EVALUATING DEMAND-RESPONSIVE TRANSPORT MODELS AT EQUILIBRIUM IN MATSIM

Federico Bigi*, Yumeng Fang, Francesco Viti
Faculty of Science, Technology and Medicine (FSTM)
University of Luxembourg, Esch-Sur-Alzette, Luxembourg, L-4364
Email: federico.bigi@uni.lu
* Corresponding author

Introduction

In recent years, cities have struggled with growing complexity in urban mobility due to sprawl, population increases, and environmental concerns. Demand-responsive transport (DRT) has emerged as a flexible solution for meeting changing travel needs, as it has the potential to complement public transport (PT) and reduce reliance on private vehicles. In parallel, PT operators are increasingly deploying electric vehicles (EVs), which require more detailed modeling to account for charging constraints and other operational factors.

In MATSim ([Horni et al., 2016]), the DRT system is implemented through a contribution available and is widely used ([Maciejewski and Nagel, 2012, Ciari et al., 2016]), but its current state of continuously recalculating routes in response to evolving agent choices can impede the system from reaching equilibrium ([Ciari et al., 2009]). Furthermore, the current DRT Module limits the integration of external algorithms, which is one of the main challenges restricting researchers who wish to test tailored optimization solutions.

To address these limitations, we propose an iterative procedure, DRT Equilibrium (**DRT EQ**), which separates the computation of DRT routes from within-day simulation. Instead of continuously rerouting DRT in each MATSim iteration, our approach uses multiple MATSim runs — each reflecting equilibrium travel demand — to successively refine the DRT routes until convergence. By treating the DRT network as a fixed transit service at each iteration, it becomes easier to incorporate real-world constraints (e.g., charging stations, depots), while also allowing researchers to insert and test any desired optimization model.

Methodology

The DRT EQ procedure integrates an external DRT optimization model into MATSim to incorporate optimized routes and reach user equilibrium (ideally and hopefully) more efficiently than the standard DRT Module.

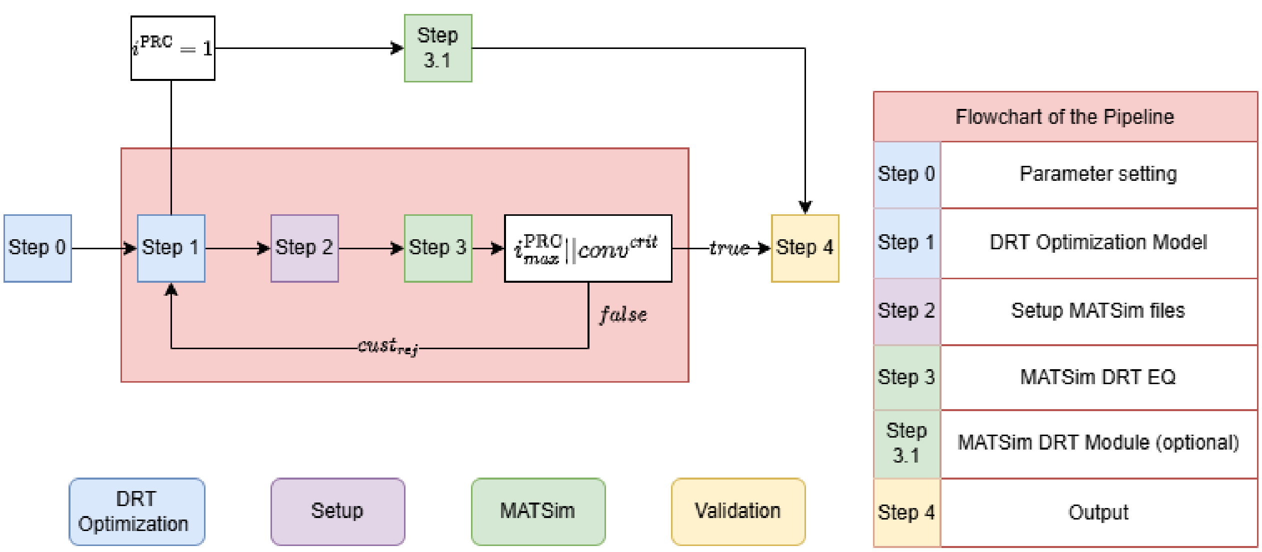

Figure 1: Flowchart of the DRT EQ.

Figure 1 shows the flowchart of the iterative procedure.

- **Step 0** (*Parameter Setup*) defines core parameters, including the number of MATSim iterations (i^{MTS}), the maximum number of procedure iterations (i^{PRC}_{max}), and convergence criteria ($conv^{crit}$).
- **Step 1** (*Optimization Model*) solves the DRT model given agent data (departure times, pickup points, destinations), producing bus routes and vehicle assignments.
- **Step 2** (*Integration with MATSim*) converts the optimized routes into MATSim-compatible inputs. First, the DRT solution is represented as traditional bus lines (*DRT EQ*, with stops and recharging points, if needed). Next, a MATSim population is created, embedding the DRT option in agent plans.
- **Step 3** (*MATSim Simulation*) we run a MATSim simulation to equilibrium. Agents satisfied with the DRT (i.e., those who used the DRT EQ in the final MATSim solution) are retained for the next iteration, while those who did not are flagged as *rejected* ($cust_{rej}$) and fed back into Step 1.
- **Step 3.1** (*Comparison with DRT Module*) optionally runs a single simulation using the original DRT Module with the same demand and vehicle specifications using data from $i^{\text{PRC}} = 1$. This allows a fair comparison of convergence and performance between the two approaches.
- **Step 4** (*Post-Processing*) compiles final key performance indicators (KPIs).

Steps 1 to 3 are iterated until either i^{PRC}_{max} or $conv^{crit}$ is reached.

Case Study, Results, Discussion

For this study, we focused on Contern, Luxembourg, where a train station connects travelers to Luxembourg City and Trier (Germany). The local industrial area generates a strong afternoon peak, motivating a first/last-mile DRT system to link workplaces with trains better. Customer locations are generated close to the companies in the area, and customers' preferred transit departure times are randomly assigned. For Step 1, we use the metaheuristic from [Ma et al., 2024], which restricts the maximum distance detour ($\delta \leq 1.5$). Population sizes range from 20 to 500, with $i^{\text{PRC}}_{max} = 50$, and $conv^{crit}$ as per [Yang et al., 2024], stopping when DRT-trip counts stabilize within 3% between iterations. Both the DRT EQ and DRT Module simulations use identical scoring functions, heavily penalizing late arrival to the train station. For each instance, DRT EQ runs for 400 i^{MTS} and the DRT Module for 900 i^{MTS}. All vehicles feature unlimited capacity, and the DRT service window is 15:58–18:30.

	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).

Table 1 compares final-iteration performance for the current DRT Module contrib. and DRT EQ. Overall, DRT EQ achieves consistently lower vehicle kilometers traveled (VKT). Although the DRT Module sometimes presents lower VKT at higher populations (400, 500), it shows larger customers experienced detours, increased unused capacity spread ($\rho_{25,75}$), and more missed connections (MC).

Now, it is clear that fixing DRT routes and iterating until equilibrium brings more stable outcomes than constantly rerouting. DRT EQ confirms the metaheuristic's effectiveness under equilibrium, as it shows lower MC and more consistent $\overline{\text{WT}}$, bringing through a higher vehicle usage. This difference stems from the constraints in [Ma et al., 2024], which cap δ and $\overline{\text{WT}}$, while the DRT Module from [Maciejewski and Nagel, 2012] tends toward fewer vehicles but higher MC, highlighting also how the DRT model's assumption propagates in MATSim. Finally, MATSim's network assumptions — particularly free-flow car speeds for the DRT Module versus a 6.94,m/s cap in our DRT EQ — limit direct time-based comparisons. Although trips with inconsistencies (e.g., distances shorter than Euclidean) were excluded, the main findings in Table 1 remain robust.

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, a repository on github that would allow an easy integration with the current ecosystem .

References

[Ciari et al., 2016] Ciari, F. ., Balać, M. ., and Axhausen, K. W. (2016). Modeling carsharing with the agent-based simulation MATSim State of the art, applications, and future developments. *Transportation Research Board*.

[Ciari et al., 2009] Ciari, F., Balmer, M., and Axhausen, K. W. (2009). Large scale use of collective taxis A multi-agent approach.

[Horni et al., 2016] Horni, A., Nagel, K., and Axhausen, K. W. (2016). *The Multi-Agent Transport Simulation MATSim*.

[Ma et al., 2024] Ma, T. Y., Fang, Y., Connors, R. D., Viti, F., and Nakao, H. (2024). A hybrid metaheuristic to optimize electric first-mile feeder services with charging synchronization constraints and customer rejections. *Transportation Research Part E: Logistics and Transportation Review*, 185:103505.

[Maciejewski and Nagel, 2012] Maciejewski, M. and Nagel, K. (2012). Towards multi-agent simulation of the dynamic vehicle routing problem in MATSim. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 7204 LNCS(PART 2):551–560.

[Yang et al., 2024] Yang, H., Wong, E., Davis, H., and Chow, J. Y. (2024). A co-simulation system that integrates MATSim with a set of external fleet simulations. *Simulation Modelling Practice and Theory*, 134:102957.