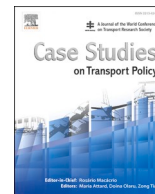


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A simulation-optimization model for analyzing a demand responsive transit system for last-mile transportation: A case study in São Paulo, Brazil

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ABSTRACT

Ride-hailing services, in particular Demand Responsive Transit (DRT) systems, have emerged in many cities worldwide as a potential solution to bridge the public transport supply gap. In such services, passengers whose itineraries and times are coincident to a certain degree can share vehicles that follow flexible routes to accommodate distinct boarding and alighting locations with minor disturbances to their convenience. In this context, this paper aims to evaluate the potential of a DRT as an alternative for a feeder to a trunk transport system, such as BRT (Bus Rapid Transit), or a metro or rail system as well. This is accomplished by a simulation-optimization model that allows determining, in very short time, the optimized way to serve each new transport request that arises dynamically over time. The model was applied to a first/last mile transportation system in an area adjacent to a subway station in the city of São Paulo, Brazil. We analyze and measure the impacts of different operational characteristics of supply and demand, measured in terms of service level to riders, number of vehicles, average occupation and total kilometer traveled per vehicle. The results evidence the potential of these DRT services as an alternative to complement the existing bus lines, as well as to attract users of individual transport, as they can offer adequate service level at a competitive cost.

1. Introduction

Demand Responsive Transit (DRT) systems, often seen as a combination of regular public transit services and privately organized taxi services, have emerged in many cities worldwide as new mobility solutions. In such ridesharing systems, flexible routes and schedules allow multiple travelers to share the seats inside a vehicle if their itineraries are somewhat ‘adjacent’ in a spatiotemporal sense (Daganzo and Ouyang, 2019). Initially, DRT services were conceived to provide transport for people with limited mobility (e.g., elderly and handicapped persons) and residents of rural areas (Rimmer, 1984). Nowadays, they have become a potential solution to reduce traffic congestion and to mitigate pollution in urban settings by attracting to shared-ride services those driving their cars to commute, as the flexibility provided by them allows different features to meet the demand and better suit local needs. Developments in vehicle automation and shared economy also contribute to a growing interest in flexible transportation services such as DRT, as it could potentially be used to provide efficient and effective public transportation in the future (Van Engelen et al.,

2018).

One of the main deterrents to the use of public transportation is the lack of alternatives for last-mile transportation (Wang, 2017), connecting residential areas to major fixed-route transit networks. In this context, a DRT last-mile service, also referred to as DRT feeder services (Chandra and Quadrioglio, 2013), in which passengers are transported to/from transit centers from/to their desired location within a pre-determined service area may be a more efficient alternative. Therefore, this paper aims to evaluate the potential of a DRT as an alternative for the so-called ‘last-mile transportation problem’, which concerns the provision of travel services from the nearest public transportation node to a passenger’s home or other destination (Wang, 2017); in other words, DRT working as a feeder system for a first and last mile solution, complementing trunk transport systems, such as rail-based services and Bus Rapid Transit (BRT) systems.

To accomplish this, we have developed a simulation-based vehicle dispatching tool that allows simulating new requests that dynamically arise over time. We treat each of them individually, in a very short time, to determine the best vehicle assignment such that the time impact

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(delay) to both the new rider requesting service and other users previously scheduled is minimized. The proposed approach has been applied to a case study in an area adjacent to a subway station in São Paulo, Brazil, which lacks alternatives to first/last mile public transport. Some different demand and operational conditions have been simulated to determine detailed results in terms of vehicle occupation, distance traveled, idle periods, etc., helping to analyze the feasibility of such a DRT system.

The DRT simulation model that we have developed receives trip demands as input and keeps track of all vehicle locations at every instant during the entire simulation. As a new request arrives, it searches for the optimum vehicle assignment considering the lowest total increment in travel time considering all active requests (i.e., for each candidate vehicle, the passengers on board as well those already scheduled to be picked up). The simulation model has allowed evaluating multiple scenarios of a DRT operation, including variation in demand and supply side, such as request rate and vehicle capacity. The simulation results provide data to analyze the DRT system feasibility, both from operators' and users' point-of-view. Our goal is to seek answers to some challenging questions, such as (i) which solution would yield to higher average vehicle occupancies and a minimum increment in average travel times; and (ii) what conditions would provide shared rides with competitive cost per passenger and service level when compared with other transportation alternatives.

The remainder of this paper is organized as follows. Section 2 provides a literature review. Section 3 presents the problem definition addressed in this paper. Section 4 details the modeling approach, while Section 5 outlines the case study, defining experimental inputs and scenario variations. Then, we present the results and analysis of an operational scenario in Section 6. Lastly, in Section 7, we summarize key findings and suggest directions for future research.

2. Literature review

The daily dispatching operation of a DRT service consists of designing vehicle routes and schedules for trips requested by individual users who specify their respective origin and destination locations. Thus, from an optimization point-of-view, it is closely related to the Vehicle Routing Problem (VRP) (Dantzig and Ramser, 1959), and particularly to the Dial-a-Ride Problem (DARP) (Cordeau and Laporte, 2007). In the static DARP version, all transportation requests are known beforehand, prior to the departure of the vehicles, while in the dynamic version requests are gradually revealed across the time, modifying vehicle schedules as a new request is accepted (Psaraftis, 1995).

Static models that have appeared in the literature typically deal with a small number of requests, as they can become computationally prohibitive to determine feasible solutions with large datasets, particularly in the general case of multiple origins and destinations DARPs. For instance, Li et al. (2018) described a mathematical model to design an enhanced ridesharing system with meet points and users' preferable time windows that was tested with 10 ride requests. Sun et al. (2018) presented a mixed-integer linear programming model for demand-responsive feeder transit services to assign vehicles located at different depots to pick up 42 passengers distributed at 15 demand points and transport them to a rail station. Pei et al. (2019) proposed a new structured transit system with a flexible bus line length based on the real-time requests of a maximum of 120 passengers/hour.

On the other hand, works related to simulation in a dynamic environment are usually more flexible about operational designs and the number of requests. However, when requests are received, they should be treated instantly and not booked in advance. Literature covers from strategic planning to replace conventional transportation to DRT systems (Pastor, 2014) to the search for feasible operational settings for a given service area and demand (Jung and Chow, 2019). Häll et al. (2012) presented a modeling system for simulation of dial-a-ride services, which can be used to investigate how the setting of service and

cost parameters and service design affect the total operator cost and users' level of service. Ronald et al. (2013) explored four spatially-varying demand patterns (random, a many-to-one scenario, all short-distance trips, and all long-distance trips) using a simulation of an ad-hoc demand-responsive bus system. Van Engelen et al. (2018) proposed an online dynamic insertion algorithm with demand forecasts, which is tested in a simulation model for a case study network in the Netherlands.

Some papers have already addressed the problem of last-mile transportation. For example, Lee et al. (2005) proposed a dispatching algorithm to use the taxi fleet as a feeder service to a mass transit station to increase ridership of public transportation in Taiwan. Wang (2017) developed routing and scheduling approaches for a last-mile transportation system and provided a general performance evaluation. Sun et al. (2018) developed an optimization model for DRT feeder services to assign vehicles located at different depots to pick up passengers at the demand points and transport them to a rail station in Nanjing City, China.

However, few studies consider existing transportation alternatives in a DRT design. Enoch et al. (2006) identified many failed DRT systems and highlighted the importance of the local market for its implementation. Kilby and Robards (2013) proposed a demand-responsive system to replace the weekend service of the public transport system in Canberra, Australia. Pastor (2014) evaluated the feasibility of a citywide DRT system in Tacoma, Washington, whether serving the same volume of demand as the local fixed-route system at a comparable cost. Martinez et al. (2015) proposed a shared-taxi system that could provide 9% of fare reduction for taxi service users in Lisbon, Portugal. Alonso-Mora et al. (2017) demonstrated that 25% of the active taxi fleet in New York City can satisfy 99% of the requests through high-capacity ride-sharing, causing an increment of about 2.5 min in mean waiting time and delay. Finally, Gilibert et al. (2019) investigated user requirements and market opportunities, from a case study conducted in Hanover, to contribute to a DRT design.

Thus, as can be observed from the above, a research opportunity arises, which is related to the investigation of what intrinsic characteristics of demand and services to be provided that would yield to a feasible and effective dynamic DRT system working as a feeder service for a trunk urban public passenger transport system. Such first/last mile public transportation systems are usually related to a single origin or destination (i.e., a terminal, denoting a one-to-many, or alternatively many-to-one, routing problem). While being less complex than typical many-to-many DARP problems, the dynamic nature of such feeder systems requires an efficient dispatching algorithm to determine the best vehicle assignment for each new request in a very short time, as the user is waiting, ready and willing to board as soon as possible. In such context, we employ a simulation–optimization based dispatching tool that is used to evaluate a DRT system as an alternative solution to feed a subway terminal station in São Paulo.

3. Problem definition

The DRT feeder system that we address combines the origins or destinations of multiple users on dynamic routes, serving as a first/last-mile connection to a single important public transportation node. The problem of dynamically designing and adjusting vehicle routes and schedules to meet a set of travel requests that arise in real-time is known as a dynamic Dial-A-Ride Problem – DARP (Cordeau and Laporte, 2007). An effective algorithm to address such a problem must ensure that the largest number of requests is combined in fewer vehicles and that all users have a positive experience, expecting that not only do they continue to use the DRT service but also promote it to others.

In this paper we focus on simulation analyses of different scenarios for an urban DRT feeder system. The demand is defined by a set of requests that are randomly generated within a specific area where the service is expected to be provided. Each travel request corresponds to a

specific time, origin and destination locations within the study area, given by their respective geographic coordinates. Requests are immediate, in the sense that they should be serviced as soon as possible, with no anticipated notice; in addition, it is not possible to schedule a trip for a later time in the future. This aims to mimic users requesting rides through a mobile application for immediate travel; thus, they must be processed as they appear. The demand patterns that can be handled by the simulator may consist of any type of geographic distribution of origins and destinations; however, as we address DRT as a last-mile transportation alternative, our focus is on many-to-one or one-to-many patterns (i.e., users heading to or departing from a single public transport station or terminal).

To determine the available vehicle that can best serve each new request, it is necessary to ensure that passenger constraints related to travel inconvenience, such as maximal waiting and travel times thresholds users are willing to accept for their rides, are respected. Since the aim is to combine as many requests as feasibly possible into fewer vehicles, deviations from the direct routes between each passenger's origin and destination may occur. To avoid excessive in-vehicle travel times that users may experience, we limit the increase of such in-vehicle travel time (caused by vehicle deviations from the shortest path) by a given maximum deviation factor, a constant that is applied to each request. In other words, the maximum deviation factor expresses the maximum in-vehicle travel time a passenger's trip could take when compared to the travel time that corresponds to the shortest path between his origin and destination by individual car, disregarding any deviations for other passengers' pick up and drop off. This maximum deviation factor refers strictly to in-vehicle travel time and does not consider the waiting time.

Each vehicle has an associated schedule, which consists of a sequence of events (or actions) to accomplish, such as picking up and dropping off riders and returning to the initial point of departure as it becomes idle. Whenever a new request arises, vehicles already carrying passengers are immediately evaluated as the first candidates to be assigned, which should lead to occupancy increase and system costs reductions, while ensuring that vehicle capacity constraints are respected. However, this assignment rule may eventually yield undesirable greater deviations and waiting times for users already assigned to vehicles. Thus, among those vehicles with available seats, we select the one whose schedule sequence provides the lowest increment to the sum of the deviations factors of all passengers already scheduled; in addition, none of the requests already assigned to the vehicle can exceed a maximum increment in travel time. It should be noted that this procedure requires an evaluation of all feasible pickup and drop-off insertions into the vehicles' schedules (i.e., all feasible ways how they can be inserted among the already scheduled stops).

The fleet is assumed to be homogeneous in terms of their capacities and costs, and the vehicles are initially spread within the area where the service is provided as to enable all requests to be met within the maximum allowed waiting time. Thus, if no occupied vehicle can feasibly serve the new request, a new idle (empty) one will be assigned. As a result, the model attempts to reach an equilibrium between supply and demand, by ensuring that all passengers will be served, and no extra or unnecessary vehicle will be assigned.

The simulation tool does not consider requests that are eventually canceled by the users, nor that users will not show up when the vehicle arrives. Therefore, if the request can be met in terms of vehicle availability and waiting time feasibility, the trip is served. Once a new request is assigned to a vehicle, passenger reallocations for other vehicles are not allowed, even if the passenger has not yet boarded. It is also not allowed to change the schedule sequence of the already scheduled requests when a new one is analyzed. The routes are defined by the scheduled events (i.e., pick-up and drop-off stops and their times), without fixed or predetermined segments.

4. Simulation model

The simulation model was built based upon Häll et al. (2012) and has four main components (Fig. 1): i) Input Manager; ii) Simulation Control; iii) Request Manager; and iv) Output Manager.

The Input Manager handles all information required as input for the simulation, such as demand (origin, destination, and time of each request), number of available vehicles and their capacity (i.e., number of passengers), the underlying street network in the study area, and thresholds for user service level (maximum waiting time and maximum travel deviation). Demand, expressed by the rate of service requests per hour (each characterized by an origin, a destination, and request time) can be either kept static (i.e., unchanged across different scenarios) or may vary. In addition, a time horizon for which the simulation should run is defined.

The Simulation Control receives input data and starts the simulation process. Its main purpose is to keep track of all events and time, as well as monitor vehicle positioning, vehicle scheduled events, and new requests that arise. All demand, in the form of requests, are handled individually as they arise, triggering the Request Manager.

As mentioned before, the routing and scheduling of vehicles in dial-a-ride systems is referred to as a dial-a-ride problem – DARP (Cordeau and Laporte, 2007). Although this is a combinatorial, NP-hard optimization problem, whose difficulty increases exponentially as the instance size becomes larger, thus requiring complex and efficient algorithms and heuristics to solve static versions, as all requests, made in advance, are handled together before the departure of the vehicles (Cordeau and Laporte, 2007). On the other hand, its dynamic version, in which each new request must be dealt immediately as it is received, can be properly handled using fast VRP insertion heuristics, as the user must receive the confirmation, which includes all the details of the scheduled trip (vehicle, estimated departure and arrival times), in a very short time.

To accurately represent this, in our proposed simulation–optimization model, travel requests are known as they appear, dynamically, as the simulation clock advances. To simulate a real DRT feeder system dispatch situation, each request must be quickly assigned to a vehicle and a specific departure time is informed to the user. So, we used a classic insertion heuristic, which determines the best vehicle and a new optimized vehicle schedule for each request individually, in only a few seconds.

Therefore, when the Request Manager receives a new request, an insertion and an optimization heuristic are executed to designate a vehicle and to establish its new schedule. First, the insertion heuristic searches and selects all vehicles with an available seat that can arrive at the pickup point (origin of the new request) within the maximum waiting time threshold. Then, it examines all feasible pickup and drop-off insertion slots in the vehicles' schedules (the pickup and drop-off positions with respect to the already scheduled sequence), considering the maximum waiting time for the user who requested the trip and the maximum in-vehicle deviation for the already scheduled users. After all feasible vehicles and insertion options have been outlined, the optimization heuristic chooses the combination that yields the best service level for the affected users (i.e., those already traveling or scheduled), measured by the lowest total increment of the individual deviation factors. Then, the paths between all scheduled events are updated, defining new routes. If there is no feasible insertion in any of the already occupied vehicles, and if there are idle vehicles available, the new request is assigned to the one that yields the lowest waiting time. The request is only deemed rejected when there is no available vehicle that matches either condition. The above simulation process is summarized in the flowchart depicted in Fig. 2.

The simulation ends when all requests have been addressed; then, the Output Manager exports all results to output files. Due to the large amount of data generated, we performed a cluster analysis of vehicles and trips with the aim to extract detailed information about the operational efficiency and the service level provided to the users (de Oña

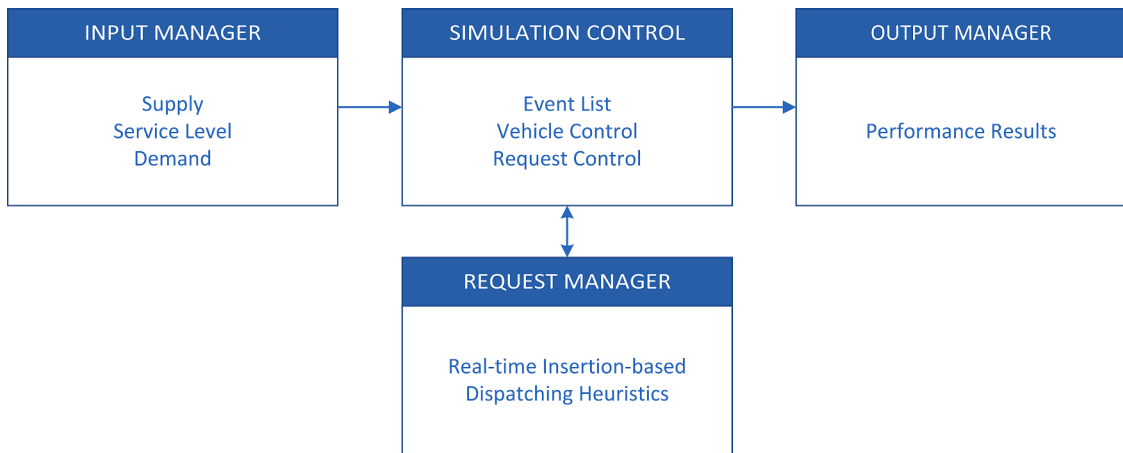


Fig. 1. Schematic description of the simulation model. Adapted from Hall (2012).

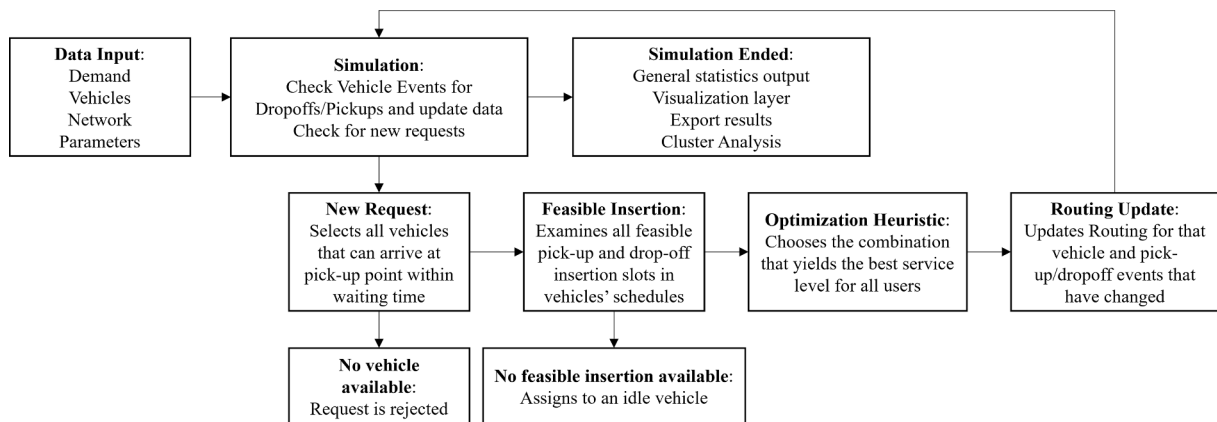


Fig. 2. Flowchart of the simulation process.

et al., 2016). This cluster analysis approach is important to allow better detecting differences between the results that arise from distinct supply and operational alternatives (including service parameters such as vehicles seating capacity), as well as distinct assumptions and demand

scenarios. Our focus is on obtaining groups of trips that share similar service levels to allow a fair and accurate comparison between bus and DRT rides; in particular, the analysis of groups of trips with similar average total travel times, but different disaggregated travel results,

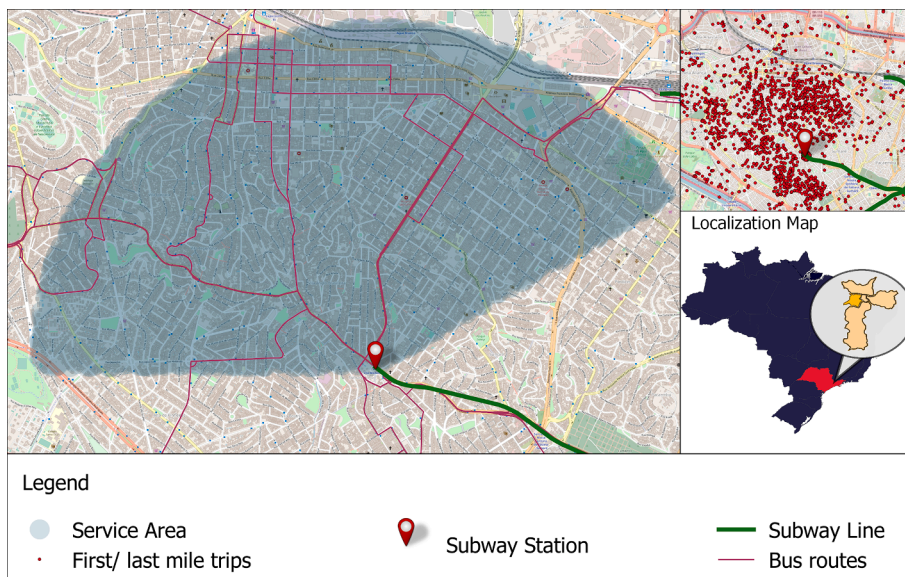


Fig. 3. Service area selected based on bus travel routes and ride-hailing travel sample.

helps transportation planners to evaluate different scenarios and to design solutions that would wield a higher adoption of a DRT service.

5. Case study

The case study comprises a selected area in São Paulo, the most populous city in Brazil and the heart of the largest megacity in South America, with a population of nearly 21 million (or 10% of the population of the entire country), which concentrates about 19% of the Brazilian GDP. The city public transport network comprises 5 subway lines, one monorail, and about 1,300 bus lines, while 8 railway system lines connect surrounding municipalities. The first and last mile service evaluated in this DRT simulation feasibility experiment connects a subway terminal station to an area of about 10 km² (Fig. 3). This area was selected to cover the majority of the bus routes that provide access to this station as well as a representative sample of trips made by an individual ride-hailing service that we had access to. This subway station is, as the term ‘terminal’ itself implies, the last one of subway line 2 (green) and receives about 30,000 riders on a weekday (Metrol, 2019). It also connects to a bus terminal, served by 11 feeder bus routes.

We also observed that the number of ride-hailing trips is limited in the non-selected area surrounding the station, as riders prefer to travel forward, towards the following station of the subway line. In addition, no bus lines were found that connect solely to the subsequent subway station that follows the terminal station we are analyzing. In other words, the significant portion of the demand is radial, originating in the selected area towards the selected terminal station. Nevertheless, our experiments also comprise other demand distributions around the station, as described below in this section.

Fictitious requests were generated, each with one stop (either to pick up or drop off) located at the subway station and the other uniformly and independently distributed within the service area. The request rate adopted ranges from 360 to 2,500 requests per hour, split equally by first or last mile (that is, origin or destination at the subway station). Request times were distributed over six hours, following a uniform and random distribution. In this context, a large number of trips could be performed and analyzed.

We assume that all potential users whose requests are being generated have similar socioeconomic conditions, that is, there is no distinction in terms of income, gender, the purpose of travel, or age group. All users have identical waiting time and in-vehicle travel time delay thresholds. As mentioned before, no user will cancel the trip or not show up at the departure point when the vehicle arrives. Thus, based on an analysis of current level-of-service parameters of different on-demand ride-hailing services, we established 10 min as the maximum waiting time for picking up passengers, measured from the moment the request is received; in other words, if no available vehicle can service a request by arriving at its boarding location within this time, it is deemed as rejected. Regarding the maximum in-vehicle travel time, we have defined that, for each request, it cannot exceed a maximum duration, given by the travel time of the shortest direct path linking the origin and the destination of the corresponding trip multiplied by a factor equal to 2.5. This assumption, though compatible with the reality of travel times, particularly for door-to-door services using shared vehicles and for the existent public transportation alternatives in São Paulo, does not mean that all trips would take such longer; in fact, our aim by establishing such multiplier value is to avoid rejecting requests in order to evaluate how different ‘intensities’ of requests (i.e., rates) impact the results, particularly the service level indicators.

An unlimited number of vehicles are distributed within the pre-determined service area at specific spots, such that all requests can be served within the maximum waiting time. Thus, at the end of the simulation, it is possible to measure the fleet size needed to meet a specific demand rate for that scenario. The fleet is assumed as homogeneous for each experiment; however, the experiments comprise varying vehicle capacity: 3, 6, or 9 passengers. When a vehicle becomes

idle (i.e., after all passengers assigned to it have been transported), it returns to its initial location and waits for new requests. To compute travel times, we assume a driving speed of 15 km/h, as it is deemed realistic given the travel speeds at peak hours in São Paulo (Reed and Kidd, 2019), as well as taking into account the characteristics of the street network in the selected area: partially hilly and curvy streets, especially where the network does not resemble the Manhattan’s grid-like structure (Jiang, 2007), as can be observed in Fig. 3. In addition, most streets are either local or collectors, whose speed limit does not exceed 40 km/h, thus preventing vehicles to achieve a higher average travel speed due to frequent stops signs and some traffic lights. It should also be noted that this driving speed of 15 km/h considers only traffic conditions, as stops have pre-defined boarding and alighting times that are added to the travel times. As in Jung et al. (2013), we adopted a fixed one-minute interval for boarding and alighting times; however, such time is deemed fixed as it better represents the local constraints related to finding a spot for parking the vehicle to allow boarding of a passenger as well as remove the influence of a variable time when evaluating the results.

Operational costs were estimated considering fixed and variable costs. The first include vehicle acquisition, vehicle depreciation, investment capital compensation, driver’s salary and labor charges, licensing and insurances, while the latter comprises fuel, tire wear, oil, maintenance, and washings. These costs differ depending on the vehicle size, except for driver salary and labor charges, and the estimates were based on market prices.

Finally, we analyzed the impacts of the demand distribution around the transportation node, always maintaining 10 km² as the service area, but varying the combination pairs of service area’s opening angle and radius as follows (Fig. 4): i) 127 degrees, 3 km; ii) 150 degrees, 2.76 km; iii) 160 degrees, 2.68 km; iv) 180 degrees, 2.52 km; v) 286 degrees, 2 km; and vi) 360 degrees, 1.78 km.

6. Experimental results and discussion

In this section, the main results are presented, together with a comparison between the fixed-route bus lines that operate in the same area and a ride-hailing service that is not shareable (i.e., a vehicle services only one request at a time; two or more passengers cannot be transported together). For this comparison, we consider that demand is unchanged (request rate of 2,500 requests/hour, with the same origins, destinations, and request times) for the three alternatives.

In the case of the fixed-route bus lines, results were mostly obtained from Google Maps API, except the waiting time which we assumed an average of 5 min as their headways are about 10 min during weekdays. For the ride-hailing services, results were acquired using the simulation model we propose, considering vehicles with the capacity of one passenger. In addition to this, a sensitivity analysis was performed with 6 and 9-passenger vehicles. Table 1 presents the average of key service level indicators: walking time, waiting times, in-vehicle travel times, total travel times, and cost per passenger expressed in Brazilian Reals (BRL).

While the fixed-route bus line system results in an average total travel time of 26.03 min at the cost (transit fare) of BRL 4.40 per passenger, the individual ride-hailing system obtained an average of 13.82 min at the cost of BRL 21.66 per passenger. Concerning the DRT systems, the average in-vehicle travel times only increased in about 4–5 min when compared to the single rider ride-hailing option, and walking distances are reduced in comparison with the bus option. Increasing the vehicle capacity from 3 to 6 passengers, a 2-minute increment in total travel time yield a reduction of 20% on the cost per passenger. However, with 9-passenger vehicles, no improvement in service level or cost per passenger has been observed, since the request rate was not high enough to allow increasing vehicle occupancy. In any of the DRT alternatives, this system could attract individual transport users, since it offers lower costs and better service level than buses.

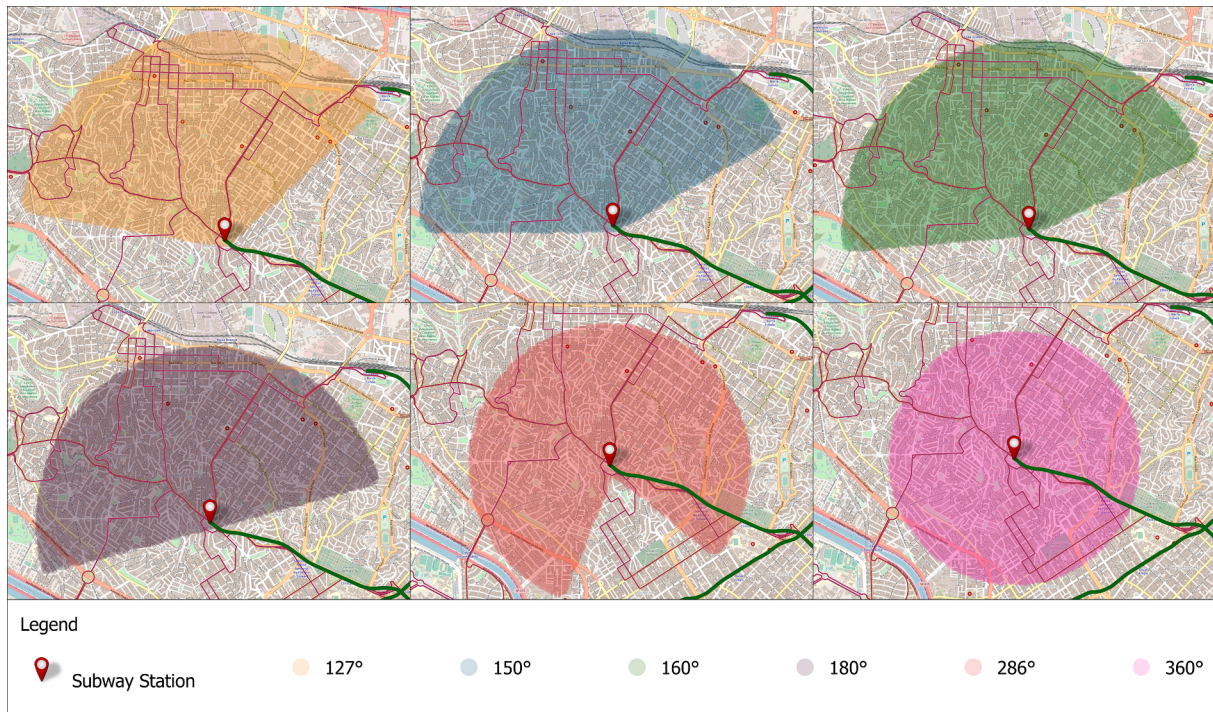


Fig. 4. Demand distribution around the transportation node by varying the angle and radius of the service area.

Table 1
Summary of average key service level indicators.

Mode	Walking time (min)	Waiting time (min)	In-vehicle travel time (min)	Total travel time (min)	Cost/ passenger (BRL)
Bus	7.24	5.00	13.79	26.03	4.40
DRT system: 3 passengers	–	7.68	15.23	22.91	9.65
DRT system: 6 passengers	–	8.26	16.58	24.84	7.78
DRT system: 9 passengers	–	8.28	16.68	24.96	9.15
Ride-hailing	–	2.70	11.12	13.82	21.66

A cluster analysis was performed to group trips with similar service level results, considering waiting time, deviation, and total travel time. Fig. 5 illustrates the results for the 3-passengers DRT system, while the outcomes for bus trips are shown in Fig. 6.

About 8% of the bus trips (cluster #A) had their best routes resulting as path entirely on foot due to the absence of bus services connecting to the metro station. In this case, the DRT system could be a feasible transportation alternative, especially to that may be using their cars to commute due to the difficulty to reach the subway station. Cluster #D, which represents 25% of the bus trips, yielded the second highest average walking time, resulting in an average total travel time of 33.69 min, despite the lowest average deviation observed. Only 31% of bus trips (cluster #C) would have compatible service level results with a DRT system, especially if the high frequency (that yield a headway of

only 10 min) can in fact be offered, which is not oftentimes the case for last-mile transportation routes, as pointed out by Wang (2017). Moreover, cluster #B, which represents 35% of the bus trips, had higher deviations than 76% of the DRT results (cluster #1 and #2). In summary, despite the lower in-vehicle travel time by bus when compared to the DRT system, the greater reliability of the waiting time and the reduction of walking distances are important elements to increase user convenience.

In respect to the individual ride-hailing users, Table 2 presents a comparison with the results obtained with a maximum of 3, 6, and 9 passengers riding together in a vehicle.

While the fleet size required to the ride-hailing service is of 728 vehicles, the DRT system reduced it by 42% with 3-passenger vehicles, and by 52% with 6-passenger vehicles to meet the same demand. As a

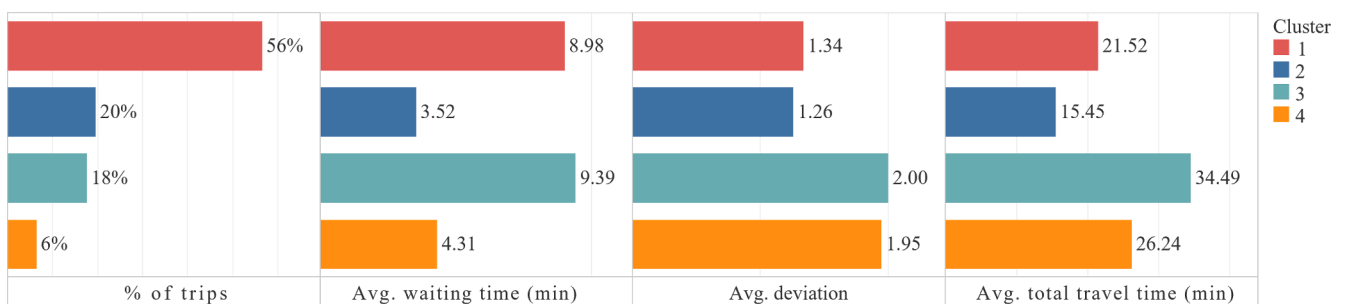


Fig. 5. Cluster analysis of DRT system's service level.

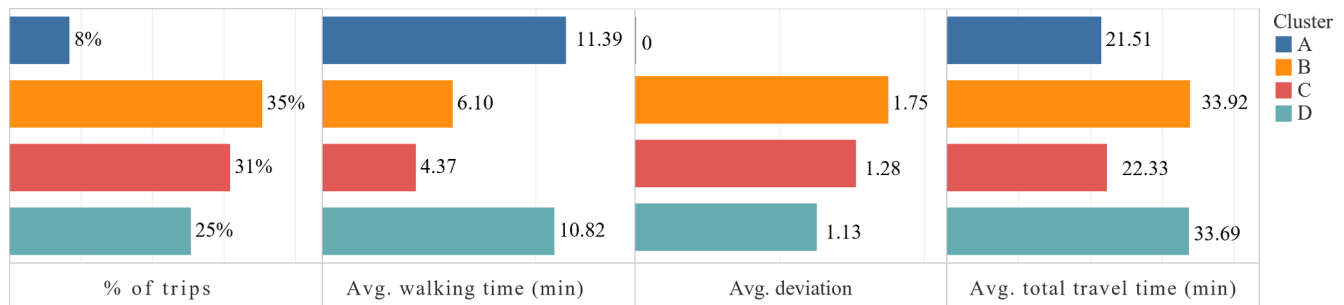


Fig. 6. Cluster analysis of bus trips' service level.

Table 2

Summary of average key operational indicators.

Mode	Fleet size	Total distance (km)	Initial idleness average (min)	Operational idleness average (min)	Average occupancy	Maximum occupancy
Ride-hailing	728	56,176	25.38	111.92	<1	1
DRT system: 3 passengers	425	30,970	24.80	46.71	1.77	3
DRT system: 6 passengers	352	24,987	30.22	22.77	2.17	6
DRT system: 9 passengers	346	24,741	28.41	22.12	2.20	8

result, an increment of only 5 min in waiting times and of 4 min in in-vehicle travel times due to deviations can lead to a 66% reduction in cost per passenger and 80% in operational idleness. Also, the results present a relevant environmental benefit with up to a 56% reduction in total distance traveled and, consequently, emissions. The reduction of the fleet size needed to satisfy the mobility needs of the users can also help to lessen congestion and other externalities related to heavy traffic.

Finally, Table 2 also presents irrelevant gains when increasing vehicle capacity from 6 to 9 passengers. On the other hand, the change from 3 to 6-passenger vehicles yielded important reductions in total traveled distance and fleet size. Despite the consequent increment of average occupancy, the average in-vehicle travel time increased in only 1.35 min.

We also analyzed different demand scenarios by changing: i) request rates; and ii) the service area. Regardless of the request rate, when the service conditions (vehicle capacity, door-to-door service, and prioritization of occupied vehicles) are maintained, the effective service level does not present a significant difference. One of the main impacts by varying the request rate is its impact on unity cost per passenger, as shown in Fig. 7. The request rate reduction to 1,500 requests/hour, generates a cost increment of less than 5%. This suggests that it is already enough to make this service feasible if the costs per passenger and the level of services considered in our analyses are attractive to users, something that is beyond the scope of the present study.

On its turn, Table 3 presents the average key indicators resulted from

Table 3

Summary of average key indicators for demand variation.

Angle (degree)	127	150	160	180	286	360
Radius (km)	3.00	2.76	2.68	2.52	2.00	1.78
Direct ride (min)	10.73	10.06	9.98	9.59	9.03	8.13
Waiting time (min)	6.9	7.1	7.3	7.4	7.5	7.7
Average deviation	1.60	1.61	1.57	1.55	1.52	1.44
Fleet size	109	106	99	97	99	94
Cost per passenger (BRL)	10.86	10.49	9.84	9.61	9.70	9.22

the service area variation according to its angle and radius measures, maintaining the same request rate. They indicate a direct influence in i) direct travel distances and times; ii) average deviations; and iii) fleet size. Therefore, despite that many authors compares demand rates associated with a specific area measure (i.e., km²), in a first/ last mile context, it may lead to different results depending on how the demand is spatially distributed next to the transportation node.

In conclusion, a DRT system has potential as a last-mile transport alternative to users once it allows picking-up and dropping-off passengers from their respective origins to their common destination (the subway station) and the opposite way as well. Such door-to-door service provides reasonable waiting times, which are compatible with the other available alternatives analyzed, a competitive cost per passenger, as well as not leading to excessive detours that impact travel times.

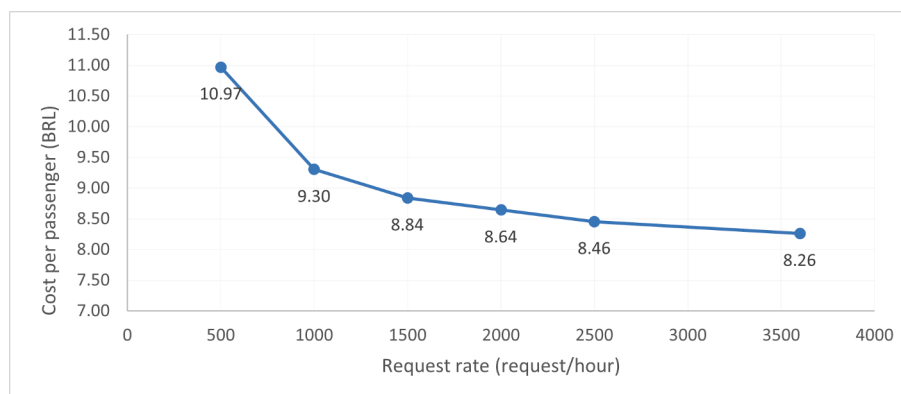


Fig. 7. Cost per passenger with respect to the request rate.

Furthermore, it can be an alternative to complement existing bus lines since they do not fully serve the region near the station to perform first/last mile service.

7. Concluding remarks

This paper aims to evaluate the potential of DRT systems for urban public passenger transport, as an addition to trunk urban public transport systems, such as a subway system. For that, a simulation model was applied to replicate different operational service strategies. The simulation made it possible to analyze the impacts of different operational characteristics of supply and demand, both in terms of effective service level, as well as in the number of vehicles, average occupation and total kilometer traveled per vehicle.

A feeder DRT service was analyzed to evaluate the best possible demand conditions to make feasible to combine requests in the same vehicles. The results highlight the potential of these services in comparison with transportation alternatives (fixed-route buses and ride-hailing), so the proposed DRT system may be an opportunity to attract users of individual transport, as it offers a better level of service than buses, at a competitive cost. Moreover, as public transportation is scarce in some areas, this service can provide a substantial improvement in the urban transportation system. That is, the DRT services can be an alternative to complement the existing bus lines since they do not fully serve the region near the subway station.

For future studies, the demand for these services should be further investigated to define more accurate related costs and to guarantee user satisfaction and use continuity. Finally, it is also important to explore alternatives for better use of the fleet, reducing its idle period.

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