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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 public individual transport (e.g. taxis), can often find themselves in a condition of social exclusion and disadvantage. Demand Responsive Shared Transport (DRST) services can help to promote the socio-economic and territorial integration of residents, favoring the connection with urban centers. By taking advantage of Information and Communication Technologies, DRST can provide "on demand" transport services booking in real time a ride on a shared vehicle.

In this paper, different DRST service configurations are compared to taxi services to understand their convenience and sustainability, by using an agent-based model applied to the case of Ragusa (Italy), a city with poor public transport offer where an innovative DRST service has been experimented.

Keywords: shared mobility; flexible transit; dynamic ride sharing; demand responsive transport; agent-based model

1. Introduction

Nowadays, 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 possibility of socialization. Young and elderly

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people, or people unable to drive, or too poor to afford other transport services, become “second class” citizens, leaning on a public transport, which is often unreliable (Ignaccolo et al., 2016). Demand Responsive Shared Transport (DRST) service can enhance public transport efficiency and equity by providing a more extended and frequent public transport, flexible mobility schemes and feeder services (Ambrosino et al., 2016). Such services can bridge the gap between collective low-quality public transport and unaffordable individual private transport (Inturri et al., 2018). Demand responsive transport (DRT) service is 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 service (Fig. 1), where a dynamic sharing of trips makes users experiment longer travel distances and times, while the vehicles drop off and pick up other passengers (like a conventional bus). It can be operated by private transport network companies (see, e.g. ride sourcing) for single rides, or it can shared, e.g. in terms of vehicle sharing or ride sharing.

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

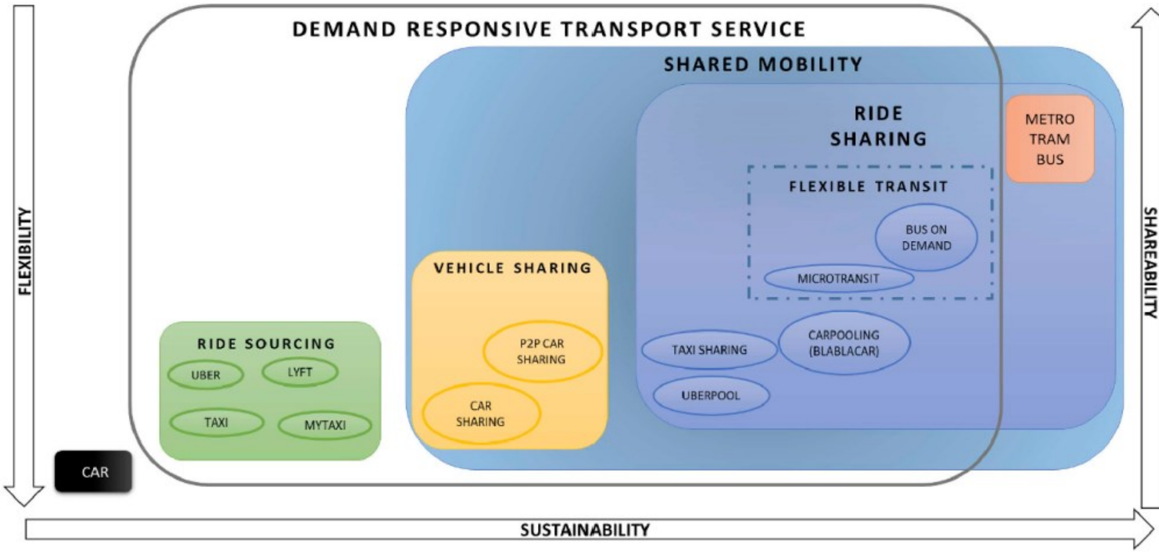

Fig. 1. The flexibility-sustainability-shareability-cost graph of motorized transport services (Inturri et al., 2019)

DRST can be stand-alone services or integrated with conventional public transport and 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 VGI provided by the members of the communities and their consequent implicit participation in trasport decision making (Giuffrida et al., 2019), enabling the implementation of effective ride sharing services: a transport operator can control a vehicle fleet via GPS, track the position of users through smartphones, monitor the service into a dynamic GIS, predict travel times and optimize the matching of drivers and riders with similar itineraries and schedule. Users can book, cancel or change easily its reservation; pay it using Internet tools; acquire information on transport modes, routes and expected travel times before and during the trip and expected arrival times. 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, which cost difference is attributed to quality of service improvements (Attard et al., 2018).

It is important to select the optimal strategy to assign vehicles to passengers' requests, so to perform high load factor and low driven distance, while minimizing the additional time and distances for travelers. Traditionally, the assignment problem is solved "statically" as a dial-a-ride problem (Stein, 1978) while, in the last years, simulation models have been used to dynamically reproduce it and find optimal solutions.

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 Kockelmann, 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 a fleet of just 2,000 vehicles with a capacity of 10 seats might serve 98% of the demand in New York City if the rides are shared, if passengers are willing to accept an average waiting time of 2.8 minutes and an average trip delay of 3.5 minutes.

DRST services have been investigated by simulation models (Quadrifoglio et al., 2008; Horn, 2002; Edwards et al., 2012), stated preference surveys, to test user potential acceptability (Frei et al., 2017; Ryley et al., 2014), or agent-based models (ABM), e.g. to evaluate the profitability of "thin flow" service providers under 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, in ABM, the microinteraction between demand and supply agents (i.e. passengers and vehicles) determines the macroscopic behavior of the system, which can be monitored, via appropriate indicators, and its performance can be evaluated to establish criteria for an optimal service 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 add more entities to the model, modify behavior, degree of rationality, ability to learn and evolve, and rules of interactions of agents (Bonabeau, 2002).

ABM provide 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. The proposed ABM takes advantage of the implementation 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 model

According to the degree of flexibility of the system, DRT services can be: partially or totally flexible services, but with departure and arrival corresponding to stops predefined and pre-set times; totally flexible services, without predefined stops and without pre-set times (like a taxi).

The ABM has been built within NetLogo, a free open source software based on an agent-based programming language and integrated modeling environment (Wilensky, 1999). 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. The model has been first described in Inturri et al. (2018; 2019). 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.

2.1. Transport network

Both fixed and flexible services are considered into the model. The DRST network is built on the actual road network and consists of a fixed route and three optional routes, composed of links, stop nodes and diversion nodes. The taxi network is the overall road network. A GIS dataset is used to implement in the model the georeferenced socio-economic data about population at the census tracts scale, through the GIS extension of NetLogo.

2.2. Demand model

Interval time 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).

2.3. Agent (passenger and vehicle) dynamics

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; 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 its 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".

Taxi passenger dynamics. In order to make the DRST and taxi services comparable, taxi requests are considered using the same abovementioned rules. The only difference between DRST and taxi passenger dynamics is that the latter do not walk to reach the nearest stop, but wait the vehicle in the same location where request is generated, coinciding with the centroid of the corresponding census track.

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). Each vehicle is generated at a random stop at the beginning of the simulation. DRST 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). Taxis always travel along the entire road network using the shortest path if there is a request; otherwise, they stand still waiting for the next request.

2.4. Route choice strategies

While taxis can drive on all the 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 model's Route Choice Strategy (RCS), i.e.:

- FR – "Fully Random"
- AVAR – "All Vehicles drive on All flexible Routes";
- EVAR – "Each Vehicle is Assigned to a flexible Route".

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).

2.5. Performance indicators

A set of performance indicators 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 could allow to evaluate the quality of service both from supply and demand side, and of the overall system.

Table 1. Simulation's performance indicators.

Type of indicator	Acronym	Indicator	Unit	Notes
Demand	NP	total number of passengers transported	pax	
Demand	NAP	total number of accepted requests	pax	
Demand	APTD	average passenger travel distance	km	
Demand	AWT	passenger travel time in terms of average waiting time	min	
Demand	AoBT	average on-board time	min	
Demand	APTT	average total travel time	min	
Demand	TPTT	total user travel time	h	including a penalty of 60 min for each unsatisfied user
Supply	ALF	average vehicle load factor	pax/vehicle	
Supply	TDD	total driven distance	km	
Supply	AVS	average vehicle speed	km/h	
Supply	TI	transport intensity	km/pax	as ratio of total driven distance and number of passengers,
Supply	OC	vehicle operation cost	€	
System	TUC	total unit cost	€/pax	TUC per passenger takes into account TPTT (h), the value of time VOT (€/h) for passengers and the cost OC (€)
System	E	effectiveness	Pax/NAP	E represents the effectiveness of the service in terms of the ratio between the number of satisfied users (Pax) and the total number of accepted users (NAP)

In particular, a total unit cost (TUC) indicator is evaluated according to the following equation:

$$TUC\left(\frac{€}{pax}\right) = \frac{TPTT(h)\cdot VOT\left(\frac{€}{h}\right) + OC(€)}{NP(pax)} \tag{5}$$

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

3.1. Territorial framework

The simulation has been performed for the case study of Ragusa, a small-medium city located in the south-eastern part of Sicily (Italy) with a poor public transport offer, a district with high touristic vocation and several facilities including a department of the University of Catania. 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, called MVMANT[1], is an urban mobility platform which enables the deployment of a dense fleet of vehicles circulating on a fixed route, matching requests in real time generated by customers. Ragusa network used for MVMANT was reproduced in the ABM (Fig. 1) with fixed (blue) and flexible (orange) routes; in the virtual map, real GIS data census zones are colored according to population (from light to dark green).

a b

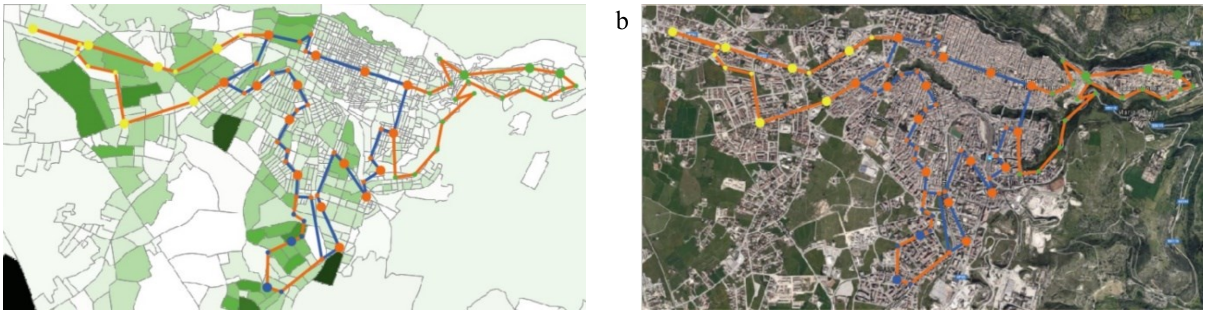

Fig. 1. (a) Virtual map; (b) Satellite map.

Three types of input variable are considered: service variables, demand variables and route choice strategy (Table 2).

Table 2. Input variables.

Type of input variable	Acronym	Input variables
service variables	-	type of service (taxi/DRST)
	-	total simulation time (h)
	n	number of vehicles
	cap	vehicle maximum capacity (seats)
	S	vehicle average speed (km/h)
demand variable	dem_rate	demand rate (request/hour)
	max_group	maximum number of passengers per demand
	mwt	maximum waiting time (min)
route choice strategy	FR	FR
	EVAR	EVAR, with a variable percentage of randomness
	AVAR	AVAR, with a variable percentage of randomness

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

3.2. Scenario simulations

Both taxi and DRST service have been tested with different input variables' sets for a first simulation test (Table 3). 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 with different levels of randomness, so to test the overall system performance during a total simulation time of 6 hours.

Table 3. Input values of scenario simulation variables.

Type of input variable	Acronym	Value	
		Taxi	DRST
service variables	n	1 to 4	
	cap	4	4 to 20
	S	30 km/h	
demand variable	dem_rate	20 to 100	
	max_group	3 to 4	
	mwt	600 s	
route choice strategy	AVAR	AVAR with 0 or 30% randomness	
	EVAR	EVAR with 0 or 30% randomness	
	FULLY RANDOM	Fully Random	

3.3. Results

The comparison between taxi and DRST with vans of different capacity was performed taking into account three indicators that highlight services' performances within different scenarios:

- TI (km/Pax)
- TUC (€/pax)
- E (Pax/NAP) always with reference to both types of transport services.

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 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.

Fig. 2-5 show TI for different fleet sizes (from 1 to 4) and single travel request with up to 4 people. For low demand rates (20 requests/h), the taxi TI is lower than the DRST. 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. In terms of capacity, as the capacity of the DRST increases (from 8 seats to 16-20 seats), TI decreases, so larger vans should be preferred. 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 by low demand rates (20-40 passengers per hour) and for smaller fleets (n = 1, Fig. 2).

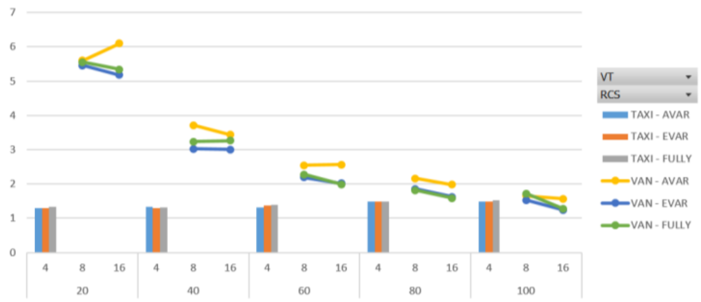

Fig. 5. TI (km/pax) for n = 4, randomness 0%

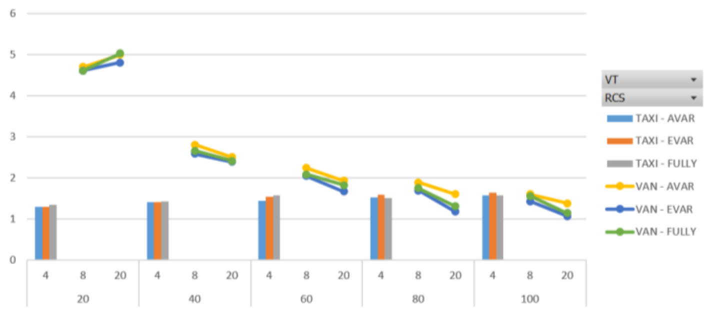

Fig. 4. TI (km/pax) for n = 3, randomness 0%

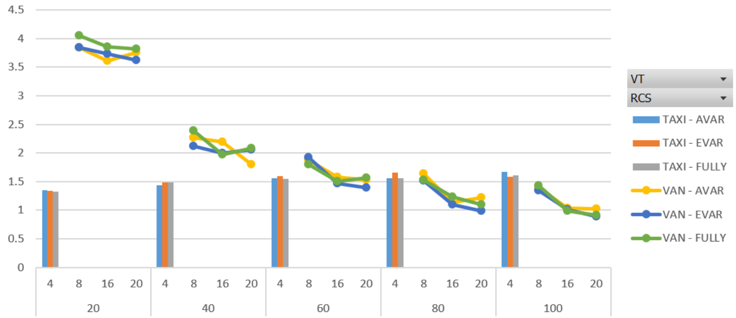

Fig. 3. TI (km/pax) for n = 2, randomness 0%.

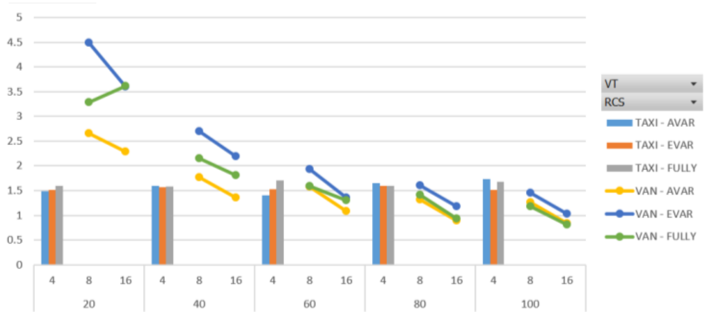

Fig. 2. TI (km/pax) for n = 1, randomness 0%.

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 a measure of the transport system efficiency.

Fig. 6-9 show growing trend of TUC as the demand rate increases, whatever the fleet size; for 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. 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). The transition in convenience between the two services is located in areas of different demand rates depending on the number of vehicles considered, passing from a range between 40 and 60 of demand rate in the case of 1-2 vehicles (Fig. 6, Fig. 7), and between 60 and 80 in the case of 3 vehicles (Fig. 8), and finally between 80 and 100 (Fig. 9) in the case of a fleet of 4 vehicles.

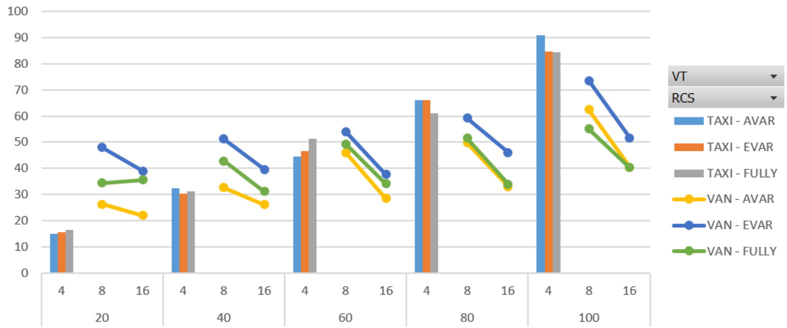

Fig. 6. TUC (€/pax) for n = 1, randomness 0%

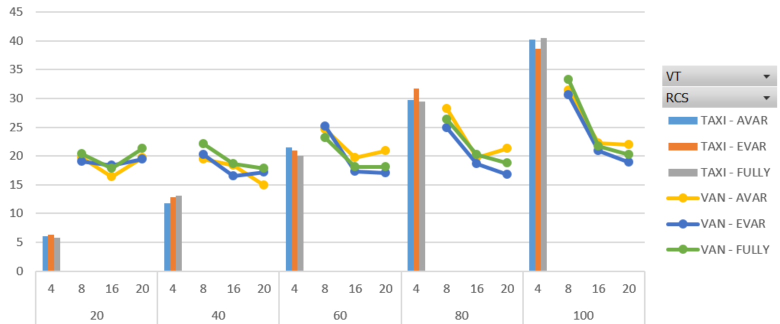

Fig. 7. TUC (€/pax) n = 2, randomness 0%.

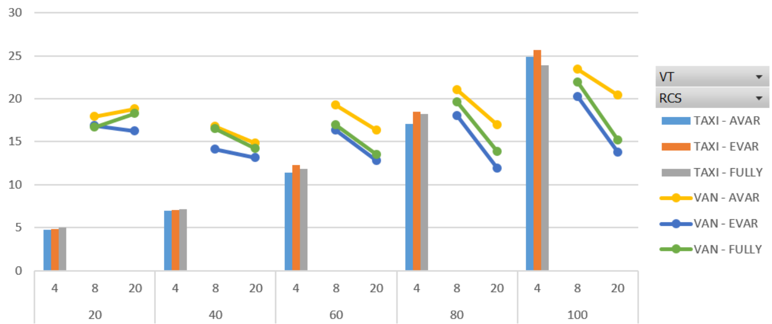

Fig. 8. TUC (€/pax) n = 3, randomness 0%.

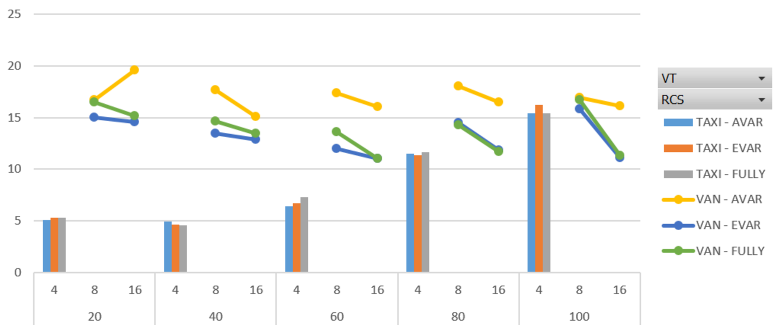

Fig. 9. TUC (€/pax) n = 4, randomness 0%.

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-seater vehicles to 16-20-seater vehicles) with the sole exception of the AVAR strategy for demand-rate 20 and number of vehicles equal to 4 (Figure 9), and this leads to prefer the use of biggest DRST vehicles for the service. 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, therefore a greater propensity to use a larger fleet in order to reduce costs and increase the users satisfied by the service. In terms of RCS, the strategy with better performance varies depending on the vehicles in the fleet. In the case of n = 1 (Figure 6), AVAR strategy prevails; with n = 2 (Figure 7) we denote a balance between the three RCS; with n = 3 (Figure 8) we have better performance of the EVAR strategy, and finally for n = 4 (Figure 9) there is a greater efficiency of the EVAR and Fully Random strategies.

3.3.3. Effectiveness (Pax/NAP)

The ratio Pax/NAP between the number of transported passengers and the number of accepted passenger requests value 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. Fig. 10-13 show that taxi prevails on DRST when the demand rate is low (20-40 passengers per hour). The opposite occurs in the case of higher demand rate (80-100 passengers per hour).

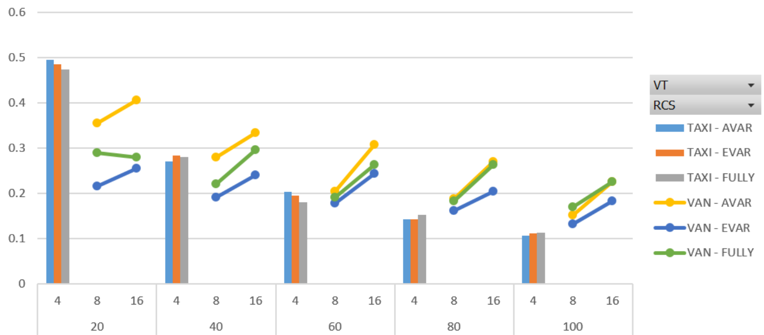

Fig. 10. Pax/NAP n = 1, randomness 0%.

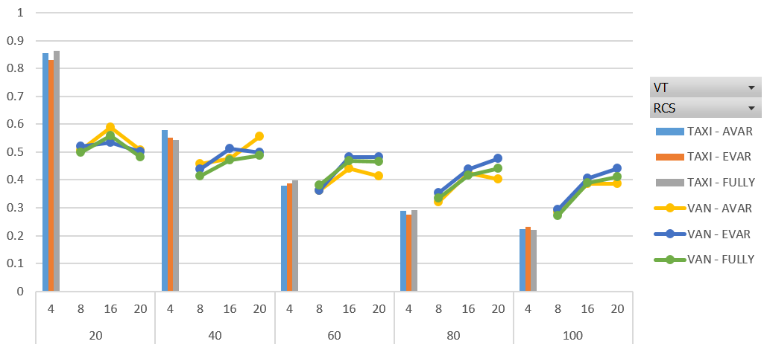

Fig. 11. Pax/NAP n = 2, randomness 0%.

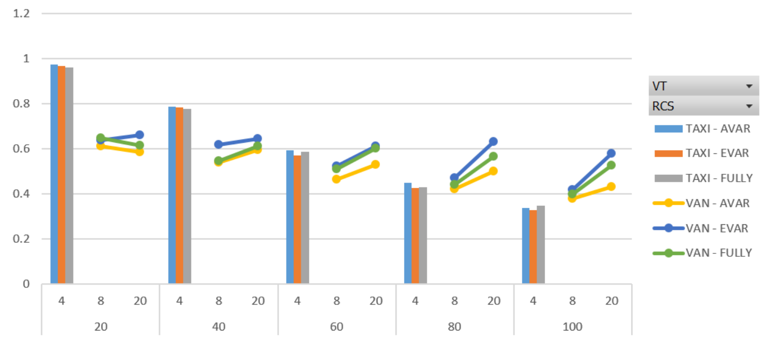

Fig. 12. Pax/NAP n = 3, randomness 0%.

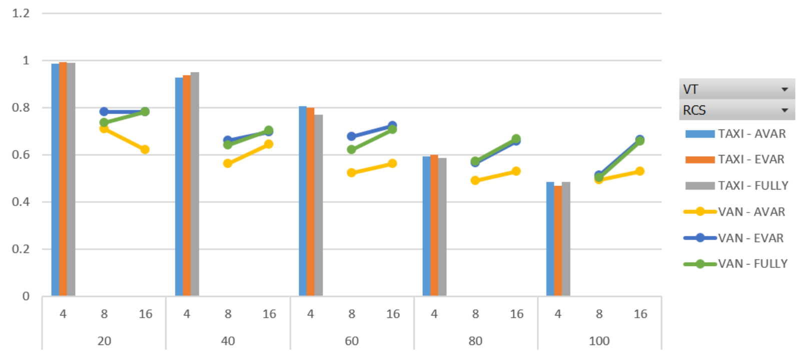

Fig. 13. Pax/NAP n = 4, randomness 0%.

In conclusion, when there is greater transport demand, DRST is more efficient than taxi, with an increased number of satisfied users. 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. 10), 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. 11) the changeover occurs between 40 and 60; in the case of a fleet of 3 vehicles (Fig. 12) between 60 and 80; finally, for a fleet of 4 vehicles (Fig. 13) between 80 and 100. Another aspect to note, as shown in all the different cases of different fleet size, is how the increase in 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 mean that the urban and suburban areas with weak demand and with a limited public transport supply suffer a gap in terms of social inclusion. DRST may be able to fill this gap by providing a shared, affordable transport service that, with the help of recent ICT, can also meet high quality standards. In this paper, an ABM is presented to test different DRST configuration in comparison with a taxi service serving the same demand. Through such simulation it has been possible to deduce some key outcomes, that will have to be tested in future studies with different scenarios configurations. Given a total of 50 different scenarios of application of the two transport systems, it was possible to identify the possible circumstances and conditions of intervention in order to achieve the greatest possible benefits in terms of pollution, operating costs, satisfaction user requests and reduction of urban and extra-urban traffic, through the analysis of three indices:

Transport Intensity (Km/Pax), Total Unit Cost (TotCost/Pax), and Effectiveness (Pax/NAP). From the simulations, carried out attributing to the model a randomness of 0% or 30%, it emerged that in circumstances with a wide demand for transport (demand rate of 80-100), 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 40-60-80 of demand rate) where there is a balance between the taxi and DRST system, 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 RCS 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.

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