Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 00 (2018) 000–000

Transportation Research Procedia

www.elsevier.com/locate/procedia

World Conference on Transport Research - WCTR 2019 Mumbai 26-31 May 2019

Modeling a Time-Differentiated Policy for Management of Loading Bays in Urban Areas

Margaret Wilson [a]*, Milena Janjevic[a], Matthias Winkenbach[a]

[a]*Massachusetts Institute of Technology, 77 Massachusetts Ave, Cambridge, MA 02139, United States*

Abstract

A model is introduced to optimally locate loading bays in an urban environment according to the demand for deliveries at various categories of non-residential locations and to assist policymakers in implementing this solution and explicitly assessing the associated costs and benefits. This model allows flexibility to consider loading bays with varying capacities, considers the capacity of each bay in terms of occupancy time including driver walking time between bay and delivery destination, and chooses from among a specified set of candidate locations for bays. The model formulation allows for selective non-allocation of loading bays in the case that the cost of urban land-use outweighs the cost of traffic disruption according to the level of ambient traffic observed, the probability of the delivery driver successfully finding on-street parking at the destination, and a baseline sensitivity factor specified by the policymaker. A method is also posed to estimate the vehicle kilometers traveled (VKT) by logistics fleets in the model scenario with and without the presence of loading bays, allowing policymakers to quantify the impact of potential solutions in terms of a relevant performance metric.

© 2018 The Authors. Published by Elsevier B.V.
Peer-review under responsibility of WORLD CONFERENCE ON TRANSPORT RESEARCH SOCIETY.

Keywords: urban freight transport; city logistics; loading bays; freight parking

1. Introduction

Due to their large populations and extensive commercial establishments, urban areas require large quantities of goods and services for commercial and domestic use (Browne et al., 2012). While robust logistics operations are essential to support commercial activity, the resulting traffic

* Corresponding author. Tel.: +1-614-425-2034.
E-mail address: mowilson@mit.edu

2352-1465 © 2018 The Authors. Published by Elsevier B.V.
Peer-review under responsibility of WORLD CONFERENCE ON TRANSPORT RESEARCH SOCIETY

flows add additional burden to the urban transportation infrastructure. Urban transportation policymakers are faced with the task of balancing the needs of multiple stakeholders in designing policies that must support efficient flow of commercial goods while reducing externalities.

Urban freight transport is characterized by important time and spatial constraints. Indeed, the urban environment is characterized by scarcity of access, e.g., congested roads, space constraints, and infrastructure limitations which restrict the efficiency and quality of urban logistics operations (Behrends, 2016). Delivery operations typically occur on the street (Aiura and Taniguchi, 2006) with the majority of freight vehicles illicitly parked (Debauche, 2006; Routhier, Dufour, & Patier, 2002) which increases the overall contribution to the congestion. Indeed, Routhier & Toilier (2007) estimate that double-parked freight vehicles contribute to one quarter of overall space occupancy of freight vehicles in an agglomeration and to up to two thirds of space occupancy in city centres. Freight carriers are also often requested to arrive at customers within specified time windows (Taniguchi, Thompson, & Yamada, 2004) often leading to conflicts over the use of the road network between the passenger and freight transport during peak hours (Routhier et al., 2002).

Delivery-related externalities caused by illegally-parked freight vehicles can be addressed by the provision of dedicated freight parking infrastructure. A classic approach is the provision of on-street or off-street loading zones. Another type of parking infrastructure is vehicle reception points which are larger loading zones that can accommodate up to 4 to 5 vehicles and where carriers can load and unload goods destined for neighboring customers (Allen, Browne, Cherrett, & McLeod, 2008). These facilities have been implemented in a number of French cities such as Bordeaux, Rouen, Lyon, Clermont Ferrand, and Montpellier under a common denomination "Espaces de Livraison de Proximité" (ELP) (Gerardin Conseil, 2004).

The demand for parking of freight vehicles tends to vary considerably throughout the day, as indicated by several studies (e.g. Lebeau & Macharis (2014), Gerardin, Patier, Routhier, & Segalou (2000). A provision of a fixed parking infrastructure does not account for this effect and typically results in a lack of capacity during peak hours of freight deliveries and underutilisation during the off-peak hours. Furthermore, urban transportation infrastructure is shared with other users of the road network. Multi-use lanes aim to adapt the use of public roads to the different operational uses and needs that emerge through the course of the day (e.g. freight loading and unloading, ambient passenger traffic, and residential parking). This concept has been implemented in several cities. For example, an experiment with one multi-use lane was implemented in 2004 at the inner-city ring road of Cologne (DE), allowing four different types of uses depending on the time of the day: freight loading and unloading, driving, paid parking and parking free of charge (NICHES, 2007). In Barcelona (ES), three lanes are dedicated to multi-use and installed with VMS (variable message signs) denoting which uses are allowed on the street at various times of day (Huschebeck & Allen, 2005; Alvarez & Calle, 2011)). A similar system has been implemented in Bilbao (ES). Systems such as these, with programmable interfaces requiring minimal intervention for operation and enforcement, are efficient along multiple fronts. By allocating space to delivery operations only at the most critical times, they control traffic when necessary and provide general accessibility when necessary. By reducing congestion and providing parking, these measures also potentially reduce emissions produced by freight vehicles looking for parking or idling in congested general-use lanes. Additionally, the information-technological aspect of these measures allows them to be paired with novel enforcement mechanisms such as occupancy detection.

Extant literature presents several contributions that aim to support policy-makers in adequately planning for freight parking infrastructure in urban areas. However, none of these allow for differentiating the use of public space throughout the day. This paper addresses this gap and presents a model that supports a time-differentiated policy for management of loading bays in urban areas. The model allows the establishment of a set of loading bays that should be active during the peak hours of delivery activity and a related subset that should remain open during the off-peak hours. The model explicitly considers trade-offs between the dedication of scarce urban land to freight parking (i.e., the cost of lost street area) and the effect on surrounding traffic caused by deliveries that occur on-street at store locations, potentially obstructing surrounding traffic.

As a final post-processing step, an estimation of vehicle kilometers traveled is presented and used to investigate the potential effect of logistics consolidation on the transportation infrastructure of the case study area.

This model is validated on a case study of a small region of Bogota, Colombia that is densely populated with numerous, mostly small commercial establishments and a highly constrained road network.

2. Literature review

Several contributions propose models and simulation tools that aim to establish the optimal number of loading bays in a given locality and investigate the effect of such policies on the overall level of traffic. Tamayo, Gaudron, & De La Fortelle (2017) propose an optimization model for locating delivery bays based on estimated demand in terms of number of deliveries per establishment type. The objective function in this study aims to minimize the demand-weighted distances to the establishments while considering trade-offs between the needs of local business and the scarcity of parking area in an urban setting. The paper presents a case study on a region of Paris that considers existing loading bay locations and proposed new candidate bay locations. The walking distance between each shop and bay is explicitly modelled although the impact of double-parked freight vehicles is not. Alho, Silva, & de Sousa (2014) provide a modeling framework integrating simulation and optimization strategies but do not apply this framework to a specific case. The model emerging from this framework would ideally consider both temporal and spatial variability in demand, traffic, and cost outcomes and would capture the effects of non-compliant (e.g., traffic-disrupting) logistics vehicles on ambient traffic in terms of enforcement rates and the number of ambient vehicles affected. This work also suggests the inclusion of variable capacity for loading and unloading bays. Alho, de Abreu e Silva, de Sousa, & Blanco, (2018) estimate the freight parking demand in Lisbon based on establishment surveys and propose an alternative delivery bay system using a capacitated maximum coverage problem. They incorporate observations of non-freight vehicle compliance with parking restrictions (i.e., non-freight vehicle misuse of parking areas) to assess the likelihood of allocated bays being serviceable for their intended use. They then compare this alternative system to the current environment using micro-simulation. The micro-simulation then outputs a variety of assessment criteria for various scenarios including delay time, emissions, lane changes (under the assumption that a double-parked freight operation will forces a lane change by trailing passenger vehicles), stop time, and speed decrease. Aiura & Taniguchi (2006) propose a model determining the optimal location of loading-unloading spaces by minimizing the total cost that is comprised of delay penalty, fixed cost, operation cost, parking fee, and waiting cost of both pickup-delivery vehicles as well as passenger cars. A unique feature of this model is the consideration of the circumstance where a freight vehicle finds a loading bay already occupied either by an illegally parked passenger vehicle or another delivery vehicle and an estimation from queuing theory of the amount of time a vehicle must wait to find an available parking space. Delaitre (2009) proposes a simulation tool comprised of two modules: one for the simulation of capacitated delivery areas at a local level based on queuing systems and the other for simulating the spread of traffic obstructions during deliveries based on system dynamics. This model also considers the availability of parking spaces potentially occupied by other delivery vehicles or by illegally parked passenger vehicles. The tool proposed in this work is intended as a simulation-based decision aid to policymakers that is capable of providing a solution at the citywide level and does not necessarily optimize facility locations. Roca-Riu, Cao, Dakic, & Menendez (2017) propose a model considering time-differentiated policy and interactions with the flow of ambient traffic at a macroscopic level, but do not integrate this with demand for freight parking. This model integrates several features from the field of traffic engineering, including traffic signal control implemented along a corridor and the effects of parking and un-parking actions on ambient traffic in terms of disturbances posed to the surrounding traffic flow. Finally, Dezi, Dondi, & Sangiorgi (2010) present a study of freight parking in a limited traffic zone in Bologna, Italy. The study considers the data collection demands relevant for an optimal allocation of loading zones in an urban area – e.g., demand for freight parking, loading bay locations relative to both demand and other loading bays, bay capacity, enforcement, and accessibility – but does not propose an optimization model.

Overall, extant literature does not explicitly consider the temporal distribution or the delivery operations within a day and a time-differentiated use of urban space on an hourly or per-period basis relative to existing temporal patterns of road use. The number and location of loading bays are generally established to serve peak-demand periods. Furthermore, several studies have examined the trade-off between allocating space to freight parking in urban settings and the disruptions caused by on-street freight deliveries. However, extant contributions do not explicitly consider trade-offs between double-parked freight vehicles and those using loading bays nor do they provide a model that offers an explicit parameter for policymakers to compare the two costs on a time-dependent basis. Indeed, the value of a loading zone will be higher, for instance, when and where freight activity is at its greatest intensity and when disruptions to ambient traffic would pose the greatest nuisance (e.g., passenger peak travel periods). However, the same space will be less valuable in periods of lower freight activity or when disruptions to ambient traffic may be more tolerable.

3. Establishing a Time-Differentiated Policy

Loading bays allocate urban land, a scarce resource, to a dedicated purpose for some period of time; thus, their costs must be considered along both spatial and temporal dimensions. For this reason, a model is proposed to compare the relative costs of decisions to open or forgo loading bays according to time-varying road use patterns over the course of a typical day. Lastly, a method is provided to assess the impact of these decisions in terms of the reduction in vehicle kilometers traveled (VKT) enabled. In this study, we propose a model supporting a time-differentiated policy for the management of loading bays in urban areas. In this section, we first present the problem setting. We then present an optimization model.

For a given urban area and from a set of candidate locations, the model establishes: (1) a set loading bays that should be active during the peak-hours of freight delivery activity, and (2) a subset of loading bays that should remain active during the off-peak-hours of freight delivery activity. It selects loading bays from a set of candidate locations that should be open during the peak-hours of delivery operations. It further indicates which of these bays should remain open during the off-peak-hours of delivery operations. The model is informed by the location, frequency, and duration of deliveries towards shops in the area during the different time periods throughout the day.

3.1 Problem Setting

We consider an urban area with a set of commercial establishments $I = \{i\}$ that that generate freight delivery operations throughout the day. Commercial establishments are categorized into $M = \{m\}$ types. A parameter β_{im} signifies if a shop i is of type m. A set $K = \{k\}$ represents candidate locations for the possible establishment of loading bays. Each candidate location is characterized by a capacity c_k. For each pair of candidate location bay k and shop i, d_{ik} and w_{ik} represent the walking distance and the walking time respectively. The parameter r represents the maximum allowable shop-to-bay walking distance.

The study day is divided into time slots $T = \{t\}$. The average intensity of freight activity at a shop varies according to the type of the shop. For each shop type m, we can define an average duration of delivery t_m and the average number of daily deliveries n_m. Furthermore, the intensity of freight activity varies according to the time of the day. For each shop type m, we define the share of daily deliveries occurring during the time slot t, α_{mt}. Consequently, for each time t and shop i, we define γ_{it} that refers to the at-store (i.e., excluding walking travel time) portion of the freight parking time demanded by shop i during time slot t and that is function of t_m, n_m, α_{mt} and β_{im}.

Each shop's demand for parking time is calculated from the estimated number of deliveries to shops of the appropriate category on a typical weekday and the times during which shops of that category receive deliveries. This is combined with the typical duration of deliveries towards shops of the given retail category. For a shop of a particular type m, it is assumed that the demand for parking, in minute occurring during time slot t is found by multiplying the duration of a typical delivery towards a shop of type m, t_m, by the number of deliveries per day towards a shop of type m, n_m, and the fraction of those deliveries occurring during time slot t, α_{tm}, where β_{im} indicates if shop i, is of type m, given by

$$\gamma_{it} = \begin{cases} \alpha_{mt} n_m t_m & \text{if } \beta_{im} = 1 \\ 0 & \text{otherwise} \end{cases} \quad , \qquad \forall i \in I, \forall t \in T. \tag{1}$$

Each time slot is characterized by a congestion factor I_t. We consider that freight deliveries cause two types of disruptions: (1) *land-use disruptions* linked to the placement of loading bays during certain time slots, and (2) *traffic-disruptions* linked to the impact of on-street deliveries on the surrounding traffic. The impact of the *traffic-disruptions* relative to the *land-use disruptions* varies throughout the day. Indeed, a double-parked vehicle will result in a greater impact on congestion during peak-traffic periods than during the off-peak traffic periods. In order to account for this effect, a factor σ_t describes the policymaker sensitivity to the *traffic disruptions* relative to the *land-use disruption* depending on the time-slot considered. Depending on the parameter σ_t chosen to describe sensitivity to *traffic-disruptions*, some deliveries may be allowed at on-street locations.

Time-slots are grouped into two periods $P \subset T$ and $O \subset T$, corresponding to peak and off-peak times of freight activity respectively.

Table 1 describes the sets of locations and times considered in the problem and Table 2 presents the relevant parameters.

Table 1. Sets of model indices

Set	Description
$K = \{k\}$	Set of potential locations for loading bays
$I = \{i\}$	Set of establishments
$M = \{m\}$	Set of establishment types
$T = \{t\}$	Set of time slots in analysis period
$O = \{o\}$	Set of time slots in freight peak period; $O \subset T$
$P = \{t\}$	Set of time slots in freight off-peak period; $P \subset T$

Table 2. Sets of model parameters

Parameter	Description
c_k	Capacity of loading bay k [vehicles]
l_p	Duration of the peak period [hours]
l_o	Duration of the off-peak period [hours]
γ_{it}	Freight parking demand of establishment i during time slot t [vehicle-hours]
σ_t	Factor equating space consumed by traffic-disrupting logistics operations (e.g. double parking) in time slot t to space consumed in non-disruptive operations []
I_t	Congestion factor in time slot t []
d_{ik}	Walking distance from shop i to bay k [meters]
w_{ik}	Walking time from shop i to bay k [hours]
r	Maximum allowable shop-to-bay walking distance [meters]
β_{im}	Parameter indicating if establishment i is of type m []
t_m	Average duration of delivery towards an establishment of type m [vehicle-hour/delivery]
n_m	Average number of daily deliveries towards an establishment of type m [deliveries]
α_{mt}	Share of deliveries occurring during time slot t for an establishment of type m [percent]

3.2 Optimization Model

The optimization model developed in this study (1) locates loading bays during the peak period of delivery operations, (2) locates loading bays during the off-peak period of delivery operations, and (3) allocates shops to loading bays during all time slots (both in peak and off-peak periods). Table 3 provides the decision variables relevant to these three model features. The optimization model aims to minimize the *land-use disruptions* and the *traffic disruptions* caused by deliveries in a certain urban area.

Table 3. Decision Variables

Set	Description
Y_k^P	Binary variable indicating if a loading by k is active during the peak period
Y_k^O	Binary variable indicating if a loading by k is active during the off-peak period
X_{ikt}	Binary variable indicating if shop i is allocated to the loading bay k during the time slot t

The model presented is as follows:

$$\gamma_{it} = \begin{cases} \alpha_{mt} n_m t_m & \text{if } \beta_{im} = 1 \\ 0 & \text{otherwise} \end{cases}, \qquad \forall i \in I, \forall t \in T, \tag{1}$$

$$min \sum_{k \in K} Y_k^p c_k l_p + \sum_{k \in K} Y_k^o c_k l_o + \sum_{t \in T} \sum_{k \in K} \sum_{i \in I} (1 - X_{ikt}) \gamma_{it} \sigma_t I_t, \tag{2}$$

Subject to:

$$\sum_{i \in I} x_{ikt} (\gamma_{it} + 2w_{ik}) \leq Y_k^p c_k l_t, \ \forall k \in K, \forall t \in P, \tag{3}$$

$$\sum_{i \in I} x_{ikt} (\gamma_{it} + 2w_{ik}) \leq Y_k^o c_k l_t, \ \forall k \in K, \forall t \in O, \tag{4}$$

$$x_{ikt} d_{ik} \leq r, \ \forall k \in K, \ \forall i \in I, \forall t \in T, \tag{5}$$

$$\sum_{k \in K} x_{ikt} \leq 1, \ \forall i \in I, \forall t \in T, \tag{6}$$

$$Y_k^o \leq Y_k^p, \ \forall k \in K, \tag{7}$$

$$Y_k^o, Y_k^p, x_{ikt} \in \{0, 1\}, \ \forall k \in K, i \in I, t \in T. \tag{8}$$

The first two terms of the model objective function Equation (2) refer to the *land-use disruptions* and represent the overall space and time occupancy of located delivery bays during the peak and off-peak periods, respectively. The third term describes the *traffic disruptions* and represents the overall space and time occupancy on-street deliveries for shops that are not allocated to loading bays, augmented by a factor σ_t.

By considering the time-specific allocations of urban land to logistics activities, the objective of this model compares the time-specific cost of allocating space to loading bays in each sub-period (slot) of the analysis period to the cost of allowing disruptive on-street deliveries to a shop during the sub-period, according to a parameter σ describing this cost relative to that associated with bay use. This parameter, while not a directly observable characteristic, offers a means of quantifying policymaker priorities and comparing externalities posed by peak periods of logistics activity on time intervals with varying levels of ambient passenger traffic or congestion. The intensity I_t of traffic during each time slot of the day is modeled as a factor relating travel times in time slot t to baseline or free-flow travel times. Both of these factors constitute the externality posed by a traffic-disrupting delivery event.

Equations (3) to (8) present the model constraints. Constraints 3 signify that the capacity of each loading bay k cannot be exceeded during each time slot t in the peak period. Constraints 4 similarly require that the capacity of each loading bay k cannot be exceeded during each time slot t in the off-peak period. The walking time w_{ik} to and from a loading bay is accounted for in the length of time a bay will be occupied while a delivery driver is serving a particular shop from there. In Constraints 5, a constraint r is provided describing the distance beyond which no deliveries will occur from a given bay to a given shop. Constraints 6 signifies that each shop can be allocated to at most one loading bay during each time slot. Constraints 7 indicates that a loading bay can only be activated during the off-peak period if it is activated during the peak period. Constraints 8 provides the solution domain of the decision variables.

3.3. Quantifying Impact on Vehicle Kilometers Traveled

To quantify the impact of the proposed loading bay policy, a performance metric is selected and implemented with the following calculation in Table 4 and Equations (9) to (22). Vehicle distance traveled, a key indicator of both congestion and environmental externalities, is the chosen performance measure.

Table 4. Nomenclature for VKT estimation

Variable	Description
v_t	Vehicles present in the system at time t
b_t	Stops per vehicle during time t
b_t^a	Stops per vehicle during time t, allocated to loading bays

b_t^n	Stops per vehicle during time t, not allocated to loading bays
s_t	Inter-stop distance during time t
f_t	Deliveries (customers) per vehicle during time t; an assumed parameter that can be related to the fragmentation of the logistics market in the study area
f_t^a	Deliveries per vehicle during time t, allocated to loading bays
f_t^n	Deliveries per vehicle during time t, not allocated to loading bays
e_t	Deliveries per stop during time t while at a loading bay
λ_t	Share of deliveries allocated to loading bays during time t
k	Circuity factor of study area road network
R	Fraction of shops within range r of a bay, averaged across all bays
β	Indicator if shop i is of type m

The assumed parameter f_t, representing deliveries per vehicle in each time slot, is used to derive the following:

$$f_t = f_t^a + f_t^n, \tag{15}$$

$$f_t^a = f_t \lambda_t, \tag{16}$$

$$f_t^n = f_t(1 - \lambda_t), D \tag{17}$$

$$b_t = b_t^a + b_t^n, \tag{18}$$

$$b_t^a = \frac{f_t^a}{e_t}, \tag{19}$$

$$b_t^n = f_t^n. \tag{20}$$

Then applying a continuum approximation to derive the total distance traveled:

$$D_t = v_t b_t s_t, \tag{21}$$

$$D_t = v_t (b_t^a + b_t^n) s_t, \tag{22}$$

$$D_t = v_t s_t \left(\frac{f_t^a}{e_t} + f_t^n \right), \tag{23}$$

$$D_t = v_t s_t \left(\frac{f_t \lambda_t}{e_t} + f_t (1 - \lambda_t) \right). \tag{24}$$

Where the following are calculated from known values in the model solution

$$v_t = \frac{\sum_i \sum_m \alpha_t n_{tm} \beta_{im}}{f_t}, \tag{25}$$

$$s_t = \frac{k}{\sqrt{\frac{b_t^a + b_t^n}{A}}}, \tag{26}$$

$$e_t = max\left[1,\ f_t^a R\right], \tag{27}$$

$$\lambda_t = \frac{\sum_i \sum_k X_{ikt}}{|I|}. \tag{28}$$

Equations (9) through (14) relate, via the chosen fragmentation parameter f_t, the number of customers per vehicle (i.e., route length), stops per vehicle b_t, and customers served per stop e_t. Equations (15) through (18) find the distance traveled by multiplying vehicles, stops per vehicle, and distance per stop. Equation (19) derives the number of vehicles by relating number of customers and the parameter describing number of customers per vehicle. Equation (20) applies the continuum approximation, using a reference value for circuity k, to find the inter-stop distance in the study area. Equation (21) defines the number of stops per vehicle in terms of the average fraction of shops that is within walking distance of a bay, enforcing a minimum of one stop per customer. Equation (22) defines the fraction of shops that are allocated to loading bays in terms of the solution values for the variable X_{ikt}.

4. Case Study: La Candelaria, Bogota

4.1 Description of the Empirical Research Setting

La Candelaria is a historic district at the southeast edge of Bogota. Bordered by mountains to the east and the urban core elsewhere, this district displays some of the highest intensity of commercial activity in Bogota. An estimated 883 stores are present in this 1 square kilometer zone, which generate thousands of daily loading and unloading operations. This is an area of vital importance for tourism, education, and government activities. Significant mobility challenges are present in this zone given the nature of its road infrastructure. Despite its intense commercial activity, little logistics infrastructure is observed and steep, narrow streets used extensively by pedestrians and street vendors are common. Examples of typical street scenes to be found in this district are illustrated in Figure 1.

Fig. 1. (a) Carrera 7 at the northern edge of the district represents a typical mixed-use street in La Candelaria.

Fig. 1. (b) Carrera 5 is representative of the district's typical side-streets.

4.2 Data Collection

A number of data sources are leveraged in this analysis to understand the intensity, temporal characteristics, and spatial characteristics of freight-related demand for parking in the study zone. Retailer surveys conducted in 2017 are used to describe temporal patterns in deliveries to shops of various retail categories. Following a study to identify zones of key importance to urban logistics operations in three major cities in Latin America, surveys were conducted at between 50-200 shops in key zones in each of these cities. The surveys, designed specifically to collect information relevant to integrating efficient logistics operations into urban areas, collect information on three facets of each establishment's operations. General information is collected about each shop's floor area, storage area, number of employees, number of supplies, product or service types, and whether parking space for freight vehicles is provided. To characterize operations, store opening and closing times, peak demand days and times, preferred delivery windows, and typical delivery mode (i.e. vehicle type) are also described. Results of these surveys are used in this model to determine the number of shops that receive deliveries each hour. For this study, the survey results from 100 shops in La Candelaria is used to estimate the fraction of shops receiving deliveries each hour.

Data from direct observations of freight activity in select districts in Latin America are also used to inform the case study scenario. This dataset was collected from 2015 to 2017 and describes urban logistics activities by providing a manually verified comprehensive census of retail activities in selected districts of major cities worldwide with a more limited datatset describing manually observed delivery operations in terms of time, location, duration, vehicle types used, product types delivered, shops and shop types served, and whether any disruptions to ambient traffic were caused. To determine a typical daily number of deliveries and duration of a delivery towards shops of a given category, 1,700 observations from the project across 11 districts in Latin America are used. Results of this estimation are found in Table 5. This dataset contains shop locations in La Candelaria of which approximately 900 have complete and unique information for location, shop type, and name. For each, it records the retail category, shop name, location, descriptions of product types, and the presence or absence of loading zone area at each shop location.

Retail categories are recorded as food service, tertiary services, supermarkets, apparel, or general (non-apparel) retail.

4.3 Case Study Scenario Parameters

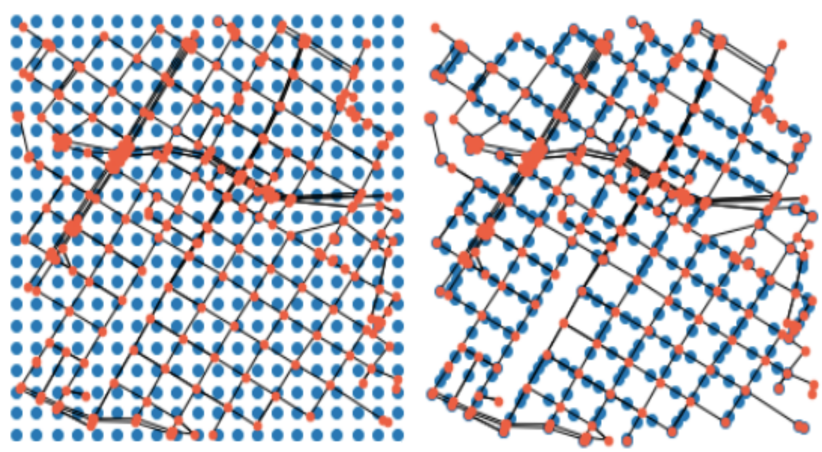

Fig. 2. (a) Candidate bay locations before snapping to road network.

Fig. 2. (b) Locations in (a) after snapping to the road network.

Candidate locations for loading bays are established by an evenly-spaced grid of points across the study area and snapped to the nearest point on the road network. This snapping operation and the resulting candidate locations are shown in Figure 2. An arbitrary large number of locations are generated such that the can activate a sufficient optimal number of them to serve shop demand. In this case study, 400 candidate locations for bays are offered to the model. This is intended to provide candidate locations that are realistic (i.e., not clustered in one location where the construction of a large number of loading bays would be politically or physically infeasible) and reasonably well dispersed throughout points of demand while still providing good coverage of demand. From this set of locations, a distance matrix is computed between all shops and all bays and walking speed is used to find the corresponding walking time between each shop and bay. Between each pair, the rectilinear distance is used to approximate the walking path of a driver traveling between shop i and bay k, d_{ik} per Equation (5). An assumed walking speed of 1.4 m/s (Bohannon, 1997) is used to find the walking time w_{ik} between each pair per Equations (4) and (3). An assumed maximum allowable walking distance r of 75 meters is assumed, cf. (Tamayo et al., 2017). Figure 3 shows the 883 shop locations in the case study zone.

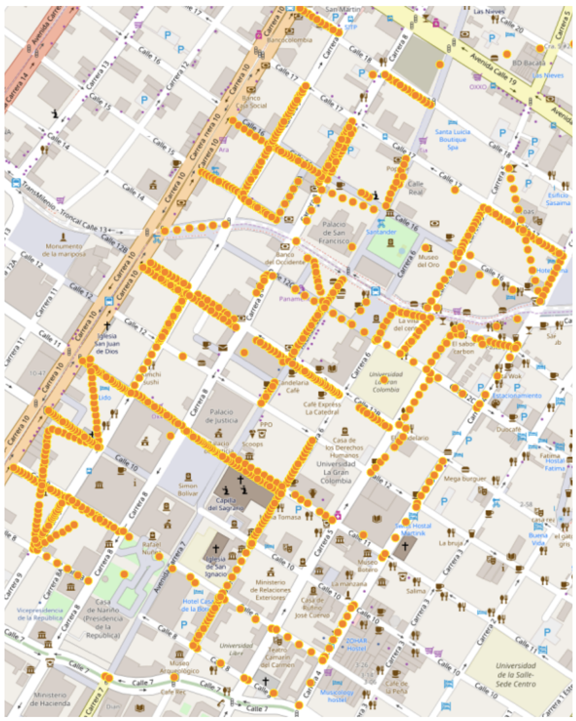

Fig. 3. Shop locations in La Candelaria

The typical weekday demand for freight parking is modelled from 6:00 AM to 7:00 PM. Based on the sample of shops surveyed in this district, this period encompasses all of the reported demand for freight parking on a typical weekday. From the hourly demand for freight-related parking shown in Figure 4, the peak freight activity period is chosen as 6:00 AM to 10:00 AM and 2:00 PM to 4:00 PM. An approximate value for delivery frequency as reported from the survey (reported frequency per supplier times number of suppliers, for the middle 70% of surveyed shops in terms of employees, floor area, and number of providers) is reported in Table 5 as the number of deliveries towards shops of that type per day. These values are reasonably comparable with the delivery frequencies found elsewhere (Allen et al., 2008; Tamayo et al., 2017). From the delivery observation data, the typical durations of deliveries towards shops of each type are determined and shown in Table 5. The congestion factor I_t for each hour is calculated by querying the Google Distance Matrix API (Google, 2017) for travel times for trips between bays and shops longer than 400 meters at the midpoint of each hour and comparing them to the average travel time found for the same trips at 12:30 and 1:30 AM (as a proxy for free-flow speed). The ratio of these two is I_t. For this analysis, a baseline value of 1.25 for σ is suggested. In the VKT analysis, a general circuity factor of 1.6 for Bogota is obtained from (Merchan, Blanco, & Bateman, 2015).

Table 5. Deliveries per day each shop type

Retail Category	Deliveries / Day	Typical Duration [min]
Food Service	2.52	10.73
Small Retail	2.20	7.15
Tertiary Services	3.17	11.54
Supermarket	2.06	8.98
Apparel	1.40	17.15

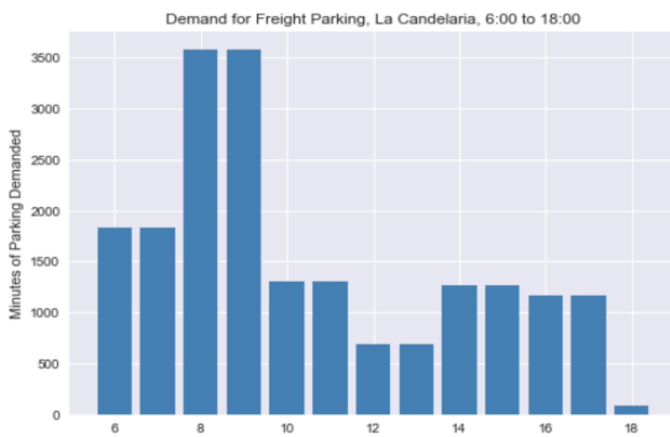

Fig. 4. Demand for freight parking in La Candelaria on a typical weekday.

4.4 Scenario Results

For this scenario, the model activates 187 locations for the peak period and 49 locations for the off-peak period. Due to the simple but strategic placement of candidate locations, it is observed that the active loading bays are well dispersed throughout the study zone, constituting only a few parking spaces per block. These locations activated during the peak and off-peak periods are shown in Figure 5. Figure 6 indicates the number of shops whose deliveries are allocated to bays during each hour of the day and Figure 7 shows the average occupancy (fraction of time occupied) across all active bays during each hour.

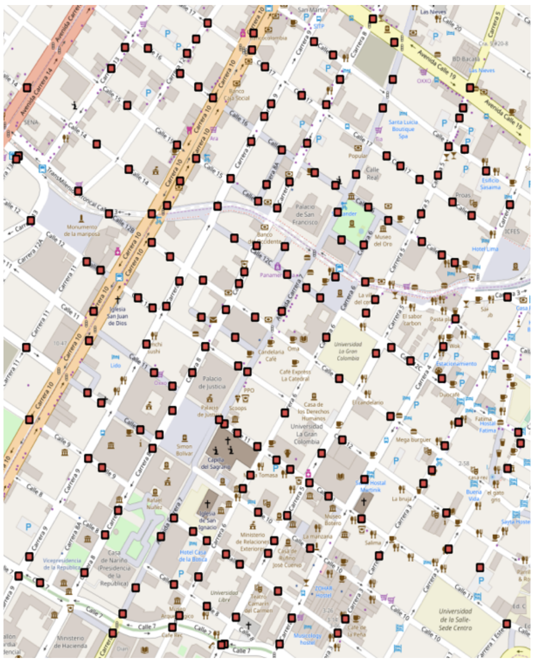

Fig. 5. (a) Peak period bays opened by the model.

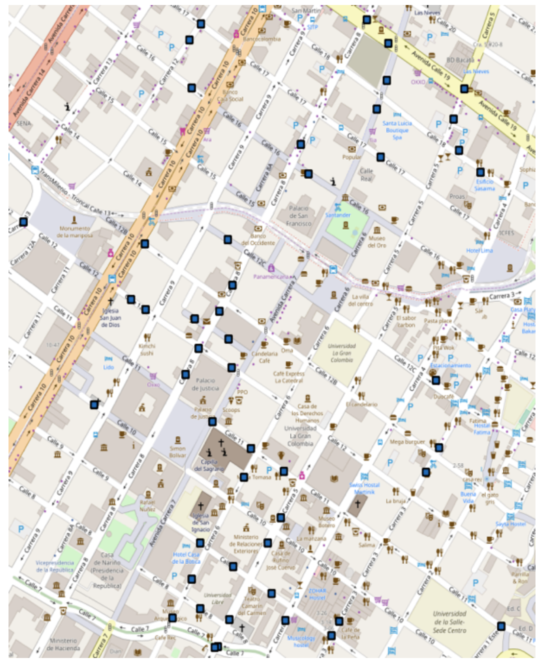

Fig. 5. (b) Off-peak bays opened by the model, a subset of bays in (a).

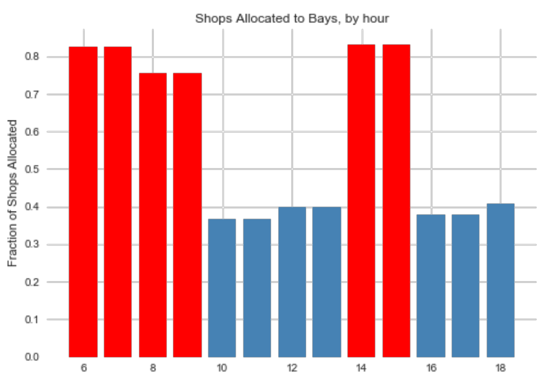

Fig. 6. Fraction of shops allocated to loading bays, by hour. Red denotes peak freight period and blue denotes freight off-peak.

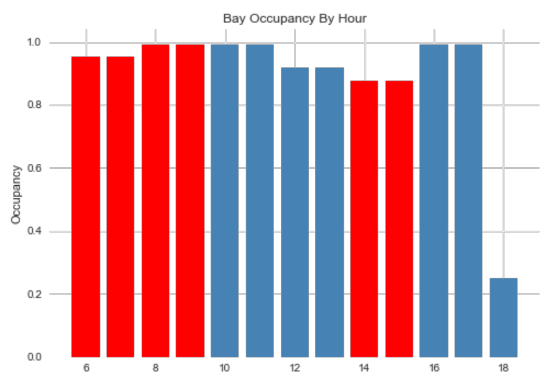

Fig. 7. Fraction of time occupied across all active bays per hour.

4.5 VKT results

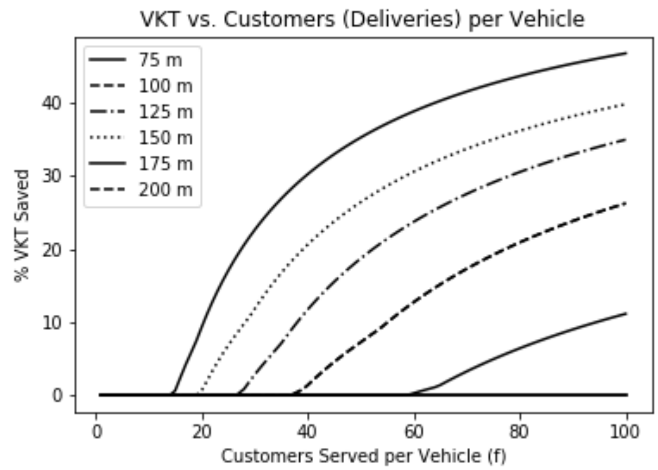

Fig. 8. Vehicle kilometers traveled in case study scenario, with varying levels of carrier market fragmentation and walking distance

The results of the distance-traveled analysis for the case study scenario are shown in Figure 8. By varying the maximum tolerated walking distance, the model allows more shops to be potentially allocated to a given bay. For each radius in the range presented above, the optimization model is solved and the distance traveled over the course of a typical day is calculated for varying values of the fragmentation factor, f_t. Walking distances of 25 meters and 50 meters are also proposed by Alho et al. (2018) and Patier, David, Chalon, & Deslandres (2014), but this model produces no savings in VKT for those results.

At each solution, a different number and allocation of active bays is chosen by the optimization model during both time periods. The distance traveled is calculated by the preceding estimation method from Section 4.3 for each hour during the study period, and the results shown in Figure 8 is the sum of distances traveled during all hours over the day from 6:00 AM to 7:00 PM. For the assumed baseline maximum allowable walking distance of 75 meters, no savings are observed at high levels of market fragmentation (low values of f in the preceding figure), but as the number of customers allocated to a single vehicle grows, indicating a lower level of fragmentation, longer delivery routes, or some kind of consolidation effort between delivery operators, significant savings are observed. The allocation of bays selected under this walking distance constraint is the same as reflected in Figure 5. For higher allowable walking distances, even higher VKT savings are observed. For the lowest two walking distances and for all distances at very high levels of fragmentation (i.e., low values of f indicating very short routes per vehicle), no savings are observed because the demand captured in range of a bay is not sufficient to allow for multiple customers to be served from one stop, meaning that, as in the case with no loading bays, one stop is made per customer.

While delivery drivers may not self-elect to walk long distances between loading bays and customers and some behavioral experimental result may be useful in determining the feasibility of these distance, it is possible that they could be achieved by heavy enforcement (e.g., if on-street operations are aggressively ticketed by enforcing agencies, delivery drivers will be more incentivized to use bays even when their customers are located farther away than they would otherwise walk). However, it is noted in the solutions for these alternative cases, though not presented here, that increasingly higher numbers of bays are activated as the allowable walking distance increases. This could lead to situations where an excessive, unpopular, or cumbersome level of parking restriction is imposed – of course, the tolerance or justification for such regulation will vary from case to case and the intent is only to demonstrate that higher savings are possible with more aggressive policy. Along a similar vein, it is suggested that parameter σ could be used to tune the allocation relative to policymakers' sensitivity to dedicated parking real estate relative to traffic disruption and change the number of allocated loading bays with according trade-offs in traffic disruption and distance savings.

5. Conclusion

The model presented here locates a reasonable number of loading bays to serve an area of intense commercial activity. The model formulation poses a trade-off between the allocation of scare urban street space to freight parking and the disruptions caused by deliveries occurring not at on-street parking locations. By explicitly considering time-varying patterns, it avoids idle bays during off-peak hours and suggests an allocation of bays that serves demand while conserving real estate. The distribution of candidate locations throughout the zone is an important factor in obtaining a model result that is reasonable in terms of implementation feasibility. While it is possible that a focused parking restriction (e.g., dedicating entire streets to freight parking) may allow for a better coverage of demand, without tailoring selection of candidate locations to case-specific conditions, the method of roughly uniform distribution used here results in active bays that are realistic in terms of coverage and proximity.

6. References

Aiura, N. and Taniguchi, E. (2005). Planning on-street loading-unloading spaces considering the behaviour of pickup-delivery vehicles. *Journal of the Eastern Asia Society for Transportation Studies*, *6*, 2963–2974.
Alho, A., de Abreu e Silva, J., & de Sousa, J. P. (2014). A state-of-the-art modeling framework to improve congestion by changing the configuration/enfor*cement of urban logistics loading/unloading bays. Procedia-Social and Behavioral Sciences, 111,* 360–369*.*
Alho, A. R., de Abreu e Silva, J., de Sousa, J. P., & Blanco, E. (2018). Improving mobility by optimizing the number, location and usage of loading/unloading bays for urban freight vehicles. *Transportation Research Part D: Transport and Environment*, *61*, 3–18.
Allen, J., Browne, M., Cherrett, T., & McLeod, F. (2008). Review of UK urban freight studies produced for Green Logistics Project*,* Universities of Westminster and Southampton, London and Southampton, UK.
Alvarez, E., & de la Calle, A. (2011). Sustainable practices in urban freight distribution in Bilbao. *Journal of Industrial Engineering and Management*, *4*(3), 538–553.
Behrends, S. (2016). Recent Developments in Urban Logistics Research – A Review of the Proceedings of the International Conference on City Logistics 2009 – 2013. *Transportation Research Procedia*, *12*, 278–287.
Bohannon, R. W. (1997). Comfortable and maximum walking speed of adults aged 20—79 years: reference values and determinants. *Age and Ageing*, *26(1)*, 15–19.
Browne, M., Allen, J., Nemoto, T., Patier, D., & Visser, J. (2012). Reducing Social and Environmental Impacts of Urban Freight Transport: A Review of Some Major Cities. *Procedia - Social and Behavioral Sciences*, *39*, 19–33.
Debauche, W. (2006). Le transport de marchandises dans le centre ville de Liège. Technical report produced for Centre de recherches routières, Brussels, Belgium.
Delaitre, L. (2009). A new approach to diagnose urban delivery areas plans. In: *Proceedings of 2009 International Conference on Computers Industrial Engineering*, 991–998, Troyes, France.
Dezi, G., Dondi, G., & Sangiorgi, C. (2010). Urban freight transport in Bologna: Planning commercial vehicle loading/unloading zones. *Procedia - Social and Behavioral Sciences*, *2*(3), 5990–6001.
Gerardin, B., Patier, D., Routhier, J.-L., & Segalou, E. (2000). Diagnostic du transport de marchandises dans une agglomération. Technical report produced for French programme "Marchandises en ville."
Gerardin Conseil, 2004. Evaluation économique et environnementale du projet ELP. Report produced for Chambre de Commerce et d'Industrie de Bordeaux, Bordeaux, France.
Google. (2017). *Google Distance Matrix API.* Retrieved from https://developers.google.com/maps/documentation/distance-matrix/

Huschebeck, M., & Allen, J. (2005). Urban consolidation centres, last mile solutions. Technical report carried out as part of BESTUFS II project (Best Urban Freight Solutions II). PTV and UoW.
Lebeau, P., & Macharis, C. (2014). Freight transport in Brussels and its impact on road traffic? *Brussels Studies - La Revue Scientifique Électronique Pour Les Recherches Sur Bruxelles / Het Elektronisch Wetenschappelijk Tijdschrift Voor Onderzoek over Brussel / The e-Journal for Academic Research on Brussels* [online only]. General collection, no. 80.
Merchan, D., Blanco, E., & Bateman, A. (2015). Urban Metrics for Urban Logistics: Building an Atlas for Urban Freight Policy Makers. Technical report produced for MIT Center for Transportation and Logistics, Cambridge, MA, USA.
NICHES. (2007). Space Management for Urban Delivery. Technical report produced for the European Commission. Retrieved from http://www.rupprecht-consult.eu/uploads/tx_rupprecht/6_space_management_for_urban_delivery.pdf.
Patier, D., David, B., Chalon, R., & Deslandres, V. (2014). A New Concept for Urban Logistics Delivery Area Booking. *Procedia - Social and Behavioral Sciences*, *125*, 99–110.
Roca-Riu, M., Cao, J., Dakic, I., & Menendez, M. (2017). Designing Dynamic Delivery Parking Spots in Urban Areas to Reduce Traffic Disruptions. *Journal of Advanced Transportation, vol. 2017*.
Routhier, J.-L. and Toilier, F., 2007. FRETURB V3, a policy-oriented software of modelling urban goods movement, In: *Proceedings of 11th World Conference on Transport Research*, Berkeley, CA, USA.
Tamayo, S., Gaudron, A., & De La Fortelle, A. (2017). Loading/unloading spaces location and evaluation: an approach through real data. In: *Proceedings of 10th International Conference on City Logistics*, 802-816, Phuket, Thailand.
Taniguchi, E., Thompson, R. G., & Yamada, T. (2004). Visions for city logistics. In: *Proceedings of 3rd International Conference on City Logistics*, 1-16, Madeira, Portugal.