Microscopic Simulation of the Cruising-for-Trucks-Parking as a Measure to Manage Freight Loading Zone

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Abstract

In this paper, it is investigated the economic truck parking behavior to implement comprehensive Freight Loading Zone (FLZ) policies. Assumptions are the deployment of the automatized and systematic double-parking fine and the technology of autonomous delivery vehicles designed for sidewalks. The proposed contribution is the quantization of the cruising-for-trucks-parking. That is, the time for delivery trucks to visit a sequence of parking until the first available parking slot is found. We use the microscopic traffic simulation based on a Manahan network and the real network of Lyon (France) with the real data of location of FLZ. We investigate the relationship between the searching time, the parking probabilities and the region's parking density. Based on our results, we propose an application to a last mile cost function.

Keyword: vacant freight loading zone probability, trucks parking policies and design, spatial and temporal evaluation of FLZ, microscopic traffic simulation, region's parking density.

1. Introduction

The transport of goods in urban areas is essential for the economy of cities. Nevertheless, urban freight delivery and pick-up movements provide at least four majors negative impacts: congestion, insecurity, pollution (Muñuzuri *et al.*, 2010) and energy consumption. More precisely, since the drivers usually have limited time for delivery, they are pushed to double-park in order to not cruise for parking. Double-parking can incur temporal reductions of the road capacity in several places. The capacity drops can consequently increase travel time delays and reduce the global performances of transportation networks (Chiabaut, 2015; Lopez *et al.*, 2016; Ramadan and Roorda, 2017; Alho *et al.*, 2018).

The Freight Loading Zone (FLZ) management is a challenge as the multi-modal demand of the existing infrastructure increases. Indeed, parking is essential for trucks to deliver and pick-up goods. Implement comprehensive urban freight policies is a challenge for public decision makers. The lack of understanding of the supply chain perspective is one of the identified difficulties (Van Duin *et al.*, 2017; Dablanc, 2007). City managers can apply numerous strategies to reduce illegal freight double-parking problems. More precisely, we identified two FLZ policies inherently linked: (i) freight double-parking fine and (ii) spatial FLZ management. Note that it is acknowledged that the compliance levels of particular vehicles to not park at FLZ can play a crucial element in reducing double-parking (Alho *et al.*, 2018).

(i) Parking price policy has been investigated for cars (Simicevic *et al.*, 2012; Zakharenko, 2016; Fulman and Benenson, 2017), carsharing (Balac *et al.*, 2016) and freight (Marcucci *et al.*, 2015). Nevertheless, few studies aim to evaluate freight double-parking fine policy as (Figliozzi and Tipagornwong, 2017; Nourinejad and Roorda, 2017). Enforcement can be considered as a reduction of the FLZ demand (Aiura and Taniguchi, 2006; Alho *et al.*, 2018). Increasing double-parking fine price can discourage the illegals but not ensure its elimination (Figliozzi and Tipagornwong, 2017). Moreover, cities are dependent of goods mobility and should not dissuade to double-park without adjusting a proper number of vacant FLZs, *i.e.*, compensatory actions. Nourinejad and Roorda (2017) proposed an equilibrium model between illegal commercial vehicle parking and enforcement policies – defined in their study by the citation fine and level of enforcement.

(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 combined: spatially, *i.e.*, the number and the location of FLZ, and temporally, *i.e.*, time window, time limit of parking or enforcement of booking system of FLZ (Patier *et al.*, 2013; David *et al.*, 2014). 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 (Muñuzuri *et al.*, 2017; Alho *et al.*, 2018). Nourinejad *et al.* (2014) evaluated reserved streets for freight parking as a potential truck parking policy. In urban areas, freight parking infrastructure has high demand and limited supply (Alho *et al.*, 2018). Malik *et al.* (2017) examined the impact of imbalance between FLZ demand and supply. This imbalance can vary considerably by area and roadway type (Chen *et al.*, 2017). Management solutions contribute to use efficiently FLZ infrastructure through space and time, optimizing their use. This optimization makes it possible to maintain a level of service while reducing the number of FLZs (Muñuzuri *et al.*, 2017). Nevertheless, a reduction of the number of FLZ increases the distance between a pair of FLZs. In the literature, numerous papers proposed to design the FLZ systems by solving an optimization problem. Muñuzuri *et al.* (2017) solved the location-allocation problem (Scott, 1970) for the FLZ spatial configuration. The authors analyzed the resulting number, location and availability of FLZs. Their indicator is the average traveled distance between the FLZ used and the customer, *i.e.*, the walking distance. The authors consider a return as the unavailability of parking space. The network scale is a street. More generally, Levy and Benenson

(2015) proposed a GIS-based approach for assessing parking pattern in urban areas, where dynamic supply and demand are considered.

We identify three major reasons which can lead the behavior of trucks to do not cruise-for-parking: (i) the probability of finding a vacant FLZ through the time. This probability is influenced by the occupancy rate (Van Nieuwkoop *et al.*, 2016), *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 FLZs can be inappropriate, *e.g.*, the FLZ locations may be inconsistent by unfollowing the economy dynamic; and (iii) the maneuvering time may dissuade drivers (Figliozzi and Tipagornwong, 2017).

In this paper, we aim to retrieve the searching time of trucks, where double-parking by delivery trucks is eliminated. We define the searching time as the cruising-for-parking time, *i.e.*, the time for a truck to find the first vacant parking. To enhance the relevance for trucks to cruising-for-parking, assumptions are the deployment of the automatized as well as systematic double-parking fine and the technology of autonomous delivery vehicles designed for sidewalks. To this end, we use microscopic traffic simulation with two case studies, a theoretical Manhattan network and the real network of Lyon (France) and its real data of FLZ location. We evaluate the FLZ system of Lyon through two axes of indicators: spatially using Voronoï diagram and temporally using the cruise-for-truck-parking.

We investigate how the searching time is affected by both of the following parameters: (1) the occupancy level of FLZs and (2) the region density of FLZs. To the best of our knowledge, there are no existing studies that focus on this line of research. Particularly, on the researching time as an endogenous function of truck's travel time to evaluate FLZ management. We assume a relationship between the cruise-for-parking and the probability of trucks to double-park. Thus, the minimization of the searching time can be an aggregated metric to evaluate both the FLZ system performance and the double-parking rate. Based on our results, we propose an application to a last mile cost function.

The paper is organized as follows. In Section 2, microscopic simulation is described integrating the parking choice model, the availability model and the traffic model. The Section 3 describes the two case studies, their relative data and transportation network. In Section 4, a spatial analysis of FLZ management is established and the quantization of the searching time is analyzed. In Section 5, an application to a last mile cost function is proposed. Section 6 concludes this paper and presents the future work.

2. Methodology

To retrieve the searching time, we propose a methodology that includes the simulation of particular vehicle traffic flow and the trucks' cruising-for-parking at the microscopically simulation scale. We propose a two-step commercial vehicle parking model including: (i) a parking choice model and (ii) an availability model.

We consider that the commercial vehicle can only park on an FLZ and not on any other kind of parking slot. Moreover, 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 – customers –, its order, the route between each pair of stop points and the stopping time duration. We assume that the properties of delivery routes do not influence the searching time. Consequently, origin, destination and stop points are set stochastically, where the sequence of stop points is not in order. In addition, the stopping time duration is deterministic.

2.1 Parking Choice Model

The parking choice model is applied for each customer. We consider that the truck choice is the first parking available which is located at the shortest traveled distance of the customer location. Indeed, we assume that the delivery truck driver aims to minimize his walking distance between the establishment to visit and the place the truck is parked. To this end, we assume that the delivery truck drivers have the entire knowledge of the topology network. Moreover, 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.

Let N_F be the number of FLZ of a given network, C be the array of customers to deliver for a given delivery route and F be the array of FLZ to visit for a given customer C_i, where the length of F is N_F. F is sorted in an ascending according to the traveled distance from the given establishment C_i to F_i where $i \in \{1, N_F\}$. Thus, we use the Dijkstra (1959) algorithm to compute the first shortest traveled distance for a given pairwise origin and destination. Traveled distance makes it possible to consider the directed graph of the network (*e.g.*, instead of Euclidean distance).

We consider an acceptance threshold of the walking distance and an acceptance threshold of the searching time, denoted by θ and δ respectively. Let W_i be the truncated F based on θ and δ. The calibration of θ and δ constraints requires a specific attention as traveled distances and travel time can be heterogeneous through the network. The limitation of this model is that the total searching distance is not optimized for the delivery route generation (*i.e.*, TSP or VRP algorithms). Indeed, the array of FLZ per customer is considered independently.

2.2 Availability Model

We consider the Bernoulli's principle to model the parking availability (Lerclercq *et al.*, 2017). Let p be the probability to find a vacant FLZ and T_0 be the occupancy rate which satisfy $T_0 = 1 - p$. We define X as the number of failure among Bernoulli trials before getting one success, *i.e.*, finding 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:

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

with $0 \leq p \leq 1$. We consider n iterations of truncated array of FLZs, where n should satisfy $n \times N_w > X$.

This availability model allows us to study various probabilities p, which can represent different rates of FLZs occupancy in urban areas. The occupancy rate of 53% is used in the study of Plantier and Bonnet (2013). Numerous solutions can contribute to decrease the rate of FLZs occupancy, *e.g.*, a better rotation of trucks parking (reduction of the limit 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 noticed that the carrousel is not a circle network, as studied by Litvak and Van Zwet (2004). Carrousel is a generic schema of the proposed availability model, where distance of a given pair of FLZs can be related to any meshed transportation network.

To analytically study the availability model, we consider a stochastic approach of the distance of a given pair of FLZs. More precisely, the distance follows the gamma probability density function (Cody, 1976). Figure 1-b shows the fit of the gamma probability density function on the distribution of link length from the network of Lyon. The mean and the standard deviation are respectively 103 and 92 meters. 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-c shows the traveled distance distribution, where $p = 0.5$. Note that a zero value means no searching distance as the first FLZ visited is vacant. Figure 1-d shows the boxplots of the distribution of various p, from 0.1 to 0.9 by step of 0.1. The use of boxplot allows us to establish a first statistical study of the properties of searching traveled distance influenced by p, *i.e.*, the mean, the median and the interquartile range. These three indicators are decreasing as a function of p.

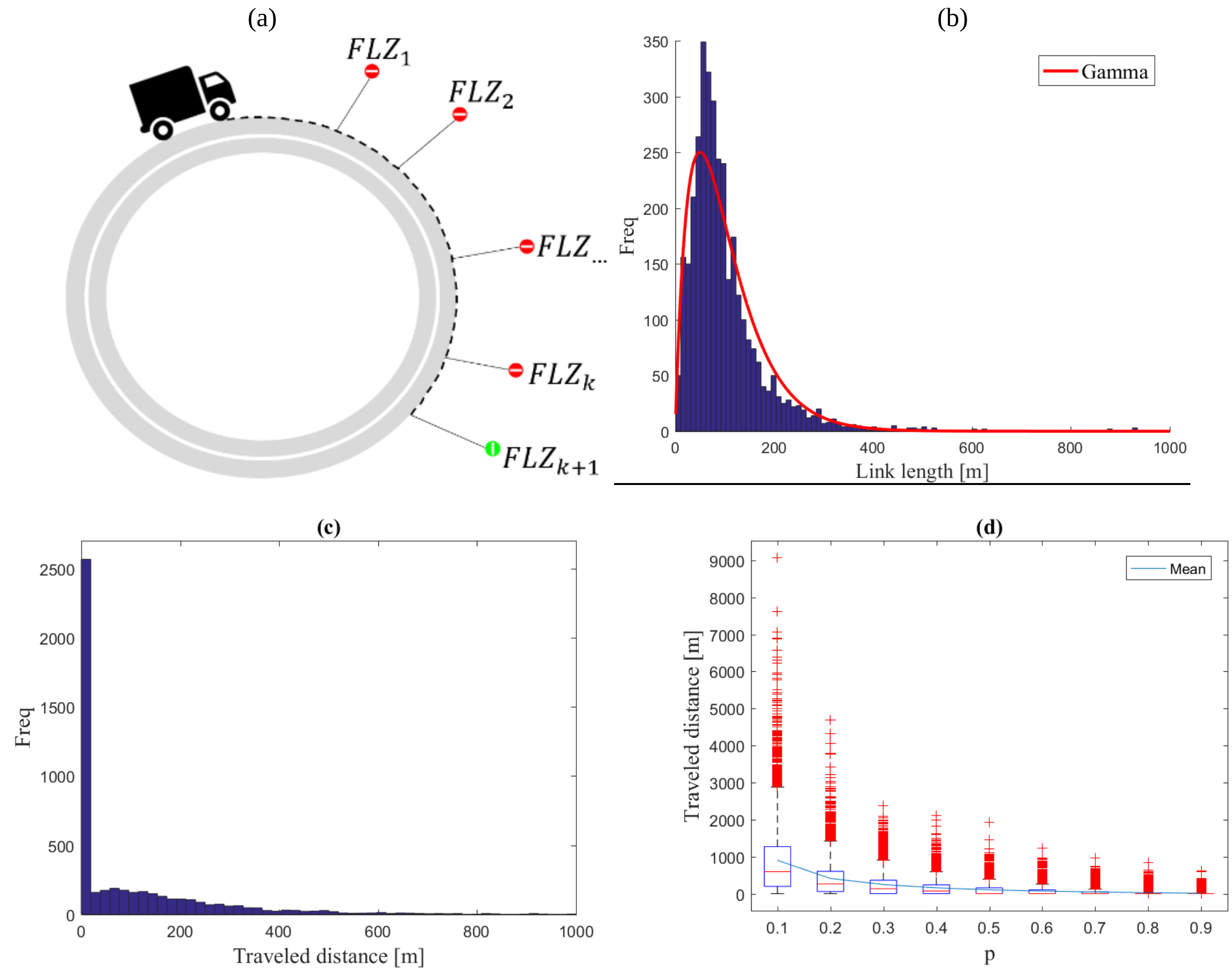

Figure 1 - (a) Carrousel schema, (b) distribution of link length from the Lyon network, (c) histogram of traveled distance where $p = 0.5$ and (d) boxplots of traveled distance

Note that if $k = 0$ (where k is the number of failure), traveled distance equals to 0. Indeed, if the first FLZ visited is available, we consider that the truck is not cruising-for-parking. 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 follows:

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

2.3 Microscopic simulation of the traffic dynamics

We use the microscopic traffic simulator SymuVia (Leclercq and Becarie, 2012) to model traffic flow. More precisely, SymuVia computes vehicles trajectories based on Newell model (Newell, 2002), which is equivalent to LWR model (Lighthill and Whitman 1955; Richards, 1956). The assignment of particular vehicles is based on the individual optimum (Wardrop, 1952).

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, especially for large-networks, large time window and for a high demand. More precisely, we focus on the commercial truck trajectories where we measure the searching time to find the first vacant FLZ for each customer. Note that we consider that park to the first closest FLZ to a given customer equal to not cruise for parking, based on the aforementioned assumptions.

2.4 Indicators

We consider two axes of indicators to evaluate an FLZ system: (i) spatially, *i.e.*, the number and the locations of FLZs through the topology of the network and (ii) temporally, *i.e.*, the searching time.

(i) We propose to use Voronoï diagram (Aurenhammer, 1991) to characterized FLZ's level of service. These convex polygons are obtained from the equidistant Euclidian distance of FLZ. Thus, each cell belongs to an FLZ. We identified three sub-measures of the Voronoï cells: the number of adjacent cell of a given cell, the area of a cell, and the density of a cell. In the literature, Voronoï diagram is used to partition an entire transportation network into a set of cells based on the spatial distribution of individuals, as data points in individual trajectories by Kim *et al.*, (2016). In this paper, we use the area and the density of Voronoï cells.

(ii) The searching time is influenced by the traffic stated, *e.g.*, congestion will increase the searching time instead of the traveled distance. This measure can be empirical (*i.e.*, real-world data) or simulated.

3. Data Description

Two cases of study are considered with the Manhattan network and the real network of Lyon. The free-flow speed denoted by v and the acceleration denoted by a of both particular vehicles and trucks are set to $v = 14$ m/s and $a = 0.5$ m/s². The maximal density denoted by k_c of particular vehicles and trucks are respectively set to $k_c = 0.17$ and $k_c = 0.1$.

3.1 Manhattan Theoretical Network

The meshed theoretical network is composed 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 (Fulman and Benenson, 2018). 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. We set a constant stopping time fixed to 3 minutes (as the service time used by Figliozzi and Tipagornwong (2017) for Service B).

Moreover, 6 configurations of FLZs 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 FLZs on the Manhattan network, where $d = 0.6$ and $d = 6.7$ respectively. Note that for a given FLZ, its location is deterministically set to the middle of its relative link.

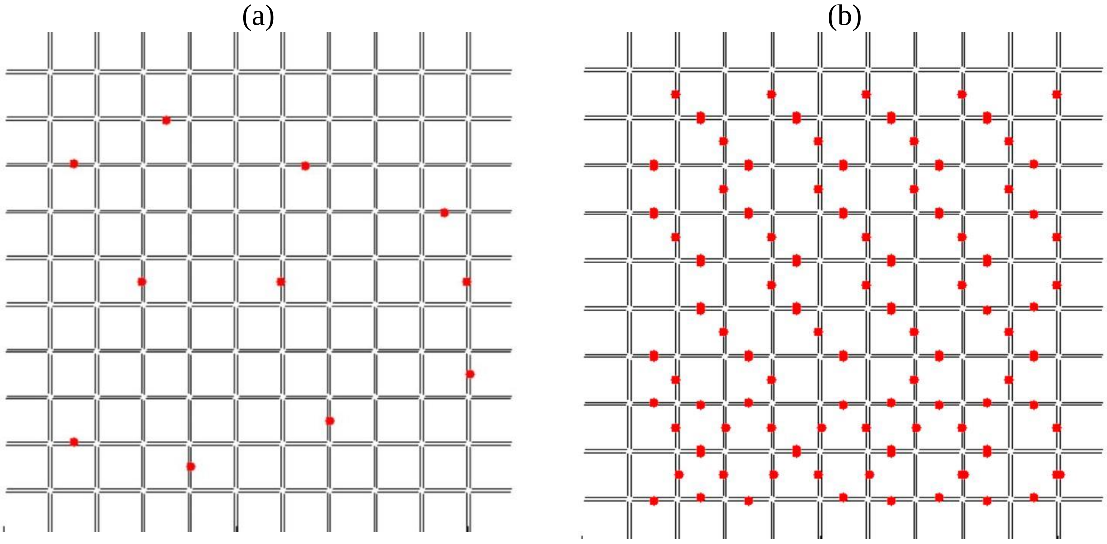

Figure 2 - (a,b) Manhattan network where d=0.6 and d=6.7.

3.2 Lyon Real Network

The Lyon network is composed of 1317 FLZs, where the real-world data are provided by *Data Grand Lyon*. In addition, 10329 establishments are registered in Lyon based on the government data SIRENE. Figure 3-a shows red and gray data points corresponding to FLZ and establishment respectively. Both variables are characterized by their coordinates. FLZ has been snap into the directed Lyon network as FLZ locations are required for the parking choice model. To this end, the FLZ is snapped to the link minimizing the Euclidean distance. The methodology of snapping objects into a transportation network is the same as that used in Lopez *et al.* (2017).

The directed Lyon network is composed of the 6th and 3rd districts of Lyon city as shown in Figure 3-b. This network is characterized by 3461 links, 1827 nodes, 233 entries and 229 exits. The particular vehicle demand and traffic lights settings are based on real data. 230 FLZs are located into the directed Lyon network considered for the microscopic simulation. We use uniformly distributed random number to select 500 delivery points. We consider 100 routes of 5 customers, where the stopping time has been set to 2 minutes. We also consider one route per simulation in order to not bias the searching time quantization with the impact of delivery routes on the traffic flow (Lopez *et al.*, 2016).

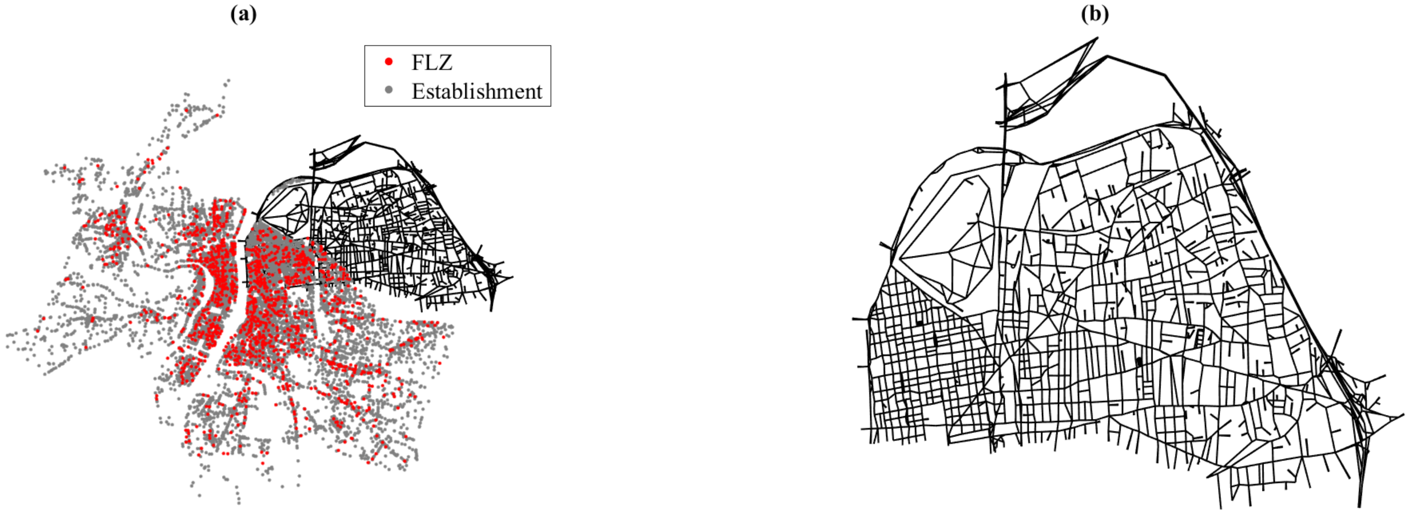

Figure 3 - (a) Visualization of real-world data: establishments and FLZ of Lyon and (b) the directed network for simulation

4. Results

The impact of the state of the demand denoted by p and the state of supply denoted by d of FLZs on the searching time are quantified, through the Manhattan and the Lyon network. First, a spatial analysis of the FLZ configuration is established on the real network of Lyon. Second, the searching time measure is used to study the FLZ system.

Figure 4-a shows the Lyon network partitioned based on Voronoï decomposition. Black cells and blue points represent respectively Voronoï polygons and FLZs. Voronoï cells properties make it possible to identify the shortest Euclidian distance of FLZ for any customer based on cell perimeter; *i.e.*, the FLZ where the customer is in the Voronoï polygon. Thus, Voronoï cells area can be used to measure the spatial FLZ level of service. The increase of the Voronoï cell area decreases the FLZ level of service. It is important to note that the FLZ location is not the centroidal Voronoï tessellation.

Figure 4-b distinguishes the density of establishments by the color of polygons, where the density is normalized from 0 to 1. Figure 4-c represents the cross-analysis of the cells based on two of its characteristics: the length area and the density. The x-axis represents the number of establishments and the y-axis represents the length area. Blue points represent Voronoï cell, called FLZ in the legend. We identify two regions of potential enhanced: (i) the region where temporal FLZ system should be enhanced, and (ii) the region where spatial FLZ configuration should be enhanced. (i) The south-east of the Figure 4-c is characterized by a low length area with a high density of establishments. These values usually belong to an FLZ configuration of a city center where the dynamic of the economy is the highest. Temporal FLZ system should be enhanced in this region as the length area is already low. Indeed, enforce FLZ turnover can be more relevant in this region that create additional FLZs as the existing infrastructure offer in city center is limited. (ii) The north of the Figure 4-c is characterized by a high length area. Spatial FLZ should increase in this region as a too high Voronoï length area can induce a high traveled distance to reach the shortest FLZ for a given customer. In further work, the spatial analysis of the FLZ level of service can be refined by the number of adjacent Voronoï cells. Moreover, the number of establishments – density cell – can be normalized by the number of movements (pickup and delivery) with the use of a freight demand model (Lopez *et al.* 2016; Kaszubowski 2018). One of the major conclusion of David *et al.* (2012) is that the number of FLZs in Lyon is generally appropriate. Their case of study was the 1st and the 2nd district of Lyon, characterized by a high commercial and residential density and congestion. Their parameters were 324 FLZ and 332 movements (representing 75% of Lyon urban freight).

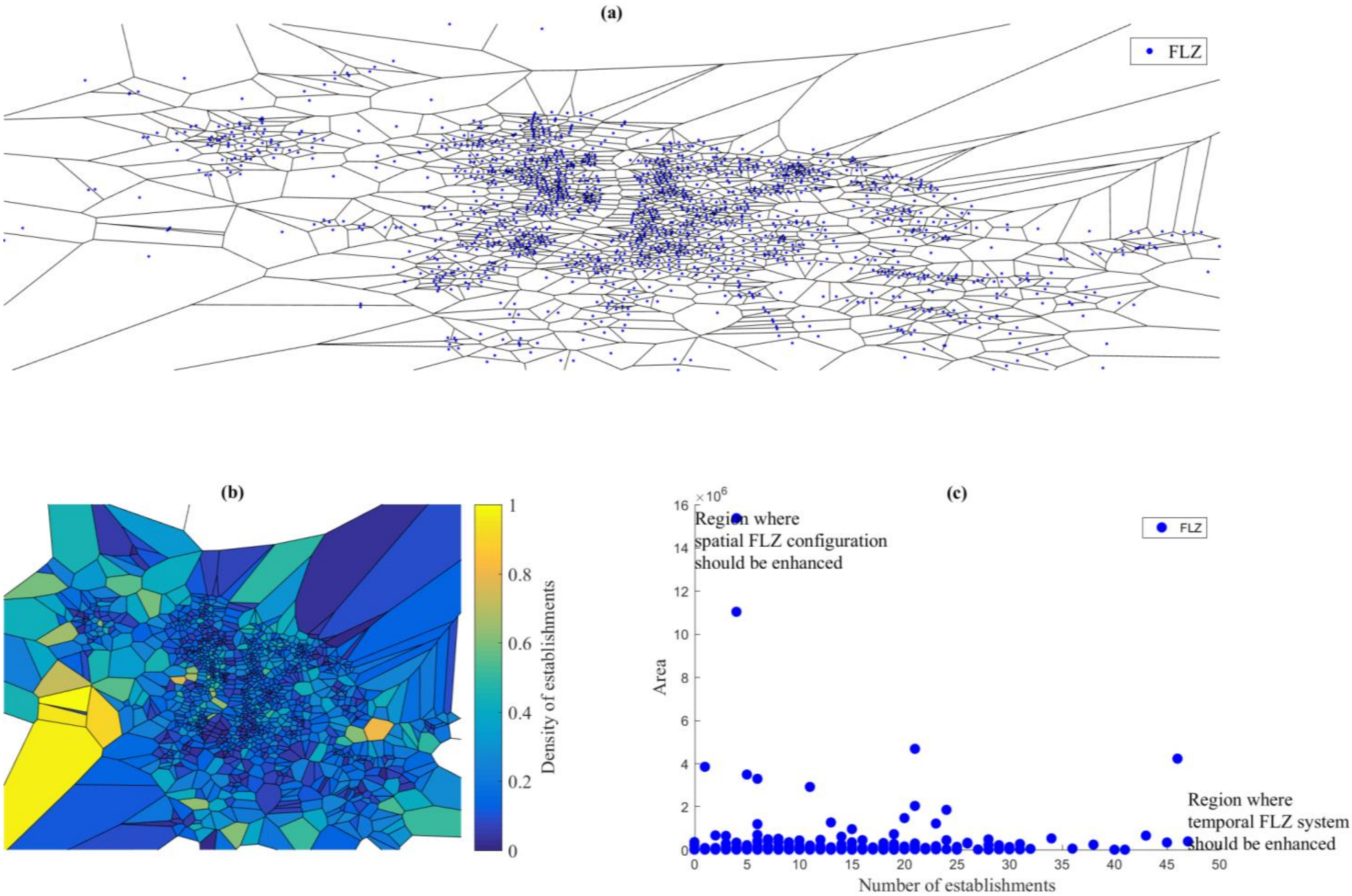

Figure 4 - Voronoï cell of the Lyon network where, (a) FLZ are displayed and (b) cell color is the density of establishments; and (c) cross-evaluation of the FLZ configuration

Stochastic simulations of the Manhattan network have been computed per p and d, where each simulation includes a route of several customers, varying from 3 to 15. This theoretical yet realistic network makes it possible to study 6 configurations of FLZs where their locations tend to be spatially homogeneously distributed. Figure 5-a shows the distribution of 220 observations of searching time, where $p = 0.4$ and $d = 2.2$ FLZ/km. The x-axis is the searching time (s) and the y-axis is the frequency.

Figure 5-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 trend of boxplots is similar to the Figure 1-d. Indeed, as studied analytically, the searching time distribution is dependent on the geometric probability function considered in the availability model (*cf.* Section 2.2). The 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 $p = 0.4$.

Figure 5-c and Figure 5-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. The highest mean observation is the mean searching time of 664s, where $p = 0.2$ and $d = 0.6$. Starting from a threshold of d, the trend of the searching time distribution through p tends to be similar. This observation can suggest that even if FLZ supply is well-furnished, the searching time is influenced by p. First, these results can be interpreted as a requirement of at least a threshold 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 5-e presents the abacus of the mean searching time [s] related to the probability p and the density d respectively on the axis x and y. Contour plot makes it possible to identify region characterized by a high mean searching time, represented in pink color. Black arrows represent the gradient slope. Results show a predominance influence of p on the mean searching time. These results can be interpreted by the following statement: the enforcement of temporal FLZ turn-over can lead to a larger decrease of the mean searching time than the creation of numerous new FLZs. We propose the use of the Searching Time Abacus (STA) to estimate the mean searching time, based on static demand and homogeneous regions from real cities and consequently evaluate FLZ system. We suggest STA as a tool for policy makers to identify comprehensive freight policies tackling illegal double-parking problems. Based on the STA, regions favorable for creating new FLZs or promoting the FLZ turnover can be identified. Indeed, we assume that both of the parameters – the occupancy rate and the density of FLZ – are affordable for city manager by survey methodology (Cats *et al.*, 2016).

(a) (b)

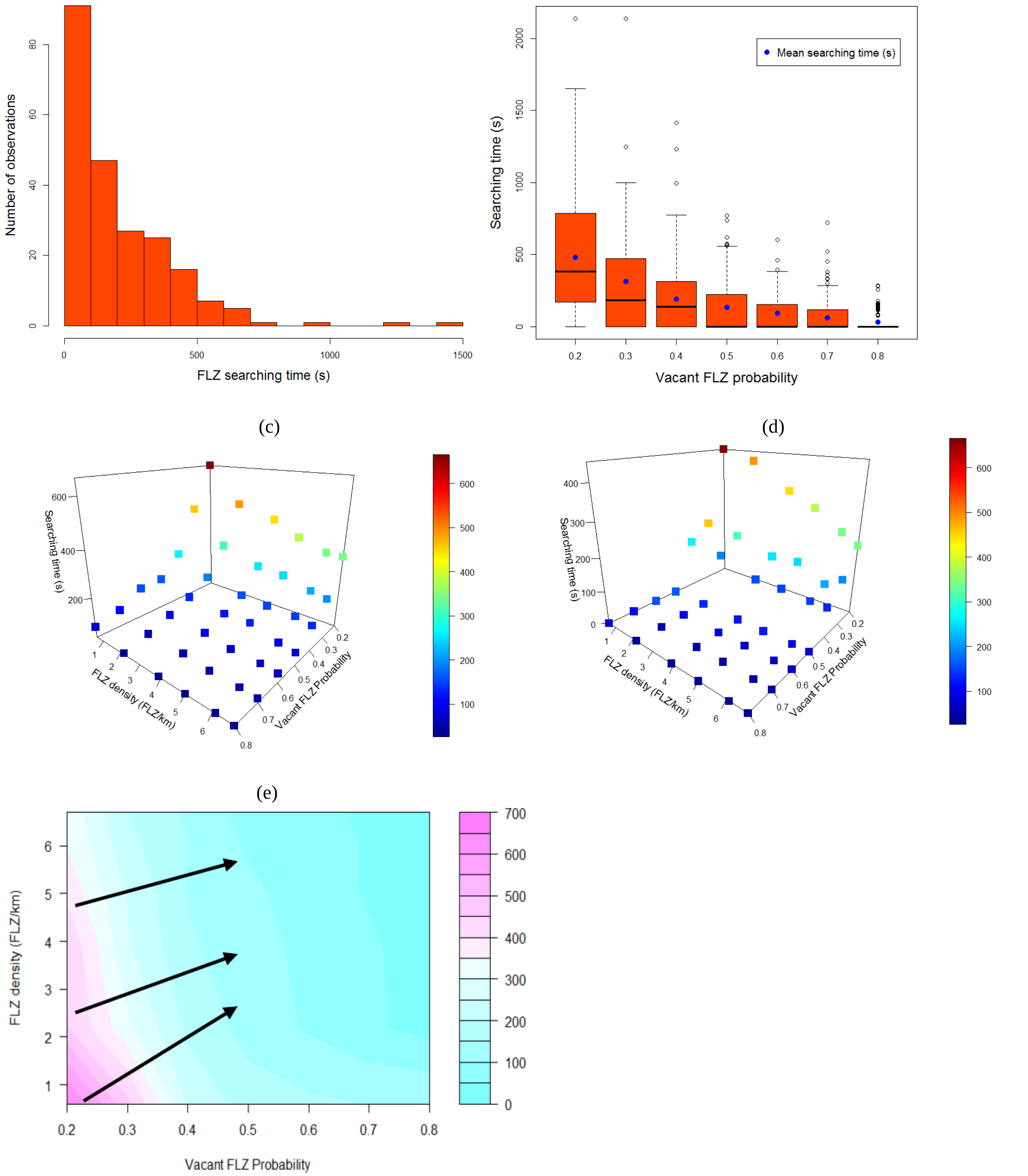

Figure 5 - Manhattan results of the searching time (a) distribution where FLZ density $d = 2.2$ FLZ/km and probability $p = 0.4$, (b) boxplots where $d = 2.2$ FLZ/km, (c and d) mean and median searching time and (e) the abacus of the mean searching time

The simulated searching times of the Lyon network have been studied, firstly with the same statistical framework than the Manhattan network. Figure 6-a shows the distribution of the searching time where $p = 0.5$. Figure 6-b shows the boxplot of cruising-for-truck-parking with respect to p, varying from 0.2 to 0.9 by step of 0.1. Each boxplot corresponds to the distribution of 500 searching time observations. More precisely, for a given p, 100 microscopic simulations of a delivery route composed by 5 establishments are carried out. The blue curve is the mean searching time with respect to p. Results present similar trends to the Manhattan network study. Nevertheless, the scales of the values are different because of the topology of the network.

Figure 6-c cross-analyze the simulated cruising-for-truck-parking observations, where the x and the y axis correspond respectively to the searching time and the walking distance. The walking distance is the shortest undirected graph distance from

the nearest first available FLZ to the customer location. The size of the data point corresponds to p, the probability to find a vacant FLZ. We identify three regions in Figure 6-c: (i) the south-west region is characterized by low values of both searching time and walking distance. These observations represent delivery customer experience where an FLZ system is well furnished. The searching time is minimized by a high probability to find a vacant FLZ and high density of FLZs in a given zone; (ii) the west region is characterized by a low searching time and a walking distance which can be high. This situation can be considered as a perspective for walking distance to be minimized by improving the FLZ configuration (the FLZ number and their locations); (iii) the east region is characterized by high searching time where the walking distance is variable. This region tends to be characterized by a low p. Indeed, the p variable has a predominant influence on the searching time.

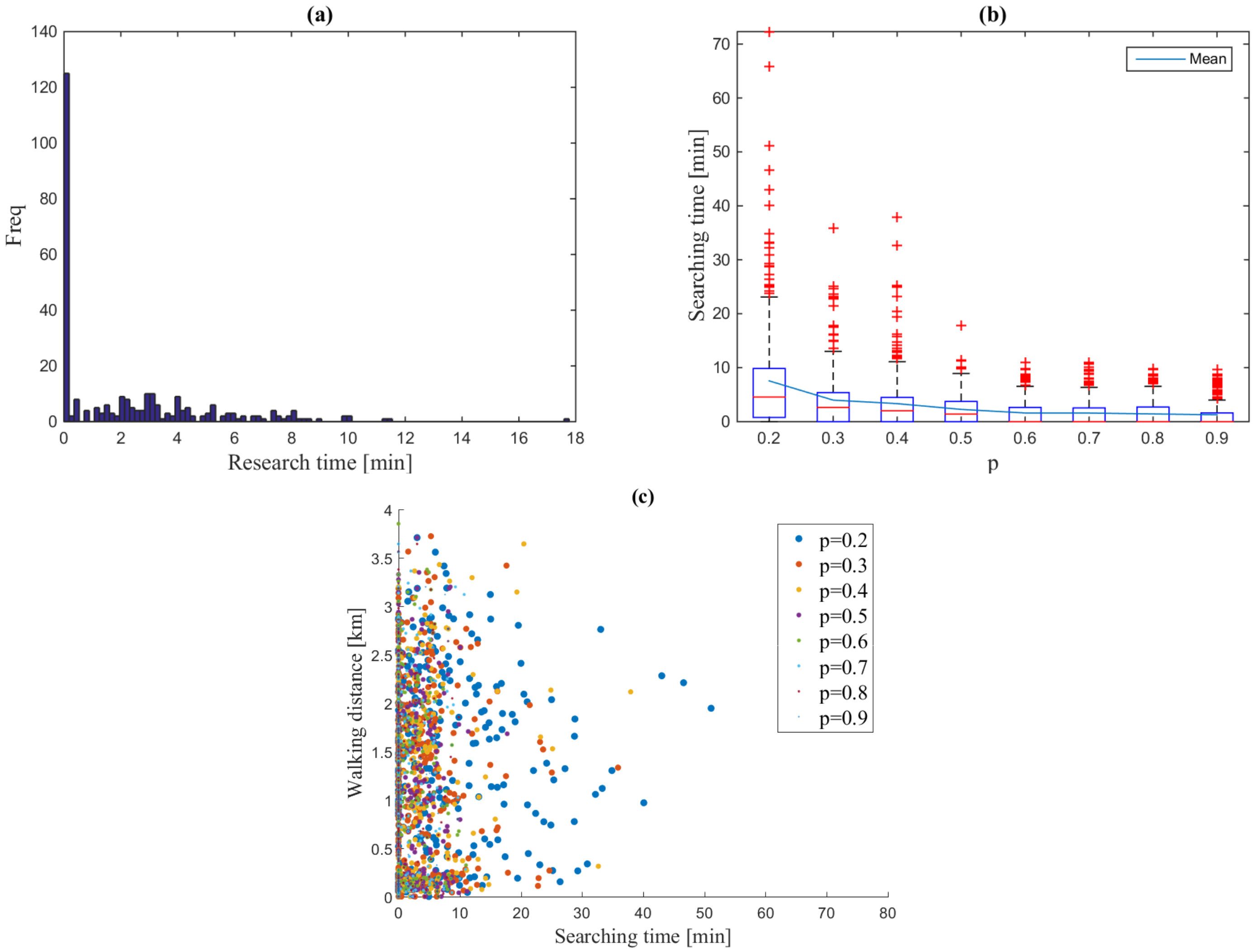

Figure 6 - Lyon network results of the searching time (a) distribution where $p = 0.5$, (b) boxplots through the probability to find a vacant FLZ, (c) the searching time through the walking time

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. 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, numerous papers investigated the value of time (VOT) (Schreiter *et al.*, 2012). Nevertheless, few studies attempt to understand the FLZ availability on the last mile cost function and truck driver behavior (Figliozzi and Tipagornwong, 2017). This section proposes to quantify the cruising-for- truck-parking using a simplified cost function, relative to a route and service characteristics as shown in Table 1.

To this end, we use an existing econometric model (Davis and Figliozzi, 2013), 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] (Motavalli, 2010).
[c] (Plantier and Bonnet, 2013).
[d] Assumes approximately the density of a region of the Lyon network based on real FLZ data from Data Grand Lyon https://data.grandlyon.com/.

The mean searching time computed by microscopic traffic models corresponds to an additional 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 additional time can be interpreted as: (i) an additional working time – and costs – or, (ii) a decreasing number of customers delivered. Note that the marginal cost of congestion is endogenous of the searching time. The advantage is that traditional information required for congestion pricing as the travel demand and the traffic flow derived are not necessary (Simoni *et al.*, 2015).

6. Conclusion

This paper has proposed the searching time indicator to measure the performance of an FLZ system. Assumptions are the elimination of double-parking by the deployment of the automatized as well as systematic double-parking. We study how this aggregated measure is influenced by the FLZ offer (the number and the location of FLZ) and the FLZ supply (the probability to find a vacant FLZ as the freight parking demand). We use the microscopic traffic models to simulate the cruising-for-parking of delivery truck. The methodology includes the parking choice model and the availability model which has been studied analytically. This research is, to our best knowledge, the first attempt to study the truck searching time by modeling a two-step commercial vehicle parking model in a microscopic traffic simulation.

Two different typologies of directed networks have been studied: the theoretical yet realistic Manhattan network and the real network of Lyon (France). First, a spatial analysis has been established where the Lyon network has been partition into cells based on real-data of FLZs. Indicators proposed make it possible to identify region where spatial FLZ configuration should be enhanced and region where temporal FLZ system should be enhanced. Second, the searching time has been quantified, where results show a predominance influence of the probability of a vacant FLZ on the cruising-for-parking and its related uncertainty. At least a threshold number of FLZ is suggested in order to access a reasonable mean searching time. Moreover, the probability to find an available FLZ should be increased to decrease the mean searching time, *e.g.*, by FLZ policies reinforcement or encouraging turn-over.

The searching time measure has numerous promising applications. The use of an econometric model based on the searching time makes it possible to estimate the retailers' reactions of imposed FLZ policies. As further work, the influence of traffic state on the searching time can be investigated. Moreover, the impact of cruising-for-truck-parking on the global performances of the network can also be investigated as established for the cruising-for-parking of particular vehicles (Leclercq *et al.*, 2017; Cao and Waraich, 2017). We proposed a framework for policy makers to properly manage an FLZ system with the use of STA. The evaluation of the STA as a model to predict the mean searching time can be studied, where uncertainty should be included (Gao and Gayah, 2017).

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