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Calabrò, G.; Homem de Almeida Correia, G.; Giuffrida, N.; Ignaccolo, M.; Inturri, G.; Pira, M. L.

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G. Calabrò, G. Correia, N. Giuffrida, M. Ignaccolo, G. Inturri, M. Le Pira

Abstract— **This paper presents a new agent-based model able to simulate innovative flexible demand responsive transport services, specifically thought to solve the last-mile problem of mass rapid transit. This is particularly needed in areas characterized by insufficient transit supply and lower sprawled demand, where new technologies have the potential to dynamically couple demand with supply. The model compares the performances of two feeder services, one with flexible routes and stops activated by the requests of users, and the other with fixed routes and stops, satisfying the same demand. The case study city is Catania (Italy), where such services could increase the ridership and coverage of a 9 km long metro line that connects the city centre to peripheral areas. Different scenarios have been analysed by comparing a set of key performance indicators based on service coverage and ridership. The first results highlight the validity of the model to identify optimal operation ranges of flexible on-demand services and pave the way for further investigation needed to understand their acceptability and economic viability.**

I. Research Framework

Mobility in urban areas is facing an unprecedented season of change. This can be attributed to the innovations brought by new information and communication technologies, which enable flexible services, spreading e.g. as complementary to conventional public transport or in substitution to it [1]. Moreover, the sharing economy paradigm applied to transport services allows a shift from a culture based on vehicle ownership to a new one based on sharing services and assets [2]. Ridesharing, car sharing, electric micromobility, are just a few examples of how these concepts are rapidly sprawling in many urban contexts [3]. Not only passenger transport but also logistics processes and related freight transport flows are rapidly changing, due to progress in information technology and unparalleled growth of consumer involvement in supply chains [4][5]. Policymakers should take advantage of these changes and appropriately plan innovative services to reach the goal of reducing private transport toward sustainable mobility. This is why it becomes important to study in advance the potential of such new services and their optimal range of operation linked to the specific context of analysis. This is particularly needed in areas with both insufficient transit supply and lower sprawled demand that makes it difficult to provide mass transit services [6]. The issue of coverage of the first/last mile of mass rapid transit is a case in point, being a Many-to-One (M-to-1) problem characterized by multiple origin/destination with a low and dispersed demand and a single destination/origin with a concentration of demand [7]. In this case, two main design choices appear, i.e. (a) the choice between scheduled feeder services (as in conventional public transport) and demand-responsive shared transport (DRST) services, and (b) the level of flexibility (in terms of routes, stops and schedule) of such DRST services. Both alternatives (fixed and flexible) have their own design questions. A fundamental one for scheduled feeder services is the optimal design of routes and frequency, while the one for flexible services is what degree of flexibility best exploits the trade-off between minimizing the cost of the system and maximizing service quality. Calabrò et al. [7] addressed the scheduled feeder design question via an ant-colony optimization within an agent-based model (ABM), finding out the best route to maximize potential demand with travel time constraints.

Literature on modelling approaches to study flexible DRST services is abundant [8]. In particular, ABM has been largely used thanks to the possibility to simulate complex environments with individual autonomous agents acting and interacting according to their objectives. This is well suited to reproduce DRST services, characterized by real-time user requests and the need to match them with vehicles in an optimal way. Recently, Di Maria et al. [9] proposed a modular simulation framework for autonomous mobility on demand and focused on the important issue of optimization strategies using the Manhattan Grid case as a testbed. Inturri et al. [10] present a multi-agent simulation to reproduce a mixed fixed/flexible route transit service with different fleet size and vehicle capacity in the city of Ragusa (Italy), showing an optimal range of operating vehicles that minimizes a total unit cost indicator, accounting both for passenger travel time and operation cost. Giuffrida et al. [11] extend the results of the previous model, studying the effects of different vehicle assignment and route strategies and comparing its performance with a ride-sharing service provided via low-capacity vehicles. Some authors have focused on the last mile problem of mass rapid transit. Scheltes and Correia [11] study the so-called "Automated Last-Mile Transport" via an agent-based simulation model whereby a dispatching algorithm distributes travel requests amongst the available vehicles using a First-In-First-Out (FIFO) sequence and selects a vehicle based on a set of specified control conditions (e.g. travel time to reach a requesting passenger). However, this type of service does not allow shared trips among passengers,

G. Calabrò, N. Giuffrida, M. Ignaccolo, G. Inturri, M. Le Pira are with the University of Catania, Via S. Sofia 64, 95125, Catania, Italy (corresponding author to provide phone: +39-095-738-2221; e-mail: mlepira@dica.unict.it).

G. Correia is with the Department of Transport & Planning, Stevinweg 1, 2628 CN Delft, Delft, The Netherlands.

which would increase the complexity of the modelling effort. Besides, while solving last mile issues, it is important to understand which level of flexibility is needed according to demand patterns.

This paper contributes to filling this gap by presenting a new ABM to simulate flexible/fixed feeder services with different vehicle fleets and demand patterns, to help solve the last-mile problem of mass rapid transit. We build on the works of Inturri et al. [10] by allowing for different levels of flexibility, Scheltes and Correia [11] for the passenger and vehicle dynamics, while allowing for ride sharing; we extended the model of Calabrò et al. [7] by reproducing the operation of a feeder service with optimally designed routes. The model also allows for a more detailed spatial representation of the demand compared to the previous ones, since requests are geocoded to the building scale. The model is specifically designed to compare the performance of the two alternative feeder services, while satisfying the same demand. The next sections will present the model applied to the case study of Catania (Italy).

II. Methodology

A. Description of the model

The rationale for using ABM is to understand the trade-off between costs and the level of service of feeder services, taking flexibility as a design parameter, while simulating different vehicle fleet capacity and demand patterns. The ABM has been implemented in the NetLogo programming environment [12], and takes as reference other previously implemented models [7][10][11]. A brief description of the model is provided in the following.

Transport network model. The network consists of fixed stops and optional stops, to encompass both fixed feeder routes and DRST flexible routes based on the real network.

Demand model. The GIS extension of NetLogo is used to map the distribution of socio-demographic data (residents and employees) at a census zone level. A further level of disaggregation is achieved by assigning socio-demographic data to each building proportionally to their surface, whose data were obtained through OpenStreetMap.

The average trip demand rate is based on historical data of the daily distribution of passengers' accessing/egressing the metro station. The service has been simulated for the current demand, but also higher and lower potential demand, to test the efficiency of the feeder services under different demand rates. A users' group trip request is generated according to a gravitationally distributed probability from an origin (O) building to the metro station and from the metro station to a destination (D) building, following a M-to-1 demand pattern. The demand model is based on [10] and it has been improved through the introduction of an index of attractiveness of the transit mode versus the walking mode to reach the terminal station. Given a set of n buildings, the trip rate TR_{ij} (where i or j corresponds to the terminal station) is calculated with equation (1), where TR_i is the generation trip rate from (and to) the building i, proportional to population density and an average trip rate per trip direction (ATR) (simulation variable), calculated with equation (2), and η_{ij} is the transit index of the attractiveness of the transit mode, which assumes values between 0 and 1, determined for each building i through the exponential function shown in equation (3).

$$TR_{ij} = TR_i \cdot \eta_{ij} \tag{1}$$

$$TR_i = \frac{Pop_i}{\sum_{k=1}^{n} Pop_k} \cdot ATR \tag{2}$$

$$\eta_{ij} = 1 - e^{\frac{(d-d_T)^2}{0.5\, d_T^2}} \tag{3}$$

where d_T is the minimum distance from the terminal station to consider the transit service attractive for the user. For distances shorter than d_T, users are assumed to walk directly to the terminal station. A trip request of a passenger group (with a maximum prefixed size) is generated according to the following rules: (i) from buildings to metro: stochastically generated, according to the demand model; (ii) from metro to buildings: Poisson distributed, every 10 minutes (metro headway).

As far as the access mode choice is concerned, we do not consider private car use, but users have a twofold choice to reach the metro station, i.e. walking and transit. In this respect, we simulate a DRST feeder service with different fleet configurations in comparison with a fixed feeder service serving the same demand.

B. Fixed feeder passenger and vehicle dynamics

After a trip request is generated, if the distance from the origin to the nearest feeder bus stop (or from the destination, if the origin is the metro station) overcomes a given threshold, the passenger group assumes the status "rejected". This is because it is assumed that passengers may decide not to use transit due to excessive access time and will use other modes. Otherwise, the request is confirmed, passengers assume the status "accepted" and move to the stop that allows them to minimize the sum of walking time and on-board time, assuming the status "waiting", while waiting for the feeder service. If a prefixed maximum waiting time is overcome before a vehicle reaches the stop, each passenger group gives up and assumes the status "unsatisfied". Otherwise, each passenger boards the vehicle assuming the status "satisfied". If the overall travel time overcomes a certain desired travel time (based on vehicle maximum travel time and the above-described index of attractiveness), the passenger assumes the status "delayed". Fleet size, vehicle capacity, and speed are set at the beginning of the simulation. Each vehicle is generated at the terminal stop (i.e. the metro station). The fixed feeder vehicle travels along the route until it reaches a stop. Passengers at their destination stop alight and waiting users board the vehicle following the First-Come-First-Served (FCFS) queue rule, but only if the passenger group size is not greater than the available seats, updating vehicle's available seats.

C. DRST passenger and vehicle dynamics

Passenger requests for the DRST service can be served at multiple potential stops either at origin or destination (according to the vehicles' availability and schedule). As in the previous case, after a trip request is generated, if the distance from the nearest stop to the origin overcomes a given threshold, the passenger group assumes the status "rejected". Otherwise, the request is processed through the dispatching algorithm and the passenger group can be assigned to a predetermined stop and vehicle according to capacity and time constraints as fully explained in the next subsection. If no vehicle can fulfil these constraints, each user of the group assumes the status “rejected”. If accepted, the dynamics of passengers originated at the metro station and those whose origin is one of the buildings follow different rules. In the first case, passengers wait for the assigned vehicle at the metro station, board it, and finally get off the vehicle at the predetermined stop, walking to their final destination located at one of the buildings. In the second case, passengers do not go to any stop until the expected time for pick-up, also taking into account the required walking time and an additional “buffer” time (in case the vehicle is earlier than the scheduled arrival time). Then, the passenger group moves to the assigned stop assuming the status “waiting”, while waiting for the vehicle. If a prefixed maximum waiting time is reached before a vehicle arrives at the stop (e.g. schedule variations and increased travel times of the vehicle due to other following user requests), the passenger group gives up and assumes the status “unsatisfied”. Otherwise, each passenger boards the vehicle, alights at the metro station, and assumes the status “satisfied”. However, if the overall travel time overcomes a desired travel time (based on the product of vehicle maximum travel time and the above described index of attractiveness), the passenger assumes the status “delayed”. The following flow charts summarize the passenger (Fig. 1) and vehicle dynamics (Fig. 2) for the flexible DRST feeder service.

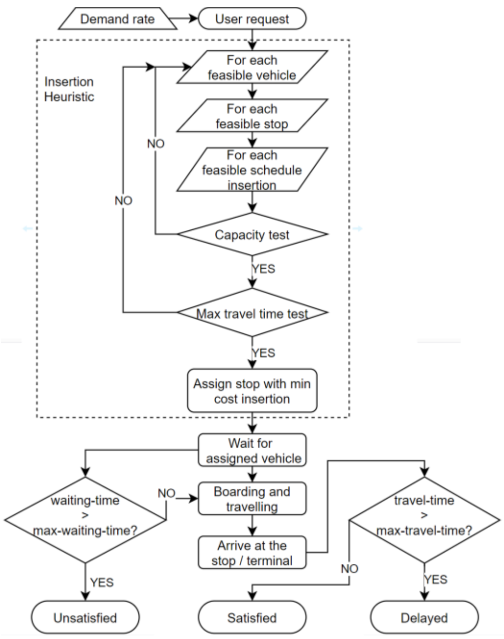

Figure 1. Passenger dynamics flowchart for the DRST feeder service

Vehicles of the flexible service start traveling from the metro station at a scheduled departure time across the street network and towards the pre-scheduled fixed stops (hereafter called waypoints). Every time that a new request is accepted and assigned to the given vehicle, its schedule is updated with the possible insertion of a new stop to be served between two already scheduled stops. Vehicles drive to pick-up passengers at their stop origin and/or to drop-off passengers at their stop destination.

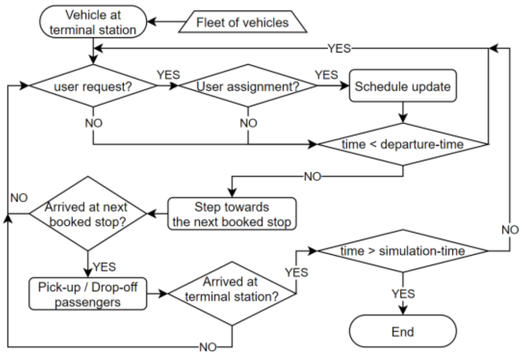

Figure 2. Vehicle dynamics flowchart for the DRST feeder service

D. The dispatching algorithm

As previously said, when a new request is generated for the DRST, an insertion heuristic algorithm is used to determine the feasibility of the insertion, and then the minimum cost insertion of the request in the current schedule of one of the vehicles. Since we deal with a dynamic procedure, vehicles can take new requests in accordance with its travel time thresholds and/or the maximum capacity constraint according to the FCFS rule and minimizing its cost function, inspired by [11]. The main novelty of the procedure lies in the three levels of explorations of feasible solutions. For the insertion of a new stop, the algorithm examines: (a) each vehicle v of the fleet, considering the list of already scheduled stops, arrival time at each stop and available seats after serving a stop; (b) each potential stop s, within a maximum radius of walking distance from/to the origin/destination of the travel request; (c) each possible insertion of s between two any subsequent stops belonging to the current schedule of the vehicle v, if s is not already scheduled. The feasibility of each combination of vehicle, stop and insertion location is evaluated by ensuring that it complies with the following constraints: (i) the extra ride time needed to serve stop, also considering the additional time lost during pick-up/drop-off operations, must not be higher than a certain threshold DTmax, in order not to spend too much travel time in one single detour; (ii) the number of available seats should never be negative.

For every new user request, the best insertion in the schedule is the one that minimizes the cost function (Eq. 4), which considers the extra waiting and ride times due to the new request insertion:

$$Cost = w_1 \cdot N_{delayed} \cdot \Delta RT + w_2 \cdot N_{UG} \cdot WT_{UG} \tag{4}$$

where $N_{delayed}$ is the number of passengers who have to bear an extra ride time ΔRT due to the insertion of the new request, N_{UG} is the number of users who make the new request at time t and need a walking time WT_{UG} to reach the stop or the destination, w_1 and w_2 are weights that regulate the importance of the additional ride time versus the waiting time for the new passenger group. In this paper, for a first test, we will set both weights equal to 1, leaving for future research the tuning of such parameters.

E. Performance indicators

The local strategies determining the interaction between passengers and vehicles give rise to global patterns that can be monitored via appropriate performance indicators. They are chosen to capture the different objectives and points of view of the system actors, i.e.: (1) a user is interested in reducing the trip cost (distance, travel time, fare); (2) a company providing the service is interested in maximizing the profit, by increasing the number of passengers within a prefixed travelled distance or, conversely, in reducing the amount of travelled distance to serve a prefixed demand; (3) the community is interested in reducing transport-related externalities. The model can monitor different key performance indicators [10]. The main indicators chosen in this paper to compare the two services are: the total number of transported passengers NP (pax); the total number of accepted requests NAP (pax); the total number of satisfied users PAX (pax); the total driven distance TDD (km); the average passenger travelled distance APTD (km); the average vehicle load factor ALF (pax/vehicle); the passenger travel time, in terms of average waiting time AWT (min), average on-board time AoBT (min), and average total travel time APTT (min); the transport intensity TI (km/pax), as the ratio between TDD and NP; the total passenger travel time TPTT (h) (including a penalty time of 60 min for each unsatisfied user); the operation cost OC (€); the effectiveness E (-) of the service, in terms of the ratio of PAX and NAP; the total unit cost TUC (€/pax), taking into account the total passenger travel time TPTT (h), the value of time VOT (€/h) for passengers, and the operation cost OC (€) as described in [10].

The next section will illustrate how the model was tested in a real-world case study.

III. CASE STUDY

A. Territorial framework

The case study focuses on improving the accessibility of the *San Nullo* metro station (SN) in Catania, a medium-sized city in the south of Italy. The station is located in an arterial road that acts as a barrier between two neighbourhoods. In particular, it stands at the outskirt of the northern residential neighbourhood where walking paths are not of great quality, making it difficult for pedestrians to access the station. In such a context, the introduction of a First Mile/Last Mile transit service would help to reduce private car use and increase service coverage. However, it is important to guarantee a good user experience, in terms of travel time, and pay attention to the operator's cost. Besides, the same service strategy and configuration could perform differently, i.e. very well during rush hours but not very well during off-peak hours, so a flexible feeder system able to switch between alternative routing and scheduling strategies in different periods of the day is desirable. We aim to evaluate the best choice between the two operating strategies (fixed vs DRST) under different demand rates and service configurations, identifying their optimal application scopes, through the comparison of user-related and cost-related performance indicators (see Section IV – A; B). Figure 3 shows the fixed feeder route (in blue) resulting from [7] and the road network used for the DRST service (in orange).

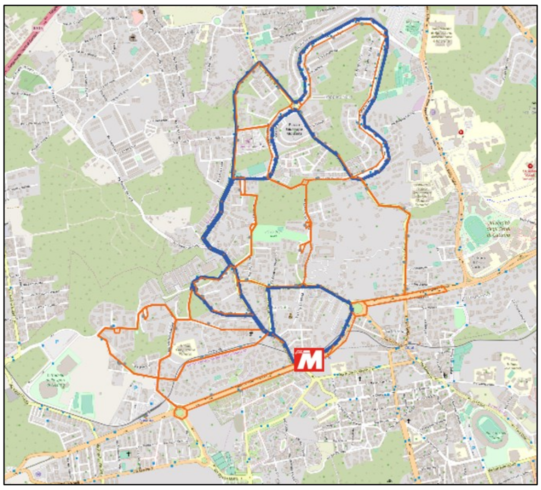

Figure 3. Road network for DRST (orange) and fixed (blue) feeder service

B. Input variables and scenario simulation

The main input variables of the system are:

- service variables, i.e.: type of service (fixed/flexible), total simulation time (h), number of vehicles (*n*), vehicle maximum capacity (*cap*, in terms of seats), vehicle average speed (*S*, in km/h);
- demand variables, i.e. demand rate (*dem_rate* in trips/hour), maximum number of users per request (*max_group*), maximum waiting time (*mwt* in min).

Scenario simulation considers service operation by combining input values according to Table 1. In order to ensure comparability between the two services, we assume the same total capacity (e.g. 45-90 seats) for the two services.

TABLE I. INPUT VALUES OF SCENARIO SIMULATION VARIABLES

Type of variable	**Abbreviation**	**Unit**	**Value**	
			Fixed	**Flexible**
Service variables	n	-	3	3, 5, 6, 10
	cap	-	15, 30	15, 9
	S	km/h	25	25
Demand variables	Dem_rate	trips/h	25, 50, 100, 200	25, 50, 100, 200
	Max_group	-	3	3
	mwt	s	600	600

IV. RESULTS

The main results of the experiments are reported below. For each scenario, five replications of the simulation were performed, given the stochastic nature of the demand in the model. The model allows real-time monitoring of the parameters and provides graphs and histograms of the main simulation variables. In Figure 4, the satisfaction plot in terms of satisfied (S), unsatisfied (U) and delayed (D) users, and the average-load-factor plot are reported for a single event in the scenario with 50 pax/h average demand rate, 45 total capacity, i.e. 3 vehicles of 15 seats for both services.

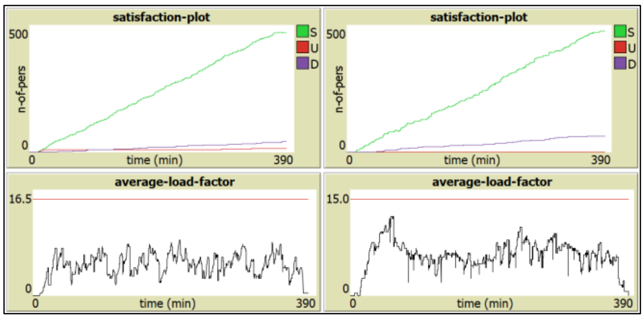

Figure 4. Satisfaction and average load factor for DRST (left) and fixed feeder (right) for 50 pax/h and 3 vehicles

A. Travel Time

Travel time reflects the experience of users and is calculated as the sum of walking, waiting, and riding times. Service configurations lead to variable results according to the demand rate. For the lowest demand rate considered (25 pax/h), the DRST with large fleet and low vehicle capacity (10x9) is the best option. For the highest demand considered (200 pax/h), the fixed feeder is preferable even it implies higher waiting times than the DRST. Results for demand rate of 50 pax/h and 100 pax/h are reported in Figure 5:

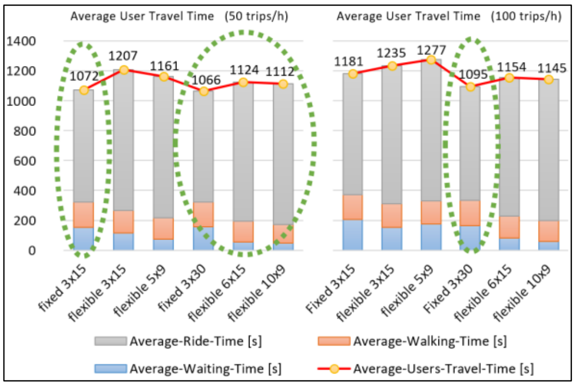

Figure 5. Average travel time for demand rate of 50 and 100 pax/h

In the case of 50 pax/h, fixed feeder services result in a lower travel time, while, when it comes to DRST, it is possible to decrease the travel time only by increasing the vehicle capacity. In particular, the fixed service and the DRST with more vehicles (10) can be considered as the best options from the user point of view. More in detail, if the highest weight would be given to waiting and walking time, users would prefer the flexible service. In the case of 100 pax/h, a lower travel time is achievable always with a higher capacity. As in the previous case, the fixed feeder and the DRST with more vehicles (10) should be preferred from the user point of view, even if the willingness to pay for the different times (walking, waiting, riding) should be further investigated. In both scenarios, the ride time weighs more on the DRST performance, due to the various detours required to serve pick-up and drop-off passengers, even though there are considerable savings in waiting and, to a smaller extent, walking time.

B. TI - E – TUC

We decided to compare the performances of different service configurations using three main indicators, i.e. TI, E and TUC. TI is the ratio between the total distance travelled by the fleet of vehicles and the total transported passengers. A low TI indicates an efficient service in terms of operation cost per travelled passenger and a low impact on the environment as well. E, which is the ratio between the number of transported passengers and the number of accepted passenger requests (Pax/NAP), should be high to increase the number of satisfied users compared to the total number of accepted requests. Finally, 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 as an overall measure of the transport system efficiency.

For low demand (25 pax/h), the high capacity DRST service (10x9) is the less convenient for TUC and TI, while E is very high and comparable with the other DRST solutions. For high demand (200 pax/h), the best results in terms of TUC and TI can be achieved by a high capacity fixed feeder service, even if with a lower E. Main results in the case of 50 and 100 pax/h are reported in Figure 6.

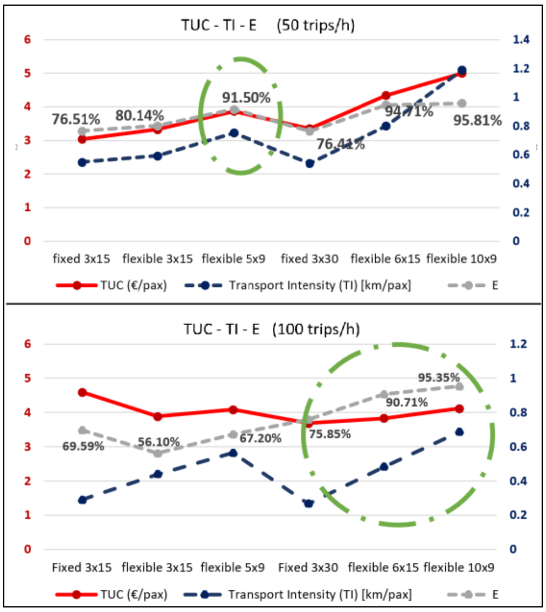

Figure 6. TUC, TI and E for 50 pax/h (top) and 100 pax/h (bottom)

In the case of 50 pax/h, the two fixed services are comparable in terms of performance, but they reach approximately 76% of accepted requests. Low capacity in the case of DRST is in general better, with comparable values of TUC. In particular, a fixed feeder would be preferable for the operator since it has lower TI and a good TUC, but with a higher percentage of rejected user requests, while it is possible to cover more than 90% of requests with a DRST service with 5 vehicles of 9 seats.

In the case of 100 pax/h, the two fixed services are also comparable, but allow reaching approximately 70-75% of accepted requests. For 100 pax/h, high capacity is in general better with comparable values of TUC, and this is evident for the DRST with a reduced fleet size, which fails to serve a large percentage of users. As for the previous case, a fixed feeder would be preferable for the operator since it has lower TI and a good TUC, while DRST with 10 vehicles is the one with the highest coverage, but with a high TI. A compromise solution would be the DRST with 6 vehicles and 15 seats, but it would be better evaluated by estimating the extra cost for the system due to each "rejected" passenger, i.e. a user who does not use the feeder service and maybe chooses to use the private car. Once again, the higher driven distance due to the various detours of the DRST service is responsible for the greater TI value compared with fixed feeder, which however is unable to serve a certain percentage of users far from its stops.

V. CONCLUSION

Fixed feeder services travel on regular routes at scheduled times, but passengers have to walk to reach the fixed stops and wait for the service. On the other hand, flexible DRST services can pick-up and drop-off passengers wherever and whenever they want, therefore it is expensive to operate, even if passengers are more satisfied [14]. This paper presents an agent-based model able to simulate both fixed and flexible mobility service, where the degree of flexibility, the fleet size and capacity, and the demand rates are chosen as parameters of different simulation scenarios. The model is tested in a case study with a real network and based on real demand data. First results with different demand rates (from low to high) identify the optimal configuration of DRST to achieve a trade-off among passengers' convenience, service coverage, operation efficiency, and environmental impacts as well. In particular, for the case study analysed, the model can tailor the service according to the current demand, where a DRST fleet with 5 vehicles of 9 seats would be suitable for an average demand rate of 50 pax/h, while a fleet of 10 vehicles of 9 seats would fit a demand rate of 100 pax/h. For lower and higher demand rate, a trade-off between coverage and ridership emerges. In particular, for higher demand rates, a fixed feeder becomes the best choice even if it implies a lower coverage. Future research should investigate the demand side, in terms of the willingness to pay related to the different components of travel time. Other interesting indicators could be added to better evaluate the services and the related externalities, e.g. CO_2 emissions. Moreover, it would be interesting to reproduce different cases with parametric road network topologies and demand, to see the impact on travelled distance and level of service. Another step forward would be to test a multi-station system, with feeder buses serving different metro stations. Finally, the use of autonomous vehicles could be tested, affecting the results of TUC (in terms of operation costs). In summary, the model can contribute to the development of flexible DRST services, resolve the coverage/ridership dilemma of rapid transit services, understand the impact of land use, road network and demand patterns on the flexible service performances.

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REFERENCES

[1] Cohen-Blankshtain, G., & Rotem-Mindali, O. (2016). Key research themes on ICT and sustainable urban mobility. International Journal of Sustainable Transportation, 10(1), 9-17.
[2] Ambrosino, G., Nelson, J. D., Boero, M., & Pettinelli, I. (2016). Enabling intermodal urban transport through complementary services: From Flexible Mobility Services to the Shared Use Mobility Agency: Workshop 4. Developing inter-modal transport systems. Research in Transportation Economics, 59, 179-184.
[3] Machado, C. A. S., de Salles Hue, N. P. M., Berssaneti, F. T., & Quintanilha, J. A. (2018). An overview of shared mobility. Sustainability, 10(12), 4342.
[4] Tavasszy, L. A. (2019). Predicting the effects of logistics innovations on freight systems: Directions for research. Transport Policy.
[5] Marcucci, E., Le Pira, M., Carrocci, C. S., Gatta, V., & Pieralice, E. (2017). Connected shared mobility for passengers and freight: Investigating the potential of crowdshipping in urban areas. In 2017 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS) (pp. 839-843). IEEE.
[6] La Greca P., Barbarossa, L., Ignaccolo, M., Inturri, G., & Martinico, F. (2011). The density dilemma. A proposal for introducing smart growth principles in a sprawling settlement within Catania Metropolitan Area. Cities, 28(6), 527-535.
[7] Calabrò, G., Inturri, G., Le Pira, M., Pluchino, A., Ignaccolo, M. (2020). Bridging the gap between weak-demand areas and public transport using an ant-colony simulation-based optimization. Transportation Research Procedia 45, 234-241..
[8] Liyanage, S., Dia, H., Abduljabbar, R., & Bagloee, S. A. (2019). Flexible Mobility On-Demand: An Environmental Scan. Sustainability, 11(5), 1262.
[9] Di Maria, A., Araldo, A., Morana, G., & Di Stefano, A. "AMoDSim: An Efficient and Modular Simulation Framework for Autonomous Mobility on Demand". In *International Conference on Internet of Vehicles* (pp. 165-178). Springer, 2018, Cham.
[10] Inturri, G., Le Pira, M., Giuffrida, N., Ignaccolo, M., Pluchino, A., Rapisarda, A., D'Angelo, R. (2019). Multi-agent simulation for planning and designing new shared mobility services. Research in Transportation Economics, 73, 34-44.
[11] Giuffrida, N., Le Pira, M., Inturri, G., Ignaccolo, M., Calabrò, G., Cuius, B., D'Angelo, R., Pluchino, A (2020). On-Demand Flexible Transit in Fast-Growing Cities: The Case of Dubai. Sustainability, 12, 4455.
[12] Scheltes, A., de Almeida Correia, G. H. (2017). Exploring the use of automated vehicles as last mile connection of train trips through an agent-based simulation model: An application to Delft, Netherlands. Int. Journal of Transportation Science and Technology, 6(1), 28-41.
[13] Wilensky, U. NetLogo. Center for Connected Learning and Computer Based Modeling. Northwestern University, Evanston, IL, 1999.
[14] Giuffrida N., Le Pira, M., Inturri, G., Ignaccolo, M. (2020). Addressing the public transport ridership/coverave dilemma in small cities: a spatial approach. Case Studies on Transport Policy, In Press. https://doi.org/10.1016/j.cstp.2020.06.008