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Transportation Research Procedia 69 (2023) 759–766

Transportation Research Procedia

www.elsevier.com/locate/procedia

AIIT 3rd International Conference on Transport Infrastructure and Systems (TIS ROMA 2022), 15th-16th September 2022, Rome, Italy

Designing demand responsive transport services in small-sized cities using an agent-based model

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Abstract

This paper presents an agent-based model (ABM) to simulate and compare two different operation strategies of a public transport service in small-sized cities, namely a fixed-route transit (FRT) and a demand-responsive transport (DRT) service, under varying demand rates and supply configurations. The ABM builds upon a previous work by the Authors, where flexible and feeder services of a Mass Rapid Transit system were simulated. In this paper, instead of a many-to-one pattern typical of a feeder service, we considered a many-to-many one. The objective is to investigate the conditions that make a DRT more attractive than a FRT in small-sized cities and guide its design considering the demand fluctuation, land-use pattern, service constraints and passenger preferences. A dispatching algorithm for the DRT allows to assign each new trip request to a vehicle, and a couple of origin and destination stops, updating the vehicle schedule in real time. The service includes fixed and virtual stops, allowing request consolidation and balancing operator-related (cost of the service) and user-related (quality of service) needs. The model is applied to Vittoria (Italy), a small city with 60,000 residents in Southern Italy where most trips are made by car, also due to the absence of an urban public transport service. First results highlight the benefits of providing a flexible service compared to a fixed one to minimize detours, waiting times and walking distances experienced by passengers while allowing for a higher shareability and efficiency of the service.

Keywords: Demand Responsive Transport (DRT); Mobility on demand; Agent-based simulation; Mass rapid transit; Low demand areas

10.1016/j.trpro.2023.02.233

1. Introduction

Accessibility-oriented transport planning is focused on increasing the mode share of public transport (PT) and promoting multi-modal integration, i.e., combining various transport modes for seamless door-to-door trips (Curtis and Scheurer, 2010; Capodici et al., 2021). Urban mobility and transport planning are facing a remarkable season of change. The sharing economy paradigm applied to transport services allows a shift from a travel behaviour based on private vehicle ownership to a new one based on sharing services and assets on an as-needed basis (Ambrosino et al., 2016). Such alteration is sustained by the disruptive innovations brought by ICT, which enable new flexible, on-demand transport services spreading, as complementary to conventional PT or in substitution to it (Cohen-Blankshtain and Rotem-Mindali, 2016). In this respect, while remaining the most sustainable way to provide high transport capacity in dense urban settlements, conventional PT shows its inefficiency in some contexts like low-demand areas, where mobility needs are spatially and temporally dispersed, or small cities with a poor (or no) PT service. In all these cases, new on-demand services can cover the gap between unsustainable, but flexible, private transport and sustainable, but inefficient, public transport (Giuffrida et al., 2021). Shared mobility is based on two different concepts of sharing, i.e., sharing of a vehicle or a passenger ride (Shaheen and Chan, 2016). Carsharing, bikesharing and, more recently, e-scooter sharing, belong to the first category. These services offer the flexibility of the individual trip planning and vehicle usage without the burden of the ownership (e.g., fuel, maintenance, insurance), since users pay a usage- and/or membership-based fee. E-scooter and bike sharing have proven to be effective in allowing a modal shift towards PT (Ma et al., 2020), by providing first/last mile access to PT lines.

The sharing of a passenger ride is made possible by the spreading of ICT, which dynamically matches supply and demand and allows travellers to request rides in real-time via mobile applications. Ridesourcing consists of real-time coupling of potential passengers with drivers via ad hoc dispatching algorithm, under a dynamic pricing model and has often outperformed the most traditional form of on-demand individual mobility, like taxis (which also have adopted "e-hail" apps to book a taxi) in an uncertain regulatory and policy climate (Shaheen and Chan, 2016). According to Sadowsky and Nelson (2017), ridesourcing services initially tended to complement PT coverage, offering themselves as last-mile solution in low-density urban areas and during night hours, where and when PT operations are reduced. However, the increasing competition between ridesourcing companies for the market share, the growth in vehicle supply and thus the fares' reduction caused, in the long term, a deteriorating effect for PT. The subsequent step toward shared mobility is represented by the pooled ridesourcing services (UberX Shared, Lyft shared ride, etc.) which offer a cheaper option thanks to accommodating different trip requests with similar origins and destinations. Finally, with the term "flexible transit" we define a group of shared mobility solutions combining a high level of shareability, typical of PT, with adequate flexibility of route and schedule, since passengers are often asked to walk a short distance to access/egress the service. For the scope of this paper, ridesharing and flexible transit are grouped under the definition of Demand Responsive Transport (DRT) given by Davison et al. (2014), i.e., a transport service which is available to the general public, provided by low capacity vehicles such as small buses, vans or taxis, responding to changes in demand by either altering its route and/or its timetable and charging the fare on a per-passenger and not a per-vehicle basis. Introducing a DRT system can be beneficial in small-sized cities where the efficiency of conventional PT is poor and where a car-oriented mobility culture is prevalent. However, it is important to appropriately design the service accounting for the transport demand and supply constraints. A distinction between two different cases can be made, based on the demand pattern: when origins and destinations of trips are uniformly sprawled over the service area (many-to-many demand pattern), the flexible service travels from a departure terminal to an arrival one; instead, when a high percentage of ridership is directed to or come from a transit station (many-to-one demand pattern) as in peak-hours commuting trips, the flexible service follows a cyclic route which "feeds" the transfer station. In the last case, the flexible transit complements and expands the coverage of the Fixed Route Transit (FRT). The many-to-one problem has been investigated by Calabrò et al. (2022) via an agent-based model (ABM) in a parametric environment. In this paper, we extended the model to the many-to-many demand pattern and compared a DRT and a FRT in the context of a small city in Sicily (Italy). An ABM is used to simulate the two services, exploiting the Geographical Information Systems (GIS) and testing the effectiveness of optimization algorithms in a unified simulation environment. The use of ABM provides a suitable environment where to test transport systems serving a demand with given characteristics and evaluate their performance under different configurations, to understand the potential effectiveness of shared services and their applicability range.

2. The agent-based model

ABMs have been widely proposed as a valid tool to study complex urban environments and transport systems (see, e.g., Basu et al., 2018; Giuffrida et al., 2020; Le Pira et al., 2020; Narayan et al., 2020). In this work, an ABM is used to evaluate the benefits of introducing a flexible transit service instead of a conventional fixed-route one, both in terms of cost and quality of service offered to the users. The ABM has been built using the NetLogo programming environment (Wilensky, 1999), taking as reference other previously implemented models (Calabrò et al., 2020; 2022). We extended these models by considering a many-to-many demand pattern, i.e., trip requests with different origins and destinations. Besides, we included multiple PT lines operating in a common service area. A brief description of the model is provided as follows. The transport network consists of fixed stops and optional stops, to encompass both fixed routes and DRT flexible routes based on the real network. The GIS extension of NetLogo is used to map the distribution of socio-demographic data (residents, employees and number of internal and external trips) at a census zone level, thus achieving a good level of disaggregation of the transport demand.

The simulation model is based on a "many-to-many" demand pattern. A trip request is randomly generated from an origin i to a destination j. Instead of using an origin-destination matrix that may be deduced from field surveys, we assume that (i) the probability of a zone j to be the destination of internal trips is proportional to the number of employees of the zone itself, and that (ii) all the external trips to be served by the urban transit service (either FRT or DRT) are directed towards a single intermodal station (i.e., railway and/or bus station), since we only focus on the first/last mile leg of longer trips. The demand rate DR_{ij} is calculated with Eq. 1; where DR is the average demand rate (input value), INT_i and EXT_i are the number of internal trips and external trips originated in i, respectively, E_j is the number of employees of zone j, and st_i (st_j) are binary variables equal to 1 if the station lies in i (j), 0 otherwise.

$$DR_{ij} = DR \cdot \left[(1-\alpha) \cdot \left(\frac{INT_i}{\sum_{k=1}^{n}(INT_k+EXT_k)} \cdot \frac{E_j}{\sum_{k=1}^{n} E_k} + \frac{EXT_i \cdot st_j}{\sum_{k=1}^{n}(INT_k+EXT_k)}\right) + \alpha \cdot \left(\frac{E_i}{\sum_{k=1}^{n} E_i} \cdot \frac{INT_j}{\sum_{k=1}^{n}(INT_k+EXT_k)} + \frac{EXT_j \cdot st_i}{\sum_{k=1}^{n}(INT_k+EXT_k)}\right)\right] \quad (1)$$

Moreover, in Eq. 1 we included a coefficient α which takes into account the period of the day (i.e., $\alpha = 0$ for the morning peak, $\alpha = 1$ for the evening peak). This is because the trips from i to j result, eventually, in a return trip from j to i. From a temporal point of view, the generation of new trip requests (consisting of a given number of travellers[1]) follows a Poisson process, with DR as the rate parameter. In our simplified model, the travellers have a twofold choice to reach the stops, i.e., by walk or by transit. For distances shorter than the walking distance threshold d_{walk}, users are assumed to walk directly from origin to destination.

1.1. The dynamics of Fixed-Route and Demand Responsive Transit

The FRT service consists of a given number n_L of fixed-route lines starting from a terminal stop, travelled by a homogeneous fleet of n_V vehicles with a given seat capacity *Cap*. According to the context of implementation, these lines can be related to the current service offer or a planned one. When a trip request arises, the FRT line able to transport the traveller (group) to the destination (without transfers) is chosen. However, if the distance from the origin (or destination) to the nearest stop of the line is higher than d_{walk}, the group is "rejected" due to excessive access time. Otherwise, the users are "accepted" and walk to the stop that allows them to minimize the sum of walking time and expected on-board time. Once arrived at the stop, they wait for the next FRT vehicle. In case a given maximum waiting time $\tau_{w,max}$ (input value) is overcome, a time penalty proportional to the extra waiting time is given. When the vehicle arrives at the stop, and only if there are available seats, each passenger boards the vehicle, travels onboard and eventually alights at the destination stop. Then, the users walk to the destination.

The DRT service also consists of n_L lines, but they have only a limited number of mandatory stops since any trip request can be served at multiple "virtual stops" (e.g., potential locations to access the service) both near the origin and the destination of the trip. Therefore, vehicle routes and schedules are dynamically updated according to travellers' requests and vehicles' availability. In this case, each request is processed in real-time by the dispatching

[1] For further details, see Calabrò et al. (2022)

algorithm (that will be presented in the next subsection), which tries to find the best match between travellers, virtual stops (both for pick-up and drop-off) and DRT vehicle, according to the passenger time windows and the vehicle capacity and time constraints. If no feasible match can be found, the user assumes the status "rejected". If the trip request is accepted, the passengers follow the steps described above for the FRT case, with the only difference that they know the expected time for pick-up, thus they can wait comfortably at home or the workplace and reach the assigned stop just in time. This is reflected in a lower weight assigned to this "pre-waiting" time. Besides, a "safety" extra time τ_w is included to avoid the risk of arriving late at the stop. This is inspired by the classical distinction between schedule-based and frequency-based transit services. In our case, we can consider the DRT as a "schedule-like" service where the users know the departure time and go to the stop just-in-time. In this respect, relevant literature shows how the access/egress time weighs more for frequency-based services than scheduled ones (Cascetta and Coppola, 2016). The time windows related to a trip request *k*, given the pick-up stop *i* and the drop-off stop *j*, include the earliest pick-up time ep_{ki}, the latest pick-up time lp_k and the latest drop-off time ld_{kj}, which formulations are given as follows:

$$ep_{ki} = t_k + wk_{ki} + \tau_w \quad (2)$$

$$lp_k = t_k + \gamma_k \cdot \tau_{w,max} \quad (3)$$

$$ld_{kj} = lp_k + \frac{d_{ij}}{v} + \delta_k \cdot \tau_{w,max} \quad (4)$$

where: t_k is the time when the request *k* arise, wk_{ki} is the walking time needed for the passenger group *k* to reach the pick-up location *i*, d_{ij} is the shortest distance from i to j, v is the cruise speed of DRT vehicles, $\gamma_k \in [\gamma_{lw}, \gamma_{up}]$ and $\delta_k \in [\delta_{lw}, \delta_{up}]$ are random coefficients accounting for travellers' individual willingness to suffer delays, also based on the purpose of their trip.

1.2. Dispatching algorithm

The dispatching algorithm proposed in this paper for the DRT service is an insertion heuristic which determines how to optimally assign each new trip request to a vehicle of the fleet and a couple of origin and destination stops. Vehicles can accommodate new requests according to the First-Come-First-Served rule, in compliance with maximum travel time thresholds, seat capacity and passenger time windows constraints. As in Calabrò et al. (2022), the algorithm explores feasible insertion solutions over three levels: (i) the set of vehicle routes, including the sequence of already scheduled stops; (ii) the set of possible pick-up and drop-off stops (virtual and/or already scheduled) within the maximum walking distance; (iii) the set of feasible insertion of such stops in the vehicle schedule. The main novelty of this work is that, since we deal with many-to-many demand patterns, each new request involves two different stops for the pick-up and the drop-off processes. Therefore, to limit the number of possible combinations, the complexity of the insertion procedure and the computational time, we choose to include the nearest three virtual stops to the user's origin (or destination), plus the nearest already scheduled stop, in order to consider the possibility to consolidate different passenger requests, thus reducing vehicle detours and allowing for a higher shareability of the DRT service. The best insertion of a new trip request in the vehicle schedule is the one that minimizes the cost function, which is based on Calabrò et al. (2022) and is given by the sum of three (time) cost components: (a) the cost for the passenger group *G* due to the insertion (weighted sum of walking, waiting and ride time), (b) the additional cost for the already scheduled passengers who suffer a delay due to the insertion and (c) the additional cost for the operator due to the detour needed to serve the new request. For each combination *i* of vehicle route, pick-up and drop-off stops and insertion in the vehicle schedule, the cost function is expressed as follows:

$$Cost_i = N_G \left(w_{wk}\, t_{wk,i} + w_{wt}\, t_{wt,i} + w_{rd} \left(t_{rd,i} - \frac{d_i}{v} \right) \right) + \left(w_{rd}\, n_{rd,d} + w_{wt}\, n_{wt,d} \right) \Delta t_i + w_0\, \Delta t_i \quad (5)$$

where N_G is the number of travellers of group *G*; w_{wk}, w_{wt} and w_{rd} are weighting coefficients related to the walking, waiting and ride time, respectively; d_i/v represents the ride time related to the shortest path from origin to destination; $n_{wt,d}$ is the number of users who will have to wait an extra detour time Δt_i at the stop due to the schedule update; $n_{rd,d}$ is the number of passengers on board affected by the detour and w_o is the weight cost related to the operator, aiming at minimizing the detours. The insertion heuristic decides the assignment that minimizes the cost function, among all the feasible solutions (if any), subjected to capacity time-related constraints.

1.3. Performance indicators

The model can monitor different outputs and performance indicators. We make a distinction between user-related and operator-related indicators. Among the former category, we highlight the total number of travellers generated during the simulation (N_U), the percentage of accepted (ACP) and rejected (REJ) users, the average walking (T_{wk}), waiting (T_{wt}) and riding (T_{rd}) time, and the average total travel time (T). The main operator-related output indicator used in this work is the total driven distance (D). However, our model can also monitor other important output indicators, such as the total energy consumption (TEC) assuming full-electric vehicles, the average vehicle occupancy (AVO) in pax/veh, the transport intensity (TI), i.e., the average distance travelled by the vehicles per transported passenger $TI = D / (N_U \cdot ACP)$ and the commercial speed (v_c), which includes the idle time at stops and terminal. We derive two comprehensive cost indicators according to the passenger and the operator perspectives. In fact, while passengers aim at minimizing their travel time, the operator is interested in maximizing its profit, i.e., serving the highest number of requests with the lowest detour possible. Such indicators are the Passenger Unit Cost (PUC) and the Operator Unit Cost (OUC), respectively. They are formulated as follows:

$$PUC(€/pax) = [w_{wk}\,T_{wk} + w_{wt}\,T_{wt} + w_{rd}T_{rd}] \cdot VoT \tag{6}$$

$$OUC(€/pax) = (D \cdot C_{km} + n_V \cdot ST \cdot C_h)/(N_U \cdot ACP) \tag{7}$$

where VoT (€/h) is the value of time for the travellers, C_{km} (€/veh km) the distance-related operator cost, C_h (€/veh·h) the hourly driver cost, and ST (h) the total simulation time. Finally, the Total Unit Cost (TUC) for each service is expressed as the sum of PUC and OUC.

3. Case study and first results

The case study is Vittoria, a small-sized city in the south of Italy. The study area, including the urbanized area (~8.40 km^2), consists of 33400 inhabitants, with a residential density of about 4000 residents per square kilometre. The intermodal station of Vittoria is located on the city outskirt, acting as railway station and extra-urban bus terminal. Currently, private cars account for most of the trips. The municipality is planning a new urban PT network (which is absent at the time), consisting of the 3 lines depicted in Fig. 1.

Fig. 1. Representation of the three FRT lines and the road network used for the DRT service, where the virtual stops are shown as grey dots. The terminal of the green and red lines is the intermodal station, while the terminal of the blue line is the city hospital.

We simulated 18 scenarios, the combination between each of the two types of service (FRT vs. DRT), 3 demand rates (60, 120 and 300 pax/h, assuming α equal to 0.5, 1 and 0, respectively) to explore a wide range of demand, and 3 different types of vehicles used (automobiles with 4 seat capacity, vans with 8 seat capacity and minibuses with 32 passengers capacity). For each scenario, the average output values of 5 simulation runs were analysed. We set VoT = 10 €/h, C_h = 20 €/veh·h and C_{km} based on the vehicle size, i.e., 0.18 €/veh·km (automobile), 0.3 €/veh·km (van), and 0.6 €/veh·km (minibus). The walking speed was set to 1 m/s, the vehicles' cruise speed to 20 km/h, while the maximum waiting time was set to 15 min. Regarding the weighting coefficients, we set w_{rd} = 1, w_{wk} = w_{wt} = 2, and w_0 = 4, as in Fielbaum et al. (2021).

Fig. 2 shows the results for T_{wk}, T_{wt} and T_{rd}. From a first glance, it is clear that DRT always outperforms FRT, with shorter average total times for all vehicle configurations and demand rates. More in detail, one can notice that all scenarios have a T_{wk} of less than 5 minutes, with DRT users experiencing shorter T_{wk}. Different results occur when it comes to T_{wt}; it is interesting to notice that, for low values of demand (60 and 120 pax/h), T_{wt} decreases for FRT with the increase of the number of vehicles, since the headway decreases, while for higher values (300 pax/h), smaller vehicles usually reach their capacity, thus implying higher T_{wt} for users.

In some cases, FRT users experience shorter T_{wt} than DRT ones. This is because T_{wt} for DRT users also accounts for a "pre-waiting" time considering the time when the request is generated, even if it is assumed to weigh 4 times less than the waiting time at stops that is, in general, lower than the one experienced by FRT users. T_{rd} is clearly the performance indicator in which the DRT stands out: the users of the DRT experience shorter times than the FRT ones, since the DRT's route does not have to follow the fixed geometry of the FRT service. In particular, the most convenient DRT scenarios in terms of passenger time for each demand rate are respectively 9x4, 18x4 and 27x4, showing that, as expected, the use of a higher number of vehicles with smaller capacities can lead to total lower experienced travel times for the users.

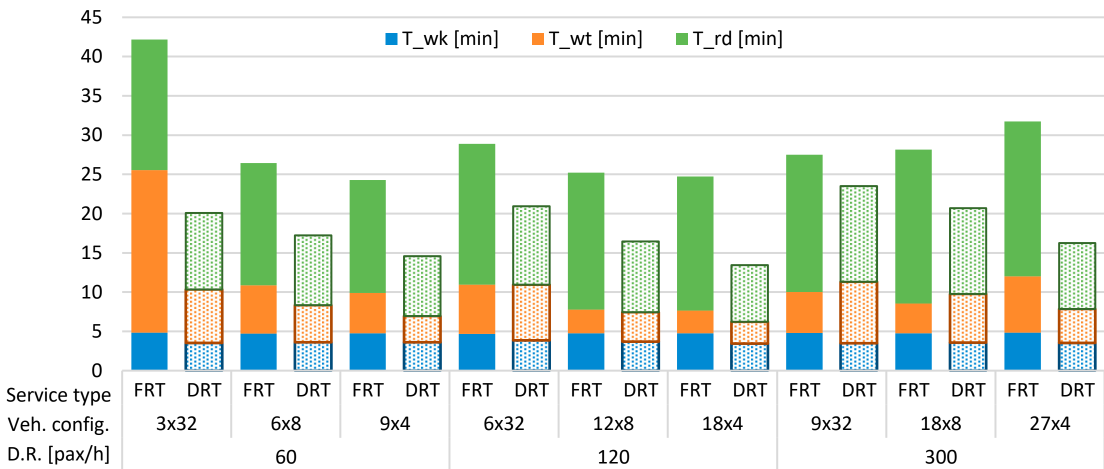

Fig. 2. Performance of the 18 scenarios in terms of passenger travel time (for result interpretation: vehicle configuration is expressed in n_V x *Cap)*.

Fig. 3 shows the simulation results for OUC, PUC and REJ. In terms of total unit costs, the graph clearly shows that DRT outperforms FRT for all vehicle configurations and demand rates. Moreover, while the FRT always has a percentage of more than 50% of rejections for the values of demand pattern that we considered (ascribable to the poor coverage instead of vehicle capacity), the DRT has less than 20% of rejected users in the case of configurations with smaller capacities but a greater number of vehicles; conversely, DRT with fewer vehicles of high capacity shows poor coverage (40 to 50 % of rejected). More in detail, for 60 pax/h, the intermediate scenario 6x8 can be considered the best design scenario, since it also has the lowest percentage of rejected users. The same applies to the case of 120 pax/h, where the intermediate vehicle configuration 12x8 outperforms the others, both in terms of costs and rejected users (only 10% of rejected). Finally, for higher demand rates, the solution with the greater number of vehicles with smaller capacities (27x4) has slightly better performance than the others.

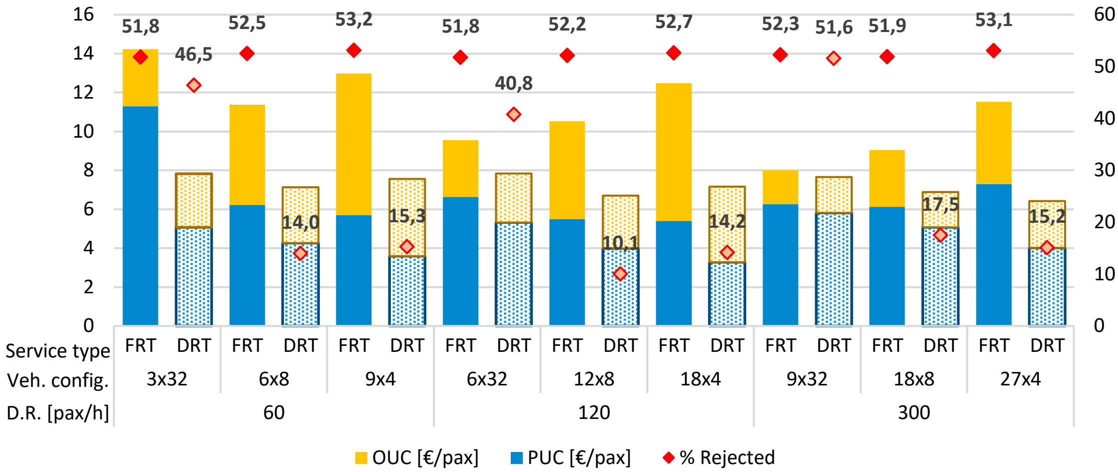

Fig. 3. Performance of the 18 scenarios in terms of passenger and operator unit cost, and percentage of rejected users (for result interpretation: vehicle configuration is expressed in n_V x *Cap*).

Combining the results from both Fig.2 and Fig.3, one can state that for lower demand rates, DRT is the best solution and, in particular, vehicle configurations with minivans with 8 seats are the most convenient design for both the user and the operator in terms of unit costs, although they imply slightly higher travel times for the passengers. With slightly higher costs for the operator, the solution 9x4 would allow users to experience shorter ride and waiting travel times and still obtain a good level of coverage of the service. For higher demand rates (e.g. 300 pax/h) DRT is still the preferred option, and the best design implies 4-seats vehicles, with convenience both in terms of costs and passenger experienced time.

This result should be interpreted with care since it is directly linked to the number of users of the service (and, thus, the percentage of rejected users), which is related to the specific FRT lines that we simulated. By simulating different FRT lines (with higher coverage), it is expected that for higher values of demand the FRT solution would be likely to be preferred (Calabrò et al., 2020). Even if in principle an FRT is more economically attractive from an operator point of view, it can lead to few users and thus higher unit cost (as visible in Fig. 3). This suggests that one should look both at the cost of the service and the users it can attract to find the best solutions and bridge the gap between coverage and ridership (Giuffrida et al., 2021) and consider the cost of the platform that would be need to operate the DRT service and allow a match between the demand and the supply.

4. Conclusions

Innovative demand responsive transport (DRT) services are gaining ever-increasing attention, being flexible services allowing the matching between demand and supply in real-time via mobile applications. Introducing a DRT system can, in concept, be beneficial in small-sized cities where the efficiency of conventional PT is poor and where a car-oriented mobility culture is prevalent. However, it is important to appropriately design the service by accounting for the transport demand and supply constraints.

The choice between a fixed or flexible service depends on the context of implementation and the point of view of the actors involved. In fact, a PT service based on a fixed route covering areas with high demand and, thus, ensuring a good ridership, can be convenient for a transit operator but not for the community, since other travellers would be excluded from the PT coverage. On the other hand, employing a large fleet of vehicles to serve a sparse but low demand would greatly improve the quality of service experienced by passengers, at the expense of operating cost and thus high service fees. The opportunity of switching between different operating strategies, and increasing or decreasing the flexibility of routes and schedules, can help face this trade-off problem.

We tested these strategies with a spatial agent-based model able to simulate scenarios of fixed and flexible transit services in a small city in Italy. First results based on 18 scenarios with varying demand and fleet size and composition highlight the benefits of providing a flexible service with respect to a fixed one, both from a user point of view and an operator one, especially if one looks at the cost per passenger. These results can be useful for transport operators and city administrators to support the planning and designing of effective and innovative public transport services, aimed at providing on-demand mobility and reduce the use of private cars, especially in particular contexts like small cities where traditional public transport is absent or ineffective.

Acknowledgements

The work is partially supported by the project "WEAKI-TRANSIT: WEAK-demand areas Innovative TRANsport Shared services for Italian Towns" (unique project code: E44I17000050001) under the programme "PRIN 2017", by the project of M. Le Pira "AIM Linea di Attività 3 – Mobilità sostenibile: Trasporti" (unique project code CUP E66C180013890007) under the programme "PON Ricerca e Innovazione 2014-2020 – Fondo Sociale Europeo, Azione 1.2 "Attrazione e mobilità internazionale dei ricercatori" and by the project "ADDRESS" under the University of Catania programme "PIACERI Linea 2".

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