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CASE STUDY AND APPLICATION

Comparison between ad-hoc demand responsive and conventional transit: a simulation study

Zahra Navidi[1] · Nicole Ronald[2] · Stephan Winter[1]

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Abstract Considering the sprawl of cities, conventional public transport with fixed route and fixed schedule becomes less efficient and desirable every day. However, emerging technologies in computation and communication are facilitating more adaptive types of public transport systems, such as demand responsive transport that operates according to real-time demand. It is crucial to study the feasibility and advantages of these novel systems before implementation to prevent failure and financial loss. In this work, an extensive comparison of demand responsive transport and conventional public transport is provided by incorporating a dynamic routing algorithm into an agent-based traffic simulation. The results show that replacing conventional public transport with demand responsive transport will improve the mobility by decreasing the perceived travel time by passengers without any extra cost under certain circumstances. The simulation results are confirmed for different forms of networks, including a real-world network proving the potential of demand responsive transport to solve the challenge of underutilised conventional public transport in suburban areas with low transport demand.

Keywords Simulation · Demand responsive transport · Mobility · MATSim

✉ Zahra Navidi
z.navidikashani@student.unimelb.edu.au

[1] Department of Infrastructure Engineering, The University of Melbourne, Parkville, VIC 3010, Australia

[2] Department of Computer Science and Software Engineering, Swinburne University of Technology, John St, Hawthorn, VIC 3122, Australia

1 Introduction

Demand responsive transport (DRT) systems, also known as paratransit services, are tailor-made public transportation systems in which the stops' locations and times are requested by the passengers. They have been originally designed for helping people with special needs in the 1960s (Nelson et al. 2010). However, the flexibility in design and operation of DRT drew transit operators' attention to make it available to everyone. As a result, DRT services were designed to consist of smaller-sized vehicles (such as taxis, minivans, minibuses) that are shared and run according to the passengers' demand, which results in lower costs compared to taxis. This puts DRT services in between taxi services and conventional fixed-route fixed-schedule public transport in terms of cost and flexibility. While older systems have relied on fixed-line telephones for passengers to book ahead, for example, the day before travel, emerging information and communication technologies facilitate the operation of more advanced DRT systems by allowing passengers to obtain real-time information about the service and book for immediate travel, and allowing operators to update schedules and communicate with drivers.

The transit operators' expectation was that the adaptive nature of this system will bring benefits to operators and customers alike. On one hand, the operators may replace underutilised and uneconomical forms of conventional public transport (CPT) with an appropriate DRT system, which operates as needed and with smaller vehicles, hence, more economically. On the other hand, customers can benefit from the door-to-door convenience of this transport mode without suffering the high cost of a taxi or their private vehicles, and without the hassle of conventional public transport that in areas of low demand operates infrequently and thus is inconvenient. In turn, this can result in reducing the number of private cars on the road, and thus have a positive impact on traffic congestion (Ronald et al. 2015b). Therefore, these systems can be expected to be advantageous not only by serving low-demand areas with poorly performing CPT (Horn 2002) but also for other regions, especially the destination regions of such trips by taking cars off the roads. Beside the indirect impact, it may even be advantageous in high-demand, easily congested regions. This context-dependency requires further studies and investigations. However, the required expenses and time for testing such a new system in the real world are considerably high, which verifies the necessity of developing proper assessment tools prior to implementation as proposed in this paper.

The main hypothesis of this work is that DRT systems perform considerably better than CPT. Demonstrating this superiority is necessary in order to justify the introduction of DRT into the current public transport system. The investigation will be based on user performance and operators' cost to be able to investigate whether a service providing higher quality mobility to users does not cost extra for operators.

Considering the high cost of real-world testing on one hand, and the recent advances in transport simulation methods and computational technology on the other hand, an in-silico approach is suggested for investigating the hypothesis in this paper. It uses an ad-hoc dynamic routing algorithm embedded in the Multi Agent Transport Simulation (MATSim) software package that normally can manage only static routing. This approach permits the exploration of large-scale scenarios with a high spatial and temporal granularity facilitating the analysis of results on an individual level. The results have certain advantages over pure mathematical modelling results, which have been in use so far in similar studies. For instance, an agent-based simulation tool, such as MATSim, is capable of considering the operational aspects of a transportation system (e.g., passengers' preferences, traffic impact, and network shapes) (Ronald et al. 2015b). Moreover, MATSim's traffic results have been validated against real-world data in previous work (Wenli et al. 2010). Therefore, it can be claimed that by using this specific tool more realistic and reliable outcomes are achievable.

Based on preliminary work (NavidiKashani et al. 2016), in this paper, an extensive comparison between DRT and CPT is performed to test the hypothesis and demonstrate the potential of the used model, not only in theoretical scenarios but also in the real world. The performance of both CPT and DRT systems are simulated and evaluated firstly in two conceptual networks with several scenarios including variations in demand and in supply level, and then in a real-world scenario. Each mode is simulated separately assuming that the passengers have no other options but the offered mode.

Analysing the simulations' output revealed the superiority of DRT in the investigated scenarios and demonstrated that implementing a DRT system significantly improves mobility in all scenarios, and without extra costs under some specific conditions. This is a significant finding for two reasons. First, it demonstrates the approaches' capability to provide a differentiated picture, in contrast to other methods. Secondly, it proves the necessity to test a DRT system for particular environments and demand patterns before implementation, and this paper provides the method.

The rest of this paper is organised as follows. A review of previous work and their shortcomings are presented in Sect. 2. The method is explained in Sect. 3 and is followed by the implementation scenarios' description in Sect. 4. The results and their analysis are presented in Sect. 5. Section 6 includes an overall discussion on the results and the method. Finally, the last section is dedicated to conclusions and future work.

2 Related work

Similar to any new system, implementing DRT can be highly risky due to its unknown financial and operational aspects. Enoch et al. (2006) have described 11 cases of failed DRT systems around the world and referred to costing and marketing as their main problem. Therefore, it was necessary to provide better understanding of the DRT, and guidelines for its implementation.

Numerous studies were conducted to survey the current status of DRT services and to find the determinant elements in their viability (Brake et al. 2004; Brake and Nelson 2007; Currie 2007; Palmer et al. 2004, 2008) or develop a qualitative framework or guideline for designing services (Brake et al. 2007; De Jong et al. 2011; Ferreira et al. 2007).

Although these studies provided valuable facts about the consequences of running DRT, they are still limited in providing effective suggestions for designing DRT systems in new areas that have completely different circumstances. Some studies strongly advise against duplicating a successful DRT system in another area without considering its new conditions (De Jong et al. 2011; Enoch et al. 2006).

Additionally, many researchers have focused on solving the route optimisation problem of the system, also known as Dial-a-Ride-Problem or Pick-up and Delivery problem, (Berbeglia et al. 2010; Cordeau and Laporte 2003; Dessouky et al. 2003), which, despite its importance, cannot help decision makers to foretell the consequences of running a DRT system. Even the work of Marković et al. (2015) on considering some real-world challenges in solving the optimisation problem does not go any further in helping the decision makers. Also, real-world systems, regardless of their impressive routing and matching algorithms, did not sustain for more than a few years, for example, Kutsuplus in Helsinki, Finland (Helsinki Regional Transport Authority 2016) or Split in Washington D.C., United States of America.[1] In order to overcome these problems, simulations are necessary to demonstrate how viable a system can be. Simulations have been developed in the recent decades to help scientists conduct controlled experiments for investigating the phenomena that are not easily operable or controllable in the real world (O'Sullivan and Perry 2013). The high cost and long time of testing a DRT system in the real world make it an appropriate case for a simulation study. Therefore, simulation is chosen as the main tool for this study and the rest of the literature review is focused on related work in simulation (for extensive literature reviews on routing algorithms and the optimisation problem see Berbeglia et al. (2010), Cordeau and Laporte (2003), Cordeau and Laporte (2007) and Pillac et al. (2013).

Deflorio et al. (2002) proposed a three-module simulation (a travel requests generator, a trip planner, and a service simulator) to assess the performance of DRT systems. Häll et al. (2012) introduced a similar modelling system to simulate DRT and compare different routing algorithms. Fu (2002) developed a system to simulate DRT with an emphasis on intelligent systems, such as automatic vehicle location and digital communication, to show their effects on paratransit system performance. Quadrifoglio et al. (2008) have applied simulation to assess more detailed characteristics of a DRT system: the time-window size setting and zoning strategies.

Although studying DRT by itself is vitally important, it is not sufficient for convincing the decision makers to switch from current transit systems to DRT. It should be demonstrated that not only DRT is a high-quality service but also is better than already existing services in terms of costs and performance. However, little work has been done that utilises simulation to compare CPT and DRT. Edwards and Watkins (2013) developed techniques to compare the efficiency of DRT and CPT regarding the users' and operators' costs. Diana et al. compared the two modes in terms of their emission (Diana et al. 2007), and their travelled distance and thus operating cost (Diana et al. 2009). Besides, there are studies working on hybrid and semi-flexible systems that investigate the impact of partially replacing CPT by DRT (Atasoy et al. 2015; Errico et al. 2013; Li and Quadrifoglio 2010).

[1] http://www.splittechnology.com/.

Additionally, other studies focused on determining the demand switch point (Chang and Yu 1996; Quadrifoglio and Li 2009), which is the exact demand density below which DRT outperform CPT in terms of user performance and operator's cost, between these two modes.

However, all of these models lacked proper traffic modelling, integration of other transportation modes, and individual passengers' preferences and requirements (Ronald et al. 2015b). To deal with these shortcomings, agent-based models have been recently introduced and suggested (Ronald et al. 2015b). In these models, each traveller is defined as an agent, who has a personal objective function, moves around according to his/her plan, and is able to improve that plan according to his/her constraints. MATSim is an example for this type of simulation software that has been also employed to study similar structures to DRT such as shared taxis (Ciari et al. 2009) and car-pooling (Dubernet et al. 2013), as well as DRT itself. Ronald et al. (2015a) have modelled and compared two schemes of DRT (fixed-time and ad-hoc) in rural Victoria (Australia). Their study demonstrated the capability of MATSim in simulating DRT.

Despite all the valuable work that has been undertaken so far, a powerful simulation tool that can consider all the important aspects of operating a DRT system (such as traffic, passengers' preferences, and their interaction with the system) is yet to be developed. Although in some occasions a more complex model does not necessarily provide more insightful results, in this case, based on the literature and the above-mentioned shortcomings of previous models, a more complicated model is deemed necessary. This work is the first step to provide such tool. To this end, an agent-based traffic simulation, MATSim, is employed that has the capability of representing individuals' travel diaries, which makes it possible to analyse the impact of DRT on an individual level. This level of detail allows for the identification of winners and losers based on their utilities in different scenarios of policy or business model evaluation. Additionally, the welfare could be calculated on individual level or aggregated level based on various sociodemographic attributes of the users. Moreover, the embedded dynamic routing algorithm (Ronald et al. 2013) models the most desirable form of DRT, ad-hoc services. An ad-hoc DRT service, unlike some of its older counterparts, let passengers request immediate pick up instead of booking in advance (before the vehicle departs or a day before), and the dynamic routing algorithm finds the car with the lowest penalty and sends it to pick up the passenger. Since the focus of this work is on this specific scheme (ad-hoc) of DRT systems, the algorithm plays a key role in this study. However, MATSim (or other simulation software packages) can allow for implementing and investigating other schemes as well. Consequently, the presented model in this work is able to accurately demonstrate the extent of DRT's impact on passengers' travel time and to find the demand switch point by conducting an extensive and comprehensive comparison between DRT and CPT.

3 Methods

This work utilises MATSim to model and compare DRT and CPT. The following describes the structure of MATSim, the embedded ad-hoc dynamic routing algorithm, and the evaluation procedure.

3.1 Simulation software

The simulation approach follows mainly the design philosophy of MATSim (Charypar and Nagel 2005). In MATSim, each agent (traveller) has a daily plan including the spatial and temporal characteristics of the agent's activities and the desired transport mode. All the plans are simultaneously executed according to an event-driven queue-based traffic flow simulation (Charypar et al. 2007), also known as Mobility Simulation. Then, all the plans are scored according to Charypar et al. (2007):

$$F = \sum_{i=1}^{n} U_{act,i} + \sum_{i=2}^{n} U_{trav,i} \tag{1}$$

where F is the fitness of the plan (score), $U_{act,i}$ is the utility of performing activity i and $U_{trav,i}$ is the (dis)utility of travelling between activities i and $i-1$. This process is repeated in several iterations until the system reaches an equilibrium state, meaning that no agent can significantly improve its plan. The utility of performing an act ($U_{act,i}$) depends mainly on its type and starting time, and the amount of time allocated to it, which is calculated according to:

$$U_{act} = U_{dur} + U_{wait} + U_{late,ar} + U_{early,dep} + U_{short,dur} \tag{2}$$

where $U_{act,i}$ is the utility of performing an act, U_{wait} is the (dis)utility of waiting to start an act (for example, if an agent arrives at store for shopping before the store's opening time), $U_{late,ar}$ is the (dis)utility of arriving late, $U_{early,dep}$ is (dis)utility of departing early, and $U_{short,dur}$ is (dis)utility of short duration of performing an act. U_{trav} is aligned with Vickrey's model of departure choice (Arnott et al. 1993) and is computed according to:

$$U_{trav(t_{trav})} = \beta_{trav} \times t_{trav} \tag{3}$$

where β_{trav} is the marginal utility of travel, and t_{trav} is the duration of travelling between two activities.

At the start of each iteration, a percentage of the agents are allowed to change their plans. This change includes choosing from previous plans (each agent has a limited memory for the previous plans with the highest scores), rerouting, or changing the activity time. Due to the modular approach of MATSim, it is also possible to define other variations such as changing mode or activity location. Since the agents' memories are limited and just the plans with the highest scores are stored, over iterations it is possible for the agents to improve their plans. At the end of each iteration, the output is a file in XML format including the spatial and temporal details of all the events of the simulation. The high granularity of the output and input (the capability of defining utility functions for each agent), which facilitates the analysis of every scenario on an individual level, is one of the main features of MATSim.

3.2 DRT modelling in MATSim

The routing algorithm is one of the most important components of a DRT system. Due to the modular structure of MATSim, it is possible to plug in any desired algorithm for DRT simulation. In this work, the dynamic routing algorithm developed by Ronald et al. (2013) is implemented that extends the standard Dynamic Vehicle Routing Problem (DVRP) module in MATSim, which has the capability of simulating a wide range of vehicle routing algorithms (Maciejewski 2016). It currently has the limitation of performing no iterations, i.e., the agents can only run their initial given plan and are not able to improve their plans over several iterations. This limitation is accepted in this work as well as previous studies (Ronald et al. 2015a, c), since it causes only underestimation (not overestimation) of the DRT performance. At each time interval, the passenger demand file is checked for new requests received during the previous time interval. If any request is found, the passenger will be allocated to a vehicle using an exhaustive search algorithm that finds the vehicle with the least additional travel time and penalty cost after considering the new request. The penalty cost is calculated according to:

$$PC_i = TTR_i = \frac{PTT_i}{DDT_i} \tag{4}$$

where PC_i is the penalty cost for Passenger i, TTR_i is the travel time ratio for Passenger i, PTT_i is the planned travel time for Passenger i (mins), DTT_i is the direct travel time for Passenger i (mins). This involves a travel time ratio for each passenger, i.e., the ratio of the planned travel time over the direct travel time.

3.3 Evaluation methods

Dowling et al. (2004, pp. 75) define Measures of Effectiveness (MOE) as “the system performance statistics that best characterise the degree to which a particular alternative meets the project objectives”. Accordingly, the MOEs in this work should demonstrate how well a transport system caters for the demand from both, passengers’ and operators’ perspective. Virtual In-Vehicle Time (VIVT) is a widely used indicator to assess the performance of a transit service (Diana et al. 2009; Edwards and Watkins 2013; Quadrifoglio and Li 2009) and operation cost is one of the key factors affecting the decision makers’ choice to operate a new system. However, qualitative criteria, such as on-board comfort that may influence passengers’ choice of mode, have not been considered here. Table 1 summarises the MOEs, their indicators, and the variables needed to calculate each indicator.

VIVT reflects the perceived travel time by travellers and is calculated according to:

Table 1 The MOEs, their indicators, and the necessary variables for their calculation

MOE	Indicators	Variables derived from simulation
User performance	Virtual in-vehicle time	Riding (actual in-vehicle) Time
		Waiting time
		Walking time (if applicable)
		No. of transfers (if applicable)
Operation cost	Cost	Kilometers driven
		Hours driven
		Number of vehicles

$$VIVT = RT + \alpha_1 \times WWT + \alpha_2 \times WLKT + \alpha_3 \times TRF \tag{5}$$

where *VIVT* is virtual in-vehicle time, *RT* is ride time on-board, *WTT* is waiting time, *WLKT* is walking time, *TRF* is number of transfers, and weighting coefficients α_1, α_2, and α_3. The perceived travel time is an important factor in travellers' decision about their mode of transportation (Beirão and Sarsfield Cabral 2007; Hensher et al. 2003). Since passengers' perceptions of the duration of different parts of travelling (e.g., riding on-board, waiting, walking) are different, coefficients are needed to normalise these times and make them comparable. The variables α_1, α_2, and α_3 are set to 1.7, 1.8 and 10, respectively, according to literature (Wardman 2004). It should be noted that the lower the *VIVT* for a mode, the more desirable that mode is for passengers.

The operation cost of a transit service mainly depends on three factors: the size of the fleet, the operating hours, and the kilometres driven by each vehicle (Australian Transport Council 2006), and is calculated according to:

$$OC = \sum_{i=1}^{n} [(OH_i \times COH) + (VKT_i \times CVKT)] \tag{6}$$

where *OC* is the operator's cost, OH_i is the operating hours of vehicle *i*, *COH* is the vehicle's cost per one operating hour, VKT_i is the total kilometres driven of vehicle *i*, *CVKT* is the cost per one kilometre driven by a vehicle, and *n* is the number of vehicles. The cost per hour and per kilometre are very different for CPT vehicles (buses) and DRT ones (cars or mini-vans). Table 2 summarises these costs for bus and taxi (as a proxy for DRT), which is taken from the National Guidelines for Transport System Management in Australia: Part 4 Urban Transport (Australian Transport Council 2006) and the Review of Victorian Taxi Costs (Lennon 2008). In this study, it is intended to compare the cost of DRT to various CPT services to

Table 2 Costs for vehicles in AUD

\$/km for taxi	1.18
\$/h for taxis	18.71
\$/km for bus	0.313
\$/h for bus	49.58

ascertain that a better mobility, and higher performance does not cost significantly more. Since the uptake is equal for both services (CPT and DRT), by assuming the same ticket price for both services, the operator's income from the tickets will be the same and could be ignored.

4 Implementation

The main contribution of this work is to present an extensive comparison of CPT and DRT to investigate if replacing the former with the latter improves people's mobility. To this end, several hypothetical scenarios including variation in demand level, network shape, and supply system are designed. Additionally, a realistic scenario has also been investigated. The details of all scenarios are described in the following sections.

4.1 Network

Two hypothetical network shapes, grid and star-shaped, and one real-world network have been modelled. While the first two have been designed and produced entirely by the researchers, the last one has been extracted from Open Street Map (OSM) data. The properties of each shape are presented as follows.

Grid network (G) Since a grid network is considered to be the perfect network type for public transport (Nielsen 2005), it provides the opportunity to compare DRT to the ideal situation of CPT. The simulated area is a square (16 km^2) divided into 25 smaller squares with a mesh of public transport. This network contains six bus lines riding on horizontal roads and six bus lines riding on vertical roads. The stops on each line are on the intersections in a convenient distance of 800 m (the black dots represent stops in Fig. 1, left), which is the ideal distance for public transport

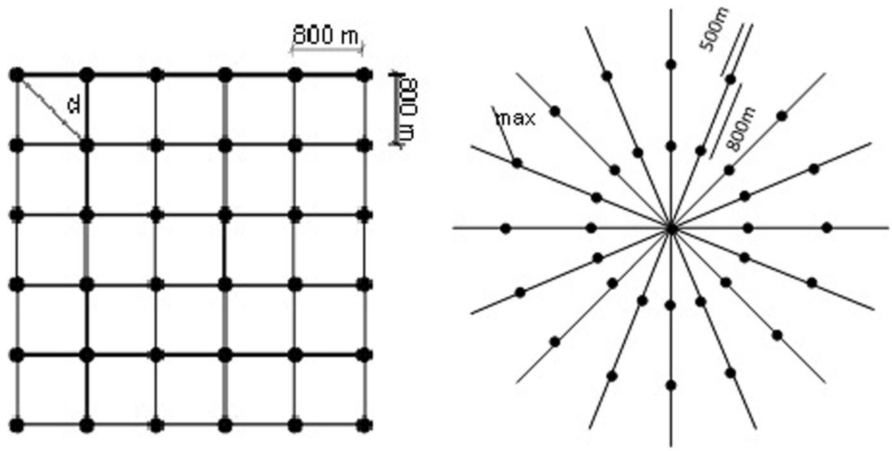

Fig. 1 Grid network (left), star-shaped network (right)

station (Nielsen 2005). Theoretically, the farthest one should travel on foot to reach a transit stop is 566 m, half the diagonal length of the small squares (d / 2).

Star-shaped network (S) Many cities have star-shaped public transport networks. It is also the underlying form of the realistic scenario discussed, which makes it possible to compare the results of a pure conceptual model with a real-world scenario. The simulated area is a circle ($r = 2.1$ km) of approximately 16 km^2 served by a star-shaped transit network (Fig. 1, right). Similar to the previous case, the distance between stops on each line is 800 m. However, in this case the maximum walking distance to reach a stop is slightly longer (max = 625 m). This transit network consists of eight bus lines riding on the eight diametrical roads.

Real-world network (B) Belgrave (Victoria, Australia) was the chosen suburb for the real world scenario in this project. This area heavily relies on feeder public transport at commuter times, and is geographically heterogeneous. It has been earmarked by the local transit operating agency, Public Transport Victoria, as a candidate for experimenting with DRT. An area of approximately 16 km^2 centred by Belgrave railway station has been selected that includes six bus lines. The bus network in this area is conceptually similar to the star-shaped network (Fig. 2).

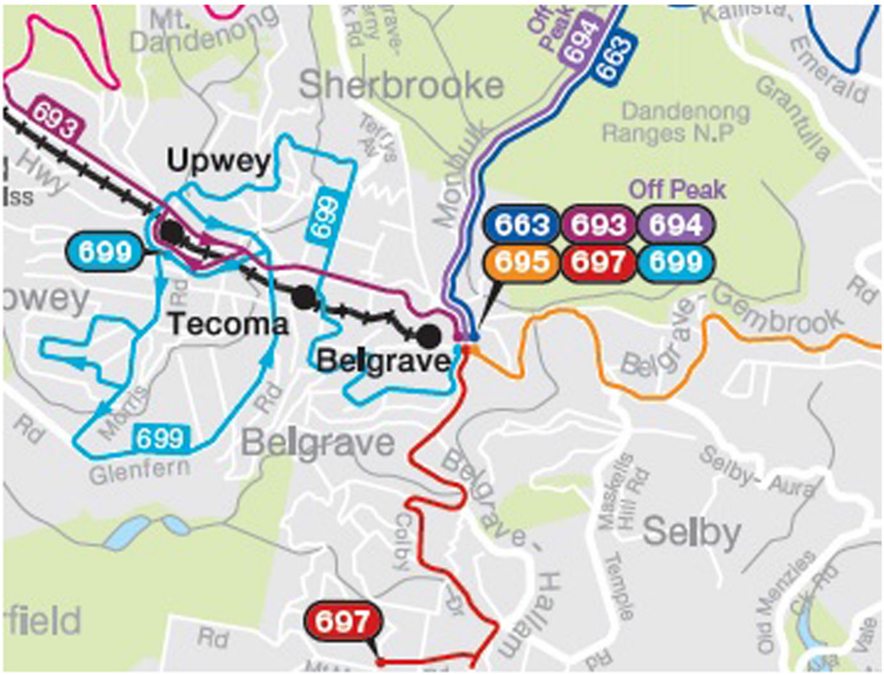

Fig. 2 Belgrave CPT network

4.2 Demand levels and modelling

The designed demand for the hypothetical networks starts from one request per minute up to five with an increment of one (this allows to investigate the lower demands more closely), and from 5 to 15 with an increment of five. Here, x number of requests per minute means the number of trips that are requested in the whole network in each minute. The time and location of the demands were generated randomly by a Python script using different random seeds. The requests were temporally spread over one hour.

The demand for the Belgrave scenario was generated mainly according to real-world data, which had been collected through surveys on bus routes. The available data includes the number of passengers boarding and alighting buses at each bus station and the estimated weekday patronage by hour for each line in percentage.

In order to generate the demand for the Belgrave scenario, the six bus lines operating in the area were chosen. 'For all the lines' stops that were inside the case study area, the number of boarding and alighting passengers were retrieved from the data source. Since the passengers' trajectories or directions are not known, the origins and the destinations of the trips were assigned randomly, in a way that total numbers of demand are equal to the number of passengers boarding on the buses in different bus stops in the chosen area during one weekday (935 trips per day). However, although at each stop the number of boarding passengers was the same as in the data set, there are more alighting passengers (compared to the data set) in some stops. This adjustment was necessary due to the inconsistent numbers for boarding versus alighting passengers in the data. This inconsistency is expected because the survey has been done in a larger area than the investigated area by this study. Also, the adaptation is so small that no significant effect on the results is expected.

Demand in the Belgrave scenario was temporally spread across 17 hours from five in the morning to nine in the evening. The demand in each hour during this time was in accordance with the average estimated weekday patronage by hour for each line in percentage (the average of six lines is presented in Table 3). For instance, there are 186 trips in the AM peak, which is equal to 20% of 935 trips.

4.3 Transit supply systems

The alternative services to be investigated in the hypothetical networks are three different headways of CPT, 7.5 mins (CPT7.5), 15 mins (CPT15), and 30 mins (CPT30), and the DRT service with zero rejection rate, meaning that for each

Table 3 Estimated weekday patronage by hour, average of all lines

Pre AM peak	5:00–6:00	4%
AM peak	7:00–8:00	20%
Interpeak	9:00–14:00	38%
PM peak	15:00–18:00	35%
PM late	19:00–21:00	3%

demand level the number of DRT vehicles was determined in a way that all the agents could reach their destination and no one was rejected due to the lack of vehicle availability. The reason for this restriction on the rejection rate is to make the comparison between DRT and CPT fair: As all agents that use CPT are able to reach their destination, so should the DRT-using agents.

However, the alternatives in Belgrave were just the current public transport headways and DRT. The public transport in Belgrave consists of one train line ending in Belgrave station, and the six regular bus lines. In this study, only the regular bus lines and their demand have been modelled, since DRT cannot and is not designed to compete with mass transit (the train). The lines' numbers, start and end times, and their headways are presented in Table 4. The bus lines were modelled using the published General Transit Feed Specification (GTFS) data and existing Java codes.

The CPT vehicles are buses with a capacity of 75 (sitting and standing) passengers, and DRT vehicles are cars with four people capacity.

4.4 Simulation

The scenarios are run according to the description in Sect. 3.1. However, the scoring function in the simulation is defined with fewer parameters. Here only the utility of performing an act U_{act} is considered for scoring the plans, which is calculated according to Eq. 8.

$$U_{act} = U_{dur} \tag{7}$$

$$U_{dur}(t_{trav}) = \beta_{dur} \times t^* \times ln\left(\frac{t_{dur}}{t_0}\right) \tag{8}$$

Here, t_{dur} is the actual duration of the activity, t^* is the duration at which the marginal utility is β_{dur}, β_{dur} is the marginal utility, and t_0 is a parameter that determines the minimum duration of and activity and its priority. β_{dur} is set to 6 in line with the default settings of MATSim.

In CPT scenarios' setting, agents can store up to five plans. To generate new plans at the start of each iteration, 80% of the agents were allowed to change between their previous plans, while 10% were allowed to change their travel starting time and 10% were allowed to change their route, i.e. using different bus routes.

Table 4 The details of bus lines in Belgrave

Line Number	Start time	End time	Headway
663	6:15:00	22:00:00	30 mins or more
693	6:20:00	21:20:00	30 mins or more
694	6:20:00	15:00:00	1 h or more
695	6:00:00	10:30:00	30 mins or more
697	6:10:00	19:35:00	30 mins or more
699	8:30:00	17:00:00	1 h or more

The required number of runs is calculated through an iterative procedure and depends mainly on three criteria, (1) confidence level ($1 - \alpha$, α: the probability of the true mean of the investigated result not lying within the confidence interval), (2) confidence interval (*CI*: the numerical span within which the true mean may sit), and (3) standard deviation (*S*) of the model results. In this work, the confidence level and the desired range (CI/S) is set to 95% and 2.0, respectively, according to published microsimulation guidelines (Dowling et al. 2004).

5 Results

Figure 3 presents the results of simulations in terms of user performance in grid (left) and star-shaped (right) networks. The VIVT for CPT users is almost the same in both networks, while it slightly differs for DRT, especially in lower demand scenarios. As expected the VIVT does not depend on the demand in CPT, while it changes for different demand in DRT. Moreover, the passengers travelling by DRT have the lowest VIVT in both networks and statistical tests on the results of VIVT revealed that this difference is significant between the different CPT services and DRT. In other words, DRT provides a significantly better service than any CPT in terms of user performance. For example, in grid network VIVT for DRT varies between 15 and 19, while it is 29 for CPT7.5, meaning that DRT provides a performance approximately twice as good as CPT7.5. Although 7.5 mins is considered a very high quality bus service and grid network is the ideal form of conventional public transport (Nielsen 2005), DRT is still outperforming a service with these characteristics.

In order to provide a better understanding of the performance of the DRT, the percentage of passengers waiting more than 10 mins has also been calculated and presented in Table 5. This number for CPT passengers is less than 2%, while for DRT passengers it goes up to 25%. As seen in the table, the figures for DRT are not monotonically proportional to the demand, as one might expect. The reason is that there are a few parameters impacting the DRT figures in each network, including the number of vehicles, and the spatial and temporal distributions of passengers' origins and destinations. Therefore, although the number of vehicles is increasing as the

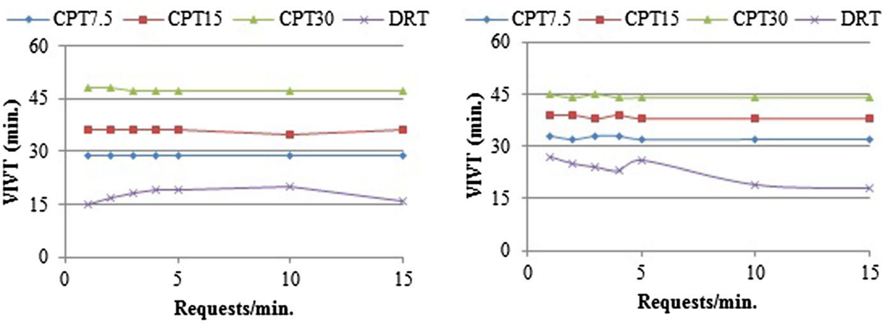

Fig. 3 Average passengers' VIVT (left: G network, right: S network)

Table 5 Percentage of passengers waiting less than 10 mins

Requests per min.	Star-shaped network				Grid network			
	CPT7.5 (%)	CPT15 (%)	CPT30 (%)	DRT (%)	CPT7.5 (%)	CPT15 (%)	CPT30 (%)	DRT (%)
1	98	98	98	63	98	98	98	87
2	99	99	99	65	99	99	99	80
3	99	99	99	70	99	99	99	77
4	99	99	99	70	99	99	99	79
5	99	99	99	66	99	99	99	78
10	99	99	99	78	99	99	99	75
15	99	99	99	79	99	99	99	84

number of calls is increasing, the percentage of passengers with short waiting times (i.e. less than 10 mins) should not necessarily change monotonically proportional to the demand. For instance, with more demand there might be more or less opportunities for matching passengers, or some passengers may like to walk further. The slightly higher percentage of DRT passengers with short waiting times in the grid network (75–87%) compared to the star-shaped network (63–79%) suggests that grid-shaped networks might provide better conditions for running DRT.

One might suggest that the fact that almost no one (less than 2% of passengers) is waiting more than 10 mins when traveling by CPT is a sign of its higher performance; however, it should be taken into account that the passengers waiting more than 10 mins for DRT are in the minority (average 25%) and they wait comfortably at home instead of rather uncomfortably at bus stops, where the CPT passengers have to wait during their transfers. Even with schedule-based transit, there may always be a waiting time for CPT users due to the uncertainty of the traffic condition or driver behaviour. Moreover, as mentioned earlier, the agents in CPT simulations have the chance of improving their plans and changing the time of their arrival to the bus stop to have the shortest waiting time, while in DRT simulation this is not possible and the agents just have one chance for trial. Another point to notice is that in CPT simulation, the agents can walk a part of their trip if its required time is lower than the waiting time and riding time with a bus. Thus, a number of agents might walk instead of waiting long times, which is expected in scenarios with 30 mins headway.

There are two main reasons for lower VIVT for DRT passengers, regardless of their higher wait time and ride time. First, DRT customers need no transfer, which is a highly undesirable action (every transfer is perceived as 10 mins ride time, see Sect. 3.3). Second, since the DRT service is door-to-door the passengers do not need to walk, instead they wait longer, which is a slightly more desirable activity in travelling (see Sect. 3.3).

Additionally, the VIVT for every single passenger has been compared in different scenarios to find out the percentage of people who are not better off using

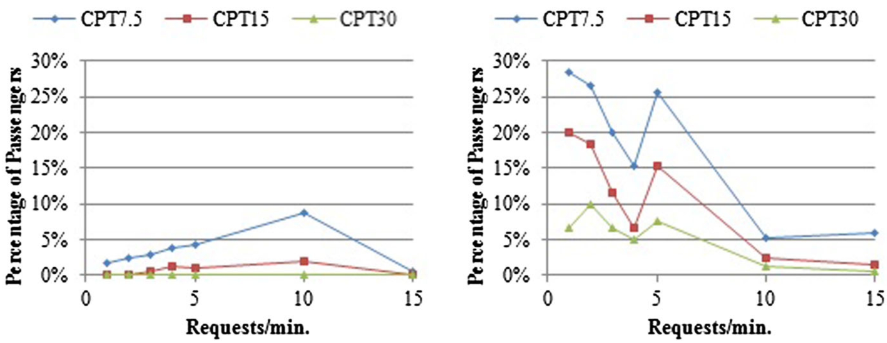

Fig. 4 Percentage of passengers with higher VIVT when using DRT instead of CPT (left: G network, right: S network)

DRT. The results are presented in Fig. 4. This percentage, predictably, decreases in both networks as the CPT headway drops, showing that replacing CPT with DRT has higher advantages in transit networks with long headway compared to the ones with shorter headway. Moreover, the minor percentage of passengers (lower than 10 and 30% in G and S network, respectively) have a higher perceived travel time (VIVT) when travelling by DRT compared to CPT. In other words, the majority of the people (more than 90 and 70% in G and S network, respectively) will have a better mobility option if the CPT services are replaced by DRT.

The percentage of passengers, who are worse off with DRT, is higher in S network scenarios in lower demands. The reason is that although the number of DRT vehicles are enough to deliver everyone to their destinations (Sect. 4.3), it is not enough to keep the waiting time for everyone at a low level. Further simulations showed that by adding just one vehicle in these situations the percentage of disadvantaged passengers drops dramatically without a significant increase in the cost. For instance, if in S network with one request per minute four vehicles run instead of three, the percentage of disadvantaged customers decreases from 28 to 2%. However, in this paper it was decided to stay with the initial assumption and keep the number of vehicles at its possible minimum.

Similar results are observable for the Belgrave scenario. The average VIVT is 18 mins for DRT travellers, almost half the VIVT of the CPT travellers (35 mins), which is considered a significant improvement in the passengers' mobility. However, this excludes a small minority (5%) of the passengers who suffer from a longer VIVT if CPT is replaced by DRT. Similar to the test scenarios, lengthy walking time is an important factor in prolonging the VIVT for CPT passengers. This problem worsens in the Belgrave scenario due to the irregular timetable of the bus lines.

Analysis of agents' individual waiting times has revealed that the number of people with waiting times less than 10 mins is almost equal for CPT and DRT passengers in the Belgrave scenario, with 91 and 90%, respectively. This figure has improved for DRT users in the real world, while worsened for CPT passengers. In this scenario, unlike CPT buses, which are bound to run in certain streets, DRT vehicles are flexible and have no limitation to use all the streets in the network. This results in lower waiting time for DRT users in the real world compared to the hypothetical scenarios, in which both modes' vehicles run on the same network. It is the same in almost any real-world environment.

For the results of the Belgrave scenario, the passengers are sorted according to the starting time of their travel to test if travelling in peak hour would affect their VIVT in both modes. However, no specific decrease or increase in the VIVT at any time was observed, meaning that the DRT performance is constant throughout a day.

The results reflect that regardless of the demand density, DRT is outperforming CPT in terms of user performance. Thus, in making decisions about replacing them the cost of operation will be the determinant factor. Tables 6 and 8 provide details on the cost of each service, and the difference between DRT and each CPT services in grid and star-shaped networks, respectively. This difference is expressed as the percentage of each corresponding CPT service's cost. For example, in the grid network, given a demand of one request per minute, 88% of CPT7.5 cost is saved if DRT runs instead. As another example, given a demand of five requests per minute in the same network, an extra 17% of CPT30 cost is required to replace the CPT30 by DRT. The point of this comparison is to find the critical demand: the demand at which DRT outperforms CPT with the same cost.

According to the Tables 6 and 8, although the operating cost of CPT in grid networks is considerably higher than in star-shaped networks, the operating cost of DRT appears to be independent from the network shape. It should be noted that the small difference between the DRT costs in different networks is caused by the difference in required vehicles for grid networks (Table 7).

According to Table 6, in the grid network, 4, 10 and 15 requests per minute are the critical demand comparing DRT with CPT30, CPT15, and CPT7.5, respectively. Meaning that, for example, it is possible to provide DRT for demand density up to 15 requests per mins (900 requests per hour) with just three percent cost difference with CPT7.5. Fifteen requests per minute could be considered even a high demand situation, where providing a public transport with 7.5 mins headway is justifiable.

Table 6 Operator's cost for each service, and DRT and CPT cost comparison in the grid network

Requests per min.	Cost to the operator				Difference between DRT and CPT		
	CPT7.5	CPT15	CPT30	DRT	CPT7.5 (%)	CPT15 (%)	CPT30 (%)
1	$4051	$2710	$1310	$479	− 88	− 82	− 63
2	$4051	$2710	$1310	$748	− 82	− 72	− 43
3	$4051	$2710	$1310	$1,007	− 75	− 63	− 23
4	$4051	$2710	$1310	$1,284	− 68	− 53	− 2
5	$4051	$2710	$1310	$1,532	− 62	− 43	17
10	$4051	$2710	$1310	$2,792	− 31	3	113
15	$4051	$2710	$1310	$3,910	− 3	44	198

Table 7 Number of required DRT vehicle in each network according to demand level

Requests per min.	Grid network	Star-shaped network
1	4	3
2	6	5
3	8	7
4	10	9
5	12	10
10	21	20
15	31	28

However, the situation is very different in the star-shaped network. At three requests per minute, DRT costs are marginally higher than CPT15 and CPT30 with two and ten percent difference. Just adding one request per minute increases this difference to 30 and 40%, respectively. However, the critical demand for CPT7.5 is yet to be determined. Further simulations revealed that at seven requests per minute DRT service costs are almost the same as CPT7.5 (just 3% difference). Accordingly, it is expected that a DRT service costs less than current CPT in Belgrave due to its similarity to one of the previous scenarios (star-shaped network with one request per minute). This expectation is met by calculating both services' cost, which confirms that the cost of providing DRT in this scenario is equal to just 43% of the current CPT service.

6 Discussion

In this paper, two modes of transport (DRT and CPT) were simulated separately and compared in terms of user performance and operator cost in different scenarios. The main objectives are to determine if replacing CPT with DRT results in an improvement in people's mobility and to identify the demand switch point.

The results show that regardless of the network, by replacing CPT with DRT, a significant increase in people's mobility occurs particularly in low demand areas. However, the higher switch point in the grid network might lead to a conclusion that there is a better chance to save the cost by replacing CPT with DRT. The reason is that providing a comprehensive public transport in a grid network requires buses to run in close proximity of each other, which is expensive. This makes DRT comparable even with a short headway (7.5 mins) CPT in a grid network in terms of not only user performance, but also operator's cost.

The only observed DRT service's drawback for the users was the longer waiting time, which is usually experienced at the comfort of their homes. It is possible to increase this convenience by providing the right communication tools to inform the DRT users about their waiting time, so they can do other activities at home.

There were also two pieces of evidence for capability of DRT in competing with CPT even in areas with medium to high demand. First, given 15 requests per minute, DRT outperformed a CPT with short headway of 7.5 mins in a grid network. Secondly, the percentage of passengers with a higher perceived travel time (VIVT)

Table 8 Operator's cost for each service and DRT and CPT cost comparison in the star-shaped network

Requests per min.	Cost to the operator				Difference between DRT and CPT		
	CPT7.5	CPT15	CPT30	DRT	CPT7.5 (%)	CPT15 (%)	CPT30 (%)
1	$1893	$956	$883	$418	− 78	− 56	− 53
2	$1893	$956	$883	$703	− 63	− 26	− 20
3	$1893	$956	$883	$973	− 49	2	10
4	$1893	$956	$883	$1243	− 34	30	41
5	$1893	$956	$883	$1448	− 24	51	64
10	$1893	$956	$883	$2655	40	178	201
15	$1893	$956	$883	$3729	97	290	322

when travelling by DRT compared to CPT dropped after a certain point (see Fig. 4) in both networks. However, congested roads, which are a usual condition in high demand areas (e.g., central business districts), might contradict this conclusion, while providing a high-quality DRT might encourage people to avoid driving a car themselves and relaxes the mentioned condition. Thus, more complex simulations are required to study DRT in this condition and provide even stronger evidence.

In terms of demand switch points, the analysis reveals differences when comparing the DRT with different CPT services. Unlike CPT, DRT operation highly depends on the demand and the situation. Thus, although it is possible to determine the demand switch point using simulation, it is hardly possible to make any general statement about it.

Finally, investigating the same hypothesis in the Belgrave scenario, including a complex network and realistic bus routes, revealed that DRT can contribute to solving the problem of underutilised buses in the real world. The density in this scenario is almost equal to one request per minute, and when comparing the results to the star-shaped conceptual network similar outcomes are observable. The VIVT of passengers is cut to half in both scenarios when replacing CPT with DRT as well as the cost of providing the service. This means that not only the customers are better off by reaching their destination in half the time, but also the transit supplier can save half the cost, which is a win-win situation for both parties. The consistent outcomes of the hypothetical scenarios and the Belgrave scenario indicate the validity of the method and its potential to be expanded further.

7 Conclusion

The extensive comparison of different scenarios in this paper confirmed the hypothesis and demonstrated that replacing CPT with DRT results in a significant decrease in passengers' perceived travel time, and in turn in an increase in the quality of their mobility with no extra cost in certain situations. Also, since perceived travel time is a determinant factor in changing people's mode choice behaviour, replacing CPT with DRT might encourage more people to use public (demand responsive) transport, which has certain advantages (e.g., fewer vehicles on the road, less congestion, and less pollution than with using private cars).

Moreover, it was shown that the performance and costs of CPT services are independent from the demand, while DRT costs depend on the demand to hold the performance high. This shows the potential flexibility of DRT for adapting to demand and avoiding unnecessary cost and is the reason why identifying a general demand switch point is impossible.

Although this work utilises a capable simulation tool, MATSim, there are still limitations. Although all passengers were modelled and analysed individually, they were homogeneous. They did not have different preferences (e.g., different perceptions of walking time), and although they have preferences, they could not make an individual choice between different modes. For example, the small percentage of people who are not better off when CPT is replaced by DRT might continue to use their own private vehicle in the real world or in a more comprehensive simulation. Moreover, the DRT users did not have the opportunity of refining their plans in iterations, which results in simulation outcomes for DRT users that are rather a lower threshold and could be even stronger in real scenarios. Nonetheless, the individual and aggregated results showed a significant superiority of DRT, and the capacity of the employed tool to provide a realistic simulation of DRT.

Overall, this paper demonstrated the benefits of DRT. DRT's unique features are promising in affecting the use of other transport modes, if implemented correctly. Thus, further studies are required to prove DRT's efficiency and advantages in a broader context, and to find the right implementation circumstances. Therefore, in the future work it is intended to expand the existing model to incorporate all transportation modes (e.g., DRT, CPT, private vehicle) with heterogeneous agents, who have the option to choose the best transportation mode according to their preferences over several iterations. Such a powerful comprehensive tool will further enlighten the understanding of the role of DRT in future transportation.

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