Enhancing Last-Mile Logistics Efficiency: A Geospatial Perspective from Casablanca's Urban Landscape

Hermann D. Kakpeu O.Dribel O.Benhlima F.Riane

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Abstract

In our study, conducted within the Moroccan context, we adopt a thorough methodology to strategically determine optimal parcel locker locations. This involves integrating clustering techniques based on attractors, population density, and surface area, utilizing the Huff model. By combining these factors, we aim to improve the precision and contextual relevance of our location selection process. Our approach provides a comprehensive and effective strategy for identifying the most suitable locations within the Moroccan last-mile delivery landscape.

1 Introduction

With the rise of e-commerce and the increasing demand for delivery services, the need for efficient parcel delivery solutions has become more prominent. Delivery solutions relying on home delivery face the challenge of delivery failures[Kawa, 2020], highlighting the need for a more efficient solution. Opting for collection and delivery points proves to be a more effective strategy for optimizing last-mile delivery, categorized into two primary forms: pick-up points and automated locker boxes, commonly referred to as parcel lockers or smart lockers. Pick-up points are predominantly found within retail stores and commercial establishments, offering a convenient option for customers to collect their parcels. The parcel lockers serve as temporary storage units for parcels, permitting customers to retrieve their items within a designated timeframe by utilizing their unique order code reference. [Lagorio and Pinto, 2020]. The intricate nature of last-mile logistics demands a high degree of efficiency. Achieving optimal functionality in parcel lockers necessitates the careful consideration of various factors. Extensive literature highlights several challenges, among which the configuration of parcel lockers holds significance. This involves decisions regarding the size of the lockers and the composition of the locker mix, encompassing mobile and static parcel lockers. [Montreuil and Faugere, 2017] assert that providers must deliberate on the number of modules per station and the specific type of modules employed. Within the context of the sharing economy, the collaborative approach, which seeks to distribute costs, tasks, and benefits, emerges as a promising concept and has garnered increasing attention in recent scientific literature. Notable studies in this domain include those by [Zhou et al., 2018] and [Fernandez-Anez et al., 2018]. Furthermore, in the pursuit of enhancing parcel locker efficiency, the challenge of optimal location selection emerges as a crucial aspect within the broader framework of last-mile logistics, affecting the willingness of customers to use the stations. We introduce the notion of attractors defined as the locations that are easily accessible and most likely to be visited regularly by potential future users. [Iwan et al., 2016] This may include for example supermarkets, train stations, and service stations.

In our study, we employed a clustering technique to minimize processing time issues by grouping attractors based on their proximity. This resulted in the identification of several dense zones. Subsequently, we applied the Huff model to each cluster, incorporating an attractiveness function based on the size of the attractor, its population density, and its accessibility.

2 Literature Review

Parcel lockers have gained increasing prominence for last-mile delivery in the realm of e-commerce. These lockers play a pivotal role in supporting the sharing economy by offering a convenient and secure avenue for users to both retrieve and deposit parcels. Their utilization aligns with the principles of resource sharing, enabling individuals to conveniently collect or deliver packages at these designated locations. By leveraging parcel lockers, users benefit from a streamlined and efficient process that minimizes complexities associated with last-mile delivery. This approach signifies a shift towards collaborative solutions within the sharing economy, presenting a promising remedy to the persistent challenges of last-mile logistics.S.Moslem (2023)
The literature focusing on parcel lockers has experienced a notable surge in recent years, underscoring the manifold advantages associated with these delivery systems.
Recent literature explores diverse aspects of optimizing parcel locker strategies for last-mile delivery. Yunusoglu (2023) focuses on effective parcel locker location and pricing decisions to enhance customer service. Rolf (2023) advocates for mobile parcel lockers transported via cargo bikes to streamline the costly last-mile delivery process. Sawik (2022) emphasizes automated parcel lockers (APLs) in urban logistics, employing simulation and optimization to solve facility location challenges. Liu (2022) introduces mobile lockers for urban last-mile delivery. Ma (2022) delves into self-collection concepts like parcel lockers, proposing a dual-perspective framework linking consumer research and operations management. Lyu (2022) investigates the 'Locker Alliance' in Singapore, focusing on network installation challenges and optimizing last-mile parcel delivery.
Wang (2022) explores parcel locker location selection by considering uncertain demands and optimizing locker counts at each location. Yalcin-Kavus (2022) proposes a hybrid decision-making framework for identifying optimal locker locations in Istanbul. Yu (2021) focuses on parcel locker pricing in urban logistics, utilizing a Traveling Salesman Problem model to analyze cost changes. Prandtstetter (2021) investigates last-mile challenges in the courier sector and examines the impact of parcel lockers on delivery efficiency. Lin (2020) presents two formulations for locker location problems and employs a Mixed-Integer Conic Quadratic Programming approach. Additionally, Lin & Wang (2020) introduce a quantitative approach for optimal locker locations, considering customer choices within self-service locker systems. Giuffrida (2016) evaluates Parcel Lockers' efficacy in minimizing missed e-commerce deliveries, comparing their costs and environmental impact against traditional Home Delivery methods.

The location of parcel lockers is important in attracting customers and maximizing profit.To increase their utilization rate and derive benefit from them, it's crucial to place them in suitable areas that ensure customer satisfaction while reducing costs. Attractors play a crucial role in the efficiency of parcel lockers. Key attractors for parcel lockers include improved access to goods, reduced travel for consumers and delivery vehicles, lower costs for delivery service providers, convenience for addressees, reduced environmental pollution and traffic congestion, and positive consumer perception.
Several studies have been conducted to address the issue of location selection, aiming to ensure the efficiency of parcel lockers. These studies focus on identifying optimal locations for placing parcel lockers, considering factors such as proximity to customers, accessibility, convenience, and cost-effectiveness. The goal is to strategically position these lockers to enhance their usability and accessibility for both senders and recipients of parcels. To achieve this, various points of attractiveness are studied, representing locations where users prefer the presence of parcel lockers nearby. According to the literature review, commonly favored points of attraction include supermarkets, shopping centers, and routes used for commuting (Table 2).
Considering these factors, it becomes essential to account for user preferences, accessibility, and proximity to frequented locations. This approach optimizes the placement of parcel lockers, catering to user needs effectively while streamlining operational efficiency.

3 Methodology and results

3.1 Data Collection

Our area of study is The city of Casablanca and its outskirts Bouskoura, Dar Bouazza and Mediouna. We collected attractors data from Overpass turbo which is an openstreemap API that provides access to geographic data. We collected information on various attractors such as supermarkets, train stations, and service stations using the Overpass turbo API, which allowed us to access geographic data from OpenStreetMap. the dataset contains longitude, latitude, name, and type for each Attractor. We then extracted the road network of Casablanca with OSMnx, a python library for retrieving, modeling, analyzing, and visualizing OpenStreetMap street networks. it is a graph of 75431 nodes and 198918 edges. We used the data collected from Overpass turbo and OSMnx to analyze the proximity and accessibility of various attractors in the study area. size and footprint area of attractors were retrieved by the measurement tool of Google Earth. Given the heterogeneous nature of data sources at our work, the need for robust strategies and models to effectively harness this data cannot be overstated. As illustrated in the research conducted by Basal (2012), one prominent approach is the utilization of data ETL (Extract, Transform, Load) tools.

In our context, where we encounter a diverse array of data types, ranging from structured to semi-structured data, employing an ETL approach emerges as a pivotal strategy. This method entails extracting data from disparate sources(OpenStreetMap, Google Earth and worldpop), transforming it into a consistent and structured format, and loading it into a structured dataset.

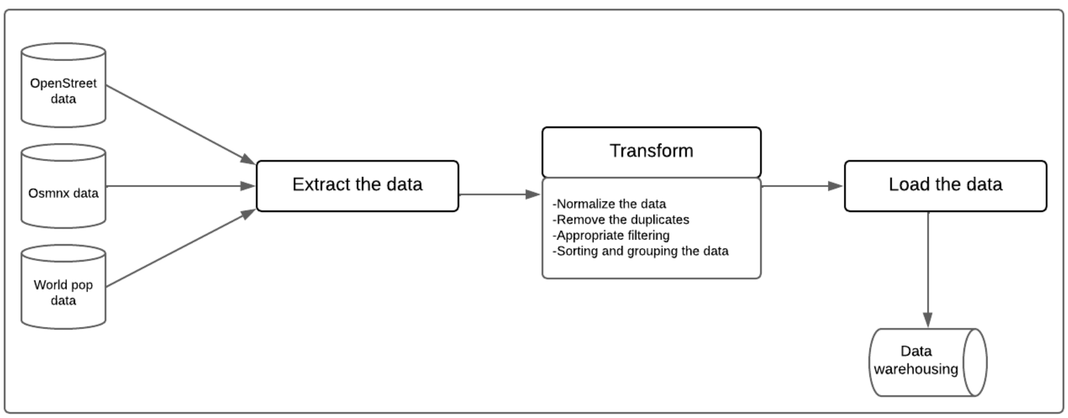
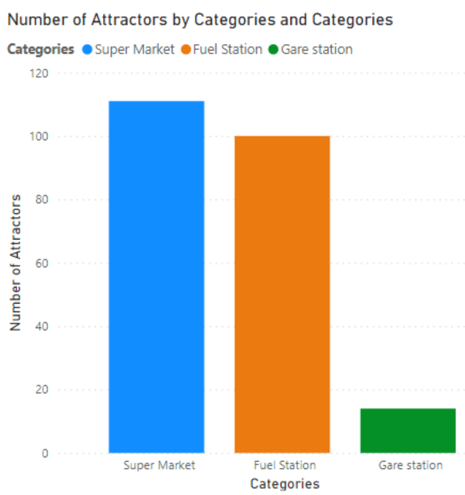


Figure 1: ETL approach

During the extraction phase, we retrieve data from diverse source systems, encompassing databases like OpenStreetMap, OSMnx, and WorldPop. These datasets are heterogeneous, residing in varied formats such as XML files and flat files. In the subsequent transformation phase, our primary objective is to refine the extracted data, ensuring its consistency, accuracy, and suitability for analysis. This phase involves a sequence of operations, including normalization, cleaning, and sorting, aimed at standardizing and augmenting the quality of the data. Finally, in the loading phase, the refined data is transferred into the data warehouse, marking the culmination of the ETL process. This prepared data is now ready for in-depth analysis and visualization, facilitating informed decision-making and insightful discoveries in our research endeavors.

In order to apply the Huff Model, we needed to calculate the probability of a consumer visiting an attractor based on its attractiveness and the distance between them. and for that we collected information on population density in the study area from a very known site web called worldpop. what would have been perfect would be to get a survey of households in the study area which contains real choices made by households regarding their preferences and behaviors towards different attractors in the study area. But in this study we generated our own dataset by assuming that the probability of visiting an attractor is solely determined by its distance as it is done in many other studies (Citer). Therefore, we acknowledge that there might be limitations in this data collection method, as it does not account for consumer preferences and behaviors. we could make a survey in the future to gather more accurate and detailed information on household preferences. Figure 1 **??** shows population density overlaid by a total of 225 attractors .



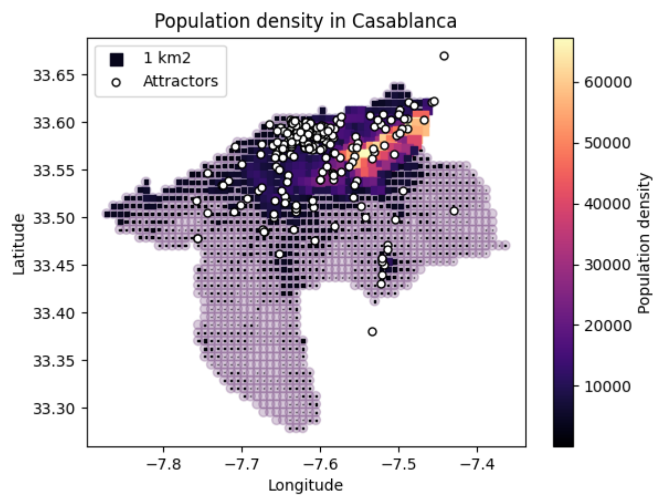


Figure 2: total attractors by categories Figure 3: Study area and population density with attractors locations.

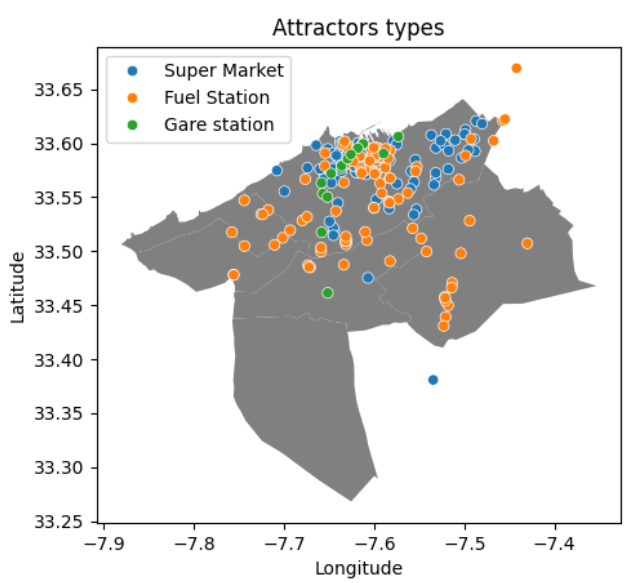


Figure 4: study area overlaid by Attrctors categories

3.2 Method for parcel locker location determination

This comprehensive approach ensures a well-rounded dataset for our study, facilitating a thorough analysis of optimal parcel locker locations in the dynamic urban landscape of Casablanca. By incorporating data on population density, proximity and accessibility of various attractors, and the road network of Casablanca, our study aims to determine the best locations for parcel lockers in the city that will maximize convenience and accessibility for residents and minimize costs for the companies. Attractors are defined as points of interest, infrastructures or locations that are likely to attract consumers. these PO are qualified by DHL, Laposte and InPoste in a study conducted by as high-demand locations for parcel deliveries and pickup. Once we have all the attractors, one might naively decide to place a parcel locker next to each attractor or subdivide the city into small equal-sized grid cells and place a parcel locker next to an attrctor in each cell. This would cover the maximum number of potential customers but may lead to inefficient use of resources and may result in overlapping coverage areas and increase costs. to adress that issue, in this paper, we first of all clustered the attractors based on their spatial proximity and population density utilizing a K-means clustering algorithm with a custumed distance metric that considers the road network connectivity between attractors in our study area. K-means is an unsupervised machine learning methodology designed to partition a dataset into distinct, non-overlapping groups. The Kmeans algorithm makes use of a distance metric (generally Euclidean) and aims to identify centroids for clusters where the intra-cluster variability is minimized, consequently reducing the inertia or the sum-of-squares criterion, as expressed in equation 1..

$$I = \sum_{j=1}^{k} \sum_{i=1}^{n} ||x_i^{(j)} - c(j)||^2 \tag{1}$$

In order to consider the geospatial nature of the data and the real traffic conditions in the city's road network, we employed, in this study, the length of the shortest path between two points in the road network as distance metric in our K-means algorithm, thereby forming distinct zones shown in figure 6.

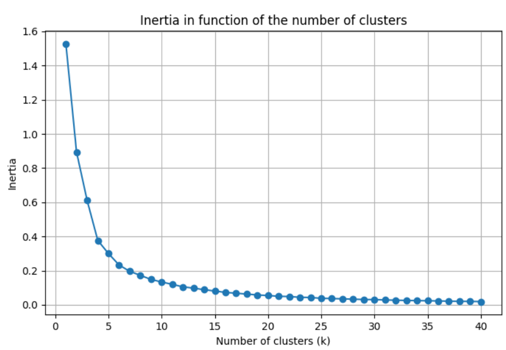


Figure 5: Elbow method

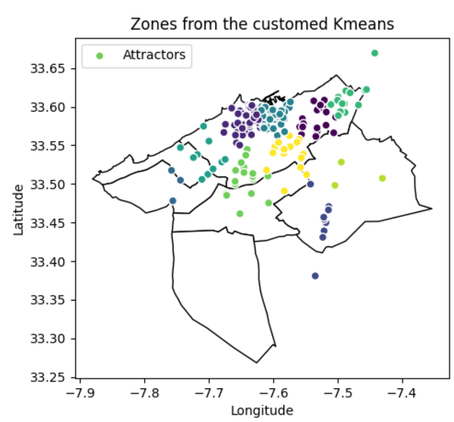


Figure 6: Clusters of attractors after Kmeans algorithm

Once the clusters have been formed, We applied the Huff Model to estimate the potential demand for each attractor in each cluster creating a ranking of attractors based on that estimated demand. This ranking of attractors, combined with the clustering results, allows us to identify the most important and densely populated areas within each cluster, which will then be suitable places for parcel lockers. The Huff Model is a widely used predictive model mostly used in retail location analysis, which takes into account the attractiveness of each location and the distance decay effect on consumer behavior (Direct, 2005)(Hong Shin, 2018)(Suárez-Vega et al., 2014). it states that the probability of a customer choosing a particular location is proportional to the attractiveness of that location and inversely proportional to the distance between the customer and the location. the probability P_{ij} for an inhabitant in location i to prefer a parcel locker situated next to an attractor j is given by the formula 2 :

$$P_{ij} = \frac{U_{ij}}{\sum_{k=1}^{N} U_{ik}} \tag{2}$$

where U_{ij} is the relative utility of the attractor j from the view of a client i. It is a ratio between an attractiveness function and the distance separating inhabitants from attractors : $Uij = A_j^{\alpha}/Dij^{\beta}$ where A_j represents the attractiveness of attractor j

$$U_{ij} = \frac{A_j^{\alpha}}{D_{ij}^{\beta}} \tag{3}$$

where Aj represents the attractiveness of attractor j and Dij represents the distance between location i and attractor j. The parameters a and b control the relative importance of attractiveness and distance in determining customer. β controls the customer´s willingness to overcome a certain distance and α is used to adjust the sensitivity of the model to Attractiveness. in order to determine the parameters α and β in the Huff Model, we use Particle Swarm Optimization (PSO) algorithm, which is an heuristic population-based optimization technique inspired by the social behavior of bird flocking or fish schooling (Yang et al., 2020).

The fundamental idea of PSO is to evolve a population of potential solutions (represented as "particles", (α , β)) within the search space based on their performance to solve a given optimization problem (minimize the fitness function in our case). Each particle in the PSO algorithm represents a potential solution and moves within the search space at a certain velocity, influenced by its own previous best performance and that of the best neighbor particle in the search space. The concept is that particles will cooperate and mutually influence each other to converge towards the best possible solutions.

To apply the PSO, we first define the fitness function to be optimized, which in this case is the sum of squared differences between observed and predicted demand values (see formulas 3).

$$F_{\alpha\beta} = SSE = (Observed - H(\alpha, \beta))^2 \tag{4}$$

Observed choices of customers are used to calculate the observed demand values, while the predicted demand values are obtained using the Huff Model.Because of the absence of real data derived for example from surveys and due to a lack of precise knowledge about the choices usually made by customers in our study area, we generated observed data with the simplified assumption that customers choose parcel lockers location based on the attractiveness of the nearby attractors and the distance to their location following this principle :

1. for each customer i we determine two options : the first one is the facility (attractor) with the greatest attractivity in the list of attractors located within a buffer of diameter γ around i , and the second is the one with the shortest distance to i among the same set of attractors or above γ.

2. then we randomly choose one option between the two trough a bernoulli trial with a probability of success defined as the ratio of the attractivity of the chosen option to the sum of the attractivities of both options.

This simple generation approach to simulate the customer choice behavior in selecting parcel lockers location is justified because in real life, attractiveness only matter below a certain limit distance the customer is willing to travel. beyond that, almost only distance matters.

Then, equally to what [Suhara, 2019] did, we determined the attractiveness function Aj by integrating internal and external factors. The internal factor refers to a characteristic directly linked to the attractor such as its size and the external ones refer to its environment characteristics such as the population density around it and its accessibility. As accessibility metric, we employed an isochronic measurement of accessibility that defines accessibility as the number of opportunities O_j or reachable destinations (Here attractors) within a given travel time threshold from a specific location (citer) :

$$Acc_i = \sum_j O_j f(c_{ij}) \tag{5}$$

We integrated multiple factors to determine the attractiveness function Aj as explain in [Suhara, 2019]. the first one is the size S_j as in many others studies ([Suárez-Vega, 2015], [Wang, 2016], [Yue, 2012], [Ratti, 2006]). Secondly, Considering that attractors are focal points of significant traffic [Lagorio, 2020], we considered the isochronic accessibility factor which is the number of opportunities (here attractors) from which access to j is obtained by traveling less than 1 kilometer [D. O'Sullivan and Shearer, 2000] : Acc_j. And the last one is the total population density PD_j in a one mile buffer zone around j. with this factor, The attractiveness of attractor j increases with the number of population residing nearby. Considering all that, the attractiveness function we used in this paper is shown in equation 3. For each type of attractor, we calculated the α and β parameters of the Huff model (see Table 1) using the Particle Swarm Optimization (PSO) heuristic optimization method :

$$A_j = S_j * Acc_j * PD_j \tag{6}$$

$$U_{ij} = \frac{S_j * Acc_j * PD_j}{D_{ij}} \tag{7}$$

Attractor s type	α	β
Transport stations	0.041	1.215
Fuel stations	-0.038	0.771
Super Markets	-0.103	0.939

Table 1: Results of the Huff model parameters obtained through the PSO heuristic optimization method

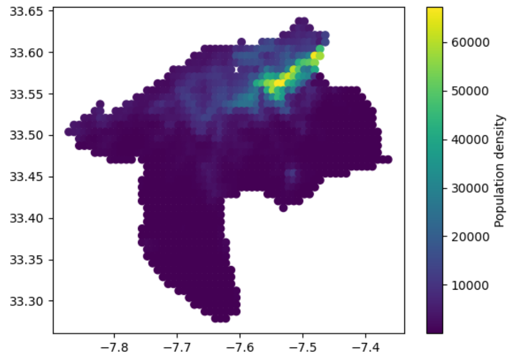
With these parameters, we applied the Huff model to each type of attractor to determine the optimal locations for parcel lockers within each cluster. Results for supermarkets and gas stations are depicted in Figure 12.

4 DISCUSSION AND CONCLUSION

The methodology we employed to determine optimal parcel locker locations in the Casablanca region integrated various geospatial data, including attractors, road networks, and population density. Using an approach based on the Huff model and PSO heuristic optimization method, we identified the most suitable locations for installing these lockers, considering the characteristics of each cluster and attractor type.

The results, depicted in Figure 12, provide valuable insights for logistics planning and deploying parcel locker networks in urban areas. We observe that the results generated by our Huff model prioritize population density for supermarkets and accessibility for gas stations. This aligns with intuitive expectations. In a future study, we may decide to choose through the aid of a well-elaborated multicriteria decision support system. By integrating geospatial data with optimization methods, our study offers strategic perspectives for enhancing last-mile delivery efficiency and meeting the growing demand for e-commerce services.

In conclusion, our approach combines advanced data analysis techniques with optimization methods to pinpoint the best locations for parcel lockers in a dynamic urban environment. These findings can



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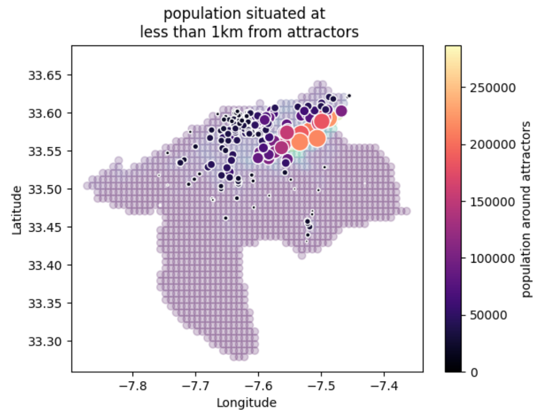

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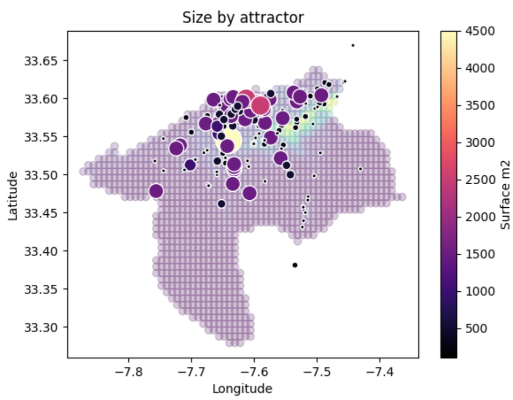

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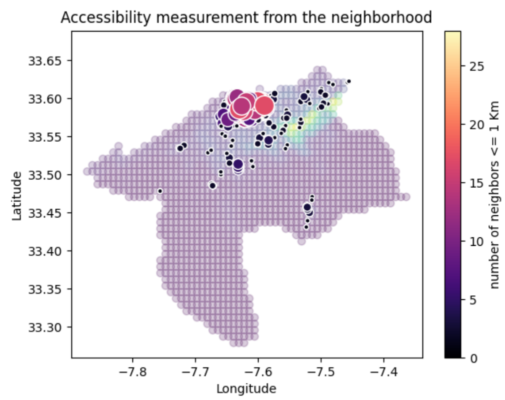

Figure 10:

Figure 11: Integrated data visualisation

inform strategic decisions for logistics companies and urban planners, contributing to the development of sustainable and efficient urban logistics solutions.

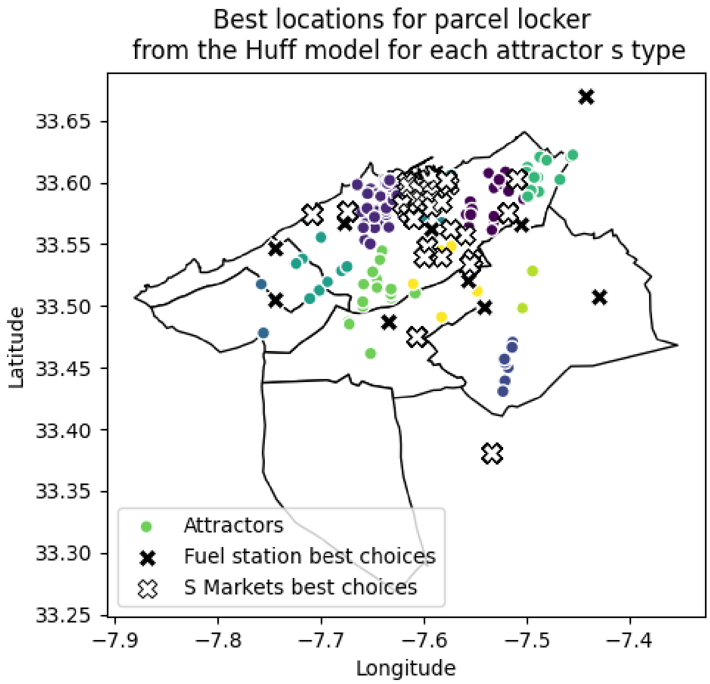

Figure 12: Optimal locations determined by the Huff model for each cluster and by type of attractor

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