Ride-Time Volatility in Demand Responsive Feeder Services with Meeting Points

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Short summary

Demand Responsive Transport (DRT) has been widely used to complement scheduled public transport services in rural areas. The DRT's routing policy is mostly characterized by user's maximum ride time constraints given a fixed level of demand. Several post-evaluations of failed DRT systems show that users are very sensitive to their daily use experience, and the volatility in user experience within the guaranteed service level (e.g., maximum waiting time, maximum detour time) could discourage users from continuing to use the services. However, it is still unknown to what extent the stochastic nature of the user's demand impacts the user's experienced variability on the level of service. In this work, we investigate to what extent user's day-to-day experience fluctuates due to demand stochasticity in a meeting-point-based DRT system. In particular, how the detour factor, a main system parameter used to bind the maximum ride time of users, impacts the volatility in users' experience. Our simulation experiments show that all users experience maximum volatility in ride time regardless of their origin location, suggesting a more fitted system design parameter is needed to reduce user's experienced variability.

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

1 Introduction

Demand Responsive Feeder Service (DRFS), a type of Demand Responsive Transit (DRT) offering first- and last-mile passenger transport, is expected to encourage the shift from private cars to mass transit by allowing door-to-door travel using mass transit systems Lee & Savelsbergh (2017). However, users of shared on-demand services like DRFS are uniquely exposed to day-to-day spatiotemporal variability, even if the aggregate demand level is constant. With mass transit services, the user experience is not affected by fluctuations in exactly which specific individuals travel each day as their routes and schedules are fixed regardless of users location. Similarly with private car trips, if the overall level of demand and hence congestion is constant, there is little variability in individual travel times. Unlike these two cases, DRT vehicles are re-routed according to the specific individuals travelling, and this can induce significant variability in each user's experience.

Figure 1 provides a simple illustration of this variability. Consider a meeting-point-based DRFS in which customers are picked up at nearby street corners or "meeting points". The order in which user A is picked up changes, as does his/her ride time from Day 1 to Day 2, depending on who else is requesting the service: A, B, and C on Day 1, and A, B, and D on Day 2. Additionally, user A's walking time changes from Day 1 to Day 3 as he/she is assigned to different meeting points based on the service requests: A, B, C on Day 1 and A, C, D on Day 3. User A may experience 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.

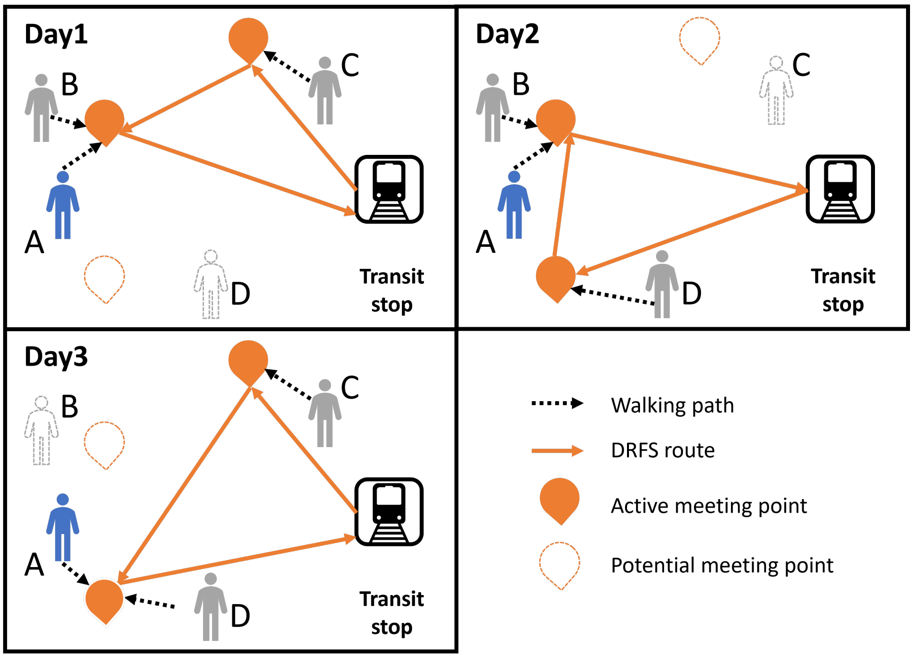

Figure 1: Day-to-day variability in user experience with DRT

To prevent users from abandoning the service and hence ensure its sustainability, it is important to provide a high and consistent level of service, but it is difficult to control the volatile user experience due to day-to-day variability in demand and the absence of fixed schedule and route. Although most shared on-demand services assume that setting their fleet size will guarantee a certain level of service (e.g., maximum waiting time, maximum detour time), volatility in user experience within this guaranteed service level could discourage users from continuing to use the 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 demand stochasticity: whether the variability experienced has any spatiotemporal structure, nor if any aspects of the operational routing algorithm(s) impact this volatility.

In addition to the demand side factors, the volatility of user's experience is also affected by the supply side (e.g., network structure, ride time constraints). Since it is infeasible to investigate the full range of system scenarios and user experiences using real-world data, 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 consider how the maximum ride time constraints, as quantified by a detour factor of user's direct ride, affect the user's day-to-day experience. To the best of our knowledge, there are few studies on this research issue. We adopt a simulation-based approach based on our previous study in DRFS. The main contributions of this paper are to answer the following research questions:

1) To what extent does the user's day-to-day experience fluctuate due to demand stochasticity in a meeting-point-based DRFS system?
2) To what extent does the user's maximum ride time constraint impact the volatility in user experience under demand uncertainty?
3) Is the volatility of user's ride-time proportional to the degree of stochasticity in demand?

The results could provide new insights into a better understanding of the impact of the maximum ride time constraint on user's ride experience and pave the way to enhance the reliability of the DRT system operation policy design.

2 Methodology

To investigate the above research questions, two experiments are designed and tested using a simulation approach. First, we describe the DRFS system, then describe the test instances, scenario design and experimental settings.

Meeting-point-based DRFS

In this study, we consider a DRFS which offers a feeder service to connect to a transit station. The system is based on the "meeting-point" concept where customers are picked up from a set of pre-defined meeting points, designed to be within a maximum acceptable walking distance from any users' origin. This kind of DRFS has been adopted in Luxembourg and other cities as a sustainable solution to reduce personal car use in rural areas (Czioska et al. (2019), Ma et al. (2021)). We use the same term DRFS for our meeting-point-based DRFS hereafter, which is characterized as follows. For a given planning period and a service area, potential customers submit their ride requests in advance, indicating their origin, the transit station where they wish to be dropped off, and their desired arrival time at the transit station (the transit service departure they intend to board). Given a set of requests, the operator communicates whether customers' ride requests are accepted and, if so, their pickup time and the suggested bus stop (pick-up point). Customers are guaranteed to arrive at the transit station within a fixed buffer time (e.g., $<=$ 10 minutes before their desired transit service). Additionally, the maximum ride time for each customer is guaranteed to be less than the direct travel time from their origin to the transit station, multiplied by the detour factor (a constant parameter of the DRFS).

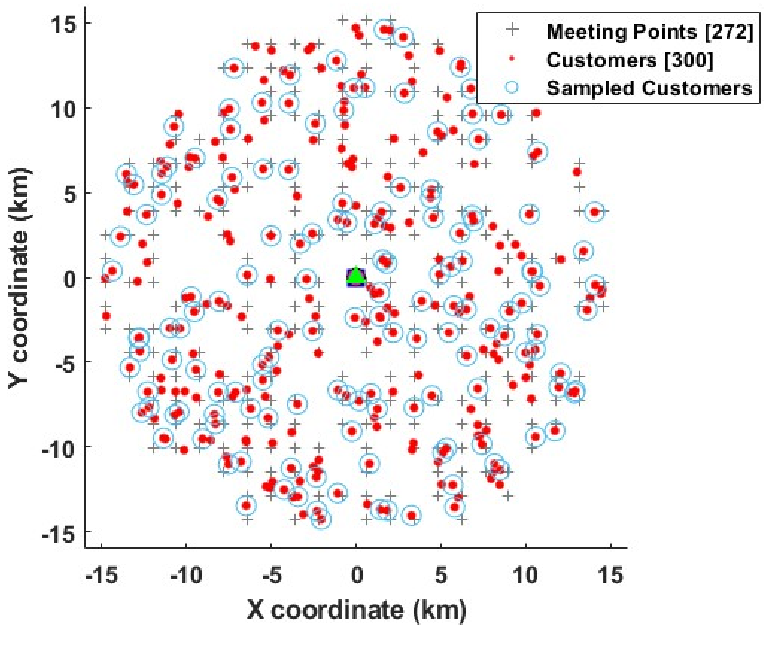

Figure 2: Area of DRFS within 15km radius of transit station and vehicle depot at the centre.

The DRFS problem is formulated as a Mixed-Integer Linear Programming (MILP) problem, extending the dial-a-ride problem (DARP) (Cordeau & Laporte (2007)), but adopting the concept of meeting points along with vehicle charging synchronization constraints (when the use of electric vehicle is assumed). It should be noted that, in this short paper, gasoline operated fleet is assumed to focus on the effects of demand stochasticity. Given a set of customer requests, the objective is to optimize vehicle routes to meet these requests while considering the trade-off between system costs and customer inconvenience. The objective function minimizes the weighted sum of the total vehicle travel time, customers' total walking time, total vehicle waiting time at transit stations before the acceptable fixed buffer time. The reader is referred to Ma et al. (2024) for a more detailed description.

Simulation experiments

We consider a circular service area with a radius of 15 km (see Figure 1). There is one transit station and one DRFS vehicle depot at the centre of the service area. The maximum walking distance of a user is assumed to be 1 km. Therefore, to ensure every customer can access at least one meeting point, a regular grid of meeting points is generated across the service area with 1.4 km separation distance (see Figure2). The maximum user waiting time at the station for transfer is set as 10 minutes. The detour factor, used to determine the maximum in-vehicle time, is set at 1.5 times the direct in-vehicle time. The pick-up time (or service time) is constant at 30 seconds. The fleet is homogeneous and conventional (e.g., diesel) vehicles. for the purposes of this paper the fleet size is assumed to be large enough that no customer rejections occur. We assume there is a fixed population of 300 first-mile users uniformly randomly located throughout the service area, all wishing to take the same train departing from the station.

Two scenarios are designed with different levels of demand stochasticity:

1) Each day 150 users are randomly selected from the fixed total population of 300. Given these requests, the DRFS solves the customer-to-meeting-point assignment and route optimization problems to minimize total system costs. The experience of each customer is saved to their individual history. This is repeated for 20 days, after which we evaluate user's individual experienced walking time and in-vehicle riding time for the days they travelled.

2) The second scenario also has 150 users travelling each day for 20 days. However, we assume this comprises 120 regular users who travel every day; these are selected at random from the population. Additionally, 30 users are randomly selected each day (from the remaining 180 non-regular users). This allows us to investigate the impact on user's experience of more regular patronage compared with the maximally random scenario where the entire customer base is re-sampled every day.

Since all 300 potential users are willing to take the same train from the same origin, variability in user experience is attributed only to the mix of users who choose to take the service on a given day.

The simulation is run 20 times for each scenario, representing the user's experience for the 20 'days'. From day to day, the set of users utilizing the service changes fully or partially depending on the scenario, causing variability in user ride time and walking time to the meeting point. The results of the simulation are analyzed to measure this variability in user ride time and walking time to the meeting point and to investigate if there are any factors that are systematically influential.

3 Results

Scenario 1: The detour factor determines not only the maximum user ride time but also limits the level of volatility in ride time.

Figure 3 shows the distribution of ride time and walk time for all 300 users over 20 days, during which each individual user will have accrued their own history of travel experiences. For each individual we draw a boxplot of their walk time (in orange) and ride time (in blue), plotted using their direct distance to the transit station as their x-coordinate. In Scenario 1, 150 users are randomly selected every day from the population of 300, hence each user travels on average 10 out of 20 days. Note that the distribution of ride times is systematically bounded below by the direct distance from the user's origin to the transit station (black dashed line) and above by their maximum ride time experiences which are defined by the detour factor constraint (black dotted line). Since the detour factor constraint is multiplicative, the two boundary lines diverge; increasing the detour factor would result in the upper boundary line being even steeper.

Some ride time experienced boxplots extend beyond the two boundary lines. Note that the boundary lines are computed based on users locations, whereas customers walk to a meeting point and travel from there. It is on the meeting point to transit station that the detour factor is applied and this allows for some ride time experiences to breach the boundaries. On the other hand, no systematic trend is observed in the distribution of walking time, which is represented by the orange box plots in Figure 3

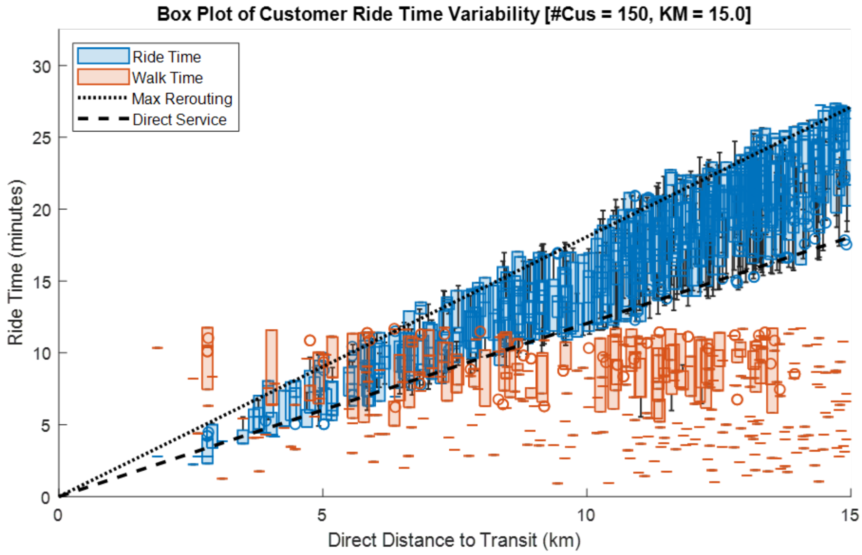

Figure 3: The distribution of ride time (blue) and walking time (orange) for each user against direct distance from their origin to the station

For each individual trip we can calculate the detour factor. The minimum detour factor will be 1, when the customer is taken directly to the station which is the case if they are the last customer to be picked up. The maximum will be 1.5 which is a constraint parameter of the simulation. Figure 4 illustrates the distribution of experienced detour factors for each user. As noted above, the detour factor sometimes exceeds 1.5 (the maximum threshold) in both Figures 3 and 4, due to the maximum ride time being based on the direct distance between the meeting point and the station, while the maximum ride time or maximum detour factor shown in Figures 3 and 4 are estimated based on the direct distance between the users' origins and the station. A key observation from Figure 4 is that users are experiencing maximum volatility in ride time at all locations throughout the service area, regardless of their direct distance from the transit station.

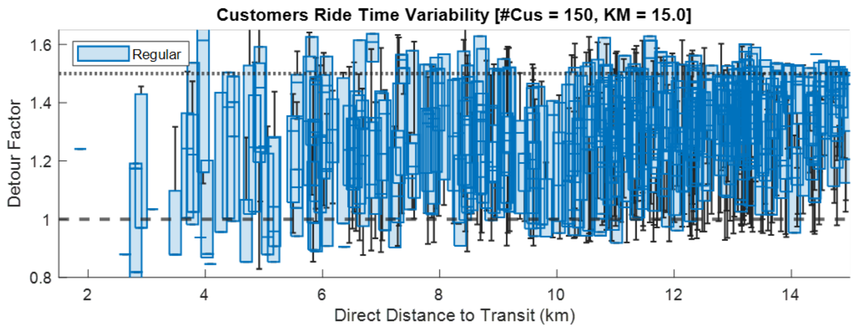

Figure 4: The distribution of experienced ride time detour factor among 20 days plotted against direct distance from the transit station

Scenario 2: Here we see the impact of having much less variability in demand: 80% of daily travellers are the same individuals. We see that having 80% regular customers does not markedly decrease the level of volatility in ride time (see Figure 5). The upper part of Figure 5 shows the distribution of ride time over 20 days for the regular users (presented in the form of a detour factor as for Figure 4) while the bottom part illustrates the experienced detour factor for the random users. In both figures, it is evident that both types of users experience maximum volatility, bounded by the detour factor. It should be noted that the variance in ride time is shorter for users located closer to the transit station. This is because the buffer provided by the detour factor (e.g., 1 km if users' origin is 2 km away from the station) is too small to accommodate picking up other users on the way to the station. Some users are always picked up last or travel as solo riders.

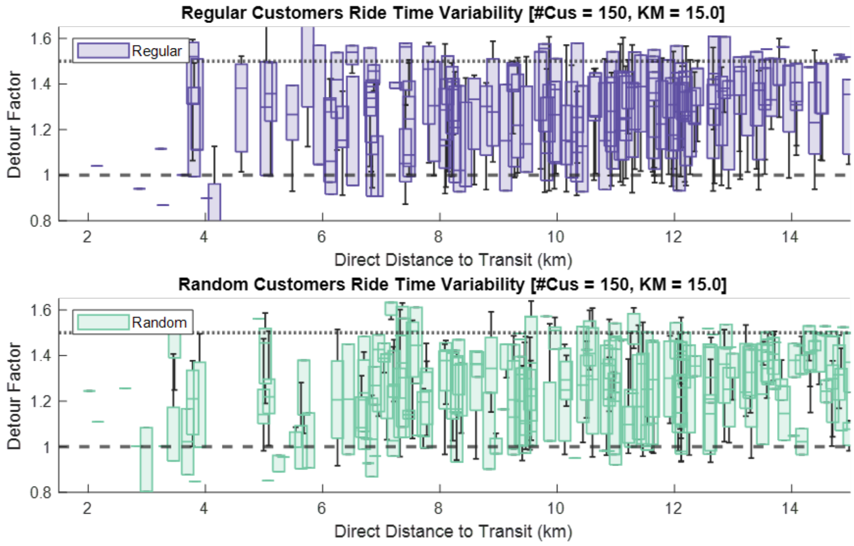

Figure 5: The distribution of ride time that user experienced among 20 days in the form of detour for regular users (top) and the random users (bottom)

4 Conclusions

In this study, we provide an initial overview of our ongoing investigations, which utilize 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 results suggest a systematic pattern that all users experience maximum volatility in ride time, bounded by the maximum ride time constraints, regardless of their location. This is also the case when 80% of users are regular customers who use the service from the same origin and have the same expected arrival time at the station every day. We are currently conducting additional simulation experiments across other dimensions (e.g., the number of meeting points) with more Key Performance Indicators (KPIs) (e.g., waiting time at the station), to identify systematic trends in the volatility of user experience.

Acknowledgements

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