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A spatial agent-based model of e-commerce last-mile logistics towards a delivery-oriented development

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A R T I C L E I N F O

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A B S T R A C T

The spread of e-commerce has driven a major growth in the parcel delivery market, bringing a negative impact on sustainability, especially due to last-mile deliveries in urban areas. It is crucial to appropriately tackle this issue to foster consolidation of deliveries, possibly by using collection and delivery points (CDPs), where customers might receive their parcels. This paper proposes a new spatial agent-based modelling approach to explore different scenarios of last-mile logistics referred to e-commerce deliveries, comparing fragmented door-to-door deliveries with consolidation-based strategies. The case study is the central urban area of Catania, a medium sized city in Southern Italy. The Agent-Based Model (ABM) reproduces feasible operations considering real-world spatial constraints and demand data, including the possible matching of customers' systematic trips and parcel delivery via CDPs with small detours from the scheduled trip. Key performance indicators consider both customer and logistics operator perspectives. Main results of the simulation show that the scenario without CDPs is the costliest and least efficient, implying a high number of failed deliveries. Using cargo bikes instead of vans to perform the delivery implies high costs, but much higher benefits in terms of reduced energy consumption. The highest logistics efficiency is achieved in the scenario with a doubled demand, implying a better use of the CDPs. The results suggest that it is advisable to incentive the use of CDPs instead of increasing their number. The ABM can provide useful information to decision-makers on how to manage growing on-demand urban deliveries and plan last-mile logistics using a delivery-oriented development approach.

Introduction

Last-mile logistics is a recent but rapidly growing phenomenon due to e-commerce spreading and the increase in the number of business-to-consumer deliveries. The growth of this phenomenon can mainly be attributed to the worldwide spread of digital technologies - in particular the Internet - which, thanks to online purchasing, make remote shopping easier. This has been further exacerbated during COVID-19 outbreak, bringing people to adapt to e-purchasing and e-groceries habits due to mobility restrictions imposed by governments (Le Pira et al., 2021b) and in response to concerns related to social distance and untypical demand needs (Melo and de Jesus Ferreira, 2022).

Fragmented door-to-door deliveries performed by different private companies generate negative externalities, hampering sustainability. Their economic efficiency is affected by failed deliveries, low vehicle load factors and long travelled distances. From an environmental perspective, logistics vehicles contribute up to 50% of Particulate matter (PM and Nitrogen Oxide (NOx) emissions in cities and they are also responsible for 40% of transport related CO2 emissions (Iclei, 2021). Social sustainability is also affected by last-mile deliveries: different logistics companies usually operate in the same city with an overlapping delivery network, generating additional congestion with respect to the one caused by individual shopping trips (WEF, 2020). Road safety is another issue, with logistics vehicles highly involved in fatal collisions (Interreg Europe, 2020).

All these challenges should be duly taken into account by policy-makers (Le Pira et al., 2017; Allen et al. 2018). Last-mile logistics needs to be included in transport planning processes by considering city

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constraints and operation costs, while keeping customers demand satisfied.

Innovative logistics solutions might come into help to this purpose. According to WEF (2020), they can be related to innovative vehicles (e.g. electric vehicles), secure deliveries, customer movement (e.g. with the use of parcel lockers), consolidation strategies, last-leg change (e.g. micro-hubs), or to the delivery environment (e.g. dynamic re-routing). A promising solution is crowdshipping, implying deliveries performed via the crowd, i.e. by travellers carrying the parcels during their scheduled trips (Marcucci et al., 2017). In this respect, Giuffrida et al. (2021) used a GIS-based approach to evaluate the spatial feasibility of crowdshipping performed by University students using public transport or active modes considering their proximity to collection and delivery points (CDPs) where the parcels could be consolidated. This example shows how a combination of different solutions is desirable to maximize the probability of success and the positive impacts of such a policy.

Consolidation strategies with customer involvement via the use of CDPs like parcel lockers, but also brick-and-mortar stores, seem a promising and ready solution to be deployed in many cities. These are usually private and customer-oriented initiatives: private companies decide the location of CDPs where parcels can be stored and directly picked up by the final customers. However, it could also be a public initiative to be included in transport and land-use planning agendas, towards a “delivery-oriented development”. This concept is here proposed and explored, by taking into account different and conflicting issues: CDPs need to be diffused and easily reachable by consumers, thus discouraging additional individual car trips; at the same time, they should not be too pervasive, jeopardizing the consolidation of deliveries and its positive impacts. The spatial distribution of both parcel demand and CDPs is thus fundamental to appropriately plan consolidation strategies aimed at increasing logistics efficiency while reducing its negative impact on city sustainability and liveability.

This paper presents a spatial Agent-Based Model (ABM) to explore different scenarios of last-mile logistics induced by e-commerce, comparing door-to-door deliveries with consolidation-based strategies, by taking into account demand and transport network data based on a real-world case study. In this study, an already implemented ABM (Calabrò et al., 2022) is integrated with a Geographic Information System (GIS), where the results of a spatial analysis are used as context input for the simulations. The novelty of the ABM is the simultaneous dynamic simulation of customer mobility and freight movements to explore the possibility of coupling customers picking up their parcels at CDPs with a small detour from their daily trip route, considering different trip purposes. In the previous study, the ABM has been applied to a synthetic case study to explore the variables that make consolidated deliveries more attractive than fragmented door-to-door ones. In this paper, the ABM is further improved, and it is integrated with GIS to reproduce a real-world environment using spatial open data related to the transport network and to potential demand at a census zone level. This is particularly relevant if one considers the importance of demand analysis and the difficulty to find official and reliable data. Thanks to the data regarding the transport network, it is possible to simulate different routing options for the deliveries at the level of detail of census zones, given that information on routes taken by private logistics companies are not easily accessible.

The ABM integrated with GIS considers important variables both related to the supply and the demand, like: (1) depot location; (2) spatial density of CDPs; (3) OD shortest-path matrix (4) vehicle fleet size; (5) vehicle type and capacity; (6) customer mobility patterns, (7) parcel demand, and (8) willingness to accept deliveries performed via CDPs.

The flexibility of the modelling environment allows the exploration of different scenarios that can be useful to both policy-makers and private companies to understand how to optimize parcel deliveries in urban areas.

The remainder of the paper is organized as follows. Section 2 (“State of the Art”) analyses the main literature endeavours related to consolidation strategies and agent-based modelling of last mile logistics, so to set the scene and present the gap of knowledge covered by this paper. Section 3 (“Methodological approach”) describes the methods used, namely the GIS approach and the ABM. Section 4 (“Case study”) introduces the case study and reports the findings of the first set of simulations, paving the way for further research that is discussed in Section 5 (“Discussion and Conclusion”), which concludes the paper.

State of the Art

Fragmented vs. consolidated deliveries

Consolidation strategies to improve the efficiency of urban deliveries have been investigated since the early 2000s with the concept of Urban Consolidation Centers (UCC) (Browne et al., 2005). UCC are logistics facilities used by different logistics providers located close to the served area (usually the city center) from which consolidated deliveries are made with small vans, avoiding the presence of heavy vehicles in urban context. Although its attractiveness, this type of initiative showed to be difficult to implement, due to their operational models which need high reliance on government support (Marcucci and Danielis, 2008). An intermediate solution for freight consolidation is constituted by the so-called micro-hubs, smaller transport provider-owned consolidation centers located at the border of the city center (Janjevic and Ndiaye, 2014); their location should facilitate the use of environmentally-friendly modes, such as light-duty electric vehicles, electric cargo bicycles and/or by foot or handcarts. Solutions to further improve the last-mile deliveries consolidation are the CDPs and, in particular, parcel lockers. CDPs are facilities located in the city centers where the customer can pick up its parcel at a convenient time; they can be automated or equipped with staff and can also be located in existing brick-and-mortar stores. They can have a 24/7 policy or opening hours. A particular case is the one constituted by the parcel lockers, which are automated CDPs where customers can redeem their parcel using a code and/or a form of identification (Schnieder et al., 2021). The efficiency of such capillary solutions in urban areas in comparison to home-deliveries is of current debate and it is one the core topic investigated in our study.

Besides, as shown in the review conducted by Lagorio and Pinto (2020), literature related to the location and usage of CDPs is quite new and the topic is still under study. However, some recent works of interest can be reported.

The feasibility of parcel lockers solution has been assessed by Van Duin et al. (2020). The authors simulated different scenarios using multicriteria analysis to identify the factors affecting the choice of each alternative and calculating delivery costs through a cost effectiveness analysis. The location of the facilities resulted the main factor, requiring a detailed analysis to provide great benefits from the parcel lockers strategy when compared with traditional solutions.

A survey of Mitrea et al. (2020) showed that the willingness to accept parcel lockers deliveries is highly affected by their proximity to daily origin/destination, in such a way that customers can easily combine the parcel collection with their systematic trips, with two third of the purchasers allowing a detour up to 10 min. More recently, the topic has been studied by Iannaccone et al. (2021) who compared consumer preferences for home delivery vs. parcel locker use, forecasting their future market shares. The study shows an overall high propensity to use parcel lockers, and that the main choice determinants are distance and accessibility. Accessibility and equity metrics for parcel lockers have also been investigated by Schaefer and Figliozzi (2021), using geographical tools and cluster analysis; they analysed the case of Portland (Oregon, US) and showed that although the facilities are located in mixed-use areas the equity metrics indicate that the current distribution of lockers could be improved to allow the access to the current unserved population.

Parcel lockers and home deliveries have been compared by Schnieder and West (2020) through the innovative concept of Time-

Area requirements, i.e. the product of the space usage and the time needed for the delivery process, considering both couriers and customer's trips. Results show that, for high parcel demand, parcel lockers are efficient only when used at high capacity. Later in 2021, Schnieder et al. (2021) tested two options to increase the utilization of parcel lockers: modular lockers (which can be adjusted periodically depending on demand) and combining parcel lockers with staffed CDPs. They used real world data for the case of London, considering seasonal and daily changes in parcel demand, missing picking up by customers, return deliveries and the net present value of the investment. Findings highlight that combining parcel lockers with staffed CDPs offers better financial performance for the case study. Leung et al. (2022) proposed a dynamic delivery strategy in order to manage and update delivery plans in real time. On the basis of a given parcel network, the authors simulated different demand scenarios in order to evaluate the suitability of such service by varying the requests in time and space. In addition, the authors underlined the importance of implementing the service with consolidated deliveries. Comi and Savchenko (2021) assessed the advantages of performing parcel deliveries with different modes of transport: car, motorcycle, bicycle and on foot by using public transport. The authors calculated a cost for each alternative considering both internal (such as fuel consumption, cost for maintenance and repair) and external (air pollution, congestion, road accidents) parameters. From the analysis carried out, it emerged that the use of public transport is certainly the most convenient, but it involves issues related to the transport of voluminous goods and delays of the delivery. This result highlights the importance of finding a trade-off between the quality of the parcel delivery service, the costs of the logistic operators and the impact in the urban context. Similarly, Kou et al. (2022) evaluated delivery strategies in a rural area by considering different modes of transport towards a multimodal transport design for last mile delivery. Results show that a combination of public transport and crowdsourcing logistica can be very effective in satisfying the e-commerce demand in a rural area.

Finally, Schwerdfeger and Boysen (2020) and Liu et al. (2021) analysed the innovative concept of mobile parcel lockers (usually constituted by vans that change their locations during the day). The former compared the performances with stationary lockers, showing that mobile lockers might considerably reduce the locker fleet size. The latter proposed a machine learning method to solve the dynamic location routing problem, showing that such type of algorithms performs better than the traditional heuristic counterpart.

This brief but recent literature review shows that many topics related to e-commerce and the use of CDPs are still an open issue. There is no structured approach for the planning of CDPs locations and their density in urban areas, based on e-commerce demand distribution, although being a crucial factor for the economic, environmental and social sustainability of such delivery solutions. Moreover, it is also important to analyse customer involvement in the delivery process, i.e. the impacts incurred in the users' trip to reach CDPs and their willingness to use them. Our paper contributes to fill these literature gaps, by proposing a spatial modelling framework to explore different scenarios in a real case study.

Agent-based modelling of last-mile logistics

ABMs are quite powerful tools to reproduce systems to a very disaggregated scale with high spatial resolution, simulate interactions among individual agents with the ability to capture complex individual behaviour dynamics and emergent collective phenomena (Bankes, 2002; Le Pira et al., 2021a). The use of ABM to simulate last mile logistics is still quite new. This is mainly due to the novelty of the problem and the fact that freight models are in general used to simulate different decision levels (i.e. strategic, tactical and operational) in relation to their reference market (Tavasszy and de Jong, 2014). The MASS-GT model (de Bok and Tavasszy, 2018; de Bok et al., 2020) and SimMobility Freight (Alho et al., 2017) are recent examples that go in the direction of a comprehensive model for freight transport. However, existing models usually do not consider individual actor behaviour and dynamic interactions at a microscale.

Specific ABMs dealing with last-mile logistics have been proposed in the last years. Anand et al. (2021) used an ABM to simulate the consolidation of freight in urban areas via the use of a UCC, introducing a cap on freight deliveries to reduce carbon emissions for last-mile logistics.

The operation of urban deliveries has been studied by Chen and Chankov (2017) who investigated the performance of the crowdsourced last-mile logistics; two main parameters are studied, i.e. the supply/demand ratio and the maximum detour time accepted by couriers. Later on, Wise et al. (2018, 2019), developed an ABM to simulate the movements of individual delivery personnel and their vehicles throughout the day. They calibrated the model with real data for the case study of London, taking into account different vehicles and including parking behaviour. However, they did not explore alternative scenarios to test the potential improvement of the current situation. In 2019, Alves et al. (2019) explored the CDP option, analysing different scenarios by changing their numbers. They developed an ABM integrated with GIS, showing that parcel lockers can reduce the missed delivery phenomenon and improve the cost effectiveness for delivery companies. A sophisticated model is the one presented in Reiffer et al. (2021) which simulates both private trips and last-mile deliveries, thus considering realistic traffic conditions and including the possibility of missing deliveries.

Other recent studies specifically focused on e-commerce deliveries through ABMs, like Sakai et al. (2020) who use the SimMobility Freight platform. Le Pira et al. (2020) dealt with e-grocery, proposing an approach based on the integration of discrete choice models and ABMs to simulate users' propensity towards different grocery/e-grocery alternatives (i.e. home delivery, click-and-pick and the traditional shopping). Always remaining in the grocery delivery field, Utomo et al. (2022) evaluated the feasibility of such delivery solutions by using autonomous vehicles (AVs); they investigated the benefits of mixed-fleets over homogeneous designs. Results show that AVs reduce operational costs and the total distance travelled. More recently, Kant & Gupta (2023) proposed an ABM to evaluating the impacts of freight consolidation centers for last-mile solutions; they studied the impact of consolidation strategies across commodities and proved differences in the impacts across commodity distribution in last-mile deliveries of goods.

Our paper contributes to the existing literature by proposing a GIS-based ABM to explore different scenarios of last mile logistics, specifically focusing on e-commerce deliveries, and considering consolidation via CDPs and customer involvement. The ABM is based on the one proposed by Calabrò et al. (2022) to dynamically simulate customer and freight movements in a parametric environment with the possibility for customers to pick up their parcels at CDPs along their daily mobility paths, considering different trip purposes and bridging freight and passenger mobility in urban areas. In this paper, the ABM is used to reproduce a real case study with spatial constraints, by integrating it with a GIS using the results of GIS analyses as input for the simulations.

Next section describes the details of the proposed methodological approach.

Methodological approach

The spatial ABM is designed to address the issue of last-mile logistics. In this paper, the GIS analysis output becomes one of the ABM inputs to simulate last-mile e-commerce delivery operations, modelling the interactions between the different "agents" of the system, i.e. the delivery vehicles (with their scheduled routes), the customers (with their scheduled trips), the parcels to be delivered, and the physical locations where parcels are delivered (or picked-up). The latter can be distinguished in customer's domicile (home delivery) and CDPs (CDP delivery).

GIS analysis

A GIS analysis is conducted according with the following steps:

(1) Definition of the study area and zoning.
(2) Import of demographic data.
(3) CDPs allocation.
(4) Calculation of the OD shortest path matrix.

The outputs of this spatial analysis are used to provide the ABM with the required inputs for the simulation of different scenarios of last-mile logistics strategies. The spatial analysis is performed using QGIS software, a GIS desktop open-source able to process and manage spatial data in a geographic environment.

More in detail, in the first step, the study area is selected and zoned, and a corresponding centroid is associated to each zone. Then, demographic information (i.e. number of residents and employees) is retrieved from the national statistics website; residents are classified in terms of age and e-commerce purchasing frequency, based on statistics reports (step 2), and are spatially assigned to the zones.

The third step involves the allocation of CDPs in the study area. To do this, the addresses of CDPs are collected from the websites of the logistics companies operating in the study area and imported into a GIS environment thanks to the use of the geocode web-service of the MMQGIS plugin.

The last step consists in the OD shortest-path matrix calculation for the centroids associated to each zone. The calculation is done for all the possible couples of centroids, using the OpenRouteService (ORS) plugin, which allows to perform routing analysis based on OpenStreetMap (OSM) road network, considering "car" as travel mode. The ORS tool calculates the travel time for each segment by using speed-limits for different OSM waytypes and adjusting them for different grades or surfaces of the road and some other factors (such as in case of residential roads). The tool provides a "shortest route" and a "fastest route" module where the "fastest route" chooses the route with high-speed roads. However, this can be considered of little interest in our case study, set in an urban environment, with similar network speeds. For this reason, it was preferred to opt for the "shortest route" option. Finally, ORS performs its calculation in the case of uncongested networks: more advanced tools and models might be used to consider traffic in the analysis.

The Agent-Based Model

The proposed ABM is built in the NetLogo programming environment (Wilensky, 1999) and the framework is based on the study of Calabrò et al. (2022). The description of the ABM is provided in the following sub-sections.

Main input parameters

The input parameters of the model are the demand characterization, the type of delivery vehicle, the service-related and simulation-related parameters.

As regards the characterization of the demand, the main input parameter is the number of customers (N_{Ci}) per day of operations generated in each zone $i \in Z$ (where Z is the set of zones) calculated as a function of the number of residents (R_{il}), the percentage of customers belonging to age group $l \in A$ (i.e. 18–24, 25–54 and > 54 years) which is an exogenous variable that characterizes the different propensity towards e-commerce (p_{lk}) and the e-commerce purchase rate (r_{lk}) of the customer $k \in C$ where C is the category of purchaser belonging to "habitual" (i.e. 1 e-commerce purchase a week), "occasional" (i.e. 1 purchase every 3 weeks) and "rare" (i.e. 1 purchase every 2 months). The computation of N_{Ci} also considers the percentage of returned parcels (K_R) and the percentage of failed deliveries (K_F), which depends on the previous days' delivery operations (Eq. (1).

$$N_{Ci} = \left(\sum_{l \in A} R_{il} \cdot \sum_{k \in C} p_{lk} \cdot r_{lk}\right) \cdot (1 + K_R) \cdot (1 + K_F) \tag{1}$$

As mentioned before, the percentage p_{lk} is related to the customer's age group. For the sake of simplicity, we assume that each customer orders one parcel. Another customer-related parameter is the maximum allowed detour time (Δt_{max}), considering the customers' willingness to deviate from their daily routes to pick-up their parcels at a CDP.

Regarding the vehicle fleet, different types of commercial vehicles can be modelled (e.g. delivery vans, cargo bikes, etc.). The input parameters related to the supply-side are the vehicle capacity (Q), the cruise speed (v), and the average energy consumption (E). We assume that the delivery operations are carried out by electric vehicles. To compute the operating cost, we do not consider the capital costs of the fleet size, but we include the distance-related cost (in €/km) and driver-related cost (in €/h), by means of the coefficients $€_{km}$ and $€_h$, respectively.

Another input parameter is the type of service $TS \in \{\text{HD}, \text{CDP}\}$ provided to the customers, namely, whether delivery operations are carried out at the doorstep (home delivery, HD) or can occur at CDPs.

Customer behaviour

Once customers "agents" have been generated according to socio-demographic data, each of them is characterized by a different "activity profile", based on their daily schedule and travel pattern. In particular, four activity profiles are modelled, namely "employee" (home-to-work trips), "student" (home-to-school trips), "leisure" (shopping trips) and "no displacements". The start and the end time of the customer travel depend on the activity profile, as well as the distance between origin (O) and destination (D) of the trip in the simulated day. In this paper, we assume that shopping trips take place with random destinations within the service area (i.e. thanks to the high density of facilities such as stores, shops, etc.), while student trips also include external destinations. Instead, the destination of home-to-work trips is chosen according to a gravity model (also considering external-internal commuting trips). The probability for a customer originating in the zone i to have destination in j is expressed as a function of the number of workplaces in j (W_j) and the distance d_{ij} between the two zones, as shown in Eq. (2):

$$p_{ij} = \frac{W_j e^{-\gamma d_{ij}}}{\sum_{j \in Z} W_j e^{-\gamma d_{ij}}} \tag{2}$$

where γ is the deterrence function parameter (Ortúzar and Willumsen, 2011).

Finally, the customers characterized by the "no displacement" activity profile stay at home, except for picking up (or returning) their parcel at the CDPs, as explained later on.

Table 1
Customer-related parameters.

Activity profile	Home-to-work (Employee)	Home-to-school (Student)	Shopping (Leisure)	No displacement
Mode of transport	Car	Bike	Walk	
Utility function (V)	$\beta_{t,car}\ t_{OD,car} + \beta_{c,car}\ d_{OD,car} + \beta_{0,car}$	$\beta_{t,bike}\ t_{OD,bike} + \beta_{0,bike}$	$\beta_{t,} t_{OD,walk}$	

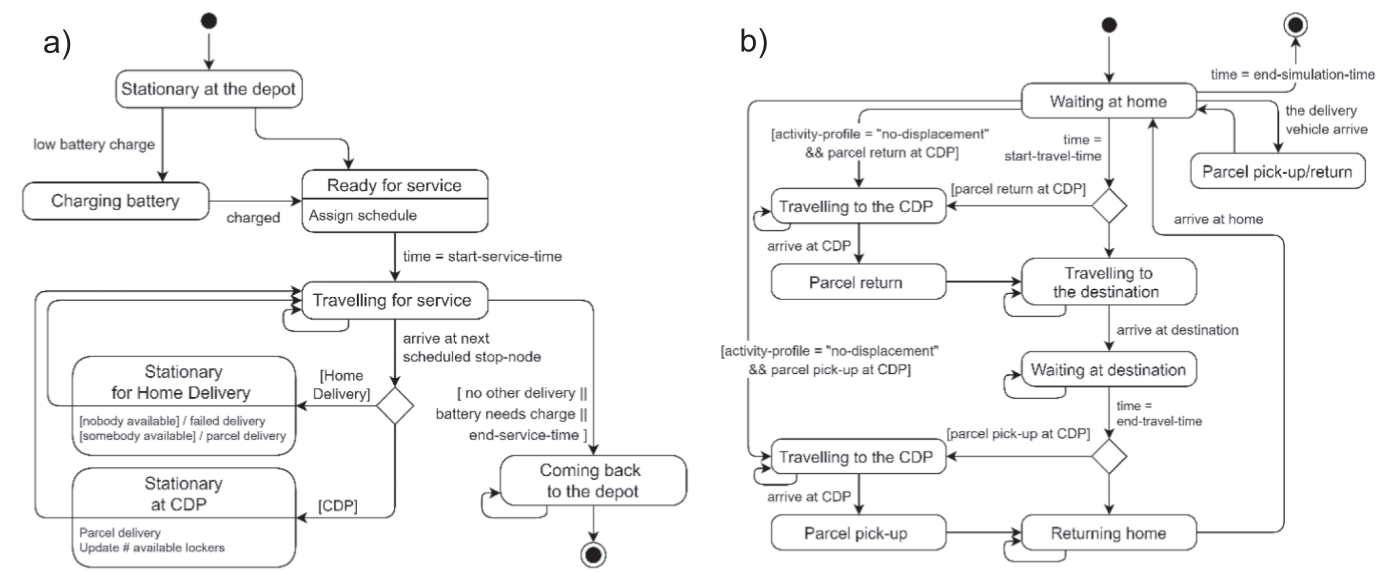

Fig. 1. (a) Delivery vehicles state chart; (b) Customer state chart. They are based on Calabrò et al. (2022).

Customers choose between different modes of transport belonging to the set $M = \{\text{private car}, \text{ bike}, \text{ walk}\}$, available to them; public transport is not considered among the options for the sake of simplicity. The mode choice is modelled as a random choice weighted by the probability S_{mr} of selecting the transport mode m by customer r, which is calculated via a multinomial logit model as shown in Eq. (3):

$$S_{mr} = \frac{e^{V_{mr}}}{\sum_{h \in M} e^{V_{hr}}} \tag{3}$$

where V_{mk} is the systematic utility calculated as a linear function (see Table 1) of generic alternative attributes (travel time t_{OD} and/or distance d_{OD},) and specific alternative attributes. We took as reference the utility functions found in Cascetta (2006).

As an alternative to home delivery, customers can choose a CDP where it is possible to collect (or return) their own parcels. We assume that the "target" CDP for a customer r is the one which minimizes the detour time to reach it, with the constraint of not exceeding Δt_{max}, i.e. the maximum allowed detour time (input parameter). The way the target CDP is chosen differs depending on the mode of transport used, with riders and drivers allowed to choose a CDP "close" to their route between origin and destination, while pedestrians only consider those located within the maximum detour time from their origin.

Customers' orders consist of parcels of various sizes, which we discretized into different categories. CDPs are able to "serve" multiple customers, thus consolidating the delivery operations. The capacity of each CDP is limited in terms of number of parcels that can be stored.

We model the probability $P_{CDP,r}$ for customer r to choose the target CDP as the delivery option according to a quadratic impedance function $\eta_{CDP,r}$. It is a function of the ratio between the detour time $t_{CDP,r}$ needed to reach k and Δt_{max}. To compute such a probability (see Eq. (4)), one should consider the availability of lockers for the parcel of customer r; this is done through a Boolean variable $x_{CDP,r}$ assuming the value 1 if there are available lockers for the parcel and 0 otherwise.

$$P_{CDP,r} = \eta_{CDP,r} \cdot x_{CDP,r} = \left(1 - \frac{t_{CDP,r}}{\Delta t_{max}}\right)^2 \cdot x_{CDP,r} \tag{4}$$

Fig. 1 reproduces the state charts of the simulated behaviour of the delivery vehicles (Fig. 1a) and the customers (Fig. 1b). As already mentioned, the customers that are not intended to perform any trip (activity profile = "no displacements") can choose the option to pick-up or return their parcels at the CDP. The model also simulates the option of customers who might not be at home during the delivery of their parcels, possibly causing a failed delivery (which can be considered an inefficiency of the system). In this respect, customers have their own activity schedule (with a random distribution) and they are not aware of the expected arrival time of the parcel. This also applies to deliveries via CDP. However, in this case there are no failed deliveries since there is a decoupling between parcel arrival and pick up by customers, which can also occur some days after parcel arrivals at the CDP. To be more realistic, we include another parameter φ, i.e. the probability for each customer to have another person who collects the parcel (e.g. a family member, a neighbour, a doorman, etc.). Finally, customers who opted to collect the parcel at a CDP behave differently depending on whether the parcel is a delivery or a return. In the first case (the most common one), customers travel to their target CDP before returning home at the end of their daily routine, while in the latter customers go to the CDP at the beginning of their trip from the origin (see Fig. 1b).

The vehicle routing problem

In real-world scenarios, the vehicle routing problem (VRP), i.e. the optimal choice of the delivery routes that minimizes the cost for the logistics operator, should be addressed by *ad-hoc* optimization algorithms (Calabrò et al., 2020), allowing the operator to obtain significant time and cost savings. In this application, we use a greedy insertion heuristic to assign vehicles to customers. This is because the primary interest is to compare different delivery strategies under diverse demand characteristics, so there is no need to push on the optimality of the solution to the VRP.

Once the demand is generated, before the simulation starts, the parcels are assigned to the delivery vehicles. In our model, there are potential delivery locations (stop-node) along the road network, where the delivery vehicle can park to serve a home delivery request or a CDP. The vehicle routing and dispatching algorithm consists of the following steps:

(1) Determine the order in which the zones of the service area should be visited. This is done by starting from the zone centroid i and sequentially choosing the next centroid j based on the shortest path between i and j, for each $i \in Z$. The chosen solution $\mathscr{Z}$ is the one minimizing the travel distance connecting all the zone centroids.
(2) Solve the travelling salesperson problem, finding a single route aimed at minimizing the total distance connecting all the stop-

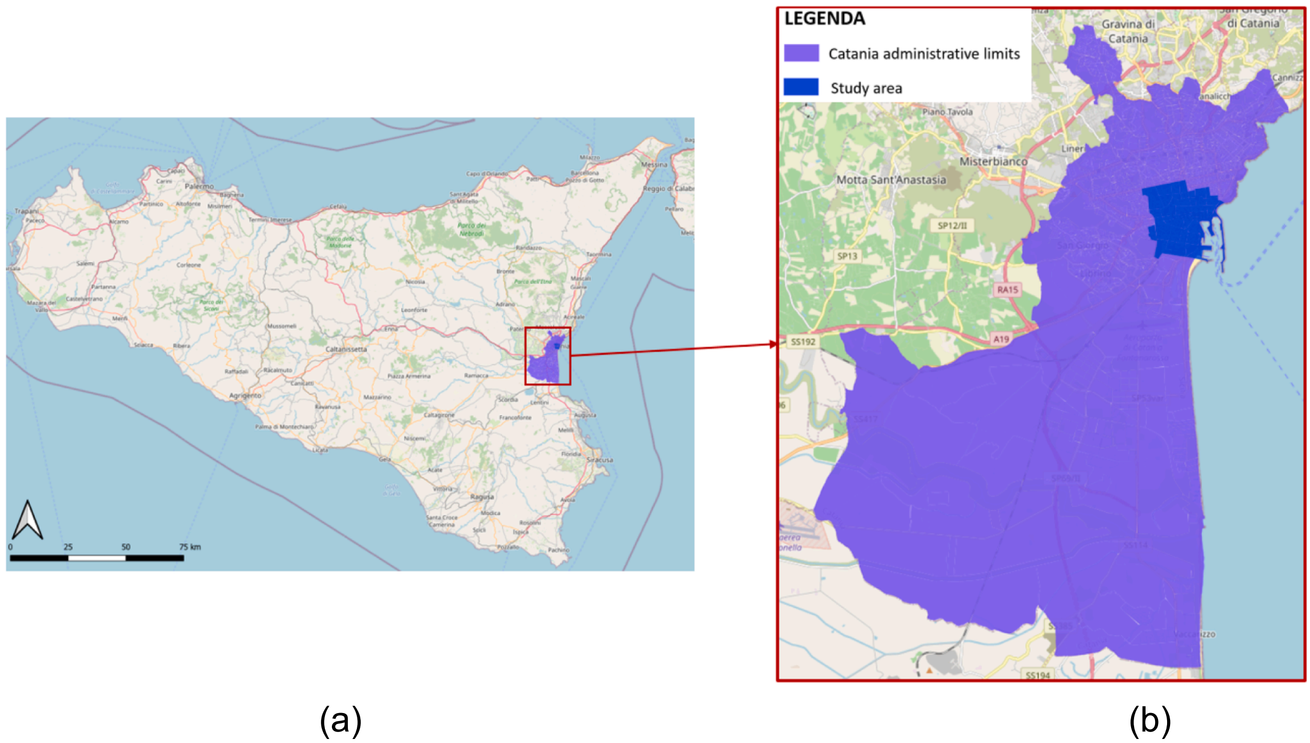

Fig. 2. (a) Territorial framework of the case study; (b) Study area definition.

nodes where the delivery vehicles stop to delivery or pick-up parcels. This problem is solved by a nearest insertion heuristic, including the following sub-steps:

a. Create the initial Cycle $\mathscr{C} = \{depot\}$, only containing the depot.
b. For each zone $i \in \mathscr{Z}$, pick the closest stop-node to the last inserted one and insert it between two stop-nodes in $\mathscr{C}$ such that the increase in the total route length is minimal. When all the stop-nodes in the zone i are inserted, consider the stop-nodes in $i+1$ and repeat the procedure.
c. End when all the delivery locations to be visited are inserted in $\mathscr{C}$.

(3) Compute the number of needed vehicles and assign them to the stop-nodes. At the beginning, the set of vehicles $\mathscr{V}$ includes one vehicle. It visits the stop-nodes following the order of $\mathscr{C}$. A new vehicle is added in $\mathscr{V}$ when one of the following constraints cannot be met:

a. The number of loaded parcels must not exceed the vehicle capacity.
b. The vehicle travel time should be limited to a maximum value (according to the rules on drivers' hours and working time). The travel time is estimated including the idle time during delivery operations, when the vehicle is parked, which consists of the additional time lost at each stop-node τ_s, including the time of acceleration and deceleration, and the delivery times per parcel τ_c (home delivery) and τ_{CDP} (CDP), depending on the type of delivery.
c. The vehicle travel distance must be less than the vehicle range on a full charge.

At the end of the procedure, a fleet of N_V vehicles is created at the depot. However, when simulating the delivery operations by means of cargo bikes, we assume that they start travelling from a micro-hub close to the service area, once high-capacity commercial vehicles have carried the parcels from the depot to the micro-hub.

Case study

The methodology has been applied to the case of Catania, a medium-sized city located in Sicily, in the south of Italy (Fig. 2a). E-commerce has become a wide developed sector in Italy.[1] This growth has led logistics and transport companies to improve their parcel delivery services. Also, in the city of Catania, in line with world and national trends, logistics operators are trying to adapt their services to the increasing demand in the online shopping sector. In this respect, a new logistics centre belonging to one of the main international e-commerce companies was recently opened in Catania, and many private companies and stores have decided to offer CDPs services.

In this study, the simulation environment is focused on the central urban area of Catania (Fig. 2b), of about 6 km2, characterized by a high concentration of CDPs (i.e. 46), points of interests and residents.

Fig. 3a shows the zoning of the study area and the associated centroids. The remaining external zones have been aggregated into macro-areas, based on the official municipality boundaries. Each zone is characterized by the number of residents and employees, based on census data provided by the Italian Statistic Institute ISTAT. In Fig. 3b, the location of CDPs is depicted. For each couple of centroids, an OD shortest-path matrix is calculated, considering car as the travel mode (Fig. 3c). The same procedure is carried out from external to internal centroids (Fig. 3d).

All the output data obtained from the spatial analysis are used as input for the ABM. The road network is built on NetLogo environment, including the location of the depot and CDPs (Fig. 4a). Fig. 4b shows the road network and the geolocation of the agents characterized according to the associated activity-profile.

[1] https://ec.europa.eu/eurostat/web/products-eurostat-news/-/ddn-20210217–1.

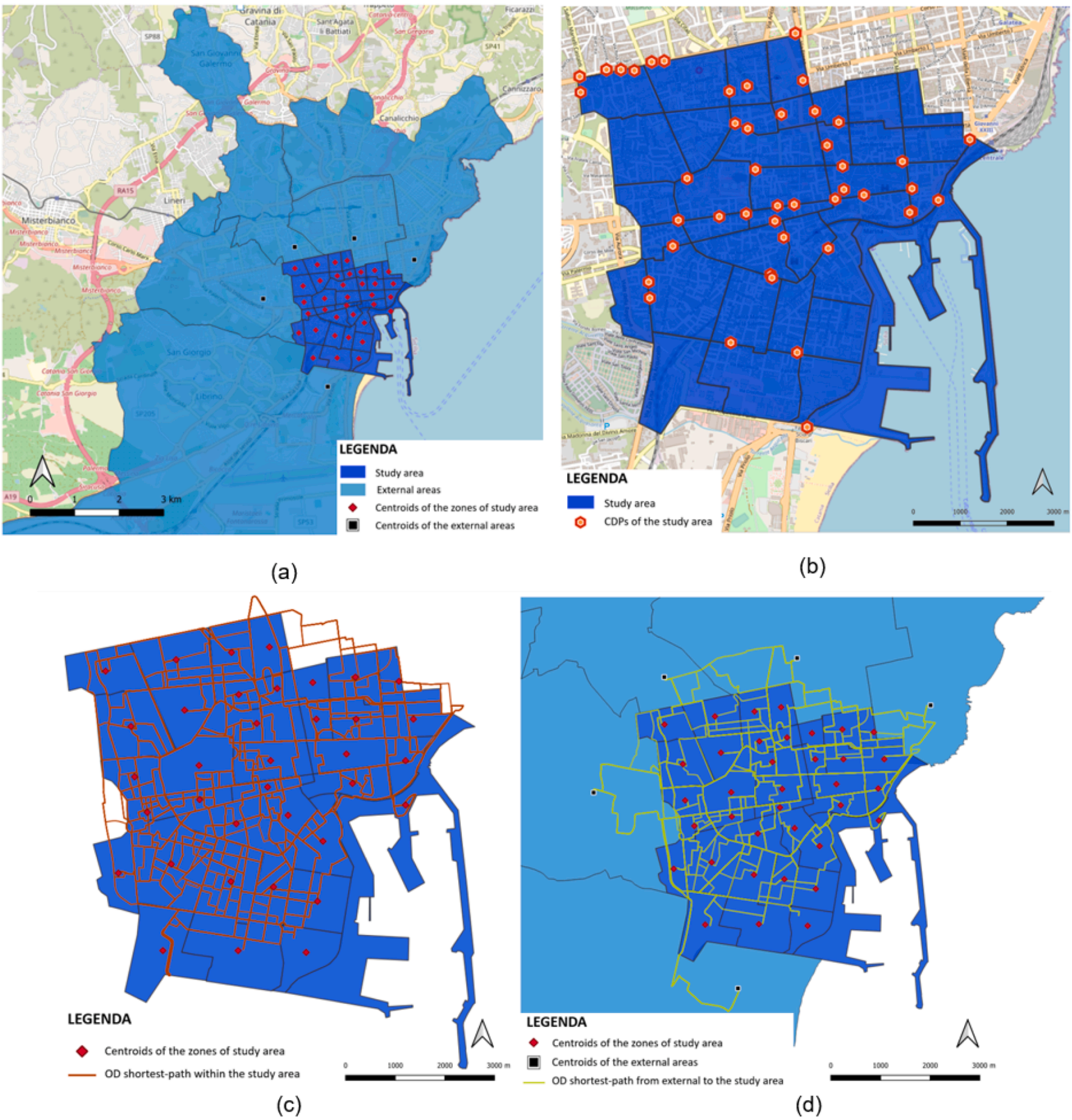

Fig. 3. (a) Zoning and centroids of the study area; (b) CDPs location; (c) OD shortest-path within the study area; (d) OD shortest-path from external zones to the study area.

Scenario simulations and results

The ABM integrated with GIS considers important variables both related to the supply and the demand, like depot location, spatial density of CDPs, OD shortest-path matrix, vehicle fleet capacity and type, customer demand patterns, and willingness to accept deliveries performed via CDPs.

Scenario analysis is performed by varying model parameters so to reproduce different delivery strategies and levels of interaction between customer trips and deliveries.

We set as fixed input parameters for our analysis the percentage of different customers attitudes towards online purchase[2] (i.e. habitual, occasional, rare and never) by age group (Table 2).

Tables 3 to 5 show the input parameters related to the different activity profiles of customers. The characterization of each customer (activity profile, mode of transport, type of parcel and delivery option) is made in the "setup" phase before the simulation starts.

We recall that, for the sake of simplicity, we do not consider the customer trips done by public transport, and thus we limit the mode

[2] https://dati.istat.it/Index.aspx?QueryId=23002.

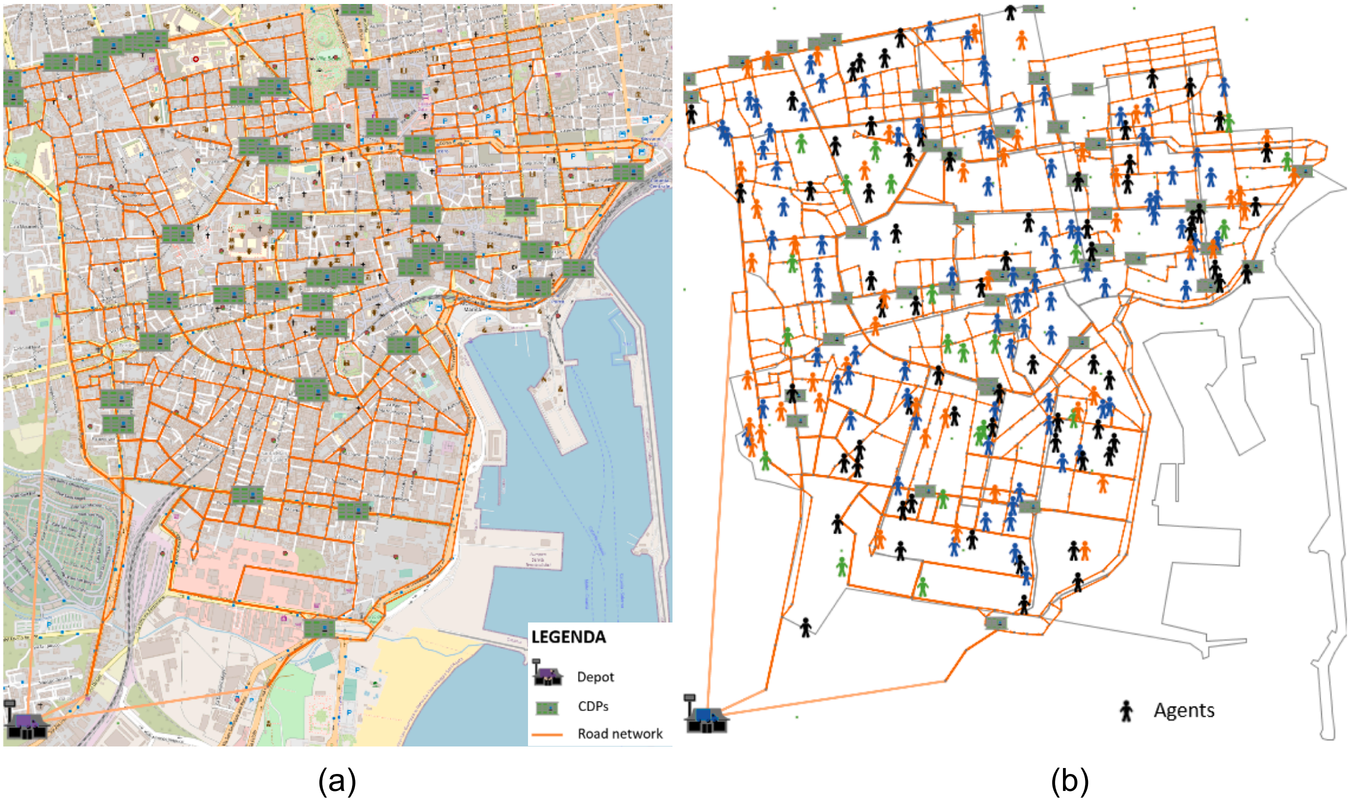

Fig. 4. (a) Road network, depot and CDPs; (b) road network and geolocated agents classified in: employee (blue agents), student (green agents), leisure (orange agents) and no displacements (black agents). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Activity profiles of customers and related input parameters (percentage of different customers attitudes towards online purchase).

Age group	Type of costumer			
	Habitual [%]	Occasional [%]	Rare [%]	Never [%]
18–24	0.47	0.18	0.17	0.18
24–54	0.44	0.17	0.19	0.20
>54	0.26	0.12	0.30	0.32

choice to three alternative modes of transport (i.e. car, bike and walk).

Also, note that all the input parameters reported in Tables 2, 4 and 5 are assumed to be deterministic, while those related to the activity profiles of customers have a lower and/or an upper bound, as reported in Table 3.

The percentages related to different parcel sizes reported in Table 5 are hypothesized considering that a standard delivery vehicle with a capacity of 10 m3 could be fully loaded with about 200 parcels (based on Llorca and Moeckel, 2021).

The ABM allows monitoring of several key performance indicators, related to both customers' and operators' points of view (Calabrò et al., 2022). This is fundamental to assess the impact of different scenarios by considering different perspectives and objectives.

Table 4
Mode of transport of customers and related input parameters.

Mode of transport	Car	Bike	Walk
Average speed [km/h]	20	12.5	5
Utility function	$-5\ t_{OD,car} - 0.3\ d_{OD,car} - 2$	$-12\ t_{OD,bike} - 1$	$-10\ t_{OD,walk}$

To test the potential of the model, we performed two sets of simulations, focusing on operator-oriented strategies and customer-oriented strategies.

Five scenarios have been simulated, i.e.:

(1) Base case scenario (BASE), considering the current number of CDPs in the study area and delivery performed by electric vans;
 – *operator-driven scenarios:*
(2) Home delivery (HD), considering only door-to-door deliveries without consolidations at CDPs;

Table 3
Activity profiles of customers and related input parameters.

Activity profile	Home-to-work (Employee)	Home-to-university (Student)	Shopping (Leisure)	No displacement
Start travel time	6:00 ÷ 8:30	7:00 ÷ 10:30	9:00 ÷ 17:00	–
Travel duration [h]	6 ÷ 10	3 ÷ 9	1 ÷ 3	–
O-D distance [km]	based on Eq. (2)	$d_{OD} > 0.2$	$0.2 < d_{OD} < 2$	–

Table 5
Input parameters related to parcels.

Parcel size	Small (S)	Medium (M)	Large (L)	Extra-Large (XL)
Percentage	40 %	45 %	10 %	5 %
Size [m^3]	0.005 m^3 (0.4 × 0.25 × 0.05)	0.04 m^3 (0.5 × 0.4 × 0.2)	0.12 m^3 (0.8 × 0.5 × 0.3)	0.36 m^3 (1 × 0.6 × 0.6)
no. of reserved lockers in a CDP	20	26	4	0

(3) Cargo bike delivery (CB), by substituting vans with cargo bikes, starting their deliveries from a micro-hub close to the study area both to CDPs and to customer homes;

– *customer-driven scenarios:*

(4) Customer willingness-to-deviate (WTD), by considering a different (minor) willingness-to-deviate threshold to pick up the parcel at the CDP.

(5) Customer demand (2D), by varying (doubling) e-commerce purchases and related parcel deliveries.

The BASE scenario is used to set the *status quo* against which the other scenarios are compared.

The CB scenario is simulated to evaluate the impact of an alternative delivery solution via cargo bike and a new micro-hub. The two customer-driven scenarios are simulated to consider a lower propensity towards the use of CDPs and a doubling in the e-commerce demand that could occur in specific situations (e.g. a stay-at-home order or sales period).

All input parameters and key performance indicators are reported in Table 6 and Table 7.

Each scenario is simulated 5 times by varying the seed, since a first test showed that results do not significantly change, in terms of standard deviations, after five repetitions. Extending the work of Calabrò et al. (2022), which simulated customers' activities during an entire working day and delivery operations during 8 working hours (from 9 A.M. to 6P. M., including a 1-hour lunch break), we simulated a working week (from Monday to Saturday). The percentage of failed deliveries (K_F) is set to zero the first day, and then it is updated with the results obtained from the previous day.

An indicator that encompasses both the customer and operator point of view is the so-called Total Transport Intensity (TTI). It considers the total distance per parcel driven using motorized vehicles, both by delivery vehicles and car customers who make a detour to/from the CDP. It is therefore equal to the sum of the Customer Transport Intensity (CTI) and the Operator Transport Intensity (OTI):

$$TTI(km/parcel) = CTI + OTI \quad (5)$$

where

$$CTI(km/parcel) = dist_{detour,car}/N_C \quad (6)$$

$$OTI(km/parcel) = TDD/N_C \quad (7)$$

With $dist_{detour,car}$ (km) we indicate the additional distance travelled by the customers with the mode of transport M = car to pick-up or drop-off their parcels at the CDP, while N_C is the number of customers, which is equal to the number of parcels.

The operation cost (OC) is evaluated by considering a distance-related cost €$_{km}$ which we set to 0.15 €/km for electric vans and 0.02 €/km for electric cargo bikes,[3] and a hourly driver cost €$_h$ which we set to 15 €/h.

$$OC(€) = €_{km} \cdot TDD + €_h \cdot ATT \cdot N_V \quad (8)$$

The main results are summarized in Figs. 5-7. All results are reported in Appendix A.

Fig. 5 reports the percentage of users choosing CDPs and the related failed deliveries. As visible, if many users choose CDPs, as in the BASE scenario, the percentage of failed deliveries drops (12.11%). The same occurs in the CB scenario, which is very similar to the BASE one, since deliveries performed by cargo bikes (instead of vans) do not affect customer choice about CDPs.

Vice versa, as expected, the HD scenario (with CDP density = 0) is the one with the highest rate of failed deliveries (22.12%). The WTD scenario, with a reduced customer willingness to deviate to reach the CDP (from 6 to 3 min), implies that fewer people choose CDPs. However, the trend is not linear, since halving the willingness to deviate implies a 10.64% variation (from 46.92% to 36.29%) of the percentage of users choosing CDPs, and an increase of only 2.05% (from 12.04% to 14.16%) of failed deliveries with respect to the BASE scenario.

The 2D scenario, where customer demand is doubled, shows similar results with respect to the previous scenario. In this case, a higher demand implies some CDPs to reach capacity and, thus, their unavailability for customers that would have been willing to use them.

Fig. 6 describes some operator-related outputs for the different scenarios in terms of total driven distances, total energy consumption, and unit operation cost. The scenario implying higher travelled distances is clearly the CB one (344 km with respect to 148 km of the BASE scenario), since cargo bikes globally travel more than vans, given the lower capacity and the need of more return trips to the micro-hub. The unit operation costs are also higher than in the BASE scenario due to the driver costs (0.58 €/parcel instead of 0.48 €/parcel), since the number of cargo bikes and related drivers are higher than the number of vans, always due to their lower capacity. However, the total energy consumption is clearly lower (10.33 kWh) than all the other scenarios where the vans are used, and the unit operation cost is lower than the HD scenario (64.52 kWh), which is the less cost efficient, and comparable to the other scenarios. The WTD scenario implies higher costs than the BASE scenario, even if the distances are comparable. This is because of the reduced consolidation opportunities (less customers choose the CDP delivery), implying higher stopping time by delivery vehicles and, thus, increased average travel time (and costs) (see Appendix A).

Table 6
Input parameters for scenario simulation.

	base	HD	CB	WTD	2D
Customer parameters					
Total Demand [customers/day]4	1885	1885	1885	1885	**3770**
Number of CDPs	46	**0**	46	46	46
Percentage of Returned Parcels [%]	10	10	10	10	10
Walking Speed [km/h]	5	5	5	5	5
Max Detour Time [min]	6	6	6	**3**	6
Operator parameters					
Vehicle Capacity [pax]	10	10	**2**	10	10
Vehicle Cruising speed [Km/h]	30	30	**15**	30	30
Simulation parameters					
Total Simulation Time [days]	6	6	6	6	6
Seed	1–5	1–5	1–5	1–5	1–5

[3] Considering an electricity price of 0.3 €/kWh, an energy consumption of 0.4 kWh/km for electric vans (https://www.mercedes-benz.it/vans/it/sprinter/e-sprinter-panel-van/technical-data) and to 0.03 kWh/km for electric cargo bikes (Llorca and Moeckel, 2021), and a maintenance cost of 0.03 €/km for electric vans and 0.01 €/km for electric cargo bikes.

Table 7
Key performance indicators.

Output	Abbreviation	Description
Service-related		
% of used CDP	%CDP	Usage of CDPs w.r.t. their overall capacity
Total Transp. Intensity [km/parcel]	TTI	Sum of the average distance travelled both by car customers (detour distance to reach the CDP) and delivery vehicles per transported parcels (Eq. (5))
Customer-related		
% Customers choosing CDP (w.r.t. TOT)	%C_CDP	% of customers that choose CDP
% Customers choosing CDP (car)	%C_CDPcar	% of customers that choose CDP and travel by car
% Customers choosing CDP (bike)	%C_CDPbike	% of customers that choose CDP and travel by bike
% Customers choosing CDP (walk)	%C_CDPwalk	% of customers that choose CDP and travel on foot
Avg Customer Detour (TOT) [min]	ACD	Average detour time to pick a parcel in a CDP
Avg Customer Detour (car) [min]	ACD_car	Average detour time to pick a parcel in a CDP by car
Avg Customer Detour (bike) [min]	ACD_bike	Average detour time to pick a parcel in a CDP by bike
Avg Customer Detour (walk) [min]	ACD_walk	Average detour time to pick a parcel in a CDP on foot
Customer Transport Intensity [km/parcel]	CTI	Average distance travelled by the car customers to pick up a parcel from a CDP (Eq. (6))
Operator-related		
% failed deliveries	%failed	% of failed deliveries per day
Total Driven Distance [km]	TDD	Total distance travelled by the delivery vehicles during the simulation time
Total Energy Consumption [kWh]	TEC	Total energy used by the delivery vehicles during the simulation time
Avg Vehicle Travel Time (TV) [h]	ATT	Average total travel time of the delivery vehicles, including the parcel delivery time
Operator Transport Intensity [km/parcel]	OTI	Average distance travelled by the delivery vehicles per transported parcels (Eq. (7))
Operation Costs [€]	OC	Sum of distance-related and driver-related costs (Eq. (8))
Unit Operation Cost [€/parcel]	UOC	OC computed per parcel

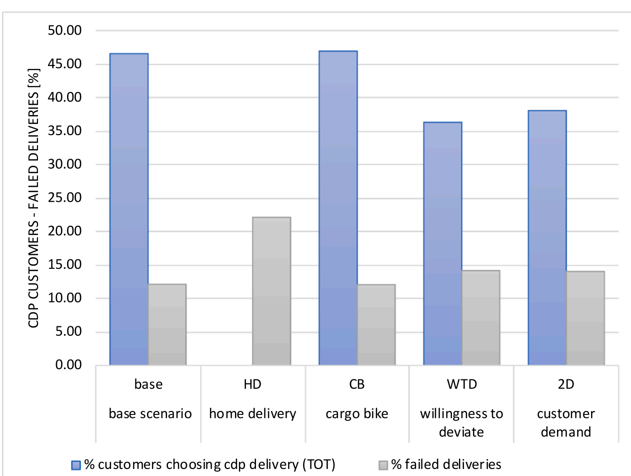

Fig. 5. Percentages of CDP users and failed deliveries.

The 2D scenario implies higher travelled distances (and energy consumption) than the BASE one, given the lower percentage of consolidated deliveries by users, as already presented in Fig. 5. An interesting result is related to the unit cost of the 2D scenario, which is very similar to the BASE one (0,49 €/parcel instead of 0,48 €/parcel). This means that travelled distances increase with a slower pace than the number of parcels, which can be ascribed to the compact study area with concentrated demand.

Fig. 7 shows some outputs that can be related to the overall logistics efficiency, i.e. Operator Transport Intensity, Total Transport Intensity and the percentage of use of CDPs (black dots).

It is interesting to monitor the gap between TTI and OTI, since it gives an idea of the impact of customer involvement in the delivery process (i.e. CTI). In this respect, if one excludes the HD scenario where the CDP is not available, it turns that the lowest gap is in scenario WTD, since few people choose the CDP option. However, this also leads to the lowest use of the available CDPs (33.6%). Vice versa, the highest gaps and, therefore, the highest impacts of customer involvement, is visible in the BASE scenario (and CB as well), and in the 2D scenario. While for the former this is ascribable to the highest number of customers choosing CDPs, for the latter this is due to the possibility of consolidating more deliveries, given the higher demand density. This implies a better use of the available capacity of CDPs, which reaches the 70.43%. This result points to the need to focus on CDP location and density in relation to the customer demand density. In other words, when the demand is high, the risk of fragmented door-to-door deliveries increases and the use of CDPs can be an effective solution to reduce the impact of delivery vehicles, even if it implies a higher impact of customer involvement. In terms of practical implications, this justifies the investment on proximity-based logistics facilities, like parcel lockers.

To summarize, the home delivery strategy is the costliest and least efficient if one looks at the failed deliveries it generates. The strategy of using cargo bikes in combination with a micro-hub is costly for the operator but more sustainable from an energy consumption point of view. Besides, one should consider the cost of building (and operating) a

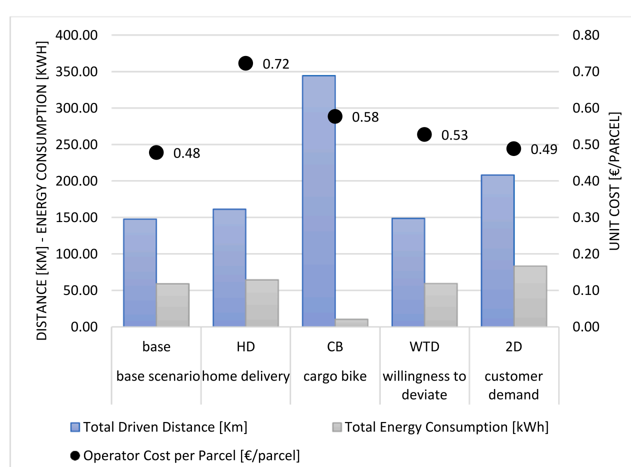

Fig. 6. Total Driven distance, Total energy consumption and Operator Cost per Parcel.

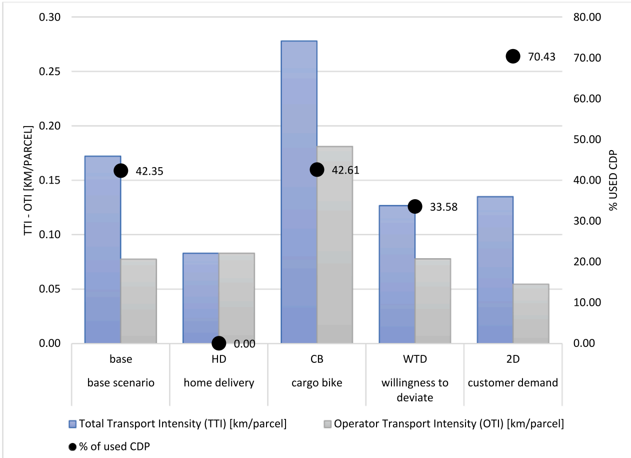

Fig. 7. Percentage of use of CDPs, failed deliveries, Operator Transport Intensity, Total Transport Intensity.

new micro-hub and the costs related to the additional transfer from the depot to the micro-hub. However, this is a feasible and promising solution that is particularly interesting for small parcels to cover the last mile in a sustainable way, perhaps with a public intervention.

For the specific case study analysed, it seems that CDP deliveries are particularly efficient when the demand is high, implying an efficient use of the current CDPs capacity. This is confirmed by the overall impact of parcel delivery considering both travelled distances driven by delivery vehicles and customer cars. Besides, from an operator point of view, increasing the demand does not change the unit cost per parcel. However, this result could be affected by the actual density and location of CDPs considered in the specific case study, which could be optimized to adequately satisfy the current demand.

Discussion and Conclusion

This paper presented a new spatial agent-based modelling (ABM) approach to explore different scenarios of last-mile logistics referred to e-commerce deliveries, comparing door-to-door deliveries with consolidation-based strategies, by taking into account demand and transport network data based on a real-world case study.

The case study is Catania, a medium sized city in Southern Italy and, in particular, its central urban area with a high concentration of CDPs, points of interests and residents. A spatial analysis is performed to characterize the study area in terms of transport network, CDP location, and customer demand. All the output data obtained from the spatial analysis are used as input for the simulation model. Five scenarios are simulated to explore possible delivery strategies and by varying parameters related both to the demand and the supply. Key performance indicators resulting from the model consider both customer and logistics operator perspectives and suggest that a trade-off between freight vehicle travelled distance, customer distance to reach the CDP and logistics costs can be found while proposing a solution to last mile parcel deliveries based on consolidation via CDPs.

Main results show that if the CDP option is not available and all the deliveries are door-to-door deliveries, this implies the highest cost and percentage of failed deliveries with respect to scenarios where the CDP option is available to customers. Cargo bikes (instead of vans) are a sustainable option even if they imply higher costs. This suggests the need to provide incentives to perform deliveries using these types of vehicles. If one looks at the use of CDP available space and the overall impact of the delivery by considering customer and delivery vehicle movements, then the best scenario is the one where the demand is doubled. This suggests that specific policies and investments in CDPs are useful especially in cases of high demand, where the risk of fragmented door-to-door deliveries (and related failed deliveries) increases.

Table A1
Results in terms of key performance indicators for the different scenarios.

Output Results					
SCENARIO	**BASE**	**HD**	**CB**	**WTD**	**2D**
Service-related					
% CDP	42.35	0.00	42.61	33.58	70.43
TTI [km/parcel]	0.17	0.08	0.28	0.13	0.13
Customer-related					
%C_CDP	46.56	0.00	46.92	36.29	38.06
%C_CDPcar	31.82	0.00	32.50	26.17	26.14
%C_CDPbike	10.76	0.00	10.87	7.51	8.93
%C_CDPwalk	3.97	0.00	3.56	2.61	3.00
ACD [min]	0.88	0.00	0.89	0.47	0.88
ACD_car [min]	0.81	0.00	0.82	0.50	0.83
ACD_bike [min]	1.08	0.00	1.09	0.47	1.06
ACD_walk [min]	0.88	0.00	0.92	0.21	0.80
CTI [km/parcel]	0.09	0.00	0.10	0.05	0.08
Operator-related					
%failed	12.11	22.12	12.04	14.16	14.03
TDD [km]	147.81	161.30	344.40	148.71	208.13
TEC [kWh]	59.13	64.52	10.33	59.48	83.25
ATT [h]	5.66	7.44	5.94	6.34	6.09
OTI [km/parcel]	0.08	0.08	0.18	0.08	0.05
OC [€]	908.46	1409.22	1097.86	1007.58	1865.14
UOC [€/parcel]	0.48	0.72	0.58	0.53	0.49

In general, for the specific case study analysed, the density of collection and delivery points (CDPs) in the study area seems to be adequate, also in scenarios of increased demand; this suggests that an incentivization for customers in the use of CDPs might be more effective than increasing their number in order to improve the operation of last-mile deliveries.

The flexibility of the modelling environment allows the exploration of different scenarios that can be useful to both decision-makers and private companies to understand how to optimize parcel deliveries in urban areas. As next steps of the research, different sets of simulations might be performed as well as sensitivity analyses, also in the logic of a comparison with the results obtained in the ideal case study (Calabrò et al, 2022) and other case studies with real data, in order to provide useful information for policy-making.

Another interesting advance would be the simulation of consolidation-based and customer-driven scenarios based on crowd-shipping and the use of other sustainable transport modes like public transport (Giuffrida et al., 2021). Finally, vehicle traffic data associated with the real case study could be included in the simulation, allowing for a better evaluation of the efficiency of the freight consolidation solutions.

In conclusion, the study shows that the spatial distribution of both parcel demand and delivery points is fundamental to appropriately plan consolidation strategies aimed at increasing logistics efficiency while reducing its negative impact on city sustainability and liveability. The proposed model can provide useful information to decision-makers to understand how to manage growing on-demand urban deliveries and to plan by using a delivery-oriented development approach.

CRediT authorship contribution statement

Giovanni Calabrò: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Michela Le Pira:** Conceptualization, Supervision, Methodology, Writing – original draft, Writing – review & editing. **Nadia Giuffrida:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision. **Martina Fazio:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Giuseppe Inturri:** Conceptualization, Methodology, Writing – original draft, Supervision, Funding acquisition. **Matteo Ignaccolo:** Conceptualization, Supervision, Funding acquisition, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A

The average values of the main outputs and key performance indicators of the five simulated scenarios are summarized in Table A1.

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