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Locating Automated Parcel Lockers (APL) with known customers' demand: a mixed approach proposal

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Logistics Service Providers (LSP) are increasingly adopting Automated Parcel Lockers (APLs) to mitigate the operational pressure of last-mile logistics. The optimal location of APL stations is key for reaching customers' demand while keeping the investment reasonable. Previous studies developed optimization algorithms and applied them to virtual instances of the problem, lacking applicability to real-life situations encountered by LSPs who aim to serve an urban area with such technology. This study proposes a novel solution to the APLs location problem by combining mixed-integer linear programming and greedy heuristics algorithms. The study tested the propose solution on real customers' demand data related to Turin, Italy. Results show that covering 90% of the estimated potential demand requires 10 to 11 APLs, on average. The adopted approach enables finding an optimal solution grounded in a real geographical context without requiring time-consuming optimization.

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1 Introduction

E-commerce has steadily increased in recent years, with annual growth rates of more than 20% until 2020 (Cramer-Flood, 2023). Even though the growth has been dwindling after the pandemic surge of 2020, e-commerce is still outperforming overall sales growth.

E-commerce home deliveries are characterized by a high frequency of orders, dispersed demand, and the possibility of customers missing the delivery (Seghezzi et al., 2022). Home deliveries are also time-consuming since drivers need to decelerate, look for parking, unload the parcel, and wait for the consignee. Additionally, last-mile logistics generates a significant number of vehicle-kilometres for each delivery route, reducing the profitability of private operators and increasing the emissions of pollutants (e.g., CO2, NOx, PM10) (Arroyo et al., 2020). Therefore, Logistics Service Providers (LSPs) must increase the productivity of their vehicle fleet, measured in the number of stops serviced by each vehicle during a daily tour, to fulfill the increasing request for last-mile deliveries while reducing their negative impacts (Cagliano et al., 2017).

Consolidating users' demand in APLs is a possible solution to the operational strains of last-mile deliveries. APLs are a type of unattended collection-and-delivery point installed in public and private areas where parcels are retained for a limited amount of time until the customer can retrieve them by using a unique code (e.g., QR code, order reference number, a PIN code) (Lai et al., 2022) or a form of identification (e.g., credit card, government issued ID) (Schnieder et al., 2021). Consolidating the demand in APLs reduces the number of delivery points, increasing vehicle productivity and reducing mean delivery time (Bailey et al., 2013).

However, APLs require investments by private operators and compel space organizers such as public authorities to grant the usage of portions of public space wherein APLs are installed (Zenezini et al., 2018). Moreover, the diffusion of APLs depends on the perception of potential customers and their inclination toward adopting technological innovations that change customer habits. While APLs implementation can instigate co-value generation processes with customers, on the other hand, it can destroy value when failures occur. This results in a vicious cycle that leads to the customer abandoning the service (Vakulenko et al., 2018).

Compatibility with the customers' lifestyle and convenience are two key factors for accepting the APL solution (Tsai & Tiwasing, 2021). Besides APLs' ease of use, which might crowd out less tech-savvy customers, one major variable driving the adoption of parcel lockers is location. Traditionally, parcel lockers are installed in controlled places that are easily accessible and close to areas with a high frequency of shipments (service stations, shopping malls, squares) (Janjevic et al., 2013). Using these sites lowers the entry barriers because they solve customer and package safety issues, often encountered in customer surveys (Lachapelle et al., 2018) and helps maximizing the APLs coverage area. Moreover, these sites can be reached by car on the route to or from customers' homes, thus avoiding a dedicated pickup trip and increasing the convenience of the APL usage process.

Wider adoption of APLs in cities worldwide is expected due to the operational benefits of such a delivery option and factoring in the estimated continuous increase in online purchases. Hence, preferred locations nowadays might not be sufficient to cover all the future demand. Furthermore, understanding the implications of the APL network design on the potential customers' demand is paramount for avoiding cost overrun while keeping the service level intact (Lin et al., 2022).

Discerning how the demand for APL will drive their diffusion on the urban territory requires an accurate ex-ante appraisal of the variables involved. To this end, this study aims to contribute to the literature by proposing a robust solution to the APL facility location problem. The solution involves simulating multiple instances of a mixed-integer linear CFLP with stochastic demand. The problem parameters are based on a survey submitted to e-consumers. Furthermore, the study strives towards practical applicability by proposing two greedy optimization algorithms that identify a road map for opening APL locations. Finally, we show a real-life application of both methods to the city of Turin.

The paper is structured as follows. Section 2 reviews the existing literature on the APL location problem. Then, Section 3 explores the research approach and data collection methods. Numerical results are described in Section 4. Lastly, Section 5 provides practical and theoretical implications and draws upon conclusions.

2 Literature review

The APL location problem represents a niche, albeit thriving, stream of research within last-mile logistics. Lachapelle et al. (2018) assessed APL locations in light of customers' preferences, such as safety, proximity to highways, and accessibility. Thus, the authors draw implications for future locations based on existing ones rather than through an optimization algorithm. Lee et al. (2019) adopted a two-step approach to the APL location problem. Firstly, they identified the potential locations following the preferred attributes by Lachapelle et al. (2018). Then, they used a set-covering model to estimate which potential locations should host an APL. However, the decision criteria for selecting the potential locations are unclear, and the numerical case study comprises a relatively small neighborhood. Deutsch & Golany (2018) proposed a more optimized approach via an un-capacitated facility location problem (UFLP). In their model, demand is lost when customers are not reached by any APL, and their willingness to move decreases with the distance to the parcel locker. A similar approach for the capacitated facility location problem (CFLP) is used by Che et al. (2022).

These works show that the APL location problem can be tackled with a long-term planning horizon. Recent studies looked at the impact of APL locations on a short-term planning horizon, integrating APLs into the Vehicle-Routing Problem (VRP). For example, Orenstein et al. (2019) optimized the assignment of parcels to both the vehicles and APL modules but assumed equal attractiveness of different APL locations for the customers, thus not considering any customers' preference in the optimization algorithm. Instead, Enthoven et al. (2020) aimed to minimize both customers' and LSP's costs, including penalties if customers are not reached via their preferred delivery method. In Jiang et al. (2022), both LSPs and customers incur operating costs for visiting the APL location. The authors aimed to maximize the LSPs' profits via a Traveling Salesman Problem (TSP) formulation.

The main objective of the APL location problem is to find the APLs locations that minimize the number of APLs to install, and the operational costs connected with traveling to those locations. Previous models considered the distance between the APL and the customer points as a static parameter. However, final customers do not all share the same appreciation and commitment for this last-mile solution. Thus, a location model should consider variability in the customers' willingness to move from their residence to pick up the parcel and their demand.

Because of the customers' preferences and the multiple delivery options they can now choose from, failing to cover a customer from an APL location can result in lost demand. Customers' choices have been recently included in the APL location problem. The attractiveness of a location can be modeled as a decaying function of the distance between the location and the customer (Lin et al., 2022; Luo et al., 2022). Moreover, solutions to the APL facility location problem should be robust to deal with the variability of the demand.

Wang et al. (2020) adopted an integer-linear programming (ILP) model to solve the location problem of movable APLs with stochastic customers' demand. In this study, all customers within an acceptable distance are assigned to a particular APL location. Robust results can be achieved by simulating multiple runs of an optimized facility location problem, as shown by Rabe et al. (2021), who adopted a Monte-Carlo simulation approach for a CFLP.

Table 1. Review of the APL facility location literature

Work	Candidate Location Set	Customers’ Willingness to Use Parcel Lockers	Capacitated	Objective Function	Demand Covered	Customers’ Demand Distribution	Solution Method	Numerical Experiment
Lee et al. (2019)	Selected according to customers’ attributes	All customers within cover radius use the APL	Uncapacitated	Maximize covered demand	Output	Deterministic	Not defined	Real instance
Deutsch and Golany (2018)	One per each city subdivision	Decreases with the distance to the APL	Uncapacitated	Minimize cost	Variable	Deterministic	Mixed integer linear programming	Real instance
Che et al. (2022)	Same as customers’ locations	All customers within cover radius use the APL	Capacitated	Maximize covered demand, APL capacity usage	Output	Not defined	Genetic algorithm	Virtual instance
Lin et al. (2022)	Simulated through uniform distribution	All customers within cover radius use the APL	Uncapacitated	Maximize covered demand, profit	Output	Stochastic	Combinatorial optimization	Virtual instance
Luo et al. (2022)	Same as potential customers’ locations	Decreases with the distance to the APL	Flexible Size	Minimize cost, maximize covered demand	Output	Stochastic	Evolutionary algorithm	Virtual and real instances
Wang et al. (2020)	Same as potential customers’ locations	All customers within cover radius use the APL	Capacitated	Minimize cost	Constraint	Stochastic	Integer linear programming	Virtual instance
Rabe et al. (2021)	One per each city subdivision	According to APL service level and accessibility	Capacitated	Minimize cost	Variable	Stochastic	Not defined	Real instance
This study	One per each city subdivision	All customers within cover radius use the APL	Flexible Size	Minimize cost	Constraint	Stochastic	Greedy algorithm	Real instance

Theoretical applications of the APL facility location problem should be easy to implement in a real-life scenario by LSPs and practitioners alike. However, most APL network design solutions are applied to virtual instances rather than real urban settings, except for Deutsch & Golany (2018), Luo et al. (2022), and Rabe et al. (2021).

This study proposes novel algorithms to solve the capacitated APL facility location problem. The algorithms aim to minimize the APL network cost while satisfying a predetermined demand share. The study applies the proposed method to a real instance assuming stochastic customers' demand.

3 Research methodology

This study presents two methods for determining the optimal number, location, and capacity of APLs to install. The first method involves optimizing a mixed-integer linear programming (MILP) model (Model 1), simultaneously determining the aforementioned variables. In contrast, the second method employs greedy algorithms (Algorithms 1 and 2) that iteratively select the next APL and determine its capacity.

Both methods entail running multiple simulations to ensure robust results. In each simulation, Procedure 1 randomizes the users' variables.

Procedure 1. Randomize Users

```
def RandomizeUsers():
  for u ← 1 to nUsers do
    area_u ← f^{-1}[U(0,1)]
    x_u ~ U(x^{min}_{area_u}, x^{max}_{area_u})
    y_u ~ U(y^{min}_{area_u}, y^{max}_{area_u})
    dem_u ← g^{-1}[U(0,1)]
    tol_u ← h^{-1}[U(0,1)]
    sat_u ← 0
    if APLs locations are not fixed then
      return x, y, sat, tol, dem
    else if APLs locations are fixed then
      for a ← 1 to nAPLs do
        D_ua ← [(x_u − x_a)^2 + (y_u − y_a)^2]^{1/2}
      return x, y, sat, tol, dem
```

For all users (for $u \leftarrow 1$ to nUsers), the procedure randomizes their location (x_u, y_u), the maximum distance they are willing to travel to reach the APL (tol_u), their daily demand (dem_u), and sets the users as not served by any facility ($sat_u \leftarrow 0$).

A user location is represented in Cartesian coordinates (x_u, y_u), with the meter being the unit of measurement, and is randomized in two steps. The procedure first randomizes the area to which the user belongs ($area_u$) by following the empirical distribution (f), which can be determined based on the city under analysis. Then, the procedure randomizes the user coordinates through a uniform distribution within the area limits (i.e., $x^{\min}_{area_u}$, $x^{\max}_{area_u}$, $y^{\min}_{area_u}$, and $y^{\max}_{area_u}$).

Concerning the APLs, if their locations are not predetermined, the procedure evaluates the Euclidean distance (D_{ua}) between the uth user and all the APLs (for $a \leftarrow 1$ to nAPLs).

3.1 MILP model

This subsection introduces the equations that make up the complete MILP model. Then, it provides a simplified version of the MILP model to allow faster simulations without compromising the reliability of the results.

Complete model

The complete MILP model consists of Equations 1-20.

minimize	$\mathrm{c}^{\mathrm{APL}} \sum_{a\in A} act_a + \mathrm{c}^{\mathrm{Module}} \sum_{a\in A} mod_a$		(1)
subject to	$\sum_{u\in U} sat_u \cdot dem_u \,/ \sum_{u\in U} dem_u \geq \mathrm{SL}$		(2)
	$D^*_{ua} = D_{ua} \cdot act_a + \mathrm{M}(1 - act_a)$	$\forall u \in U, \forall a \in A$	(3)
	$D_{ua} = [(x_u - x_a)^2 + (y_u - y_a)^2]^{1/2}$	$\forall u \in U, \forall a \in A$	(4)
	$mD_u \leq D^*_{ua}$	$\forall u \in U, \forall a \in A$	(5)
	$mD_u \geq D^*_{ua} - \mathrm{M}(1 - ass_{ua})$	$\forall u \in U, \forall a \in A$	(6)
	$\sum_{a\in A} ass_{ua} = 1$	$\forall u \in U$	(7)
	$tol_u - mD_u + \epsilon - \mathrm{M} \cdot sat_u \leq 0$	$\forall u \in U$	(8)
	$mD_u - tol_u - \mathrm{M}(1 - sat_u) \leq 0$	$\forall u \in U$	(9)
	$\sum_{u\in U} ass_{ua} \cdot dem_u \leq \mathrm{cap}^{\mathrm{APL}} + \mathrm{cap}^{\mathrm{Module}} \cdot mod_a$	$\forall a \in A$	(10)
	$mod_a \leq \mathrm{mod}^{\max} \cdot act_a$	$\forall a \in A$	(11)
	$\sum_{a\in A} act_{ua} \leq \max_{a\in A} a$		(12)
	$act_a \in \{0,1\}$	$\forall a \in A$	(13)
	$sat_u \in \{0,1\}$	$\forall u \in U$	(14)
	$ass_{ua} \in \{0,1\}$	$\forall u \in U, \forall a \in A$	(15)
	$mod_a \in \mathbb{N}$	$\forall a \in A$	(16)
	$D_{ua} \in \mathbb{R}^+$	$\forall u \in U, \forall a \in A$	(17)
	$D^*_{ua} \in \mathbb{R}^+$	$\forall u \in U, \forall a \in A$	(18)
	$mD_u \in \mathbb{R}^+$	$\forall u \in U$	(19)
	$x_a, y_a \in \mathbb{R}^+$	$\forall a \in A$	(20)

As in Procedure 1, the subscript a denotes the ath APL facility, while the subscript u refers to the uth user. In each simulation, users' variables are treated as parameters.

Equation 1 is the objective function to minimize and consists of the sum of the total cost of the APLs ($\mathrm{c}^{\mathrm{APL}} \sum_{a\in A} act_a$) and the total cost of the additional modules ($\mathrm{c}^{\mathrm{Module}} \sum_{a\in A} mod_a$). The variable act_a is Boolean (as per Equation 13) and indicates whether the ath APL is installed ($act_a = 1$) or not ($act_a = 0$). Instead, the variable mod_a is natural (as per Equation 16) and refers to the number of modules to install in the ath APL. Equation 11 limits the maximum number of modules per APL to $\mathrm{mod}^{\max}$ due to volumetric constraints and prevents any module from being installed if an APL is not active ($act_a = 0$). To ensure that the optimization routine prefers expanding existing APLs by installing additional modules over activating new APLs, the cost of installing an APL ($\mathrm{c}^{\mathrm{APL}}$) must be greater than the cost of an installing an additional module ($\mathrm{c}^{\mathrm{Module}}$).

Equation 2 expresses the service level constraint, which ensures that the percentage of expected satisfied demand ($\sum_{u\in U} sat_u \cdot dem_u \,/ \sum_{u\in U} dem_u$) meets or exceeds the target service level (SL). The variable sat_u is also Boolean (as per Equation 14) and determines whether the uth user' is considered covered ($sat_u = 1$) when its demand (dem_u) is assigned to any APL.

Equations 3-7 pertain to the distances (D_{ua}, Equation 17) and minimum distances (mD_u, Equation 18) between the users and the APLs. Equation 4 computes the Euclidean distance (D_{ua}) between the users and the APLs. Equation 3 prevents an APL from being assigned to any user if the APL is not active ($act_a = 0$), as the distance between them would be set to M. Equations 5-6 determine the distance between the uth user and its nearest active APL (mD_u), while Equation 7 assigns the user's demand (dem_u) to that APL ($ass_{ua} = 1$). Equations 10 and 12 relate to calculating the expected demand to be satisfied by each APL. Specifically, Equation 10 ensures that no APL is assigned more demand than its capacity, which is the sum of its standard capacity ($\mathrm{c}^{\mathrm{APL}}$) and the capacity of each additional module ($\mathrm{cap}^{\mathrm{Module}} \cdot mod_a$). Equation 11 fixes the maximum number of modules to be installed to 10, which is reasonable given the amount of space each module requires for its location, while Equation 12 prevents the module from being installed (mod_a) to an APL facility whenever such APL is not activated ($act_a = 0$). Equations 8-9 ensure that whenever the distance between a user and its nearest APL (mD_u) is less than or equal to the user's tolerated travel distance (tol_u), the user is assigned to that APL (Equation 7), and its demand is considered satisfied ($sat_u = 1$). While multiple APLs may serve one user's demand, this assumption simplifies the problem and reduces computation time. This formulation assigns a user's demand to its nearest APL.

Simplified model

The simplified MILP model (Equations 21-35) shows key differences from the complete model, summarized as follows.

$$\text{minimize} \quad \left(\mathrm{mod}^{\max} \cdot \mathrm{c}^{\mathrm{Module}} + \mathrm{c}^{\mathrm{Module}}\right) \sum_{a\in A} act_a + \mathrm{c}^{\mathrm{Module}} \sum_{a\in A} mod_a \tag{21}$$

$$\text{subject to} \quad \sum_{u\in U} sat_u / \mathrm{nUsers} \geq \mathrm{SL} \tag{22}$$

$$D^*_{ua} = \mathrm{D}_{ua} \cdot act_a + \mathrm{M}(1 - act_a) \qquad \forall u \in U, \forall a \in A \tag{23}$$

$$mD_u \leq \mathrm{D}^*_{ua} \qquad \forall u \in U, \forall a \in A \tag{24}$$

$$mD_u \geq \mathrm{D}^*_{ua} - \mathrm{M}(1 - ass_{ua}) \qquad \forall u \in U, \forall a \in A \tag{25}$$

$$\sum_{a\in A} ass_{ua} = 1 \qquad \forall u \in U \tag{26}$$

$$tol_u - mD_u + \epsilon - \mathrm{M} \cdot sat_u \leq 0 \qquad \forall u \in U \tag{27}$$

$$mD_u - tol_u - \mathrm{M}(1 - sat_u) \leq 0 \qquad \forall u \in U \tag{28}$$

$$\sum_{u\in U} ass_{ua} \cdot \mathrm{SF} \cdot \overline{\mathrm{dem}} \leq \mathrm{cap}^{\mathrm{APL}} + \mathrm{cap}^{\mathrm{Module}} \cdot mod_a \qquad \forall a \in A \tag{29}$$

$$mod_a \leq \mathrm{mod}^{\max} \cdot act_a \qquad \forall a \in A \tag{30}$$

$$act_a \in \{0,1\} \qquad \forall a \in A \tag{31}$$

$$sat_u \in \{0,1\} \qquad \forall u \in U \tag{32}$$

$$ass_{ua} \in \{0,1\} \qquad \forall u \in U, \forall a \in A \tag{33}$$

$$mod_a \in \mathbb{N} \qquad \forall a \in A \tag{34}$$

$$mD_u \in \mathbb{R}^+ \qquad \forall u \in U \tag{35}$$

Firstly, the maximum number of APLs ($\max_{a\in A} a$) is limited to the number of postcodes used by postal and logistics providers (nAPLs). To achieve this, each postcode area is mapped onto a coordinate system, and the APL locations are fixed to the centers of gravity of the respective postcode area. The relevant postcode data can be found in Table 3.

Secondly, the users are aggregated into fewer demand collection points, and, to account for the same demand, a scaling factor (SF) is introduced.

Thirdly, the cost of each APL is set to $\mathrm{mod}^{\max} \cdot \mathrm{c}^{\mathrm{Module}} + \mathrm{c}^{\mathrm{Module}}$. These values guide the optimization routine to prefer saturating APLs, when possible, instead of activating new ones.

Finally, the model uses the mean values of demand ($\overline{\mathrm{dem}}$) and tolerated travel distance ($\overline{\mathrm{tol}}$) for each demand point.

For the first assumption, assuming an average demand approach is a justifiable measure for two key reasons. Firstly, the literature on the impact of socio-demographic factors on e-commerce consumer behavior has presented conflicting findings (Agudo-Peregrina et al., 2016). Secondly, the COVID-19 pandemic and the ongoing trend towards digitalization have led to a narrowing in the behavior of e-commerce consumers, irrespective of their socio-demographic characteristics.

The second assumption stems from the survey analyses presented in previous papers (Mitrea et al., 2020; Ottaviani et al., 2020). The studies found that the average tolerated distance does not depend on socio-demographic factors. Tolerance is a highly variable factor, both from individual to individual and from the same individual. In other words, the tolerated travel distance is a function of the means the individual uses to collect their order and how long they are willing to divert their daily commute to collect their order. These factors could vary depending on the user, the current traffic, the value of the order content, the urgency to collect the order, and other factors unrelated to the socio-demographic characteristics.

For these reasons, using mean values is consistent with the assumption of homogeneity of the population within each area. This approach allows for a simpler, computationally feasible model while still capturing the essential aspects of the problem. However, using mean values may result in some loss of information and potential inaccuracies, especially if the actual demands or travel distances vary significantly within the area.

3.2 *Algorithms*

This study presents two greedy algorithms that determine the number of APLs, their location, and their capacity. Doing so allows for evaluating the expected satisfied customers' demand curve depending on the number of APLs. In contrast, the MILP formulation does not provide a sequence of APLs to be installed because it determines the optimal solution by solving a mathematical optimization problem that considers all possible scenarios.

These MILP and greedy algorithms approaches have different advantages and disadvantages. The MILP model provides an optimal solution but has high computational complexity. Instead, the greedy algorithms are computationally efficient but may not guarantee an optimal solution. However, both algorithms implement the following procedures, which are consistent with findings from Luo et al. (2022) and Wang et al. (2020).

Procedure 2 loads the previous APLs. It first takes as input variables the ordered sequence of APLs ($\boldsymbol{APL\_order}$), the next APL candidate (APL^*), the array of satisfied users ($\boldsymbol{sat}$), and the user/APL distances matrix ($\boldsymbol{D}$). Then, it evaluates the potential number of users (pot_users) and respective demand (pot_demand) that each APL in the ordered sequence can cover. Next, the procedure determines the number of modules (mod_a) that each APL can accommodate and assigns users accordingly, up to mod^{max}. Finally, it marks the users as covered by their assigned APL ($sat_u \leftarrow 1$).

Procedure 2. Load Previous APLs

```
def LoadPreviousAPLs(APL_order, sat, D, APL*):
    for a ∈ APL_order do
        if a ≠ APL* then
            pot_users ← 0
            pot_dem ← 0
            for u ← 1 to nUsers do
                if sat_u = 0 and D_ua ≤ tol‾ then
                    pot_users ← pot_users + 1
                    pot_dem ← pot_dem + tol‾
            mod_a ← 0
            cap_a ← cap^APL
            it_1 ← 0
            while it_1 ≤ mod^max and pot_users > 0 do
                if it_1 > 0 then
```

```
                    mod_a ← mod_a + 1
                    cap_a ← cap_a + cap^Module
                if min(cap_a, pot_dem) = cap_a then
                    sats^temp ← cap_a / dem‾
                else
                    sats^temp ← pot_users / dem‾
                for it_2 ← 0 to sats^temp do
                    for u ← 0 to nUsers do
                        if sat_u = 0 and D_ua ≤ tol‾ then
                            sat_u ← 1
                            pot_users ← pot_users − 1
                it_1 ← it_1 + 1
    return sat
```

Procedure 3 evaluates the next APL candidate (APL^*). To accomplish this, it takes the ordered sequence of APLs (***APL_order***), the array of satisfied users (***sat***), and the user/APL distances matrix (***D***) as input variables. The procedure then loops through the APLs that are not already in ***APL_order*** and selects the APL that could cover the highest potential number of users or demand.

Procedure 3. Evaluate Next APL

```
def EvaluateNextAPL(APL_order, sat, D):
    APL* ← 0
    max_dem ← 0
    for a ← 1 to nAPLs do
        if a ∉ APL_order then
            pot_dem ← 0
            for u ← 1 to nUsers do
                if sat_u = 0 and D_ua ≤ tol‾ then
                    pot_dem ← pot_dem + tol‾
            if pot_dem ≥ max_dem then
                max_dem ← pot_dem
                APL* ← a
    return APL*
```

Procedure 4 evaluates the potential demand of the set APL, increases its modules if they do not reach their maximum ($\mathrm{mod}^{\max}$), and sets all covered users as satisfied ($sat_u = 1$).

Procedure 4. Load Next APL

```
def LoadNextAPL(sat, D, APL*):
    pot_users ← 0
    pot_dem ← 0
    for u ← 1 to nUsers do
        if sat_u = 0 and D_ua ≤ tol‾ then
            pot_users ← pot_users + 1
            pot_dem ← pot_dem + tol‾
        mod_a ← 0
        it_1 ← 0
        while it_1 ≤ mod^max and pot_users > 0 do
            if it_1 > 0 then
                mod_a ← mod_a + 1
                cap_a ← cap_a + cap^Module
            if min(cap_a, pot_dem) = cap_a then
                sats^temp ← cap_a / dem‾
            else
                sats^temp ← pot_users / dem‾
            for it_2 ← 0 to sats^temp do
                for u ← 0 to nUsers do
                    if sat_u = 0 and D_ua ≤ tol‾ then
                        sat_u ← 1
```

$pot\_users \leftarrow pot\_users - 1$
$nSats \leftarrow nSats + 1$
$it_1 \leftarrow it_1 + 1$
return $\boldsymbol{sat}$, $nSats$

Algorithm 1

Algorithm 1 involves two main steps. In the first step (A1S1), the users are randomized S times, and the sequence of APLs is determined ($\boldsymbol{APL\_order}$). The percentage of covered demand is evaluated for each APL in the sequence. Once A1S1 is completed, the APLs are sorted based on the average percentage of covered demand across all S simulations, thus providing an ordered sequence of APLs for the second step (A1S2). The second step consists of another round of S simulations, which allows for the determination of the average covered demand by each APL ($\overline{pcts_a}$).

Algorithm 1. Sequence-provided algorithm

Data: **x**, **y**
Result: APLs location and capacity evaluation given fixed sequence
initialization
/* Step 1 (Facultative) */
init: $\boldsymbol{pcts}$
for $s \leftarrow 1$ **to** S **do**
  $APL^* \leftarrow 0$
  $\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{sat}, \boldsymbol{tol}, \boldsymbol{dem}, \boldsymbol{D} \leftarrow$ RandomizeUsers()
  for $a \leftarrow 1$ **to** nAPLs **do**
    $\boldsymbol{sat} \leftarrow$ LoadPreviousAPLs($\boldsymbol{APL\_order}$, $\boldsymbol{sat}$, $\boldsymbol{D}$, APL^*)
    $APL^* \leftarrow$ EvaluateNextAPL($\boldsymbol{APL\_order}$, $\boldsymbol{sat}$, $\boldsymbol{D}$)
    $\boldsymbol{sat}, nSats \leftarrow$ LoadNextAPL($\boldsymbol{sat}$, $\boldsymbol{D}$, APL^*)
    $pcts_{s,APL^*} \leftarrow nSats/$nUsers
for $a \in \boldsymbol{APL\_order}$ **do**
  $\overline{pcts_a} \leftarrow \sum_{s=1}^{S} pcts_{s,a}/S$
Sort APLs by descending order of $\overline{pcts_a}$ OR provide APLs sequence manually
/* Step 2 (Mandatory) */
init: $\boldsymbol{pcts}$
for $s \leftarrow 1$ **to** S **do**
  $\boldsymbol{D}, \boldsymbol{sat} \leftarrow$ RandomizeUsers()
  for $a \in \boldsymbol{APL\_order}$ **do**
    $APL^* \leftarrow a$
    $\boldsymbol{sat}, nSats \leftarrow$ LoadNextAPL($\boldsymbol{sat}$, $\boldsymbol{D}$, APL^*)
    $pcts_{s,APL^*} \leftarrow nSats/$nUsers
for $a \in \boldsymbol{APL\_order}$ **do**
  $\overline{pcts_a} \leftarrow \sum_{s=1}^{S} pcts_{s,a}/S$
Sort APLs by descending order of $\overline{pcts_a}$

Algorithm 2

The output of Algorithm 2 consists of a sequence of APLs, evaluated as follows. Firstly, S simulations are conducted nAPLs times to evaluate and select the next APL to install. At each step, the algorithm considers the presence of previously installed APLs that already cover a portion of users. Once the best APL has been selected most often out of the S simulations, another round of S simulations is conducted to calculate its mean expected covered demand. This process is repeated for nAPLs times, resulting in a unique sequence of APLs expected to provide the highest level of demand coverage.

Algorithm 2. Sequence-evaluation algorithm

Data: **x**, **y**
Result: APLs location and capacity evaluation with greedy evaluation sequence
initialization

init: $\boldsymbol{APL\_order}, \boldsymbol{pcts}$
$it \leftarrow 0$
for $it \leftarrow$ **to** nAPLs **do**
  init: $\boldsymbol{APL\_maxs}, \boldsymbol{pctss}$
  $APL^* \leftarrow 0$
  for $s \leftarrow 1$ **to** S **do**
    $\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{sat}, \boldsymbol{tol}, \boldsymbol{dem}, \boldsymbol{D} \leftarrow$ RandomizeUsers()
    $\boldsymbol{sat} \leftarrow$ LoadPreviousAPLs($\boldsymbol{APL\_order}$, $\boldsymbol{sat}$, $\boldsymbol{D}$, APL^*)
    $APL^* \leftarrow$ EvaluateNextAPL($\boldsymbol{APL\_order}$, $\boldsymbol{sat}$, $\boldsymbol{D}$)
    $APL\_maxs_s \leftarrow APL^*$
  $APL^* \leftarrow$ Mode($\boldsymbol{APL\_maxs}$)
  $APL\_order_{it} \leftarrow APL^*$
  for $s \leftarrow 1$ **to** S **do**
    $\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{sat}, \boldsymbol{tol}, \boldsymbol{dem}, \boldsymbol{D} \leftarrow$ RandomizeUsers()
    $\boldsymbol{sat} \leftarrow$ LoadPreviousAPLs($\boldsymbol{APL\_order}$, $\boldsymbol{sat}$, $\boldsymbol{D}$, APL^*)
    $\boldsymbol{sat}, nSats \leftarrow$ LoadNextAPL($\boldsymbol{sat}$, $\boldsymbol{D}$, APL^*)
    $pctss_s \leftarrow nSats/\text{nUsers}$
  $pcts_{it} \leftarrow \sum_{s=1}^{S} pctss_s/\text{S}$

4 Numerical experiments

This section presents the results of the simplified MILP model and Algorithms 1 and 2 applied to the case study under analysis.

Equation 36 provides the empirical distribution of the user population, where $z \sim \text{U}(0,1)$.

$$f\,(z) = \begin{cases} 1 & z \leq .1548 \\ 2 & .1548 < z \leq .2999 \\ 3 & .2999 < z \leq .4416 \\ 4 & .4416 < z \leq .5825 \\ 5 & .5825 < z \leq .7031 \\ 6 & .7031 < z < .8129 \\ 7 & .8129 < z \leq .9101 \\ 8 & z > .9101 \end{cases} \tag{36}$$

The empirical distribution was based on the data collected from the city municipality office, as of Table 2 (Comune di Torino - Ufficio di Statistica, n.d.).

Table 2. Areas bounds, inhabitants' percentages, and inhabitants' cumulative percentages

Area	$x^{\min}$	$x^{\max}$	$y^{\min}$	$y^{\max}$	pct	pct_{cum}
1	-4200	-500	-6300	-1800	.1548	.1548
2	-1100	2200	-5300	1600	.1451	.2999
3	-6000	-1600	-2300	500	.1417	.4416
4	-6000	-1600	2500	5200	.1409	.5825
5	-1600	1600	2800	5000	.1206	.7031
6	-6000	-1600	-500	1600	.1098	.8129
7	-1600	3000	1600	3000	.0972	.9101
8	-1500	500	-2200	1600	.0899	1

The demand data used were collected via a survey submitted to e-commerce users. The survey results, presented in Mitrea et al. (2020) and Ottaviani et al. (2020), were used to estimate the model parameters, namely the overall APL daily demand and the average tolerated distance by the APL users. The APL daily demand (dem_u) is randomized through the exponential distribution with shape parameter $\lambda = \overline{\text{tol}} = 0.027$ (Ottaviani et al., 2020) as a function of the share of APL potential users and the overall demand for parcels by e-commerce users (Fig. 1).

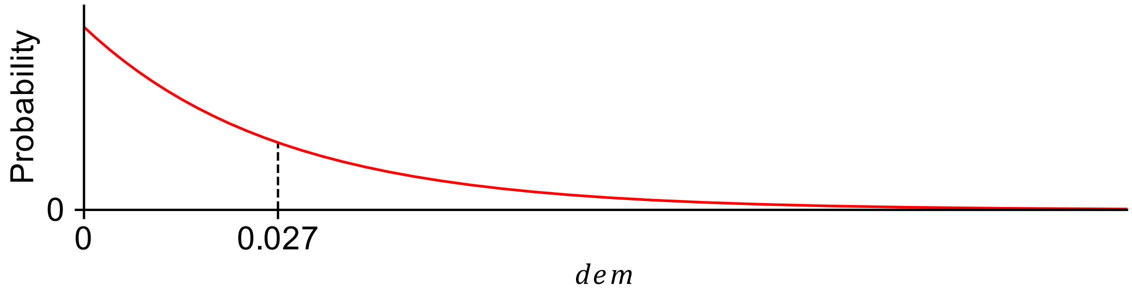

Figure 1. APL daily demand probability density function

The users' tolerated travel distance (tol_u) is randomized through the beta distribution, extended to the domain [0,6670], with shape parameters $\alpha = 1.23$ and $\beta = 3.27$ (Ottaviani et al., 2020). The distribution is portrayed in Figure 2, where 1800 indicates the mean – $\overline{\text{tol}} = 6670 \cdot \alpha/(\alpha+\beta) = 1.23/(1.23+3.27) \sim 6670 \cdot 0.27 \sim 1800$.

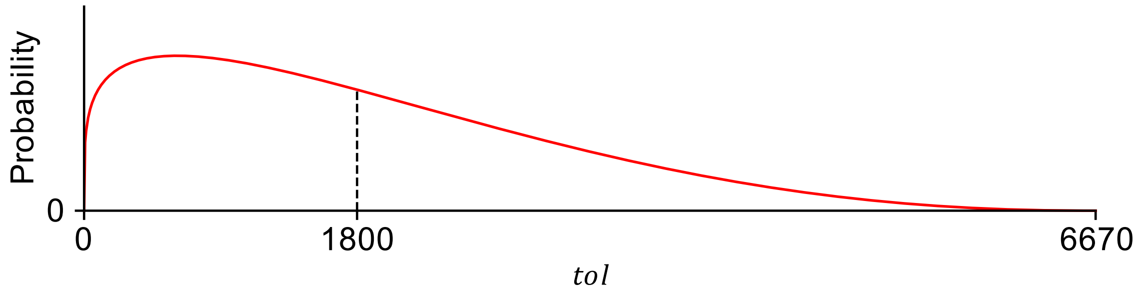

Figure 2. Tolerated travel distance probability density function

For simplicity, the APL network is assumed to be able to serve the entire city demand. This assumption would equate to a scenario where a single LSP delivers all parcels to APL customers. Hence, to set the estimated number of e-commerce users, the maximum number of users surveyed is multiplied by the percentage of the whole population based on the survey, resulting in nUsers = 102000. We then aggregated the number of users to 1020 demand collection points, where each point accounts for 1000 users.

The number of potential APL locations was determined based on the number of postcodes in the urban area of Turin, which resulted in a maximum of nAPLs = 33 APL locations.

Table 3. Areas bounds, inhabitants' percentages, and inhabitants' cumulative percentages

Postcode	$x^{\min}$	$x^{\max}$	$y^{\min}$	$y^{\max}$	x_a	y_a
10121	-1450	0	0	700	-725	350
10122	-1450	0	700	1570	-725	1135
10123	0	1150	0	1000	575	500
10124	0	1600	980	1600	800	1290
10125	0	780	-1000	0	390	-500
10126	0	1200	-4000	-1000	600	-2500
10127	-1000	900	-6000	-4000	-50	-5000
10128	-700	0	-1900	0	-350	-950
10129	-1400	-700	-1950	-280	-1050	-1115
10131	1200	5000	-1400	1500	3100	50
10132	1800	4000	1250	5000	2900	3125
10133	1100	5000	-4500	0	3050	-2250
10134	-1100	0	-4100	-1800	-550	-2950

10135	-3600	0	-6800	-4100	-1800	-5450
10136	-3600	-1100	-3200	-2000	-2350	-2600
10137	-3300	-1100	-4500	-2900	-2200	-3700
10138	-3100	-1400	-800	1000	-2250	100
10139	-4400	-2200	-900	0	-3300	-450
10141	-4800	-1400	-2300	-900	-3100	-1600
10142	-5700	-3200	-2500	-900	-4450	-1700
10143	-3100	-1400	0	1500	-2250	750
10144	-2700	-1400	1000	2600	-2050	1800
10145	-3800	-3100	-200	1200	-3450	500
10146	-5900	-3700	-1000	400	-4800	-300
10147	-3100	-1400	2800	4600	-2250	3700
10148	-4800	-1400	3700	5700	-3100	4700
10149	-3800	-1400	1800	3600	-2600	2700
10151	-6200	-3100	1500	4000	-4650	2750
10152	-1400	600	1500	3000	-400	2250
10153	0	2600	1500	3000	1300	2250
10154	-400	1200	2400	4800	400	3600
10155	-1400	-400	2000	5600	-900	3800
10156	-400	2500	5000	8000	1050	6500

As the population distribution for the different postcodes was unavailable, the demand collection points were assumed to be uniformly distributed across the 33 postcodes.

Figure 3 displays eight city areas and the APLs predetermined locations.

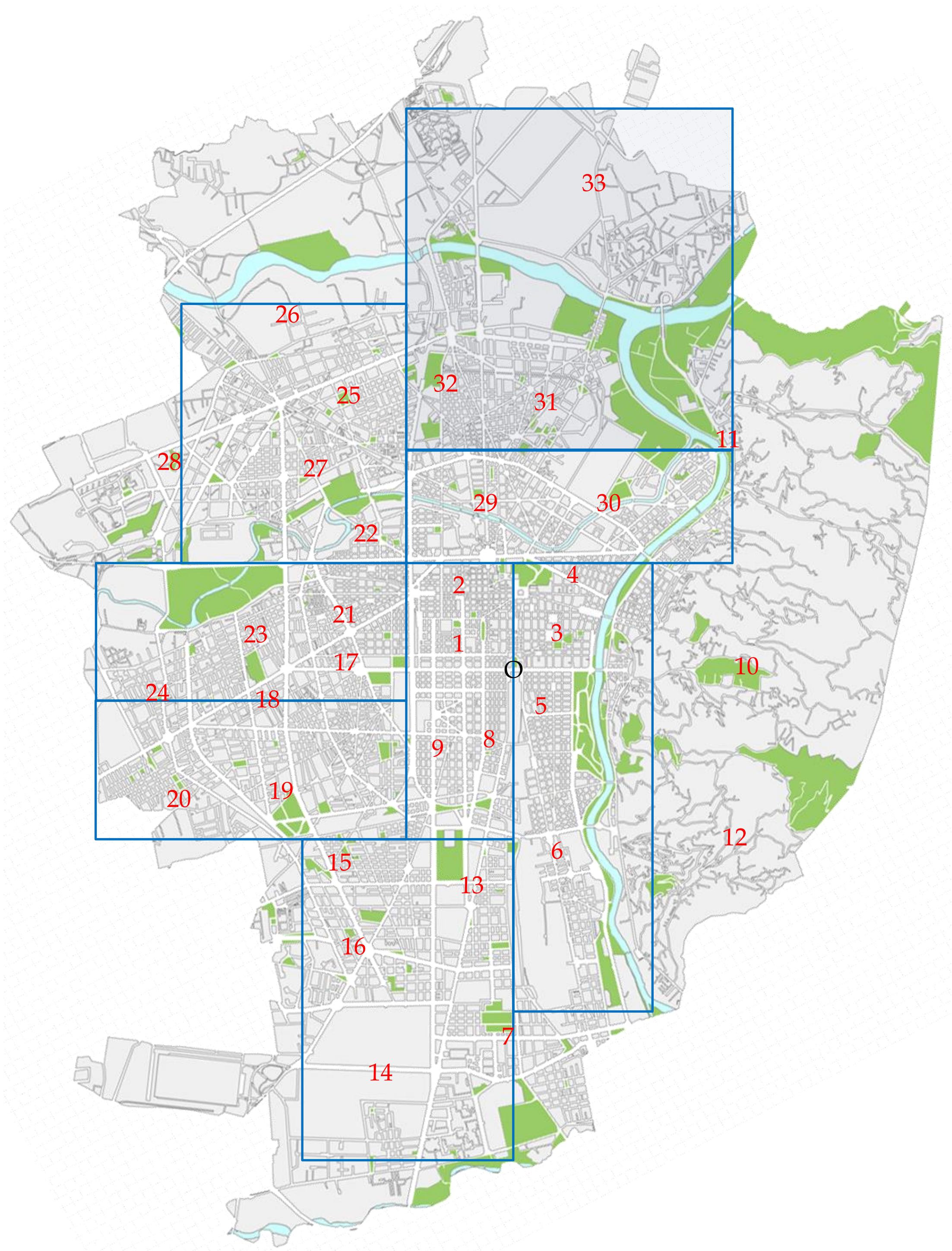

Figure 3. City eight areas (blue) and APLs predetermined locations (red)

4.1 Fixed scenario

We simulated the simplified MILP model 1000 times using the FICO® Xpress v8.13.0 optimization library in Python 3.9.12. Table 4 presents the optimization results, which took approximately 1 minute per run. On the other hand, the algorithms were executed using Julia 1.8.5. We set the total number of simulations to 10000 in A1S1-A1S2 and MILP-A1S2, while we set it to 1000. A2 took approximately 2 minutes to execute. Instead, A1S1-A2S2 and MILP-A1S2 took approximately 2 minutes and 20 seconds, respectively. We ran all scripts on an Intel® Core™ i7-10750H CPU.

Table 4. Areas bounds, inhabitants' percentages, and inhabitants' cumulative percentages

APL	x_a	y_a	(a)	(b)	(c)	(d)
24	-725	350	1	5.89	173.00	.946
28	-725	1135	1	2.55	106.58	.919
6	575	500	.96	2.41	101.11	.893
14	800	1290	.95	1.73	87.36	.877
31	390	-500	.95	5.32	157.79	.921
30	600	-2500	.83	2.80	101.76	.841
7	-50	-5000	.79	.40	50.82	.696
26	-350	-950	.75	1.54	72.48	.757
5	-1050	-1115	.61	2.58	86.17	.739
15	3100	50	.60	2.80	89.24	.737
22	2900	3125	.48	1.67	58.98	.599
21	3050	-2250	.46	2.14	68.17	.632
16	-550	-2950	.45	1.12	48.08	.550
25	-1800	-5450	.44	1.69	58.02	.587
20	-2350	-2600	.32	.55	28.74	.378
19	-2200	-3700	.30	1.26	42.22	.468
3	-2250	100	.25	.81	30.17	.372
11	-3300	-450	.15	.00	6.31	.097
9	-3100	-1600	.15	.59	20.20	.263
17	-4450	-1700	.15	.82	24.43	.300
1	-2250	750	.14	.62	20.29	.262
32	-2050	1800	.12	.52	17.38	.230
8	-3450	500	.08	.36	11.66	.162
4	-4800	-300	.06	.18	7.05	.103
18	-2250	3700	.04	.16	5.42	.079
10	-3100	4700	.04	.00	0.77	.012
29	-2600	2700	.04	.12	4.76	.071
13	-4650	2750	.03	.03	2.26	.034
27	-400	2250	.03	.00	1.64	.025
23	1300	2250	.03	.12	4.08	.060
2	400	3600	.03	.08	3.18	.048
12	-900	3800	.02	.00	0.60	.009
33	1050	6500	.00	.00	0.00	.000

Table 4 presents the APLs coordinates (x_a, y_a) along with their activation frequency ($act_a = 1$) over the S simulations in column (a) of Table 4. Column (b) shows the average number of modules installed at each APL, while column (c) indicates the average daily demand that each facility is expected to serve. Finally, column (d) represents the average saturation of each APL.

Column (a) of Table 4 reveals that at least ten APLs have an activation frequency of 50%, with an average saturation ranging from approximately 69.6% to 95% and an average number of modules of around three. To cover at least 95% of the estimated potential users in each simulation, between 11 and 13 APLs are required. The same results were obtained by executing Algorithm 1 in its entirety and, separately, by replacing its step one output with the MILP APL sequencing. Algorithm 2 also led to the same conclusions. The results of the various algorithms used are presented in Table 5.

Table 5. Algorithms' results (with $\overline{\textbf{tol}} = \mathbf{1800}$, $\overline{\textbf{dem}} = \mathbf{0.027}$)

nth	A1S2	A1S1-A1S2			A2			MILP	MILP-A1S2		
APL	APL	APL	$\%dem$	$\%dem_c$	APL	$\%dem$	$\%dem_c$	APL	APL	$\%dem$	$\%dem_c$
1	18	18	.16	.16	18	.16	.16	24	31	.15	.15
2	24	31	.15	.32	29	.16	.32	28	24	.14	.29
3	31	16	.11	.42	8	.12	.44	6	6	.10	.39
4	16	9	.10	.53	16	.10	.55	14	15	.09	.48
5	29	29	.07	.60	25	.09	.63	31	22	.09	.57
6	9	28	.07	.67	28	.06	.69	30	5	.08	.64
7	28	24	.06	.73	31	.06	.75	7	14	.07	.72
8	30	25	.06	.79	24	.05	.80	26	28	.07	.79
9	25	6	.04	.83	7	.04	.84	5	26	.06	.85
10	32	30	.04	.87	30	.04	.88	15	30	.06	.91
11	14	14	.03	.90	6	.02	.91	22	21	.03	.93
12	26	20	.02	.92	14	.02	.92	21	7	.02	.95
13	6	7	.01	.93	20	.01	.94	16	20	.01	.96
14	8	26	.01	.94	26	.01	.95	25	16	.01	.96
15	1	8	.01	.95	22	.01	.96	20	25	.01	.97
16	13	5	.01	.96	10	.01	.97	19	3		.97
17	7	22	.01	.96	5		.97	3	10		.97
18	5	1		.97	33		.97	11	12		.97
19	4	13		.97	32		.97	9	32		.97
20	20	10		.97	27		.97	17	1		.97
21	22	4		.97	23		.97	1	9		.97
22	15	12		.97	21		.97	32	19		.97
23	3	3		.97	19		.97	8	29		.97
24	27	32		.97	17		.97	4	11		.97
25	23	2		.97	15		.97	18	2		.97
26	17	11		.97	13		.97	10	4		.97
27	19	15		.97	12		.97	29	8		.97
28	2	17		.97	11		.97	13	13		.97
29	21	19		.97	9		.97	27	17		.97
30	10	21		.97	4		.97	23	18		.97
31	12	23		.97	3		.97	2	23		.97
32	11	27		.97	2		.97	12	27		.97
33	33	33		.97	1		.97	33	33		.97

The sequence A1S1.APL represents the order of APLs evaluated using Algorithm 1 Step 1, while A1S1-A1S2.APL is the result of Algorithm 1 Step 2 with A1S1.APL as the fixed input sequence. The differences between these sequences imply that activating two or more facilities may prevent the placement of the other ones and vice versa. A2.APL is the output of Algorithm 2, while MILP.APL refers to the APL column in Table 4, which is used as input to Algorithm 1 Step 2 to obtain the MILP-A1S2.APL facilities sequence.

The A1S1-A1S2.APL, A2.APL, and MILP-A1S2.APL sequences share both similarities and differences. Although the first APLs in A1S1-A1S2 and A2 are mostly the same, with minor differences in their order, the MILP-A1S2 sequence is completely different. The only exception is APL 31, which appears in the seventh, second, and first positions in the three sequences, respectively. To cover around 90% of the estimated demand, a minimum of ten or eleven APLs is required. In all three cases, the first APLs cover approximately 15.5% of the total estimated demand (the intersections with the y-axis), and each additional facility provides similar increments in coverage (curvature). This is due to the combined effect of users' homogeneous demand towards APL usage (Ottaviani et al., 2020) and the volumetric capacity of the facilities.

Figure 4 visually represents the A1S1-A1S2, A2, and MILP-A1S2 facility networks to clarify the differences in the three approaches.

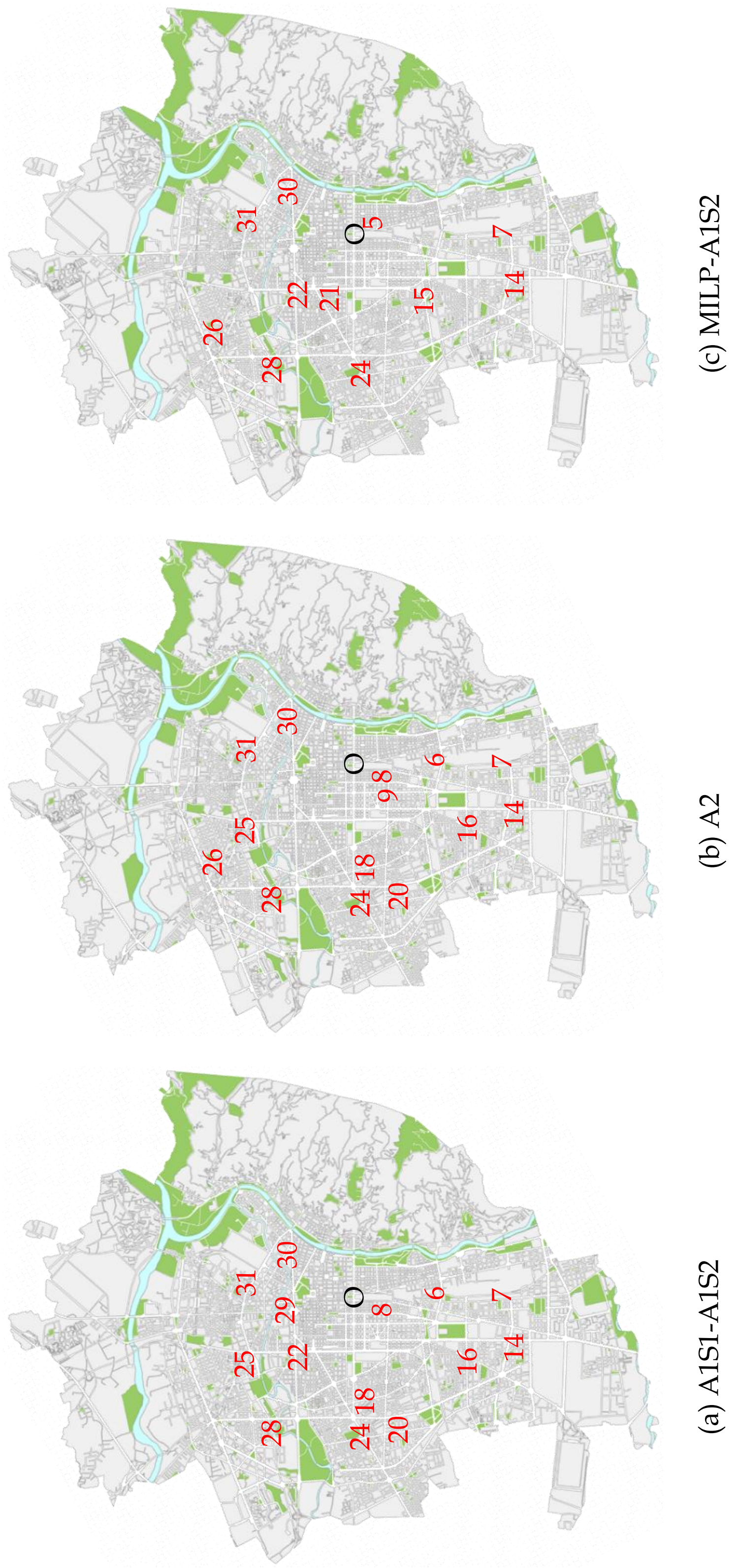

Figure 4. Three approaches results

4.2 *Sensitivity analysis*

We conducted a sensitivity analysis to assess the impact of average tolerated travel distance ($\overline{tol}$) on the performance of the three algorithms. The sensitivity analysis involved testing a range of values (i.e., from 0 meters to 6600 meters, in increments of 100), and evaluating the resulting maximum covered demand ($\max \%dem_c$) as well as the minimum number of activated APLs required to achieve 95% coverage (when possible). Given that the capacity of APLs can be increased through expansion, whereas the distance between facilities is fixed, the sensitivity analysis focused solely on varying the average tolerated travel distance while keeping the average demand constant.

Figure 5 shows the results of the sensitivity analysis. The number of APLs activated is plotted as continuous lines on the left y axis, while the dashed lines on the right y axis indicate the maximum percentage of covered cumulative demand ($\max \%dem_c$). Based on the results, the number of APLs decreases by half when $\overline{\text{tol}} > 1600$. For $\overline{\text{tol}} = 1800$, the same results as in Table 5 apply. We observe that A1S1-A1S2 is not monotone decreasing in the region $\overline{\text{tol}} \geq 3100$, as the algorithm follows a greedy approach and does not optimize globally. In contrast, both A2 and MILP-A1S2 exhibit monotone decreasing behavior.

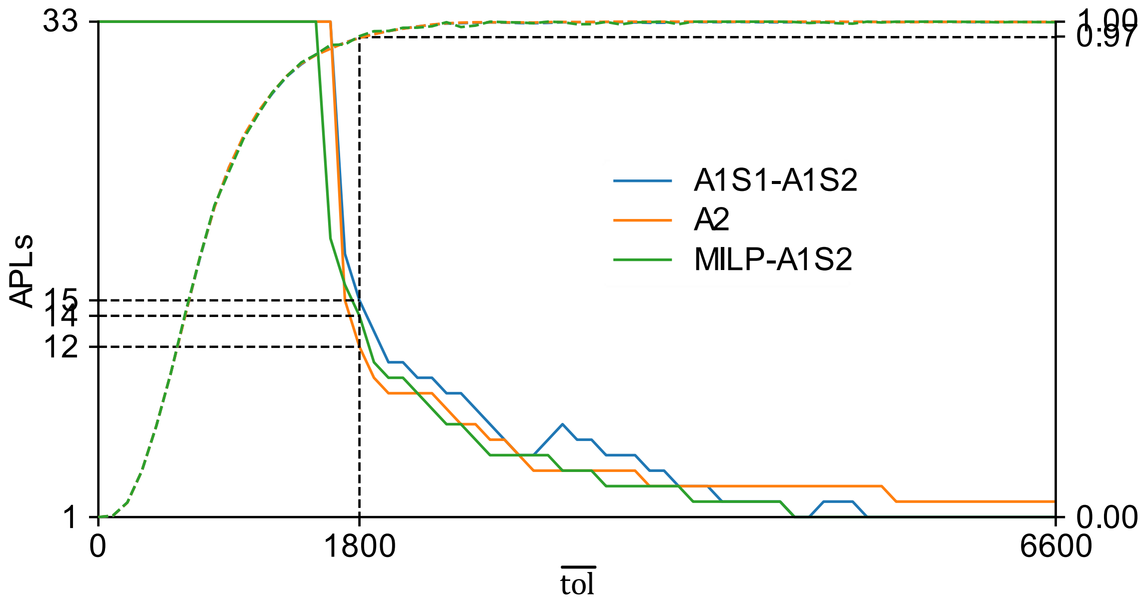

Figure 5. Sensitivity analysis (with $\overline{dem} = 0.027$). Continuous lines represent the number of APLs required to cover 95% of the demand. Dashed lines represent the maximum $\%dem_c$

5 Discussions and conclusions

This work generates both theoretical and practical contributions.

The theoretical contribution of the study is related to the two approaches to solving the covering location problem of an APL network and their application to the city of Turin. The first approach consists of the robust optimization of a MILP model. The model is described in terms of the objective function, constraints, decision variables, and parameters involved. A simplified version is suggested whereby the possible locations of the facilities to install are fixed. This model is thus optimized S times, changing the user-related variables during each simulation. We averaged the results from the S runs, obtaining a custom ranking of the APLs based on their activation frequency and time. The second approach is represented by the execution of an ad-hoc APLs selection algorithm. In this regard, two criteria for selecting the next APL to install are tested: for the first criterion, the same input sequence of order is simulated; for the second criterion, the selection of the next APL depends on the simulated outcomes of the following possible option.

The practical implications of the study are the following. Practitioners are provided two approaches for solving the covering location problem related to the APL network installation. The MILP approach is focused on the simultaneous optimization of the APLs and the number of extra modules per facility. Nevertheless, it does not allow identification of the incremental percentage of satisfied demand provided by the individual APL activation. On the other hand, the algorithmic approach considers the APLs and their capacity one at a time, allowing for the evaluation of the total percentage of the satisfied demand curve according to the ath APL. In this perspective, all approaches provide similar results (i.e., reach 95% of total satisfying demand with 10 to 11 APLs). The algorithms provide an equivalent level of performance as the MILP, and thus they can easily be replicated in different geographical contexts. This allows an understanding of how many facilities are required per square meter, given the population-tolerated travel distance to pick up an order. Therefore, LSPs can use the proposed solution to fine-tune their APL strategy according to the level of service proposed (i.e., the percentage of demand reached by the APL) and exogenous variables such as the customers' propensity and flexibility towards the usage of the parcel locker.

This study has some minor limitations. Firstly, only distances from customers' households are considered, whereas it has been proven that some customers prefer to pick their online purchases during their commuting. This would have required knowing all the workplace locations for all customers involved in the survey, which would have significantly hindered the generalization of the results. Secondly, users coordinates are randomized uniformly within the eight areas. In any case, we believe that the differences between a uniform distribution and the actual distribution of the population within the areas are not likely to result in variation in the output variables of the methods tested.

Future research can improve the study in several ways. On the one hand, one can analyze the default locations to install facilities based on several factors evinced from the literature (e.g., pre-existing facilities, logistical hubs, public spaces, etc.). On the other hand, one can relax the assumptions on which the methods are based, e.g., that the entire demand of a user is assigned to the nearest active APL, or include emission-related costs in the objective function and constraints.

Notation List

This manuscript utilizes the following abbreviations: unformatted abbreviations represent parameters, italicized abbreviations denote variables, bolded abbreviations indicate vectors, and bolded and capitalized abbreviations signify matrices.

Table 6. Acronyms with definitions

Acronym	Definition
u	User index
a	APL index
nUsers	Total number of users
nAPLs	Total number of APLs
U	Users set
A	APLs set
z	Uniformly distributed random variable
x	Cartesian coordinate
y	Cartesian coordinate
dem	User daily demand
tol	User tolerated travel distance
sat	User Boolean coverage variable
D_{ua}	Euclidian distance between uth user and ath APL
pct	Users' frequency for given area
pct_{cum}	Users' cumulative frequency for given area
λ	Exponential distribution shape parameter
α	Beta distribution shape parameter
β	Beta distribution shape parameter
$\mathrm{c}^{\mathrm{APL}}$	APL installation cost
c^{Module}	APL module installation cost
act_a	APL Boolean activation variable
SL	Service level

M	Linear programming big M parameter
ϵ	Linear programming small ϵ parameter
mD_u	Distance between uth user and closest APL
ass_{ua}	ath APL assignment to uth user Boolean variable
cap^{APL}	APL orders capacity
$\text{cap}^{\text{Module}}$	APL module orders capacity
mod_a	ath APL number of modules
mod^{max}	Maximum number of modules per APL
SF	User population scaling factor
APL^*	Candidate APL
max_dem	Maximum demand covered by candidate APL
pot_dem	Potential demand covered by candidate APL
pot_users	Potential number of users covered by candidate APL
$nSats$	Total number of users covered by selected APL
$pcts$	Matrix of percentage covered demand values by each APL
$pctss$	Matrix of percentage covered demand in each simulation
APL_maxs	Array of candidate APLs
APL_order	Sequenced array of APLs

Data Availability Statement

All data and models used during the study are available in a repository online in accordance with funder data retention policies. All models or code that support the findings of this study are available from the corresponding author upon reasonable request.

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