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Hidden Carbon Emissions Induced by Functional Curbside Capacity Loss in Urban Freight Systems

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Abstract

Curbside saturation in dense commercial corridors compromises the sustainability of last mile logistics. This study investigates the impact of "authorized but non functional occupancy" (Class S), referring to service and tradespeople vehicles, on the operational capacity of loading and unloading zones (LUZ). Based on direct field observations of 474 real vehicle entries in a zone in Zaragoza (Spain), an Erlang B no wait queuing model (M/M/1/1) using weighted occupancy time was applied to contrast current saturation levels with a regulated functional scenario. The results demonstrate that the infrastructure is structurally sufficient: removing inefficient uses reduces traffic intensity from 1.31 to 0.48 Erlangs, increasing service potential by 121.84%. Class S was identified as consuming 36.62% of the lost capacity, exceeding the impact of unauthorized private cars. Total Hidden Carbon Emissions (HCE) amounted to 45.34 kg CO_2, establishing an environmental impact of 0.066 kg CO_2 per misused linear meter. The study concludes that proper utilization of loading zones is sufficient to accommodate logistics demand and effectively reduce CO_2 emissions.

Keywords: urban freight logistics; loading and unloading zones; carbon emissions; last mile delivery; urban sustainability; curbside management; functional capacity loss

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1. Introduction

Urban freight transport relies heavily on the availability of curbside space to perform loading and unloading operations close to delivery destinations. Ghizzawi et al. (2024)[1] define this space as a critical interface where commercial vehicles must temporarily access public areas while minimizing disruptions to traffic circulation and pedestrian activity. However, curbside infrastructure is increasingly subject to intense competition from multiple urban uses, including passenger transport, service vehicles, and private cars. Alho et al. (2018)[2] argue that this competition transforms the curb into a structural bottleneck that limits the efficiency of metropolitan logistics. As urban freight demand continues to grow due to the expansion of e-commerce and last mile delivery services, the management of this resource has become a priority for city planners. Ma et al. (2022)[3] highlight that the "instant delivery" paradigm has multiplied stop frequencies, making the efficient allocation of space a critical issue for balancing mobility and environmental sustainability.

When delivery vehicles arrive at a loading and unloading zone (LUZ) and find it occupied, drivers often adopt alternative operational behaviors to complete their tasks. Amaya et al. (2023)[4] have documented that these behaviors include circulating around the block searching for space, a phenomenon known as cruising for parking. Alternatively, drivers may stop in double parking positions or perform deliveries from locations far from the destination. Saki et al. (2024)[5] emphasize that such search behavior significantly increases vehicle kilometers traveled (VKT) and fuel consumption. As a consequence, inefficiencies in curbside access generate additional traffic disturbances and emissions that are not directly associated with the logistics activity itself. Castrellon et al. (2024) [6]indicate that these externalities are often underestimated in conventional traffic studies because they occur at the microscopic level of the delivery stop.

A key source of this inefficiency arises from the improper or non functional use of loading zones. Ezquerro et al. (2020)[7] have documented that a substantial proportion of LUZ occupancy is attributed to unauthorized private vehicles. Furthermore, commercial vehicles often exceed the permitted parking duration, further reducing turnover. Muriel et al. (2022)[8] argue that these time overruns collapse the system�s capacity even when the physical space exists. However, a significant distorter that remains insufficiently explored is the authorized but non functional occupancy. This refers to vehicles used by tradespeople such as plumbers, electricians, and maintenance services who are formally authorized to use commercial bays but do not perform freight loading or unloading tasks. Instead, these users utilize the LUZ as a long term parking space while performing services in nearby buildings. Comi et al. (2022) [9]note that while these vehicles may be legal from a licensing perspective, their operational profile lacks the high rotation required by modern logistics, representing a functional loss of curbside capacity.

From an operational perspective, curbside occupations can be classified according to their legality and functional impact. Within designated loading zones, three main situations of inefficiency occur: unauthorized private vehicles, commercial vehicles exceeding the 30 minute limit, and authorized vehicles not performing logistics functions. Outside these zones, illegal stopping may occur with varying impacts. Alho et al. (2014)[10] differentiate between stops that block circulation, such as double parking, and those that occupy sidewalks or pedestrian crossings. For analytical purposes, curbside demand can be segmented into two operational classes: service vehicles (tradespeople) and delivery vehicles (productive logistics). Ramirez Rios et al. (2023) [11]maintain that while both categories have legitimate claims to the curb, only the latter contributes to the intended logistical function of high turnover loading zones.

Recent research has proposed new indicators derived from industrial efficiency metrics to evaluate this infrastructure. Gil Gallego et al. (2025) [12]adapted the Overall Equipment Effectiveness (OEE) model to LUZs, enabling the measurement of efficiency based on availability, performance, and quality. Building on this logic, Les et al. (2024)[13] introduced the OEEM (Overall Equipment Effectiveness for Mobility) to monitor transport routes in real time. These studies have paved the way for quantifying not only time losses but also environmental impacts. Gil Gallego et al. (2026)[14] identified Hidden Carbon Emissions (HCE) as the extra CO_2 generated by vehicle recirculation and idling induced by capacity loss. However, previous analyses generally considered capacity loss in aggregate terms without distinguishing the specific impact of each source of occupancy.

In practice, the presence of authorized but non functional vehicles represents a silent erosion of capacity. Although these vehicles comply with general access rules, they prevent delivery vehicles from performing productive operations. Dalla Chiara et al. (2022) [15]suggest that providing real time information could mitigate this, but the structural issue remains the competition for space. When a delivery vehicle is rejected due to a tradesperson�s van occupying a spot for several hours, the resulting recirculation generates emissions that remain invisible in conventional assessments. Palacios-Argüello et al. (2025)[16] emphasize that the transition from pilot projects to permanent policies requires understanding these success and failure factors in curbside management. The environmental consequences of this functional curbside capacity loss remain insufficiently quantified in the current literature, especially regarding the cost per meter of misused space.

To address this gap, the present study investigates the operational and environmental consequences of functional capacity loss. Using detailed observational data collected in a loading and unloading zone (LUZ) in Zaragoza (Spain), this study distinguishes between functional logistics demand and authorized but non functional use. This zone was specifically selected because its street width (9.2 m) allows double parking without total traffic blockage, providing a unique scenario to

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observe real driver behavior. Gil Gallego et al. (2026) [14]previously utilized Erlang B queuing models to demonstrate that LUZs are self sufficient if regulations are strictly enforced. This paper evolves that framework by constructing a counterfactual scenario that removes not only unauthorized cars and time overruns but also non functional occupations.

The main novelty of this work is the calculation of HCE per linear meter "misused" by the behavior of authorized and unauthorized users. While previous work quantified emissions per meter "stolen" by physical elements like hospitality terraces, this research focuses on the behavioral loss of efficiency. By applying the M/M/1/1 Erlang B model with a single service point, justified by the use of weighted occupancy time (t_p), the study simulates how the system could absorb all current arrivals if rotation was prioritized. This approach provides city governance with a data driven tool to justify stricter enforcement and the derivation of service vehicles to alternative parking facilities. By linking curbside management with environmental performance indicators, this study contributes to a better understanding of how operational inefficiencies translate into measurable externalities.

Based on this framework, the study tests the following research hypotheses:

(i) H1. Non functional curbside occupancy (tradespeople) reduces the effective operational capacity of loading zones and increases the number of delivery vehicles that cannot be legally served upon arrival.

(ii) H2. Delivery vehicles rejected due to functional curbside capacity loss generate additional CO_2 emissions through recirculation and idling behaviors that are structurally induced by the infrastructure management.

(iii) H3. The environmental impact of curbside misuse can be quantified through indicators linking non functional curbside occupancy with the resulting Hidden Carbon Emissions (HCE) per misused linear meter.

2. Literature Review

2.1. Curbside Infrastructure and Demand Management

The design and spatial allocation of loading and unloading zones have been identified as determining elements for the economic competitiveness of dense urban districts. Ma et al. (2022) [3]maintain that the proliferation of delivery points driven by e-commerce has transformed the curb from a static space into a high criticality infrastructure. Alho et al. (2018) [2]demonstrate that a suboptimal location of delivery bays not only increases service time but also degrades traffic fluidity across the adjacent network. Muñuzuri et al. (2017)[17] propose that the geometric configuration of these zones must adapt to street morphology to minimize pedestrian interference. Furthermore, Ochoa-Olán et al. (2021) [18]indicate that the lack of objective criteria for dimensioning LUZs generates a chronic mismatch between space supply and logistics demand. In this sense, Castrellon et al. (2024)[6] highlight that the use of data analytics is essential for transitioning toward smart loading networks. The concept of the "Smart Loading Zone" has gained relevance as a tool to manage demand in real time according to Castrellon et al. (2024)[6]. Dezi et al. (2010) [19]add that planning must consider seasonal demand peaks to avoid operational collapse.

2.2. Driver Behavior and Queuing Theory at the Curbside

Uncertainty in the availability of legal spaces radically conditions the operational strategies of carriers. Ghizzawi et al. (2024)[20] argue that commercial parking behavior is mediated by time pressure and the perceived risk of sanctions. Amaya et al. (2023)[4] document that, when faced with LUZ saturation, drivers initiate circular search processes that increase local congestion. Mor et al. (2020) [21]suggest that the implementation of reservation systems can mitigate the randomness of arrivals into the system. To model this dynamic, literature has adopted advanced stochastic frameworks. Abhishek et al. (2021) [22]formulate queuing systems to evaluate the interaction between dedicated delivery bays and general parking. Legros et al. (2024) [23]validate the use of Erlang loss systems to model the curb, assuming that drivers do not wait in physical lines but instead leave the system upon finding it full. Xiao et al. (2018) [24]reinforce that the "no wait queue" model is the most faithful to the reality observed in high density environments. Ismael et al. (2025)[25] maintain that optimal allocation must differentiate between vehicle types to maximize the service rate. On the other hand, Kalahasthi et al. (2022) [26]propose joint models of arrival and duration to capture the heterogeneity of commercial use.

2.3. Identification of Non Functional Occupancy and Curbside Abuses

LUZ inefficiency does not stem solely from a lack of linear meters but from usage patterns that erode logistics turnover. Ezquerro et al. (2020) [7]quantify that illegal occupancy by private vehicles represents a capacity loss of over 25% in historic centers. Gil Gallego et al. (2025) [12]demonstrate through the OEE model that time overruns by authorized carriers drastically reduce operational availability. However, a critical distorter arises, termed in this study as authorized but non functional occupancy. Ramirez-Rios et al. (2023) [11]classify tradespeople and service vehicles (e.g., plumbers, electricians, maintenance) as commercial users but emphasize that their prolonged dwell times are incompatible with last mile logistics. Saki et al. (2024) [27] indicate that these vehicles use the infrastructure as temporary storage while performing technical services, blocking access for productive delivery vehicles. This "legal appropriation" of the curb generates a functional inefficiency that, according to Muriel et al. (2022)[8], forces functional delivery drivers to resort to double parking systematically. Comi et al. (2022)[9] maintain that segmenting demand by function is the necessary prior step for efficient curbside management.

2.4. Environmental Externalities and Hidden Carbon Emissions (HCE)

Urban freight transport is responsible for an increasing fraction of the carbon footprint of smart cities. Middela et al. (2024) [28]emphasize that last mile CO_2 emissions are highly sensitive to idling and recirculation cycles induced by infrastructure. Gil Gallego et al. (2026) [14]introduced the concept of Hidden Carbon Emissions (HCE) to quantify the environmental impact of operational inefficiency that is not reflected in standard route logs. Saki et al. (2024) [29] demonstrate that every additional minute of parking search translates into a direct increase in local emissions. The use of sustainable mobility indicators such as OEEM allows for linking industrial efficiency with environmental protection according to Les et al. (2024) [13]. Middela et al. (2024) [30]confirm that commercial vehicles idling during irregular parking generate concentrated emissions at critical points in the road network. El Amrani et al. (2026) [31]argue that dynamic curbside management is one of the most effective levers for urban decarbonization without requiring total fleet electrification. Burns et al. (2024)[32] estimate that optimized curbside handling can reduce energy consumption and double parking by more than 20%.

2.5. Advanced Modeling and Curb Digitalization (Logistics 4.0)

The transition toward proactive curbside management depends on the integration of Logistics 4.0 technologies. Rubino et al. (2025)[33] propose system dynamics models to evaluate how access policies affect global logistics productivity. Xie et al. (2025) [34]develop deep reinforcement learning algorithms to dynamically configure reservable spaces. Burns et al. (2025) [35]maintain that digitalization allows for curbside orchestration that maximizes vehicle accommodation without expanding physical space. Wu et al. (2024)[36] demonstrate that the use of geofencing enables the monitoring and allocation of spaces to heavy vehicles with high spatiotemporal precision. Ahmadian et al. (2025)[37] suggest that carrier satisfaction is linked to the predictability offered by these digital tools. On the other hand, de Bok et al. (2024)[38] use simulations to demonstrate that urban micro hubs can relieve pressure on the curb by transferring cargo to green micromobility vehicles.

2.6. Research Gap

Despite advances in modeling supply and demand, a fundamental gap persists in quantifying the impact of non productive commercial occupancy. Gil Gallego et al. (2026)[14] demonstrated through queuing theory that the current infrastructure in Zaragoza is sufficient under conditions of regulatory compliance, but they did not isolate the effect of service vehicles (tradespeople). Most previous studies, such as those by Dalla Chiara et al. (2022)[39] or Patier et al. (2014)[40], assume homogeneous logistics demand within LUZs. This article addresses this gap through an original approach that treats the zone as a single server based on weighted occupancy time (t_p), a metric that integrates space and time to diagnose lost functional capacity. Furthermore, while Gil Gallego et al. (2026) [14]calculated the environmental impact per meter "stolen" by physical elements like hospitality terraces, this work provides the first metric for HCE per linear meter "misused" due to the inefficient behavior of both authorized and unauthorized users, providing a climate governance tool unprecedented in the current literature.

3. Conceptual Framework

3.1. Functional Curbside Capacity as an Operational Asset

Urban loading and unloading zones (LUZ) are interpreted as service systems that provide temporary capacity within the broader transport network. Ghizzawi et al. (2026)[41] define curbside infrastructure as a limited access resource whose performance is determined by both spatial availability and occupancy duration. Castrellon and Sanchez-Diaz (2024)[6] emphasize that the curb is a contested shared resource where logistics demand frequently exceeds the regulated supply. In this context, Gil Gallego et al. (2025)[12] proposed analyzing LUZs as industrial assets using the Overall Equipment Effectiveness (OEE) model. This framework allows for the measurement of efficiency based on availability, performance, and quality, treating the loading bay as a production unit. Building on this, Les et al. (2024)[13] introduced the OEEM indicator to capture the spatiotemporal efficiency of transport routes. Subsequent research by Gil Gallego et al. (2025) [42]established that the effective capacity of an LUZ is not merely physical but operational, as it depends on the strictness of access control and dwell time compliance.

3.2. Segmentation of Demand: Functional vs. Authorized Non Functional Occupancy

In real world urban environments, curbside spaces are occupied by a heterogeneous mix of vehicles performing diverse activities. Ezquerro et al. (2020)[7] have documented that a significant portion of this occupancy is attributable to unauthorized private cars. Furthermore, authorized commercial vehicles often reduce system turnover by exceeding the 30 minute limit. However, this study introduces a more nuanced distinction: the separation between Functional Logistics Demand (Class D, from Delivery) and Authorized but Non Functional Occupancy (Class S, from Service). Ramirez-Rios et al. (2023)[11] classify service vehicles, such as those used by tradespeople (e.g., plumbers, electricians, or maintenance technicians), as legitimate commercial users. Nevertheless, Gil Gallego et al. (2025)[42] observed that these vehicles use the LUZ as long term parking rather than for high turnover loading tasks. While Class D vehicles represent the productive logistics demand, Class S vehicles occupy capacity without contributing to the intended logistical function of the zone. This situation leads to a functional loss of curbside capacity, where the physical space exists but is effectively unavailable for delivery operations.

Figure 1 provides an empirical instance of functional saturation observed in the zone. The image shows three small vans simultaneously occupying the LUZ's longitudinal capacity. A functional assessment identifies a critical operational mismatch: while the GLS van represents a Class D (functional logistics) operation characterized by high turnover, the other two vehicles exemplify Authorized but Non Functional Occupancy (Class S). Specifically, a maintenance van (Tarma) and a pest control vehicle (Rentokil) are utilizing the bay as stationary parking while performing technical services in nearby buildings. As noted by Ramirez-Rios et al. (2023)[11], these service providers often exhibit dwell times that significantly exceed delivery thresholds, creating what Gil Gallego et al.

(2026)[14] term as a "legal appropriation" of the curb. This usage pattern effectively displaces productive logistics demand toward double parking or recirculation loops, thereby degrading the node's overall operational efficiency.

Figure 1. Empirical instance of functional curbside saturation in the zone.

3.3. Stochastic Nature of Curbside Access and Loss Systems

The interaction between delivery vehicles and curbside infrastructure is inherently stochastic and characterized by the absence of physical waiting lines. Legros and Fransoo (2024)[23] validate the interpretation of LUZs as loss systems, where vehicles that find the server occupied are rejected and must exit the system. Gil Gallego et al. (2026)[14] justified the application of the Erlang B (M/M/1/1) model by introducing the weighted occupancy time (t_p). This metric integrates the vehicle length and the dwell time into a single variable, allowing the entire LUZ to be modeled as a single service point regardless of its physical dimensions. Xiao et al. (2025)[43] support the "no wait" assumption, noting that delivery drivers in dense areas typically recirculate or park illegally rather than forming a queue. This behavioral pattern implies that any occupancy by Class S vehicles or unauthorized cars directly translates into an increase in the system's blocking probability.

3.4. Hidden Carbon Emissions (HCE) per Misused Linear Meter

When the operational capacity of an LUZ is compromised, the system generates negative externalities that are often omitted from standard emissions inventories. Gil Gallego et al. (2026)[14] introduced the concept of Hidden Carbon Emissions (HCE) to quantify the additional CO_2 produced by vehicle recirculation and idling following a service rejection. While that previous work focused on emissions per meter "stolen" by physical obstructions like hospitality terraces, the current framework evolves toward the HCE per linear meter "misused" by inefficient behavior. Saki et al. (2024)[5] demonstrate that every additional minute of cruising for parking significantly increases the carbon footprint of the last mile. Middela et al. (2024)[30] argue that reducing idling time is a primary lever for urban decarbonization. By linking curbside occupancy patterns with observed driver behavior, this framework allows for the estimation of how much environmental damage is caused by each meter of curb that is occupied by non functional or unauthorized users. This logic provides a data driven basis for city governance to prioritize rotation and enforcement as climate mitigation strategies.

4. Methodology

4.1. Study Area and Data Collection Protocol

The empirical research was conducted in Zaragoza (Spain), a city that functions as a national laboratory for smart mobility and urban logistics. Gil Gallego et al. (2025)[42] previously characterized the commercial density of the central business district, where the competition for curbside space is particularly high. The analysis focuses specifically on one zone, located on Arzobispo Doménech street. This zone was selected due to its unique geometric profile: a street width

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of 9.2 meters, which according to Ghizzawi et al. (2024)[1] is a critical design factor as it allows for temporary double parking without completely obstructing the general traffic flow.

Data were captured through direct manual observation during 21 working days in May 2025, covering the authorized delivery windows (9:00–12:00 and 14:00–17:00 h). This representative period reflects standard urban activity without the seasonal bias of holidays or school closures. A total of 474 vehicle entries were recorded specifically in the zone. The observation protocol registered the exact arrival time, vehicle category, serial signage (to identify specific activities), and the effective dwell time. Ma et al. (2022)[3] emphasize that microscopic data collection is essential for modeling the high frequency/low volume stops characteristic of modern e-commerce. In the zone, the presence of a dark store acts as a significant traffic generator, attracting a high volume of delivery vans and personal mobility vehicles as noted by Gil Gallego et al. (2025)[42].

Figure 2 illustrates the spatial layout of the zone on Arzobispo Doménech Street. The red rectangle defines the legal loading and unloading zone (LUZ), while the blue line indicates the double parking area utilized by commercial vehicles when curbside capacity is exceeded. The green arrows delineate the 384 meter recirculation loop around the urban block, which serves as the primary physical parameter for quantifying the Hidden Carbon Emissions (HCE) induced by functional capacity loss.

Figure 2. Operational layout of the zone and recirculation pattern.

4.2. Functional Demand Segmentation and Characterization

Traditional urban logistics studies often treat delivery demand as a homogeneous flow. However, this study proposes a functional segmentation to isolate the impact of different user types on curbside capacity. Three categories of inefficient occupancy were identified:

(i) Unauthorized Private Vehicles: Passenger cars that park illegally for personal convenience, which Ezquerro et al. (2020)[7] identify as a structural barrier to delivery efficiency.

(i) Authorized Time Overruns: Commercial vehicles that exceed the 30 minute maximum stay permitted by the Zaragoza Mobility Ordinance (2020)[44]. Gil Gallego et al. (2025)[42] quantified that such abuses reduce nominal availability by more than 30%.

(iii) Authorized but Non Functional Occupancy (Class S): This category, the core novelty of the present work, consists of tradespeople and service technicians (e.g., plumbers, electricians, maintenance crews). Ramirez-Rios et al. (2023) [11]recognize these as legitimate commercial users; however, we classify them as "non functional" because they utilize the loading zone as long term stationary parking rather than for the active movement of goods.

For the counterfactual analysis, Functional Logistics Demand (Class D) is defined as the subset of vehicles performing active loading or unloading while strictly complying with regulatory time limits. Dezi et al. (2010)[19] maintain that segregating this demand is a prerequisite for effective curbside management.

4.3. Stochastic Modeling via Queuing Theory: Erlang B (M/M/1/1)

To evaluate the operational capacity of Z1, we apply a no wait queuing model characterized as M/M/1/1 in Kendall's notation. The choice of the Erlang B loss system is justified by the behavioral patterns observed in the field: drivers in dense urban settings do not form physical queues in the travel lane but instead recirculate or park illegally when the loading zone is full. Xiao et al. (2018) [24]support this "recirculation instead of waiting" assumption as the most faithful representation of high density curbside environments.

A critical methodological contribution of this research series is the treatment of the entire loading zone as a single service point (c=1). This approach, established by Gil Gallego et al. (2026)[14], is made possible by the use of weighted occupancy time (t_p), which integrates the physical space consumed and the dwell duration into a single metric. The formula for t_p is:

$$t_p = \frac{L_{veh}}{L_{LUZ}} \cdot t_{real} \tag{1}$$

Where L_{veh} is the vehicle length and LLUZ is the total zone length (15 m for this zone).

By normalizing service capacity as a continuous space-time resource, the system can be modeled with a single server where traffic intensity (ϱ) reflects the offered Erlang load. Legros and Fransoo (2024) [23]demonstrate that this framework effectively captures service denial probabilities in curbside systems without wait buffers. The blocking probability (pB) for this single server configuration is defined as:

$$pB = \frac{\rho}{(1 + \rho)} \tag{2}$$

This metric allows us to estimate the number of Class D vehicles that would be legally accommodated if the system were purged of inefficient uses, following the simulation methodology proposed by Gil Gallego et al. (2026)[14].

4.4. Environmental Externality Quantification: Hidden Carbon Emissions (HCE)

The environmental cost of infrastructure saturation and functional failure is quantified using the Hidden Carbon Emissions (HCE) indicator, developed originally by Gil Gallego et al. (2026)[14]. This metric captures the additional tailpipe CO_2 generated by rejected vehicles, encompassing both functional Class D and non functional Class S arrivals, that are forced into inefficient search behaviors. The calculation is based on the deterministic trajectories observed in the 384 meter loop (D_{loop}) surrounding the urban block of the zone. According to the methodological framework established in the third stage of this research series, the total HCE for an operational period T is computed as the sum of recirculation and idling components:

$$HCE(T) = HCE\_rec(T) + HCE\_idle(T) \tag{3}$$

(i) Recirculation component (HCErec): This accounts for emissions originating from the additional distance traveled by vehicles seeking legal curbside access. Following the distance based approach of Gil Gallego et al. (2026)[14], the formula is defined as:

$$HCE_{rec}(T) = EF_{km} \cdot D_{loop} \cdot \sum_{i=1}^{N\_r(T)} L\_i \tag{4}$$

Where Nr(T) is the total number of rejected freight vehicles and Li represents the number of full recirculation loops observed for each vehicle i. We adopt a distance based emission factor (EFkm) of 185.4 gCO_2/km, which represents the EU level average for new light commercial vehicles (vans) reported by the European Environment Agency (EEA) for 2024. Saki et al. (2024) [27]demonstrate that even single search loops in high demand nodes significantly inflate the carbon footprint of individual deliveries.

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(ii) Idling component (HCEidle): This quantifies the emissions produced during illegal stopping events where the engine remains active. The formula is expressed as

$$HCE\_idle(T) = \sum_{i=1}^{N_{r(T)}} t_i \cdot EF\_min \quad (5)$$

Where EFmin is the idling emission factor of 27.77 gCO_2/min. As specified in the methodology of our previous work, this value is derived by applying a standard diesel carbon intensity (2.64 $kgCO_2$/L) to a representative fuel consumption rate of 0.63 L/h for urban fleets under steady idling. To ensure spatial realism, the effective idling time (ti) for each rejected operation is governed by observed engine shut off thresholds (θc):

$$t_i = \min\left(\tau_i, \theta_c(i)\right) \quad (6)$$

Where τ_i is the total duration of the illegal stop recorded during the field study. Based on the behavior documented in the first stages of this research, θ_c is set at 4 minutes for light vans and up to 18 minutes for heavier refrigerated vehicles (3.5 Tn MMA and 7.5 Tn) that require continuous auxiliary power. Middela et al. (2024) [30]identify the reduction of this infrastructure induced idling as a high priority lever for achieving urban decarbonization targets

4.5. Attribution Framework and Counterfactual Analysis

This study introduces a precise attribution model to link specific behavioral inefficiencies with the resulting carbon footprint. The total Hidden Carbon Emissions (HCEtotal) of the zone are distributed among the user groups based on their proportional contribution to the Total Misused Weighted Time (Tp_{misuse}). As established by Les et al. (2024)[13], the use of weighted occupancy time provides the most rigorous basis for connecting industrial effectiveness indicators with environmental sustainability. The attribution weight (Wg) for each category g is defined as:

$$W_g = \frac{\sum t_{p,g\_misuse}}{T_{p\_misuse}} \quad (7)$$

The logic for determining the misused weighted time (tp_{misuse}) per operation is applied as follows:

(i) Unauthorized Private Vehicles: Given their lack of legal access rights, 100% of their observed t_p is classified as misuse.

(ii) Non Functional Authorized Vehicles (Class S): 100% of their t_p is considered misuse, as their long term stationary profiles are functionally incompatible with the high rotation logistics intended for LUZ nodes.

(iii) Authorized Functional Vehicles (Class D): Only the t_p portion corresponding to the excess duration beyond the 30 minute ordinance limit is attributed as misuse; the initial legal period is treated as productive service.

The resulting environmental responsibility for each group is then calculated by Equation ():

$$HCE_g = W_g \cdot HCE_{total} \quad (8)$$

Two main scenarios are evaluated to isolate these impacts:

(i) Baseline Scenario (Current Situation): Reconstructs the empirical operational timeline using the 474 recorded entries to reflect actual saturation levels.

(ii) Functional Scenario (Counterfactual): Simulates a restored system by removing 100% of unauthorized cars, 100% of Class S vehicles, and the time overruns of Class D vehicles.

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To provide city planners with a standardized decision tool, we introduce the HCE per misused linear meter (HCEm). This indicator captures the environmental cost of behavioral non compliance relative to the physical space occupied by inefficient users:

$$HCE_m = \frac{HCE_{total}}{\sum L_{misused}} \tag{9}$$

Where sum $\sum L_{misused}$ represents the cumulative longitudinal footprint of the three misuse categories recorded during the study. Castrellon and Sanchez-Diaz (2023)[45] emphasize that such granular metrics provide the empirical evidence required to transition from temporary pilots to permanent curbside governance policies based on digital orchestration and rotation enforcement. These formulas allow for the traceable quantification of the per vehicle impacts (e.g., 0.109 kg CO_2 for Class D overtime) that ultimately define the sustainability of the Arzobispo Doménech logistics node.

5. Results

This section presents the diagnostic and comparative analysis of the zone, following a logical sequence from the current state of operational saturation to the simulated scenario of high logistical rotation and its corresponding environmental impact.

5.1. Spatiotemporal Characterization of Current Throughput (Baseline Scenario)

The initial stage of this results section focuses on the empirical characterization of the operational dynamics currently observed in Arzobispo Doménech street. According to the direct fieldwork conducted in May 2025, the zone represents the only designated loading and unloading infrastructure within its immediate street segment. Within the analyzed timeframe of 21 working days and 126 hours of active reservation (6 h/day), the system recorded a total demand of 474 vehicle arrivals. Gil Gallego et al. (2025)[42] noted that the presence of a dark store at this node generates high frequency arrival patterns that strain the available curbside capacity. Out of these 474 attempts, only 273 vehicles successfully obtained service within the LUZ, a figure that includes unauthorized passenger cars occupying the area illegally. The average weighted occupancy time (t_p) for these serviced units was recorded at 20.94 min.

Based on these empirical observations, the system's effective arrival rate (λ) is determined as follows:

$$\lambda = 474/126 = 3.76 \text{ vehicles/hour}$$

Given that each individual operation occupies the zone for an average of 20.94 min, the service time per vehicle is 0.35 h/vehicle.

$$Service\ time\ per\ vehicle = 20.94/60 = 0.35$$
h/vehicle

Consequently, the service rate (μ) representing the infrastructure's ability to process demand is calculated as:

$$\mu = 1/0.35 = 2.87 \text{ vehicles/hour}$$

The resulting traffic intensity (ϱ), which characterizes the Offered Erlang Load for the zone, is:

$$\rho = \lambda/\mu = 3.76/2.87 = 1.31$$

Ma et al. (2022) [3] emphasize that a load factor $\varrho > 1$ identifies a structurally saturated system where the demand for space-time resources exceeds the nominal service supply. In this scenario, the system is non functional without the presence of a queue, leading to high loss rates and the induction of negative externalities. As established in the conceptual framework and supported by the research

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of Gil Gallego et al. (2026)[14], the use of weighted occupancy time (t_P) as the primary time variable allows the loading zone to be modeled as a single server consolidated channel (c=1). This metric treats the curb as a normalized unit where each vehicle contributes its temporal dwell time proportional to its longitudinal footprint, preserving spatial realism while enabling stochastic modeling.

Let us now consider the probability of loss or blockage in the area. The general formula for the Erlang B model is:

$$p_B = \frac{\left(\frac{1}{c!}\rho^c\right)}{\sum_{n=0}^{c}\left(\frac{1}{n!}\rho^n\right)} \tag{10}$$

In our case, as there is only one service position, c = 1, it is as follows:

$$pB = \frac{\rho}{(1+\rho)} = \frac{1{,}31}{(1+1{,}31)} = 0{,}5676 \tag{2}$$

The interpretation of this result is that 56.76% of vehicles arriving at the LUZ do so when it is already occupied and therefore cannot be served. This value is independent of the actual number of vehicles observed and is based solely on the balance between the arrival rate and the service rate. If we compare the number of vehicles not served in the actual observation (474 − 273 = 201), we see that this is a rate of 42.4% compared to the model's rate of 56.76% (0.5676 × 474 = 269 vehicles). The Erlang B model may overestimate the results as it is an idealised probabilistic model that assumes perfect randomness in arrivals and services (Poisson and exponential), when in reality vehicles arrive without a fixed pattern of arrival sequence. The model assumes that arrivals, according to the Poisson distribution, are constant, which is not the case, and that occupancy times follow an exponential distribution, in which, despite assuming randomness, the probability of a vehicle finishing unloading at a specific time t decreases exponentially as time increases, i.e., vehicles tend to be served faster on average, but the exact time needed for each vehicle to unload may vary, so this blocking probability for the Erlang B model does not provide us with reliable data, and we will now refer to the actual data collected in the field observation. Another reason why the blocking probability of this model loses validity is that using weighted occupancy time as a time variable leads the system to believe that, with only a single service point and a single occupancy, the system would be full, when there may be spaces available.

In terms of usage times for the area, compared to the total weighted available time of 7560 min, the weighted usage time for the area was:

273 veh × 20.94 min/veh = 5716.62 min, 75.62% time occupancy

Despite these modeling limitations, the data confirms that the zone is operating at maximum capacity, with serviced vehicles consuming 5716.62 minutes of weighted time, representing a 75.62% utilization of the 7560 available minutes. These baseline findings empirically support Hypothesis H2, confirming that unrestricted use, characterized by unauthorized passenger cars and excessive stay durations, leads to a systemic failure where one out of every two delivery attempts is rejected. This functional colapse forces drivers into the double parking behaviors documented by Amaya et al. (2025)[46], resulting in the loss of logistical efficiency and the degradation of urban mobility on Arzobispo Doménech street.

5.2. Simulation of a Regulated Counterfactual: Functional Class D Exclusive Access

This simulated scenario evaluates an idealized operational state where curbside governance is strictly enforced through two primary levers: the exclusion of non logistics actors (unauthorized private cars and Class S service vehicles) and the rigid application of the 30 minute stay limit for authorized carriers. According to Alho et al. (2018)[2], managing the demand side criteria is often more effective for system restoration than increasing physical supply. Under these controlled parameters, the monthly demand is limited to 258 functional Class D vehicles. The empirical data for this scenario reveals that only 105 functional operations are currently conducted within the legal 30 minute threshold, resulting in an average weighted occupancy time (t_p) of 14.12 min.

Applying the M/M/1/1 Erlang B framework to this regulated input, the following systemic indicators are obtained:

λ = 2.05 vehicles/hour

μ = 4.25 vehicles/hour

ϱ = 0.48 Erlangs, Sistema viable ya que $\varrho < 1$. No hay riesgo de colapso o saturación, puesto que la capacidad del sistema supera la tasa de llegada de vehículos.

pB = 0.3252

A traffic intensity factor of $\varrho < 1$ demonstrates that the Arzobispo Doménech infrastructure is perfectly viable and resilient when restricted to its intended logistical function. In this regime, the system operates with a significant safety margin, virtually eliminating the risk of structural saturation or the induction of illegal double parking. The transition from the baseline to this regulated model liberates a substantial volume of space-time resources, termed as the Weighted Occupancy Time Freed Up (Tliberated). This metric represents the latent capacity recovered by purging the system of behavioral ineficiencies. The value is calculated as the delta between unrestricted occupancy and the constrained functional demand:

$$T_{liberated} = T_{unrestricted} - T_{occupied\_with\_constraints} \quad (11)$$

$$T_{liberated} = (273 \times 20.94) - (105 \times 14.12) = 4234.02 \text{ min}$$

To translate this temporal surplus into a serviceable vehicle count, it is necessary to establish a standard occupancy profile for a representative unit. This was achieved by calculating the weighted average stay of the authorized fleet based on the observed distribution of vehicle categories (Table 1).

Table 1. Weighted occupancy time by vehicle type (only D and S Class).

Vehicle Type	nº	%	t_p	Global
Light Truck 7.5 Tn GVW	7	1,84%	14,71	0,27
Chassis Cab 3.5 Tn GVW	41	10,76%	7,47	0,80
Large Volume Van	24	6,30%	7,83	0,49
Small Van	152	39,90%	11,49	4,59
Delivery Van	157	41,21%	13,18	5,43
Total	381			11,58

Utilizing the global weighted average of 11.58 min per generic vehicle, the potential for accommodating additional logistical operations within the liberated time is:

$$N_{Additional\ vehicles} = \frac{T\ weighted\ liberated}{t\ weighted\ average\ per\ vehicle} = \frac{4234.02}{11.58} = 365.58 \text{ additional vehicles}$$

The simulation indicates that by implementing strict rotation and access control, the zone could legally process up to 470.58 operations per month (the current 105 compliant ones plus the 365.58 newly accommodated). To validate the robustness of this expanded capacity, the Erlang B model was reapplied using the total authorized arrival rate of 381 vehicles/month. This second order simulation yields a theoretical blocking probability (pB) of 0.3252.

The analysis reveals that while the model predicts 83.90 theoretical rejections (0.3252 x 258 arrivals), this figure is significantly lower than the 212.58 excess operations that the liberated weighted time can support. Consequently, we can categorically conclude that the current infrastructure is not only sufficient but actually oversized for the existing functional demand, provided that the municipal ordinance is enforced without exception. These findings provide definitive empirical support for Hypothesis H1, confirming that the perceived saturation of the curb is a consequence of authorized but non functional "legal appropriation" and unauthorized intrusion, rather than a physical deficit in street meters.

5.3. Results: Hidden Carbon Emissions (HCE) Induced by Functional Inefficiency

This subsection evaluates the environmental externalities associated with functional curbside capacity loss in the zone. The indicator for Hidden Carbon Emissions (HCE), as defined by Gil Gallego et al. (2026)[14], is utilized to quantify the additional tailpipe CO_2 generated by freight vehicles that could not be legally accommodated due to structural saturation and were subsequently forced into recirculation or illegal stopping. The analysis captures the delta between the observed baseline and the counterfactual functional scenario, holding demand and external variables constant over the 21 day representative operational month. According to Gil Gallego et al. (2026)[14], the close numerical agreement between the theoretical blocking probabilities of the Erlang B model and the empirical rejections observed in Arzobispo Doménech street provides a robust internal validation for the proposed computational framework.

5.3.1. Emissions from Vehicle Recirculation (HCErec)

Out of the 201 delivery vehicles rejected due to the functional capacity constraints of Z1, a subset of 96 drivers attempted at least one full recirculation loop around the block. Field observation recorded that 33 vehicles performed two loops and 12 vehicles performed three loops, resulting in a total of 198 observed loops (N_{loops}). Given the block perimeter of 384 m, the cumulative additional distance traveled due to infrastructure induced search behavior was calculated as follows:

$$D\text{rec} = 198 \times 0.384 = 76.03 \text{ km}$$

For the calculation of tailpipe impact, we adopt a distance based emission factor (EFkm) of 185.4 gCO_2/km. As specified in the methodology of the third article of this research series, this value corresponds to the EU level official average for new light commercial vehicles (vans) reported by the European Environment Agency (EEA) for 2024. The total recirculation related emissions are determined as follows:

$$HCE_{\text{rec}} = 76.03 \times 185.4 = 14096{,}33 \text{ gCO}_2 \approx 14.09 \text{ KgCO}_2 \quad (4)$$

Saki et al. (2024)[5] emphasize that even short additional search distances significantly inflate the carbon footprint of individual deliveries in dense logistics nodes.

5.3.2. Emissions from Illegal Stopping and Idling (HCEidle)

The totality of the 201 rejected vehicles eventually resorted to illegal stopping behavior, either immediately upon arrival or following recirculation attempts. The average observed illegal stopping duration reached 18.0 min per vehicle. Gil Gallego et al. (2025)[42] attribute these prolonged durations to the significant walking distances required when legal curbside access is denied. However, the effective idling time is constrained by engine shut off behavior. Heavier vehicles, including 3 light trucks (7.5 Tn) and 35 chassis cabs (3.5 Tn MMA), were assigned thresholds of 18

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and 12 minutes respectively due to refrigeration needs, while the remaining 163 light vans followed a 4 minute threshold.

The resulting average effective idling time per rejected attempt was 5.60 min. The idling emission factor (EFmin) utilized is 27.77 gCO_2min. This rate is derived from the methodological framework established by Gil Gallego et al. (2026)[14], which applies a carbon intensity of 2.64 $kgCO_2/L$ to a representative diesel fuel consumption of 0.63 L/h under steady idling conditions. Consequently, the idling related emissions are:

$$HCE_{idle} = (201 \times 5.60) \times 27.77 = 31257.91\ CO_2 \approx 31.25\ KgCO_2 \quad (5)$$

These results corroborate the findings of Middela et al. (2024)[30], who identify infrastructure induced idling as a dominant and avoidable source of urban greenhouse gas emissions.

5.3.3. Total Hidden Carbon Emissions and Indicator Normalization

The total Hidden Carbon Emissions attributable to the functional capacity loss in Z1 during the 21 day period are obtained as the sum of the recirculation and idling components:

$$HCE_{total} = 14.09 + 31.25 = 45.34\ kgCO_2 \quad (3)$$

To enhance policy relevance, these results are expressed through two normalized environmental indicators. The first, HCE per rejected operation, yields a value of 0.225 $kgCO_2$ per vehicle rejected. This metric captures the structural environmental penalty induced by each failed curbside attempt. The second indicator, HCE per meter misused, is derived from the total longitudinal footprint of non compliant occupancy observed in Z1. Summing the physical lengths of private cars, Class S service vans, and the overtime segments of Class D vehicles, the analysis recorded 679.5 meters of misused space. The resulting impact is:

$$HCE/m = 0.066\ kgCO_2/m \quad (9)$$

As each non compliant vehicle in Z1 has an average length of 4.044 m, the emissions per vehicle are quantified at 0.268 $kgCO_2$. These findings provide empirical validation for Hypothesis H3, confirming that the environmental impact of curbside misuse can be quantified through indicators that link non functional occupancy to specific tailpipe externalities.

5.3.4. Behavioral Attribution of Environmental Responsibility

A final quantification assigns a specific weight to each type of functional non compliance based on the percentage of misused weighted occupancy time (t_p). This identifies the proportional responsibility of unauthorized passenger cars, time overruns by Class D vehicles, and the newly defined Authorized but Non Functional (Class S) category (Table 2).

Table 2. Attribution of HCE responsibility and per vehicle emission impact.

Category	nº	t_p	Total	%
Authorized vehicles only t_p of overtime	99	20,10	1990	40,74%
Private vehicles	92	12,02	1106	22,64%
Class S	77	23,23	1789	36,62%

Figure 3 below illustrates the proportional attribution of misused weighted occupancy time (t_p) in zone, which functions as the deterministic basis for the Hidden Carbon Emissions (HCE) responsibility model. The analysis reveals that 77% of the functional capacity loss, and consequently

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the induced environmental penalty, is directly attributable to professional or authorized users. Specifically, authorized functional vehicles exceeding the regulated stay duration (Class D) represent the largest single source of inefficiency at 41%. Furthermore, Authorized but Non Functional Occupancy (Class S) accounts for a substantial 36% of the total, significantly outweighing the impact of unauthorized private vehicles, which contribute only 23%. This evidence highlights that curbside saturation is primarily driven by professional behavioral factors and a lack of functional rotation rather than external private vehicle intrusion.

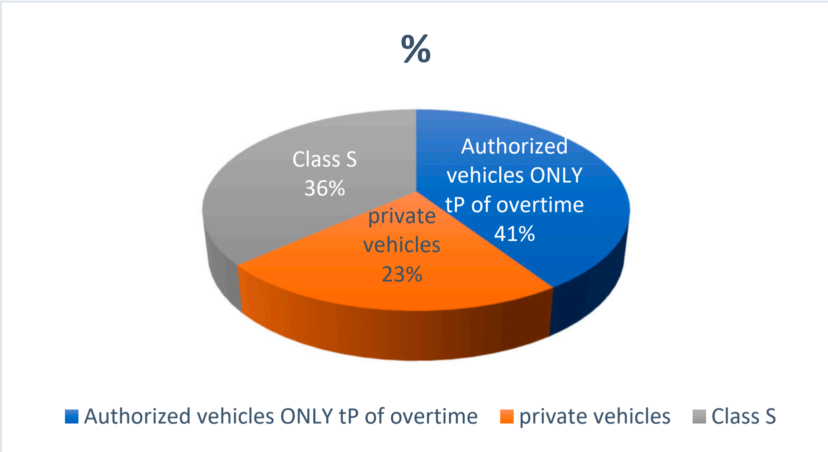

Figure 3. Behavioral Attribution of Environmental Impact (HCE).

The attribution analysis reveals that Class D vehicles exceeding the permitted stay duration generate the highest individual footprint at 0.109 kg CO_2 per vehicle. This is followed by the newly defined Authorized but Non Functional (Class S) category, which produces a per vehicle impact of 0.098 kgCO_2, while unauthorized private cars contribute 0.060 kg CO_2 per unit. This confirms that "legal" users, including both functional delivery drivers failing to comply with time limits and tradespeople performing stationary technical services, are the primary drivers of hidden environmental damage in high demand nodes like this zone, with individual impacts that significantly exceed those of illegal passenger cars. This empirical evidence provides city governance with a robust basis to prioritize rotation and digital enforcement as essential climate mitigation strategies, as discussed by Castrellon and Sanchez-Diaz (2024)[6] and Les et al. (2024)[13].

6. Discussion

The empirical evaluation of the zone provides a robust diagnostic of curbside management priorities, highlighting a fundamental shift from addressing physical infrastructure deficits toward mitigating behavioral inefficiencies. According to Ghizzawi et al. (2024), commercial parking behavior in dense urban cores is primarily driven by immediate proximity to delivery points rather than the legal status of the space. Our results confirm this premise through a baseline load factor of $\rho = 1.31$, which characterizes a system in a state of chronic functional failure. However, as suggested by Ma et al. (2022)[3], the fragmentation of delivery flows can be managed through effective spatiotemporal orchestration. The reduction of traffic intensity to $\rho = 0.48$ in the functional counterfactual proves that the existing 15 meter bay is indeed oversized for the actual demand, provided that rotation is strictly applied. This finding aligns with the research of Alho et al. (2018)[2], who argue that managing demand side criteria is significantly more effective for system restoration than physical supply expansion.

A central scientific contribution of this study is the formal identification of Authorized but Non Functional Occupancy (Class S) as a primary operational bottleneck. While Ezquerro et al. (2020)[7] identified private vehicle intrusion as a major distorter, this work proves that Class S users, such as tradespeople and service technicians, sequester high demand nodes for stationary tasks, consuming

36.62% of the lost functional capacity. Ramirez-Rios et al. (2023) [11]clearly distinguish between freight activity and service visits, noting that the latter require significantly longer dwell times. The presence of Class S vehicles forces functional delivery drivers to resort to the double parking behaviors documented by Amaya et al. (2023)[4]. This creates a "legal appropriation" conflict where service vehicles are license compliant but operationally non functional, suggesting that loading zones in critical nodes must be reserved exclusively for high rotation Class D logistics to preserve system viability.

From an environmental perspective, the Hidden Carbon Emissions (HCE) indicator establishes the penalty for behavioral non compliance at 0.066 $kgCO_2$ per misused linear meter. Saki et al. (2024)[27] emphasize that parking search time is a critical variable in urban emissions profiles. In the zone, the 45.34 kg of tailpipe CO_2 generated over the study month is a direct consequence of the 42.41% rejection rate induced by infrastructure saturation. A disruptive finding of this environmental analysis is the dominance of idling emissions, which represent 68% of the total impact, challenging the traditional policy focus on reducing vehicle kilometers traveled. As maintained by Middela et al. (2024)[28], reducing infrastructure induced idling represents a high return mitigation priority. The attribution model reveals that professional users, encompassing Class D time overruns and Class S stays, are responsible for over 77% of these avoidable emissions, providing a robust empirical basis to justify digital control strategies.

The transition from "pilot to policy" requires demonstrating tangible public benefits, as advocated by Palacios-Argüello et al. (2025)[16]. Our results provide such evidence: restoring functional capacity reduces congestion, eliminates double parking, and cuts avoidable CO_2 immediately. We advocate for a shift toward Digital Curbside Orchestration using the geolocation based systems proposed by Gil Gallego et al. (2026)[14]. Such tools allow for real time monitoring of weighted time (t_p) and automated detection of non functional stays, transforming the loading bay into a managed asset. While limited by the manual capture at a single node, this research marks a threshold for future large scale automation using computer vision and artificial intelligence. Ultimately, sustainable urban logistics does not require more physical space, but a smarter, more rigorous, and digitally enabled governance of existing assets to reclaim the misused meters of our cities.

Table 3 shows a comparison of the actual indicators for the area versus the counterfactual situation.

Table 3. Summary of System Restoration Potential in the zone.

Parameter	Current Situation	Counterfactual Regulated	Improvement (%)
Traffic Intensity (ϱ)	1,31 (Saturated)	0,48 (Viable)	-63,35%
Theoretical Blockage (pB)	56,76%	32,72%*	-42,35%
Service Potential (Veh/month)	273 (Real)	606 (Simulated)	121,84%
Hidden CO_2 (Avoidable)	45,34 kg	0 kg	-100,00%

*Note: Theoretical pB remains in the simulated model to account for stochastic randomness even under compliance.

7. Conclusions

This study provides a definitive conclusion to a systematic investigation into urban curbside health by demonstrating that the perceived scarcity of space in dense commercial corridors is fundamentally a behavioral artifact rather than a physical deficit. By isolating the dynamics of a zone in Zaragoza, we proved that a transition from a saturated baseline (ρ = 1.31) to a regulation compliant scenario (ρ = 0.48) would liberate sufficient space-time resources to accommodate an additional 121.84% of logistical operations. This quantified proof of system sufficiency confirms that existing infrastructure is structurally oversized for its intended task, provided that professional compliance regarding dwell times and functional use is strictly enforced. These results effectively validate the core hypotheses of the research, establishing that behavioral orchestration is the most efficient lever for restoring urban logistics throughput without resorting to costly and disruptive civil works.

The major scientific contribution of this work is the formal characterization of Authorized but Non Functional Occupancy (Class S) as a critical distorter of curbside rotation. While municipal policies often prioritize the removal of unauthorized private vehicles, our data reveals that the "legal" appropriation of loading zones by tradespeople and service technicians represents a more severe operational bottleneck, accounting for 36.62% of total capacity loss. Furthermore, the introduction of the Hidden Carbon Emissions (HCE) per linear meter misused indicator (0.066 $kgCO_2/m$) advances the state of the art by providing a parsimonious metric for urban climate governance. By proving that professional users, encompassing Class D exceeded time and Class S stays, are responsible for 77.36% of the 45.34 kg of avoidable CO_2 recorded in the study period, this research provides city authorities with the evidence needed to prioritize professional rotation as a direct climate mitigation strategy.

The primary limitation of this research is the reliance on manual data capture in a single urban block. While this quasi experimental setup provided high accuracy for behavioral tracking, it lacks the scalability of automated systems. Future work should integrate artificial vision and IoT sensors to validate the OEE and HCE indicators at a city wide level. Additionally, while the M/M/1/1 Erlang B model proved to be a robust diagnostic tool, the assumption of perfect randomness in arrivals (Poisson) may overlook temporal clusters during morning peaks. Future research using non homogeneous Poisson processes or discrete event simulation could refine the blocking probability estimations. Finally, expanding the environmental scope to include NOx and particulate matter would provide a more holistic assessment of the public health benefits of functional curbside restoration.

From an industrial perspective, these findings advocate for an immediate shift toward Digital Curbside Orchestration. The observation that 68% of the total carbon penalty originates from engine idling during illegal stops suggests that digital monitoring of weighted occupancy time (t_P) and the automatic detection of non functional stays are urgent priorities. While limited to a single node and manual capture, this research offers a scalable blueprint for sustainable logistics, demonstrating that the path to a zero emission last mile starts with the smarter governance of existing assets to reclaim the misused meters of our cities.

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Abbreviations

The following abbreviations are used in this manuscript:

UDG	Urban distribution of goods
LUZ	Loading and unloading zones
OEE	Overall Equipment Effectiveness
HCE	Hidden Carbon Emissions

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