to *temperature* = $1/4$ and the yellow bars correspond to *temperature* = 4.

Figure 3 shows histograms for the total daily travel time expressed in minutes for the countrywide Dutch population. The vertical axis shows relative occurrence values. The left histogram applies to the travel duration predicted by



(a) PWF for a randomly chosen predicted schedule.

(b) Average PWF computed over all schedules.

Fig. 2: Probability weight functions for the total daily travel duration. Each bin C_i represents 15[min] (the range of the diagrams covers 6[hours]). The probability values for *temperature = 1* correspond to the softmax weights of the ANN.

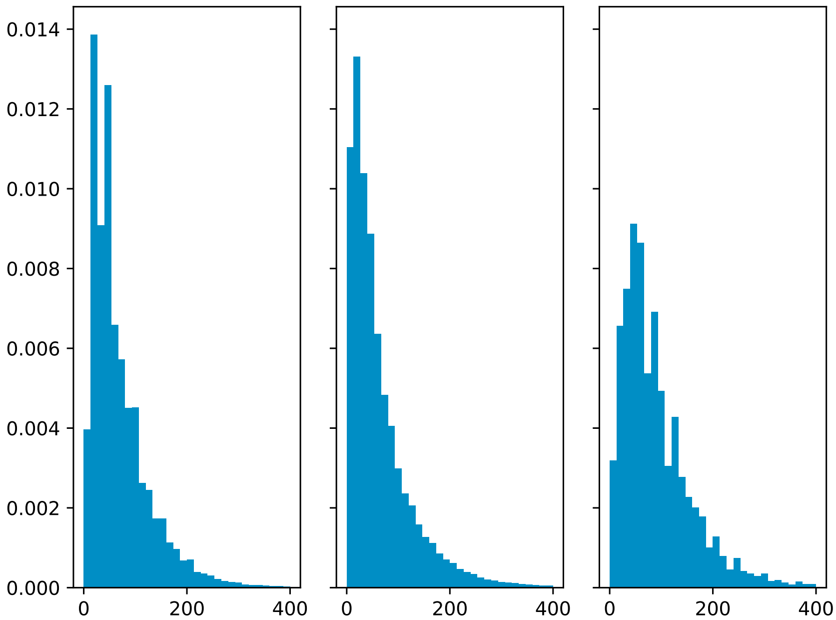


Fig. 3: Distribution of daily total travel duration in minutes: all predicted schedules. Left: FEATHERS (TAZ resolution), Center: FEATHERS-tazToAddrDisAggr tool chain (address resolution), Right: ODiN observation.

FEATHERS. The central histogram applies to the values derived by tazToAddrDisAggr from the FEATHERS prediction by disaggregating TAZs to addresses. The rightmost histogram shows the travel duration directly extracted from ODiN observations. The predictions seem to underestimate the total daily travel duration.

Figure 4 compares histograms for the total travel duration distribution in three different subsets of the disaggregated schedules generated by tazToAddrDisAggr. The left histogram applies to the subset of pure **inter**Zonal schedules. For each trip the origin and destination TAZs are different and predicted by FEATHERS which imposes constraints on the options available to tazToAddrDisAggr. The histogram in the center applies to all pure **intra**Zonal schedules. The travel duration is predicted solely by tazToAddrDisAggr. The rightmost histogram applies to pure **intra**Zonal

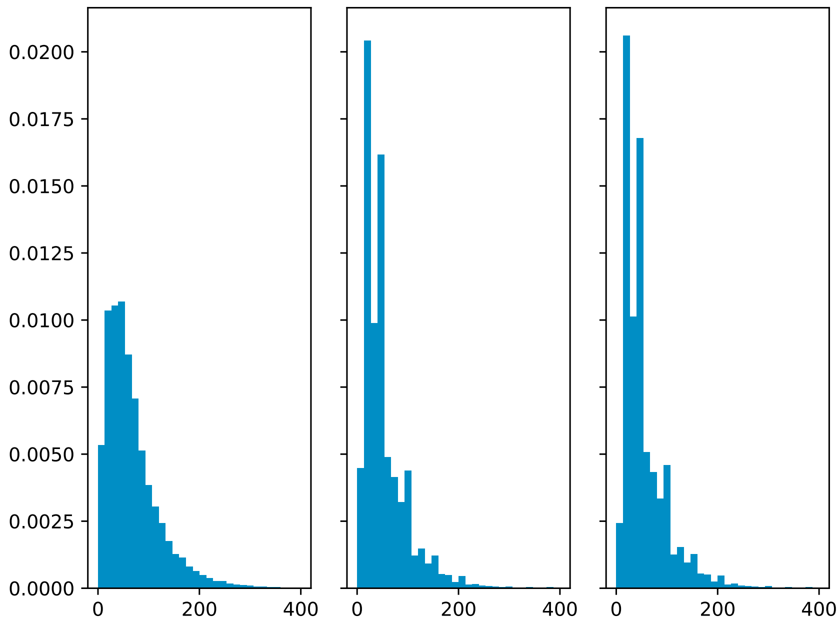


Fig. 4: Distribution of daily total travel duration in minutes. Left: Pure **inter**Zonal (countrywide, FEATHERS prediction). Center: Pure **intra**Zonal (countrywide, tazToAddrDisAggr prediction). Right Pure **intra**Zonal (large zones, tazToAddrDisAggr prediction).

schedules for large zones only. In such zones there are plenty of options where to execute an activity. Uniformly sampling locations independently may lead to unrealistic total daily travel duration (and distance). It must be noted that this histogram is based on 6873782 schedules whereas the central one applies to 7174849 schedules. Hence, the **intra**Zonal travel in the central diagram is dominated by the large TAZs.

Figure 5 considers the total daily travel duration for *pure* **intra**Zonal schedules in *large* TAZs. All histograms do apply to the same subset of schedules. The leftmost (L) histogram applies to the FEATHERS predictions. The other histograms apply to tazToAddrDisAggr predictions for temperature values 0.25, 1 and 4 respectively.

6. Conclusion - Future research

The schedule variant generator/selector concept used in tazToAddrDisAggr results in schedules for which the distribution of the total daily travel duration is realistic.

The comparison of the distributions for FEATHERS and tazToAddrDisAggr predictions on one hand a ODiN observations on the other hand suggests the need to search for the cause of the underestimation.

The ANN training and prediction can be improved by integrating additional person and travel properties such as household income category and the use of a company car (who pays the travel cost?).

Considering pure **intra**Zonal schedules for *large* zones allows to eliminate the effect of the location choice sub-models in the TAZ based schedule predictor. This suggests future research by evaluating the schedules in *huge* TAZs in order to find out whether the proposed technique can support replacement of TAZ based location choice models.

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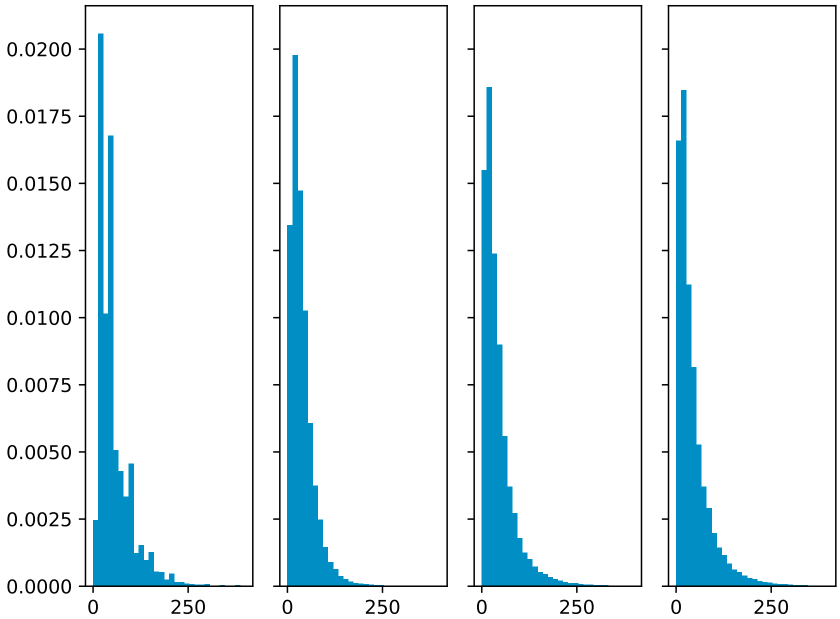

Fig. 5: Distribution of daily total travel duration in minutes for Pure **intra**Zonal travel in large TAZs. (L) FEATHERS (reference, temperature independent) , (CL) Temp = 0.25, (CR) Temp = 1, (R) Temp = 4

References

[1] Adnan, M., Outay, F., Ahmed, S., Brattich, E., di Sabatino, S., Janssens, D., 2021. Integrated agent-based microsimulation framework for examining impacts of mobility-oriented policies. Personal and Ubiquitous Computing 25, 205–217. URL: https://doi.org/10.1007/s00779-020-01363-w, doi:10.1007/s00779-020-01363-w.

[2] Adnan, M., Pereira, F.C., Azevedo, C.M.L., Basak, K., Lovric, M., Raveau, S., Zhu, Y., Ferreira, J., Zegras, C., Ben-Akiva, M., 2016. SimMobility: A multiscale integrated agent-based simulation platform, in: Transportation Research Board 95th Annual Meeting (10/01/16 - 14/01/16), Transportation Research Board, Washington, DC, USA. URL: https://eprints.soton.ac.uk/390938/.

[3] Arentze, T.A., Timmermans, H.J.P., 2004. A learning-based transportation oriented simulation system. Transportation Research Part B: Methodological 38, 613 – 633. URL: http://www.sciencedirect.com/science/article/pii/S0191261503000948, doi:10.1016/j.trb.2002.10.001.

[4] Bao, Q., Kochan, B., Bellemans, T., Janssens, D., Wets, G., 2014. Geographical Extension of the Activity-based Modeling Framework FEATHERS. Procedia Computer Science 32, 774–779. URL: https://www.sciencedirect.com/science/article/pii/S1877050914006905, doi:10.1016/j.procs.2014.05.490.

[5] Bao, Q., Kochan, B., Shen, Y., Creemers, L., Bellemans, T., Janssens, D., Wets, G., 2018. Applying FEATHERS for Travel Demand Analysis: Model Considerations. Applied Sciences 8. URL: https://www.mdpi.com/2076-3417/8/2/211, doi:10.3390/app8020211.

[6] Bellemans, T., Kochan, B., Janssens, D., Wets, G., Arentze, T., Timmermans, H.J., 2010. Implementation Framework and Development Trajectory of FEATHERS Activity-Based Simulation Platform. Transportation research record 2175, 111–119.

[7] Bowman, J., Bradley, M., Gibb, J.A., 2006. The Sacramento activity-based travel demand model: estimation and validation results.

[8] Bradley, M., Bowman, J.L., Griesenbeck, B., 2010. SACSIM: An applied activity-based model system with fine-level spatial and temporal resolution. Journal of Choice Modelling 3, 5–31. URL: https://www.sciencedirect.com/science/article/pii/S1755534513700277, doi:10.1016/S1755-5345(13)70027-7.

[9] Hörl, S., Balac, M., 2021. Introducing the eqasim pipeline: From raw data to agent-based transport simulation. Procedia Computer Science 184, 712–719. URL: https://www.sciencedirect.com/science/article/pii/S1877050921007274, doi:https://doi.org/10.1016/j.procs.2021.03.089.

[10] Javanmardi, M., 2012. Integration of the ADAPTS Activity-Based Model and TRANSIMS.

[11] Knapen, L., Adnan, M., Bellemans, T., 2023. Location disaggregation for zone based travel plans. Procedia Computer Science 220, 283–290. URL: https://www.sciencedirect.com/science/article/pii/S1877050923005720, doi:https://doi.org/10.1016/j.procs.2023.03.037.

[12] Knapen, L., Adnan, M., Kochan, B., Bellemans, T., van der Tuin, M., Han, Z., Snelder, M., 2021. An Activity Based integrated approach to model impacts of parking, hubs and new mobility concepts, in: Procedia Computer Science, Elsevier, Warsaw, Poland. pp. 428–437. doi:10.1016/j.procs.2021.03.054.

[13] Lu, Y., Adnan, M., Basak, K., Pereira, F., Carrion, C., Saber, V.H., Loganathan, H., Ben-Akiva, M., 2015. SimMobility Mid-Term Simulator: A State of the Art Integrated Agent Based Demand and Supply Model, in: Transportation Research Board 94th Annual Meeting, Transportation Research Board, Washington, DC, USA. URL: https://trid.trb.org/view/1338341.

[14] Moeckel, R., Kuehnel, N., Llorca, C., Moreno, A.T., Rayaprolu, H., 2020. Agent-Based Simulation to Improve Policy Sensitivity of Trip-Based Models. Journal of Advanced Transportation 2020, 1902162. URL: https://doi.org/10.1155/2020/1902162, doi:10.1155/2020/1902162. publisher: Hindawi.

[15] Müller, J., Straub, M., Richter, G., Rudloff, C., 2022. Integration of Different Mobility Behaviors and Intermodal Trips in MATSim. Sustainability doi:10.3390/su14010428.

[16] Neumann, A., Balmer, M., Rieser, M., 2012. Converting a Static Macroscopic Model Into a Dynamic Activity-Based Model to Analyze Public Transport Demand in Berlin, International Association for Travel Behaviour Research.

[17] Rieser, M., Nagel, K., Beuck, U., Balmer, M., Rümenapp, J., 2007. Agent-Oriented Coupling of Activity-Based Demand Generation with Multiagent Traffic Simulation. Transportation Research Record 2021, 10–17. URL: https://doi.org/10.3141/2021-02, doi:10.3141/2021-02.

[18] Roorda, M.J., Miller, E.J., Habib, K.M.N., 2008. Validation of TASHA: A 24-h activity scheduling microsimulation model. Transportation Research Part A: Policy and Practice 42, 360–375. URL: https://www.sciencedirect.com/science/article/pii/S0965856407000924, doi:10.1016/j.tra.2007.10.004.

[19] Sallard, A., Balac, M., Hörl, S., 2021. An open data-driven approach for travel demand synthesis: an application to São Paulo. Regional Studies, Regional Science 8, 371–386. doi:10.1080/21681376.2021.1968941.

[20] Wee, B.v., Rietveld, P., Meurs, H., 2006. Is average daily travel time expenditure constant? In search of explanations for an increase in average travel time. Journal of Transport Geography 14, 109–122. URL: https://www.sciencedirect.com/science/article/pii/S0966692305000402, doi:https://doi.org/10.1016/j.jtrangeo.2005.06.003.

[21] Yasmin, F., Morency, C., Roorda, M.J., 2015. Assessment of spatial transferability of an activity-based model, TASHA. Transportation Research Part A: Policy and Practice 78, 200–213. URL: https://www.sciencedirect.com/science/article/pii/S0965856415001366, doi:10.1016/j.tra.2015.05.008.

[22] Zhuge, C., Shao, C., Gao, J., Meng, M., Xu, W., 2014. An Initial Implementation of Multiagent Simulation of Travel Behavior for a Medium-Sized City in China. Mathematical Problems in Engineering 2014, 980623. URL: https://doi.org/10.1155/2014/980623, doi:10.1155/2014/980623. publisher: Hindawi Publishing Corporation.

[23] Ziemke, D., Knapen, L., Nagel, K., 2021. Expanding the analysis scope of a MATSim transport simulation by integrating the FEATHERS activity-based demand model. Procedia Computer Science 184, 753–760. URL: https://www.sciencedirect.com/science/article/pii/S1877050921007997, doi:10.1016/j.procs.2021.04.022.

[24] Ziemke, D., Nagel, K., Bhat, C., 2015. Integrating CEMDAP and MATSIM to increase the transferability of transport demand models. Transportation Research Record: Journal of the Transportation Research Board 2493, 117–125. doi:10.3141/2493-13.