An improved procedure for simulation of demand-responsive transport services in agent-based transport simulation framework

Chengqi Lu[1], Christian Rakow[1], and Kai Nagel[1]

[1]Technische Universität Berlin, Chair of Transport Systems Planning and Transport Telematics, Straße des 17. Juni 135, 10623 Berlin, Germany

Short summary

Demand-responsive transport (DRT) is gaining popularity in transport planning. While more efforts are devoted to the optimization of DRT operational strategies, the challenges of simulating DRT in the context of transport planning, such as long simulation time and the high sensitivity of DRT systems to demands, receive relatively less attention. In this study, we develop an improved procedure for simulating DRT in agent-based transport simulation frameworks, based on the concept of estimation and teleportation. A DRT estimator is constructed based on real-world data and the knowledge of the transport system. During the simulation, the estimator provides estimated trip data for each DRT ride. The agents are then teleported to the destination based on the estimation. By removing the explicit modelling of DRT during the transport simulation, many challenges associated with conventional simulation approaches can be addressed. This approach can also be applied to policy studies of other emerging transport modes.

Keywords: Demand-Responsive Transport (DRT); Agent-Based Transport Simulation; Transport Planning; Mobility as a Service

1 Introduction

Demand-responsive transport (DRT) is a widely discussed topic in transport planning. This mode of transport bridges the gap between conventional taxis and public transportation. Typically comprising a fleet of minivans, it offers on-demand services to customers. Without fixed routes or timetables, DRT is more flexible than conventional public transport, making it particularly suitable for first- and last-mile mobility and for areas with lower population density, such as city outskirts and rural regions. Unlike conventional taxis, DRT is oriented toward ride-pooling, which improves vehicle and road usage efficiency. This often results in more affordable fares and greater sustainability. With growing number of DRT services being introduced to the transportation systems worldwide, DRT becomes increasingly important in transport planning. Performing simulations is one effective way to predict the potential impact of introducing a new DRT service or expanding an existing one in a city or region.

From the literature, there are numerous studies focusing on the optimization of the vehicle scheduling, such as in Alonso-Mora et al. (2017); Kucharski & Cats (2020); Ruch et al. (2021), and empty vehicle relocation, such as in Pavone et al. (2012); Bischoff & Maciejewski (2020); Ruch et al. (2020). Meanwhile, there are also many studies exploring the potential impacts of introducing DRT into various cities or regions (Bischoff et al., 2017; Hörl et al., 2021; Hörl et al., 2019).

There are, however, several challenges related to the simulation of the DRT, especially in large scale scenarios. First, simulation of DRT is time-consuming, especially for those more advanced strategies. This becomes even worse when it is paired up with iterative approaches, which are commonly used in agent-based transport simulations, making the computational workload prohibitively high. Second, the performance of the DRT system is more sensitive to the demand pattern than the other modes, and some DRT operational strategies are adaptive to the demands. The DRT operation and the agents in the simulations may co-evolve in the iterative process. This may result in systematic bias in the distribution of the demand and the service quality across the service area (Schlenther et al., 2023). Finally, most of the existing studies in the literature that project the potential reactions of people towards DRT systems heavily rely on hypothesis and assumptions. As more and more DRT systems are being rolled out in different places, we can acquire more real-world operational data. By comparing real-world operational data with the simulated DRT services, systematic discrepancies are often observed, particularly in service quality and mode choice behavior. These discrepancies may further undermine the reliability of the simulation results.

One solution to tackle the above-mentioned challenges is to replace the explicit modelling of DRT systems during the transport simulation process with estimation and teleportation. A DRT estimator is constructed based on the real-world data and the knowledge of the transport system we are working with. During the transport simulation, the estimator will estimate the travel time and distance of each DRT trip. The agents are then teleported to the destination based on the estimation. By removing the explicit modelling of DRT during the transport simulation, we can reduce the computational workload. The problem of high-sensitiveness of the DRT mode to the reactions of the agents can also be mitigated. Furthermore, when real-world data is available, the estimator can be easily fitted to the real-world data and this can eliminate the systematic discrepancy between the simulated DRT service and the actual operations.

In this study, we develop an improved procedure for simulations of DRT services in an agent-based transport simulation framework, based on the above-mentioned concept. We also conduct systematic experiments to evaluate the performance and characteristics of the new simulation procedure.

2 Methodology

In this study, the new approach is developed in the framework of MATSim, an agent-based transport simulation tool (Horni et al., 2016). It should be noted that while there are specific adaptations to the MATSim framework, the main idea of this approach is also compatible with other agent-based transport simulation frameworks.

MATSim is a meso-scopic transport simulation framework, which is capable of simulating city- and region-wide traffic with a high level of detail within a relatively short amount of time. The simulation framework adopts an iterative approach (see Figure 1). Within the MATSim framework, there is a DRT extension that enables the simulation of DRT service in MATSim (Maciejewski et al., 2016). In the DRT extension, there is a basic request matching strategy and several empty vehicle relocation strategies (also known as rebalancing strategies) (Bischoff & Maciejewski, 2020; Lu et al., 2020).

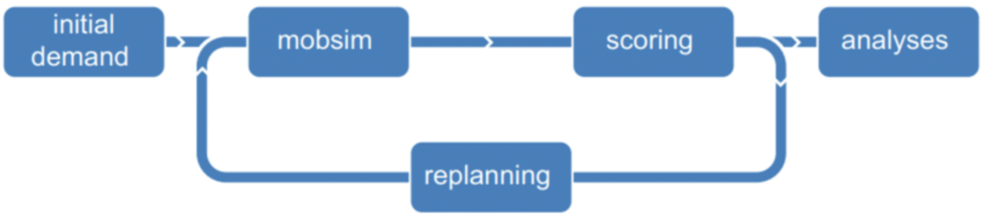


Figure 1: Illustration of the MATSim simulation procedure (adapted from Horni et al. (2016))

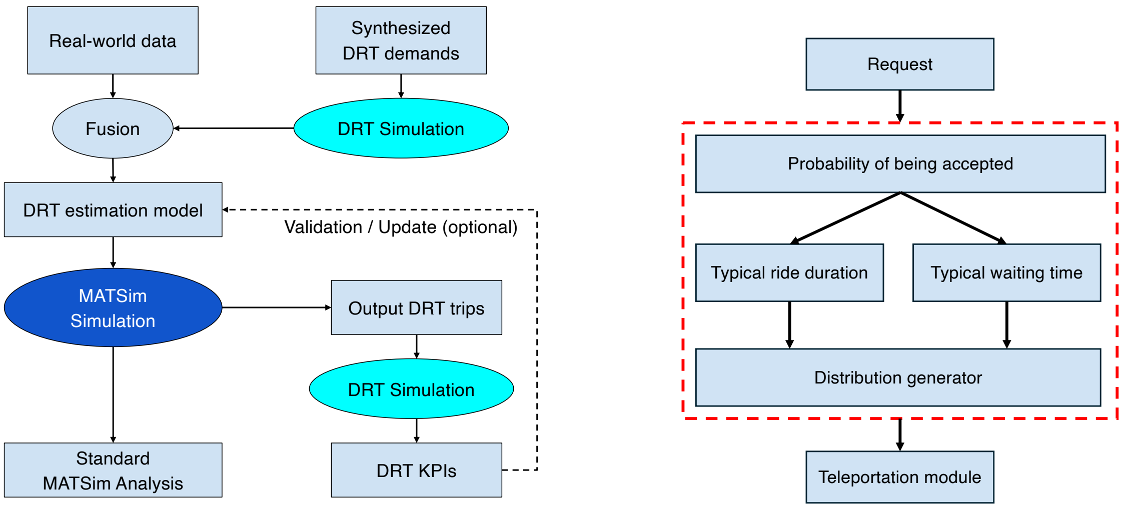
2.1 DRT estimate and teleport: the new approach

The new approach is based on the idea of estimation and teleportation. The schematic drawing of this new approach is presented in figure 2. Figure 2a illustrates the new work flow of the simulation. Instead of simulating DRT systems explicitly within the main MATSim simulation loop (i.e., mobsim – scoring – replanning in Figure 1), we first build a DRT estimation model based on actual operational data (when available) and preliminary DRT simulations. To perform preliminary simulations, we can use both the DRT extension within the MATSim framework and external DRT simulation and optimization tools, such as those proposed in Engelhardt et al. (2022) and Ruch et al. (2018).

During the MATSim simulation, no explicit DRT simulation will be carried out. This not only speeds up the simulation procedure, but also reduces the potential noise and inaccuracy of the output. After the MATSim simulation, the standard output, including mode split and potential DRT trips, will be written out as usual.

To acquire the key performance indicators (KPIs) of DRT systems, such as required fleet size, vehicle kilometers travelled (VKT), and service quality experienced by each passenger, post-simulation based on the potential DRT trips can be conducted using the MATSim DRT extension or other simulation and optimization tools. Since the post-simulation is based on fixed DRT demand, it does not require a high number of iterations, as in the standard MATSim simulation procedure, resulting in a reduced total computational workload. Furthermore, with fixed demand, the output of the DRT simulation is more reproducible and reliable.

The application of the new procedure includes two types of use cases. The first use case is to design a DRT service for a city or region and estimate the required fleet size. In this case, the service quality is pre-defined, so the validation and update loop is not necessary. The second use case is to evaluate the potential number of users given fixed resources (e.g., fleet size) and operational setup. In this scenario, the validation and update loop may be needed. If the actual service quality experienced by passengers, as obtained from the post-simulation, deviates significantly from the estimated value, the DRT estimation model must be updated. A new MATSim



(a) Updated simulation procedure (b) A closer look at the DRT estimation model

Figure 2: Illustration of the new simulation procedure with DRT

simulation can then be conducted based on the updated model. This process can be repeated until the service quality experienced by passengers aligns with the estimated value.

2.2 A closer look at the DRT estimation model

The DRT estimation model provides estimation for the following three parameters for each request: waiting time, ride duration, and probability of the request being accepted. For the estimation of waiting time and ride duration, a typical value will be generated. On top of the typical value, an artificial disturbance can also be added, such that the uncertainty and day-to-day fluctuation can be simulated. Figure 2b summarize the work flow of the DRT estimation model.

Estimation of the typical waiting time

Typical waiting time $t_{wait,typical}(r)$ can be interpreted as the amount of time a passenger expects to wait before a vehicle arrives. Depending on the available data and required level of details, the typical waiting time can be constant or time-, location-, and person-dependent.

Estimation of the typical ride duration

To estimate the typical ride duration of a trip, we use a linear model. The typical ride duration $t_{ride,typical}$ is calculated based on the direct car travel time t_{direct} on the network, taking into account the traffic conditions at the departure time. A slope k and constant term C are then used to calculate the typical ride duration of that trip:

$$t_{ride,typical}(r) = k \cdot t_{direct}(r) + C \tag{1}$$

To identify the value of k and C, we can apply linear regression to real-world data or to the outputs of preliminary simulations based on synthesized demands.

By default, we assume the typical ride durations of all the requests follow the same model. When additional data is available, the parameters in the typical ride duration model can also be request-dependent (i.e., k and C become $k(r)$ and $C(r)$). The interface also allows a more complex relation (e.g., non-linear mapping) to be implemented.

Modelling the uncertainty in DRT systems

To simulate the day-to-day fluctuations and uncertainty in the DRT system, a distribution model is included in the DRT estimation model. The distribution model will generate random numbers distributed around the typical durations:

$$t_{wait,estimated}(r) = t_{wait,typical}(r) \cdot \gamma_1 \tag{2}$$

$$t_{ride,estimated}(r) = t_{ride,typical}(r) \cdot \gamma_2 \tag{3}$$

$$\gamma_1 \sim D_1 \tag{4}$$

$$\gamma_2 \sim D_2 \tag{5}$$

Two commonly used distribution models are included: log-normal distribution and normal distribution. Custom distribution model can also be implemented when needed. An interface is provided for the implementation of custom distributions.

As indicated in the Equation 2 to 5, the two distribution models D_1 and D_2 are independent. That is to say, distributions with different parameters or even different distribution types can be used for the waiting time estimation and ride duration estimation respectively.

Probability of rejection

In the actual operation of the DRT, especially for private operators, it is possible that some of the requests are rejected due to various reasons. In order to simulate this situation, the estimation for rejection is included. Similar to the waiting time estimation, the probability of being rejected can be a constant value throughout the service area. It can also be location-, time-, and request-dependent. For the cases where we do not want to include rejections (e.g., for transport planning), we can simply set the probability of rejection to 0.

It is to be noted that, if a DRT request is rejected in the MATSim simulation, the agent will either get stuck at that leg, causing the subsequent elements in the plan to be abandoned, or "walk" to the destination (i.e., teleported to the destination at the speed of walk). In either case, it is likely that the agent will end up with a rather poor score. This may lead to some additional fluctuation in the mode choice. Therefore, special care needs to be given when the probability of rejection is set to a non-zero value.

3 Experiments with the new approach

3.1 Generation and calibration of a small scale scenario for the experiments

To investigate the behavior of the new DRT simulation approach and its impact on the results, we conduct systematic simulations in a small-scale scenario. First, we create a base scenario into which the DRT service will be introduced. The base scenario is constructed based on the MATSim Kelheim scenario (Schlenther et al., 2022). We extract all the trips that could be served by DRT service, which leads to 8513 trips in one day. Then we calibrate the base scenario such that the mode share approximates the reality. We only include car, bike and walk. The other modes (e.g., public transport, ride) are excluded, as they only count for a small mode share in the reality. The mode share progression and the final mode share in the calibrated base case are summarized in figure 4.

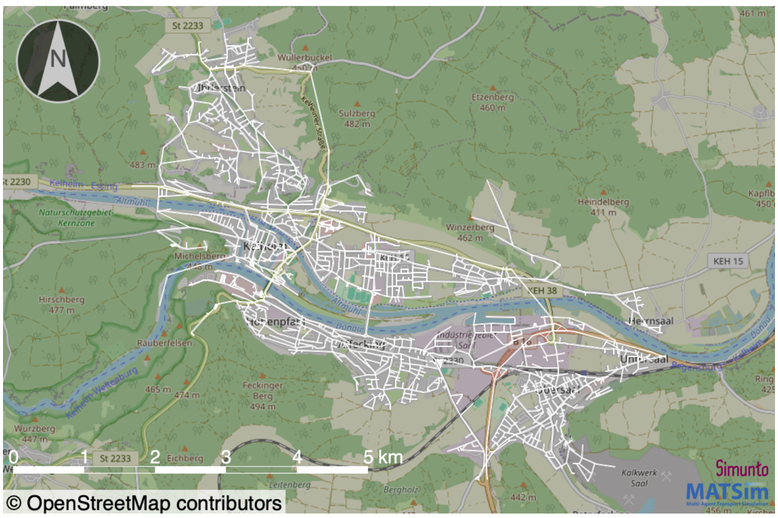
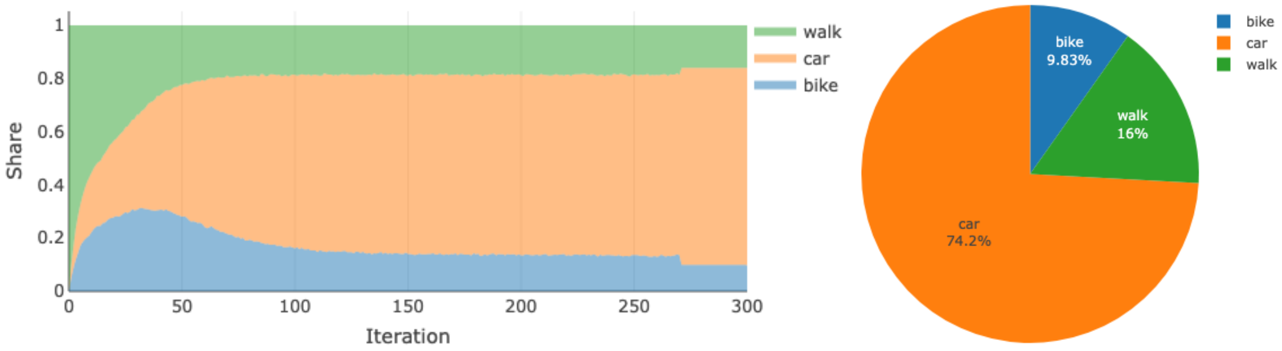


Figure 3: The network of the small scale scenario

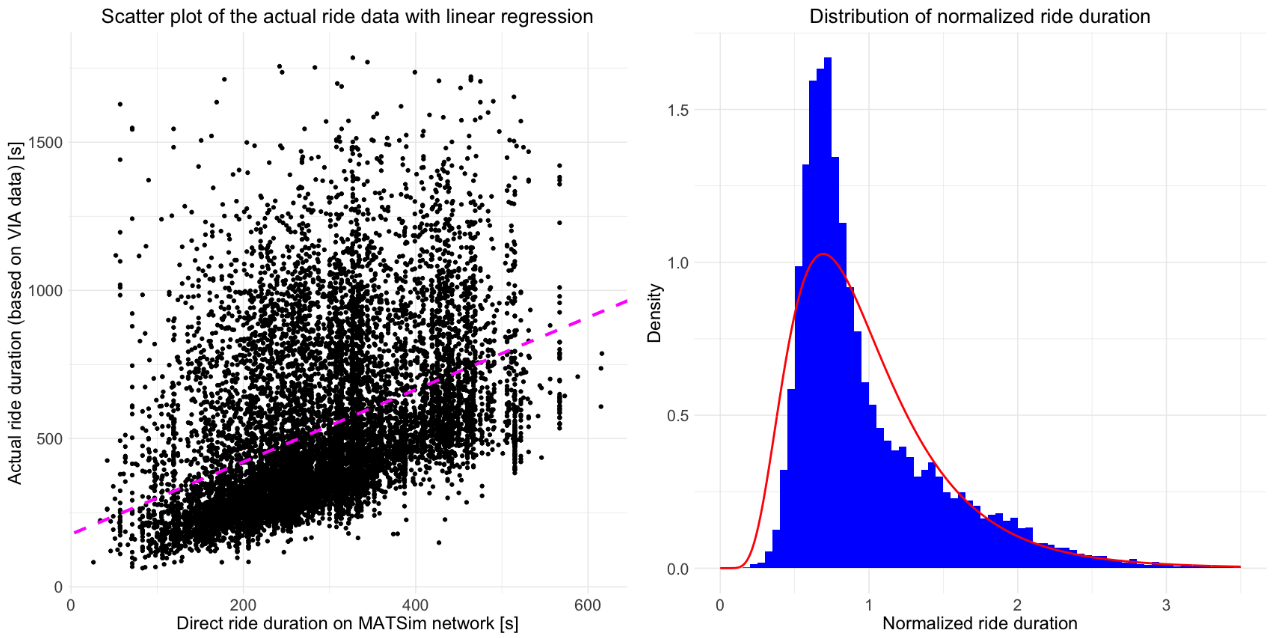


(a) The mode share progression during the simulation (b) The final mode share

Figure 4: Mode share information in the calibrated base scenario

3.2 Simulations and results

For the new approach, we build the DRT estimation and teleportation model based on the real-world DRT operational data from the pilot project KelRide[1]. Because of limited available data and privacy protection reasons, we identify the parameters for the aggregated system (i.e., the parameters are not request-dependent). The typical waiting time $t_{wait,typical}(r)$ is set to 300 seconds. A normal distribution $D_1 \sim N(1, 0.3)$, with a lower bound value of 0, is applied to the waiting time estimation. By performing the linear regression, we acquire parameters for the ride duration estimation: $k = 1.22$, $C = 177.5$. The distribution model for the ride duration can be approximated by a log-normal distribution. Figure 5 illustrates the fitting process, where the fitted log-normal distribution ($\mu = -0.122$, $\sigma = 0.496$) is represented by the red curve.



(a) Linear regression on the ride duration (b) Distribution of the ride duration and fitted log-normal distribution

Figure 5: Example Distribution model of a real-world DRT operation

For the conventional approach, where DRT is to be simulated explicitly during the MATSim iterations, we apply the default request matching strategy. We perform two sequence of simulations with the conventional full simulation approach: one with limited fleet size, where only 10 minivans are available, and one with very large fleet size, where 500 minivans are used. In each minivan, there are 8 passenger seats.

In the experiments, we fix all the other parameters and only vary the Alternative Specific Constant (ASC) for DRT mode. The output mode share of the DRT will be observed. The results are summarized in figure 6.

[1] https://kelride.com/en/

Same as in the discrete choice models, the absolute value of ASC is not relevant. Rather, we are more interested in the changes in the ASC under different setups.

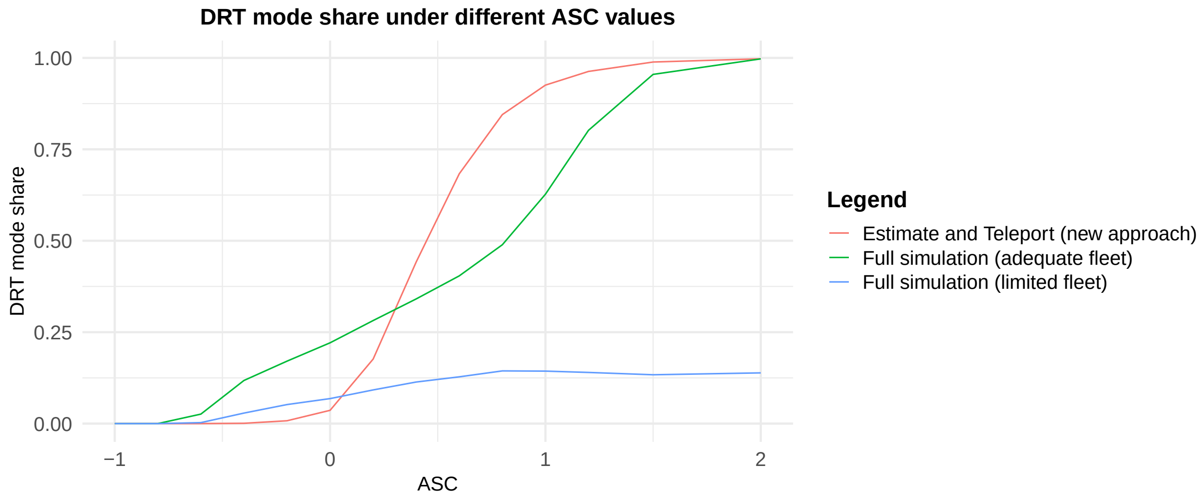


Figure 6: Mode share of DRT under different ASCs, with different simulation approaches

The shape of the curves indicates that the new approach is more similar to the logit curve. Additionally, the mode share demonstrates greater sensitivity to the ASC when the new approach is employed. Next, we look at the results from the conventional approach (represented by the cyan and purple curves). We can see that the curves are less regular in shape. When an adequately large fleet is present, the input-output-response between the ASC value and the DRT mode share is somewhat linear. When fleet size is limited, on the other hand, the DRT mode share converges to a certain level of mode share as the ASC value increases, which corresponds to the maximum number of trips the fleet can serve. The plateau mode choice curve is clearly not ideal. In this region, the mode share becomes insensitive to changes in the ASC. This could make it difficult to determine appropriate parameters for the DRT mode during the calibration process. Applying the new approach can effectively solve this problem.

4 Discussion

4.1 More flexible and controllable service quality

With the new approach, the service quality of the DRT system is fully controllable. The values are produced by the estimator based on the real-world operational data. This improves the reliability of the calibration result. When the conventional approach is used, the service quality of the DRT systems varies as the ASC value changes. Furthermore, when limited fleet size is used, the service quality of DRT system also fluctuate significantly across the iterations, and agents may not be able to acquire accurate perception of the service quality of the DRT. The new approach eliminates these fluctuations and improves the reliability of the outcome.

Besides, as we can explicitly specify the typical waiting time and riding time of a request based on the location and departure time, it provides us with extra flexibility and controllability during the transport planning process. For example, if we make the waiting time location-dependent, by reducing the typical waiting time for requests departing from the highlighted areas in Figure 8 from 300 seconds to 180 seconds, then we can explicitly impact the resulting DRT demands, as illustrated by Figure 7.

4.2 Computational time

As mentioned in Section 2, the new approach for DRT simulation is more efficient, as it avoids the repetitive explicit simulations of DRT systems during the MATSim iterations, which consumes a lot of time. To quantify the computational time reduction, we perform the simulations with new approach and conventional approach on the same scientific computational node, and compare the computational time. A 10-core Intel Xeon E5-2630 CPU with a clock speed of 2.2GHz is used for the benchmarking. Two ASC values, 0.4 and 1.0, are used for the benchmarking. For each setup, the number of iterations in MATSim is set to 1000. The results are summarized in table 1. From the table, it can be seen that the new approach can reduce the simulation time by around 25%, compared to the full simulation case with a small fleet. Furthermore, unlike the conventional approach, the simulation time of the new approach is also not sensitive to the fleet size, the number of demands, or DRT

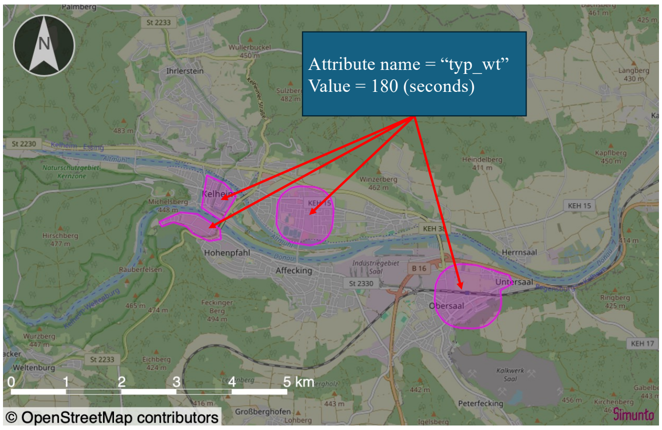


Figure 7: Illustration of an example input Shapefile for the waiting time estimator

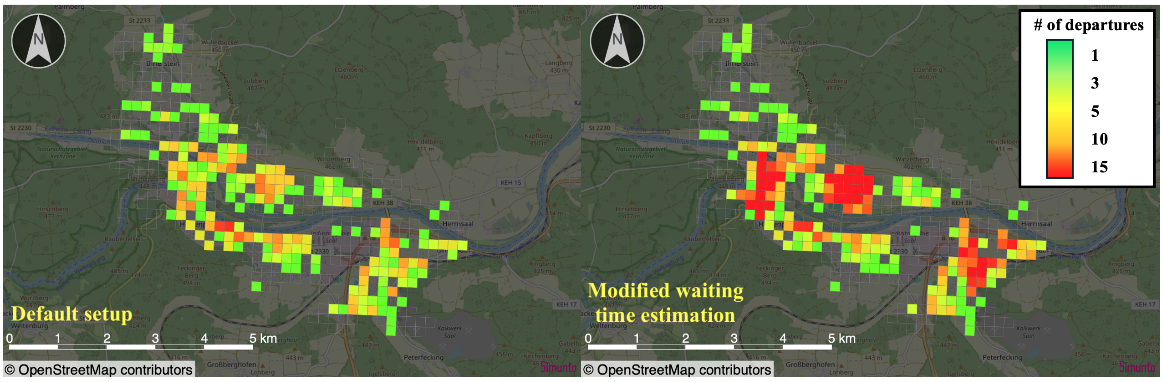


Figure 8: The impact of including the shape-file based waiting time estimation

operational strategy. It needs to be pointed out that in the full simulation case, the default DRT operational strategy is used, which is relatively simple and fast. If a more complex operational strategy is used, the time savings brought by the new approach will be even more significant.

Table 1: Comparison of simulation time

Setup	Complete simulation time	Δ
ASC = 0.4		
Full simulation, fleet size = 10	143 minutes	reference
Full simulation, fleet size = 500	220 minutes	+53.8%
New approach	108 minutes	-24.5%
ASC = 1.0		
Full simulation, fleet size = 10	138 minutes	reference
Full simulation, fleet size = 500	274 minutes	+98.6%
New approach	105 minutes	-23.9%

5 Conclusion

In this study, we implement an improved procedure to simulate DRT in an agent-based transport simulation framework. The new approach replaces the explicit simulations of the DRT during the iterative process with estimation and teleportation model. Agents explore the DRT mode during the iterative process based on a predefined service quality, which is based on real-world data or systematic preliminary simulations. To acquire

KPIs for the DRT system, post-simulations can be conducted based on the resulting DRT demands.

According to the experiments results, it can be observed that the new approach can tackle the challenges faced by the conventional approach. The first key advantages of the new approach over the conventional approach is that the results are more reliable and controllable. The performance of the DRT system is highly sensitive to mode choice and other aspects (e.g., fleet size, fleet distribution, parameters in operational strategies). By replacing the explicit simulation of DRT with estimation and teleportation, the undesired disturbance can be excluded and the reliability of the results can be improved. Another key advantage of the new approach is that it can resolve the systematic discrepancy between the simulated performance of DRT and the real-world data. Since the estimation model is fitted to the real-world data, realistic estimation of the DRT trips can be reproduced during the simulation. Finally, the new approach can also speed up the simulation process by excluding the online optimization of DRT schedule, which is computationally expensive, from the main simulation procedure. This is very helpful for the simulations of large-scale scenarios.

The new approach also comes with certain limitations. The first drawback is that the induced traffic caused by DRT vehicles are not included in the traffic simulation. This may lead to non-trivial underestimation of traffic congestion in the cases where DRT vehicles play a major role in the traffic. One potential solution to mitigate this limitation is to reduce the capacity of the network accordingly during the simulation process, which may be determined empirically. Another limitation is that there is not yet a systematic study on the convergence behavior of the validation/update loop (see figure 2a). As mentioned in Section 2.1, there are two major types of use cases: (1) the service design where service quality is predefined, and (2) the resource is pre-defined (e.g., fleet size). In the former case, the optional validation/update loop is not required. In the later case, however, the validation/update loop may need to be performed several rounds, until the estimated service quality matches the actual service quality that can be provided by the given resources (e.g., fleet size). As a rule of thumb, the updated estimation of the service quality should be located somewhere between the previously estimated value and the currently observed value:

$$Q_{est}(i+1) = \alpha Q_{est}(i) + (1-\alpha) Q_{obs}(i) \tag{6}$$

where $Q_{est}(i)$ is the estimated service quality used in the simulation at round i, $Q_{obs}(i)$ is the observed service quality based on the post-simulation at round i. The term $\alpha \in (0, 1]$ is a variable that determines the learning rate of the estimator. A good α value that leads to faster convergence needs to be determined empirically and may be case-specific.

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