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Efficient operation of demand-responsive transport (DRT) systems: Active requests rejection

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Abstract

Demand-responsive transport (DRT) is getting more attention in the public sectors. In DRT systems operated by public sectors, providing a good and equal service to the public is more important than maximizing the revenue. This brings additional challenges to the operation of DRT systems. In this study, we explore the idea of actively rejecting requests in DRT systems based on the alternative travel options, such as conventional public transport. By rejecting requests that have good alternatives, we can focus on the passengers without suitable alternative travel options. This can reduce the fleet size of DRT systems while maintaining a good and fair service. To explore the impact of this idea, we develop and implement an active request rejection mechanism in an agent-based transport simulation framework and carry out simulations on a real-world scenario. Results have shown that a fleet size reduction of around 20% can be achieved, without compromising the overall mobility level in terms of travel time, if the active request rejection mechanism with dynamic threshold is used. Furthermore, results have also shown that when a DRT system is overloaded, it may break down, and the service quality will suffer a significant drop. The active request rejection mechanism can prevent this from happening in some cases.

Keywords: Demand-responsive transport (DRT); Integrated transport system; Equality in mobility service

1. Introduction

Demand-responsive transport (DRT) is a popular topic in the field of transportation. Ranging from taxi-style service to ride-pooling and on-demand buses, DRT service of different kinds can be found almost everywhere around the world. While the majority of the DRT services are currently operated by taxi companies and ride-hailing service providers (e.g., Uber, Lyft, DiDi), public sectors are also showing more and more interest in this field. For example, in Germany, there are several pilot projects, where DRT service is operated by the local authority or public transport (PT)

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provider: In Kelheim, a small town in Bavaria, a small-scale DRT service called KEXI is popular among the residents. Consisting of both human-driven and autonomous vehicles, the service is being extended under the framework of KelRide project[1]; in Rendsburg, Schleswig-Holstein, a fleet of several cars and minivans provides on-demand mobility services during the night[2]; in Hamburg, the transport authority is integrating the DRT service operated by a private company into the public transport system[3].

When the DRT service is operated as a public service, making profits will no longer be the main goal for the operators. Instead, adequate attention should be paid to other aspects, such as improving the accessibility of the residents and providing equally good service across the whole service area [19, 23]. Unlike private operators who can simply reject requests that are less profitable or difficult to serve, a DRT service operated by the public sector should not discriminate against customers in such a way. Furthermore, the necessity for public operators to provide affordable DRT services introduces additional operational challenges, particularly in financial aspects. Financial support from the authority is usually crucial in this kind of DRT services. For example, BVG, the PT provider in Berlin, once operated a DRT service called Berlkönig. The service could not be maintained after the city authority decided to not cover the losses of the operation [16].

To improve the equality of DRT services and improve the overall accessibility of the residents, we can actively relocate empty vehicles. This process is also known as rebalancing, as we are trying to balance out demands and supplies. Several studies have investigated the impact of rebalancing operations. Results have suggested that the rebalancing operations can reduce waiting time and improve the service quality [3, 5, 14]. On the other hand, rebalancing will also lead to extra driving distance, which will incur more operational costs.

To increase the efficiency of the DRT fleet and thus to reduce the operational costs, we can encourage passengers to pool their rides and pre-book their trips. With ride pooling, a smaller fleet can serve the same number of passengers and the total fleet travel distance can be reduced [1, 18]. This leads to a reduction in the cost to operate and maintain a DRT system. With pre-booking, the vehicle routing algorithm will have more room and time to explore a better solution. One study has shown that the total operational cost of a DRT system for school children in a rural area can be reduced by 35% when trips are pre-booked [10]. With a rolling horizon approach, a similar level of cost savings can also be reached with a pre-booking time of (only) 30 minutes [11, 12]. Furthermore, pre-booking can also play a beneficial role in the mixed case, where both pre-booked and spontaneous requests exist [4].

While the studies mentioned above focus on improving the efficiency and service quality of the DRT system via vehicle operation and vehicle routing, recent studies on DRT systems have focused on improving efficiency through strategic prioritization of DRT requests. These include algorithms for prioritizing requests in high-demand areas [15], zones with high rejection rates [20], based on available alternative mode, and urgency [21, 22]. However, these approaches do not fully address operational challenges due to variable demand and limited supply.

To bridge this gap, this study explores the idea of active request rejections in DRT operations. This method involves rejecting requests when good alternative travel options are available, such a good PT connection. By doing so, the capacity of the DRT fleet can be reserved for passengers who do not have good alternative travel options. The overall accessibility of the residents can therefore be improved. To examine the impact of the active request rejection on DRT systems, we implement this idea in an agent-based simulation framework. Systematic experiments are conducted in a real-world scenario, followed by detailed analysis. All the code implementations, as well as the input data, are open-sourced and publicly available[4].

2. Methodology

The active requests rejection mechanism filters out travel requests with good alternative options, such that those requests will not enter the DRT system. In this study, we consider PT and walking as the alternative options. An alternative option is considered a good option if the total travel time to take the alternative option is lower than a certain threshold. The threshold is determined based on the potential travel time if DRT is used. The threshold can

[1] https://kelride.com/en
[2] https://nahshuttle.de/en/home-2/
[3] https://www.hamburg.com/getting-around/15678904/moia/
[4] https://github.com/matsim-vsp/accessibility-drt-optimizer

either be a fixed one, or a dynamic one which varies throughout the day depending on the workload of the DRT system.

To examine the impact of the active requests rejection mechanism, we incorporate it into a new DRT operational strategy and then perform simulations in MATSim, an open-source agent-based transport simulation framework [6]. The DRT extension in MATSim enables the simulation of the DRT system [13].

A basic vehicle dispatching algorithm that supports ride-pooling is available in the MATSim DRT extension. Our new operational strategy with active rejection is built based on this algorithm. When a travel request is submitted, the algorithm tries to insert the requests into a vehicle such that this leads to a minimum additional workload (i.e., driving time). In order to maintain a reasonable service quality, constraints on the waiting time and the total travel time are imposed. When performing insertion, passengers need to be picked up within the maximum waiting time constraint. This applies to the passengers currently being processed, as well as the accepted passengers who are waiting to be picked up. In this study, the maximum waiting time is set to 600 seconds (i.e., 10 minutes). In addition, the total travel time, including waiting time and onboard riding time, should be lower than the maximum total travel time. The maximum total travel time is calculated as in Equation 1:

$$t_{max} = \alpha \cdot t_{direct} + \beta, \tag{1}$$

where t_{direct} is the travel time of a direct trip by car. α and β are parameters to be tuned. In this study, α is set to 1.5 and β is set to 900 (seconds). Apart from the waiting time and travel time constraints, there is also a vehicle capacity constraint: a vehicle should never be overloaded during the operation.

While the vehicle capacity is a hard constraint, the waiting time and total travel time constraints can either be hard or soft constraints. When they are implemented as hard constraints, then a request will be rejected if there are no suitable vehicles. On the other hand, the two time-based constraints can also be implemented as soft constraints. In this case, an insertion is still considered feasible even if the time constraints are violated. Instead, a penalty will be given according to the amount by which the constraints are violated. With that, rejections of requests will not happen unless the requests cannot be finished by the end of DRT service hours. As in many other studies on the topic of DRT in transportation planning, we opt for the soft constraints approach [2, 7]. This is because, with our newly implemented feature, we already filter out requests with good alternative travel options. For the requests that have passed through the filter, we should try to serve all of them and do not make additional rejections due to the time-based constraints. As we are treating the DRT as a public mobility service in this study, it is desirable to provide good mobility solutions to all the users.

In addition to the vehicle dispatching algorithm, there are also rebalancing strategies in the MATSim DRT extension [9]. In the present study, the min-cost-flow rebalancing strategy is used [3]. This rebalancing strategy tries to maintain a distinct number of free vehicles in each zone while minimizing the extra driving time caused by rebalancing. The target value for each zone is calculated as in Equation 2:

$$T_i = TargetAlpha \cdot n_{i,est} + TargetBeta, \tag{2}$$

where $n_{i,est}$ is the number of expected departures in zone i. For the present study, $TargetAlpha$ is set to 0.2 and $TargetBeta$ is set to 0.8. The rebalancing algorithm will be called every 15 minutes.

Then we define the criteria to determine whether a passenger should take the alternative travel option. The logic shown in Equation 3 is used to actively reject travel requests that should take the alternative option:

$$\text{Active rejection} = \begin{cases} True, & \text{if } t_{alt} \leq \gamma \cdot t_{max} \\ False, & \text{otherwise} \end{cases} \tag{3}$$

t_{alt} is the fastest travel time of the alternative mode for the travel request. $\gamma \in [0, 1]$ is the threshold, which can be a fixed value or a time-varying value, and in that case it will become $\gamma(t)$. t_{max} is the maximum allowed total travel time as calculated in Equation 1. A $\gamma = 1$ thus means that in cases where PT is slower than t_{max}, then DRT is "permitted". A $\gamma = 0.8$ (say) means that in cases where PT is slower than $0.8 \cdot t_{max}$, then DRT is "permitted". Etc.

When simulating a dynamic threshold, an iterative approach is used to determine $\gamma(t)$. We first discretize the time into 15-minutes time bins. At time bin k, the threshold $\gamma(t_k)$ is calculated by Equation 4:

$$\gamma(t_k) = \left\langle \frac{t_{i,actual}}{t_{i,max}} \right\rangle_k , \tag{4}$$

where the average $\langle ... \rangle$ is taken over all departures during time bin k. $t_{i,actual}$ is the actual total travel time of the request i and $t_{i,max}$ is the maximum allowed total travel of the request calculated based on Equation 1. That is to say, we will reject a travel request if the alternative option is faster than the average total travel time when taking DRT. Since the number of requests we actively reject will also impact the average total travel time of DRT trips, we determine $\gamma(t)$ iteratively. Here we introduce the term $\gamma^*(t_k, j)$, which represent the $\gamma(t)$ at iteration j. Starting from $\gamma^*(t_k, 0) = 0$ for all t_k, the values of $\gamma^*(t_k, j)$ is updated based on Equation 5:

$$\gamma^*(t_k, j + 1) = \lambda \cdot \gamma(t_k, j + 1) + (1 - \lambda) \cdot \gamma(t_k, j), \tag{5}$$

The term $\lambda \in (0, 1]$ is the learning rate of the iterative approach. Based on some preliminary experiments, λ is set to 0.05 in this study. With this setup, 200 iterations are adequate to stabilize the value of $\gamma^*(t_k, j)$.

3. Experiments and results

3.1. Experiments setup

As mentioned in Section 1, the main goal of a DRT system operated by the public sector is to provide good and fair mobility to all the residents in the service area. The following two evaluation criteria will be used in the experiments: the overall satisfaction rate and the system total travel time. A trip is defined as satisfactory if the total travel time is smaller than the t_{max} defined in Equation 1. A satisfactory trip can either be served by a DRT vehicle, or an alternative option is used. That is to say, when active rejection mechanism is enabled, we assume that rejected requests will take the best alternative option (i.e., either PT or walking). This also applies when we calculate the system total travel time. On top of the main criteria, we will also look at the vehicle utilization rate under different setups.

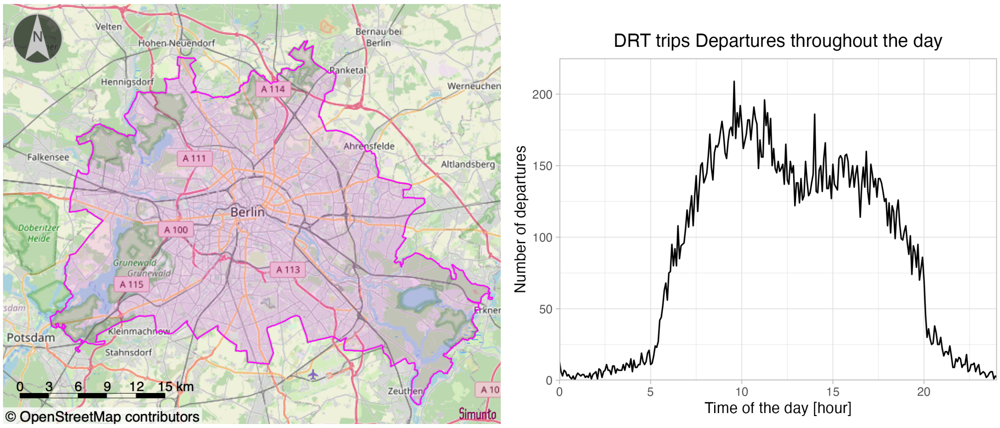
In the experiments, the fleet size and the γ are varied. We first perform experiments with fixed rejection threshold (i.e., with fixed values of γ). When $\gamma = 0$, there will be no active rejection, which is equivalent to the case where the default operational strategy is used, and this will be the benchmark case. Then we perform simulations with γ equals to 0.2, 0.4, 0.6, 0.8 and 1.0. Finally, we perform simulations with dynamic rejection threshold, i.e., with $\gamma(t)$.

For each γ, we vary the fleet size and observe the outcome. Generally, the more vehicles there are, the better the performance will be. On the other hand, a larger fleet means higher costs. To reach a balance between the service quality and the costs, we aim for an overall satisfaction rate of 95%. Note that the value of γ is never greater than 1, which means that a request will not be rejected if there is not a satisfactory alternative option.

3.2. Simulated scenario

In this study, we perform experiments on the Berlin scenario, which is based on the real-world transport data of the city. The DRT demands in Berlin scenario are derived from the 10 percent population model of the Open Berlin Scenario, version 5.5 [24]. The demands are generated based on the hypothetical case where an adequately large DRT fleet is introduced to the city of Berlin, with ride-pooling enabled. After the standard MATSim iterative process, it ends up with 24988 DRT trips (for the 10% scenario). Those trips represent potential DRT users in Berlin, and are very suitable for this study. Figure 1 illustrates the Berlin DRT scenario. The service area is shown in 1a, which is also the city boundary of Berlin. Figure 1b shows the temporal distribution of DRT trips throughout the day. The values shown on the plot are aggregated to 5-minutes time bins. The DRT demands are also available in the MATSim DRT scenario library [8].

As the focus of this study is to develop the active request rejection mechanism and quantify the potential impact of that mechanism on the DRT system as well as the accessibility of the people, we use fixed demands in the simulations. The exclusion of the mode choice model enables a better quantitative analysis of the operational strategy. It also



(a) DRT service area

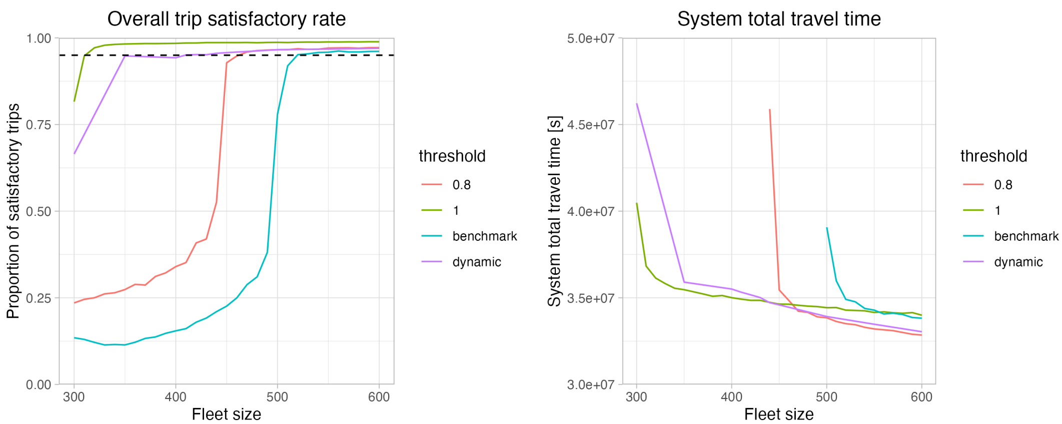
(b) DRT trips departures (aggregated to 5-minutes time bin)

Fig. 1: Illustration of the Berlin DRT scenario

reduces the required simulation time, as we do not need to wait for the convergence of the mode choice. This enables more systematic experiments on the parameters of the active rejection mechanism.

3.3. Results and analysis

Based on the evaluation criteria mentioned in Section 3.1, the main results of the simulations are summarized in Figures 2 and 3. Table 1 summarizes some of the key results numerically. The results of fixed threshold cases with $\gamma = 0.2$, 0.4 and 0.6 are very close to the benchmark case and are therefore omitted on the plots for better illustration purposes. This means that the alternative travel options (PT and walk) are rarely if ever faster than $0.6 \cdot t_{max}$.



(a) satisfaction rate

(b) System total travel time

Fig. 2: Overall satisfaction rates of all trips

Figure 2 shows the overall satisfaction rates. A target value of 95% is indicated by a black dotted horizontal line in the plots. With this, the minimum fleet size under each setup can be determined. From the results, it can be seen that, compared with a "serve everybody" strategy, the minimum fleet size can be reduced by 9.6%, when $\gamma = 0.8$; and by 38.5%, when $\gamma = 1.0$; and by 21.2%, when a dynamic threshold is used. The shapes of $\gamma(t)$ at different fleet sizes can be found in Figure 4 below.

For fixed γ values, the required fleet size reduces as the value of γ increases. This is reasonable, as more requests are actively rejected when the threshold is higher, and the burden on the DRT system becomes smaller. With a dynamic

Table 1: Summary of experiments results

	Benchmark	$\gamma = 0.2$	$\gamma = 0.4$	$\gamma = 0.6$	$\gamma = 0.8$	$\gamma = 1.0$	Dynamic
Minimum overall satisfaction rate = 95%							
Min fleet size	520	520	520	520	470	320	410
Total system travel time [$10^7 s$]	3.49	3.50	3.47	3.46	3.42	3.61	3.53
Average requests per vehicles	48.0	48.0	47.9	47.0	45.6	41.8	50.8
With a fixed fleet size of 550 (i.e., with an adequate supply)							
Total system travel time [$10^7 s$]	3.43	3.43	3.43	3.41	3.32	3.41	3.35
Average requests per vehicles	45.4	45.4	45.3	44.4	39.0	24.3	41.4

threshold, the overall satisfaction rate curve is located between $\gamma = 0.8$ and $\gamma = 1.0$. A higher overall satisfaction rate means good accessibility for the public. Therefore, when the DRT fleet is limited, it is an effective way to maintain the overall accessibility by actively rejecting requests with good alternative options.

Figure 2b shows the system total travel time. The system total travel time decreases as the fleet size increases under all the setups. When the fleet size is adequately large (i.e., larger than 520), an appropriate fixed threshold (e.g., $\gamma = 0.8$) and dynamic threshold lead to a lower system total travel time, compared to the benchmark case. This suggests that by actively rejecting some requests that have good alternative travel options, we can actually improve the social benefits, in terms of travel time.

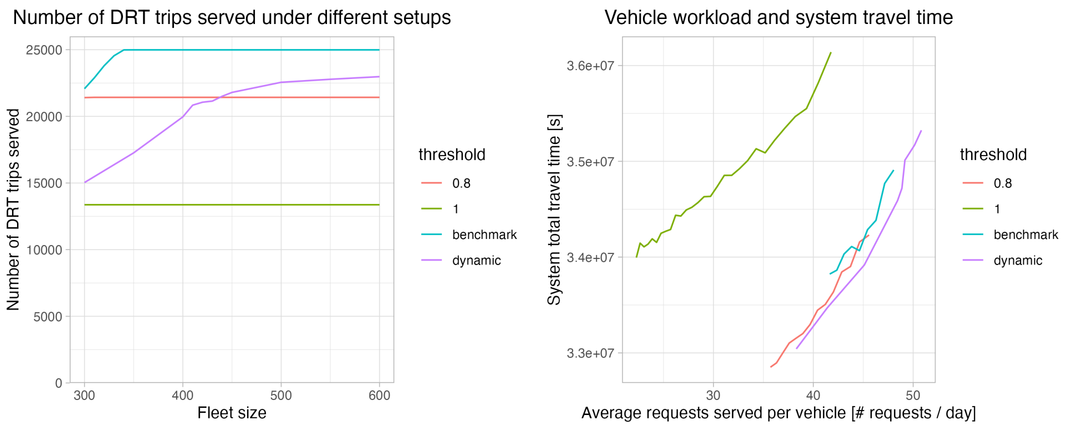
One interesting observation from the two plots in Figure 2 is that the system breaks down when the fleet size reaches a critical value. When the critical fleet size is reached, a further reduction in the fleet size will lead to a significant drop in the overall satisfaction rate and a very large increase in the system total travel time.

Figure 3 demonstrates the workload of the DRT system under different setups. Figure 3a shows the number of DRT trips served with different thresholds. With fixed thresholds, all the requests that pass through the initial screening process will be served. Therefore, the number of DRT trips served remains constant, unless the fleet size too small to complete all the requests before the end of the day. With a dynamic threshold, the number of DRT trips served increases with the fleet size. This is because a larger fleet size will reduce the average total travel time of the DRT system. This will lead to a lower threshold value, and thus more travel requests will be accepted. In addition, it is also worth pointing out that with a threshold of 0.8, around 86% of the total trips are served by DRT vehicles; while with a threshold of 1.0, only around 53% of the total trips are served by DRT vehicles.

In the simulations, the average direct travel distance of the requests remains relatively constant. Therefore, the average number of requests served by a vehicle is a good indication of the workload. Figure 3b shows the relation between the average work load of vehicles and the system total travel time under different setups. To only show feasible setups, the lines are cut off at the minimum required fleet sizes. A higher workload indicates a better utilization of the fleet. On the other hand, we should also try to keep the system total travel time low. Therefore, data points in the bottom right corner are desired. From the plots, it can be seen that the dynamic threshold has the best performance if we look at the system total travel time and the average workload at the same time. With a dynamic threshold, more travel requests will be accepted when there is adequate capacity from the DRT fleet. This increases vehicle utilization compared to the cases with fixed thresholds.

Now we will take a closer look at the dynamic threshold approach. The iterative process to determine dynamic thresholds and the resulting shapes of the $\gamma(t)$ are summarized in Figure 4a. From the plot, we can see that the system reaches a steady state by the end of the iteration process for all fleet sizes. A large fluctuation in the satisfaction rate can be observed for the fleet size of 400. At some points, the satisfaction rate will suddenly drop significantly, which indicates that the system is at the boundary of the break-down point. This phenomenon is somewhat similar to the network break-down effect when identifying the user equilibrium with the iterative approach [17]. With an adequate supply, the large fluctuations in the satisfaction rate are no longer observed.

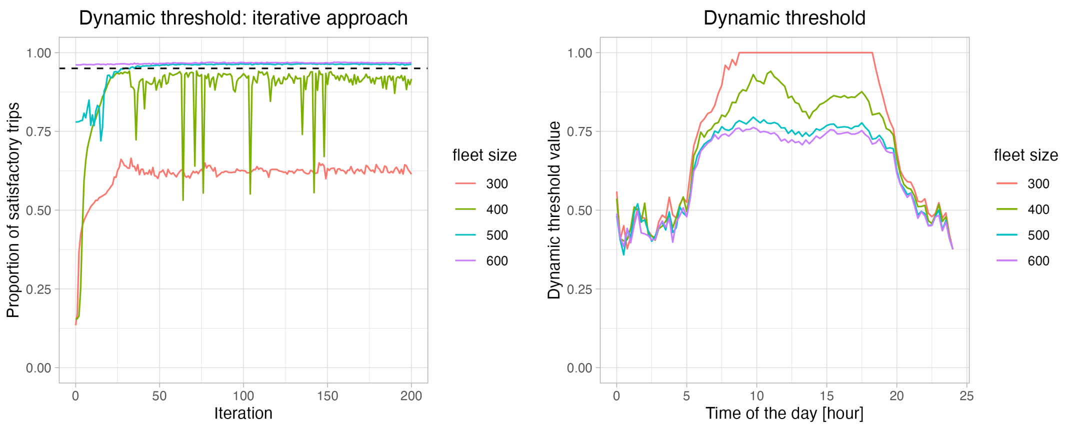
Figure 4b shows the resulting values of $\gamma(t)$ throughout the day. The $\gamma(t)$ is acquired from the iteration with the best results in terms of overall trip satisfaction rate. As expected, the threshold is generally lower with a larger fleet size, indicating that more travel requests will be served by DRT vehicles. If we look at Figure 1b and 4b side by side, we can find out that the peaks in the number of departures roughly match the peaks in the dynamic threshold. If the fleet size is not large enough (i.e., in fleet size = 300 case), the dynamic threshold will remain at 1.0 until the number of departures becomes significantly lower.



(a) Number of DRT trips served

(b) DRT workload versus system total travel time

Fig. 3: DRT system workload analysis



(a) Iteration summary

(b) Value of $\gamma(t)$ throughout the day

Fig. 4: Summary of experiments results with dynamic threshold, Berlin scenario

4. Discussion

From the results, we can see that active request rejection is effective in reducing fleet size, while preserving the accessibility of the system. As the result analysis focuses on the DRT operational side, we include a comparison plot of the accessibility throughout the system. To quantify the accessibility, we introduce the term travel time index. The travel time index is calculated similarly to the dynamic threshold (Equation 4). But rather than aggregating the values in time, we aggregate the values in space. For the Berlin DRT scenario, a 2 km by 2 km square grid is suitable for the spatial aggregation. For each cell in the grid, we calculate the average value of $t_{i,actual}/t_{i,max}$ for all the trips departing from that cell. Then we can illustrate the spatial distribution of the accessibility. The results are summarized in Figure 5.

On the top left of Figure 5, there is no DRT service in the area and all the trips have to be made with the alternative modes (i.e., either PT or walk). As can be seen from the figure, in many of the cells, the average travel time exceeds the 1.0 limit. In the city boundary area, the accessibility is generally worse than in the city center.

Comparing the benchmark with 520 vehicles (top right) and the dynamic γ with 410 vehicles (bottom right), we can see that a similar level of accessibility can be reached with a smaller fleet, if we actively reject travel requests that have good alternative options. On the other hand, if we compare the benchmark with 410 vehicles (bottom left) and

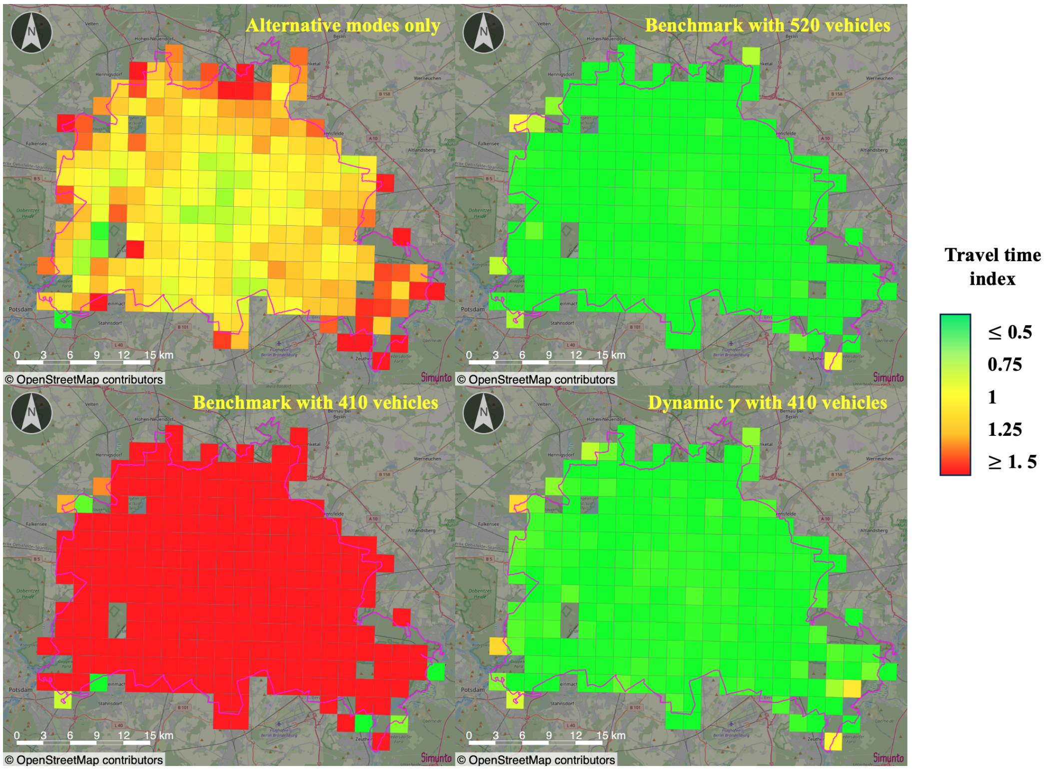


Fig. 5: Spatial distribution of the accessibility under different setups, Berlin scenario

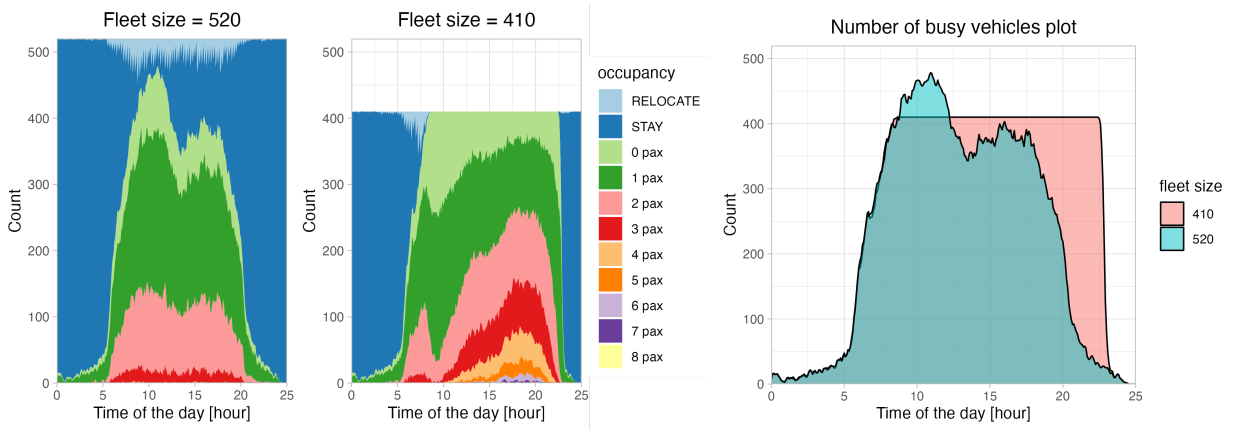
dynamic γ with 410 vehicles (bottom right), a huge improvement in the accessibility can be observed by switching on the active request rejection mechanism.

It can also be noticed in the Figure 5 that the benchmark with 410 vehicles (bottom left) is even much worse than the alternative modes only case (top left). This brings us to the next discussion point: the breakdown of the DRT system. When inserting requests into vehicles, if soft constraints are used (i.e., no rejections due to violation of time constraints), the DRT system will behave poorly when the workload exceeds a certain limit. Furthermore, the significant drops in trips satisfaction rate and the steep increases of system total travel time in Figure 2 indicate that there is a tipping point: if the critical value is reached, the breakdown will happen suddenly.

To better understand this breakdown effect, we plot the fleet status for the benchmark cases in Figure 6. We use the fleet size of 520 and 410, which correspond to the two benchmark cases shown in Figure 5. In Figure 6a, the detailed occupancy plots are shown. In Figure 6b, the number of busy vehicles for the two cases are plotted on the same figure, such that they can be compared more easily. Note that the term busy vehicles refer to vehicles that are driving with passengers, picking up or dropping off passengers, and driving to passengers. Rebalancing vehicles are not included, as they are not associated to any customers.

From the plots in Figure 6, we can see that with a fleet size of 520 the DRT system is working properly. The patterns of the number of departures throughout the day can be roughly reflected in the vehicle occupancy plot and the number of busy vehicles plot. Besides, there are still some freely disposable vehicles, even during the highest peak. When the fleet size is reduced to 410, the fleet occupancy and the number of busy vehicles plot are no longer synchronized with the number of departures from around 9 am. At that time, all the vehicles are busy. Because of that, most of the departures have to be delayed. This lead to a drop in the overall trip satisfaction rate and the prolonged total travel time. Because of the relatively high workload during the afternoon, the whole fleet is busy until the end of the day.

The areas below the curves in Figure 6b represent the total busy vehicle hours. By comparing the curves, we can observe that the fleet size 410 case has more busy vehicle hours than the fleet size 510 case. More interestingly, it appears that the inadequate supply during the peak time at around 9-12 am lead to a much more additional work



(a) Occupancy comparison (b) Busy vehicles comparison

Fig. 6: A closer look at the fleet status

load in the afternoon and the evening. If there are extra supply during that time, or if some travel requests with good alternative options are actively rejected, then the breakdown could be avoided. The service quality of the system could then be significantly improved, and the total busy vehicle hours could also be reduced.

Because of this breakdown effect of DRT system, special care needs to be taken both in real-world operations and agent-based simulations. In the actual operation, the operator should avoid overloading the DRT system. When demands are reaching the critical value, some actions should be taken. In the short term, active request rejection or increased fare can be an effective way. In the long run, the operator should consider increasing the supply at the bottlenecks. In agent-based simulations with mode choice, the DRT system should stay away from the breakdown point, otherwise agents may have false information about the service quality of the DRT system. Failing to take the breakdown effect of DRT systems into consideration may lead to unrealistic parameters for the DRT mode in the model.

5. Conclusion and outlook

In this study, we develop the active request rejection mechanism and explore the impact of this mechanism on the DRT system. By actively rejecting the requests that have good alternative travel options, we can reserve more capacity for people who have to use DRT to get to the destination within a certain time limit.

Experiments on a real-world scenario have shown that the active request rejection mechanism can reduce the required DRT fleet size, while maintaining a good accessibility for all the residents within the service area. With a dynamic threshold for active request rejection, the required fleet size can be reduced by 21.2%.

The active request rejection mechanism can be particularly useful for DRT systems operated by public sectors or as public service. By taking advantage of the existing PT infrastructure, the cost to operate a DRT system that brings good accessibility to the public can be reduced. Furthermore, unlike most of the existing studies on DRT systems, where request are rejected due to the capacity limit or profitability reasons, the active request rejection mechanism considers the alternative travel options of each travel request, and will not reject any request that does not have viable alternatives. With this, a fairer mobility service can be achieved.

Moreover, the active request rejection mechanism also has an additional advantage: it prevents the DRT system from breaking down. As the workload on the DRT system reaches a critical value, the system is likely to break down. When the breakdown happens, the total travel time in the DRT system will increase significantly, leading to a very unsatisfactory service quality. By enabling the active request rejection mechanism, we can reduce some burden from the DRT system. In some cases, this will prevent the DRT system breakdown from happening.

Based on the positive results of this study, some potential follow-up studies can be identified. Currently, we use the existing PT network and schedules to calculate the alternative travel options. An integrated PT-DRT system can further improve the efficiency of the transport system and improve the accessibility of the public. For example, the low frequency PT routes in the less populated areas can be withdrawn, and the gap can be filled by DRT service. On top of that, intermodal trips can also be included to fully utilize the advantage of small and flexible DRT vehicles and the high efficiency of the conventional PT vehicles. In future studies, further advanced prioritization strategies should be explored, particularly focusing on trips with mobility-impaired individuals, VIPs, and urgent travel needs. Effective prioritization of these specific groups within the integrated PT-DRT system is essential to bridge the accessibility gaps and provide a more inclusive and effectively prioritized transport service.

References

[1] Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., Rus, D., 2017. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. Proceedings of the National Academy of Sciences 114, 462–467. doi:10.1073/pnas.1611675114.

[2] Bischoff, J., Führer, K., Maciejewski, M., 2019. Impact assessment of autonomous drt systems. Transportation Research Procedia 41, 440–446. doi:https://doi.org/10.1016/j.trpro.2019.09.074.

[3] Bischoff, J., Maciejewski, M., 2020. Proactive empty vehicle rebalancing for demand responsive transport services. Procedia Computer Science 170, 739–744. doi:https://doi.org/10.1016/j.procs.2020.03.162.

[4] Engelhardt, R., Dandl, F., Bogenberger, K., 2022. Simulating ride-pooling services with pre-booking and on-demand customers. arXiv preprint arXiv:2210.06972 .

[5] Hörl, S., Ruch, C., Becker, F., Frazzoli, E., Axhausen, K.W., 2019. Fleet operational policies for automated mobility: A simulation assessment for zurich. Transportation Research Part C: Emerging Technologies 102, 20–31.

[6] Horni, A., Nagel, K., Axhausen, K.W. (Eds.), 2016. The Multi-Agent Transport Simulation MATSim. Ubiquity, London. doi:10.5334/baw.

[7] Kaddoura, I., Schlenther, T., 2021. The impact of trip density on the fleet size and pooling rate of ride-hailing services: A simulation study. Procedia Computer Science 184, 674–679. doi:https://doi.org/10.1016/j.procs.2021.03.084.

[8] Lu, C., Maciejewski, M., 2023. The MATSim DRT Scenario Library. doi:10.5281/zenodo.7921064.

[9] Lu, C., Maciejewski, M., Nagel, K., 2020. Effective operation of demand-responsive transport (DRT): Implementation and evaluation of various rebalancing strategies. Working Paper, TU Berlin, Transport Systems Planning and Transport Telematics.

[10] Lu, C., Maciejewski, M., Wu, H., Nagel, K., 2023a. Demand-responsive transport for students in rural areas: A case study in vulkaneifel, germany. Transportation Research Part A: Policy and Practice 178, 103837. doi:https://doi.org/10.1016/j.tra.2023.103837.

[11] Lu, C., Maciejewski, M., Wu, H., Nagel, K., 2023b. Optimization of demand-responsive transport: The rolling horizon approach. Procedia Computer Science 220, 145–153. doi:https://doi.org/10.1016/j.procs.2023.03.021.

[12] Lu, C., Schlenther, T., Meinhardt, S., Nagel, K., 2023c. Quantifying the benefits of pre-booking in demand-responsive systems based on real-world scenarios. Preprint, TU Berlin, Transport Systems Planning and Transport Telematics.

[13] Maciejewski, M., Horni, A., Nagel, K., Axhausen, K.W., 2016. Dynamic transport services. The multi-agent transport simulation MATSim 23, 145–152.

[14] Pavone, M., Smith, S.L., Frazzoli, E., Rus, D., 2012. Robotic load balancing for mobility-on-demand systems. The International Journal of Robotics Research 31, 839–854. URL: https://doi.org/10.1177/0278364912444766.

[15] Pouls, M., Ahuja, N., Glock, K., Meyer, A., 2022. Adaptive forecast-driven repositioning for dynamic ride-sharing. Annals of Operations Research , 1–34.

[16] Prösse, C., 2022. Aus für BerlKönig: Nett, aber verzichtbar. URL: https://taz.de/Aus-fuer-BerlKoenig/!5869695/. accessed: 2023-11-10.

[17] Rieser, M., Nagel, K., 2008. Network breakdown "at the edge of chaos" in multi-agent traffic simulations. The European Physical Journal B 63, 321–327.

[18] Ruch, C., Lu, C., Sieber, L., Frazzoli, E., 2021. Quantifying the efficiency of ride sharing. IEEE Transactions on Intelligent Transportation Systems 22, 5811–5816. doi:10.1109/TITS.2020.2990202.

[19] Schlenther, T., Leich, G., Maciejewski, M., Nagel, K., 2023. Addressing spatial service provision equity for pooled ride-hailing services through rebalancing. IET Intelligent Transport Systems 17, 547–556. doi:https://doi.org/10.1049/itr2.12279.

[20] Schuller, P., Fielbaum, A., Alonso-Mora, J., 2021. Towards a geographically even level of service in on-demand ridepooling, in: 2021 IEEE International Intelligent Transportation Systems Conference (ITSC), IEEE. pp. 2429–2434.

[21] Tiwari, S., Nassir, N., Lavieri, P.S., 2023a. Ride-hailing vehicle dispatching and matching strategies to prioritize and complement public transport use. Working Paper .

[22] Tiwari, S., Nassir, N., Lavieri, P.S., 2023b. Testing request prioritization strategies to improve the quality of a shared autonomous vehicles service: a melbourne case study. Australasian Transport Research Forum 2023 .

[23] Ziemke, D., Bischoff, J., 2023. Accessibilities by shared autonomous vehicles under different regulatory scenarios. Procedia Computer Science 220, 747–754. doi:https://doi.org/10.1016/j.procs.2023.03.099. the 14th International Conference on Ambient Systems, Networks and Technologies Networks (ANT) and The 6th International Conference on Emerging Data and Industry 4.0 (EDI40).

[24] Ziemke, D., Kaddoura, I., Nagel, K., 2019. The matsim open berlin scenario: A multimodal agent-based transport simulation scenario based on synthetic demand modeling and open data. Procedia Computer Science 151, 870–877. doi:https://doi.org/10.1016/j.procs.2019.04.120.