The searching time to measure the Freight Loading Zone Accessibility using microscopic traffic simulation

Stéphane Magniol [1], Clélia Lopez [1*], Jésus Gonzalez-Feliu [2], Nicolas Chiabaut [1], Ludovic Leclercq [1]

[1] Université de Lyon, ENTPE / IFSTTAR, LICIT, Vaulx-en-Velin Cedex, France
[2] EVS-PIESO, Institut Henri Fayol, Ecole des Mines de Saint-Etienne,
158 urs Fauriel, 42023 Saint-Etienne Cedex 2, France
[*] Corresponding author
{stephane.magniol@gmail.com, clelia@clelialopez.com, jesus.gonzalez-feliu@emse.fr,
nicolas.chiabaut@entpe.fr, ludovic.leclercq@entpe.fr}

Abstract. This paper proposes the use of the searching time to measure the accessibility of Freight Loading Zone (FLZ). Cruising for parking is the time for a delivery truck to visit a sequence of FLZ until the first vacant one is found. To our best knowledge, the capture of the truck searching time has not been studied for the line of research that we address in this paper. The methodology includes a parking choice model and an availability model. The impact of FLZ demand and supply on the searching time are quantified. The use of microscopic traffic models makes it possible to include traffic lights and particular vehicles demand into the simulations. Results show the mean searching time scale, related to the FLZ density and the occupancy rate. Moreover, a cost function is used to access the additional cost of the last mile by considering the searching time.

Keywords: Freight Loading Zone Accessibility, level of delivery service, last mile modeling, truck parking searching time, additional cost of finding a vacant truck parking.

1. Introduction

In urban areas, Freight Loading Zone (FLZ) management influences the last mile cost function as parking availability impacts routes planning. Commercial driver's behaviors can include the use of double parking instead of cruising-for-parking, involving minimizing the walking distance. Additionally, to be dangerous for other users, those illegals can increase travel time delays and reduce the global performances of transportation networks [3], [14], [21], [1].

Three major reasons which can lead the delivery driver not to cruise for parking are identified: (i) the probability of finding a vacant Freight Loading Zone (FLZ) trough the time. This probability is influenced by the rate of occupancy [25], *e.g.* FLZ may be already occupied illegally by particular vehicles or by another delivery truck. The consequences are an uncertain time for cruising, additional delays and fuel consumption. (ii) The spatial configuration of FLZ can be inappropriate, *e.g.* the truck length may be larger than the length of a FLZ, FLZ locations may be inconsistent by unfollowing the economy dynamic. (iii) The maneuvering time may dissuade some drivers [8].

City managers can apply numerous strategies to reduce illegal freight double-parking problems. Two FLZ policies inherently linked can be identified: (i) freight parking fine and (ii) spatial FLZ management. Note that it is acknowledged that the compliance levels of a particular vehicle to not to park on FLZ can play a crucial role in reducing double-parking [1]. (i) Parking price policies have been investigated for cars [9] and carsharing [2]. Nevertheless, few studies aim to evaluate FLZ fine policy [19]. Increasing fine price can discourage the illegals but not ensure its elimination [8]. Moreover, cities are dependent on goods mobility and should not dissuade to double-park without offering a proper alternative solution. (ii) The management of FLZ's location is a dynamic problem through space and time. We identify two management solutions, which can be used separately or simultaneously: spatially, *i.e.* the number and the location of FLZ, and temporally, *i.e.* limit delivery time or enforcement of booking system of FLZ. Despite the fact that there is no generally acknowledged framework to identify the optimal spatial configuration and management system of FLZ, some papers proposed methodologies to establish their number, location and usage [16], [1]. In urban areas, freight parking infrastructure has high demand and limited supply [1]. Management solutions contribute to use efficiently FLZ infrastructure through space and time, optimizing their use. This optimization makes it possible to maintain a high level of service while reducing the number of FLZs [16]. Nevertheless, a reduction of the number of FLZ increases the distance between pair of FLZ. In this paper, we aim to retrieve the truck searching time for parking, where double-parking by delivery trucks is eliminated. To enhance the relevance for trucks to cruising-for-parking, we assume the deployment of the automatized as well as systematic double-parking fine and the technology of autonomous delivery vehicles designed for sidewalks.

In the literature, numerous papers proposed to design the FLZ systems by solving an optimization problem. [16] solved the location-allocation problem [23] for the FLZ spatial configuration. The authors analyzed the resulting number, location and availability of FLZ. Their indicator is the average traveled distance between the FLZ used and the customer, *i.e.* the walking distance. The authors considered a return as the unavailability of parking space. The network scale is a street. More generally, [16] proposed a GIS-based approach for assessing parking pattern in urban areas, where dynamic supply and demand are considered. Microscopic simulation makes it possible to evaluate ex-ante a solution [18], [4], *i.e.* before the implementation. In this paper, we propose the searching time as an indicator to evaluate urban truck parking policies.

We define the searching time as the cruising-for-parking time, *i.e.* the time for a truck to find the first vacant FLZ. We investigate how the searching time is affected by both of the following parameters: (1) the occupancy level of FLZ and (2) the region density of FLZ. Firstly, we establish a statistical analysis of the relationship between the FLZ density and vacant probability. Secondly, we quantify the simulated searching time based on microscopic traffic models. To the best of our knowledge, there are no existing studies that focus on this line of research, particularly, on the research time as an endogenous function of truck's travel time to evaluate freight policies.

The rest of the paper is organized as follow. In Section 2, the methodology proposed is described, including the parking choice model, the availability model and the microscopic traffic simulation. In Section 3, the case study is described. Section 4 presents the results and discussion. Finally, Section 5 concludes this paper.

2. Methodology

We propose a methodology that includes a commercial vehicle parking model into traffic simulation at the microscopical scale. More precisely, we propose a parking choice model and an availability model of delivery trucks in urban areas. The commercial vehicle can only park on FLZ and not on any other kind of parking slot. We consider the state of demand as the probability to find a vacant FLZ and the supply as the number of FLZs normalized by area, *i.e.* the FLZ density [FLZ/km]. We identify five characteristics to simulate delivery routes: the origin and the destination, the sequence of stop points, its order, the route between each pair of stop points and the stopping time duration. We assume the properties of delivery routes are independent of the searching time. Moreover, origin, destination and stop points are set stochastically where the sequence is fixed.

Let N_f be the number of FLZs, N_c be the sequence of customers. Firstly, the sequence of customer to visit is computed. The delivery driver must visit all the establishments at least one time.

2.1. Parking Choice Model

Note that the parking model scale is at the customer scale. The parking model is applied for each customer, where the N_f FLZs are increasingly ordered, based on the travel distance from the given establishment to FLZs. Indeed, we assume that the delivery truck driver aims to minimize his walking distance between the establishment to visit and the place his truck is parked.

We use the Dijkstra algorithm [7] to compute the first shortest traveled distance for a given pairwise origin and destination. Indeed, we assume entire topology network knowledge of the delivery truck driver.

The limit of this model is that FLZs to visit are considered independently. Thus, a route of FLZs is not computed and total distance traveled is not minimized as we assume that the delivery truck has no information of the FLZs occupancies, *e.g.* the location of the first FLZ vacant for a given customer.

2.2. Availability Model

We consider the Bernoulli's principle to model the parking availability [12]. Let p the probability to find a vacant FLZ and T_0 the occupancy rate as $T_0 = 1 - p$. We define X as the number of failure among Bernoulli trials before getting one success, *i.e.* find the first available FLZ. The geometric distribution gives the probability of k where k is the number of failures required to get the first success, defined as:

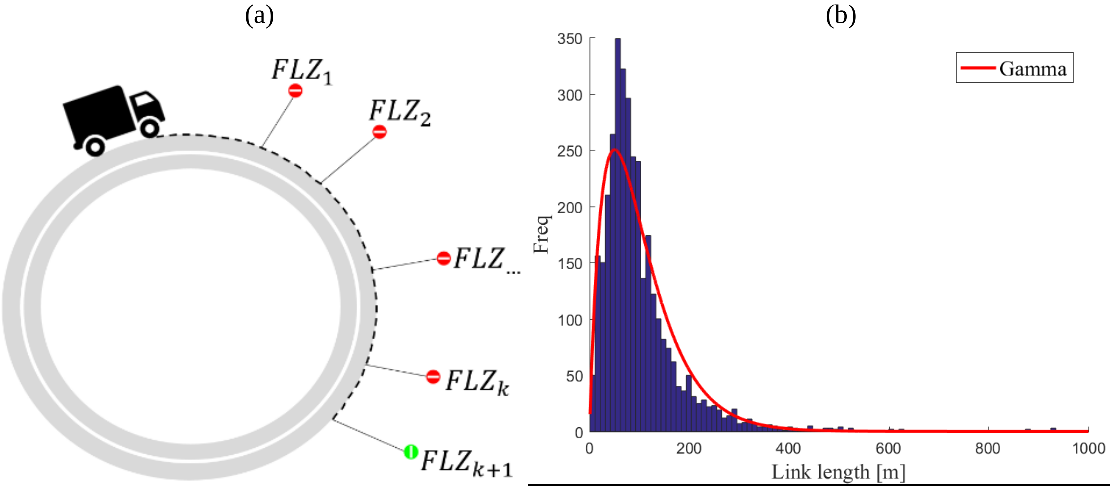
$$Pr(X = k) = (1 - p)^{k-1} p \quad \textbf{(1)}$$

where $0 \leq p \leq 1$. This availability model allows us to study various probabilities p, which can represent different rates of occupancy of FLZs in urban areas. The occupancy rate of 53% is used in the study of [20]. Numerous solutions can contribute to decrease the rate of occupancy, *e.g.* a better rotation of trucks (reduction of the delivery time), the enforcement of particular vehicle to not to park on FLZ, or increasing of the number of FLZ. More precisely, occupancy rate (state of the demand at time t) and the supply are inherently linked where each one impacts the other.

We introduce the study of a carrousel in order to analyze phenomenon related to our model of availability. The carrousel - Figure 1 (a) - is a single direction infinite circle where the truck travels until finding the first vacant FLZ, as described in the parking choice model. It should be notice that the carrousel is not a circle network, as studied by [11]. This carrousel is proposed as a generic schema of the availability model, where distance of a given pair of FLZ can be related to any measure from a meshed transportation network.

We define two approaches to study analytically the availability model: the travel distance of a given pair of FLZ is (i) determinist, as a constant set to the mean link length and (ii) stochastic, as the travel distance follows a probability density function. We use the gamma function [5] as it validates the distribution of link length from the network of the city of Lyon - Figure 1 (b). The mean and the standard deviation are respectively 103 and 92 meters.

(a) (b)



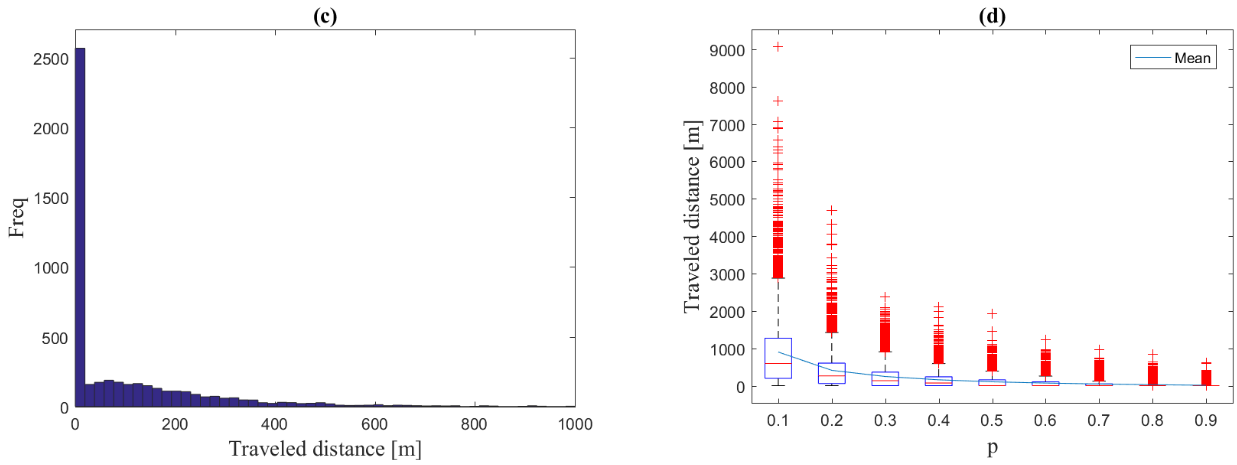


Figure 1: (a) Carrousel schema, (b) distribution of link length from the Lyon network, (c) histogram of traveled distance where $p = 0.5$ and (d) boxplot of traveled distance.

Let l_{ij} be the travel distance between FLZs i and j. For a given customer, the total travel distance cruised for parking (TD), considering the availability model is defined as follow:

$$TD = (k-1)l_{ij} \quad (2)$$

Figure 1 (c) shows the traveled distance distribution, where $p = 0.5$ and the distance of a given pair of FLZ is stochastic. Indeed, distance between a pair of FLZ belongs to the gamma probability density function. Let the two parameters be the shape denoted by A and the scale denoted by B, which are set respectively to $A = 1.95$ and $B = 52.8$. Figure 1 (d) shows the boxplots of the distribution of various p, from 0.1 to 0.9 by step of 0.1. Results show that the searching time is dependent on the geometric probability function. In our case study, a sensitive analysis of simulated searching time has been computed on p, which varies from 0.2 to 0.8 by step of 0.1.

2.3. Microscopic Traffic simulation

We use the microscopic traffic simulator SymuVia to model traffic flow. More precisely, SymuVia computes vehicles trajectories based on Newell [17] model, which is equivalent to LWR (Lighthill Whitman Richard) [10], [22] model. The assignment of particular vehicles is based on the individual optimum [26].

Trajectories are the Lagrangian data returned by the simulator. Fine information of particular travelers is available at each instant t. The resolution of vehicle trajectories is complex, specifically for large-network, large time window and for a high demand. More precisely, we focus on the commercial truck trajectories where we measure the searching time for a vacant FLZ for each customer. For a given customer, the searching time is the time the first vacant FLZ is reached minus the time the closest FLZ is reached. Thus, we assume that park to the first closest FLZ to a given customer equals to not cruise for parking.

3. Case study

We use a meshed network of 440 links and 100 nodes. The double-way one lane network has a constant link length of 200 meters. This theoretical network yet realistic to Manhattan network makes it possible to study a standard grid topology representative of some urban cities. The green light parameter is set to 30s for a cycle of 60s. The traffic demand is set to reach free-flow traffic states and the assignment is distributed through entrances to avoid traffic border effects.

Moreover, 6 configurations of FLZ are considered: the number of FLZs is varied and their locations tend to be spatially homogeneous distributed. The density $d = [0.6; 2.2; 3.9; 5; 6.1; 6.7]$ FLZ/km. Figure 2 (a and b) show two configurations of FLZ on the Manhattan network, where $d = 0.6$ and $d = 6.7$ respectively. Note that for a given link, the FLZ location is determinist and set in the middle of the link.

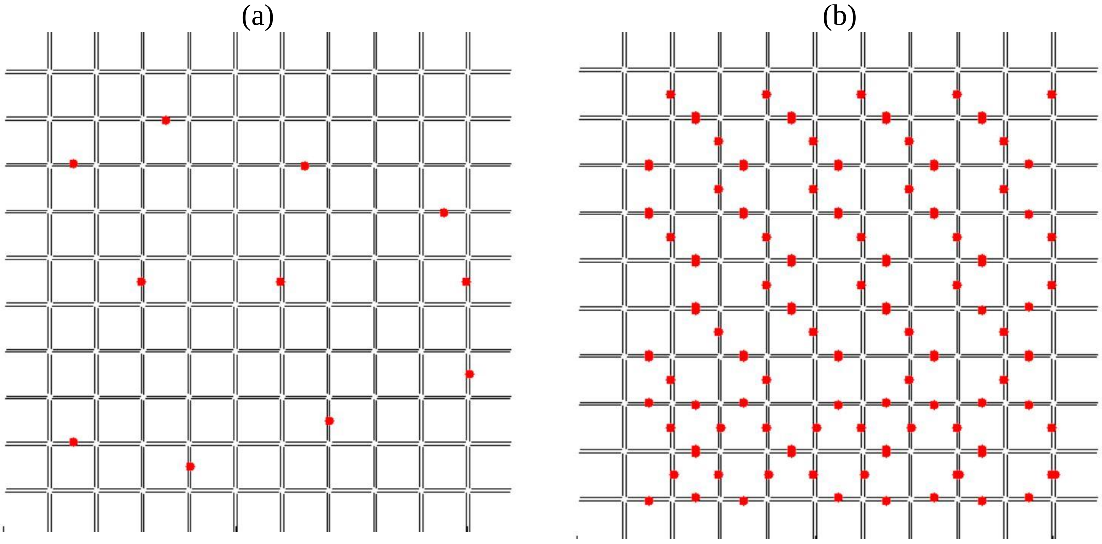


Figure 2: (a,b) Manhattan network where $d = 0.6$ and $d = 6.7$.

Trucks parameters are the free-flow speed v and the acceleration a, which are set respectively to $v = 14$ m/s and $a = 0.5$ m/s².

4. Results

The impact of the state of the demand, denoted by p and supply denoted by d of FLZs on the searching time are quantified. Stochastic simulations have been computed per p and d, where each simulation includes a route of several customers, varying from 3 to 15. Figure 3 (a) shows distribution of 220 observations of searching time, where $p = 0.4$ and $d = 2.2$ FLZ/km. Note that a zero value means no searching time as the first FLZ visited is vacant.

Figure 3 (b) shows the boxplots for each p varying from 0.2 to 0.8 where the density is set to $d = 2.2$ FLZ/km. The use of boxplot allows us to establish a first statistical study of the properties of searching time influenced by p, *i.e.* the mean, the median and the interquartile range. These three indicators are decreasing as a function of p. Mean searching time equals to 482s and 31s respectively for $p = 0.2$ and $p = 0.8$. Moreover, the interquartile range can represent the uncertainty of the searching time, which is equal to 616s and 0s respectively for $p = 0.2$ and $p = 0.8$. This interquartile range significantly decreases from $p = 0.2$ to $p = 0.4$. Note that the mean searching time is higher than the median because of the influence of outliers.

Figure 3 (c and d) visualize respectively the mean and the median searching time [s] depending on p and d. 3D-plots make it possible to analyze the dual-impacts of p and d on the cruising for truck parking simulated. The highest mean observation is a mean searching time of 664s, where $p = 0.2$ and $d = 0.6$. The FLZ density influences the scale of the searching through p where d is low. Starting from a threshold of d, the evolution of the searching time tends to be similar, *i.e.* even if FLZ supply is well-furnished, the searching time depends to p. First, these results can be interpreted as a requirement of a minimal number of FLZs for a given urban area, in order to access a reasonable searching time for delivery trucks. Second, the probability should be increased to reduce the mean searching time and its related uncertainty, *e.g.* by FLZ policies reinforcement or encouraging turn-over.

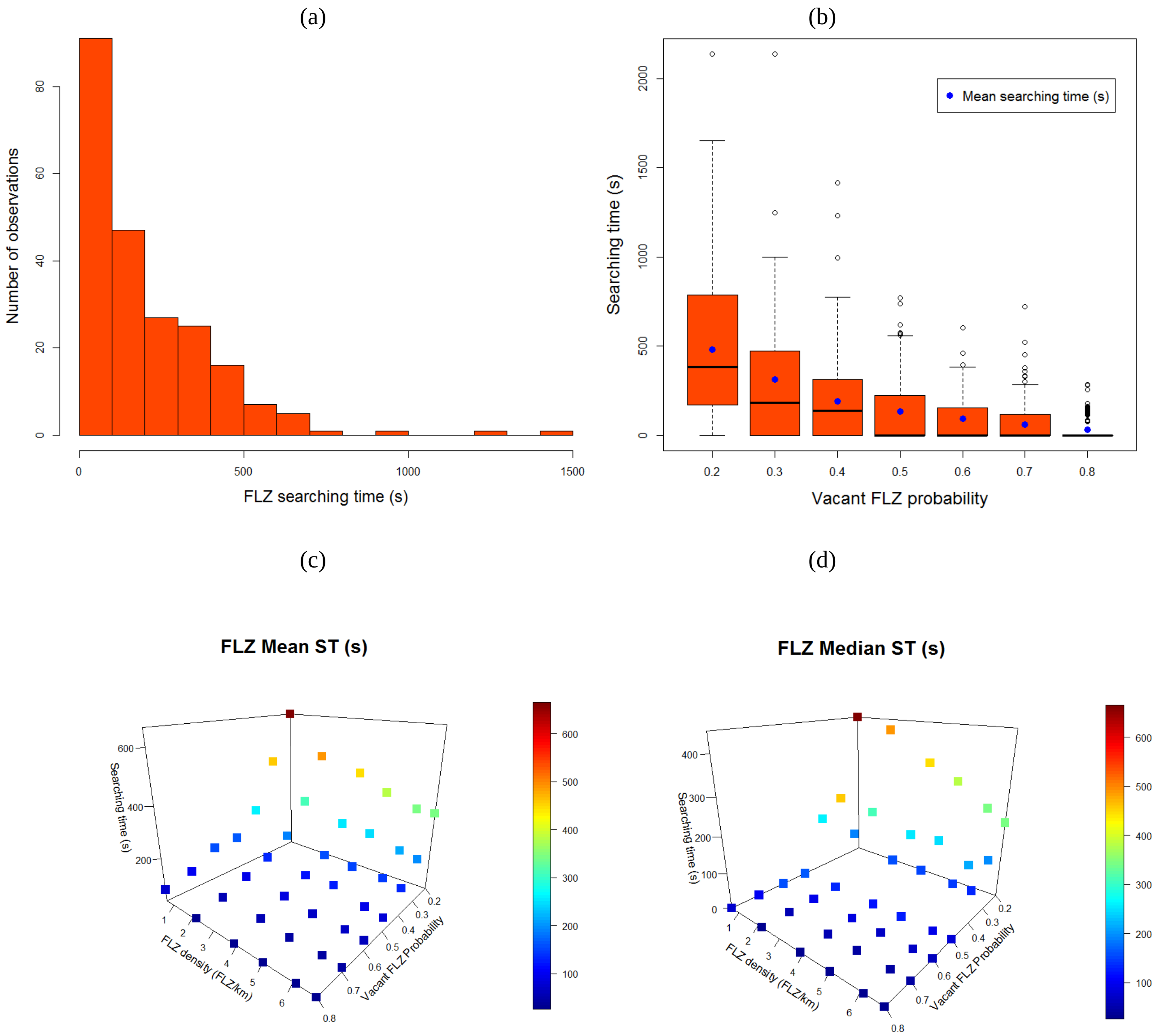


Figure 3: The searching time (a) distribution where FLZ density $d = 2.2\ FLZ/km$ and probability $p = 0.4$, (b) boxplots where $d = 2.2\ FLZ/km$, (c and d) mean and median Searching Time (ST).

5. Application to a last mile cost function

This section aims to assess the additional cost of the last mile by considering the searching time. We assume the elimination of the illegals by the deployment of the automatized as well as systematic double-parking fine. The use of econometric model based on the searching time makes it possible to estimate the retailer's reactions of imposed FLZ policies. In the literature, few studies attempt to understand the FLZ availability on the last mile cost function and truck driver behavior [8]. This section proposes to quantify the cruising-for parking truck using a simplified cost function, relative to a route and service characteristics.

To this end, we used an existing econometric model [6], based on long-term service cost, which includes vehicle maintenance cost and consumption costs. Table 1 shows the variables used to formulate the searching time cost function.

Table 1: Variables used to formulate the searching time cost function.

Variable	Description	Value
c_i	Diesel cost [€/km][a]	0.54
m	Maintenance cost [€/km][b]	0.32
p	Occupancy rate [%][c]	53
d	FLZ density [FLZ/km][d]	3
s_t	Mean searching time [s]	120
N_p	Number of customers	20
v	Average speed traveled [km/h]	30
N_d	Number of working days per week	6
N_w	Number of weeks per month	4

[a] French national statistic on fuel prices for commercial diesel vehicle https://www.prix-carburant.gouv.fr.
[b] [15].
[c] [20].
[d] Assumes approximately the density of a region of the Lyon network based on real FLZ data from *DataGrandLyon*.

The first study of the cost of the searching time considers the route and service characteristics showed in Table 1. The mean searching time computed by microscopic traffic models corresponds to an excess time of 40 minutes for a route. The linear cost function model applied presents results of the additional cost of the searching time of 17.2, 103.2 and 412.8 €, corresponding respectively to the temporal scale of the day, the week and the month.

Moreover, this total searching time for a given delivery driver is compared to a driver who would double-park for each customer. Monthly, 16 hours in average could be used to cruise for parking, considering the aforementioned variables. This excess of time can be interpreted as an additional working time – and costs – or a decreasing number of customers delivered.

6. Conclusion

The searching time for a vacant FLZ in a delivery tour has been quantified using microscopic traffic simulation, under various probability p to find a vacant FLZ and density of FLZs. We have proposed the searching time as an indicator of FLZ accessibility as it considers jointly the FLZs offer and supply in urban areas. Microscopic traffic models allow us to measure the cruising for parking for a delivery truck under the assumption to not use double-parking. We identified at least three applications where the searching time can refine: (i) routing problems, including FLZ constraint, a mean searching time per zone and uncertainty to find a vacant FLZ; (ii) last mile cost function to understand economic impacts of FLZ policies and (iii) urban freight transport model where cruising for truck parking can be considered into traffic study.

Firstly, we established a statistical analysis of the relationship between the FLZ density and the probability a FLZ is vacant. We highlighted that results are dependent on the availability model based on a geometric probability function. Secondly, we quantified the searching time using microscopic traffic models. Results show a decreasing of the mean, median and interquartile range searching time, depending on the probability to find an available FLZ. Moreover, the FLZ density influences the searching time, especially where the density value is low. This trend suggests the existence of a threshold of the number of FLZs for a given area to ensure a reasonable level of FLZ accessibility. Nevertheless, the probability seems to be the predominant parameter of influence. Indeed, the mean searching time is constrained by the availability model. The increase of the probability can be enhanced for examples by FLZ policies reinforcement, or by encouraging turn-over. A cost function was applied to the searching time to access the additional cost of finding a vacant FLZ. Results showed that strict parking policies may lead to numerous consequences on delivery drivers, increasing the total cost of the last mile.

We have proposed an indicator to evaluate management system of FLZ for policy makers. As further work, effects of policy can be investigated. [24] studied the effect of introducing or changing the particular vehicle parking price and time limitation. The impact of the searching time on the traffic conditions can be also accessed through different occupancy rates. Moreover, the searching time and the walking distance should be balanced under various traffic states.

Acknowledgments
This study has received funding from Region Rhône Alpes ARC-7 program and the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (grant agreement 646592 – MAGnUM project). The authors would like to thank Zhengui Xue for proofreading this paper.

7. References

1. Alho, A., De Abreu e Silva, J., Pinho de Sousa, J., Blanco, E.: Improving mobility by optimizing the number, location and usage of loading/unloading bays for urban freight vehicles. Transportation Research Part D: Transport and Environment, in press (2017)
2. Balac, M., Ciari, F., Axhausen, K.W.: Modeling the impact of parking price policy on free-floating carsharing: Case study for Zurich, Switzerland. Transportation Research Part C: Emerging Technologies, 77, 207-225 (2016)
3. Chiabaut, N.: Investigating Impacts of Pickup-delivery Maneuvers on Traffic Flow Dynamics. Transportation Research Procedia, 6, 351-364 (2015)
4. Chiabaut, N., Lopez, C., Leclercq, L.: Evaluation of the performance of an urban freight system using a Multi-use Lane Arterial. 95th Annual Meeting of the Transportation Research Board, 16-0167 (2016)
5. Cody, J.: An Overview of Software Development for Special Functions. Lecture Notes in Mathematics, 506, Numerical Analysis Dundee, G. A. Watson (ed.), Springer Verlag, Berlin (1976)
6. Davis, B.A., Figliozzi, M.A.: A methodology to evaluate the competitiveness of electric delivery trucks. Transportation Research Part E: Logistics and Transportation Review, 49 (1), 8-23 (2013)
7. Dijkstra, E.W.: A note on Two Problems in Connexion with Graphs. Numerische mathematik, 1, 269-271 (1959)
8. Figliozzi, M., Tipagornwong, C.: Impact of last mile parking availability on commercial vehicle cost and operations. Supply Chain Forum: An International Journal, May 2017, 1-9 (2017)
9. Fulman, N., Benenson, I.: Simulating parking for establishing parking prices. Procedia Computer Science, 109, 911-916 (2017)
10. Lighthill, M.J., Whitham, G.B.: On kinematic waves II. A theory of traffic flow on long crowded roads. Proceedings of Royal Society, 229(1178), 317-345 (1955)
11. Litvak, N., Van Zwet, W.R.: On the minimal travel time needed to collect n items on a circle. Annals of Applied Probability, 14 (2), 881-902 (2004)
12. Leclercq, L., Sénécat, A., Mariotte, G.: Dynamic macroscopic simulation of on-street parking search: A trip-based approach. Transportation Reseach Part B, 101, 268-282 (2017)
13. Levy, N., Benenson, I.: GIS-based method for assessing city parking patterns. Journal of Transportation Geography, 46, 220-231 (2015)
14. Lopez, C., Gonzalez-Feliu, J., Chiabaut, N., Leclercq, L.: Assessing the impacts of goods deliveries' double line parking on the overall traffic under realistic conditions. Information systems, Logistics and Supply chain, Bordeaux, France (2016)
15. Motavalli, J.: Frito-Lay Adds Electric Trucks to Its Fleet. NYTimes.com. <http://wheels.blogs.nytimes.com/2010/09/08/frito-lay-adds-electric-trucksto-its-fleet/> (accessed 29.07.11) (2010)
16. Muñuzuri, J., Cuberos, M., Abaurrea, F., Escudero, A.: Improving the design of urban loading zone systems. Journal of Transport Geography, 59, 1-13 (2017)
17. Newell, G.F.: A simplified car-following theory: a lower order model. Transportation Research Part B: Methodological, 36 (3), 195-205 (2002)
18. Nourinejad, M., Wenneman, A., Nurul Habib, K., Roorda, M.: Truck parking in urban areas: application of choice modelling within traffic simulation. Transportation Research Part A, 64, 54-64 (2014)
19. Nourinejad, M., Roorda, M.J.: Parking enforcement policies for commercial vehicles. Transportation Research Part A: Policy and Practice, 102, 33-50 (2017)
20. Plantier, T., Bonnet, G.: Aires de livraison : planifier, aménager et gérer l'accueil des véhicules. CEREMA (2013)
21. Ramadan, A., Roorda, M.J.: An integrated traffic microsimulation model of illegal on-street parking in downtown Toronto. The 96th international conference of Transportation Research Board, 17-05970 (2017)
22. Richards, P.I.: Shock waves on the highways. Operations Research, 4, 42-51 (1956)
23. Scott, A.J.: Location-allocation system: a review. Geographical Analysis, 2 (2), 95-119 (1970)
24. Simićević, J., Vukanović, S., Milosavljević, N.: The effect of parking charges and time limit to car usage and parking behaviour. Transport Policy, 30, 125-131 (2013)

25. Van Nieuwkoop, R., Rutherford, T.F., Axhausen, K.W.: A Traffic Equilibrium Model with Paid-Parking Search. Journal of Transport Economics and Policy, 50 (3), 262-268 (2016)
26. Wardrop, J.G.: Some theoretical aspects of road traffic research. Proceedings of the Institute of Civil Engineers, Part II, 1, 325–378 (1952)