Parking Guidance and Geofencing for Last-Mile Delivery Operations

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Abstract— **The current shortage of road and parking capacity to accommodate freight traffic poses a significant challenge in cities. This study develops and analyzes alternative traffic management strategies for last-mile delivery operations. Three alternative implementations of parking guidance involving allocating commercial vehicles to dedicated loading/unloading bays are investigated alongside a vehicle-specific geofence strategy. Methodologically, an agent-based model framework is employed to reproduce the interactions among (parking and cruising) carriers, the surrounding traffic, and a traffic controller. An efficient metaheuristic is integrated with simulation to address the corresponding optimization. The effectiveness of the strategies in reducing traffic congestion and other externalities varies depending on the level and configuration of freight demand. Among the parking guidance strategies, those weighing more on carriers' convenience mitigate potential risks of equity and acceptability issues but at the cost of an efficiency loss. Geofencing is less problematic due to the minor operational modifications, offering comparable traffic performance improvement for low and medium demand levels.**

Index Terms— **Curbside management, simulation-based optimization, parking guidance, geofencing, last-mile delivery.**

I. INTRODUCTION

PARKING space scarcity and poor management represent a serious sustainability issue in cities worldwide. Freight last mile operations (cruising and parking) significantly impact traffic congestion, pollutants, and livability in cities [1], [2]. The increased competition among multiple curb users, including regular vehicles, and ride-hailing services, makes this problem even more compelling. Furthermore, e-commerce's rise results in shorter but more frequent stops of delivery vans carrying parcels and adds another layer of complexity to the problem [3]. Closely related to the issue of commercial parking space, cruising (the action of searching for parking near the desired destination) represents an important source of externalities too. Cruising represents an important component in commercial trips, accounting for several hundred meters per route segment [4], and therefore increasing traffic and pollution impacts of urban freight deliveries.

Standard approaches like enforcing restrictions and creating more dedicated infrastructure are often ineffective. Increasing fines and controls does not considerably affect carriers' behavior since they are relatively inelastic and integrate this cost into the delivery charges for providing a service in that area [5]. Devoting additional curbside space to delivery vehicles is also an unfeasible solution given the already burdened urban road infrastructure and the amount of space that all urban freight operations would require [6]. In recent years, new policy solutions aimed at managing more efficiently the available infrastructure space through dynamic commercial vehicle load zones, off-hours delivery, and curbside reservations, have become popular among transport policy-makers and researchers [7].

In particular, progress in wireless communication, computational, and sensing technologies occurred in the previous decade have paved the path towards more advanced Intelligent Transport System (ITS) solutions to improve transportation systems' operations. Parking guidance and vehicle access control systems have been successfully implemented worldwide since the Seventies through cameras and Variable Message Signs. Recent Vehicle-to-infrastructure (V2I) communication systems enable more complex solutions by allowing fast and customized transfer of information between vehicles and the road infrastructure manager. Sensors can be employed to monitor parking availability and traffic information in real-time and exchange information with equipped vehicles via 5G cellular networks [8]. Based on these technologies, new traffic management strategies for delivery vehicles in urban areas could be developed to achieve a more balanced utilization of the curbside and reduce traffic congestion.

This paper defines, models, and investigates alternative strategies for managing last-mile delivery operations. The investigated strategies rely on two main technical solutions that offer flexibility in their implementation to achieve specific objectives (as detailed in Section III-C). The first consists of a guidance system that identifies the best assignment of commercial bays to carriers based on the incoming delivery vehicles' parking requests and potential negative effects from illegally parked and cruising operations. The second consists of a geofencing system that identifies vehicle-specific access areas (set of streets) that should be open to freight operations to reduce the negative effects of their illegal parking and cruising. The inefficiency arising from detouring original vehicles' trips can also be considered in the optimization problem.

The contributions of this paper are several. First, novel, more comprehensive last-mile freight management strategies that consider delivery operations' traffic externalities are proposed. The integration of guidance and geofencing systems for commercial operations, particularly in relation to dynamic

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traffic models, remains an area that has received limited attention thus far. While a few studies have examined this concept in the context of specific road segments, the few operations research studies adopting a network-level perspective have predominantly focused on optimizing carriers' route efficiency, overlooking the broader impact on traffic congestion (see the following section for further details). The proposed study aims to fill this gap by adopting a network-wide approach and explicitly modeling carriers' operations and delivery trips, and their influence on traffic congestion patterns and vice versa. This is possible due to the hybrid nature of the developed framework, which combines macroscopic modeling of traffic flows with microscopic modeling of carriers' movements and operations.

Second, this study thoroughly explains the implications of four alternative implementation strategies through a comprehensive analysis of their performance in realistic settings, considering various demand and supply conditions. The analyses address city authorities' objectives, such as the reduction of traffic congestion, pollution mitigation, and curbing illegal parking. Concurrently, freight carriers' priorities, such as delivery efficiency and detours, are considered. Several key performance indicators (KPIs) are adopted, allowing for a thorough assessment of the strategies' effectiveness.

Finally, from a methodological perspective, the proposed strategies rely on a simulation-based optimization approach where an agent-based model is coupled to an optimization metaheuristic to identify the best-performing solutions. The proposed approach is accurate and realistic since it reproduces carriers' delivery operations at the individual level and network phenomena like traffic congestion. The illegal parking behavior is modeled as a temporary reduction of road throughput. The cruising behavior is modeled through a Markov process depending on parking availability and deviation from the original route. An important advantage of the proposed framework is its computational efficiency, allowing for the rapid evaluation of hundreds of potential solutions within minutes. This efficiency facilitates extensive scenario analysis and decision-making processes.

The remainder of this paper offers the following: a review of the related literature and real-world case studies, a description of the strategies and corresponding modeling and optimization framework adopted, an analysis of different scenarios, and conclusions.

II. RELATED LITERATURE AND REAL-WORLD APPLICATIONS

The limited parking available for commercial vehicles is undoubtedly a key concern among the other inefficiencies connected with the last mile of the urban freight distribution (e.g., pollution, congestion, and safety) [3]. According to a survey done in Chicago by Kawamura et al. [9], trucks were unlawfully parked more than 28 percent of the time, compared to 3 percent for passenger vehicles. In Paris, a similar survey conducted by Dablanc and Beziat [10] identified more than 50 percent of delivery operations as illegally parked. While these numbers might vary considerably across cities and during the day, urban delivery operations can disproportionately impact network congestion and pollution levels. For example, the overall levels of NOx and PM2.5 pollutants can grow by more than 50 percent, depending on the shares of truck traffic [11]. Similarly, the traffic performance of a large urban corridor can decrease by more than 20 percent, with around 20 illegal parking operations per hour [12]. Cruising for parking also represents a source of externality. In addition to the time spent for searching a delivery location by carriers, extra driving represents an additional source of traffic and pollution (air and noise). Due to the difficulty of monitoring commercial vehicles' cruising movements, little is known about the extent and effects of this phenomenon. Empirical research estimated a contribution between 20 and 30 percent of total vehicle miles traveled in cities from cruising [13] and a median deviation in delivery trips of 2.3 minutes [14]. Nevertheless, it is difficult to generalize these results since they depend on a number of variables, including transport infrastructure, parking choice, vehicle type, parking congestion, and expected dwell time [4].

In the past decade, a growing number of studies have addressed the issue of curbside by developing simulation-based curbside management solutions. Roca-Riu et al. [15] propose a centralized commercial bay management system and formulate the corresponding optimization as an assignment problem. The dynamic management of commercial bays is addressed by means of simulation by Comi et al. [16] who highlight its considerable potential benefits. Letnik et al. [17] investigate a sizing problem combined with the management of commercial bays and identify several potential benefits, including reduced energy consumption and delivery times. The solution method involves the combination of clustering and routing sub-models. To determine the number of commercial bays and their position for a given demand, Pinto et al. [18] employ the "covering principle," based on the acceptable walking distances from the carrier final destinations. Yang et al. [19] propose an auction-based system that optimizes the usage of pre-booked loading and unloading facilities to maximize the system's social welfare. The booking requests' time preferences and service duration are considered for determining the best potential assignment. Mor et al. [20] adopt a more extensive perspective by including the carriers' routing and scheduling dimension in the management problem and its influence on the optimal assignment. Different degrees of carrier flexibility seem to affect the overall rates of illegal parking and therefore the efficiency of the proposed system.

Only a handful of studies has focused on the traffic perspective by adopting traffic simulation to evaluate delivery operations management solutions. McLeod and Cherrett [21] develop a loading bay booking and control system for truck deliveries and investigate the potential effects for the case of Winchester High Street (London). The corresponding algorithm, which is based on a series of rules, is tied to an AIMSUN simulator. The authors highlight the detrimental effects of advanced booking of loading bays in the presence of early and late vehicle arrivals. To assess parking rules on a few-block scenario in Toronto, Nourinejad et al. [22] couple a parking choice model with microscopic simulation using Paramics. Aditjandra et al. [23] use a microsimulation method to analyze in detail the environmental impact of a large freight traffic generator (although they did not consider curbside). Transmodeler is adopted by Ukkusuri et al. [24] to examine the effects of an off-peak delivery program in Manhattan and compare the findings to a regional travel demand model. Munuzuri et al. [25] propose their own ad-hoc microsimulation to investigate double-parking and loading/unloading activities on a four-link network. Roca-Riu et al. [26] adopt an analytical approach to design shoulder lanes that can be dynamically used for delivery on a single link. Simoni and Claudel [27] adopt a hybrid simulation approach where traffic is modeled macroscopically while trucks movements and operations are reproduced microscopically to identify the optimal location of delivery stops on a single link. Generally, as the case studies' scale demonstrates, mesoscopic and microscopic simulations are best suited to evaluating small scenarios due to their high computing costs and demanding calibration procedures.

Few studies have also been conducted on the design and development of geofences, but none on freight traffic and delivery operations. Relevant works include applications to designated or forbidden areas for autonomous driving in scenarios with mixed flows [28], [29]. Similarly, all the research on parking guidance systems (PGS) has focused on the passenger segment. For a recent up-do-date overview of PGS' technical description and algorithms for passenger traffic applications the reader is referred to [30] and [31].

Among real-world applications of freight curbside management, of particular relevance is the "CurbFlow" pilot program run in Washington D.C. during 2019, where both commercial operators and private users could reserve curbside space among nine available slots for 30 minutes [32]. The initial results of this three-month pilot seem promising as double-parked delivery operations reduced by 64 percent. Other major cities in the U.S., like Los Angeles, San Francisco, Chicago, and New York, have dedicated curbside space for delivery operations in central business districts during certain times of the day [33]. Still, no reservation system for freight seems to be in place. In Europe, relevant real-world experiences include the "Straightsol" pilot project (December 2011-March 2012) in Lisbon [34], and the "ALF" project in Lyon [35]. In the first one, a system of parking meters and loop detectors was installed to improve the efficiency of loading and unloading operations. In the second, a dedicated app was developed for reserving commercial bays for a limited amount of time with a 24-hour notice.

The first geofencing trial projects for freight have been implemented in some European cities between 2010 and 2020. The Smartfusion project involved a real-traffic trial in Berlin to determine electric mode "sensitive" geofences along a specific route [36]. A geofencing solution for freight movements has been tested in Stockholm to support off-peak delivery with electric vehicles [37]. Similar systems for hybrid delivery vans to control emissions levels have been tested in Cologne (Germany), Turin (Italy), London (U.K.), and Valencia (Spain) [38].

III. METHODOLOGY

This study focuses on the modeling and analysis of alternative curbside management strategies for last mile freight operations, employing a simulation-based optimization framework. The framework involves two key types of agents: a "parking manager" and carriers. These agents interact based on parking behavior, traffic impacts, and optimization utilizing a metaheuristic approach.

Section III-A introduces the fundamental concepts and assumptions underlying the alternative strategies implemented by the parking manager and describes the overall simulation framework. The corresponding optimization problem formulation, along with the solution method, is elaborated in Section III-B. The modeling of carriers' operations, encompassing cruising and parking behaviors, as well as their interactions with the surrounding traffic, are detailed in Section III-C.

A. Problem Setup and Simulation Framework

One solution to deal with the adverse effects of trucks' cruising and illegal parking is to manage the existing commercial parking infrastructure through control systems regulated by public authorities (parking manager). A practical implementation of this solution could rely on a web app that requires carriers approaching the designated area for management to notify their planned delivery location, estimated arrival time, and planned duration of the unloading/loading operation. The parking manager processes carriers' information and provides guidance and recommendations based on the selected strategy.

In the parking guidance-based strategies, the parking manager processes carriers' notifications as 'requests' and performs an assignment to commercial bays based on alternative objective function formulations, which could represent the estimated traffic network delay or carriers' inconvenience. Not all the requests might be fulfilled depending on the demand and supply levels. When such circumstances occur, the parking manager does not provide any directions to carriers that are not assigned. The primary rationale behind this solution is to reduce the most 'critical' illegal parking operations and decrease cruising. In the geofence-based strategies, the parking manager identifies areas accessible to vehicles where cruising and parking are allowed. Unlike the previous approach, the parking manager does not identify a specific commercial parking spot but rather indicates the carriers a set of streets (links) where trucks cannot perform delivery operations. Unlike traditional geofencing methods, the proposed solution is 'vehicle-specific' since it tailors a dedicated geofence for each approaching vehicle. Similarly, parking guidance-based strategies, such a choice can be made to minimize the total network traffic delay or include broader objectives. To account for carriers' perspective, guidance and geofence strategies can include the inconvenience of detouring trips in their optimization formulation (see Section III-B).

Both parking guidance and geofencing focus on the short-term (e.g., upcoming 15 minutes with known predicted traffic flows) and circumscribed locations (e.g., neighborhoods, 10 to

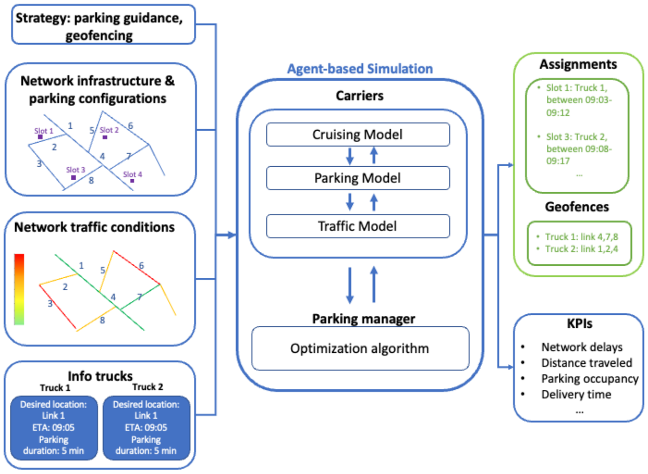


Fig. 1. Overview of the proposed curbside management approach.

30 blocks) with limited availability of commercial bays. All delivery vehicles are positioned outside the managed area when they communicate with the parking manager. Since the system must operate in real-time with a rather small time horizon, the problem only considers a single delivery per carrier. This is a reasonable assumption given the large uncertainties that characterize urban delivery routes (a typical urban delivery route includes around 100 daily stops), which would eventually preclude a booking system from operating well with longer time horizons. Given the short time frame and limited area considered for this problem, it is reasonable to assume that carriers do not reschedule their stops depending on the outcome of the curbside management system. In this study, carrier agents comply with the given recommendations or restrictions in terms of assigned parking slots and delivery areas. In parking guidance strategies, if no parking is allocated to an approaching truck, it drives to the desired destination, cruise for parking (depending on availability of space), and perform curbside delivery (legally or not). All the requests are known in advance as if the system would process the declared parking requests altogether.

The modeling approach to determine the most efficient implementations of the management strategies is based on a simulation-optimization framework. Within this framework, the parking manager agent derives the most efficient geofencing or guidance solutions leveraging information on the network's available commercial bays, carrier agents' delivery operations, and their potential effects on traffic patterns. This process follows a simulation-based optimization process that accurately models traffic impacts corresponding to alternative parking assignment configurations. The proposed simulation of carrier agents allows an accurate evaluation of the potential effects of detours and illegally parked deliveries on the surrounding traffic (see Section III-B for further details). Simulation-based optimization is particularly suitable for complex objective functions that cannot be easily derived analytically. Figure 1 illustrates a high-level overview of the problem architecture and highlights how the simulation and optimization models are linked to the input and output.

The input includes carriers' information, such as the desired stop location, delivery routes, estimated arrival time, and parking duration. Additional input includes the parking infrastructure supply, traffic conditions, and the objective of the parking manager (reflecting a selected strategy). From an output perspective, the adopted simulation produces detailed information in addition to the guidance or geofencing solution. This includes traffic delays and average speeds at the link level, parking occupancy over time, and individual carriers' routes and delivery operations realizations.

B. Optimization

The problem formulation for parking guidance-based strategies is based on some key assumptions. First, the overall simulation horizon can be split into smaller time slots (e.g., 1 minute) for curbside assignment purposes. Second, an increase in stop duration occurs each time there is a deviation from desired stop location due to the parking manager's assignment. This increase is determined by considering the additional distance from the original delivery destination and the average walking speed. Finally, in order to account for trucks' inconvenience of detours, a threshold distance from the desired stop location is set in the assignment problem for both strategies.

The model proposed is an extension of standard integer programs for assignment problems. The input of the problem consist of each truck j entering the network with the corresponding destination and stop duration (this information is communicated to the parking manager). The decision variable x_{ijt} indicates whether a certain parking slot i has been assigned to truck j during the time slot t. An auxiliary variable y_{ij}, is adopted for indicating the assignment of parking slot i to truck j.

Sets

- H: set of network links h
- I: set of candidate parking slots i
- J: set of trucks j
- T: set of time slots t

$$\begin{aligned} \underset{x_{ijt},y_{ij}}{\text{minimize}} \ & \sum_{h\in H}\Big[\sum_{t\in T}(N_{uh}(t+\Delta t)-N_{dh}(t))\Delta t\Big] \\ & + \sum_{j\in J}\Big[\sum_{i\in I}(\beta y_{ij}d_{ij}) + \Big(1-\sum_{i\in I} y_{ij}\Big)\phi\Big] \qquad (1) \end{aligned}$$

$$\text{subject to} \quad \sum_{j\in J} x_{ijt} <= 1 \quad \forall i \in I, t \in T \qquad (1b)$$

$$\sum_{i\in I} x_{ijt} <= 1 \quad \forall t \in T \qquad (1c)$$

$$\sum_{t\in T} x_{ijt} = d_{ij} \quad \forall i \in I, j \in J \qquad (1d)$$

$$\sum_{t\in T} x_{ijt} <= y_{ij}M \quad \forall i \in I, j \in J \qquad (1e)$$

The first component of objective function consists of the total network delay expressed as vehicle loss hours. It is calculated by summing the differences between the cumulative curves of arrivals N_d and departures N_u at each interval Δt, for each link h within the network. The total network delay is affected by the decision variables x_{ijt} (not explicitly shown in the notation for simplicity) and it is determined throughout traffic simulation. The second component of the objective function consists of the penalty associated with detouring trucks and expresses the inconvenience for a truck to stop at a different location from the preferred one. Such a penalty is derived as the product between the whole parking duration and a fixed penalty rate parameter β. A penalty cost ϕ for not assigning trucks is expressed throughout the auxiliary variable y_{ij}.

Constraint 1b ensures that the same parking slot is not assigned to two different trucks simultaneously. However, it is worth noting that it is still possible for two different trucks to be assigned to the same parking slot but at different times. To ensure a certain time span before and after the truck's planned operations and minimize the risk of conflicts between trucks assigned to the same slot at different times, a buffer time can be introduced in the assignment process.Constraint 1c ensures that one truck is not assigned more than one slot. Constraint 1d enforces the minimum duration of the parking assignment to accommodate the truck needed stop time. Such a stop time d_{ij} can be pre-computed by extending the original stop time with the the time spent to reach the final destination from the assigned parking slot i (return trip). An additional Constraint 1e is introduced to guarantee consistency between the two decision variables. By specifying a fixed value of M, it is possible to enforce a maximum detour constraint by limiting the duration of the truck's stop.

Geofence strategies can be expressed by a more compact formulation. Here, the decision variable x_{j_h} represents whether a link h can be accessed (geofenced) by truck j. According to this formulation, the objective function can be expressed by the total network delay alone since the size of geofence (i.e., number of links) directly affects the carriers' inconvenience. Constraints 1b-1e are replaced by the following constraint:

$$\sum_{h \in H} x_{jh} <= q \quad \forall j \in J \tag{2}$$

where 2 ensures that a maximum number of links q is geofenced for each truck. This threshold can be established as a problem input depending on the policymakers' decision.

The adopted optimization approach to solve the defined mathematical problems consists of the metaheuristic technique of the memetic algorithm (MA). MAs are particularly suitable for simulation-based optimization since they do not require a closed-form mathematical model for the related objective (which is hard to derive for traffic networks). In this optimization strategy, a set of randomly generated solutions (initial population) is improved through an iterative procedure. The algorithm terminates upon reaching a predefined maximum number of iterations or upon achieving a convergence of solutions. The convergence is determined by considering the evaluation of multiple runs for each solution. New generations of "child" solutions are created from the best-performing solutions (parents) through genetic operators (mutation, crossover, and selection). Considering the inherent randomness of the parking process, each solution undergoes evaluation through multiple runs (initially set at 10 per solution, but adjustable as necessary). In parking guidance-based strategies, solutions (chromosomes) are represented as a sequence of one-minute time slots for each parking slot present on the network (Figure 2). Each slot is characterized by a binary value based on the assignment to trucks on the network (0, when assigned). Solutions are bred throughout a two-point crossover procedure to generate child solutions, and simple removal procedures ensure their feasibility. Random mutations, consisting of parking slot re-assignments and new assignment additions (between 10-20%), are included to guarantee search space exploration. The process accounts for truck travel times and constraints (e.g., assignment overlap and maximum detour). Thus, certain modified solutions are discarded. In geofence-based strategies, each solution is given by combining each truck sequence of geofenced links as illustrated in Figure 2. A similar crossover procedure is applied in order to create new solutions at each iteration. Random mutations consist of random changes of geofenced links (between 10-20%).

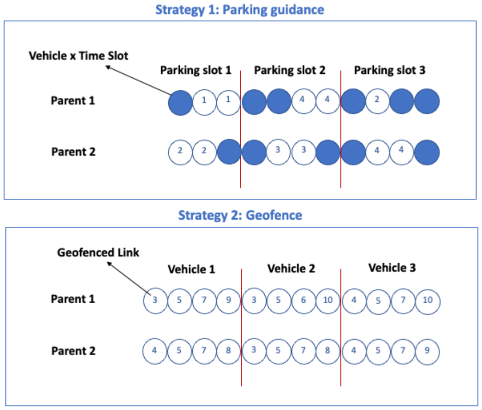


Fig. 2. Metaheuristic solution representation.

C. Carrier Simulation

Carriers (trucks) are modeled as agents aiming at performing delivery, interacting with each other and with the surrounding traffic.

A traffic module involves a macroscopic simulation based on the LWR model for reproducing the main flows on the network ([39], [40]). Within this framework, trucks movements and operations are microscopically modeled according to the theory of moving bottlenecks ([41], [42], [43]) is developed for this study. A moving bottleneck consist of any temporary traffic obstruction characterized by lower speeds. The solution to the resulting modeling problem can be obtained by coupling an Ordinary Differential Equation (ODE) expressing the trucks trajectories with a Partial Differential Equation (PDE) expressing the surrounding traffic flows. To accurately reproduce real-world mobility patterns, the traffic volumes entering and leaving the network, along with the turning proportions at intersections, can be fine-tuned using available traffic data. Additional information on the formulation and corresponding numerical method are provided by Simoni and Claudel [44]. The adopted numerical method to solve this problem consists of the Lax-Hopf algorithm [45]. In the LWR model, road traffic is assumed to follow the main properties of fluid streams.

More specifically, traffic flow follows two main laws: the conservation of mass (meaning no vehicles can appear or be lost), and an explicit relationship between density and outflow usually referred to as Fundamental Diagram:

$$\frac{\partial k(t,x)}{\partial t} + \frac{\partial Q(k(t,x))}{\partial x} = 0 \tag{3}$$

where, for a given time t and position x, k represents the density in vehicles per unit of length and Q corresponds to the outflow. The Fundamental Diagram $Q(k(t,x))$ is a positive concave function defined on $[0, k_j]$ where k_j is the maximal density (jam density). In this study we adopt a triangular FD [46]. The problem is solved numerically based on the Hamilton-Jacobi partial differential equation (PDE) formulation of the LWR model, which is solved through a Lax-Hopf formulation [45], [47]. The Hamilton-Jacobi PDE is expressed as follows:

$$\frac{\partial N(x,t)}{\partial t} + q\left(-\frac{\partial N(x,t)}{\partial x}\right) = 0 \tag{4}$$

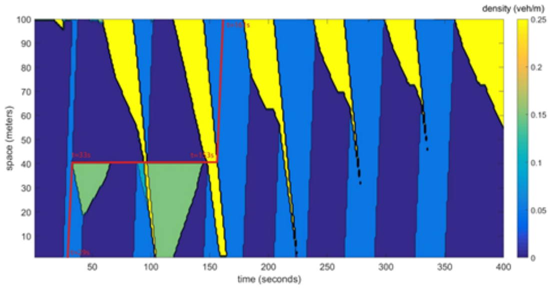
where $N(x,t)$ represents the cumulative vehicle count (Moskovitz function) for given time t and position x. Considering a space-time domain for a road segment simulation defined by $[0,\ L] \times [0,\ T]$, it is possible to solve the PDE by means of the Lax-Hopf formula associated with the value condition functions $c(.,.)$:

$$c(x,t) = \begin{cases} c^{l}_{ini}(x) & t = 0, x \in [(l-1)\Delta x, l\Delta x] \\ c^{j}_{up}(t) & x = 0, t \in [j\Delta t, (j+1)\Delta t] \\ c^{k}_{down}(t) & x = L, t \in [j\Delta t, (j+1)\Delta t] \\ c^{n}_{int}(x,t) & x \in [x_{b,n}, x_{e,n}], t \in [t_{b,n}, t_{e,n}] \end{cases} \tag{5}$$

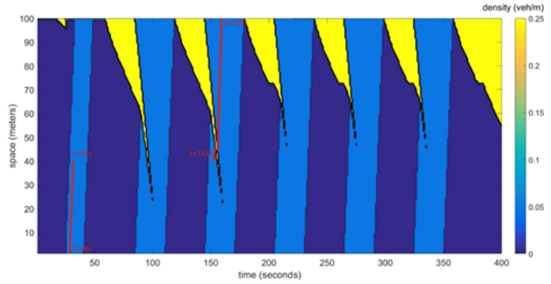
which represent, respectively, initial, upper boundary, downstream boundary, and internal conditions. The interested reader can find additional details on the Lax-Hopf solution approach in Claudel and Bayen [48] and Mazare et al. [49]. Simoni and Claudel [27] provide a comprehensive formulation of the model and the algorithmic steps of the simulation of truck operations in traffic networks based on Lax-Hopf.

This study considers delivery vehicles with a maximum speed equal to the "regular" traffic, a reasonable assumption in urban settings characterized by low speed limits. In this study, the primary obstruction to traffic flows occurs when trucks double-park at the curbside to accomplish their delivery. The space-time-density diagrams in Figure 3 illustrate the results of the adopted simulation framework for a vehicle entering and performing a delivery (red trajectory) on a road stretch characterized by two lanes over 5 minutes. When the delivery vehicle finds no parking spot, it illegally parks and causes a congestion spillback upstream (3a). If commercial parking is present on the link, such a vehicle will not produce any traffic disruption (3b).

The simulation includes a parking module in the simulation framework, which is dynamically applied each time a delivery vehicle approaches its destination. The agents are represented by trucks, which have delivery routes and aim to utilize commercial bays for delivery operations. The model is probabilistic and is based on several factors, such as network layout, the availability of delivery bays, and parking demand levels. Each delivery route, consisting of a sequence of links on the considered network, can be split into two segments: a 'traveling' component and a 'cruising' component. Each truck's delivery routes are precomputed based on Dijkstra's shortest path algorithm, connecting the origins, delivery destination, and exit destination. Routes can be modified according to assignment or geofence management strategy results and then utilized as input for the simulation. The origins and destinations are represented as nodes located at the edges of the network. The traveling component consists of that fixed portion of a route representing the access to the destination (at this stage, parking is not considered).



(a) Space-time-density diagram for double-parked delivery



(b) Space-time-density diagram for regularly parked delivery

Fig. 3. Simulation of delivery operations. Source [27].

The cruising component represents the second variable portion of a route where the truck attempts to find a stop location. It comprises a sequence of links surrounding the delivery stop. When the vehicle travels across a 'cruising link', it searches for an available commercial bay. Regardless of the implemented strategy, a truck will always aim at using a commercial bay, whose availability depends on other trucks and is, therefore, deterministic. If no commercial bay is available, the truck continues to the following cruising link of its route. This process is repeated until the truck finds a commercial bay or reaches the final cruising link. If no commercial bays are available, the probability of double-parking is determined by considering regular parking demand as a parameter. This information can be obtained from surveys or land-use data. A binomial distribution is used to indicate the likelihood of finding parking, which relies on the number of lots on the connection and the levels of parking demand. Finally, if all cruising links are traveled without success in finding parking, the vehicle commits an infraction and illegally parks. In this study, the cruising component is derived based on empirical

TABLE I

OVERVIEW OF CURBSIDE MANAGEMENT STRATEGIES

Name	Adopted Technical Solution	Objective	Parameters
Strategy 1 (S1)	Parking guidance	Minimize traffic congestion	β=0; ϕ=[20-5]*
Strategy 2 (S2)	Individual geofencing	Minimize traffic congestion	q=5
Strategy 3 (S3)	Parking guidance	Minimize carriers' delays	β=100; ϕ=[20-5]
Strategy 4 (S4)	Parking guidance	Minimize overall system costs	β=10; ϕ=[20-5]

*decreasing range for the increasing investigated instance size (20 to 50 trucks)

work by Chiara and Goodchild [14], who estimated an average commercial cruising time of 2.3 minutes in Seattle (U.S.) downtown. For each truck, the cruising length is determined from a normal distribution reflecting this value. Accordingly, a feasible sequence of links connected to desired destination is derived. Depending on the amount of aggregation and number of features considered (parking availability, price, and propensity of drivers to commit infractions), other cruising and parking models, such as equilibrium and logit models, may be used to simulate commercial cruising and parking behavior. The cruising and parking behavior is modeled according to a Markovian process expressed as follows: $\prod_{c \in C} P_c(s(c), s(c'))$ where the probability of parking at cruise link $s(c)$ depends on the number of curbside spots available, a general probability and the presence of other cruising links set C; this directly affects the probability of parking in the following cruising link which depends on $s(c')$.

The cruising and parking operations are affected differently by the investigated strategies described in Table I. Strategy 1 (S1) focuses on reducing traffic congestion through parking slot assignment by prioritizing the minimization of delays in the objective function (Eq. 1). Strategy 2 (S2) shares the same goal of reducing traffic congestion but through individual geofencing, shifting the focus from parking operations to cruising (a significant contributor to congestion). Strategy 3 (S3) employs parking slot assignment to minimize delays for carriers, prioritizing the objective function component related to carriers' detours. This is done by increasing penalty parameters for detouring trucks and unassigned parking spaces in the objective function (Eq. 1), making the delay minimization component negligible. Strategy 4 (S4) aims to reduce overall user delay, including traffic congestion and carriers' delays, utilizing parking slot assignment. Conducting a systematic analysis of the relationship between formulation parameters, corresponding objective function values, and impacts for parking guidance strategies exceeds the scope of this study. Therefore, our focus is on the most representative cases (S1, S3, and S4).

IV. RESULTS

A. Case Study and Instances

The proposed strategies are evaluated on the layout of the Austin (U.S.) downtown network, which correspond to an area of about 0.86 square kilometres. The network consists of two hundred and one links and a hundred and twenty nodes. Most of the intersections are signalized, and each link has between one and three lanes (about 90 percent). We only simulate green/red phases in this study for simplicity's purposes, and we use the same triangle Fundamental Diagram for all links with $q_{\max}$=0.4625 veh/s, v=12.5 m/s, and k_j=0.1295 veh/m. The area has 35 parking slots whose location is illustrated in Figure 4. Traffic volumes and turning proportions at intersections have been calibrated using traffic data from the "Bluetooth Travel Sensors - Individual Address Files (IAFs)" (City of Austin Transportation Department, 2017), which included traffic counts and average travel times during different times of the day [27]. The simulation and optimization processes are conducted for a specific time interval of 15 minutes (with 4 seconds time steps), aiming to replicate the traffic patterns of Austin's downtown network at 8 AM. Each commercial bay is characterized by 1-minute time slots for the optimization problem.

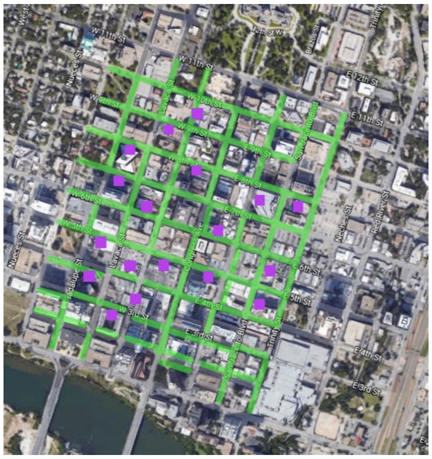
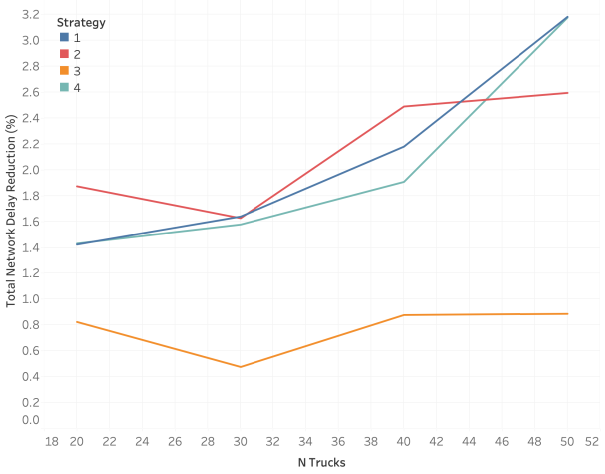


Fig. 4. Commercial bay layout in downtown Austin (2018).

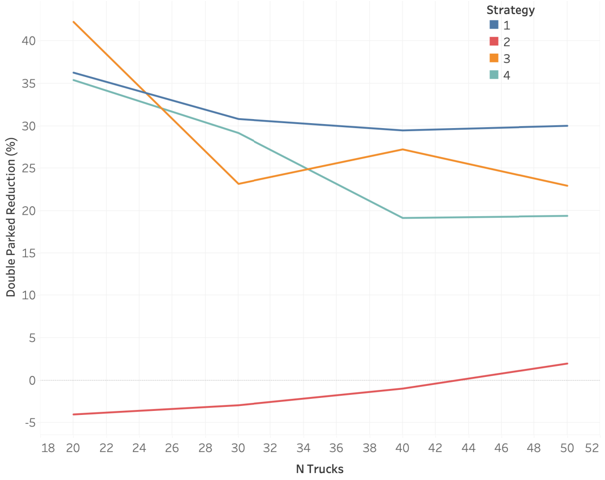
Different instances are created based on alternative combinations of commercial parking demand (number of trucks) and its spatial distribution (dispersion of delivery stops across the area). Four alternative levels of overall demand intensity (20, 30, 40, 50 trucks) and spatial configurations characterized by different spatial distributions (e.g., clustered vs. homogeneously spread) are considered for a total of 48 instances. For each instance, ten runs of the optimization algorithm are performed (since converge of the solution is not guaranteed). The input parameters and corresponding optimization results for S1 are described in Table II (Appendix). A summary of computational and efficiency tests for the other three strategies is reported in Table III (Appendix). Depending on the instance size, the best identified solutions deviate within 3% from the "optimal solution" identified by running the metaheuristic for a 1800-second threshold (network delays can be computed only through simulation, therefore, benchmarking with a closed form solution is not feasible). The deviation from the optimal is consistent across different strategies for the same instance sizes, allowing a fair comparison of the strategies' impacts.

B. Efficiency of Strategies

Parking guidance (declined into three different strategies) and geofencing seem to effectively reduce the network's traffic delays for different demand levels and patterns. However,



(a) Impacts on Traffic Network Performance



(b) Impacts on Double Parking

Fig. 5. Efficiency of strategies.

the four strategies achieve different results based on the demand levels. Overall, S2, seems to perform better than any parking guidance-related strategy for low and medium levels of parking demand (20, 30, and 40 trucks) (Figure 5a). Depending on the amount of simulated trucks, S2 achieves delay reductions between 1.6-2.6% whereas S1, S3, S4 achieve decreases between 0.5-3.2%. Interestingly, S1 and S4 provide increasing delay reductions for increasing levels of parking demand, while the performance of S2 deteriorates for large-size instances. The efficiency of S3, which achieves significantly lower reduction than other parking guidance-related strategies (ranging between 0.5% and 0.9%), is not considerably affected by the demand levels. These results suggest that, for lower and medium demand volumes, geofencing (S2) is more efficient than parking guidance strategies considering traffic delay minimization (S1 and S4). However, when only carriers' detour is prioritized in parking guidance (S3), the results consistently remain low, irrespective of demand levels. Generally, scenarios characterized by uniformly spread parking demand can benefit more from introducing dynamic management strategies than those with clusters of demand. The delay reduction in the former can be as 0.8% higher than in the latter.

As expected, S1, which focuses on managing the existing parking infrastructure, determines a significant reduction in illegal parking (Figure 5b). The highest reduction (about 35%) is reached for low demand configurations (20 trucks). Due to physical constraints such as slot capacity and the maximum detour of trucks, the parking guidance strategy cannot achieve significantly greater reductions (around 30%) in illegal parking for higher levels of demand. Interestingly, the parking reduction efficiency of the two other parking guidance-related strategies, S3 and S4, which is comparable to S1 for low demand (20 trucks), deteriorates faster for higher levels (22-26%). S2 has little influence on the amount of illegal parking, with the highest reduction of about 2.5%. In configurations with low demand, there is even a slight increase in double parking (3.5% for 20 trucks).

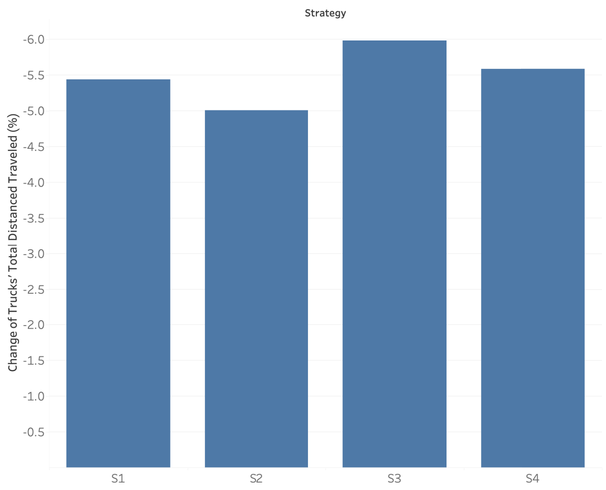
These results suggest that geofencing can significantly reduce traffic delays by focusing on trucks' cruising and affecting the final portion of their routes. At the same time, alternative parking guidance implementations can yield different impacts from a network and parking efficiency perspective. Strategies that prioritize traffic congestion mitigation, can achieve comparable results regardless of double-parking reduction. Conversely, parking guidance focused on carrier detour minimization, lead to distinct parking configurations, characterized by similar reductions in double-parking but minimal improvement in traffic network performance.

These findings are line with the impacts on the utilization of parking space. Notably, S1 demonstrates a substantial enhancement in parking utilization, exhibiting increases of over 12% and 22% in low demand (20 trucks) and high demand configurations (50 trucks), respectively. Under S1, parking utilization grows almost linearly for increasing levels of demand between 20 and 50 trucks. S3 and S4 exhibit a similar trend. In line with the illegal parking effects, S2 does not affect significantly the utilization of existing commercial bays since changes are less than 1%.

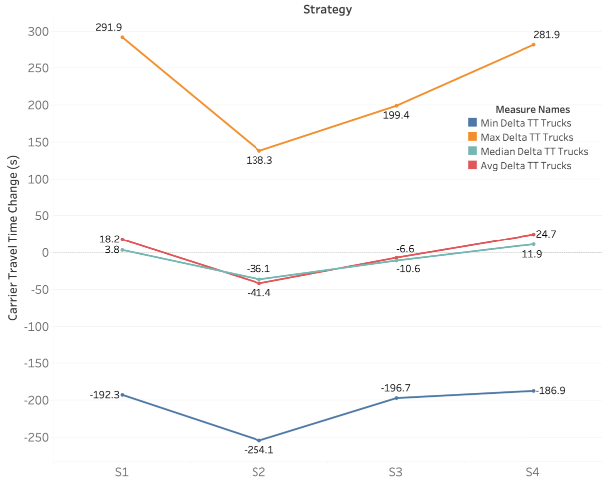
C. Distributional (Equity) Impacts

Not only the four strategies have different effects regarding traffic efficiency improvements, they can also have significantly different impacts on individual carriers. To gain a better understanding of the distributional effects and trade-offs between the perspectives of traffic network operators (public stakeholders) and carriers, we analyze the effects of strategies at both the aggregate and individual carrier level.

An analysis of carriers' change in total distance traveled (Vehicle Kilometers Traveled, VKT) provides insights into the overall effects of the alternative strategies on delivery efficiency (6a). The total distance traveled can be adopted as a proxy for pollutant emissions and energy consumption (although average speed also plays a significant role). Generally, despite the detours, the implementation of parking guidance leads to a reduction in VKT (between 5.5-7%), likely attributed to a decrease of cruising and double-parked delivery operations. Geofence (S2) achieves similar results with an almost 5% reduction in VKT.



(a) Impacts on carriers' overall delivery efficiency



(b) Distributional effects on carriers' performance

Fig. 6. Benefits and costs of strategies.

While reductions in total network delay are associated with decreases in carriers' VKT, no strong correlation is observed (correlation coefficients between 0.13 and 0.19). Interestingly, the reduction in double-parking is only weakly correlated with the overall delay reduction (correlation coefficients between 0.3 and 0.5). These results suggest that while the overall reduction in carriers' distance traveled and double-parking contributes to traffic efficiency improvements, avoiding double-parked operations and cruising for parking on specific links may be more crucial. These findings align with previous research [27] that identified different degrees of response to freight access policies based on traffic patterns and network layout.

From an individual carrier perspective, descriptive statistics such as the minimum, maximum, median, and mean of carriers' travel time (TT) changes provide valuable insights into the fairness and distributional effects of different strategies (6b). Notably, all strategies exhibit a positive maximum change and a negative minimum change, indicating that some carriers would benefit from improved delivery performance while others may experience a worsening. However, when considering curbside management S1 and S4, their larger range and skewness indicate a greater disparity in effects among carriers compared to geofencing (S2) or the carrier-oriented guidance strategy S3. In the former strategies, the range corresponds to 483s and 467s, while in the latter ones, the range corresponds to 392s and 395s. Furthermore, the positive skewness in their distributions suggests that a few carriers might encounter significant increases in delivery times. On the contrary, S2 and S3 not only demonstrate a decrease in median and mean travel times (indicating improved performance), but also their closer values suggest a more balanced distribution of impacts across carriers. These strategies exhibit a more equitable distribution of effects, with a reduced likelihood of extreme variations in travel time changes.

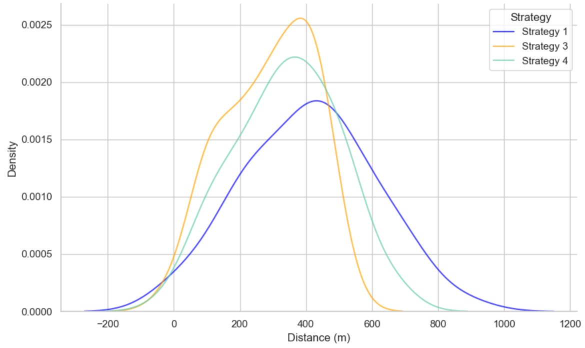
A more focused analysis of scenarios characterized by clustered demand highlights how parking assignment can differ across carriers (Figure 7a). In line with the previous analyses, S1 shows a wider range of detour distance across carriers and a higher average detour (around 450 m) than S3 and S4 (around 350 m). This strategy also allows higher parking occupancy than the other two strategies((Figure 7b), irrespective of whether the parking slot is in high or low demand. Although the utilization of parking slots in high demand can vary by approximately 15% between S1 (the strategy achieving the maximum) and S3 (the strategy achieving the minimum), this disparity can widen to 30% for slots in low demand. This result is in line with the previous outcomes, highlighting achieving higher utilization of parking infrastructure (particularly, for less attractive slots) is likely to generate distributional issues among carriers (uneven detour distances).

In summary, S1 appears more effective in improving overall network traffic performance. However, from a distributional perspective, it may present potential issues. Imposing tighter detour constraints could help reduce disparities but may compromise traffic efficiency. Carriers that are more likely to trigger congestion phenomena are prioritized in the assignment, but could also be detoured by a significant distance. Interestingly, despite S3 explicitly prioritizing carriers' operations, it is outperformed by S2 in both traffic efficiency and distributional aspects.

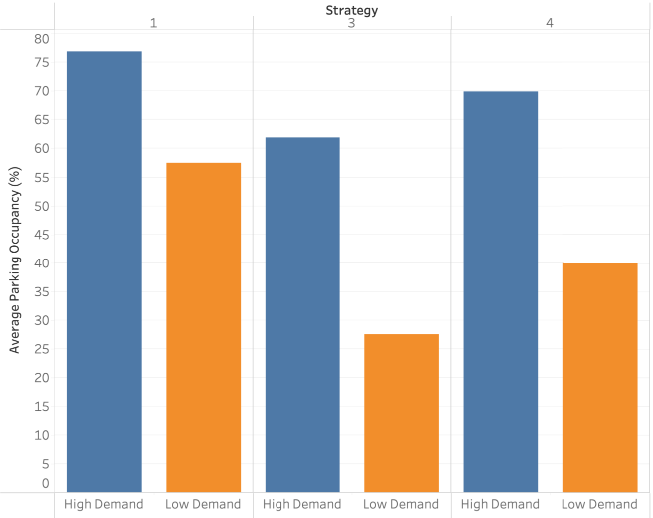
D. Influence of Demand and Supply Layout

To investigate the effectiveness of the parking guidance strategy across different scenarios characterized by not only different demand patterns but also supply patterns, this study considers 10 alternative configurations characterized by randomly generated parking supply configurations, with the same number as in the Austin downtown. When combined with medium-sized instances of size 30, 120 combinations of demand-supply configurations are obtained. The average distance between nearest neighbors for demand and supply is adopted as an indicator of spatial dispersion. This indicator quantifies the average distance between each delivery destination/commercial bay and its closest neighboring point in the dataset. Mathematically, it can be expressed as:

$$\bar{D}_{\mathrm{NN}} = \frac{1}{N}\sum_{i=1}^{N} \min_{j\neq i}\left(|\mathbf{x}_i - \mathbf{x}_j|\right) \tag{6}$$



(a) Distributions of assignment detours

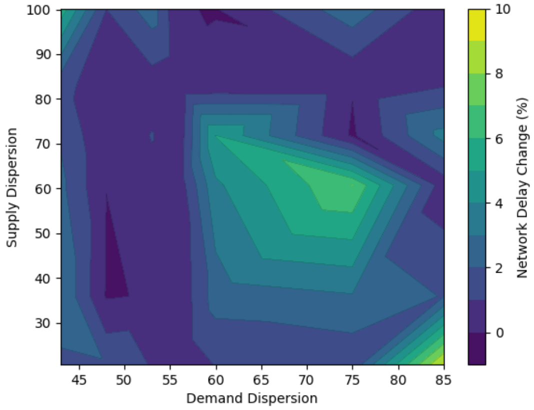


(b) Parking occupancy for high- and low-demand slots

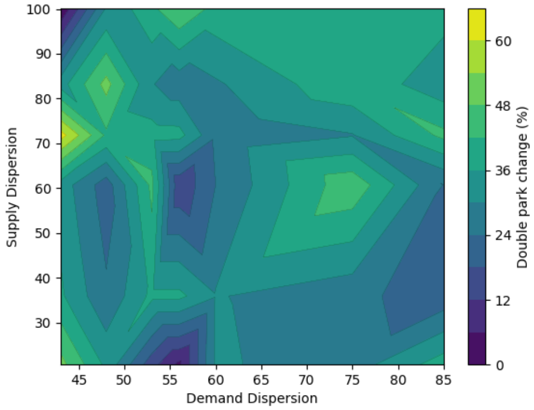
Fig. 7. Benefits and costs of strategies.

where x_i and x_j represent the coordinates of the i and j parking demand/supply points, respectively, and Ndenotes the total number of parking demand/supply points in the dataset. A low value of $\bar{D}_{\mathrm{NN}}$ indicates a high spatial concentration or clustering of parking demand/supply points.

As anticipated, the layouts characterized by a relatively homogeneously spread demand and supply exhibit the highest delay reductions (5-10%) (8a). This result is reasonable since a well-balanced distribution of delivery destinations and commercial parking can guarantee a broader range of feasible assignment solutions (complying with carriers' detour constraints). Interestingly, higher increases in traffic performance can be observed in scenarios characterized by clustered supply (with $\bar{D}_{\mathrm{NN}}$ below 30) and highly dispersed demand (with $\bar{D}_{\mathrm{NN}}$ above 80). One possible explanation for these findings is that, even with homogenously spread deliveries, the parking guidance can guarantee efficient solutions by prioritizing the "most critical" carriers' operations and assigning them to the nearest cluster of commercial bays. These hyphotesis is supported by an analysis of double-parking reduction((8b), which suggests no significant differences are found for these scenarios.



(a) Efficiency and demand-supply layout



(b) Double-park change and demand-supply layout

Fig. 8. Impacts of demand and supply layout.

E. Implications for Policy-Making and Implementation

The investigated strategies reduce traffic delays and improve curbside infrastructure utilization to a different extent. However, the analyses suggest that city and traffic authorities may prioritize one strategy over the other based on their specific objectives regarding urban freight traffic externalities, considering significant differences in key performance indicators (KPIs). Geofencing (S2) achieves comparable results, if not higher than parking guidance in improving traffic performance for low-medium demand levels. However, parking guidance (S1,S3,S4) surpasses geofencing by achieving significantly higher parking utilization and mitigation of illegal parking. For the investigated scenarios, parking guidance strategies (S1 and S4) explicitly accounting for network delay can preferred to geofencing for reducing delays and truck traffic-related pollution. If the primary focus is on parking infrastructure utilization and addressing safety concerns related to illegal parking, then parking guidance should be given higher priority regardless of the demand level. When looking at emissions, noise, and energy consumption, the alternative strategies achieve similar reductions in carriers' distance traveled (a reasonable proxy if combined with speed data) by reducing cruising for parking.

From an individual carrier perspective, which is focused on delivery performance, the parking guidance and geofence strategies may lead to controversial effects. S2 brings tangible benefits to every carrier due to the general improvements in traffic conditions. Instead, while S1 improves overall traffic performance, it exhibits a greater disparity in effects among carriers due to detours. Some carriers may experience significant increases in delivery times, leading to potential equity concerns. Therefore, public acceptability concerns related to this solution might arise. This issue can be mitigated by increasing the weight of carriers' detour costs in the optimization problem formulation (as in S3 and S4). However, these implementations might partly address this issue but at an efficiency cost. Prioritizing carriers in the assignment process (S3) can improve distributional effects, but it may not yield significant benefits in terms of overall traffic improvement.

Under these conditions, it becomes important to accurately assess the investment and maintenance needs for the alternative strategies. The investigated solutions would rely on a monitoring component, a controller, and a communication system for real-world implementation. Both parking guidance and geofencing would require a real-time traffic monitoring system that allows, with the support of prediction and simulation models, short-term accurate traffic estimation. Collecting granular traffic data with cameras and detectors is becoming standard practice in many urban areas. Parking guidance strategies would require a system to monitor parking spaces. For this purpose, surface or overhead sensors could be installed at the commercial bays. Geofencing would require retrofitting vehicles with navigation devices. Finally, all strategies need to rely on V2I technologies for fast and reliable communication of guidance and directions between the parking manager and carriers. Recent advances in connectivity (5G networks) provide new prospects for addressing this issue.

TABLE II

SUMMARY OF COMPUTATIONAL RESULTS. (*) SIMULATION THRESHOLD REACHED

Instance Size	**Pop Size**	**Generations**	**Best sol (%)**	**Deviation from Opt (%)**	**Sim time (s)**	**Avg. time (s)**
10	20	10	2.1	0.6	1.4	200
10	20	20	2.1	0.7	1.4	381
10	30	10	2.1	0.6	1.4	320
10	30	20	2.1	0.5	1.4	561
10	40	10	2.1	0.5	1.4	359
10	40	20	2.1	0.7	1.4	744
20	20	10	2.5	0.9	2.3	335
20	20	20	2.5	1.1	2.3	671
20	30	10	2.6	1.2	2.3	522
20	30	20	2.6	1.1	2.3	1001
20	40	10	2.5	1.0	2.3	572
20	40	20	2.5	1.1	2.3	1143
30	20	10	1.8	1.8	3.2	472
30	20	20	1.9	2.1	3.2	905
30	30	10	1.9	2.4	3.2	670
30	30	20	2.1	1.7	3.2	1231
30	40	10	2	2.1	3.2	869
30	40	20	2.1	2.2	3.2	1711
40	20	10	2.3	3.0	4.3	616
40	20	20	2.5	2.6	4.3	1195
40	30	10	2.3	2.7	4.3	988
40	30	20	2.5	-	4.3	1800*
40	40	10	2.4	0.1	4.3	1467
40	40	20	2.5	-	4.3	1800*
50	20	10	2.6	1.2	5.2	752
50	20	20	2.8	1.1	5.2	1650
50	30	10	2.8	1.3	5.2	1123
50	30	20	3	-	5.2	1800*
50	40	10	2.8	1.0	5.2	1683
50	40	20	3	-	5.2	1800*

TABLE III

SUMMARY OF EFFICIENCY TESTS FOR ALTERNATIVE STRATEGIES

Strategy	**Instance Size**	**Tot time (sim+opt)**	**Dev from Best sol (%)**
S2	20	1023	2.2
S2	30	1210	2.1
S2	40	1800*	-
S2	50	1800*	-
S3	20	1051	2.1
S3	30	1288	2.3
S3	40	1800*	-
S3	50	1800*	-
S4	20	1010	2.3
S4	30	1289	2.6
S4	40	1800*	-
S4	50	1800*	-

V. CONCLUSION

This paper proposes multiple last-mile management strategies for urban freight operations: three based on parking guidance and one based on geofencing. Unlike other approaches, the proposed solutions explicitly address traffic delays in their corresponding problem formulations. For this reason, a simulation-based optimization based on metaheuristics is developed to identify high-performance solutions efficiently. The experiments indicate that the proposed strategies can be potentially implemented in real settings with minor improvements in algorithm efficiency and optimized codes. Future research will involve the development of rolling horizon-based approaches for solving the strategies in a streaming fashion

According to various KPIs, both strategies show promising results to a different extent, depending on demand levels and patterns. Geofencing achieves higher delay reduction with minimum changes in the last-mile operations while parking guidance is very beneficial for parking utilization and illegal parking mitigation. Therefore, if the primary policy goal is reducing network traffic congestion for low and medium demand, it is still possible to achieve that without eliminating illegal parking. The relation between parking demand, parking supply layout, and existing traffic patterns holds significant importance. This suggests that strategies that concentrate on specific operations and critical areas within the networks could be exceptionally valuable. Hence, future research should investigate the relevance of these strategies in other cities, characterized by different demand patterns and diverse infrastructure layouts, to gain a more comprehensive understanding.

Carrier-focused concerns, which include equity and acceptability, can be addressed by prioritizing carriers' convenience (minimizing detours), but with potential efficiency trade-offs. The analyses show how in urban freight delivery operations management, much like in other transportation sectors, the "system optimum" may yield uneven costs to carriers. These outcomes suggest that, while parking guidance is more suitable from a city planners' perspective (focused on minimizing traffic disruptions), geofencing achieves a better balance between different objectives. Future work will deal with novel strategies based on this framework aimed at a compromise between stakeholders (i.e., city and carriers) through novel problem formulations.

APPENDIX

See Tables II and III.

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