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Bridging the gap between weak-demand areas and public transport using an ant-colony simulation-based optimization

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Abstract

This paper presents the first results of an agent-based model aimed at designing feeder bus routes able to cover the gap between public transport coverage and ridership in weak demand areas. The optimized design of feeder bus routes has been approached as a Vehicle Routing Problem applied to passenger transport, using Ant Colony Optimization (ACO) to find the minimum cost paths within a road network. The methodology proposed has been applied to the case of Catania (Italy), where a metro line is being extended to the city centre to peripheral areas. A GIS approach has been used to build the road network, select all potential bus stops, and weight them via accessibility indicators, as a proxy of the potential transport demand. Then, the ACO algorithm has been developed and implemented in *NetLogo*, a multi-agent programming and modelling environment for simulating complex systems, in order to find an optimal set of feeder bus routes, where the terminal is a given metro station. These routes are chosen to maximize the potential demand of passengers while complying with the constraint of a desired travel time. Different scenarios have been analysed by comparing a set of key performance indicators based on service coverage and ridership. First results highlight the validity of the method to find suitable routes to cover the gap between conventional public transport and weak demand urban areas and provide useful suggestions for the operation and design of a feeder service.

Keywords: Feeder bus design; Public transport; Ant Colony Optimization; Accessibility indicators; Multi-agent simulation

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1. Introduction

In the last decades, the external costs produced by the dependence on private transport have determined the social, economic and environmental unsustainability of urban mobility (Newman and Kenworthy, 2006; Ignaccolo et al., 2016). It is evident that the most sustainable transport mix will largely be determined by the strength and reliability of both land use and transport policy interventions that minimize sprawl, increase the centralization of workplaces, and generally improve accessibility to urban services by paying special attention to soft mobility, transit system optimization and intermodal transport development (La Greca et al., 2011).

Under this respect, public transport (PT) should aim at reducing the mobility gap experienced by several people to have a good access, in a spatial sense of the term, to all the opportunities and services throughout a metropolitan area, e.g.: workplaces, education and healthcare services, leisure activities. From this perspective, by offering a mobility potential to all categories of users, PT stands as a determining factor for social inclusion policies (Giuffrida et al., 2017). This problem is further exacerbated in weak demand urban areas characterized by low residential density and high motorization rate, where conventional PT is unable to ensure both coverage and ridership. An effective design of feeder bus lines connecting weak demand areas with mass rapid transit nodes could therefore help to shift passenger's mode of transport from individual to collective mobility, thus enhancing the accessibility to urban facilities and services. Most of accessibility measures depend on the amount of opportunities in a given zone and the generalized transport cost to reach it. Among the different existing formulations, gravity-type accessibility indexes (Hansen, 1959) provide a continuous measure where the opportunities are weighted by a spatial impedance function, usually depending on travel distance or time. Moreover, Cascetta (2009) makes a distinction based on land use between the active (origin) accessibility and the passive (destination) accessibility. This classification will be further addressed in the next section.

During the last five decades many researches have been carried out in the field of transit network design (Guihaire and Hao, 2008; Farahani et al., 2013, Ibarra-Rojas et al., 2015). The Feeder Bus Network Design Problem (FBNDP) was addressed by Kuah and Perl (1989) determining a set of feeder-bus routes and the related service frequency, in order to achieve the optimal balance between operator and user cost. The mathematical model of FBNDP basically constitutes a multiple vehicle-routing type model, in which a non-linear objective function must be satisfied, given a set of constraints. Due to the NP-hard nature of such optimization problems, conventional mathematical programming methods can be suitable only for small simplified networks, while for real large networks, heuristic and, more recently, metaheuristic methods have been used and combined to find "good" suboptimal solutions to the FBNDP. Under this respect, Kuan et al. (2006) proposed to improve initial solutions by using Genetic Algorithms (GA) and Ant Colony Optimization (ACO) algorithms. Mohaymany and Gholami (2010) developed an approach to solve a multimodal feeder network design problem based on minimizing costs of users, operator, and society. They used an ACO algorithm for the development of routes in a given service area, calculating frequency of all modes on each route. Martínez and Eiró (2012) considered the timetable of the mass rapid transit as a constraint to which a minibus feeder service has to adjust, taking into account commuters' time windows. Huo et al. (2014) proposed a rational optimization of the school bus routing operation based on ACO. The circular route model proposed by Zhu et al. (2017) included GA to find a route starting and ending at urban rail transit stations, with the major objective of maximizing the potential demand.

All these approaches proved valid to support an optimized design of feeder bus routes. However, there is still a gap between modelling sophistication and the practicality of urban transport planning. Under this respect, they usually act as "black boxes", difficult to understand by non-experts, and do not include a detailed spatial representation of geographical constraints and of different transport demand segments. Based on this premise, this paper presents a new modelling framework applied to a real case study for the optimized design of feeder bus routes, by integrating GIS data, accessibility indicators with real transport networks in a multi-agent programming environment. The main contribution of this work with respect to the existing literature is the use of ACO to determine the best set of feeder-bus stops to be served in order to strike a balance between area coverage and ridership.

The remainder of the paper is organized as follows: section 2 will outline the methodology with the details of the agent-based model (ABM) and of the ACO algorithm; section 3 will describe the case study of the *San Nullo* metro station in Catania (Italy), whose accessibility should be improved by designing a feeder bus service, and will discuss the first results. Finally, section 4 will resume the paper, providing some considerations for further research.

2. Methodology

In this work, the optimized design of feeder bus routes has been approached as a Vehicle Routing Problem (VRP) applied to passenger transport. Simulations were carried out by using *NetLogo* (Wilensky, 1999), a multi-agent programming and modelling environment for simulating natural and social phenomena, which allows users to model and simulate complex systems, reproducing their main characteristics and allowing the visualization of their significant parameters in real time. ABM have been widely proposed as a valid tool to study complex urban environments, e.g. energy distribution networks (Fichera et al., 2018). Special kinds of artificial agents are those created by analogy with social insects, such as ant colonies, which teach us that very simple organisms can form systems capable of performing highly complex tasks by dynamically interacting with each other (Teodorović, 2008). These systems turn out to be well suited for an engineering approach, with the implementation of models and algorithms for Swarm Intelligence, requiring a centralized control. Moreover, a powerful extension supported by *NetLogo* is the Geographic Information Systems (GIS) extension, which allows vector and raster data to be imported into models. This is useful to build simulations based on the actual population (residents and employees) of a certain area at census zone level, thus allowing the integration of theoretical models with real data sets (Inturri et al., 2019).

2.1. Transport network and transit demand via accessibility measures

The first step involves the creation of the directed graph of the street network to be used for the simulations. It consists of non-congested links and two types of nodes: intersection and stop nodes. The latter are equipped with a value representing the potential transport demand of the specified bus stop. Each graph link *ij* is characterized by a generalized cost (C_{ij}) that only includes the average travel time along the link itself, given by the ratio between the length (l_{ij}) and the assumed commercial speed of the bus (V_{bus}). Location and distance between stops must be studied appropriately considering different factors, including the travel time incurred by users moving from or to the bus stop, speed performances of buses (such as the commercial speed, which is also influenced by the time spent at each stop) and the potential overlap of stops' catchment area.

We used a Many-to-One (M-to-1) demand pattern (Kuah and Perl, 1989), assuming that (a) passengers have the transfer station as common destination, (b) each bus stop can be served by one feeder-bus route, (c) each bus route is linked to exactly one rail station and (d) buses have standard commercial speed and no capacity constraints. We also assume that transport demand is concentrated at bus stops, around which a "passenger catchment area" of the feeder bus service gravitates. The following considerations are made, in order to estimate the potential demand: (i) the potential demand of a feeder bus stop is directly proportional to the transport demand of the areas around, thus depending on demographic and social factors; (ii) the more a potential user is far from the nearest stop, the less he/she will be attracted to the feeder service; (iii) the more a stop is far from the terminal station, the more it will be attractive to passengers; (iv) the presence of other PT lines serving the same stop reduces the potential demand for the feeder service, depending on their frequency and service coverage area.

In view of this, travel demand is expressed in terms of accessibility of a bus stop. Regarding the choice of the impedance function, Kwan (1998) indicates the inverse power function $d_{ij}^{-\alpha}$, the negative exponential function $exp(-\beta d_{ij})$ and the modified Gaussian function $exp\,(-d_{ij}^2/\gamma)$. According to Ingram (1971), the latter has the advantage of having a slow rate of decline close to the origin, in comparison with the first two functions. Therefore, two impedance functions are used to estimate the number of potential users of a feeder bus stop (hereafter called "stop-node"): the first takes in account the effect of decreasing attractivity due to the increase of walking distance (1), while the second considers the effect of increasing attractivity due to the greater distance from the metro station (2), based on:

$$f_b(d_{i,k}) = e^{-\frac{d_{i,k}^2}{2\gamma_s^2}} \qquad \text{if } d_{i,k} < d_{walk.max} \tag{1}$$

$$f_t(d_{t,k}) = 1 - e^{-\frac{(d_{t,k}-d_{\min})^2}{2\gamma_t^2}} \qquad \text{if } d_{t,k} < d_{min} \tag{2}$$

where $d_{i,k}$ is the walking distance from the centroid of the traffic zone k to the nearest stop-node i, $d_{walk.max}$ is the radius of an area around stop-nodes where demand for feeder service can arise, $d_{t,k}$ is the distance from the terminal node (e.g. a mass rapid transit station), d_{min} is the radius of an area around the station with no demand for feeder service due to the short distance, γ_s and γ_t are constants to be calibrated. In addition, as suggested by Zhu et al. (2017), the model considers the potential demand reduction for the feeder service due to the other bus lines that are operating via the bus stop through a coefficient M_i. Based on the above analysis, the potential demand for a feeder stop-node i can be calculated in terms of active and passive accessibility, as shown in eq. (3):

$$A_{act,i} = M_i \cdot \sum_{k\in Z} f_b(d_{i,k}) \cdot f_t(d_{t,k}) \cdot R_k \tag{3}$$

where Z is the set of traffic zones gravitating around the stop-node i and R_k is the number of residents of zone k. By the same token, passive accessibility $A_{pas,i}$ is calculated by replacing R_k with W_k, or the number of employees of zone k. To assign to each stop-node a single accessibility value, we chose to express this value as a linear combination of active and passive accessibility, weighted respectively by w_{act} and w_{pas} coefficients, ranging from 0 to 1. Furthermore, for each stop-node accessibility is normalised by dividing by the highest accessibility value A_{max} in the study area.

2.2. The ACO algorithm

The route design model proposed in this paper deals with an NP-hard problem in the field of operations research. For this type of instances, several heuristic procedures have been developed in order to find good suboptimal solutions with acceptable computational efforts, often inspired by natural mechanisms and known under the name of metaheuristics. ACO algorithms (Dorigo and Stützle, 2004) are inspired by the social behaviour of certain ant species and their ability to find shortest paths between their nest and a food source, simply by exploiting communication based on pheromone trails, a volatile substance that ants may deposit on the ground and smell. This principle can be applied to find minimum cost routes compatible with a set of constraints, by employing a population of ants to jointly solve the optimization problem. The algorithm implemented in our model derives from Ant Colony System (Dorigo and Gambardella, 1997), and particularly from MAX-MIN Ant System (Stützle and Hoos, 2000), which are the two main improvements of the first Ant System, originally applied to the Travelling Salesman Problem.

In this model the three subsequent steps are taken, which are schematically shown in Fig. 1 (a), i.e. (i) initial setup of network topology and GIS dataset (t = 0); (ii) setup of the ACO parameters (t = 0), (iii) simulation run (t > 0). In Fig. 1 (b) a flow chart of the routing algorithm implemented on the *NetLogo* platform is outlined. At the start of a simulation, a colony of m artificial ants is generated on the start-node (i.e. the metro station). At every iteration, ants explore the network recording the visited stop-nodes and the crossed links and updating its travel time. After visiting a stop-node, each ant updates its own Coverage attribute CV_k, given by the sum of *Accessibility* of the visited stop-nodes. When all m ants have completed their tour, the best ant is selected and the pheromone updating rule (shown below in Eq. 6) is applied. The objective function is calculated for each ant as a route efficiency indicator E to be maximized, as follows:

$$\text{Maximize} \qquad E_k(t) = CV_k - 2 \cdot \frac{CV_k}{T_{path,k}} \cdot \Delta T_{excess} \tag{4}$$

In eq. (4), $\Delta T_{excess} = (T_{path,k} - T_{des})$ if $T_{path,k} > T_{des}$, otherwise it is equal to zero. In this way, a penalty is given to the Coverage when the travel time of ant k exceeds the desired route travel time. The constraints of the model can be summarized as follows: (i) each stop-node can be included in at most one feeder route; (ii) each route must start and end at the same metro station; (iii) if the travel time ($T_{path,k}$) exceeds a specified threshold ($T_{shortcut}$), the ant comes back to the start-node through the shortest path completing its tour. In this regard, the $T_{shortcut}$ should be close enough (at most equal) to the desired route travel time (T_{des}).

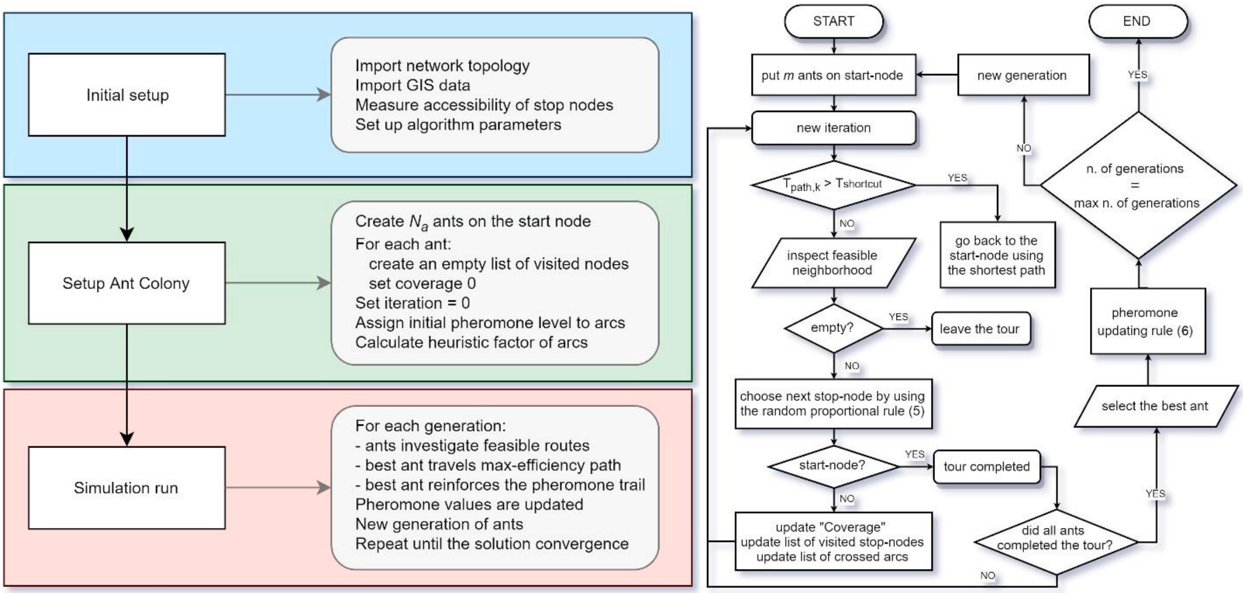

Fig. 1. (a) the three main steps of the simulation; (b) flow chart of the ACO algorithm.

As previously stated, each ant builds a route by applying a random proportional rule to decide the next stop-node to go. Therefore, the probability with which ant k, currently at stop-node i, chooses to go to stop-node j is given by:

$$p_{ij}^{k}(t) = \frac{\left[\tau_{ij}(t)\right]^{\alpha} \cdot \left[\eta_{ij}\right]^{\beta}}{\sum_{l \in \mathrm{N}_i^k} \left[\tau_{il}(t)\right]^{\alpha} \cdot \left[\eta_{il}\right]^{\beta}} \qquad \text{if } j \in \mathrm{N}_i^k \tag{5}$$

where α and β are parameters that control the relative importance of the pheromone trail τ_{ij} versus the heuristic information η_{ij}, N_i^k is the feasible neighbourhood of ant k when being at stop-node i, or the set of stop-nodes linked to i and not visited yet. While the pheromone trail is updated after every generation t, the heuristic information is available a priori and is given by the ratio between the potential demand (accessibility) of stop-node i and the distance between i and j, or the length of link (i, j), measured on the road network: $\eta_{ij} = A_i / d_{ij}$. If $\alpha = 0$, the process acts as a greedy algorithm and the closest stop-nodes are more likely to be chosen; on the other hand, if $\beta = 0$, only pheromone amplification is at work and this would lead to the rapid emergence of solutions stagnation and hence to strongly sub-optimal solutions. Each generation of ants concurrently builds circular routes starting and ending at the metro station. Once all the m ants have completed the tour, only the "best" ant (i.e. the one that founds the solution that maximizes or minimizes the desired objective function) is allowed to reinforce the pheromone trail, to better exploit the best solutions found by every generation, by means of the following updating rule:

$$\tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij}^{best}(t) \qquad \text{with} \qquad \Delta\tau_{ij}^{best}(t) = Q \cdot \frac{E^{best}(t)}{E^{global-best}} \tag{6}$$

where ρ is the evaporation rate, ranging from 0 to 1, $\Delta\tau_{ij}^{best}$ is the amount of pheromone deposited on link (i, j) used by the best ant at iteration t, E^{best} indicates the highest value of the objective function among all the m ants at generation t, $E^{global\text{-}best}$ is the best value of E found from the start of the simulation and Q is the diffusion rate. Moreover, the pheromone trail is limited to a lower value τ_{min} to avoid stagnation of the search.

In the end, if the number of generations is still lower than a specified maximum, another generation of m ants is launched on the network searching for the best route, otherwise the algorithm stops and outputs the results.

3. Case study and first results

Improving urban accessibility by PT service is a subject of significant interest for Catania, a city of about 300,000 inhabitants located in the eastern part of Sicily (Italy), which has been affected by a process of decentralization of housing settlements and commercial services to peripheral areas, modifying the citizens' travel patterns, increasing the amount of commuter traffic and producing air pollution. A metro line currently connects the city centre with the north west zones of the city and it is subjected to further development. The case study focuses on improving the accessibility of the *San Nullo* metro station (SN), thanks to the optimized design of feeder bus routes. The station is located in a peripheral area, where the only access routes to the station are not equipped with sidewalks and present high slopes, constituting a real obstacle for pedestrians and therefore reducing the attractiveness of the station itself.

Once the study area has been identified, the potential stops of the feeder service have been placed on the map, partially based on existing stops of public transport. The study area is divided up into a grid of patches (i.e. cells in *NetLogo*, each one having own spatial coordinates), to which a number of residents aged 15 to 74 and of employees is assigned, based on demographic data provided by the most recent ISTAT database (dating back 2011). Demand is generated only within a specified radius around stop-nodes, which accessibility A_i is calculated using eq. (3).

3.1. Scenario simulations

For a first test of the model, the design of two feeder routes has been carried out, seeking to obtain the widest coverage possible in accordance with travel time constraints. Various scenarios have been analysed and compared, by setting different desired travel times. Input parameters are shown in Table 1. They have been chosen after several tests which resulted in better computational times and model outcomes.

Table 1. Input parameters set.

w_{act}	w_{pas}	d_{min} (m)	d_{max} (m)	V_{bus} (km/h)	n. ants	Initial ph. value	Q	ρ	α	β
0.60	0.20	250	400	16.0	100	10.0	1.00	0.025	1.00	0.50

Table 2 and Fig. 2 show the results of 7 scenario simulations, performed by increasing T_{des} from 10 to 40 minutes.

Table 2. Comparison of simulations results.

Scenario No.	Route No.	Num.of gener.	T_{des} (min)	T_{route} (min)	CV (%)	CV_{tot} (%)	E (%)	E_{tot} (%)	$\Delta E / \Delta T_{des}$ (s^{-1})	$\Delta E_{tot} / \Delta T_{des}$ (s^{-1})
1	1	50	10	10.4	3.35	9.12	3.09	5.44	0.309	0.272
	2	50	10	14.2	5.77		2.35		0.235	
2	1	100	15	18.5	10.37	19.00	6.49	12.31	0.680	0.687
	2	100	15	17.9	8.63		5.82		0.694	
3	1	100	20	20.6	13.87	24.03	13.03	22.26	1.308	0.995
	2	100	20	21.0	10.16		9.23		0.682	
4	1	150	25	25.4	20.44	35.33	19.86	32.04	1.366	0.978
	2	100	25	27.5	14.89		12.18		0.590	
5	1	200	30	30.4	28.10	44.27	27.46	43.42	1.486	1.138
	2	100	30	30.0	16.17		16.28		0.790	
6	1	200	35	34.6	32.07	51.39	29.87	51.39	0.956	0.797
	2	100	35	34.9	19.32		18.79		0.638	
7	1	200	40	41.1	34.42	55.95	34.89	53.92	0.096	0.253
	2	100	40	40.2	21.53		21.36		0.410	

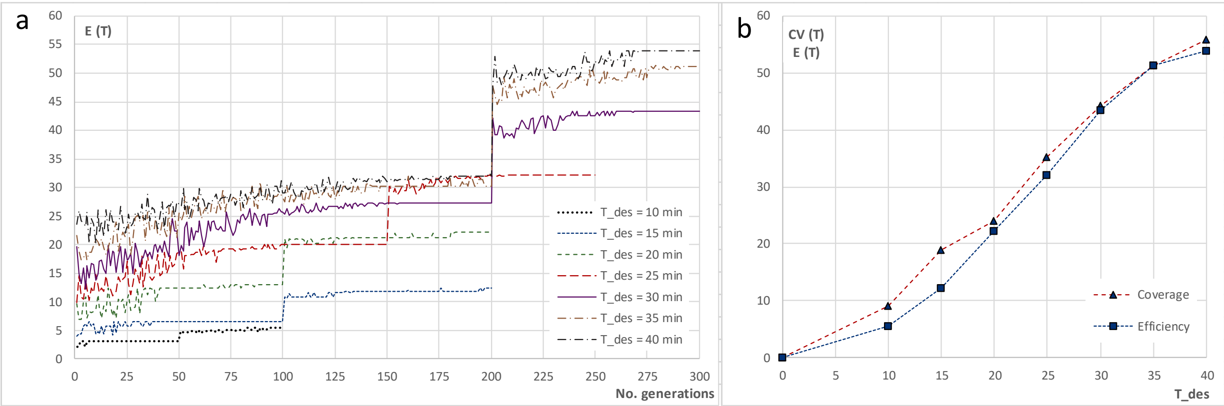

Fig. 2. (a) convergence process of Efficiency; (b) total coverage and efficiency in each scenario.

Fig. 2 (a) shows the convergence process of the objective function E after each ants' generation, for given different T_{des}. As can be observed in Fig. 2 (b), as well as in the last column of Table 2, Efficiency shows higher growth rates when desired travel times are set between 20 and 30 minutes. Based on this result and considering that the route travel time affects service costs, the best compromise between demand coverage and operational costs is represented by the 5th scenario, involving two routes with a travel time of 30 minutes.

From the graphical output of the three simulations shown in Fig. 3, it emerges that routes extend towards areas which are more distant from the terminal station, when increasing the desired travel time. It should be noted that if a simulation produces a wide circular route, this result could not be optimal for a feeder line, as it would force some passengers who get on the shuttle to bear unjustifiably high travel times before reaching the station. In this case, two circular routes that run in opposite directions could be provided.

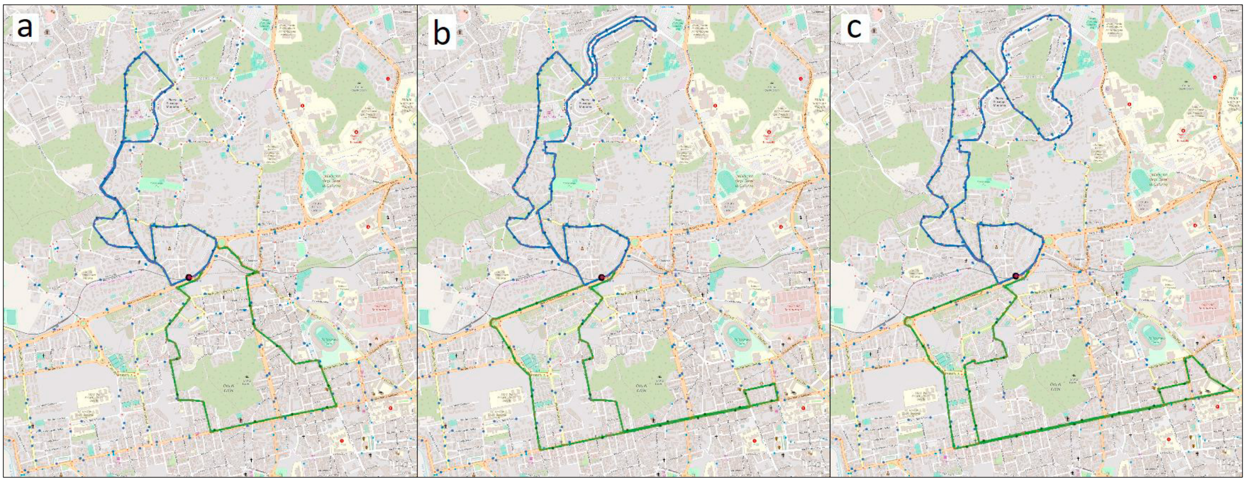

Fig. 3. Graphical output of three simulations: couple of feeder routes setting T_{des} equal to (a) 20 min; (b) 25 min; (c) 30 min.

4. Conclusions and further research

This paper has focused on the development of a new simulation model for the route optimization problem of feeder bus services, which mainly serve for "the last mile" of residents' travel, enhancing the effectiveness of the whole transit system. In this regard, metaheuristic methods have also made it possible to tackle large size problems more efficiently. Starting from the integration of the road network in a GIS-based demand model, the implementation of an Ant Colony Optimization algorithm in the *NetLogo* platform allowed to design optimal routes aiming at maximizing the service coverage in terms of potential transport demand and in accordance with a desired travel time. Thanks to the possibility of dynamically interacting with the simulation environment and visualizing routes on the map, with an easy transferability to other contexts, our model can serve as a practical and flexible tool for public transport planners and companies. First simulations were carried out regarding the case study of the *San Nullo* station of the Catania metro line. By varying travel times, several routes have been originated allowing some conclusions to be drawn, regarding both the service coverage and operating costs. In this regard, for the specific case study, a couple of routes with 30 minutes travel time seems a good compromise between the effectiveness and efficiency of the service.

Future development would focus on improving the model by considering the assignment of feeder lines serving different terminal rail stations. Besides, Demand Responsive Transport services would be simulated, reproducing the dynamic matching between users' requests and vehicles and introducing user perspective into the model.

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