Accessibility of Pooled Demand Responsive Transport

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Short summary

This paper introduces a methodology for calculating accessibility for demand responsive transport (DRT) within the agent-based simulation framework "MATSim". A difficulty that arises in DRT accessibility calculations involves the mode's sensitivity to supply and demand: explicitly simulating DRT trips for accessibility distorts demand patterns, on which accessibility calculations depend. Our solution involves estimating DRT travel and wait times based on the outputs of MATSim simulations of DRT trips; this is combined with the access and egress walks to the relevant DRT stops. To our knowledge, this is the first instance of a DRT accessibility methodology for a stop-based and pooled service within an agent-based model. To demonstrate this methodology, we calculate DRT accessibility for the city of Kelheim. Future work should adapt the DRT trip estimation to be more sensitive to origin location and departure time.

Keywords: Accessibility, Agent-Based Model, Demand Responsive Transport, MATSim, Mobility-On-Demand, Transport Simulation

1 Introduction

This paper presents a methodology for calculating accessibility for demand responsive transport (DRT) within an agent-based model (ABM)—"MATSim"—which is then applied to Kelheim (Bavaria, Germany). MATSim (Horni et al., 2016), is an open-source framework for large-scale transport simulations. Within a simulated day, agents use different modes to travel between activity locations; this single day is iterated hundreds of times, giving agents a chance to improve their daily plans.

One mode that can be simulated within MATSim is DRT, as described by Maciejewski (2016) and Bischoff et al. (2017). DRT systems are generally free-floating, meaning that vehicles are not bound by fixed routes or timetables; optionally, DRT systems can allow pooling, meaning multiple customers share portions of their rides. This can be an alternative to traditional public transit (PT), especially in areas where the transport demand is diffused over a large region. The potential of DRT is especially high for people who do not drive.

Accessibility describes the potential to overcome spatial separation to take advantage of opportunities, and is thus a useful analysis tool for transport/land-use scenarios. MATSim has an official extension (Ziemke, 2016) to calculate accessibilities for various modes; case studies include Switzerland (Nicolai & Nagel, 2014) and South Africa (Joubert et al., 2015). Ziemke (2016) argues that MATSim is well-suited for accessibility calculations because it is inherently sensitive to the four central facets of accessibility, as delineated by (Geurs & van Wee, 2004): transport, land-use, temporal, and individual components. MATSim scenarios consider transportation infrastructure, as well as coordinate-based activity facilities. The model's dynamic mobility simulation allows the accessibility of different modes to be calculated for different times of the day. Finally, as MATSim is an ABM, each member of the population is endowed with an individual set of socio-demographic attributes.

While MATSim is capable of simulating DRT travel, and can calculate accessibilities of many modes, there is an inherent difficulty in the combination: calculating accessibility of DRT. As mentioned in Ziemke & Bischoff (2023) and Wang et al. (2023), DRT accessibility is very sensitive towards DRT supply and demand patterns. In other words, the length of time that a person must wait to be picked up, and the degree to which the trip is detoured to pickup/drop-off other passengers, depends on (a) the number of vehicles currently on-duty (supply) and (b) the number of customers requesting rides at that time (demand). Given a limited supply, explicitly simulating DRT trips for every pair of measuring point and opportunity would skew the demand patterns, which would, in turn, affect accessibility measurements.

Ziemke & Bischoff (2023) were the first to calculate DRT accessibility based on a MATSim model of Berlin. Their methodology explicitly simulates DRT trips, but assumes arbitrary supply and demand patterns; they randomly reassign 10% of PT rides to DRT to find the average wait times per location. After pickup, DRT trip time is calculated analogously to a taxi; no ride-sharing takes place. Diepolder et al. (2024) also develop a methodology for calculating DRT accessibility in conjunction with MATSim, focusing on DRT as a feeder to conventional PT; using the outputs of a fully-iterated MATSim scenario they estimate DRT wait and travel times for all possible feeder relations, creating time tables which can be implemented as part of the PT network. As compared to Diepolder et al. (2024), our methodology allows stand-alone DRT services to be analyzed and does not require additional software for the processing of the MATSim output.

To address the intricacy capturing DRT accessibility within an ABM without skewing the DRT demand patterns, we integrated an innovation by Lu et al. (2025) into the accessibility pipeline: the DRT Estimator. This allows for the estimation of DRT travel time for any origin-destination pair—based on calibration on real or simulated data—without explicitly simulating the DRT trip. One of the main benefits of our methodology is that it integrates seamlessly into the MATSim ecosystem. This is beneficial because the DRT accessibility analysis can (a) be attached to a MATSim simulation with minimal additional effort (b) be coherently compared to accessibilities of other modes, (c) leverage fine-grained information from agent attributes, (d) make use of the many specialized and interchangeable modules (e.g., teleported walk router can be exchanged for a network-based walk router) and (e) be sensitive to different DRT operation schemes, such as ridepooling or rebalancing strategies. This paper contributes a methodology to calculate accessibility of pooled and stop-based DRT, integrated into an established ABM.

2 Methodology

The following derivation of an econometric accessibility measure is described in Nicolai & Nagel (2014), and is based on the work by Ben-Akiva & Lerman (1979). Given an individual with a choice set of opportunities, accessibility is defined as the maximum utility of the all alternatives. Given an origin location l, we define the utility of an opportunity alternative k as

$$U_{lk} = V_k + V_{lk} + \epsilon_{lk}, \tag{1}$$

wherein V_k is the utility (usually positive) associated with realizing the opportunity, V_{lk} is the utility (usually negative) of traveling to the opportunity, and ϵ_{ik} is a random term which absorbs randomness and uncertainties in V_k and V_{lk}. If we assume that all opportunities k have the same systematic utilities $V_k \equiv V$, and ϵ_k is Gumbel distributed with a mean of

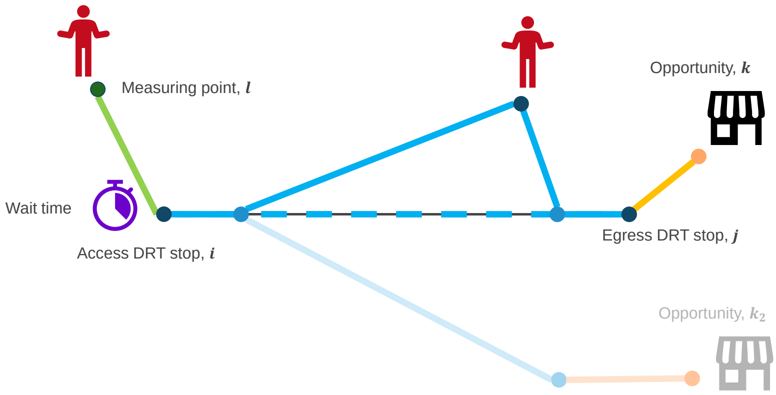


Figure 1: To calculate the accessibility from measuring point l, the travel (dis)utility to each opportunity k is combined, as shown in Eq. (3). For a single measuring point / opportunity relation, we see that a DRT trip is made up of three legs: the access walk from the measuring point l to the pickup DRT stop i (green line), the DRT trip between DRT stops i and j (solid blue line) and the egress walk between the drop-off DRT stop j to the opportunity k (yellow line). Additionally, a wait time for the vehicle at the access DRT stop needs to be included (purple timer). The DRT Estimator is used to calculate the travel time of the DRT route (solid blue line)—which takes a detour to pickup a passenger—based on the shortest path (segmented blue line).

zero and the same width parameter for each k, then expectation value of U_l becomes:

$$E(U_l) = E(\max_k U_{lk}) = \ln \sum_k e^{V_{lk}} + Const = A_l + Const \tag{2}$$

$A_l + Const$ is the maximum utility of selecting the optimal k (including ϵ_{lk}), traveling to it, and receiving $V + \epsilon_k$ once there. Under normal circumstances, this value is positive. However, since $Const$ is just an additive shift of the result, it is normally left out for accessibility computations, resulting in A_l which is often negative. This leaves us with a simplified form of the accessibility from an origin l:

$$A_l := \ln \sum_k e^{V_{lk}}. \tag{3}$$

The calculation of V_{lk} depends on the mode being examined; this paper's main contribution is a process of calculating the utility of a DRT trip between origin l and opportunity k in a stop-based system:

$$V_{lk,drt} = \underbrace{V_{li}}_{\text{Access}} + \underbrace{V_{ij}}_{\text{DRT Trip}} + \underbrace{V_{jk}}_{\text{Egress}} + \text{ASC}_{drt} \ , \tag{4}$$

wherein (see also Figure 1)

1. V_{li}: the access walk from the measuring point l to the pickup DRT stop i,
2. V_{ij}: the DRT trip between DRT stops i and j,
3. V_{jk}: the egress walk between the drop-off DRT stop j to the opportunity k,
4. ASC_{drt} is the "alternative specific constant" for DRT, which can be interpreted as the baseline attitude or preference of agents towards the mode relative to the walk mode (which has an ASC of 0).

In a stop-based DRT system, the access walk (see 1) and egress walk (see 3) may have a significant impact on accessibility for the entire trip. As a first step, the *closest* DRT stop to the measuring point and opportunity, respectively, are identified. The travel time and distance of the walk trips are estimated using the euclidean distance, an average detour factor, and an average walk speed of 3.8 km/h.

Next, the travel distance and travel time of the DRT trip (see 2) between these two stops have to be estimated. This is not a trivial task: the wait time and circuitousness of the DRT route depends heavily on where DRT vehicles are at the time of request, and how many other customers are requesting rides. It therefore does not make sense to, within the DRT accessibility calculation, physically simulate a DRT trip between every measuring point and every opportunity, as this would not represent realistic DRT booking patterns.

We therefore employed the "DRT Estimator" tool by Lu et al. (2025) to estimate DRT travel time as a function of direct car travel distance. MATSim's trip router for mode "car" was used to calculate the direct car travel distance between the access DRT stop and the egress DRT stop. This allows effects of, e.g., congestion to be included in this calculation. Eq. (5) is then used to calculate a DRT travel time that also includes the detours to pickup and drop-off other passengers in a pooled ride. This estimated travel time is combined with an estimate for the wait time, wherein the agent waits at the curb for the vehicle to pick them up. The parameters α and β required for Eq. (5) are estimated using a linear regression model, on the basis of MATSim-simulated DRT trips (see also Figure 2).

$$t_{drt} = \alpha \cdot t_{car} + \beta \tag{5}$$

3 Results and Discussion

Schlenther et al. (2023) developed a 25% sample MATSim scenario for the city of Kelheim (Bavaria, Germany). The model is calibrated against real DRT ride data from the KEXI service operating in the area since 2020(Landkreis Kehlheim, n.d.). For the ASC_{drt}, we assume a value of 0.0, which corresponds to the portion of the population that is ambivalent towards DRT; they have the same base preference towards DRT, as they do to walk or PT. To parametrize the DRT Estimator, as shown in Figure 2, we used the outputs of a MATSim simulation with a small DRT fleet of 3 vehicles (corresponds to real-life service).

To understand the mechanics of the DRT accessibility calculation, we will begin by examining a single opportunity. Figure 3a shows the DRT accessibility to the train station in Saal an der Donau (towards the south-east of the service area) at 12:00pm. As to be expected, DRT stops close to the train station have higher accessibilities than the further-away DRT stops; DRT accessibility depends on the DRT travel time, as shown in V_{ij}. We can see clearly that V_{ij} depends not on the euclidean distance but on the network distance. Although measuring point "b" is closer to the train station by euclidean distance, the route along the network is more circuitous and thus longer than from measuring point "a". Furthermore, longer access/egress walks lead to lower accessibility; see the municipality of Ihrlerstein to the north-west of Kelheim (annotated by "c").

The effects of three design decisions for DRT accessibility calculations can be observed in the case of Herrnsaal (annotated by "d"):

1. Only the DRT route between the closest DRT stop to the measuring point and the closest DRT stop to the opportunity (by euclidean distance) is calculated.
2. A DRT route is replaced by a walk route if either (i) the pickup and drop-off DRT stops are identical or (ii) the (dis)utility of a direct walk to the destination is greater (less negative) than the DRT trip.

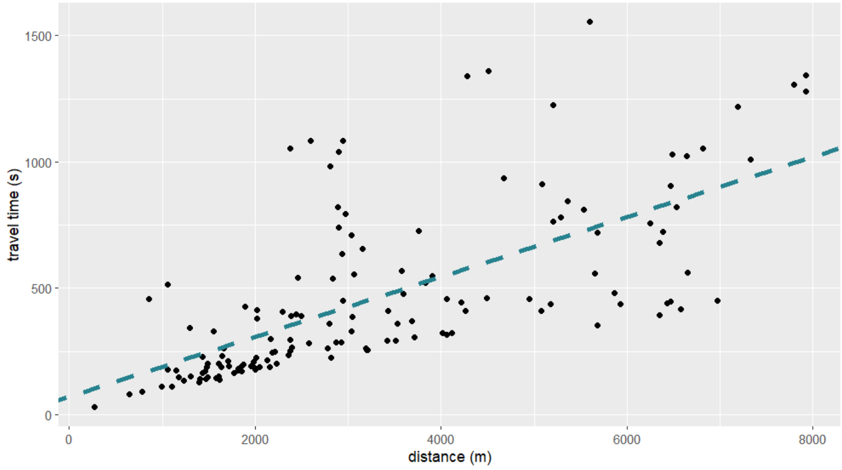


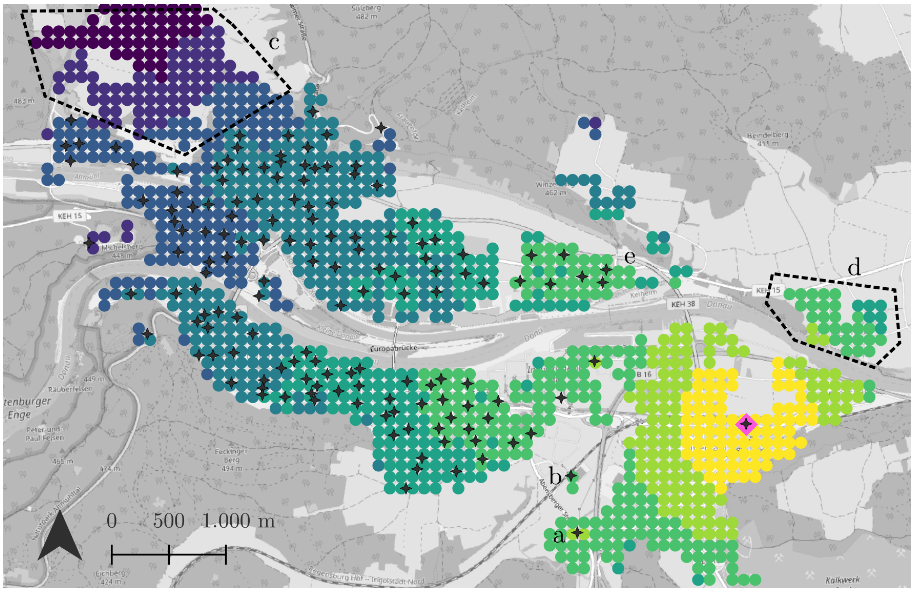
Figure 2: To use the DRT Estimator, parameters α and β in Eq. (5) need to be calculated using a linear regression. The data points (n = 172) represent simulated DRT trips generated by a 3-vehicle fleet; the y-axis shows the DRT travel time (including detours), and the x-axis shows the direct network-distance (excluding detours). The resulting parameters are $\alpha = 0.119$ and $\beta = 71.82$, wherein $R^2 = 0.44$

3. The (dis)utility of walk routes (whether access, egress, or direct walks) is based on the euclidean distance rather than network distance.

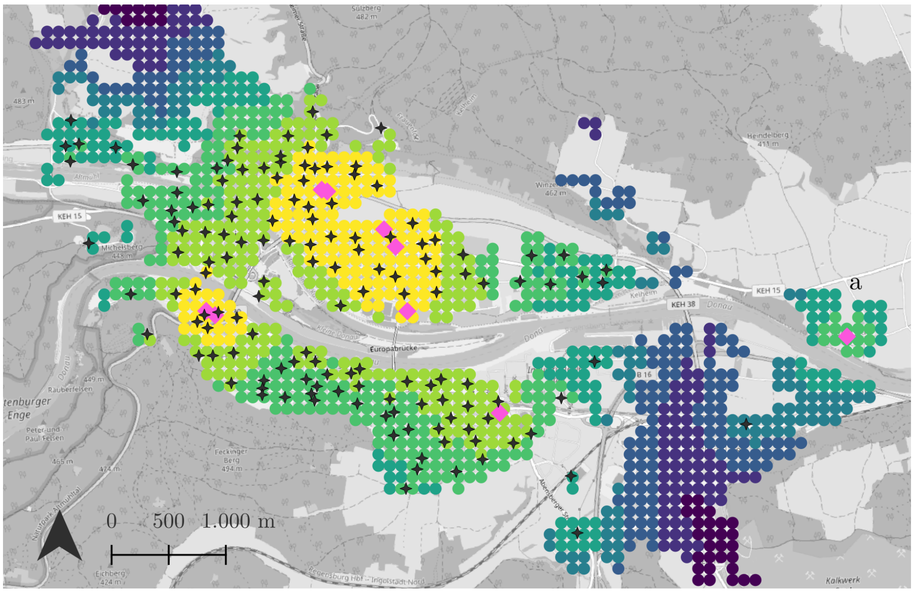
The closest DRT stop to the measuring point in Herrnsaal and to the opportunity are identical: the DRT stop at the train station. Thus, the accessibility algorithm instead assigns the trip to the mode "walk". However, the walk router calculates travel time on the basis of euclidean distance, which does not account for the separation effect of the river Danube (the nearest bridge is approximately 3km west of the measuring point), and therefore overestimates the accessibility. If the algorithm allowed for the second-closest DRT stop to be considered, the logical route would be for the person to walk to the DRT stop "e", and take a DRT vehicle to the train station. The three above-mentioned simplifications were made for computational reasons; future work needs to weigh the benefit to the results of reducing the artifacts against the prolonged simulation time.

To explore the effect of multiple opportunities on DRT accessibility, we will now turn to an amenity with multiple instances in Kelheim: supermarkets, see Figure 3b. Compared to the accessibility analysis of the train station, the accessibility values for supermarkets are higher across the board. The larger number of supermarkets causes this increased accessibility because (i) the average distance to at least one supermarket is generally shorter than the distance to the single train station and (ii) the log-sum accessibility calculation, shown in Eq. (3), does not only examine the closest opportunity but all opportunities in the study area. The log-sum econometric approach from Eq. (3) assumes that residents benefit from having a broad choice in amenity; e.g. they might prefer the second-closest supermarket rather than the closest one. This explains the relatively low value for DRT accessibility surrounding the supermarket in Herrnsaal (see "a"); since the area lacks DRT stops, it is not well connected to the other supermarkets in the center of Kelheim.

The methodology presented in this paper, and demonstrated in the case of Kelheim, will allow for analyses of diverse DRT case studies; specific policy analyses are, however, out-of-scope for this paper.



(a) DRT Accessibility to Train Station



(b) DRT Accessibility to Supermarkets

Figure 3: DRT accessibility to (a) the train station in Saal an der Donau and (b) supermarkets. Measuring points are arranged in a spatial grid wherein pixels are spaced at 100 meters; pixels are not rendered if they do not contain buildings (according to OpenStreetMaps). The coloring of the pixels indicates the accessibility (yellow is higher accessibility); the bin sizes are defined using the Jenks optimization method.

4 Conclusions

This paper has presented a methodology for estimating accessibility for pooled and stop-based DRT within an ABM. The main challenge was that accessibility is strongly dependent on the supply (available vehicles) and demand (customers) for the DRT service. This makes it difficult to calculate the potential accessibility from all measuring points, as the ensuing supply and demand patterns would not be realistic. Thus, instead of physically simulating these DRT trips within MATSim, we used a model which estimates the time of a DRT trip based on the direct travel distance. This estimated time includes not only the waiting time, but also the extra time associated with ride-pooling, wherein the DRT vehicle makes a detour to pickup or drop-off further passengers. The approach leverages the outputs from MATSim to get a more expressive values for accessibility than previous approaches in literature.

To further leverage the fine-grained information of simulated DRT trips in MATSim outputs, it would be low-hanging fruit to differentiate α and β parameters (see Eq. (5)) depending on the start location/time of the trip, as done in Diepolder et al. (2024) and Ziemke & Bischoff (2023). The infrastructure developed in collaboration with Lu et al. (2025) would allow this disaggregation in future work. This stronger spatio-temporal influence would, e.g., lower DRT accessibilities in outskirts of the city (depending on rebalancing strategy), at times with high demand (rush hour) or low supply (nights).

Additionally, future work should explore the option of inter-modal accessibility; e.g., using DRT as a feeder to traditional PT. Another consideration is that the DRT accessibility does not limit the distance an agent can walk to a stop; long walk-distances are untenable for much of the population, especially those with mobility impairments.

Amid ongoing budgetary challenges, non-urban municipalities face significant hurdles in offering residents viable alternatives to car-based mobility. Within this context, assessing the efficacy of DRT systems becomes an increasingly pertinent area of research, particularly when considering the potential rise of autonomous vehicles. This underscores the relevance of our proposed methodology in addressing these critical mobility challenges.

Acknowledgments

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