TACKLING THE PROBLEM OF RIDE-TIME VOLATILITY IN DEMAND RESPONSIVE TRANSPORT

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Abstract: Demand Responsive Transport (DRT) systems can struggle with user retention due to variability in ride-time experiences, even within guaranteed service levels. Under constant aggregate demand, the stochasticity of users' daily travel decisions can alter the order of pick-ups and hence ride-time. Simulation results indicate that users can experience very high levels of ride-time volatility, regardless of their origin. This work investigates how the detour factor, as an individual level-of-service constraint, can limit experienced ride-time fluctuations and hence mitigate against users leaving the system.

Keywords: DRT, day-to-day demand stochasticity, service volatility, shared mobility

Introduction

The fundamental insight of this paper is that users of shared on-demand services are uniquely exposed to day-to-day variability in the level of service they experience, even under constant demand. DRT is fundamentally different from traditional modes of public or private transport: changes in the passengers choosing to travel each day necessitates re-routing demand-responsive vehicles through different pickup locations, and this results in regular users experiencing highly volatile travel times. By contrast, public transport is characterized by having fixed routes and schedules. On-board congestion arises due to the aggregate level of demand and may result in users experiencing crowding, but passenger ride time is not affected by exactly which individuals travel on each day. Similarly with private car trips; delays due to congestion result from the overall level of demand; there is little variability in travel times due to the specific individuals driving each day.

The DRT we consider in this paper is a Demand Responsive Feeder Service (DRFS) in which passengers are picked up at walkable "meeting points" (see e.g. Cortenbach et al. 2024). Figure 1 illustrates how ride-time volatility arises in this case for an example user 'A'. The pick-up order changes each day depending on who is requesting the service: A, B, C on Day 1, then A, B, D on Day 2, and A, C, D on Day 3. Additionally, user A's walking time changes from Day 1 to Day 3 as they are assigned to different meeting points based on the service requests. Hence user A experiences significant variability in pick-up time, walk time and ride time, despite being a regular traveller and despite the total daily DRT demand being constant. As with all public transport, providing a consistent LoS is important to maintain patronage. However, with DRT it is difficult to control the systematic volatility in user experience due to the day-to-day variability in passenger demand.

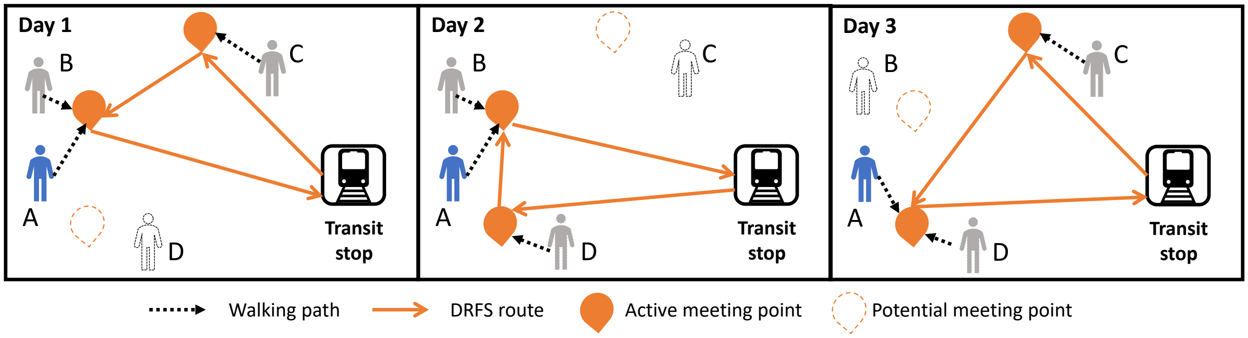

Figure 1: Day-to-day variability for a regular user (A) of meeting-point based DRFS with constant demand.

Volatility in user experience could discourage ongoing use of such services (Beirigo et al. (2022); He & Ma (2022)). In terms of user experience volatility, existing literature often focuses on investigating users' perceptions towards service volatility/reliability (e.g.,Geržinič et al. (2023)), the impact of service volatility on mode choice (e.g.,Bansal et al. (2019)), and pricing schemes considering service volatility (e.g., Li et al. (2022)). However, none of the studies have investigated the range of volatility that users experience within a given DRT service under constant aggregate demand but with stochastic passenger locations: whether the variability experienced has any spatio-temporal structure, nor if any aspects of the operational routing algorithm(s) impact or can ameliorate this volatility. The volatility of user's experience is also affected supply side factors (e.g., network structure, ride-time constraints), but these are not the focus of this paper.

It is not feasible to systematically investigate wide ranges of scenarios and user experiences using real-world data, and so we resort to a simulation approach. In a previous study we developed a meeting-point-based DRFS as a transit connector service (Ma et al., 2024). In that study, we assessed the impact of different system parameters (i.e. meeting point separation distance, and fleet size) on different key performance indicators (i.e. service rate, total kilometres travelled of the fleet, etc.). In this paper we examine the day-to-day variability in the ride times experienced by repeat users of DRFS.

This paper aims to answer the following research questions for a meeting-point-based DRFS:

1) Under constant total demand, how variable are users' day-to-day experienced ride times?
2) Can ride-time volatility be limited by imposing a maximum detour factor constraint?
3) How is ride-time volatility affected by demand density and the level of passenger 'turnover'?

Methodology

We consider a DRFS that connects to a transit station. Passengers are not picked up at their origin, but instead are assigned to meeting points (MP) within maximum acceptable walking distance, W. The operating area is covered with a grid of potential MPs, spaced to ensure all passengers can access at least one MP. For a given planning period and service area, passengers submit their ride requests in advance. The operator communicates their pickup time and allocated meeting point. The DRFS with meeting points is formulated as a Mixed-Integer Linear Programming (MILP) problem. The full specification and formulation is provided in Ma et al. (2024), along with a meta-heuristic to find (near) optimal solutions that we use in this paper. Several additional complexities accommodated within the formulation of Ma et al. (2024) are ignored here. We assume (i) all passengers go to the transit station and have the same desired arrival time, (ii) the fleet size and individual vehicle capacities are sufficiently large that no passenger rejections occur (iii) vehicles do not require re-fuelling/charging. We assume DRFS vehicles travel at constant speed, so that vehicle kms and travel times are directly proportional.

The objective function used to determine optimal DRFS vehicle routes, Z, minimizes the sum of the total vehicle travel time (VTT), passengers' total walking time (PWT) and passengers' total travel time (PTT):

$$Z(\lambda) = VTT + PWT + \lambda PTT\,. \tag{1}$$

We will demonstrate below that the weight (λ) of the PTT term can, to some extent, help control the ride-time volatility, especially since the relative magnitudes of VTT and PTT vary across different scenarios.

Default parameter values are: Maximum Walking Distance = 1 km; Meeting Point Grid Spacing = 1.4 km; Walking Speed = 5.1 km/h (0.085 km/min); Bus Speed = 50 km/h (0.83 km/min).

We consider a circular service area with a radius of 15 km (see Figure 2). There is a single transit station at the centre, which is also the origin of our coordinate axes and the DRFS vehicle depot from where vehicle tours begin. Users' maximum walking distance is 1 km so all locations can be served by a regular square grid of MPs with 1.4 km separation. A passenger's in-vehicle time includes travel time from the pick-up meeting point, via all subsequent passenger pick-ups, to the station. Each subsequent pick-up along the route incurs 30 seconds boarding time (regardless of the number of passengers boarding).

To investigate variability in ride time due to day-to-day changes in which users travel, we track individual passengers over several days making multiple trips. First we generate a population of $P = 100$ users who may or may not use the service on any particular day. Their 'home' locations are uniformly randomly distributed throughout the service area. However, no passengers are located within walking distance of the station since this would allow them to walk directly to their desired destination (see Figure 2).

For 20 days, each day we randomly select 50 passengers who will request to travel, from the total population of 100. For these 50 trip requests, we solve the passenger-to-meeting-point assignment and route optimization problems to minimize the total DRFS system costs according to the objective function Eqn (1). The experience of each passenger, including ride time, pick-up MP location and walked distance, are saved to their individual history.

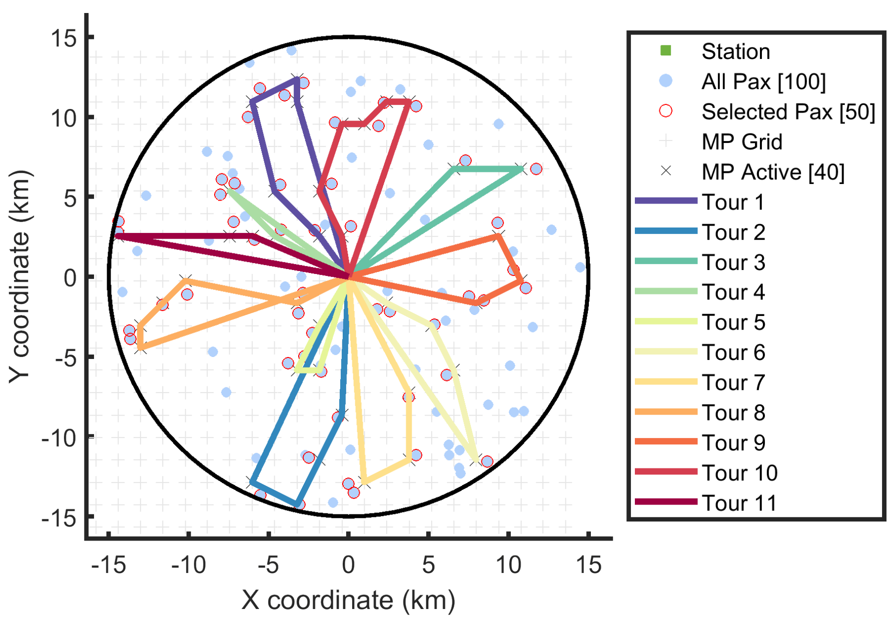

Figure 2: 50 passengers (selected from 100) and the optimal MP-based DRFS routes for this day.

Each passenger accrues multiple experiences of ride time; this is 10 trips on average, but since users are randomly selected they make different numbers of trips. In Figure 3, each of the 100 passengers contributes one 'box-and-whiskers' in blue for their ride time, and another in orange for their walking time; both are displayed vertically above their location, with the x-axis showing direct distance from the station. For each passenger, the thin blue 'box' extends from the lower quartile to the upper quartile of their ride times (or walk-times), with black whiskers extending to their min/max. The diagonal dashed line corresponds to the ride time for a direct service from the passenger's origin (x-coordinate) to the transit station.

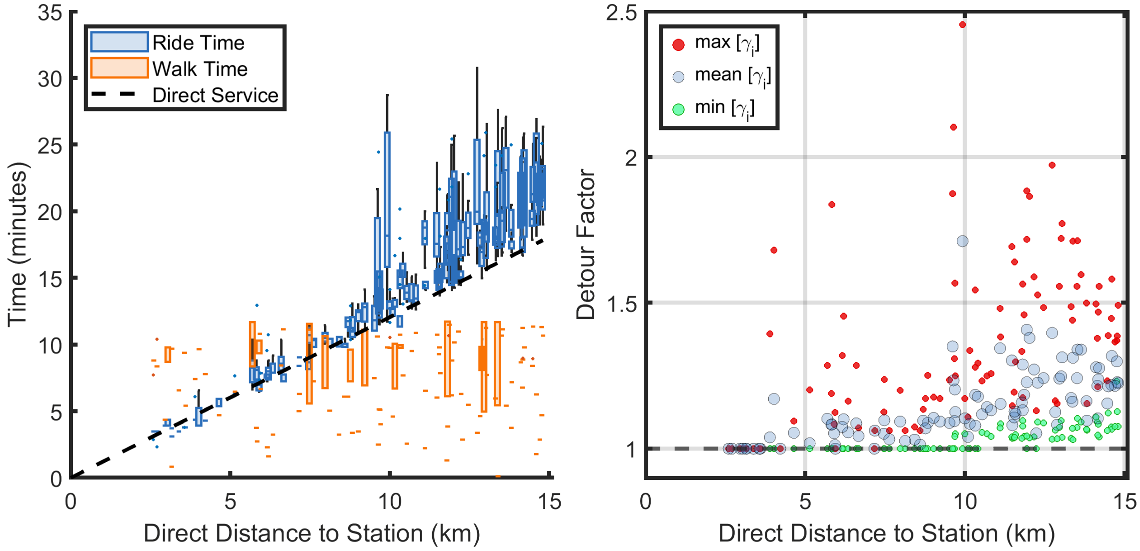

Figure 3: Data for 100 users over 20 days. [Left] Ride time and Walk Time. [Right] Detour Factor.

Ride-times naturally tend to increase with distance from the station. However, a key feature of Figure 3 is that the blue boxes show a wide range of experienced ride times throughout the entire operating area. Moreover, the maximum ride times appear to be quite 'noisy'. Closer inspection of ride times reveals that the lower boundary is exceeded in some places. This is because the dashed line is computed based on passengers' home location, rather than based on the MP they are assigned. By contrast, experienced walk times do not vary systematically with distance from the station, due to the regularly spaced grid of MPs. Many passengers are always assigned to the same MP (possibly due to travelling on very few days) in which case the orange 'box' appears to be flat.

To understand if there is any systematic change in the relative (in)efficiency experienced by passengers living closer to the station versus those living further away we use a normalized measure of the LoS: the *detour factor*. Passenger i on day j is picked up at meeting point, MP_i^j. Their direct ride time to the station would be DTT_i^j, whereas their experienced travel time (output from the optimization) is PTT_i^j which includes 30 seconds boarding time at every en-route stop. The detour factor, whose minimum value is 1, is hence defined to be

$$\gamma_i^j = \frac{PTT_i^j}{DTT_i^j} \qquad i = 1, ..., 100 \quad j = 1, ..., 20. \tag{2}$$

Note that walking time is not included. The detour factor data are shown in Figure 3 [right]. For each individual passenger, the mean detour factor over their multiple trips is shown in blue. Red points mark the worst (longest) detour factor experienced by each individual regardless of how many days they travel, green points show the best (minimum).

The mean detour factor increases with distance from the destination. Passengers closest to the station are more likely to be picked up last, whence they will be taken directly to the destination and record a detour factor of 1.0. This phenomenon is reflected in the mean detour factor typically being lower for passengers closest to the centre. The red points mark the worst (longest) detour factor experienced by each individual regardless of how many days they travel. Despite the mean falling for passenger locations near the station, passengers may nevertheless experience a high detour trip. The minimum experienced detour for each passenger is plotted in green, and passengers further from the station are less likely to ever experience a direct trip with detour factor equal to 1. This is intuitively reasonable. Given PTT in the objective function, buses tend to drive empty to the perimeter, first pick up the most distant passenger(s) and then collect additional passengers on the way back towards the station at the centre.

Since the optimization objective function in Eq 1 includes PTT, it seems reasonable that minimization of passenger ride time results in low detour factors. Indeed Table 1 shows that across all passenger trips, approximately 95% of detours are less than $\gamma = 1.5$. However, if we consider the worst detour experienced by each passenger (recall that $P = 100$) during the 20 simulated days, more than 25% of individuals experience $\gamma_i^{max} \geq 1.5$, despite the good aggregate statistics. Moreover, recall that the average traveller makes only 10

	Percentile	50	75	90	95	99
$Z(1)$	All γ_i^j	1.09	1.20	1.38	1.51	1.85
	γ_i^{max}	1.28	1.51	1.72	1.87	2.28
$Z(2)$	All γ_i^j	1.07	1.14	1.24	1.34	1.50
	γ_i^{max}	1.20	1.35	1.47	1.57	1.82

Table 1: Percentiles of all detour factors γ_i^j, and per-person maximum detour factors γ_i^{max}.

trips in total, so this one "bad" trip is noticeable. Indeed according to behavioural paradigms such as prospect theory (Kahneman & Tversky, 1979), users can react very strongly to negative experiences and hence these bad trips can have a significant impact for repeated users of the service.

One way to mitigate this would be to increase the weight of PTT in the objective function of the optimization. We set $\lambda = 2$ in Eq 1 and re-run exactly the same passenger requests over 20 days and examine the results. Increasing the weight of PTT results in smaller detours overall, at the expense of increasing VTT. Nevertheless, we still have 7% of passengers experiencing $\gamma_i^{max} \geq 1.5$.

Controlling the LoS, as measured by the detour factor, by using the weight on PTT in the objective function poses two problems. Firstly its impact is only on the total PTT which does not impose a bound on the worst single trip; we still have some passengers experiencing very large detours. Secondly, it is difficult to determine the appropriate weighting factor λ that will give a desired LoS. Even if we accept that not all passengers will then receive this LoS. Every scenario and demand level will require λ to be recalibrated.

We therefore consider a new problem formulation which directly controls the LoS for each passenger.

Problem Formulation With Detour Factor Constraint

Instead of seeking a desired LoS by weighting PTT in the objective function, we adopt the objective function $Z(0)$ and impose a strict detour factor constraint, γ, on each trip. With a slight modification to our earlier notation, we now seek to minimize

$$Z(0,\gamma) = VTT + PWT \quad \text{such that} \quad \gamma_i^j \leq \gamma \quad \forall i, j \tag{3}$$

We run exactly the same trip requests as above, but under this new formulation Eq. 3. The results are shown in Figure 4. This confirms that all trips have detour factor below 1.5 as expected. The upper dotted line in the left figure shows the maximum detour ride time. Compared with Figure 3, the experienced ride time blue box plots are less 'noisy', and at most locations fill the range of feasible ride times. By imposing a strict constraint on the detour factor, it appears that ride-time volatility is now maximum within the feasible limits of the formulation, throughout all locations.

In Table 2 we report results from additional tests with different numbers of passengers travelling ($N = 25, 50, 150, 500$), sampled from a population double the value of N in each case. For each N-scenario we

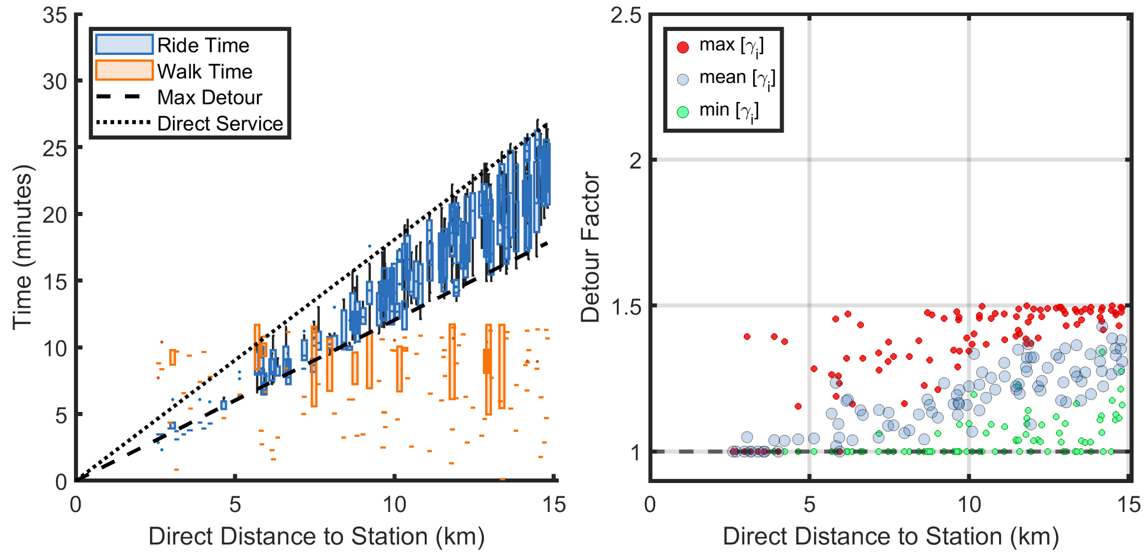

Figure 4: With Detour Factor Constraint. [Left] Ride Time and Walk Time. [Right] Detour Factor.

generate 20 days of passenger requests and compute the optimal DRFS routes in 3 different ways: (i) objective function $Z(0)$ and detour factor constraint $\gamma = 1.5$ (ii) objective function $Z(1)$ and no detour factor constraint, (iii) objective function $Z(2)$ and no detour factor constraint. All results in Table 2 are averaged over 20 days.

N (Pop)	nMP	PWT	λ	γ	nV	Occ	VTT	PTT	$Z(0)$	$Z(1)$	$Z(2)$	$\gamma^{\%}_{1.5}$
				1.5	7.4	3.4	242.9	354.4	414.0	768.3	1122.7	0.0
25 (50)	22.7	171.1	1.0		6.7	3.8	222.5	348.5	393.5	742.0	1090.6	34.0
			2.0		8.3	3.1	252.6	326.3	423.7	749.9	1076.2	13.7
				1.5	11.7	4.3	391.4	713.2	743.8	1457.0	2170.2	0.0
50 (100)	42.5	352.4	1.0		10.4	4.8	352.4	685.2	704.8	1390.0	2075.3	25.0
			2.0		12.7	4.0	399.1	651.3	751.4	1402.8	2054.1	7.0
				1.5	24.9	6.1	842.0	2211.8	1896.4	4108.1	6319.9	0.0
150 (300)	104.6	1054.3	1.0		21.3	7.1	713.8	2071.8	1768.1	3839.8	5911.6	10.7
			2.0		27.6	5.4	844.0	1973.6	1898.3	3871.9	5845.6	1.7
				1.5	47.3	10.6	1560.6	7266.5	5020.3	12287.0	19553.0	0.0
500 (1000)	210.4	3459.7	1.0		45.9	10.9	1411.6	6582.4	4871.3	11454.0	18036.0	2.2
			2.0		60.4	8.3	1721.9	6369.8	5181.6	11551.0	17921.0	0.3

Table 2: Results for $N = 25, 50, 150, 500$ using either detour factor constraint $\gamma = 1.5$, or $\lambda = 1, 2$ with no constraint. Data averaged over 20 simulated days for each row. Green highlight shows minimum objective function value in each group.

The assignment of passengers to MPs does not change when we change the objective function as described. Hence for a given N we see the same number active MPs (nMP) and the same PWT. However, other quantities do change: the number of vehicle tours (nV) and average vehicle occupancy (Occ), along with the total vehicle travel time (VTT) and total passenger travel time (PTT). For each case we also evaluate the objective function at $\lambda = 0, 1, 2$. The final column, $\gamma^{\%}_{1.5}$, shows the percentage of all users (in the population) who experience at least one trip with $\gamma \geq 1.5$.

Some observations about the results shown in Table 2:

- Total PWT, VTT and PTT all increase with N. However, average (per person) walking time and average passenger travel time do not change significantly. By contrast, average VTT per person decreases with N, along with nV (while average vehicle occupancy increases). Hence increasing demand density increases system efficiency and reduces overall experienced detours.
- With no detour factor constraint, $\lambda = 1$ becomes increasingly effective as N increases. With $N = 25$, 34% of users experience $\gamma \geq 1.5$, whereas for the same objective function, with $N = 500$, this is only 2.2%. Nevertheless, increasing λ is not effective at achieving $\gamma^{\%}_{1.5} = 0$. It does decrease total PTT and the number of trips with $\gamma \geq 1.5$, but bad trips still occur and incurs increased VTT cost. Note that each $\gamma = 1.5$ constraint row has lower VTT than $\lambda = 2$ in the same N-scenario.
- The detour factor constraint is highly effective at capping detours, but ignores any potential further improvements in PTT. This highlights the importance of integrating both operators' and customers' costs (e.g. VTT and PTT) in the objective function, while also constraining maximum ride times to reduce ride-time volatility (as mentioned by Su et al. 2024).
- Achieving $\gamma^{\%}_{1.5} = 0$ can be expensive in terms of increasing both VTT and PTT.

Impact of Passenger Turnover

In the scenarios tested so far, all passengers were resampled each day from the underlying population giving the maximum level of daily *turnover* in locations for the DRFS to visit. We test to see if this extremely high degree of passenger variability contributes to the ride-time volatility exhibited above.

For illustration we consider the case of $N = 150$ with a population of 300. We fix a fraction $F \in \{0, 0.2, 0.4, 0.6, 0.8, 1\}$ of the daily demand, then randomly select these regular passengers (from the population of 300) and they travel on all 20 days. The total daily demand is constant and comprises these regular passengers, plus the requisite number of additional passengers randomly sampled each day from the remaining population. This allows us to investigate the impact of regular patronage compared with the scenario (above) where the entire demand is re-sampled every day.

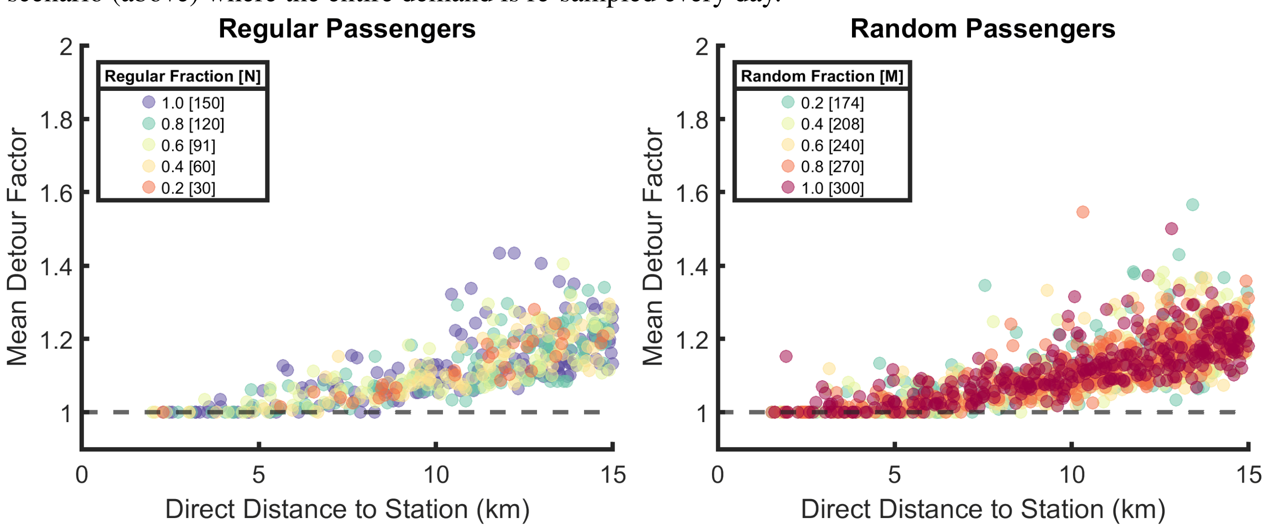

Figure 5: Mean individual detour factors, under different fractions of regular/random passengers.

Recall that each passenger travels multiple times during the 20 days and experiences a distribution of ride times. For each passenger we plot their mean experienced detour factor; if they are a regular passenger in the left plot, if they are a random passenger in the right plot. Each fraction of regular/random passengers corresponds to one colour in all plots of Figure 5. Regular fraction = 0.8 (green) corresponds to random fraction = 0.2. 120 regular passengers travel every day, plus 30 passengers randomly selected from the remaining population of 180 (= 300 - 120). In this case, 174 different random individuals travel during the 20 days; they appear in the right hand plot. The different fractions/colours are superimposed to illustrate that the different regular/random compositions do not systematically change the individual detour factor distributions experienced by passengers, whether passengers themselves are regular or random.

The key observation (substantiated in additional plots and analysis that we do not have space to show here) is that even with minimal turnover, where 75% of passengers travel every day, *all* passengers experience the entire feasible range of detour factors. Reducing passenger turnover is ineffective at reducing ride-time volatility.

Conclusions

Users of DRT are uniquely exposed to variability in the LoS they experience due to day-to-day changes in the composition of demand, even when the aggregate demand level is constant. This study uses ensembles of simulation experiments to understand the impact of stochastic demand on the volatility of user experience of a meeting-point-based DRFS. This work focuses on how the maximum ride time affects the volatility in users' ride time and their walking time to meeting points. The ride-time volatility passengers experience can be mitigated by adjusting the objective function and constraints of the vehicle routing problem. However, increasing weight on PTT is not effective at eliminating the occurrence of high detour trips, and capping the detour factor alone can result in all passengers experiencing the maximum (allowable) range of ride times. Combining these two aspects to minimize total operational costs and customers' inconvenience given user's maximum detour factor constraints would be most beneficial for both operators and users. The phenomenon of ride-time volatility is persistent even with low levels of passenger turnover, though it does show some tendency to reduce as the demand density increases; this needs further investigation.

Acknowledgements

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