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Taxi vs. demand responsive shared transport systems: An agent-based simulation approach

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ABSTRACT

Public transport in urban and suburban areas is not always able to meet population's need of accessibility to jobs, education, health and other opportunities in terms of routes and frequencies; therefore, those who do not own a private vehicle, or who cannot afford individual public transport (e.g. taxis), are often in a condition of social exclusion. Taking advantages of new ICT tools and facilities, Demand Responsive Shared Transport (DRST) services can provide "on demand" transport gathering ride bookings of different users and routing a fleet of vehicles to satisfy passengers' needs while minimizing the cost for the operator.

In this paper, different DRST service configurations are compared to taxi services to investigate their economic attractiveness and sustainability. This is done by using an agent-based simulation model applied to the case of Ragusa (Italy), a city with poor public transport supply, where an innovative DRST service has already been experimented. A set of 50 different scenarios has been simulated, by varying the numbers of vehicles and seat capacity, and considering different demand rates and route choice strategies of the vehicles. Results are analyzed according to different key performance indicators, mainly showing that the DRST system is more advantageous than taxis when dealing with higher demand rates. On the other hand, the efficiency of the DRST system is rather limited compared to taxis in the case of low transport demand and fleets with a small number of vehicles. Between high and low demand there is a balance between the taxi and the DRST systems, where one should deepen the analysis to identify optimal operational parameters. These results pave the way for further analyses to help the planning and design of intermediate transport services like DRST, which are able to bridge the gap between collective and individual transport in urban and suburban areas.

1. Introduction

Cities are evolving into complex and fragmented systems where the proximity to activities, job places and other opportunities provide a social advantage and an increase of the possibility of socialization (Lucas, 2012), highlighting the importance of planning for accessibility as a tool to achieve sustainable mobility (Banister, 2008). Young and elderly people, people unable to drive, or too poor to afford other transport services, become "second class" citizens, leaning on public transport, which is often unreliable (Giuffrida et al., 2017a,b). Demand Responsive Shared Transport (DRST) services can enhance public transport efficiency and equity by providing a more extended and frequent service, flexible mobility and feeder schemes (Ambrosino et al., 2003). Such services can bridge the gap between collective low-quality public transport and unaffordable individual private transport (Inturri et al., 2018). In general, DRST services are emerging with innovative forms thanks to new technologies, standing between an expensive/unsustainable conventional exclusive-ride door-to-door service (like a conventional taxi) and a cheaper/sustainable public transport service (Inturri et al., 2019). They can be operated by private transport network companies (see, e.g. ride-hailing companies) for single rides, or it can be shared, e.g. in terms of vehicle sharing or ride sharing.

From these premises, it is clear the importance of comparing different transport systems that respond to the same needs, but have different performances and affordability.

DRST can be stand-alone services or integrated with conventional

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public transport e.g. for the last leg of the trip, which is very challenging from a transport planning perspective because of some critical issues related to its reliability and cost-effectiveness (Nocera et al., 2020). DRST can use vehicles of different capacities, from vans to minibus. New Information and Communication technologies (ICT) applied to transport and their widespread implementation on smartphones has led to a wide use of data coming from Volunteered Geographic Information (VGI) provided by the members of the communities and their consequent implicit participation in transport decision-making (Giuffrida et al., 2019), enabling the implementation of effective ride sharing services. In this respect, a transport operator can control its fleet through remote sensing technologies and geolocate users by retrieving data from their smartphones, in order to forecast travel times and optimize the coupling of vehicles and riders with similar routes. Users can book, cancel or easily change their reservation; pay it using Internet tools; acquire information on transport modes, routes and expected travel times and expected arrival times before and during the trip. At the same time, ICT facilitate service management for operators, who can collect aggregated booking requests based on location, time of departure and destination; select vehicle carriers, based on the number of passengers, trace flexible routes and estimate travel times with high load factor and low driven distances; collect and store service's performance data (Amisano et al., 2011). Such a trade-off between efficiency and service quality guarantees an effective management and operation of these services on a large territorial context.

ICT-enabled DRST services have been successfully tested, e.g. in a University context in Malta, showing that the cost of the service approximately doubles the cost of local buses, and this difference is attributed to quality of service improvements (Attard et al., 2018).

Literature on methods and models able to reproduce shared mobility services has increasingly grown in the last years. To deal with the complexity of mobility systems, various modelling paradigms have been employed, i.e. analytical modelling, simulation modelling and agent-based simulations, as well-established approaches for analyzing the behavior of complex socio-technical systems (Čertický et al., 2016).

Many studies focus on taxi sharing (Santi et al., 2013; D'Orey et al., 2012; Lioris et al., 2010), car sharing (Lopes et al., 2014; Martínez et al., 2017), shared autonomous transport systems (Fagnant and Kockelman, 2014; Winter et al., 2016; Krueger et al., 2016; Scheltes and Correia, 2017). In general, it has been demonstrated that ride sharing services can ensure efficiency and sustainability by providing "timely and convenient transportation to anybody, anywhere, and anytime" (Alonso-Mora et al., 2017). In this respect, Alonso-Mora et al. (2017) show how the 20% of the taxi fleet size in New York City (2000 vehicles) with a capacity of 10 seats might serve 98% of the demand if the rides are shared and passengers are willing to accept an average extra waiting time of 2.8 min and an average trip delay of 3.5 min.

DRST services have been investigated by simulation models (Quadrifoglio et al., 2008; Horn, 2002; Edwards et al., 2012) to measure their performance, by stated preference surveys to test user potential acceptability (Frei et al., 2017; Ryley et al., 2014), by spatial analyses to assess service accessibility and social inclusion (Giuffrida et al., 2020a) and by agent-based models (ABM), e.g. to evaluate the profitability of low demand transport service providers under the condition of public compensation (Cich et al., 2017).

In general, simulation models reproduce top-down processes with a single entity controlling the system, limiting the autonomy of interactions, communication or negotiation among individual actors (Čertický et al., 2015). Vice versa, the ABM approach can be considered a bottom-up approach, since the micro-interaction between agents (i.e. transport users and vehicles) can determine emergent collective system behavior (Le Pira et al., 2015; Calabrò et al., 2020b). Monitoring of indicators allows to evaluate the service performance and to address decisions on its design and operation. Besides, demand models, such as discrete choice models, can be integrated in the design of ABM, allowing a realistic representation of agents' behavior (Marcucci et al., 2017; Le Pira et al., 2017). ABM provide a natural description of a system and are useful to capture emergent phenomena; they are flexible, making it possible to extend the scale and modify the model, in terms of agents' behavior and their rules of interaction (Bonabeau, 2002).

ABM represent a suitable environment where to test transport systems and evaluate their performance under different configurations. In this respect, it becomes interesting to compare different transport systems serving the same demand, to understand the potential effectiveness of shared services and their applicability range.

In this paper, an agent-based simulation approach is presented to explore the differences between the performance of a conventional taxi service and a DRST system by means of appropriate indicators able to monitor their quality and efficiency and give suggestions on planning, management and optimization of the transport system. The proposed ABM takes advantage of the implementation of a real GIS-based demand model and network, implying an easy transferability to other contexts (Inturri et al., 2018). The methodology has been applied, for a first simulation test, to the city of Ragusa in the south of Italy, where a DRST service has already been implemented.

2. The agent-based modelling approach

The ABM has been built within NetLogo, a free open source software based on an agent-based programming language and integrated modelling environment (Wilensky, 1999); it is written in Scala and Java and runs on the Java Virtual Machine. The main features of the model are the transport network, the demand model, agent (passenger and vehicle) dynamics, route choice strategies and a set of indicators to evaluate the service performance. A first description of the model is presented in Inturri et al. (2018; 2019). It has been used to validate the results of a pilot in the city of Dubai and to compare the performance between the DRST and an intermediate ridesharing service in Giuffrida et al. (2020b). An updated version is here presented with the aim to make a comparison between a DRST and a taxi service serving the same demand pattern.

In this study, we test two demand responsive transport services, which, according to the degree of flexibility and the shareability of the system, can be described as: (i) partially or totally flexible shared services, but with departure and arrival corresponding to predefined stops and pre-set times (DRST); (ii) totally flexible individual services, without predefined stops and pre-set times (Taxi). The transport network for the DRST service is limited to a fixed route and three optional routes selected on the actual road network; it is composed of links, stop nodes and diversion nodes. Taxis use the overall road network of the study area. A GIS dataset is used to implement the georeferenced socio-economic data about population and employees at the census tracts scale in the model, through the GIS extension of NetLogo.

2.1. Demand model

The time interval between two requests is randomly generated according to a negative exponential distribution. The trip rate TR_{ij} generated from an origin i to a destination j is proportional to density population with a gravitationally distributed probability that depends on the number of employees and distance between any pairs of zones. More details on the formulation can be found in Inturri et al. (2019).

2.2. Agent (passenger and vehicle) dynamics

2.2.1. DRST passenger dynamics

Any request can group more passengers per time, sharing the same trip. A passenger group's trip request assumes the status "rejected" if the origin/destination (OD) exceeds a prefixed walking distance threshold to the nearest stop; if the OD pair is within the walking distance range, the group moves to the nearest stop, assuming the status "waiting"; when a vehicle with an appropriate number of available seats reaches the stop, each user boards and alights at the nearest stop to his/her required destination, assuming the status "satisfied"; if no vehicle reaches the passenger group within a maximum waiting time, each user gives up and assumes the status of "unsatisfied".

2.2.2. Taxi passenger dynamics

In order to adequately compare the performance of the DRST and taxi services, taxi requests are generated using the same above-mentioned rules, but with two differences: passenger groups cannot share the ride and they do not walk to reach the nearest stop, but wait for the vehicle at the same location where the request is generated, coinciding with the centroid of the corresponding census track.

Passenger dynamics for both the DRST and taxi services are reported in the flowchart of Fig. 1, where the two service routines (i.e. DRST and taxi) work in parallel. This is to compare the performances of the two services with the same generated demand to be satisfied.

2.2.3. Vehicle (DRST/taxi) dynamics

The number of vehicles, their seat capacity and their speed are set at the beginning of the simulation. In order to ensure comparability between the two services, fleet size is the same for DRST and taxi, but taxi vehicle capacity is always the same (i.e. 4 seats), while DRST's one is variable. Each DRST vehicle is generated at a random stop at the beginning of the simulation. It starts traveling along the fixed route until it reaches a stop where waiting users are loaded following the First-Come-First-Served queue rule, updating vehicle's available seats. If there are waiting passengers or on-board passengers' destinations along the flexible route, a vehicle can shift to it at a diversion node. More details on the dynamics can be found in Inturri et al. (2019) and Giuffrida et al. (2020b). Taxis are randomly generated and travel along the entire road network always using the shortest path, but only if there is a request; otherwise, they stand still, waiting for the next request. Vehicle dynamics, both for DRST (Fig. 2a) and Taxi (Fig. 2b), run in loop until the end of the simulation time. It should be underlined that the algorithm foresees that at the end of the simulation time new requests are not accepted, but vehicles keeps running until all passengers are brought to their destination.

2.3. Route choice strategies

While taxis can drive on the entire road network, DRST vehicles always drive on fixed routes, and may drive on a flexible route at diversion nodes according with one of the three Route Choice Strategy (RCS), i.e.:

- FR – "Fully Random": at each diversion node the vehicle chooses at random if taking the flexible route or keeping the fixed;
- AVAR – "All Vehicles drive on All flexible Routes"; each vehicle is allowed to run on a flexible route, but it does it only when demand is present;
- EVAR – "Each Vehicle is Assigned to a flexible Route": each vehicle has an assigned flexible route to drive on.

All the strategies can have a randomness component, due to its beneficial role in increasing the efficiency of social and economic complex systems (Pluchino et al., 2010).

2.4. Performance indicators

The set of performance indicators reported in Inturri et al. (2019) is monitored during the simulations, both to test the impact of different vehicle RCS on the service efficiency and effectiveness, and to compare the two transport services; indicators allow to evaluate the quality of service both from supply and demand side, and of the overall system as well.

The comparison between taxi and DRST with vans of different capacity was performed using three aggregated indicators that highlight service performances in different scenarios; the use of such indicators instead of specific ones allows an overall comparison between the two services:

- Transport Intensity TI (km/pax): ratio of total fleet driven distance and number of served passengers
- Total Unit Cost TUC (€/pax): TUC per passenger takes into account the Total Passenger Travel Time TPTT (h), the Value of Time VOT (€/h) for passengers; the Operation Cost OC (€) and the total number of passengers transported (NP), as shown in Equation (1):

$$TUC\left(\frac{€}{pax}\right)=\frac{TPTT(h)\cdot VOT\left(\frac{€}{h}\right)+OC(€)}{NP(pax)} \tag{1}$$

- Effectiveness E (pax/NAP): in terms of the ratio between the number of satisfied users (pax) and the total number of accepted users (NAP)

3. Application of the ABM to DRST/taxi services in the urban area of Ragusa

3.1. Territorial framework

The model has been applied to the case study of Ragusa, a small-medium city located in the south-eastern part of Sicily (Italy) with a poor public transport supply, a district with high touristic vocation and several facilities including a university department. An innovative DRST service has already been experimented in Ragusa in 2016 during three weeks, connecting the upper town and the lower and older town; the service was provided by MVMANT,[1] an urban mobility platform which enabled the deployment of a dense fleet of vehicles circulating on a fixed route, matching requests in real time generated by customers. The Ragusa network used for the MVMANT pilot was reproduced via the ABM (Fig. 3) with fixed (blue) and flexible (orange) routes; in the virtual map (Fig. 3a), GIS data census zones are colored according to population (from light to dark green). Although a pilot of the service has been carried out, the data collected is too small to be used to estimate a demand for the service. For this reason, we decided to use census tracks as zones and the related socio-demographic data, and apply, both in the case of the DRST service and for taxis, the demand model described in section 2.1.

3.2. Scenario simulations

Simulation runs have been launched to test both taxi and DRST services with different input variables' sets (Table 1) for a total of 50 different scenarios. The sets consider system operation with different numbers of vehicles, DRST with different seat capacities and different demand rates; simulations have been performed with different RCS and levels of randomness, so to test the overall system performance during a total simulation time of 6 h. The simulations were carried out on various computational machines of intermediate performance: the running times of the simulation proved to be adequate for the needs of the study, for a maximum duration of less than 10 min.

Simulations have been performed by applying the following levels of randomness to route choice strategies: AVAR with 0 or 30% randomness; EVAR with 0 or 30% randomness; Fully Random.

3.3. Results

3.3.1. Transport Intensity (km/pax)

The ratio between the total travelled distance by the fleet of vehicles and the total transported passengers is the inverse of an efficiency

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

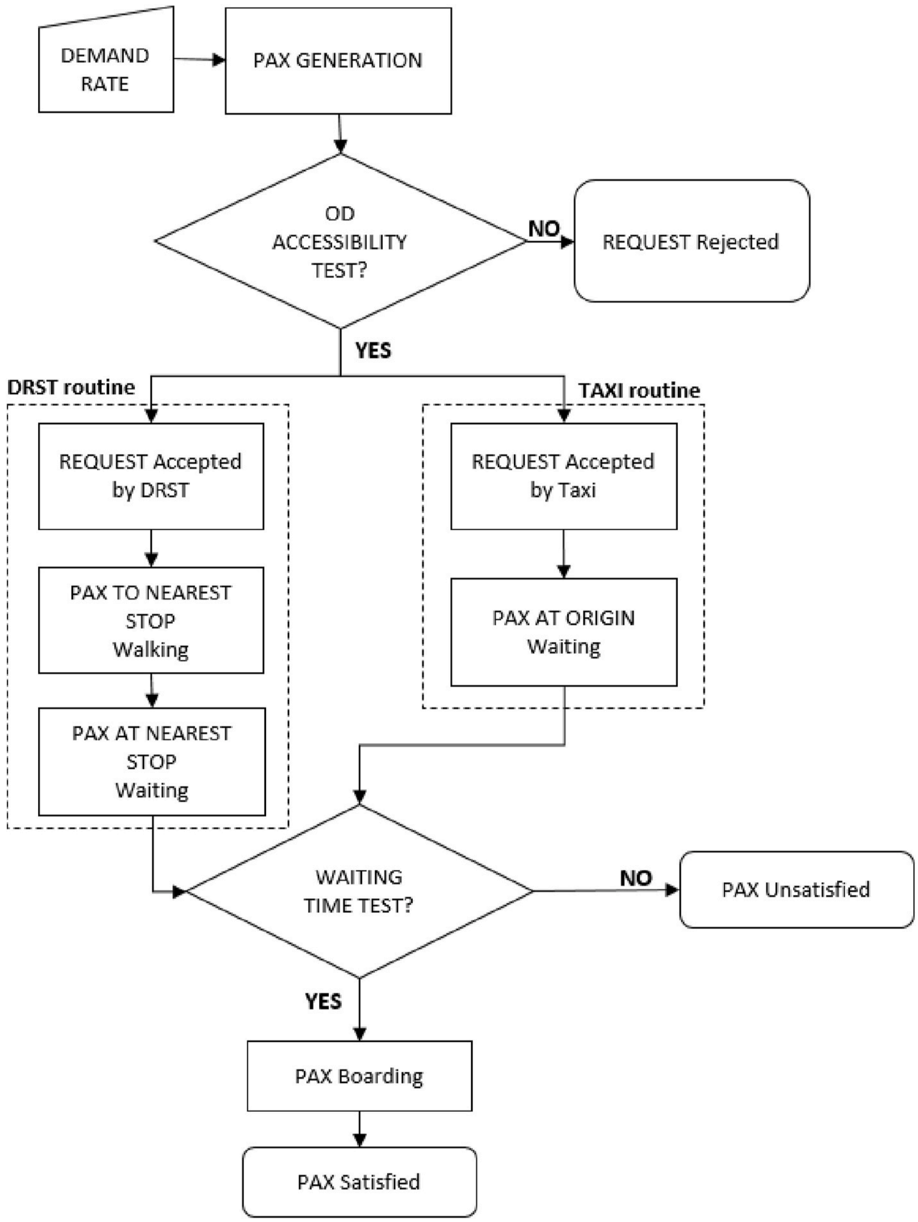

Fig. 1. (a) Passenger dynamics.

measure that we called Transport Intensity (TI). A low TI indicates an efficient service in terms of operation cost per travelled passenger and a low impact on the environment as well.

Figs. 4–7 show TI for different fleet sizes (n from 1 to 4) and single travel requests with up to 4 people. In each graph, the values of TI are shown in the y-axis, while the demand rate values (20, 40, 60, 80 and 100 pax/h) are shown in the x-axis for vehicles with different capacities (4, 8 and 16 seats). For low demand rates (20 requests/h), the taxi's TI is lower than the DRST one, whatever the fleet size and RCS, while for higher demand rates (80–100 request/h), there is an opposite trend. There is a clear disparity between the two systems, with the taxi service more advantageous for low demand rates, and vice versa the DRST service for high demand rates, which can be seen for all fleet sizes (Figs. 4–7). In terms of vehicle capacity, as the one of the DRST increases (from 8 seats to 16–20 seats), TI decreases for all fleet sizes, so larger vehicles should be preferred. Both results can be explained as follows: a greater number of passengers corresponds to a greater probability of having the same OD couples, reducing average detours. There is an opposite trend in the case of low demand rates (equal to 20): in these cases, it is preferable to reduce the capacity of the DRST to have a lower TI. Finally, considering the RCS, it emerges that the three RCS have a similar trend with greater differences highlighted for low demand rates (20–40 passengers per hour) and smaller fleets ($n = 1$, Fig. 4), since bigger fleets allow a greater coverage of optional routes.

3.3.2. Total Unit Cost TUC (€/pax)

TUC should be as low as possible to reduce the total costs of the system (operator and user) and increase the number of satisfied passengers. In this respect, it can be considered an indicator of the transport system efficiency.

Figs. 8–11 show growing trend of TUC as the demand rate increases, whatever the fleet size; for the taxi service there is a more progressive trend, while for the DRST service it is quite homogeneous, almost tending to decrease as the number of vehicles increases (Figs. 10 and 11). For low demand rates (20–40 requests/h) the taxi service has lower TUC values than the DRST service and therefore it is more advantageous, while the opposite occurs for high demand rate (80–100 requests/h), for all fleet sizes and RCS. Given that a shared service is more convenient

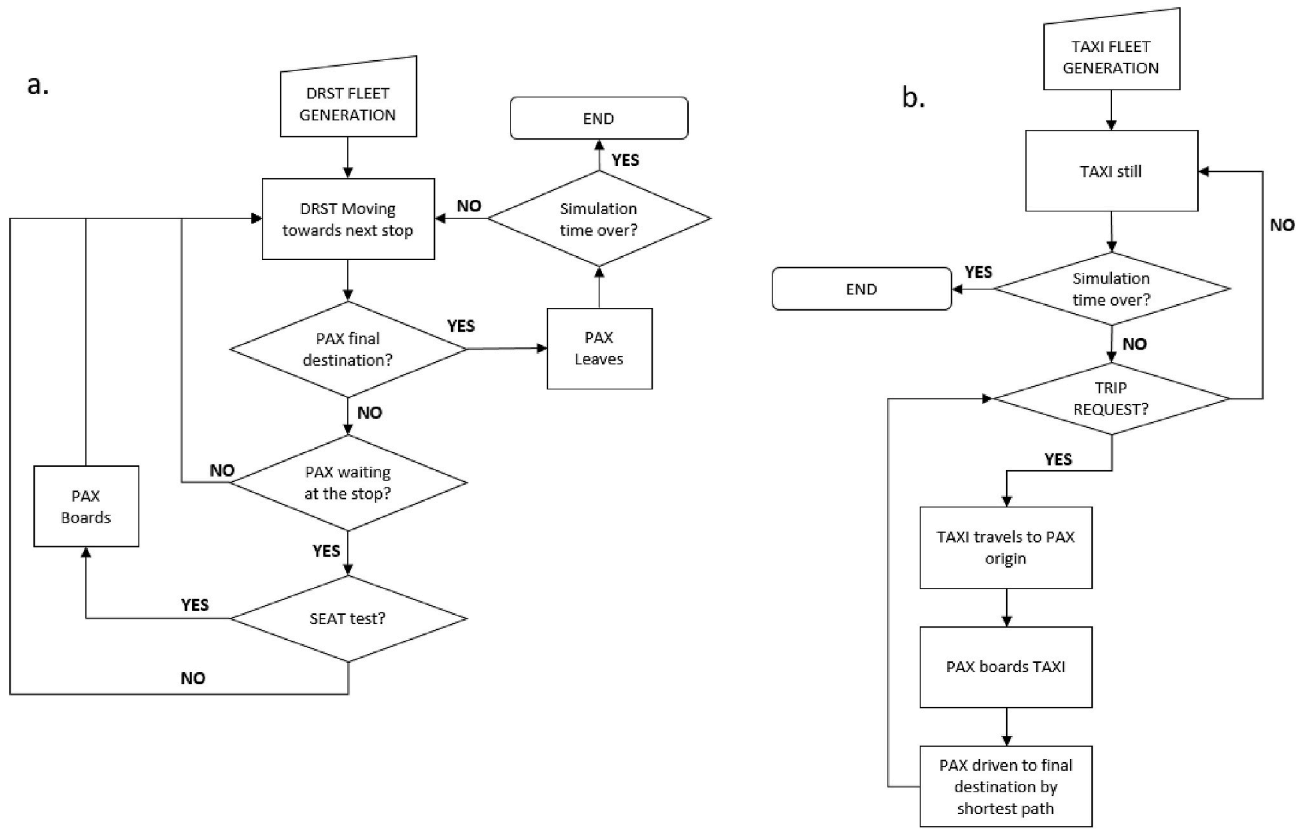

Fig. 2. (a) DRST vehicle dynamics; (b) Taxi dynamics.

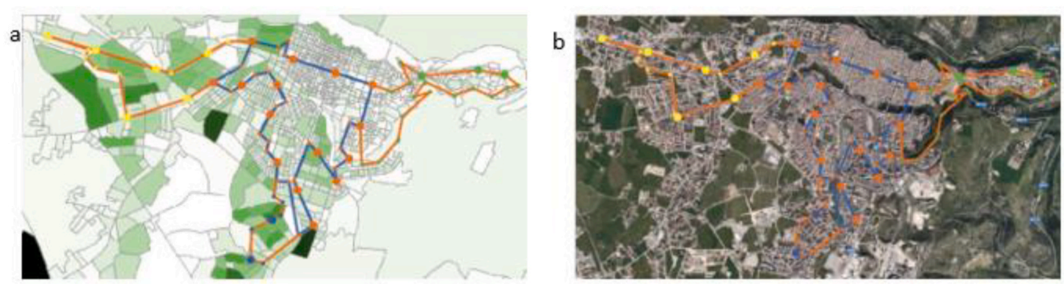

Fig. 3. (a) Virtual map; (b) Satellite map.

Table 1
Input values of scenario simulation variables.

Acronym	Variable name	Value	
		Taxi	DRST
N	number of vehicles	1 to 4	
Cap	vehicle maximum capacity (seats)	4	4 to 20
S	vehicle average speed (km/h)	30 km/h	
dem_rate	demand rate (request/hour)	20 to 100	
max_group	maximum number of passengers grouped per request	3 to 4	
Mwt	maximum waiting time (min)	600 s	

from an economic point of view, these results can be ascribed to the low probability of shared trips in the case of low demand rates so that the economy of DRST sharing does not emerge. The transition in the attractiveness between the two services is located in areas of different demand rates depending on the number of vehicles, from a range between 40 and 60 of demand rate in the case of 1–2 vehicles (Figs. 8 and 9), between 60 and 80 in the case of 3 vehicles (Fig. 10), and finally between 80 and 100 (Fig. 11) in the case of a fleet of 4 vehicles.

Finally, two other aspects are considered. As for the DRST service, it is clear that TUC tends to decrease as vehicle capacity increases (from 8-seat vehicles to 16-20-seat vehicles) with the sole exception of the AVAR strategy for demand-rate equal to 20 and number of vehicles equal to 4 (Fig. 11), and this would suggest the use of biggest DRST vehicles for the service, due to the greater sharing opportunities. The last aspect to consider is the decrease of the TUC value with the increase of the number of vehicles in the fleet of the system (Fig. 11), therefore a greater propensity to use a larger fleet in order to reduce costs and increase the users satisfied by the service. This is due to the fact the TUC includes the point of view of users in terms of total travel time (TPTT), so a greater number of vehicles, providing less detours, allows a reduction of TPTT. However, since TPTT includes both waiting time and on-board time, and a "penalty" for each unsatisfied user, a deeper investigation of users' willingness to pay for different time components should be performed to come up with better practical implications of the results. In terms of RCS, the strategy with better performance varies depending on the

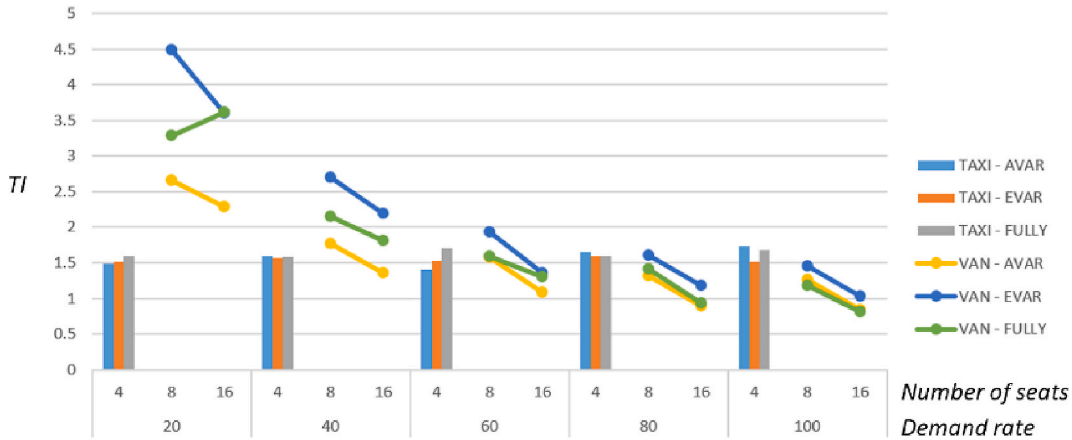

Fig. 4. TI (km/pax) for n = 1, randomness 0%.

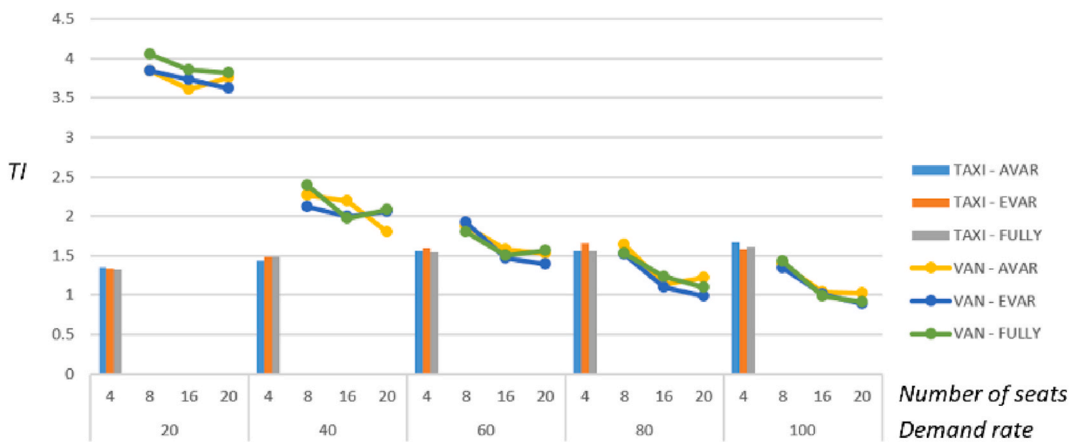

Fig. 5. TI (km/pax) for n = 2, randomness 0%.

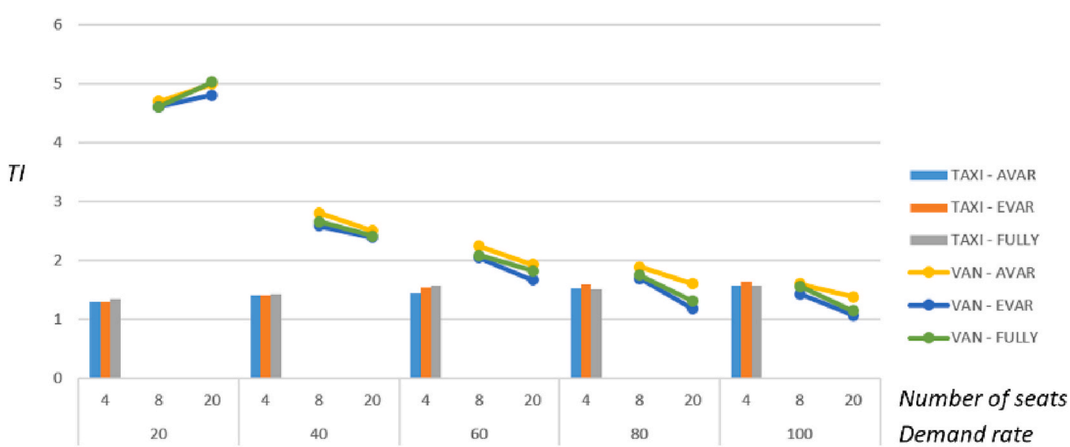

Fig. 6. TI (km/pax) for n = 3, randomness 0%.

vehicles in the fleet. In the case of n = 1 (Fig. 8), AVAR strategy prevails; with n = 2 (Fig. 9) one can notice a balance among the three RCS; with n = 3 (Fig. 10) we have better performances of the EVAR strategy, and finally for n = 4 (Fig. 11) there is a greater efficiency of the EVAR and Fully Random strategies. This suggest that it can be more efficient to assign all vehicles to all routes if a small fleet is used, while it is better to assign specific routes to each vehicles (or assigned them randomly) if the fleet increases so to avoid unnecessary travelled distance.

3.3.3. *Effectiveness (Pax/NAP)*

The ratio Pax/NAP between the number of transported passengers and the number of accepted passenger requests should be the highest to increase the number of satisfied users compared to the total number of users. It can be considered a measure of effectiveness of the transport system. Figs. 12–15 show that taxi prevails on DRST when the demand rate is low (20–40 passengers per hour), whatever the fleet size and RCS, while the opposite occurs in the case of higher demand rate (80–100 passengers per hour).

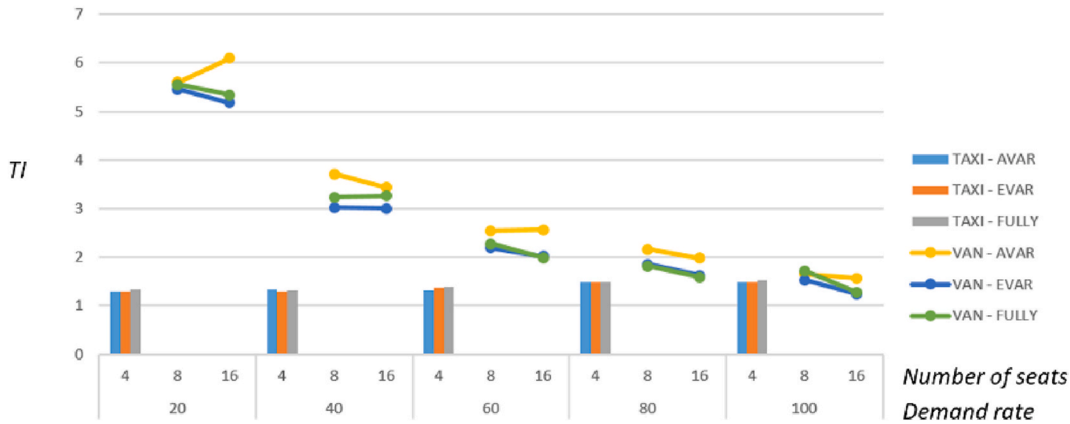

Fig. 7. TI (km/pax) for n = 4, randomness 0%.

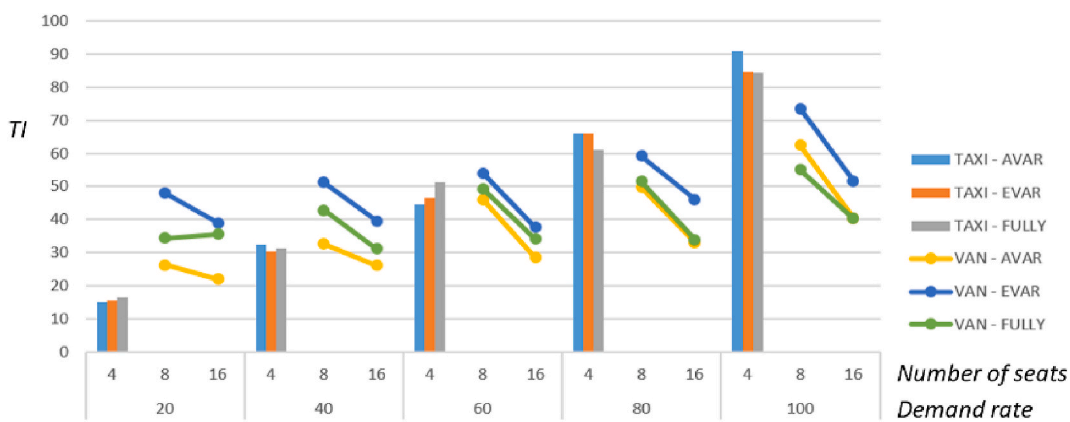

Fig. 8. TUC (€/pax) for n = 1, randomness 0%.

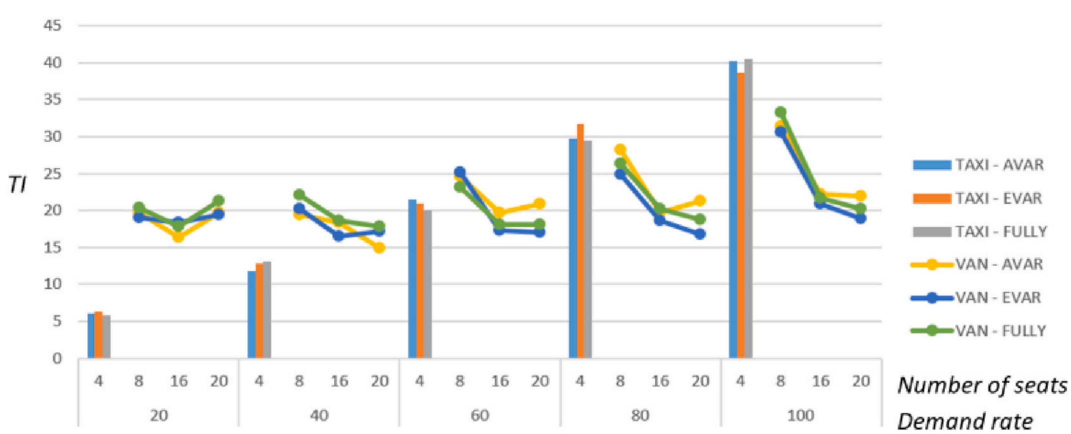

Fig. 9. TUC (€/pax) n = 2, randomness 0%.

In conclusion, when there is greater transport demand, DRST is more efficient than taxi, with an increased number of satisfied users. This is because, in case of higher demand rates, the taxi service is not able to satisfy the demand due to the low capacity, while the sharing of the DRST allows a greater coverage. The change in trend between the two services can be identified at different demand rate ranges depending on the number of vehicles. In the case of a fleet of a single vehicle (Fig. 12), the change takes place at a demand rate between 20 and 40 passengers per hour, and then tends to increase in the case of a greater number of vehicles. For a fleet of 2 vehicles (Fig. 13) the changeover occurs between 40 and 60; in the case of a fleet of 3 vehicles (Fig. 14) between 60 and 80; finally, for a fleet of 4 vehicles (Fig. 15) between 80 and 100. Another interesting result, which is shown in all the different cases of fleet sizes, is how the increase of E is directly proportional to the increase of the number of vehicles (from 1 to 4) and vehicle capacity (from 8 to 16–20 seats), so one should prefer fleets consisting of many vehicles able to transport as many people as possible simultaneously.

4. Conclusion

The sprawl of cities and the consequent spatial spread of activities result in urban and suburban areas with low demand and with a limited

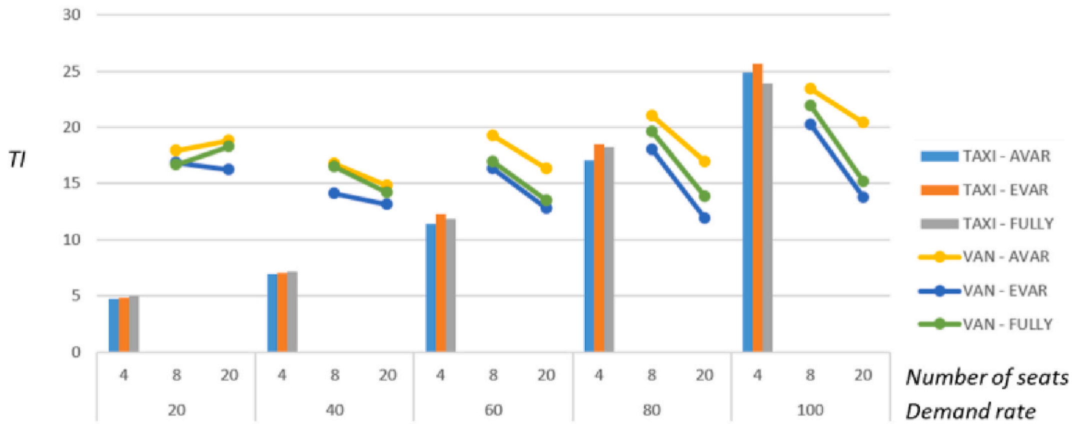

Fig. 10. TUC (€/pax) n = 3, randomness 0%.

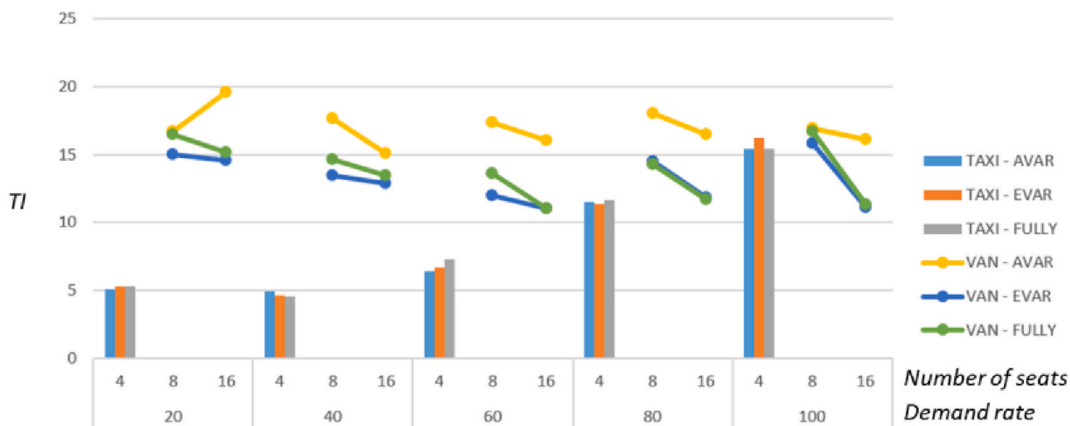

Fig. 11. TUC (€/pax) n = 4, randomness 0%.

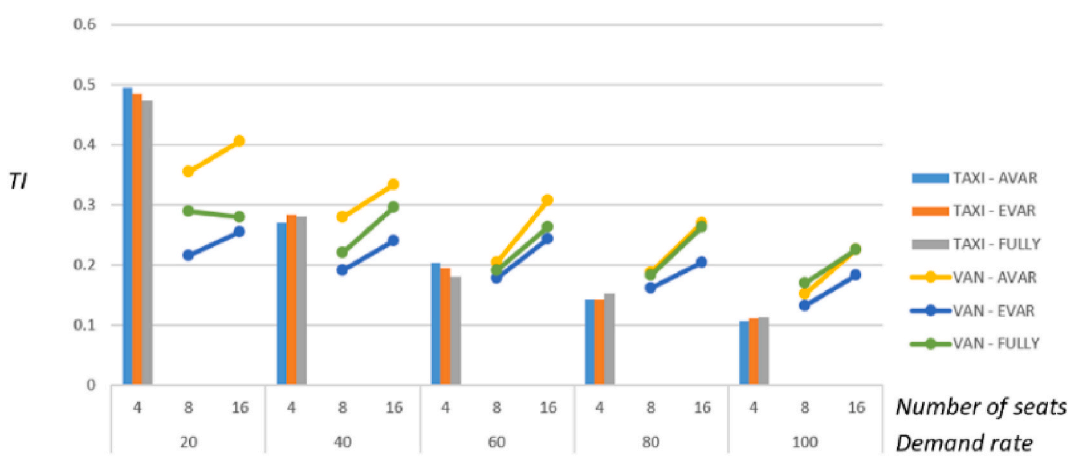

Fig. 12. Pax/NAP n = 1, randomness 0%.

public transport supply that suffer a gap in terms of social inclusion. DRST may be able to fill this gap by providing a shared, affordable transport service that can also meet high quality standards with the help of recent ICT. In this paper, an ABM is presented to test different DRST configuration in comparison with a taxi service serving the same demand. This is interesting to understand the range of application of such shared on-demand service, testing it in a real case study with different scenario configurations. Given a total of 50 different scenarios of operation of the two transport systems, it was possible to identify the possible circumstances and conditions to achieve the greatest potential benefits, through the analysis of three indicators, i.e.: Transport Intensity (Km/pax), Total Unit Cost (TotCost/pax), and Effectiveness (pax/NAP). The first is the ratio between the total travelled distance by the fleet of vehicles and the total transported passengers; it should be as low as possible to have an efficient service in terms of operation cost per travelled passenger and impact on the environment as well. The second can be considered an indicator of the transport system efficiency, since it is based on the total cost of the system (operator and user) and the

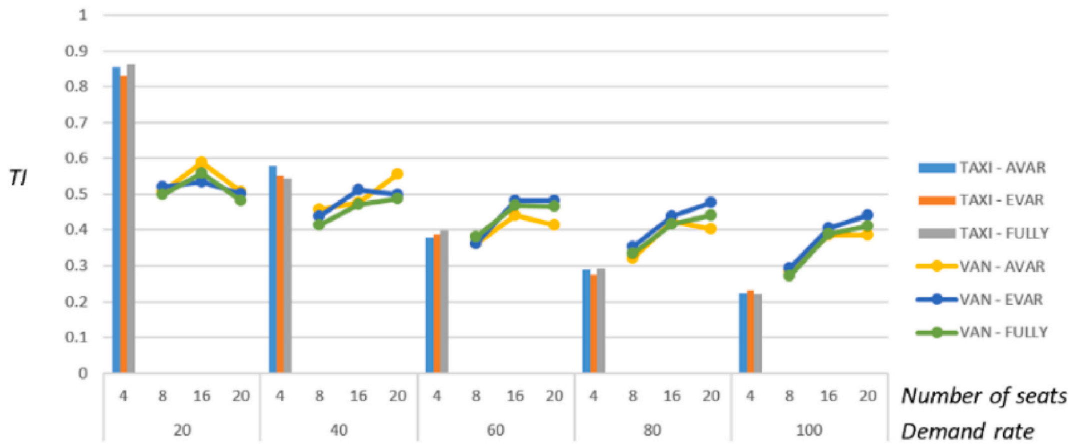

Fig. 13. Pax/NAP n = 2, randomness 0%.

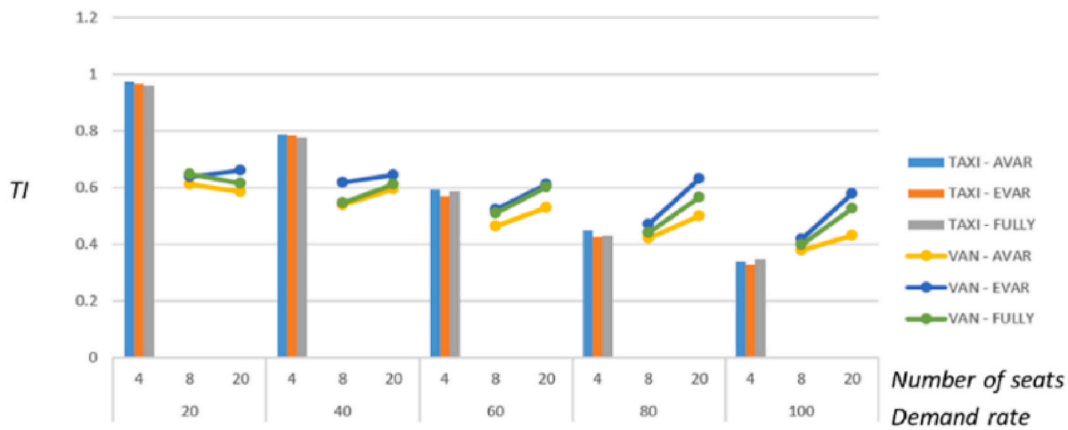

Fig. 14. Pax/NAP n = 3, randomness 0%.

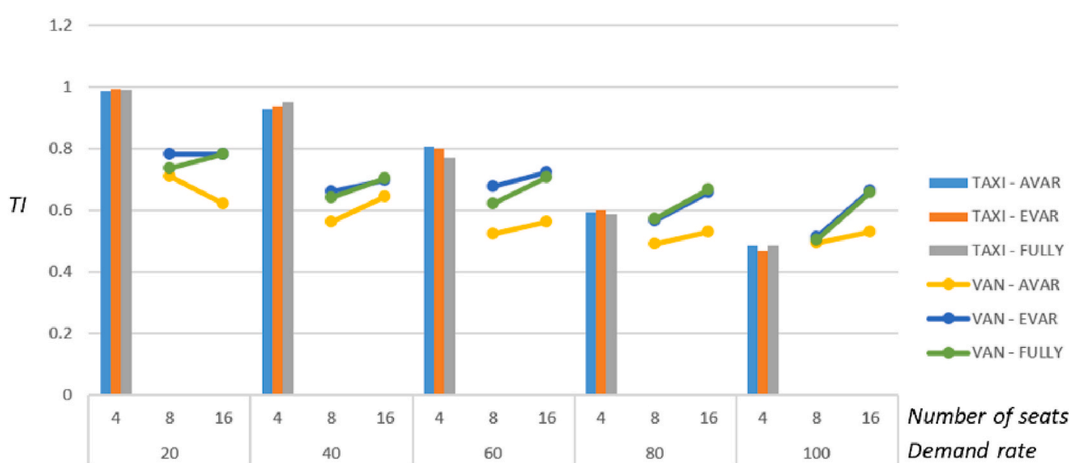

Fig. 15. Pax/NAP n = 4, randomness 0%.

number of satisfied users. The last one evaluates the number of satisfied users compared to the total number of users and, in this respect, can be considered as an indicator of effectiveness of the system. From the simulations it emerged that with a higher transport demand (demand rate of 80–100), and a greater number of vehicles (3–4 vehicles) with high capacity (8-16-20 seats), the DRST system is more advantageous than the taxi service. On the other hand, the efficiency of the DRST system is rather limited compared to taxis in the case of low transport demand (20 of demand rate), fleets with a small number of vehicles (1–2 vehicles) and excessive capacity. In the middle, there is a wide range of transport requests (between 40 and 60–80 of demand rate) where there is a balance between the taxi and the DRST systems, where one should deepen the analysis to identify the optimal operational parameters.

Different sets of input variables could be studied in future research, varying the service and demand data, the route choice strategies and their level of randomness; further performance indicators could be studied increasing the number of vehicles in the fleet and considering vans with intermediate capacity. Besides, DRST services with intermediate levels of flexibility (e.g. in terms of routes) could be tested and compared to understand how to plan and customize the service according to the specific context and demand patterns (Calabrò et al., 2020a). It is also important to model user behavior when choosing alternative transport systems. In this respect, *ad hoc* investigations should be performed to include user preferences in the model (Le Pira et al., 2017). Finally, it would be interesting to simulate the operation of flexible services in conjunction with traditional ones (i.e. public transport, private transport), and test the impact of different public policies (e.g. pricing policies) on the overall transport system performances (Inturri and Ignaccolo, 2011; Cavallaro et al., 2018).

These first results point to the need of *ad hoc* simulation environments able to test different service configurations to help the planning and design of intermediate transport services like DRST. This is both new and needed given their potential in closing the gap left by conventional public transport, by integrating it or substituting it according to the specific contexts.

Author contributions

Conceptualization, N.G., M.L.P., G.I., M.I., R.D, A.R. and A.P.; methodology, N.G., M.L.P., G.I., M.I., A.R. and A.P.; software, A.P. and N.G.; resources, N.G. and R.D.; writing—original draft preparation, N. G., M.L.P. and G.I.; writing—review and editing, N.G., M.L.P., G.I., M.I.; supervision, G.I., M.I., A.R., A.P. All authors have read and agreed to the published version of the manuscript.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tranpol.2021.01.002.

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