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Smart loading zones. A data analytics approach for loading zones network design

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ABSTRACT

Urban public space is often provided for freight delivery operations in the form of on-street (un)loading zones (LZ). Since public space is scarce and demanded by several users, city authorities have the challenge of managing LZ by gaining knowledge about freight curbside needs and utilization. Although technological solutions and enforcement practices have become popular among policymakers to capture curbside dynamics, there is still an open and promising research field for designing analytical frameworks that shape LZ decision-making processes. This fact has motivated the authors to define the concept of Smart Loading Zones (SLZ) as the involvement of technology and data analytics in the planning and management of LZ in a responsive and user-oriented way. Besides proposing a conceptual approach for the study of SLZ, this paper implements data analytics tools for enhancing decisions on LZ network design, using the City of Vic (Spain) as a case study. The machine learning techniques *k-means*++, DBSCAN, and integer linear programming prescribed the LZ number, location and service assignment based on establishments' coordinates, walking distances and freight demand. Results from the case study showed how an optimized number, location, and size of LZ improved occupation levels, i.e., from 18 % to 80 %, while freeing up curbside space for other users. Service coverage was also improved by allocating LZ to establishments within walking distances no greater than 75 m. Further development of methods and tools for SLZ at tactical and operational decisions are recommended for future studies.

Introduction

Demand for goods in urban areas has intensified amid trends such as cities' densification, consumption growth, digitalisation, and e-commerce. Consequences derived from the increased demand for freight transport coupled with a slow response in corresponding infrastructure provision, i.e., a supply–demand infrastructure mismatch, have led to externalities hampering urban sustainability (Xiao et al., 2021). Although more awareness of the need to include freight activities in city development plans is evident in mobility and urban planning research, practice, and policy, planning for urban freight operations remains in its infancy (Rodrigue, 2020).

Cities worldwide have adopted various initiatives to mitigate the adverse effects of freight transport through infrastructure-, vehicle-, regulation-, land use- and logistics-related strategies (Russo and Comi, 2010; Holguín-Veras et al., 2020). These Urban Freight Transport (UFT) initiatives aim at satisfying goods movement demand at the lowest economic, social and environmental cost (Ogden, 1992). Gonzalez-Feliu and Sánchez-Díaz (2019) classified research approaches supporting UFT initiatives based on their geographical scope, impact and handled issues into macroscopic (i.e., long-term, infrastructure mega-projects, regional and metropolitan range), mesoscopic (i.e., medium-term, traffic regulation, inner-city lanes) and microscopic levels (i.e., short-term, right-of-way allocation decisions, street level).

Curbside space allocation for freight operations has been found to be one of the most effective tools for reducing the negative impacts of last-mile deliveries in urban areas (Boussier et al., 2011; Comi et al., 2022), i.e., an infrastructure-related initiative at the microscopic level. Likewise, Manzano Dos Santos and Sanchez-Díaz (2016) identified parking as the primary obstacle to efficient UFT from the carriers' perspective. Providing curbside space for freight deliveries is becoming critical, majorly because freight vehicles typically try to park as close as possible to the delivery location. Freight vehicles spend 40–80 % of their operational time parked due to loading and unloading (L/U) operations

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(Sanchez-Diaz et al., 2020). When the curbside space is occupied or missing for freight deliveries, operators often drive around to find available space, i.e., cruising, and if they cannot find it, they either continue cruising or double-park while they deliver (Dalla Chiara and Goodchild, 2020). Frequent illegal parking, congestion impacts due to cruising for parking, inefficient curbside controls and, lack of empirical data on infrastructure service levels, are some of the issues that have pushed cities' need for curbside management solutions targeting objectives of efficient and sustainable UFT (Muñuzuri et al., 2019; Santos Junior and Oliveira, 2020).

Curbside infrastructure for freight takes the form of (un)loading zones (LZ), defined by transport departments as on-street reserved areas for L/U heavy or bulky goods (Regal-Ludowieg et al., 2022). According to Holguín-Veras et al. (2020), 17 out of 56 surveyed cities had implemented LZ as part of their mobility plans, which were widely acclaimed by practitioners, freight companies, and society as an effective solution to urban mobility issues. However, the implementation of these initiatives has faced challenges due to the lack of knowledge and tools required to achieve a balance between the supply and demand of LZs, which is crucial for effective freight curbside management. This lack of knowledge explains inefficiencies in the provision and management of LZ with the corresponding negative impacts on city sustainability (Nourinejad and Roorda, 2017; Iwan et al., 2018; Castrellon and Sanchez-Diaz, 2022).

Intending to provide city authorities with tools and insights to solve these issues, research has concluded that parking fines and enforcement are not enough to spur efficient use of the curbside and to mitigate negative impacts on traffic from freight deliveries, e.g., cruising, and double-parking (Jaller et al., 2013; Figliozzi and Tipagornwong, 2017). Although researchers agree that public policies should be more proactive in assessing curbside demand/supply based on data-driven decisions, several works identified the lack of data and the high cost of acquiring them (Gatta and Marcucci, 2016). This leads to unclear LZ authorization and management processes that rely on perceptions or biased requests more than on ex-ante assessments about the number, size, or LZ location, coupled with ex-post analyses about the use, service levels, performance, or adequacy of spaces (Muñuzuri et al., 2019).

One of the opportunities to overcome this challenge is to frame LZ management – here defined as the process of designing, implementing, operating, and monitoring LZ – within the Smart City concept, to engage public and private actors in the implementation of digital technologies that enhance the interactions among them during freight delivery operations (Cronemberger and Gil-Garcia, 2019). To do so, this paper proposes the concept of Smart Loading Zones (SLZ) as *stop delimitated areas, where freight loading and unloading operations take place, equipped with technology that provides real-time information for vehicle detection, parking space monitoring, and parking assignment, where data coming from connected infrastructure and mobile devices are used by public authorities, space owners/managers and private companies to make informed decisions that enhance operational efficiency and urban liveability*.

Developing SLZ represents a promising practice in curbside decision-making processes to meet sustainable development goals while improving freight transport efficiency (Castrellon and Sanchez-Diaz, 2022). However, evidence is needed to understand to what extent SLZ implementation contributes to closing curbside management gaps related to i) insufficient knowledge about curbside demand and service levels, ii) weak enforcement conducing to LZ misuses, iii) the lack of differentiation in regulations to freight operations and to other curbside users, and iv) the so-called *big-no data* paradox, i.e., limited data analytical tools to process vast amounts of data collected from installed curbside technologies (Ionita et al., 2018; Comi et al., 2018; Gonzalez-Feliu, 2019; Allen and Piecyk, 2022).

Therefore, this paper aims to propose a conceptual approach to study and develop SLZ and to assess how data analytics tools contribute to enhancing decisions regarding SLZ network design, i.e., gaps i) and iv). The paper also illustrates the benefits of digitalisation in providing data to inform decisions in freight curbside management.

To achieve this aim, the authors explored the current literature on LZ. A data analytics approach to SLZ management is presented, focusing on decisions related to parking infrastructure network design, i.e., the number, service assignment, and size of LZ. Empirical data came from a case study, i.e., the City of Vic (Spain), consisting of more than 100 K freight curbside operations from more than 340 establishments located in the city centre. These operations were tracked by the mobility office via the parking management system provided by Parkunload®, a tech-based company that uses the Internet of Things (IoT) to control parking conditions on the curbside. The paper shows the results from the data analytics models and presents their discussion in terms of practical and theoretical implications. Finally, conclusions and future research directions are suggested.

Conceptual framework of LZ management studies

LZ management has recently emerged in the academic literature within the urban freight management concept (Olsson et al., 2019). In (Alho et al., 2014), the authors proposed that LZ studies should address tools for deciding on LZ location, size, number of parking stalls and enforcement. Santos Junior and Oliveira (2020) classified problems related to LZ based on approaches for addressing data collection, number, and location of LZ, parking type, booking and control system, sizing of LZ, operation of LZ, and how to reduce double parking. Galindo-Muro, et al. (2020) split the LZ research into two areas: methods for the design and operation of LZ and, the study of LZ impacts on mobility, congestion, and parking practices. Although there is not a generally accepted framework for the study of LZ, these several approaches have opened the discussion about aspects that range from the strategic decision levels, i.e., long-term actions that imply policies and high investments, to the operational ones, i.e., day-to-day actions, from both the public and private perspectives. In this paper, the authors propose grouping LZ research approaches by decision levels in terms of temporal implications i.e., strategic, tactical, and operational, for the involved stakeholders, i.e., public, and private sectors, as explained in Fig. 1.

The strategic level includes LZ network design, i.e., the definition of the LZ quantity, location, and number of parking stalls. It also includes technological assessments regarding stationary devices for LZ management, i.e., sensors, cameras, parking meters or other fixed devices. From the private sector perspective, the strategic level refers to allocating transport resources based on freight demand, access regulations, and LZ availability at the specific city zone.

The tactical level refers to decisions about duration limits, pricing, LZ dimensions and mobile technology that should be implemented by different LZ users. The private sector defines fleet allocation in terms of the type of vehicles, size, and technology that best suit traffic policies and customer requirements.

At the operational level, public sector defines enforcement schemes, information-sharing initiatives among users, operations impact evaluation on traffic, environment, land use and logistics efficiency. Private sector makes decisions about routing under parking stalls availability and freight demand constraints.

Strategic, tactical, and operational decisions drive actions within the scope of: i) LZ infrastructure, ii) curbside regulations, iii) information and communication technologies (ICT) implementation and, iv) private sector operations based on urban conditions (infrastructure + regulations) provided to move and deliver goods.

Table 1 summarizes the state of the art in LZ management, grouping research contributions by decision level, scope, and type of decision. Each decision is motivated by relevant questions that organizations from the public and private sectors commonly ask themselves to satisfy their specific objectives. In general, recent contributions suggest research opportunities towards improved modelling developments in curbside demand estimation based on automated data collection and their analytics (Tamayo et al., 2018), coupled with novel tools for dynamic

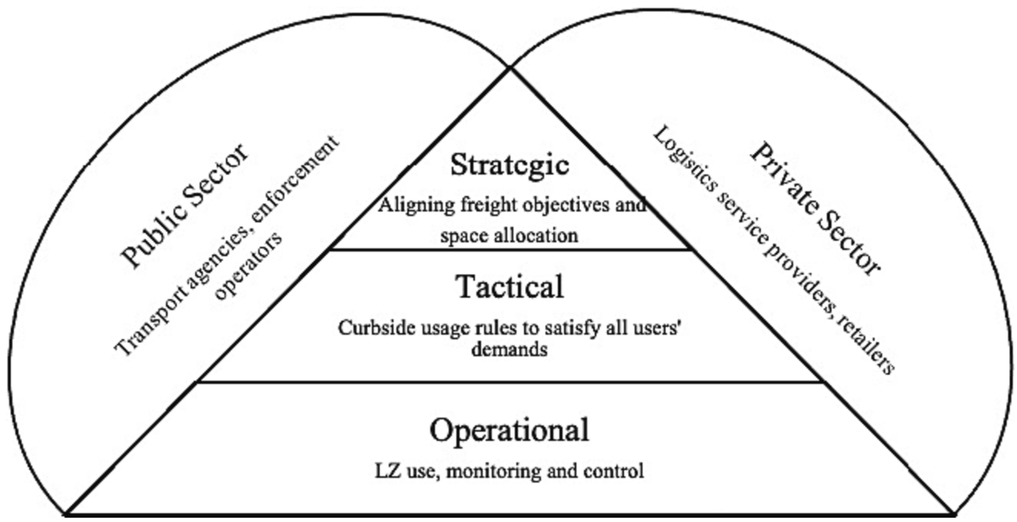


Fig. 1. Decision levels in LZ management.

Table 1
Summarized list of references addressing LZ management decisions.

Decision Level	Scope	Type of Decision	Relevant questions	Contributions
Strategic decisions	Infrastructure	Number of LZ, service assignment	What is the demand for LZs at different locations?Where and how many LZs should be allocated?How many parking stalls should be provided?	(Aiura and Taniguchi, 2005; Dezi et al., 2010; Jaller, et al., 2013; Gardrat and Serouge, 2016; Muñuzuri et al., 2017; Roca-Riu et al., 2017; Alho et al., 2018; Prata et al., 2018; Dey et al., 2018; Letnik et al., 2018, 2019; Tamayo et al., 2018; Pinto et al., 2019; Letnik et al., 2020; Ochoa-Olán et al., 2021; Comi et al., 2022)
	Regulations	LZ authorization process	How do public agencies plan the allocation of LZs in the city? What are the relevant criteria?	
	ICT	Stationary technology for LZ	What is the most suitable LZ technology for meeting the city's sustainability-related objectives?	
	Private Operation	Resource allocation for urban deliveries	What transportation means should be allocated for urban deliveries based on the LZ network?	
Tactical decisions	Infrastructure	LZ Dimensions	What is the size of LZ parking stalls?	(Boussier et al., 2011; McLeod and Cherrett, 2011; Cherrett et al., 2012; Patier et al., 2014; Velázquez-Martínez et al., 2016; Comi et al., 2017; Figliozzi and Tipagornwong, 2017; Cao and Menendez, 2018; Iwan et al., 2018; Yang et al., 2019; Low et al., 2020; Mor et al., 2020; Pinto and Lagorio, 2020; Sayarshad et al., 2020; Regal-Ludowieg et al., 2022; Castrellon et al., 2022)
	Regulations	Duration and pricing conditions	What length of space should be provided to LZs? How to design space and time regulations by vehicle size and technology? What is the typical duration of an operation in each LZ? What is the distribution of operations' durations for each LZ?	
	ICT	Mobile technology for LZ	What is the most suitable mobile technology for involving actors in the efficient use of LZs?	
	Private Operation	Type of vehicle for urban deliveries	What is the most cost-efficient split of vehicle technologies to comply with emissions and traffic restrictions?	
Operational decisions	Infrastructure	Public space management	Which LZs are underutilised and which are fully used at times? What is the demand (i.e. number of vehicles and parking durations) for LZs per time of day? What is the likelihood that a parking stall is available at each LZ at different times of the day?	(Alho et al., 2014; Comi et al., 2018; Delaître and Routhier, 2010; Ezquerro et al., 2020; Galindo-Muro et al., 2020; Gatta and Marcucci, 2016; Letnik et al., 2020; Lopez et al., 2019; Muñuzuri et al., 2019; Nourinejad and Roorda, 2017; Santos Junior and Oliveira, 2020; Zhang and Thompson, 2019; Jaller et al., 2021; Dalla Chiara et al., 2022)
	Regulations	Enforcement mechanisms	Which LZs have the highest number of violations? What are the most common types of violations, types of vehicles and parking durations? What are the features of the most common violators? How can the routing of wardens be allocated and designed?	
	ICT	Users' interactions with LZ ICT	How can a data-sharing scheme be designed to foster the efficient use of LZs?	
	Private Operation	Routing planning	What is the best route based on LZ availability during the day? How many customers should be served per vehicle stop?	

schemes of curbside allocation regulations according to time, type of user, weather, type of commodity, city zone, etc. (Jaller et al., 2021).

A comprehensive view of all the decision levels and interventions can provide a holistic perspective aiming at fostering shared benefits of efficient use of the public infrastructure to the involved stakeholders. Adding the "smart" component to this view of the LZ management implies the definition of data sources, data collection processes, their analytics, and finally, user-oriented data-driven decisions. The scope of this paper is diving deep into data analytics for strategic decisions, i.e., LZ network design. The following sub-section reviews previous research contributions in LZ management at the strategic level.

Literature review on LZ network design

LZ network design, i.e., defining the number and location of LZ, is a strategic decision aiming at both satisfying users' demands and enhancing the proper use of the scarce curbside space (Comi et al., 2017). This review on data-driven methods for LZ network design identified contributions that inform decisions on LZ number definition, LZ service assignment and ICT for LZ monitoring.

Regarding the *LZ number* definition, several studies have taken this number as a system input given by public authorities or road network designs (Aiura and Taniguchi, 2005). Others follow design guidelines or quantitative models that support the definition of this number based on freight operations' needs and curbside capacity (CERTU, 2009). Underestimating this number could provoke double parking and increments in total driving distances (Letnik et al., 2020), but overestimating it could lead to extra costs and negative effects on cities' sustainability (Malik et al., 2017).

One common approach to estimate the number of areas needed to cover freight parking demand is by approximating the ratio D/C. Demand (D) is calculated as the sum of the total establishment's product of deliveries frequency in a week by delivery time, and capacity (C) is the number of time bins by week, e.g., 90 in (Muñuzuri et al., 2017) or 80 in (Alho et al., 2018). This method does not consider that the relationship between the number of deliveries and the number of stops per route is not linear which may lead to an inaccurate consideration of distances between each establishment and LZ (Pinto et al., 2019).

Overcoming this drawback has motivated the development of discrete optimization problems that define the number and size of LZ using deterministic parameters of distance and service time but without considering the multiple establishments that a single vehicle can serve per stop (Dezi et al., 2010; Pinto, Lagorio and Golini, 2019). Comi et al. (2022) proposed a two-step procedure for estimating LZ number using queueing theory and discrete-event simulation, contributing to the modelling of the dynamic and stochastic behaviour of urban freight operations.

The coverage radius of each LZ is one of the constraints for these types of models to represent the maximum walking distance between LZ and establishments. It is assumed as 50 m in (Dezi et al., 2010; Alho and de Abreu e Silva, 2015; Tamayo et al., 2018; Muñuzuri et al., 2019), 100 m in (McLeod and Cherrett, 2011), and up to 200 m in (Ochoa-Olán et al., 2021). Shorter distances contribute to cargo accessibility and are convenient for drivers/porters. In (Santos Junior and Oliveira, 2020), the authors found that a maximum distance of 75 m provides a good level of cargo accessibility service.

Once defined the LZ number, LZ network design requires micro-location assessments and establishments allocation to LZ, i.e., *LZ service assignment*. Contributions to modelling LZ service assignment differ in data collection processes, parameters estimation, modelling structure, and solving algorithms. Freight curbside demand estimations are the most common input for these models. Traffic surveys and sample surveys are traditional approaches to collecting data (Dezi et al., 2010; Muñuzuri et al., 2017; Ochoa-Olán et al., 2021) and support the implementation of Freight Trip Generation (FTG) models (Sánchez-Díaz, 2017). FTG models estimate weekly deliveries using as predictors the number of employees, the total retail area, and the establishments' industrial sector (Gardrat and Serouge, 2016; Alho et al., 2018). The static nature of the collected data, mismatches between stated data in surveys versus real behaviours, aggregation/generalization errors, and the unclear relationship between establishments' freight demand and parking demand, are all pitfalls that remain unsolved in the literature (Ochoa-Olán et al., 2021; Comi et al., 2022).

Besides freight generation, delivery durations are also needed to estimate freight curbside demand. Durations have been a given parameter (Dezi et al., 2010; Letnik et al., 2018), a random value based on observed data (Alho et al., 2018; Pinto et al., 2019), or a dependent variable on factors such as the vehicle type, stop type, the number of stops in the round, the density of the zone and type of activity delivered (Gardrat and Serouge, 2016; Castrellon et al., 2022).

Regarding modelling structure, several optimization procedures have supported decisions on LZ service assignment: warehouse location-routing problem (Aiura and Taniguchi, 2005); maximized capacity coverage (Alho et al., 2018); MinDist-MiniMax approaches (Muñuzuri et al., 2017; Prata et al., 2018); quadratic allocation problem (Tamayo et al., 2018); capacitated maximum covering location; discrete-event simulation (Pinto et al., 2019); and fuzzy *k-means* clustering analysis (Letnik et al., 2018).

In terms of *technology*, several initiatives in Europe have been implemented to improve LZ management (Letnik et al., 2018). Conclusions from these implementations suggest further research in testing dynamic LZ management based on remote technology tools for reservation, use, monitoring and control. Also, some cities in the US have moved on to the installation of stationary technology as in-ground sensors, time-lapse photography, and parking meters (Dey et al., 2018; Dalla Chiara et al., 2022). Evidence showed challenges related to installation and maintenance costs, battery life, sensor communication, manual procedures for data download and analysis, limited space for the technology installation, and accuracy.

This paper sheds light on the need for LZ strategic decisions supported by analytical techniques that capture dynamic parking behaviour through technological implementations. SLZ take advantage of the possibility of big data gathering to overcome the drawbacks of demand estimation. New technologies help incorporate parameters such as walking distances taken from GIS tools, establishments locations, measured durations from the whole population of operations, and greenfield analyses for asymmetric urban morphologies.

Data analytics approach for SLZ network design

This paper proposes a three-step procedure for the SLZ network design shown in Fig. 2. The first step consists of defining the number of LZ for the study area, followed by the optimal service assignment optimization of LZ based on establishments' locations, access to the curbside, and freight demand (second step). Finally, the third step corresponds to the evaluation of stationary technology that will capture data needed for LZ monitoring. In this section, greenfield analysis and integer optimization methods are proposed for steps 1 and 2 respectively, of the proposed procedure for SLZ network design.

Step 1 – Definition of the number of LZ: Greenfield analysis

Greenfield analysis is a traditional tool in facility location problems where a continuous and unrestricted space is explored for deciding infrastructure location. A spatial clustering analysis serves as the first approximation for gravity centres identification, i.e., centroids, and thus the number of LZ that provide service coverage to the establishment from a study area. The data needs, models, and outputs for the greenfield analysis implementation are shown in Table 2.

The *k-means* clustering algorithm is one of the most popular unsupervised machine learning models to make N data partitions or clusters C_i such that $N = \{C_1, C_2, \cdots, C_N\}$. In the context of LZ greenfield analysis, the algorithm clusters each point from the data set $X = \{x_1, x_2, \cdots, x_M\}$, where x_j represents each establishment location, to the closest centroid (gravity centre) calculated. The most widely used clustering criterion is the sum of the squared Euclidean distances between each data point x_j and the centroid n_i (cluster centre) of the subset C_i which contains x_j.

K-means algorithm has had performance improvements such as *k-means++* with a randomized seeding technique for centroids initialization (Arthur and Vassilvitskii, 2006). The authors proposed a modified *k-means++* algorithm to consider actual walking distances and to assign more weight to establishments with higher freight curbside demand. Given that urban form determines paths and walking distances, this change in the algorithm was needed to avoid underestimations of Euclidean or Manhattan distance assumptions for connecting two locations in a city zone with irregular morphologies, i.e., impossible to link by either a straight line or orthogonal trajectories. Also, adding more weight to establishments with higher freight demand makes the algorithm locate clusters' centroids, i.e., potential LZ location, closer to freight-intense establishments. The proposed algorithm is as follows:

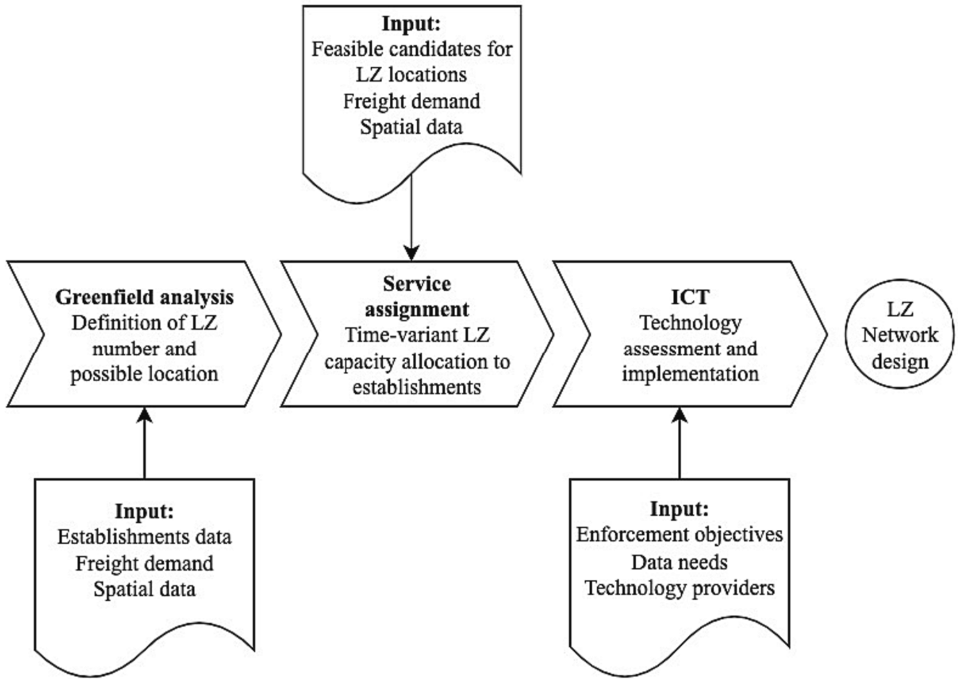


Fig. 2. SLZ network design flowchart.

Table 2
Greenfield analysis workflow.

Input Data	Model	Output
Establishments' location Establishments economic activity Walking distance between establishments Spatial information from the study area (maps, roads…) Vehicles' arrival rates Parking durations	Machine Learning clustering models – performance comparisons are needed to identify the best algorithm (e.g., *k-means, DBSCAN*) based on the urban form	Number of potential LZ Approximate location of the LZ Establishments allocation to potential LZ represented by cluster's centroids.

1. Select a centroid n_1 at random from the data set x.
2. Use **Equation (1)** to calculate the weighted squared walking (WSW) distance from each other establishment in the dataset to n_1, and randomly choose the second centroid n_2 from X according to the observed distances. The higher the WSW distance between x_j and n_1, the higher the chance to pick x_j as centroid n_2.

$$WSW_{j\in M} = \tau_j \|x_j - n_i\|^2 \tag{1}$$

Where:
$WSW_{j\in M}$ = Weighted squared walking distance from establishment j to centroid n_i.
τ_j = Freight parking demand from establishment j.
x_j = Location of establishment j.
n_i = Location of centroid i.
$\|x_j - n_i\|$ = Walking distance using GIS.

Estimation of τ_j depends on data availability. Some studies assume FTG calculations or survey data (Ochoa-Olán et al., 2021). Since LZ app-based management tools commonly record data on vehicle arrivals λ and durations μ, the **Equation (2)** uses these inputs for estimating parking demand per establishment j based on Little's Law from queueing theory (Little, 1961). θ is the acceptable curbside service level that public authorities may expect (Kalahasthi et al., 2022).

$$\tau_j = \frac{\lambda\mu}{\theta} \tag{2}$$

Data availability may allow calculations of λ and μ by commodity type, zone of the city, time of the day, day of the week, etc. Since the model requires demand estimations aggregated by LZ, using data at establishments level will require assumptions about the number of establishments served per vehicle stop. Deterministic factors have assumed 1.5 deliveries/stop (Letnik et al., 2018) or 3 deliveries/stop (Jaller, Holguín-Veras and Hodge, 2013). The definition of this factor can vary depending on establishments area or establishments density in a specified city area. In this paper, parking demand per hour from each establishment was computed according to the following expression based on **Equation (2)**:

$$\tau_{jt} = \frac{\lambda_{kt}\mu_c}{\theta} WA_j^k \tag{3}$$

In **Equation (3)**, λ_{kt} represents the arrival rate calculated with parking data from LZ k at time t. μ_c corresponds to the specific parking duration computed for the economic category c that the establishment j belongs to. θ keeps the interpretation from **Equation (2)** and in this paper it assumes a value of 85 %. WA_j^k denotes the weighted factor for the area proportion that establishment j represents among all the ones that belong to the same cluster k.

3. Repeat the same procedure with subsequent centroids, but instead randomly choose those according to the WSW distance to the closest of the centroids already selected

The algorithm iterates by decreasing ϕ such that,

$$\phi = \sum_{x\in X} min_{n\in N} WSW_{j\in M} \tag{4}$$

K-means++ hyperparameter is the number of clusters N, i.e., number of LZ. Since this information may not be known beforehand, a modified elbow method analysis is proposed to evaluate model outputs based on a 'covering principle' i.e., the longest distance an operator is willing to walk from the LZ (Pinto, Lagorio and Golini, 2019). The algorithm iterates on different values of N until finding the output that satisfies the maximum walking distance d_{max} constraint. After several iterations varying the number of clusters, the 'covering principle' analysis will allow identifying the number of LZ as an input for the service assignment model.

Density-based spatial clustering of applications with noise (DBSCAN) is a different clustering algorithm that avoids the definition of the number of clusters as a hyperparameter as in *k-means++*. This method picks one random point x_i from the data set X, and it attempts to build a cluster by grouping its $\in$−neighbourhoods, i.e., directly reachable points from x_i. The hyperparameter $\in$ is the maximum distance between a pair of points to be considered from the same cluster. The following is the DBSCAN algorithm proposed in (Ester et al., 1996):

1. Select an establishment x_i at random from the data set X.
2. Calculate the distance coverage from establishment x_i and reach all the possible neighbours in a maximum distance $\in$. For LZ greenfield analysis, this distance follows the calculation defined in **Equation (1)**.
3. If no such establishment is available, x_i is labelled as noise.
4. If some are available, for these establishments, their directly reachable establishments are added, and so on, until the cluster cannot be expanded any further.
5. Then, it selects another non-visited establishment and performs the same steps, until all establishments have been visited.
6. We then know the clusters and the noisy points.

In the results section, a performance comparison between *k-means++* and DBSCAN is discussed for the specific case study.

Step 2 – Service assignment model: Integer linear programming

Greenfield analysis provides the estimated number of LZ needed in a city area. A multi-objective optimization model would skip the cluster analysis implementation, solving both the number and service assignment of LZ to establishments. Nonetheless, decision-makers should have known beforehand the possible LZ locations as a model input. In the absence of this knowledge, greenfield analysis represents a convenient approach to first define rough LZ locations. Although, the preidentified clusters' centroids could have been located at unfeasible locations.

The optimization model below adjusts greenfield results by determining the best allocation of LZ to establishments based on feasible LZ locations, i.e., considering curbside features and infrastructure availability. The data needs, models, and outputs of the service assignment model are shown in Table 3.

The proposed optimization model aims at solving the so-called generalized assignment problem (GAP) by examining the minimum cost assignment (i.e., minimum public space use) of a certain amount of jobs (i.e., freight parking demand) to a certain number of agents (i.e., LZ stalls), such that each job is assigned to one agent subject to capacity restrictions of the latter (Cattrysse and Van Wassenhove, 1992). Thus, the model objective is determining the optimum allocation of LZ stalls to establishments that satisfies freight parking demand during the time window t, from establishments located around a maximum walking distance d_{max}.

Table 3
Optimum service assignment analysis workflow.

Input Data	Model	Output
LZ number and location (from greenfield analysis) and list of feasible locations close to clusters centroids	Integer linear programming for LZ service assignment to establishments	Optimum allocation of LZ to establishments
Parking demand Establishments' area		Optimum time-variant number of parking stalls per LZ

The objective function in **Equation (5)** optimizes the demand for public space from L/U operations by minimizing the distance d_{ij} travelled from the LZ i, that belong to the N set of LZ predefined in the greenfield analysis, to the establishment j, multiplied by the binary variable e_{ijt} if an establishment j is served from the LZ i or not, i.e., the movement $i \rightarrow j$ is performed at time t.

$$Min \sum_{i \in N} \sum_{j \in M} d_{ij} \sum_{t \in T} e_{ijt} \tag{5}$$

subject to

$$\sum_{i \in N} e_{ijt} = 1 \forall j \in M, \forall t \in T \tag{6}$$

$$\sum_{i \in N} d_{ij} e_{ijt} \leq d_{max} \forall t \in T \tag{7}$$

$$\sum_{j \in M} e_{ijt} \tau_{jt} \leq S_{it} \forall i \in N, \forall t \in T \tag{8}$$

$$e_{ijt} \in \{0, 1\} \quad \forall i \in N, \ \forall j \in M, \ \forall t \in T \tag{9}$$

$$S_{it} \in \mathbb{N} \forall i \in N, \forall t \in T$$

Equation (6) is the single sourcing condition which also ensures that parking service needs from each establishment j are always satisfied at each time window. In **Equation (7)**, the model restricts walking distance from LZ to establishments d_{ij} to a maximum d_{max}. **Equation (8)** compels the model to satisfy LZ capacity constrain by doing S_{it}, the number of stalls of LZ i, greater than the parking needs τ_{jt} for all the establishments at time t. τ_{jt} is calculated using **Equation (3)** according to establishment cluster features such as area, economic activity, and time of the day. Due to data availability in the case study, λ_i and μ_i are stochastic parameters. Based on **Equation (8)** shadow prices can be analyzed to estimate public space occupation rates. **Equation (9)** establishes the binary character of the decision variable e_{ijt} and the non-negative integer character of the stalls number S_{it}. The number of stalls is obtained following expression in **Equation (10)**.

$$S_{it} = \lceil e_{ijt} \tau_{jt} \rceil \tag{10}$$

Data description from a case study: The City of Vic (spain)

The City of Vic is a town in Catalonia (Spain) located 69 Km from Barcelona with a population of 45,040 and a density of 1,500 inhabitants per Km^2. The main economic activities are food industry, service industry, agriculture, and construction (Statistical Institute of Catalonia, 2021). Fig. 3 shows the location of 348 establishments. The parking data for the study was provided by Parkunload®. The company

Fig. 3. LZ Location in Vic (Spain).

run a pilot test between June 2018 and December 2019 in collaboration with the Vic municipality, where the system was implemented in 8 LZ at the city centre (Fig. 3).

LZ are located between 40 m (LZ2 to LZ3) and 200 m (LZ1 and LZ2) from each other and have different capacities. LZ3 has the lowest capacity with two stalls, and it is 12 m in length, followed by LZ1 and LZ6 with four stalls and 20 to 23 m in length, LZ2 has six stalls and 46 m in length, and LZ7 has 7 stalls and 43 m in length. LZ4, LZ5 and LZ8 are the LZ with the largest capacity, having 8 stalls and between 46 and 49 m in length.

Operations at each LZ were reported using the Parkunload app. Users checked-in once they parked at the LZ, providing information about vehicle size and technology, economic activity, and driver identification. A total of 103,967 operations took place from July 2018 until December 2019. These records correspond to the whole universe of operations in the city centre during the studied period. The number of operations per year and average occupation rates computed according to **Equation (3)** are shown in Fig. 4. Since LZ occupation rates did not exceed 18 % during the observed time window, an assumption of overcapacity makes the analysis of LZ network design pertinent to figure out how to make the most of the available public space.

Drivers also used the app to check-out from the LZ after completing L/U operations. The difference between initial and final time gave the total parking duration. Probability distributions for arrival rates and durations are estimated in (Kalahasthi et al., 2022). Arrival rates followed a negative binomial distribution with specific λ per LZ and time of the day (Table 4). Weibull distribution had the best score in fitting parking durations with estimated μ for economic activities and LZ according to hypotheses tests. Kruskal-Wallis non-parametric test failed to reject the null hypothesis about the no significant difference among parking durations for LZ 1 – 4 and 6 (test statistic H = 9.2895 and *p-value* = 0.0542). The same test rejected the null hypothesis of no significant difference among parking durations per economic activity (test statistic H = 36.9998*p-value* < 0.05), i.e., parking durations vary according to the economic activity as listed in Table 5.

Establishments' data correspond to coordinates of 348 points located around the main street and main square of the city centre where the LZ need to be assessed. Based on OpenStreetMap (OSM) data, manually augmented with data read from Google Maps, for each establishment there are attributes such as economic activity (category and subcategory), total area (m^2), and access points on the road. Walking distances among establishments, from them to the cluster centroids – used in the greenfield analysis –, and from them to the LZ – used in the service assignment optimization – were calculated using Google Maps API 4.4.5 function in Python 3.7.10.

Table 4
Arrival rates.

	λ(vehicles / hour)							
	LZ1	**LZ2**	**LZ3**	**LZ4**	**LZ5**	**LZ6**	**LZ7**	**LZ8**
8 h	2.67	3.25	1.91	5.53	6.46	2.77	5.00	4.67
9 h	2.67	3.62	2.06	6.56	7.96	3.22	5.90	4.96
10 h	2.21	3.32	1.96	6.17	7.17	2.92	5.12	4.59
11 h	1.23	1.93	1.24	3.33	3.63	1.71	2.77	2.84
12 h	0.53	0.72	0.50	1.32	1.35	0.73	1.13	1.21
13 h	0.60	0.78	0.57	1.28	1.29	0.63	1.19	1.38
14 h	1.00	1.31	0.92	2.09	2.93	1.19	2.38	2.40
15 h	1.17	1.43	1.10	3.01	4.40	1.66	3.27	2.74
16 h	0.84	1.23	0.87	2.82	3.58	1.41	3.03	2.48
17 h	0.76	0.85	0.50	1.81	2.68	0.87	1.98	1.56
18 h	0.35	0.28	0.13	0.59	0.93	0.28	0.52	0.38

Source: Modified from (Kalahasthi et al., 2022).

Table 5
Parking durations.

	μ(min)			**Economic Activity**	μ(min)	
LZ	**Mean**	**Std. Dev**			**Mean**	**Std. Dev**
				Unspecified	22.33	11.58
LZ 1	18.30	11.68		Install & Maintenance	14.71	10.57
LZ 2	17.46	11.35		Transport & parcels	22.18	11.54
LZ 3	17.77	11.68		Construction	19.04	11.58
LZ 4	17.27	11.22		Local commerce	20.15	11.19
LZ 5	18.06	11.51		Commercial Agent	14.86	10.40
LZ 6	18.00	11.64		Food and Markets	16.23	10.66
LZ 7	17.74	11.58		Automotive	16.00	11.65
LZ 8	17.80	11.65		NA*	15.77	10.71

*NA = Not applicable.
Source: Modified from (Kalahasthi et al., 2022).

Data analytics implementation and discussion

The scope of this case study starts from a greenfield analysis that would evaluate the number of LZ and their service coverage along with LZ size definitions. By having this approach, the authors contrasted the current network design (base case with the current LZ locations and sizes) against the proposed network design resulting from the SLZ data analytics approach for strategic decisions.

Greenfield analysis

Greenfield analysis compared the performance of the DBSCAN and *k*-

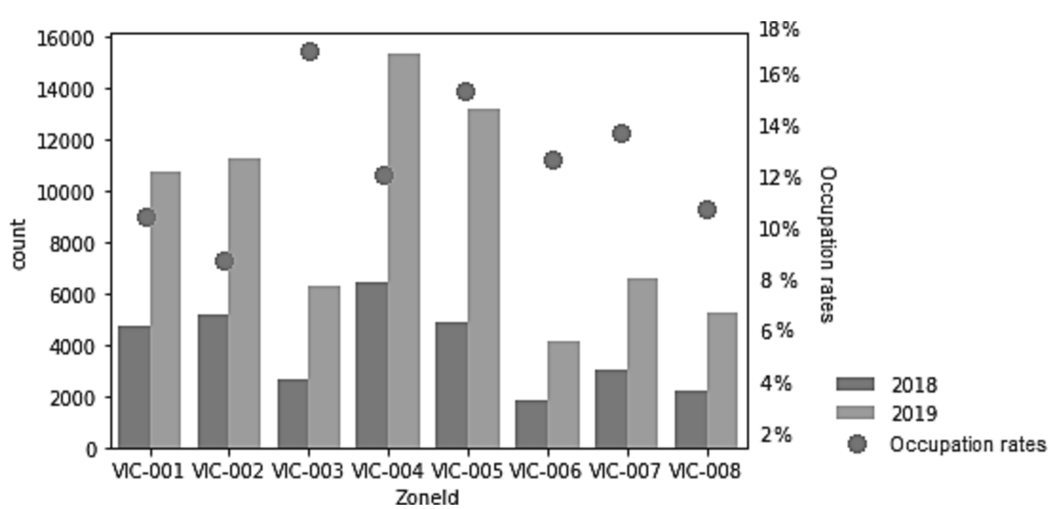


Fig. 4. (Un)loading operations per LZ in Vic.

means++ algorithms from the Scikit-learn library. Comparison metrics corresponded to the number of establishments outside the 75 m walking distance from the cluster centroids. The walking distance threshold was selected as 75 m based on results from (Santos Junior and Oliveira, 2020). The analysis began with DBSCAN since it does not require a predefined number of clusters. Instead, it needs a hyperparameter ε as the maximum distance between two establishments to be considered within the same cluster. Different ε values from 30 m to 75 m were tested to evaluate the best performance based on the 'coverage principle' metric.

Results showed that $\varepsilon = 0.47$ was the cutoff point. Diminishing rations in the performance metric are no longer worth with additional reduction in ε. With this hyperparameter, the number of clusters was five (5) as shown in Table 6. $k = 5$ was also defined as a hyperparameter for the *k-means*++ algorithm according to 'coverage principle' metric.

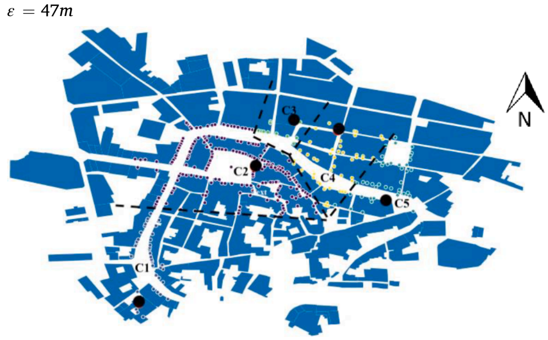
Greenfield analysis concluded that five (5) centroids can cover, in a walking distance no greater than 75 m, 67.5 % and 83.9 % of the establishments in DBSCAN and *k-means*++ algorithms, respectively. Nonetheless, their location could not be feasible according to city plans for LZ, but they provide an estimate on the number of LZ that suit establishments' needs in terms of distance, i.e., LZ service coverage.

The main difference between DBSCAN and *k-means*++ is that the former looks for connectivity while the latter search for compactness. In other words, DBSCAN (Table 6 **a**) group establishments based on how close they are to each other while *k-means*++ (Table 6 **b**) group them based on how close they are to the centroid. This latter logic is more suitable for the purposes of LZ location since the aim is to minimize the distance between LZ (cluster centroid) and establishments. Nonetheless, algorithm performance will strongly depend on the urban form.

Results from the greenfield analysis provided a general grasp of the

Table 6
(a) DBSCAN, (b) *k-means*++.

(a) DBSCAN $\varepsilon = 47m$



Cluster	#Est.	Area avg.	Area std.	Walking distance metrics	
C1	39	292.69	129.03	mean	62.304
C2	204	224.80	152.22	std.	48.222
C3	13	386.23	153.04	25 %	28.000
C4	48	352.91	185.83	50 %	58.000
C5	44	424.31	154.22	75 %	79.000
Total	348			113 establishments above 75 *m*	

(b) *k-means*++ $k = 5$

Cluster	# Est.	Area avg.	Area std.	Walking distance metrics	
C1	40	293.25	127.41	Mean	39.465
C2	88	240.65	142.65	std.	35.966
C3	75	247.64	194.34	25 %	8.000
C4	75	229.02	137.91	50 %	29.500
C5	70	418.14	164.73	75 %	62.250
Total	348			56 establishments above 75 *m*	

need for establishments' connectivity and accessibility to LZ. Clustering analysis allowed the assessment of LZ service coverage needs based on both walking distances and how intense the freight activity was for each establishment. According to the results, DBSCAN seems to be more suitable for portering operations that imply walking from one establishment to another after parking in a LZ. This fact is evident when evaluating the number of establishments per cluster. C2 is the most densely populated since it connects 204 establishments located near the city's central square (58.6 % of the total demand). Nonetheless, when analyzing distances from the centroid to establishments, the threshold of 75 m is violated in more than 25 % of the cases. This condition led to the decision of choosing *k-means++* results as the input for the location-allocation optimization.

Both algorithms grouped bigger establishments assumed to have more intense freight activity, into a separate cluster, i.e., C5, which corresponds to the furthest zone from the city's central square. Subsequent analysis on tactical decisions regarding durations, pricing and LZ dimensions should consider this condition to differentiate LZ management.

K-means++ results allow decision-makers to have a first approach to strategic decisions related to how many LZ a specific city area needs, where they should be located and the estimated demand for public space at different locations. Matching clustering results to space availability and city plans for LZ is a unique process for every city and even for every city area, so conclusions about the best algorithm for greenfield analysis could not be generalizable. For the case of Vic centre, *k-means++* performed well keeping most of the establishments within a 75 m radius and the centroids closer to valid LZ locations.

By matching centroid locations from the *k-means++* algorithm with the city plan for LZ, i.e., current LZ locations at the case study, the following LZ were selected as the input for the location-allocation model: LZ1 (C1), LZ4 (C2), LZ5 (C3), LZ6 (C4) and LZ8 (C5). Under this selection, around 96 % of the establishments satisfied the walking distance constraint from at least one of the LZ.

Service assignment model

The extended educational license of Lingo® 18.0.56 run the optimization model described for LZ service assignment. A total of 17,450 variables, 3,540 constraints and the branch-and-bound solution method were required for solving this integer linear programming problem. Fig. 5 shows the number of stalls allocated after convergence per LZ during the day computed using **Equation (10)**. Maximum system capacity at peak hours optimized the base case by almost 80 %. Fig. 5 also presents occupation rates during the day at each LZ based on the shadow price analysis from capacity constraint in **Equation (8).**

The optimized service assignment to establishments had a significant impact on occupancy levels, as demonstrated by the results. Average occupancy levels increased from 18 % in the current scenario to 80 % in the optimized scenario, while also freeing up curbside space for other users, as freight operations varied throughout the day. The total number of LZs was reduced from eight in the current scenario to five in the optimized one. The number of stalls at each LZ needed to satisfy freight parking demand was also reduced, e.g., maximum stalls activated (current → optimized) in LZ1: 4 → 2, LZ4: 7 → 2, LZ5: 8 → 4, LZ6:4 → 1and LZ8: 8 → 1.

The objective function had its minimum value at 13,021 m after convergence, meaning the total distance covered from the assigned LZ to

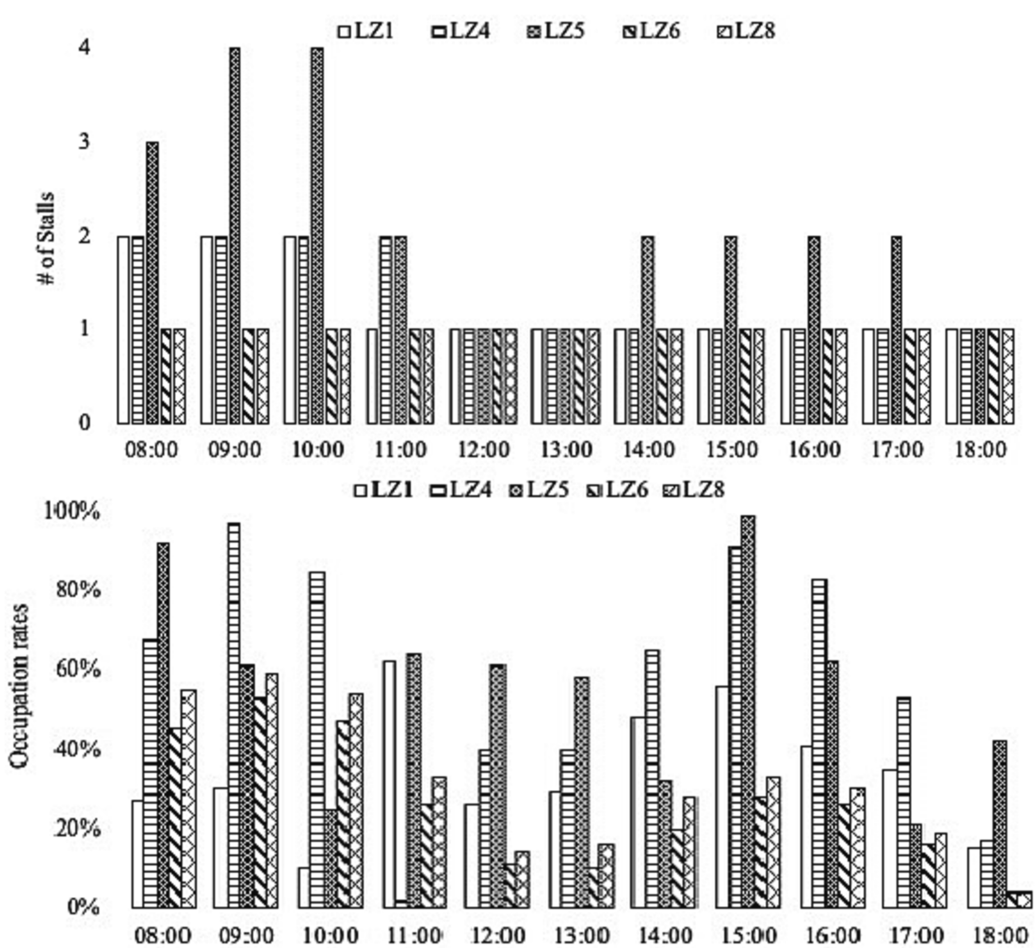


Fig. 5. Number of stalls per LZ (top) and occupation rates (bottom).

establishments. Given the case study conditions regarding the LZ infrastructure oversupply, upper limits for the variable S_{it} did not represent a bounding constraint. However, this might not be the case for conditions where there is limited infrastructure for freight parking operations. In those cases, the sensitivity analysis should consider an additional capacity constraint, i.e., $S_{it} \leq K_{it}$, where K_{it} is the maximum number of stalls at LZ i as used in (Muñuzuri et al., 2017). While changing the maximum walking distance limit, i.e., d_{max}, made the objective function sensitive to reach feasible solutions. Although service coverage was enhanced by allocating LZs to establishments within walking distance of no more than 75 m, this constraint was relaxed up to 130 m in the sensitivity analysis due to 6 % of the establishments were left out of the 75-meter range. Despite this constraint relaxation, the upper limit of 130 m is still convenient in last-mile deliveries as reported in (Ochoa-Olán et al., 2021).

The service assignment optimization model provided the tools for answering how many stalls should be available during the day at each LZ and the establishments allocated to each LZ. Unlike greenfield analysis, service coverage is not the only target at this step, but also the efficient use of the scarce public space. By dynamic sizing of LZ during the day, unoccupied places can be destined for alternative uses, i.e., pedestrian space, bikes, or private vehicles parking. Case study results confirmed the assumption of LZ overcapacity and provided a clearer idea to decision-makers about freight space allocation. The proposed two-step method thus expands upon past research (e.g., Comi et al., 2022) by considering the stochastic behaviour of parking demand by using big data about parking operations and flexible sizes of LZs across time.

Conclusions

The paper deployed a data analytics approach for SLZ network design, starting with the definition of the SLZ concept itself and the scope of the strategic, tactical, and operational decisions. The study focused on the strategic decisions for SLZ network design. Through a case study, machine learning and optimization methods illustrated the use of app-based data to support decisions and the potential policy implications of using data analytics for LZ network design.

When planning LZ infrastructure, public policy agencies face the trade-off between land use optimization (urban plans) and service provision (need for efficient operations). The deployed SLZ modelling approach allows decision-makers to find equilibrium in their choices based on clustering analysis for the need for service provision, and service assignment optimization for the adequate scarce public space allocation to freight operations. For instance, dynamic urban land use for LZ, e.g., per hour, provides a solution to find that system equilibrium.

The proposed data analytics approach for strategic decisions demonstrated the feasibility of designing an SLZ network using app-based systems to collect relevant data on parking demand. The SLZ features constitute the advantage, compared to traditional collection methods, of having measured data from the whole universe of parking operations, instead of samples or stated data from freight surveys. SLZ also implies software capabilities on GIS and machine learning that unlock the possibility of dynamic decisions over time, based on real-time data feedback and ongoing validations.

Research on tactical and operational aspects of LZ management is needed to complement strategic decisions. Simulation techniques and big data analytics are on the agenda to further research that informs these decisions. Also, guidelines for gathering data, technologies assessment, data analytics and their practical implications can be the focus of future research.

Authors contribution

Juan Pablo Castrellon: study conception and design, analysis and interpretation of results, draft manuscript preparation. **Ivan Sanchez-Diaz:** study conception and design, data collection, analysis and interpretation of results, reviewing and editing. **Jorge Gil:** data collection, analysis and interpretation of results, reviewing and editing.

CRediT authorship contribution statement

Juan Pablo Castrellon: Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Ivan Sanchez-Diaz:** Conceptualization, Funding acquisition, Writing - review & editing, Supervision. **Jorge Gil:** Data curation, Writing - review & editing.

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

The data that has been used is confidential.

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