EVALUATING DYNAMIC-RESPONSIVE TRANSPORT AT EQUILIBRIUM WITHIN AN AGENT-BASED SIMULATION ENVIRONMENT

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Short paper submitted for presentation at International Conference on Advanced Systems in Public Transport and TransitData 2025

July 1-4, 2025, Kyoto, Japan

Abstract: This study proposes a new approach to assess Demand-Responsive Transport. We developed the DRT Equilibrium (***DRT EQ***) within an agent-based simulation environment, an iterative procedure in which DRT routes are defined at each procedure iteration and treated as conventional bus lines, with the routes refined at each iteration based on equilibrium performance. To assess the performance of this methodology, we tested it against MATSim's dynamic DRT module using a case study from Luxembourg. We show that under a stress test scenario, the DRT EQ performs better and more consistently than the DRT Module from both the customers' and provider's perspective.

Keywords: Agent-Based Modeling, Demand-Responsive Transport, MATSim, Transportation Simulation

1. Introduction

In recent years, cities and regions worldwide have searched for new sustainable solutions to address the growing complexity of urban mobility. With increasing pressures from urban sprawl, population growth, environmental concerns, and the demand for more adaptable transit solutions, transportation researchers are turning to emerging models that can support and synergize well with traditional public transport (PT) systems. Demand-responsive transport (DRT) has gained attention for its ability to flexibly accommodate shifting passenger needs in real-time, offering the potential to improve accessibility to PT and reduce reliance on private vehicles. Moreover, PT companies are investing a lot, to adapt to their sustainability goals, into more Electric Vehicles (EV), which have higher requirements and require more precise modeling.

To study the potential impact of DRT systems within modern urban transport systems, researchers have increasingly moved towards agent-based modeling (ABMs), which allows for the simulation of individual interactions within complex, dynamic environments. DRT systems, by nature, must operate flexibly in response to real-time passenger needs and the changing conditions of urban networks. ABMs are particularly suited to capture these interactions as they can simulate individual agents — e.g. each representing a passenger or a vehicle — who make decisions based on unique preferences, current system conditions, and available options. This granularity allows researchers to test and refine DRT strategies in a simulated environment, evaluating outcomes on both individual and system-wide scales, Ronald et al. (2015). In this study, we will rely on the well-established open-source software MATSim, Horni et al. (2016), a popular ABM for transportation that not only simulates these interactions but incorporates a feedback mechanism in which agents continually adapt their decisions based on past experiences, aiming for optimal plans over multiple "days". This is done through agents saving their experience of each MATSim iteration (i^{MTS}), and evaluating them through a scoring function, which describes their "satisfaction" with the experience, Nagel et al. (2016).

Maciejewski and Nagel (2012); Ciari et al. (2016) developed extensions that allowed MATSim to simulate DRT services (e.g. taxis) within the simulation environment (***DRT Module***). This module simulates DRT services by dynamically generating routes responding to passenger requests during each i^{MTS}, with the objective function aimed at minimizing total travel times and costs. As agents move through the simulation, they are given the option at each i^{MTS} to opt for DRT services under specific conditions. Once the requests are collected, the DRT Module computes and generates new service routes to accommodate these requests given that specific customer setting. However, dynamic routing introduces significant complexity to the simulation process. Each time agents adjust their plans — such as changing modes of transport, departure times, or routes — the DRT module must recompute the routes to accommodate these changes. As the scoring mechanism is the primary driver for agents selecting their next plan, this constant adjustment creates a feedback loop where agents' choices influence the DRT service configuration, and in turn, affect agents' subsequent choices, potentially preventing agents from effectively evaluating and settling on optimal plans.

The same problem has also been noted in the very early stages of DRT modeling in MATSim (Ciari et al. (2009)), where it is stated that the dynamic interplay between agent decisions and operator adjustments in MATSim can lead to complex equilibrium challenges, given that both service characteristics and user choices continuously evolve. This constant change might lead to either complex or unstable equilibrium conditions, reducing the simulator's ability to make agents converge on their best possible plan, and thus forcing MATsim further away from achieving a stable (and reasonable) user equilibrium in an appropriate amount of i^{MTS} Moreover, another main limitation of the DRT Module is the unavailability of the integration of external algorithms to solve the DRT routing and scheduling problems, creating a closed environment that forces researchers to rely on the module's specific setup and limitations. The inability to implement custom optimization solutions restricts the capacity of researchers throughout the world to use MATSim with their own developed solutions. Therefore, while the DRT Module remains a perfectly viable solution for simulating

DRT within the transportation system, it does not fulfill the needs of understanding these systems properly, supporting effective management, and testing native DRT models and optimization algorithms.

To overcome some of the above-mentioned limitations, Yang et al. (2024) present a co-simulation system, Fleet Demand (FD) Simulator, which integrates MATSim with external fleet simulators to enhance the simulation of advanced fleet-based services, such as ride-pooling and DRT. During each i^{MTS}, they collect the potential pool of clients from MATSim, simulating the DRT mode option in the simulation through teleportation. After this, information on the agents, together with the network and traffic conditions, are sent to another simulator, which simulates the fleet-based service more accurately, with the output of the simulation given back to MATSim in the form of plans adjustments based on the travel time and/or distance of the experienced plan in the other simulator environment. The FD simulator tackles elegantly some of the shortcomings of the DRT Module, which may be difficult to represent using MATSim's current toolbox, especially due to the complexity of integrating new modules in the simulator.

Nonetheless, some problems might arise when adopting this approach: first, the impact of the choice of agents in the simulation, which undergone the parallel simulation, is not reflected in the scoring of the other agents which instead were not teleported. This might lead to equilibrium which is still correct from a purely theoretical point of view, but might not represent the real state of the system. Moreover, as per the DRT Module, the presented research potentially lacks the chance to implement other optimization models within it, as it relies on an external simulation environment. Finally, as the FD is using an external simulator, as per the presented implementation in Namdarpour et al. (2024), no possibility to implement additional constraints that are problem-related and might help practitioners and researchers to understand DRT under all the reality constraints - e.g. charging stops and/or stations for EV vehicles problems looks available - limiting the application to classical DRT systems.

Therefore, to address all the presented shortcomings, we implemented an iterative procedure that uses multiple MATSim simulations, modeling the DRT system with classical MATSim bus lines, named DRT Equilibrium (***DRT EQ***).

The main rationale for developing the DRT EQ is that we do not need to simulate a DRT system within a transportation environment, but we want to test and understand the behavior of any DRT solution at equilibrium conditions in a pseudo-realistic scenario. In the DRT EQ, agents test predefined routes and evaluate their effectiveness at user equilibrium, recomputing the routes across different Procedure Iterations (i^{PRC}) based on the equilibrium demand at the previous i^{PRC}. until convergence is reached, in contrast with the implementations presented in Yang et al. (2024) and Ciari et al. (2016) which reroute the DRTs throughout the single i^{MTS}. Additionally, DRT EQ allows for the incorporation of real-world operational constraints like charging stations and depots as part of the fixed route structure, which simplifies certain strategic evaluations that would otherwise be challenging in a dynamic system. Finally, our presented approach allows for any kind of optimization model to be implemented and tested within MATSim, allowing researchers to test their solution in their desired scenario.

The remainder of the paper is organized as follows. Section 2 describes in depth the procedure development. Section 3 describes the case study. In Section 4 we discuss the results and the implementation of the DRT EQ, with Section 5 summarizing the findings and indicating future directions.

2. Methodology

The objective of the DRT EQ is to overcome the shortcomings of the DRT Module by introducing a procedure that integrates an external DRT optimization model's solution within MATSim's simulation framework, allowing us to incorporate optimized routes within the MATSim environment. This iterative procedure allows the evaluation of DRT services by generating fixed routes during each i^{PRC}, and adapting them to the reaction of the MATSim simulation at equilibrium, in contrast with DRT Module, which dynamically adjusts routes in response to each i^{MTS}. demand. Our goal is to reduce computational complexity and provide a stable environment for the system to reach user equilibrium.

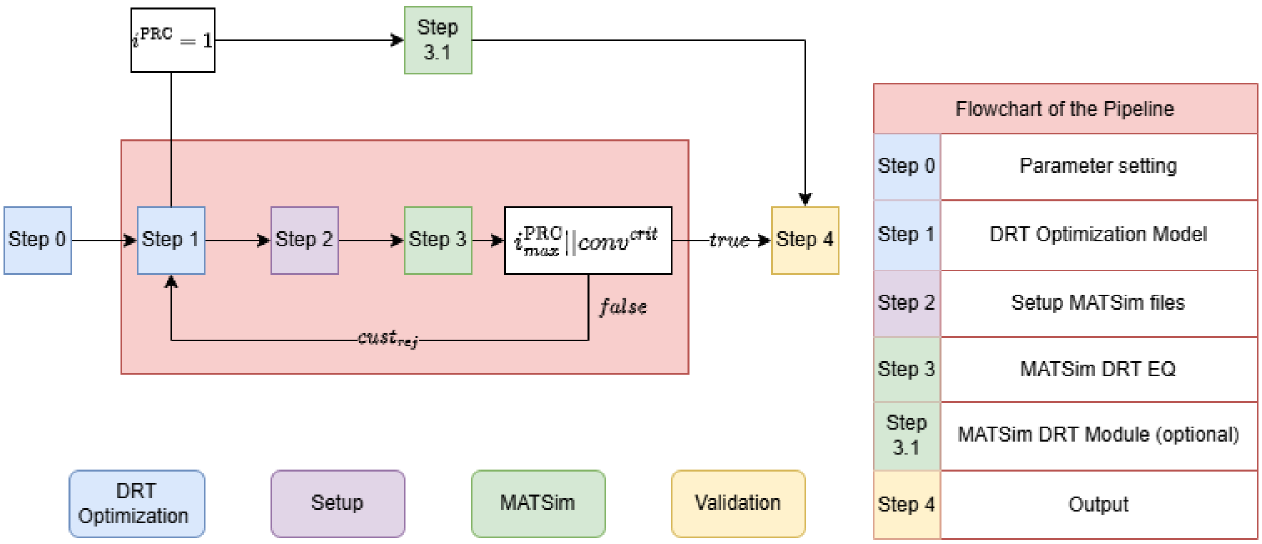

Figure 1: Flowchart of the Methodology.

Figure 1 shows the flowchart of the iterative procedure integration for implementing the DRT EQ within the MATSim environment.

Step 0 is the parameter configuration step, in which we can set the parameters necessary for the simulations. Specifically, we can set the number of i^{MTS}, maximum i^{PRC} (i^{PRC}_{max}) and other parameters, such as criteria convergence ($conv^{crit}$), the path to the runnable files, and so on.

Step 1 involves running the chosen DRT model to get the optimized solution. The input includes customer data, including their preferred departure time, pickup point, and destination, as well as the index of customers rejected. The output generates bus schedules and customer itineraries, which are used to optimize bus routes and minimize operational costs.

Step 2 bridges the optimization model and the MATSim environment. Its purpose is to convert the locations of customers, bus routes, and other relevant data into MATSim-compatible files, preparing them for simulation. This step has two parts: generating the "DRT bus" lines and setting up the files for the MATSim simulations.

The first part involves modeling the DRT service as a traditional bus within MATSim, with predefined bus routes and stops derived from the output of Step 1. The generated files are the respective *transit schedule* and *vehicle* files for a MATSim simulation. The former includes transit stops, and end of the lines, but also allows us to model recharging stops, which are all converted into stops in MATSim's simulation, while the latter includes information regarding the capacity of the bus, the number and name of the bus, and so on. The second step involves generating the population generation step based on the customer's demand and embedding in the customer's plan the necessary details for simulating Step 3. This includes the bus schedule information to match it with the DRT bus, pickup time, and destination location.

Step 3 uses a MATSim simulation to test the DRT EQ into user equilibrium. The idea is to evaluate whether the estimated optimal DRT routes from Step 1 remain optimal for the clients considering that other agents could behave differently, such as choosing another mode of transport, changing routes, etc.

Once the MATSim simulation is concluded, we consider the agents who used the DRT EQ to reach their destination as *satisfied* by the experience, under the assumption of user equilibrium for the MATSim simulation, and treat them as *customers* for the next $i^{\text{PRC}}+1$. To achieve this, agents that did not opt for the DRT, therefore considered as *rejected* ($cust_{rej}$ in Figure 1), are fed back to Step 1 for i^{PRC}. *i+1*, such that Step 1 will optimize the route of the DRT for the customers who were satisfied with the service. This whole procedure is repeated until either i^{PRC}_{max} or $conv^{crit}$ is met.

For this study, we opted to develop and implement an additional step, namely, **Step 3.1** which simulates the DRT system using the DRT Module, Maciejewski and Nagel (2012). To run it, we use the demand and vehicle specification (number and capacity) as per$i^{\text{PRC}} = 1$, *Step 1*, allowing for a fair comparison of the two models at equilibrium conditions. This is still considered correct, as a higher number of vehicles for the DRT Module does not necessarily result in their full utilization, which in our case is cleaned in the post-processing phase. This simulation is mainly run for comparison reasons, is run only once during the whole iterative process, and usually is run at a higher i^{MTS} count compared to Step 3, mainly due to the slower convergence that comes with this module.

Finally, **Step 4** is the post-processing and cleanout phase, in which we can compute the output for either the different iterations of the procedure and the key performance indicators (KPIs) for both the DRT bus and the DRT Module.

3. Case Study & Results

Case Study

For this study, we selected a town in Luxembourg, Contern, where a train station serves travelers going in two opposite directions: Luxembourg City and Trier, Germany. An industrial area is located in the town, and companies in the area generate a considerable afternoon peak demand for train services, which would justify the implementation of a DRT system for first/last mile connectivity. Therefore, the goal is to simulate requests for such a hypothetical DRT system connecting the customers from their origin workplace to the train station, allowing them to synchronize with the train schedule for the two above-mentioned directions. The underlying assumption is that, as DRT works well to connect less-connected areas to the main PT network, customers would be willing to pay for a service that connects them to the train network to bring them to their final destination. For this case study, we used as a model for Step 1 the metaheuristic presented in Ma et al. (2024), which proposed a first-mile DRT model, where customers are randomly generated, with specified preferred train station, departure, and direction. Regarding the Step 0 parameters, we decided to set i^{PRC}_{max} at 50, with $conv^{crit}$ based on the moving average threshold approach used by Yang et al. (2024), which stops the procedure once the n-cycle moving average of DRT trips of our implementation, set at $conv^{crit}$ ±3% over the last 5 i^{PRC} for this study. We simulated 5 pickup points over a radius of ≈ 2 km from the main station, and we simulated customers varying from 20 to 500 customers. Each DRT vehicle is simulated with unlimited capacity, and the running time of the DRT service ranges from 15:58 to 18:30. The optimization runs of the heuristic model of Ma et al. (2024) is set to 10, meaning that the model will be run 10 times, selecting the solution which best fit the objective function. To compare our implementation with the DRT Module, we run each of the DRT EQ for 400 i^{MTS}, while the simulation of the DRT Module for 900 i^{MTS} For both the DRT Module of MATSim and our DRT EQ, we applied the same scoring, with a heavy penalty for late arrival at the station and the same parameters for the travel through PT/DRT.

	DRT Module								DRT EQ							
Pop Size	**VKT**	δ	$\overline{\text{WT}}$	**MC**	**# Veh**	ρ	ρ_{25}	ρ_{75}	**VKT**	δ	$\overline{\text{WT}}$	**MC**	**# Veh**	ρ	ρ_{25}	ρ_{75}
20	21.52	1.36	7.51	0%	1	20	20	20	16.67	1.19	8.18	15%	3	6.67	5.5	8
30	34.94	1.30	8.67	10%	4	7.5	1.75	8.25	23.72	1.18	7.38	3%	3	10	9	10.5
50	37.00	1.48	7.63	8%	4	12.5	3.25	16.75	29.04	1.44	8.59	4%	4	12.5	9	15.5
100	49.91	1.41	7.96	19%	2	50	31	69	34.96	1.27	8.33	4%	5	20	10	28
200	47.58	1.74	6.88	14%	4	50	30.5	60.5	38.39	1.45	8.65	10%	6	33.33	21.75	45.25
300	66.56	1.76	6.55	23%	4	75	59.75	91.75	49.03	1.26	8.65	6%	10	30	24	35.25
400	46.44	1.69	7.21	6%	4	100	85.75	108.75	57.19	1.35	8.24	8%	13	30.77	19	39
500	59.86	1.87	8.64	25%	5	100	51	149	68.45	1.22	9.96	13%	15	33.07	23.5	40.5

Table 1: Simulation results for DRT Module and DRT EQ
Abbreviations: VKT (Vehicle Kilometers Traveled), δ (Average customer experienced distance detour), $\overline{\text{WT}}$ (Average Waiting Time at Train Station in minutes), MC (Missed Connection Ratio), # Veh (Number of Vehicles), ρ (Average Passengers per Bus, with $\rho_{25,75}$ as per the respective percentiles).

Results

Table 1 shows the results across multiple instances of the DRT Module against our DRT EQ. All these results have been collected by analyzing the output of the last i^{PRC} for both models, assuming that both reached equilibrium conditions at that stage. In the results, the Vehicle Kilometers Traveled (VKT) of DRT EQ remains consistently lower than that of DRT Module across different population sizes, along with a lower ρ. For instances 400 and 500, the DRT Module provides lower VKT compared to the DRT EQ., mainly due to the choice of a lower vehicle count use. Nonetheless, we can observe that δ, computed as the actual travel distance divided by the beeline distance, keeps trending up to 1.87 for the DRT Module, while it fluctuates stably under less than 1.5 for the DRT EQ This can be explained by the heuristic employed in this study (Ma et al. (2024)), which has specific constraints that restrict δ ($\delta \leq 1.5$), as reflected in Table 1. While this constraint increases the number of used vehicles, it lowers δ leading to a better customer experience. Moreover, the higher δ for the DRT Module is also reflected in the higher $\rho_{25,75}$, which tends to spread more as the instance increases. This translates into higher δ for the DRT Module's clients and a more unbalanced fleet utilization from the provider's perspective. Regarding the average Waiting Time ($\overline{\text{WT}}$), we computed it as per the difference between customers' actual train departure time and their arrival time at the station. We specify *actual* as the train departure that they preferred might be different from the one they actually manage to take. In this case, this is considered a Missed Connection (MC) due to DRT delays.

Figure 2 further explores the distribution of $\overline{\text{WT}}$ over the different instances, paired with the MC ratio. The $\overline{\text{WT}}$ of our DRT EQ tends to remain more consistent across all iterations, with $\overline{\text{WT}}$ of DRT Module tending to disperse more, especially in the more stressful instances (300,400,500). While the dispersion might not look as great, we want to remind the reader that the $\overline{\text{WT}}$ is computed based on the *actual* train departure, not the preferred one. This, paired with the constant growth of the MC ratio, highlights the struggle of the DRT Module to serve clients adequately, with MC peaking at 25% for the DRT Module at higher population densities, while the DRT EQ tends to remain more stable, peaking at 13% for the 500 instances.

4. Discussion

What is evident (and expected) is that fixing the DRT routes and letting the system "rotate" around it, adapting the routes through an iterative approach, provides stability in exploring the solution space, facilitating agent convergence without the uncertainty of dynamically changing routes, which can be seen by more consistent results from the DRT EQ compared to the DRT Module. Moreover, the stability offered by our approach confirms that the initial estimations from the metaheuristic remain effective under equilibrium conditions, at least for this small test case. This, paired with more consistent $\overline{\text{WT}}$, lower MC, and σ, means that our

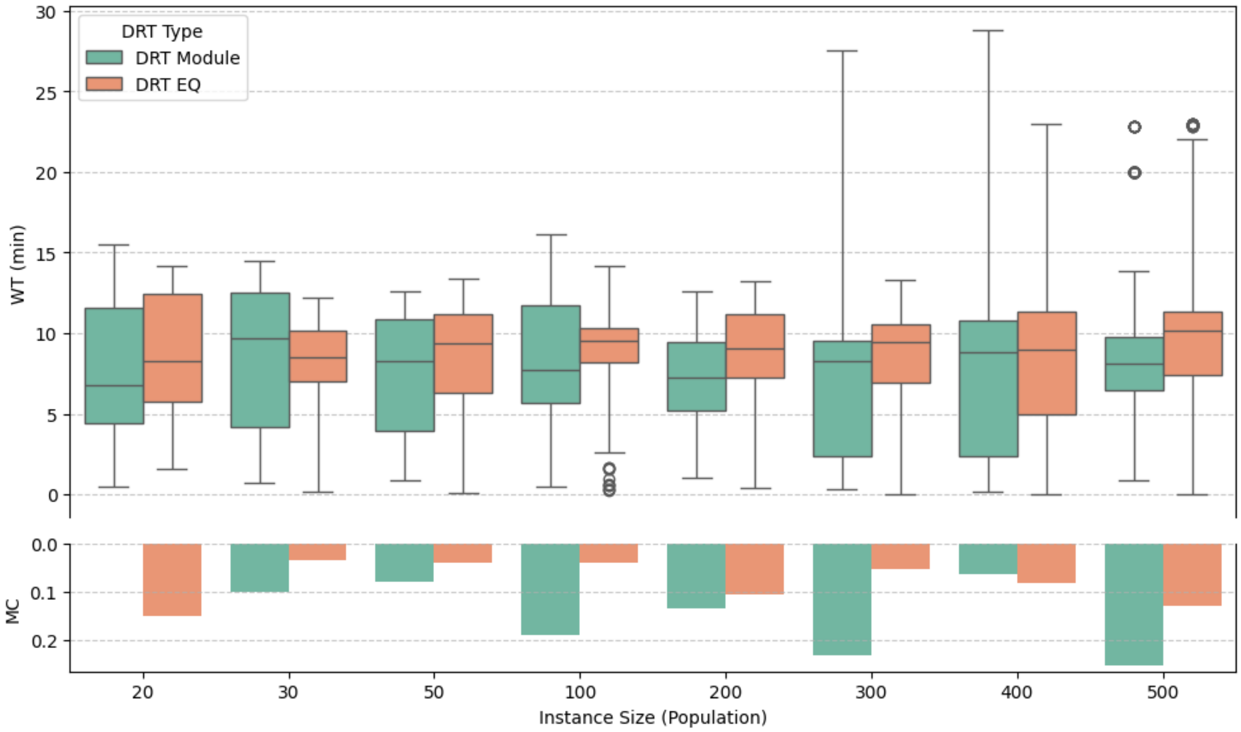

Figure 2: $\overline{\text{WT}}$ and MC distribution across instances.

DRT EQ provides a more satisfactory experience for the clients. Nonetheless, the higher VKT and vehicle used might mean more cost for the service provider, which is still balanced by a more compact distribution of passengers per bus. This can be justified by the model of Ma et al. (2024), as it sets maximum ride time constraint and maximum waiting time constraint to ensure customer convenience. The same discourse on the objective function can be done for the DRT Module, as it is interesting to point out that, while it had the chance to use more vehicles (as per the implementation described in Section 2, Step 3.1) it just opted not to use it. This behavior can be explained by the objective function that this module tries to seek, as per Maciejewski and Nagel (2012).

One last point that is important to raise is that the limitations in MATSim's network representation led to discrepancies in travel speeds and distances for our small-scale study. First of all, the DRT Module operates at car network free-flow speeds, which differs significantly from our DRT EQ, capped at 6.94 m/s to align with metaheuristic results. This led us to exclude time-related KPIs and trips with data errors—such as traveled distances shorter than Euclidean distances—which minimally impacted the presented KPIs as per Table 1.

5. Conclusions

In this paper, we presented an alternative approach to DRT modeling in MATSim called DRT EQ, an iterative procedure whose aim is to model DRT routes as fixed, changing them across different MATSim simulations. Our approach differs from the DRT Module mainly in route handling. While the DRT Module dynamically adjusts routes each iteration based on real-time demand, our DRT routes remain fixed throughout each i^{MTS}, generated from a metaheuristic solution and treated like conventional bus lines with scheduled stops. This allows us to evaluate the DRT system at equilibrium, testing whether the initial estimations remain optimal under user equilibrium conditions in MATSim. Moreover, the DRT EQ not only allows for in-house models to be tested within the MATSim environment, but also the inclusion of real-world operational constraints, like for

EV charging stations, by treating them as bus stops that impact travel times, features that the DRT Module is missing. Future studies should include tests on larger scenarios, the implementation of real customer demand, and the consideration of external factors such as passing through traffic.

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ACKNOWLEDGMENT

We would like to acknowledge the EU projects ACUMEN (N. 101103808) and ODIN (European Regional Development Fund – Programme ERDF “investissement pour la croissance et l’emploi” 2021-2027).