

Time Windows for Demand Responsive Transport in Low-Density Areas: A Simulation-Based Study

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RESUMO

Transportes de Passageiros Flexíveis (TPF), são uma alternativa efetiva ao ineficiente uso de transportes públicos convencionais em áreas de baixa densidade populacional. Estes sistemas adaptam-se dinamicamente à demanda existente, operando apenas quando solicitados. Entretanto, considerando a natureza complexa dos TPFs e suas diversas configurações possíveis, projetar um sistema eficiente é uma tarefa difícil. Uma característica de extrema importância é a janela de tempo, um período dentro do qual o passageiro pode ser apanhado. Pequenas janelas de tempo potencialmente aumentam a satisfação dos passageiros, enquanto grandes janelas permitem a otimização da rota e a redução de viagens negadas. Este trabalho tem como objetivo estudar, através de um modelo de simulação, o comportamento de diferentes janelas de tempo e como estas afetam a eficiência de transportes flexíveis em zonas de baixa densidade. Para tal, estudamos o comportamento de diversos indicadores de performance produzidos pela simulação destes sistemas em diferentes cenários.

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Tópicos: Cidades inteligentes

ABSTRACT

Flexible transport, such as Demand Responsive Transport (DRT), is an effective alternative to the inefficient use of conventional public transport in low-population density areas. These

systems dynamically adapt to existing demand, operating only when requested. However, considering the complex nature of DRTs and the various possible configurations, designing an efficient system is a challenging task. One aspect that must be carefully analyzed is the duration of the time windows, a period within which a passenger can expect to be picked up. Smaller time windows can potentially increase passenger satisfaction, while larger windows allow for better route optimization and a reduction in denied trips. This study analyzes, through a simulation model, the behavior of different time windows and how they impact the efficiency of flexible transport systems in low-density areas. To this, we examine the performance of various indicators generated by the simulation of these systems under different scenarios.

KEYWORDS. Flexible Transport. Transport System Design. Door-to-Door.

Paper topics: Smart Cities

1. Introduction

Flexible Transports (FT) are a set of dynamic systems capable of quickly adjusting their operations to meet different requirements [Nelson et al., 2010]. Among FTs, Demand Responsive Transport (DRT) stands out. These systems can adapt their service according to real-time demand fluctuations by altering one or more of their fleet, route, or schedule characteristics.

In areas with low population density, where traditional fixed-route and fixed-schedule public transport services have proven inadequate, the flexibility of routes and schedules, along with their ride-sharing characteristics, makes DRT a powerful transport alternative [Ellis and McCollom, 2009]. However, the complex design process for DRT systems—hindered by the high number of possible configurations—and the heterogeneous nature of low-density areas pose challenges in developing a one-size-fits-all solution. Therefore, for a service to be effective and efficient, each service area requires a tailor-made solution [Papanikolaou et al., 2017].

Although DRTs offer different levels of flexibility in their operations [Burkhardt et al., 1995], services operating in low-density areas usually require trips to be booked in advance. This approach allows these services to plan their operations according to demand, accommodating a larger number of trips by designing optimized routes. To maximize the benefits of route planning, another common practice for services in these areas is the establishment of pick-up and drop-off time windows. Time windows can be understood as the permissible delay or advancement in the pick-up and drop-off of a trip, within an established time tolerance. This feature is used to provide service to a greater number of trips while optimizing the vehicle's route, minimizing deadheading and long waiting periods [Diana et al., 2006].

However, from a passenger's perspective, long time windows create uncertainty about the exact pick-up time when requesting a trip, reducing the perceived reliability and comfort of the system. Additionally, for time-sensitive trips (such as commuting to work or school), large time windows make it impractical to use the service. Therefore, the size of a time window must strike a balance between its positive impact on the efficiency of DRTs and its negative impact on users' willingness to use the system. Consequently, selecting a time window interval is a complex decision that directly affects the performance of the system.

This study aims to present a discrete event simulation model to examine how different time window sizes influence the performance of a door-to-door configuration. Through a literature review, we identified the most commonly used Key Performance Indicators (KPIs) for both DRTs and transport operations in low-density areas. Additionally, we conducted operational testing of DRTs in a virtual environment for different demand levels, time windows, and distributions of pick-up and drop-off points.

At the end of this document, we provide an objective analysis of the impact that different time window sizes have on the performance of DRTs operating in low-density areas. By simulating the operation of these systems in a virtual environment across various scenarios, we were able to observe the effects of different time window sizes on operational performance. This study is part of a broader project aimed at developing a decision support system (DSS) for designing effective DRTs in low-density areas.

The remaining sections of the manuscript are organized as follows. Section 2 presents the KPIs identified in the literature. Section 3 describes the scenarios and inputs used for the tests. Section 4 presents and discusses the test results. Finally, Section 5 provides our final analysis and conclusions.

2. Key performance indicators for DRTs

To evaluate and compare the performance of different system configurations, it is necessary to establish measures that can represent the operation of these systems across various aspects.

The literature provides a variety of Key Performance Indicators (KPIs) that allow for quantifying not only the technical performance of the system but also the perceptions of passengers, operators, and governments regarding the system.

By analyzing previous studies on performance indicators for both DRTs and transport systems in low-density areas, including the works of D'este et al. [1994], Potts et al. [2010], Gomes [2012], Ronald et al. [2013], Morse et al. [2017], and Inturri et al. [2019], we established a comprehensive list of KPIs that encompass the different aspects of DRT operations.

There is a wide range of KPIs used to evaluate the performance of DRTs. However, when analyzing the system, it is crucial to include indicators that reflect both the operators' and users' perspectives. Passengers value comfort (e.g., low vehicle occupancy, short waiting and travel times) and low fare costs, while operators typically focus on efficient and cost-effective operations.

Table 1 lists all the variables necessary for calculating the KPIs. These variables may either be part of the initial conditions under which the system operates (such as the number of initial requests, the distance between pick-up and drop-off points, and the original start time of a trip) or need to be collected after the system's operation (such as the actual pick-up and drop-off times, the time distance between two nodes, and the number of passengers in a vehicle at a given time).

Table 1: Variables used to determine the KPIs

Variables	Details	Unit
i_t	Number total of requests	Requests
i_f	Number of dismissed requests	Requests
i_p	Number of passengers in trip i	Passengers (Pax)
i_{os}	Original start time of trip i	Minutes (Min)
i_{rs}	Real start time of trip i	Minutes (Min)
i_{oe}	Original end time of trip i	Minutes (Min)
i_{re}	Real end time of trip i	Minutes (Min)
i_{od}	Original distance of trip i	Km
i_{rd}	Real distance of trip i	Km
$v_{n,n+1}$	Distance between node n and the following node $n + 1$ in the path of vehicle v	Km
V	Number of vehicles operating	Vehicles (Veh)
v_n^t	Time t a vehicle v visits node n	Minutes (Min)
$v_{n,n+1}^p$	Number of passengers p between node n and the following node $n + 1$ in the path of vehicle v	Passengers (Pax)
FC	Fixed costs of the operation	€
VC_v	Variable cost per vehicle	€/Vehicles
VC_{km}	Variable cost per kilometer	€/Km
VOT	Perception of the cost of time for passengers	€/Hour
Sub	Total subsidy received	€
Rev	Total Revenue	€
CO_v	Amount of CO_2 produced per vehicle v per km	CO_2 /Km

Table 2 presents KPIs that utilize time-related variables. The implementation of time windows allows for adjustments in pick-up times, waiting times, and the duration a passenger remains in the vehicle. While the flexibility to modify pick-up and drop-off times enables the service to accommodate more trips and optimize vehicle routes to reduce operational costs, it is important to remember that time is a limited resource. Excessive delays caused by deviations and adjustments can discourage the use of the system.

Table 2: Time-related KPIs

KPI	Details	Calculation	Unit
Average travel time (ATT)	Average duration of a trip	$\frac{\sum_i (i_{rs} - i_{re})}{i_t}$	Min/trip
Average waiting time (AWT)	Time a passenger waits to be picked-up	$\text{if}(i_{rs} \geq i_{os}) \frac{\sum_i i_{rs} - i_{os}}{i_t}$	Min/Trip
Average difference time (ADT)	Time difference between request and pick-up	$\frac{\sum_i i_{rs} - i_{os} }{i_t}$	Min/Trip
Excess travel time (ETT)	Average additional duration of a trip	$\frac{\sum_i (i_{re} - i_{rs}) - (i_{oe} - i_{os})}{i_t}$	Min/Trip
Vehicle running time (VRT)	Total time a given vehicle v operates	$v_n^t - v_0^t$	Min
Average Trip Requests (ATR)	Average number of trips operational time	$\frac{i_n}{\sum v VRT_v} \times 60$	Trip/Hour
Average total travel time (APTT)	Average total travel time (waiting + boarding)	$ATT + AWT$	Min/Trip

Table 3 lists the KPIs that use distance-related variables. The distance a vehicle travels is directly linked to the variable costs of the operation. The ride-sharing characteristics of DRTs, combined with the time flexibility of trips, allow vehicles to adjust pick-up and drop-off sequences, thereby optimizing the overall route. Distance KPIs are an effective measure for understanding how the service's overall flexibility impacts its efficiency, particularly in door-to-door operations where vehicles may need to make significant deviations to pick up and drop off passengers. Table 4 includes KPIs that analyze aspects of vehicle operation (such as average speed, occupancy, number of passengers transported per hour, and the ratio of served to canceled trips), costs (such as the average cost of trips and the relationship between costs and subsidies), and environmental factors.

Table 3: Distance-related KPIs

KPI	Details	Calculation	Unit
Distance travelled (DTv)	Total distance travelled by a vehicle v	$\sum_n v_{n,n+1}$	Km
Vehicle-km travelled (VKT)	Total distance travelled	$\sum_v DT_v$	Km
Average Trip Distance (ATD)	Average length of a trip	$\frac{VKT}{i_n}$	Km/Trip
Excess travel distance (ETD)	Average additional length of a trip	$\frac{\sum_i (i_{rd} - i_{od})}{i_t}$	Km/Trip
Average distance-vehicle (ADV)	Average Driven distance of a vehicle	$\frac{VKT}{V}$	Km/Veh
Percentage of Deadheads (PD)	Percentage of deadhead length over total travel distance	$\frac{\sum nv_{n,n+1}^{p=0}}{TDD}$	%

Table 3: Distance-related KPIs

KPI	Details	Calculation	Unit
Passenger trips per VKT (PVKT)	Number of trips with passengers per the average distance travelled	$\frac{1-PD}{VKT}$	%

Table 4: Cost and Operation-related KPIs

KPI	Details	Calculation	Unit
Number of passengers transported (TD)	Total number of passengers transported	$\sum nv_{n,n+1}^p$	Pax
Percentage of dismissed trips (PDT)	The average percentage of trips that cannot be attended	$\frac{i_f}{i_t}$	%
Number of passengers transported per hour (PPH)	Average number of passengers transported in an hour	$\frac{\sum nv_{n,n+1}^p}{VRT}$	Pax/Hour
Average Vehicle Occupancy (AVO)	The average occupation of the vehicles during operational hours	$\sum_v^{n,n+1} \frac{v_{n,n+1}^p}{VRT_v} \times (v_{n+1}^t - v_n^t)$	Pax
Average Vehicle Speed (AVS)	Average speed of the vehicles	$\frac{\sum i_{ire-irs}}{i_n}$	Km/Hour
Variable Cost (VaC)	Total Variable Cost	$(VC_v \times V) + (VC_v \times VKT)$	€
Operation Cost (OC)	Total cost of the operation (Fixed and variable costs)	$FC + VaC$	€
Operational Cost per trip (OCT)	The average operational cost for a trip	$\frac{OC}{i_t}$	€/Trip
Subsidy per passenger-trip (SPT)	The average subsidy an operator receives per trip	$\frac{Sub}{i_t}$	€/Pax/Trip
Subsidy per vehicle-hour (SVH)	The average subsidy an operator receives per vehicle operating hour	$\frac{Sub}{\sum nVRT}$	€/Veh/Hour
Subsidy per vehicle-km (SVK)	The average subsidy an operator receives per vehicle per km	$\frac{Sub}{\frac{VRT}{V}}$	€/Veh/Km
Subsidy per passenger-km (SPK)	The average subsidy operator receives per passenger	$\frac{Sub}{\frac{i_n}{PAX}}$	€/Veh/Km
Ratio of revenue to operating cost (RROC)	Percentage of the operating costs are covered by the revenue	$\frac{Rev}{OC}$	%
Kg CO2 per passenger (CO2p)	Amount of CO2 produced per passenger	$\frac{\sum_v DT_v \times CO_v}{TD}$	CO2/Pax

3. Performance of a DRT in a simulated environment

In this section, we present our approach for determining the door-to-door DRT route, as well as the scenarios, parameters, and trip configurations used to test the services in a simulated environment.

In this study, we approached the routing problem of a door-to-door DRT as a Vehicle Routing Problem with Pick-up and Delivery and Time Windows (VRPPD-TW). We used the formulations presented by Lin et al. [2012] and Chevrier et al. [2012] for determining a vehicle path in a door-to-door DRT system as a base for a VRPPD-TW problem. This allowed us to adapt and use

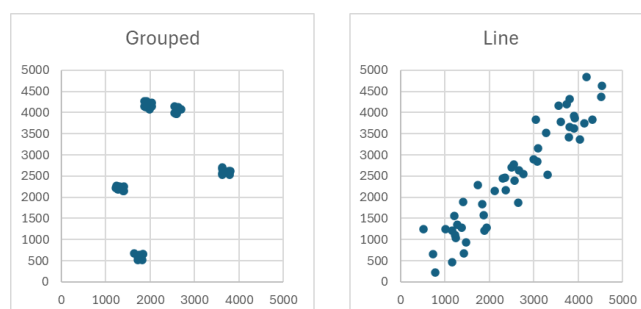
commercially available solvers to select the optimal vehicle path and pick-up and delivery times. In this work, we utilized Google's OR-Tools solver.

In the traditional Vehicle Routing Problem with Pick-up and Delivery (VRPPD), each request consists of a pick-up point, a corresponding destination, and a demand (the number of objects to be transported between these two points). When time-window constraints are included, each pick-up and delivery point is associated with a time interval during which it can be visited.

To evaluate how different KPIs are affected by the length of time windows, we analyzed the performance of a DRT in a simulated scenario, using different sets of trips and varying time window duration. In this study, we examined the performance of a door-to-door DRT system, where passengers are picked up and dropped off at precisely the requested locations. In addition, the trips were booked in advance.

We analyzed the system's performance in two randomly generated scenarios: a grouped scenario (where PUDOs were distributed in groups of 10, with no two points more than 200 meters apart) and a line scenario (where PUDOs were arranged along a line, distancing no more than 200 meters from the central line). Both scenarios were generated within a 5000-square-meter service area, with a total of 50 PUDOs. Figure 1 illustrates the two generated scenarios.

Figure 1: The two PUDOs distributions in the tests: Grouped and Line distributions.



To find the best route within the available time limit, we applied Google's OR-Tools solver, with a processing time limit of 600 seconds, for each instance. In its processing, the solver aimed to minimize the sum of the distances traveled by the vehicles, plus the penalty cost for each trip that could not be attended. Additionally to the solution cost, the solver provided a path for each vehicle, considering the time a vehicle should be in a location (a passenger's pick-up or drop-off).

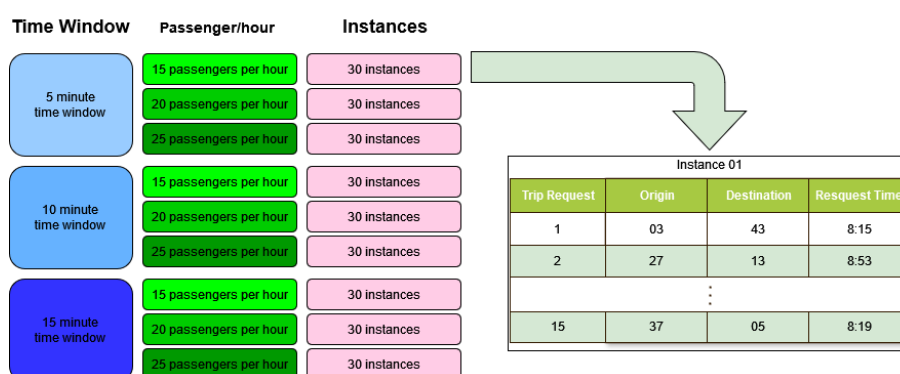
In each scenario, we conducted tests using three groups of time windows: 5, 10, and 15 minutes. Within each time window group, we evaluated three levels of demand: 15, 20, and 25 trips per hour. Each combination of time window and demand was tested using 30 instances. For each instance, trip requests were generated by randomly selecting an origin and destination PUDO within the scenario, along with a start time within a one-hour period. Figure 2 provides a visual representation of the distribution of the instances.

To perform this analysis in a virtual environment, the available computational power necessitated some simplifications of the real-world scenario. The testing parameters are as follows:

- The vehicle speed was fixed at 9,6 km/h. We selected this speed considering an operation in rural areas, with low infrastructure.
- There was no limit on how long a passenger could wait for a trip or be in a vehicle (as long the starting and ending times of the trips were respected within the selected time window).
- There were no distance limits a vehicle was allowed to travel.

- The solver received all requests at once and all had the same penalty for not attending. The penalty for not attending a trip was the same for all requests. The penalty for dropping a trip was about 100.000 times the distance of the two furthest points in the grid.
- The distance of two points was the shortest (Euclidean distance). Combined with the fixed vehicle speed, this simplification turned the time travel time directly proportional to distance.

Figure 2: Parameters of tested instances



4. Results and Discussion

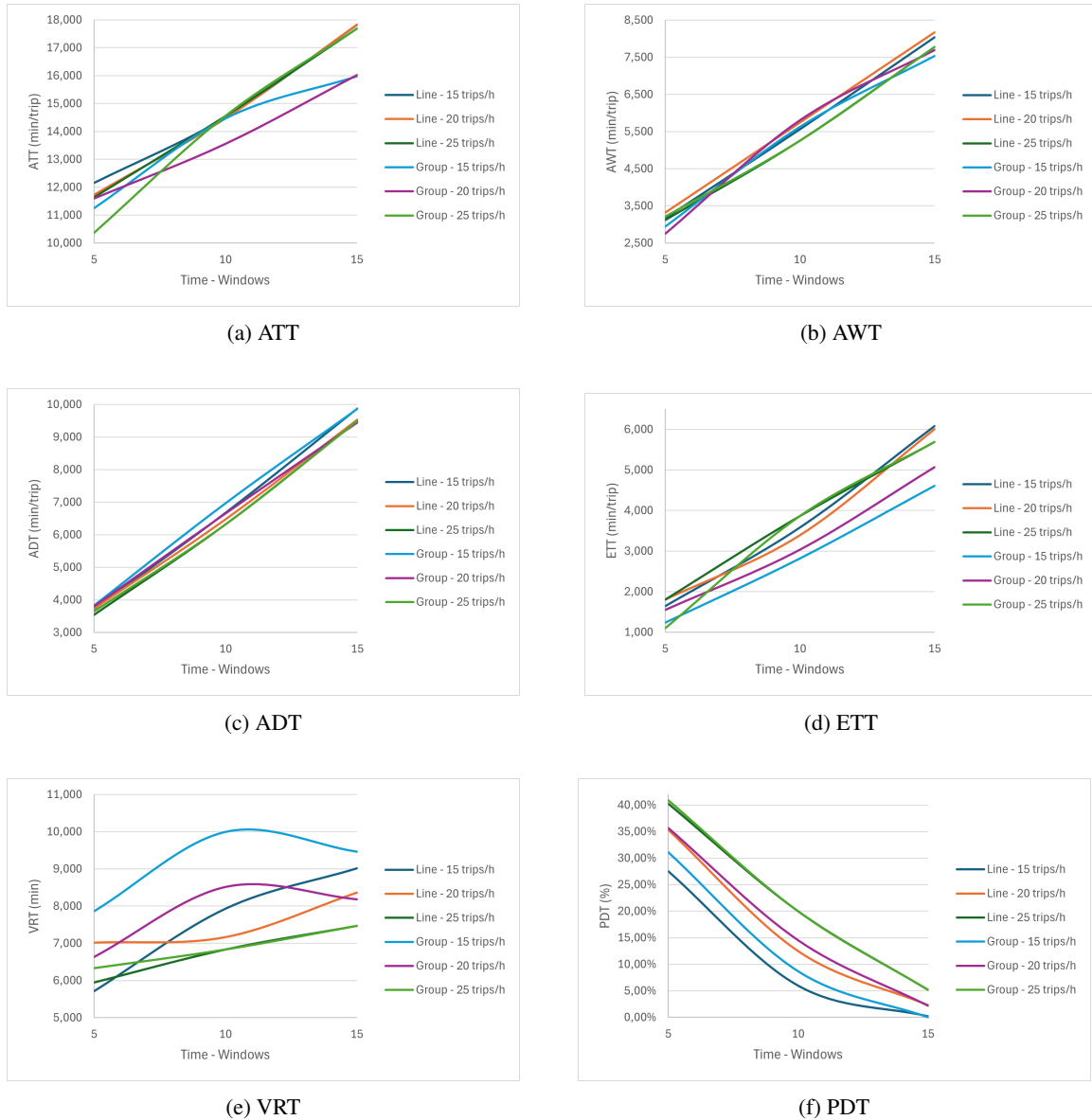
Due to the simplifications, time and distance were directly related. As a result, KPIs related to distance, as well as other distance-related variables such as cost KPIs, were not analyzed. Instead, the simulation focuses on diagnosing, in a representative manner, the KPIs related to time, as well as the number of trips served (one of the key motivations for applying time windows). Despite the reduced number of variables, we believe these can provide a general overview and offer valuable insights into the effects of different time windows on the operation of door-to-door DRTs. Figure 3 presents the main results of our simulations.

Initially, we expected the instances conducted in the scenario with PUDOs distributed in a line to have lower time KPI values than those with grouped PUDOs. We assumed that in the line scenario, PUDOs would be more evenly distributed across the service area, allowing for more efficient pick-ups and drop-offs along with longer trip requests. In contrast, in the grouped PUDOs scenario, there are no PUDOs between clusters, resulting in longer vehicle travel times and distances, and consequently, longer passenger waiting times. An example of a vehicle path for both scenarios is shown in Figure 4. In (a), the vehicle travels longer distances without passing through a PUDO, whereas in (b), the intervals between PUDOs are shorter. However, this could not be verified in our randomly generated trip instances, as the grouped PUDO scenarios presented equivalent—and in some cases, lower—KPI values compared to the line PUDO scenarios.

Furthermore, as shown in Figure 3, it is clear that the increase in time windows has a noticeable effect on the overall KPIs across all scenarios. One KPI that deserves particular attention is the Percentage of Dismissed Trips (PDT). In instances with a high number of trips per hour, the trip rejection rate reached around 40%. However, as the time window increases, this refusal rate quickly decreases, approaching 0% in some cases.

This suggests that larger windows significantly enhance the system's capacity to accept and execute trip requests. This is important to consider when analyzing the effects of time windows on other KPIs. Although some KPIs typically related to passenger comfort (such as ATT and AWT) are adversely affected by larger time windows, the increased capacity allows more passengers to

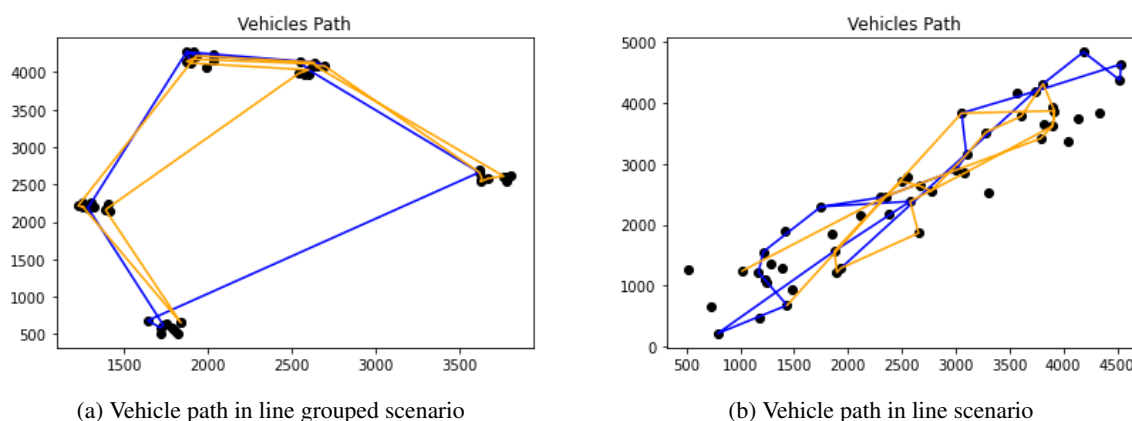
Figure 3: KPI obtained by testing multiple scenarios in a virtual environment



use the service, which is crucial for overall user satisfaction. Therefore, stakeholders must clearly understand the goals of their intended services and find a balance between user satisfaction and user comfort.

As mentioned, the Average Waiting Times (AWT) and the Average Difference Between pick-up and drop-off Times (ADT) gradually increase as time windows expand. This effect is expected, as larger time windows allow for greater variations between the original trip request time and the actual pick-up and drop-off times to accommodate more requests along the route. This variation is perceived in all instances, regardless of the number of trip requests per hour. One possible explanation for the consistent growth observed across all scenarios, regardless of the number of trips, is that the analyzed system - which is operating with two vehicles - may already be serving the maximum number of simultaneous trips possible considering the geographical constraints. To

Figure 4: Differences of vehicle paths in the line and grouped PUDO scenarios



verify this hypothesis, it would be necessary to evaluate the vehicle occupation rate and conduct simulations with additional vehicles. Unfortunately, due to limitations in computing power and time, we were unable to perform these tests.

The impact of time windows on KPIs varies, with the most significant increase observed in the Excess Travel Time (ETT) - about 500% in some scenarios -, which measures the difference between the requested pick-up time and the actual pick-up time. This aligns with expectations, as longer time windows allow for more optimized routes, leading to greater deviations from the requested pick-up times. The increase in ETT should be approached cautiously by stakeholders, as large discrepancies between requested and actual pick-up times may reduce the system's suitability for time-sensitive trips, diminishing passengers' perception of the system's utility and potentially reducing the demand.

The Vehicle Running Time (VRT) KPI showed varied behavior across the different scenarios. The highest values, representing longer vehicle operating times, were observed with the lowest demand levels, which was not initially expected. However, certain characteristics of how this KPI is calculated and the way the simulations were conducted may help explain this behavior: the calculation of this KPI is based on the vehicle's departure and return times to the depot; in this study, the vehicle does not return to the depot between trips, only after completing all selected trips; additionally, trips were randomly generated over one hour, allowing for non-homogeneous distributions throughout the journey.

It is possible that - for some instances - trips were concentrated at the beginning and end of the journey, and the vehicle's prohibition to return to the depot during waiting periods between trips may have contributed to this unexpected KPI behavior. This KPI requires further investigation to draw adequate conclusions. Future simulations should consider different trip-generation parameters and scenarios where the vehicle is allowed to return to the depot between trips.

5. Conclusion

Through this study, we identified the main KPIs used for analyzing the performance of DRTs and the methodology for calculating them. Additionally, we examined the behavior of some of these KPIs in two different scenarios with varying time windows.

We found that increasing the time windows significantly impacts time-related KPIs, particularly the Excess Travel Time (ETT), Average Waiting Time (AWT), and Average Difference between pick-up and drop-off Times (ADT). We also observed a sharp decrease in dismissed trips as the time windows were extended. This flexibility can be a powerful tool for enhancing system

efficiency. However, the length of the time window must also consider the needs and objectives of the passengers using the system.

Although this may not be a concern for shopping or medical-related trips, the increase in overall travel time, along with waiting time and the difference between requested and actual trip times, can be a decisive factor in determining the system's suitability for time-sensitive passengers, such as those making school or work trips. However, as indicated by the PDT, longer time windows may increase the overall number of passengers served. Stakeholders must carefully consider the type of passengers the system is targeting when determining the appropriate time windows.

It is important to note that our analysis has limitations due to the use of a virtual environment. For the simulation, certain parameters, such as vehicle speed, were fixed or simplified, as was the case with the distance between points of interest. Additionally, due to the computational power required to test all possible scenarios, the study was conducted with a limited variation of parameters.

For future research, it is recommended to analyze these indicators in scenarios more closely resembling real-world conditions, with PUDO distributions and vehicle routes more aligned with actual operations. Aside from the simulation with different vehicle capacities and fleets, developing a trip generation model that considers the target audience of the transport could be highly valuable, as it would enable a more nuanced analysis of KPIs - as the VRT - and their results based on the perceived usefulness of the system for different user groups.

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