24th International Congress on Modelling and Simulation, Sydney, NSW, Australia, 5 to 10 December 2021
mssanz.org.au/modsim2021

Assessing last mile delivery strategies – A hybrid solution approach

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Abstract: Urban freight is growing faster than other transport activities, and its adverse effects bring consequences to people, the environment and the liveability of cities. Although understanding its dynamics has become a priority for governments, the multiplicity of actors with conflicting objectives makes it a significant urban planning challenge. This paper develops a hybrid (simulation-optimisation) methodology to evaluate the impact of different last mile delivery strategies over the network traffic flow. The model is focused on the use of one type of on-street parking infrastructure: the loading zone (LZ). We refer to on-street LZs as parking areas that occupy space directly on the road lane. The design and management of parking systems, especially on-street LZs, is considered one of the most powerful traffic control measures with a substantial influence on the efficiency of the urban freight system. The methodology considers the decision-making process made by the road users, their interaction, and the variability of stochastic parameters (traffic conditions, competition, cruising, and illegal parking). The framework combines a stochastic cellular automata (CA) traffic microsimulation, with a metaheuristic and a commercial solver. The CA model has two layers, the lower layer describes the road network, its entry and exit points, LZ locations, traffic demand, speed limits, intersections, and traffic light settings. The upper layer manages the agents (private vehicles (PV) and delivery vehicles (DV)), their size, speed, motion, lane changing, vehicle routes, illegal parking decisions and the duration of the delivery stops. To optimise the routes of DVs, we use a greedy randomised adaptive search procedure – GRASP to solve a two-level (trucking and walking) optimisation problem and the CPLEX optimiser to re-optimise mid-route decisions. The model was developed in the Java programming language.

The methodology is applied to a CBD network simulating realistic conditions and evaluate three urban logistics strategies: *Alternative LZ, Illegal Parking and Last Delivery*. Although the results conclude that to minimise the impact of DVs the best strategy is *Illegal Parking*, important considerations need to be addressed. For instance, the location of the LZs in the study network were equally spread over an edge, with two illegal parking areas. This aspect certainly limited the well-known congestion consequences of illegal parking. For example, LZs that are located close to up- or down-stream intersections with more illegal parking will certainly spread the congestion shockwave to adjacent edges, attaining different results. A similar situation occurs when delivery vehicles parked illegally are blocking the access to buildings, side streets or public transport.

The fact that the *Illegal Parking* strategy derived better results in this study may seem counterintuitive and is likely to be controversial. However, a logical explanation is that the city might be better off by relaxing parking restrictions to help DVs finishing their routes faster, than by tightening regulations that increase DVs cruising time and cause more congestion. Since the benefits and responsibility for the implementation of more relaxed illegal parking measures lie entirely in the city's hands, is an additional incentive to consider it as a feasible traffic management policy.

Keywords: *Traffic simulation, city logistics, urban logistics, illegal parking*

1. INTRODUCTION

Urban freight represents a major challenge in modern urban areas. It accounts for around 18% of road traffic, 40% of total urban transport energy consumption (Browne et al. 2007) and between 20% to 30% of total vehicle kilometres (Behrends et al. 2008). It generates unsustainable effects on people (traffic accidents, noise, visual intrusion, emissions), the economy (reduced accessibility, attractiveness and liveability) and the environment. Despite its importance in sustaining urban living, last mile deliveries are categorised as the least efficient stage of the supply chain (Ranieri et al., 2018). The engagement of different logistics providers delivering small quantities, results in a high degree of fragmentation and incoordination (Kin, 2018). Empirical studies found that urban freight vehicles have an average load factor of 30 to 40% (Dominguez et al. 2012) with more than 20% of vehicles driving empty (Tozzi et al., 2014). To address these challenges, it is necessary to design logistics strategies that reflect the dynamics of urban freight, its vast complexity and the interaction between the different actors in the road network (Dablanc, 2011). However, the available space within the built environment is limited and the ability to reconfigure the current infrastructure, enhance the transport network, and expand parking areas will not be enough to meet the growing demand for urban freight and the need for efficient, environmentally sound and affordable solutions (Marcia, 2009).

In this study we present a hybrid traffic microsimulation-based methodology to evaluate the impact of different delivery strategies over the network traffic flow. The methodology is focused on the use of on-street parking areas (LZs). It considers the decision-making process made by the road users (PVs and DVs), their interaction, and the variability of stochastic parameters (traffic conditions, competition, cruising, and illegal parking). The model is applied to a medium size network and evaluate the impact of three last mile deliveries strategies. Although a lattice network is used as an example, the model can be easily customised to support other configurations.

2. LITERATURE REVIEW

Microsimulation is a widely applied methodology to evaluate the effects of last mile distribution on traffic congestion and to test managerial and infrastructural alternatives. Practical applications have been developed for different cities (Letnik et al., 2020, Dalla Chiara and Goodchild, 2020, Nourinejad et al., 2014, Iwan et al., 2018). Some works have focused on the traffic flow effects of illegal parking (Simoni and Claudel, 2018) and the impact of varying levels of law enforcement (Aiura and Taniguchi, 2005, Romano Alho et al., 2021).

Although previous studies have addressed similar urban logistics problems, they have key structural differences with our model. Trott et al. (2021) used a simulation/optimisation framework to evaluate routing solutions using different scenarios varying the type of LZs (on-/off-street) and the walking delivery radius. Contrary to our problem, they optimised the DVs routes for a single transportation company and the walking routes are not optimised explicitly. Amer and Chow (2017) studied the relationship between PVs and DVs behaviour. The social optimum is found by solving a nonlinear optimisation problem. Unlike our work DVs' trucking and walking routes are not considered. Zhang and Thompson (2019) developed a model for optimising urban deliveries using LZs. The model is combined with agent-based simulation to model the carriers' behaviour. Contrary to our model, a course-grained approach is used that limits the model capability to calculate the impact of DVs on traffic congestion.

3. PROBLEM DESCRIPTION

The proposed framework combines a stochastic CA traffic microsimulation based on the Nagel-Schrekenberg (*NaSch*) model (Nagel and Schreckenberg, 1992), with a metaheuristic and a commercial solver that optimise the decisions made by the DV. The CA model has two layers, the lower layer describes the road network, its entry and exit points, LZ locations, traffic demand, speed limits, intersections, and traffic light settings. The upper layer manages the agents (PV and DV), their size, speed, motion, lane changing, vehicle routes, illegal parking decisions and the duration of the delivery stops. Most of the current research do not optimise the decisions made by the DVs, assuming given entry routes. In our model we use a greedy randomised adaptive search procedure - GRASP to solve a two level (trucking and walking) optimisation problem, and the CPLEX optimiser to re-optimise mid-route decisions. The simulation and optimisation models were developed in Java. Since computational times are a frequent concern in microscopic simulation, we use an object-oriented approach with light data structures and stream parallelism to guarantee a high running efficiency for a medium-sized network.

3.1 Network structure

The graphical description of the network is shown in Fig. 1. The road network is represented as a strongly connected digraph $G = (V, E)$ where V is the set of vertices and E the set of edges. The vertices represent the road intersections where a vehicle $i \in I$ can traverse between an *inlane* and an *outlane* edge. Fig. 1 (bottom) shows an example of this structure for one directed edge and two vertices. Each edge is composed by two lanes which contain cells that can take binary values specifying if it is occupied by a vehicle or free, and an additional feature indicating if the cell is used as part of a LZ. Additionally, the front and rear cells of a LZ can be used for illegal parking according to the behaviour of DVs.

Let $E_{inflow} \subseteq E$ and $E_{outflow} \subseteq E$ be the corresponding inflow and outflow edges that act as the network boundaries. Inflow edges have a vehicle generator that locates a PV if any of the lanes has the first PV_{size} cells empty. The number of DVs that will enter the network during the simulation is a fixed value and they will be inserted randomly throughout the edges. If the inflow edge has no space to allocate a DV, it will enter a queue with a higher entry priority than PVs. To achieve a realistic behaviour at the intersections, we introduce traffic signals with phases and paths shown in Fig. 1 (top). Every vertex has four phases (A, B, C, D) that run sequentially following the green wave method. At any time, each vertex has an active phase with a predefined cycle time (green time), and each vehicle makes a turning decision according to its active path. A vehicle i can only cross the intersection if its active path belongs to the vertex's active phase, otherwise they will queue at the end of the lane.

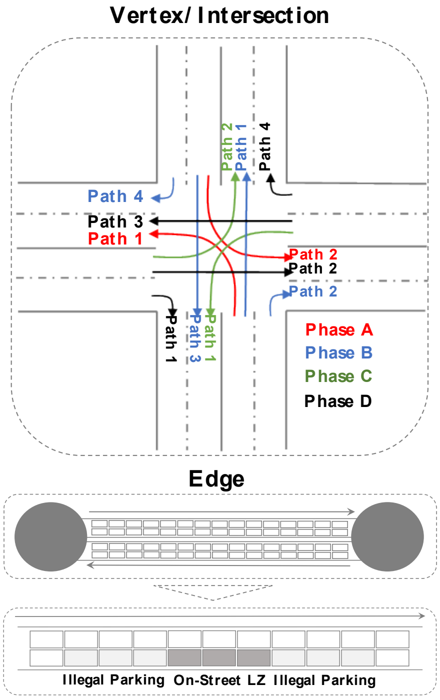

Figure 1. Network structure

Traffic demand

In most real networks, traffic demand is heterogenous. To model this situation, we define critical edges and introduce biased travel preference. When a PV enters the network through a critical edge is assigned a route that it must follows. Otherwise, it will continue to randomly cruise the network until it enters an outflow edge. DVs on the other hand must always follow a route determined by the LZs where they must stop and the customers that need to visit. PVs and DVs have different driving behaviours. While PVs have more aggressive driving, DVs have s more passive driving due mainly to its larger size and weight.

Agent behaviour

- **New speed ($v_{i,t+1}$):**

$$\text{DV:}\begin{cases}\min\left(v_{i,t} + a_i, gap_i^{fs}, gap_i^{LZ}, v_{max}^{i\in DV}\right) \text{ if } e_{DV} = e_{LZ} \\ \min\left(v_{i,t} + a_i, gap_i^{fs}, v_{max}^{i\in DV}\right) \text{ otherwise}\end{cases} \qquad \text{PV:}\, min(v_{i,t} + a_i, gap_i^{fs}, v_{max}^{i\in PV})$$

Where $v_{i,t}$ is the speed of vehicle i in the iteration t, a_i is the acceleration, gap_i^{fs} is the frontal gap in the same lane, gap_i^{LZ} is the gap to a LZ and $v_{max}^{i\in PV}$ ($v_{max}^{i\in DV}$) is the vehicle maximum speed. $e_{DV} = e_{LZ}$ indicates if a DV is in the same edge where it must make a delivery.

- **Random deceleration:**

$$DV\text{:}\begin{cases}\max\left(0, min\left(v_{i,t} - a_i, gap_i^{fs}, gap_i^{LZ}\right)\right) \text{ if } e_{DV} = e_{LZ} \\ \max\left(0, min\left(v_{i,t} - a_i, gap_i^{fs}\right)\right) \text{ otherwise}\end{cases} \qquad PV\text{:}\max\left(0, min\left(v_{i,t} - a_i, gap_i^{fs}\right)\right)$$

Deceleration happens with probability p_{dec} in the same magnitude as the speed increase. When a DV is in the same edge as the delivery, it must consider the front gap to LZ,gap_i^{LZ}.

- **Lane Changing:**

Desirable change:

$$DV\text{:}\begin{cases}gap_i^{fs} < \min\left(v_{i,t} + a_i, v_{max}^{DV}\right) \wedge \\ gap_i^{fo} > gap_i^{fs}\end{cases}$$

$$PV\text{:}\begin{cases}gap_i^{fs} < \min\left(v_{i,t} + a_i, v_{max}^{PV}\right) \wedge \\ gap_i^{fo} > gap_i^{fs}\end{cases}$$

Safe change:

$$DV\text{:}\begin{cases}Z_i^{ob} \wedge gap_i^{bo} \geq 0 \vee \\ gap_i^{bo} > v_{max}^{DV}\end{cases}$$

$$PV\text{:}\begin{cases}Z_i^{bo} \wedge gap_i^{bo} \geq 0 \vee \\ gap_i^{bo} > \min\left(v_t^{bo} + a^{bo}, v_{max}^{PV}\right) - \min\left(v_{i,t} + a_i, v_{max}^{PV}\right)\end{cases}$$

PVs and DVs change lane with probability p_{LC}^{PV} (p_{LC}^{DV}). gap_i^{fo} is the front gap in the other lane for vehicle i, gap_i^{bo}, v_t^{bo} and a^{bo} are the gap, speed and acceleration of the preceding vehicle in the other lane, respectively. Z_i^{bo} is a binary variable that indicates if the preceding vehicle in the other lane is a DV. PVs evaluate the *Desirable change* and *Safe change* rules in every iteration. DVs on the other hand, first evaluate if the edge location (e_{DV}) is equal to the LZ where it must make the delivery (e_{LZ}) then:

- ✓ If the DV lane location is equal to the LZ location, it will not make any lane changes if any of the following conditions are met: *(i)* the distance to the LZ is less than a predefined gap ($gap_i^{LZ} \leq gap_{Min}$) and the LZ is available; or *(ii)* $gap_i^{LZ} \leq gap_{Min}$ and the LZ is not available, but the rear illegal parking is, and the DV is allowed to park illegally.
- ✓ When the DV is not in the same lane as the LZ, it must evaluate the following conditions: *(i)* make a *Safe change* only (even if it is not a *Desirable change*) if $gap_i^{LZ} \leq gap_{Min}$ and the LZ is available; or when the LZ is not available but the rear illegal parking is, and the vehicle is allowed to park illegally (rear illegal parking). *(ii)* A *Safe change* must also be made if the DV has overtaken the LZ, is no more than DV_{size} cells after the LZ, the LZ is not available but the front illegal parking is, and the vehicle can park illegally (front illegal parking). In the case when $gap_i^{LZ} \geq gap_{Min}$ a *Desirable change* and *Safe change* are be evaluated.

When a DV is not in the same edge as the LZ, it evaluates the *Desirable change* and *Safe change* conditions.

- **Slow to Start (STS)**

Slow to start rules simulate the delayed behaviour of drivers that come to a complete stop due to a traffic jam or a red light. At every time step $t \in T$ a PV (DV) $i \in I$ with speed $v_{i,t} = 0$ and $gap_i^{fs} = 0$ will keep its position x_i for the next n_{sts}^{PV} (n_{sts}^{DV}) time steps with probability p_{sts}^{PV} (p_{sts}^{DV}), or will accelerate with probability $1 - p_{sts}^{PV}$ $(1 - p_{sts}^{DV})$.

$$x_{i,t+1} = \begin{cases} v_{i,t} = 0 \wedge gap_i^{fs} = 0 \rightarrow x_{i,t} \; with\, probability\, p_{sts}^{PV}\,(p_{sts}^{DV}) \\ x_i + v_{i,t+1} \; with\, probability\, 1 - p_{sts}^{PV}\,(1 - p_{sts}^{DV}) \end{cases}$$

- **DV On/Out of delivery**

First the algorithm evaluates if the DV is already On Delivery. In this case, if the time in the LZ is equal to the required stopping time for the active delivery, takes the DV out of delivery and sets the delivery as made. If all the delivery tasks are completed**,** it assigns the route for the outflow edge to leave the network. Otherwise, it assigns the route to next delivery. To set the DV On Delivery, the algorithm evaluates two options: *(i)* if it is located on the same cells as the LZ or, *(ii)* if it is in the front or rear of the LZ where it can park illegally, the LZ is not available, and the vehicle is allowed to park illegally.

- **Movement:**

The movement equation for time $t + 1$ is simply the current position x_i plus the new speed: $x_{i,t+1} = x_i + v_{i,t+1}$. Initially, the algorithm ignores all the DV*s* that are On Delivery and the vehicles that, in the previous time step, were delayed by the *STS* rule. Then it evaluates the *STS* rule again. When the new vehicle location $x_{i,t+1}$ is greater than the edge size, then:

- ✓ If the edge is an outflow edge, the vehicle exits the network and is removed from the vehicle set I;
- ✓ Otherwise, the algorithm evaluates two conditions: *(i)* if the vehicle current path is within the vertex's active phase; and *(ii)* if there is enough space in any of the new edge's lanes. If these conditions are met, the vehicle is moved to the new edge with a predefined speed $v_{i,t+1}$. In any other case, the vehicle will queue at the traffic light.

3.2 Description of the Model Dynamics

Algorithm 1 shows the high-level dynamics of the simulation and the optimisation model. After reading the network structure and the input parameters, the model starts inserting PV*s* into the network. When the simulation reaches the $warmUp$ period, the DVs are created, and GRASP finds the best solution for the first- and second-level routes and translates them into delivery tasks and route paths. The DVs that cannot enter the network will wait in the edge's queue and enter the network when there is space in any of its lanes. Lane changes and movements are updated in parallel, therefore every vehicle makes decisions for time $t + 1$ based on the locations and movements of all the vehicles in time t.

4. EVALUATION OF DELIVERY STRATEGIES

For this experiment we ran 100 simulations for each strategy. Each simulation has a network with 50 DVs, 10,800 seconds of simulation time, and a $warmUp$ period of 1,000 seconds. There is a total of 15 vertices, 76 edges with 12 critical streets, and 48 customers (each point can be interpreted as a cluster of customers, for example, a commercial building) shown in Fig. 2. There are 32 LZs at fixed locations in the network.

Algorithm 1 General model dynamics

```
Read entry parameters
Output: density, speed, flow
Construct the graph G = (E, V) representing the transportation network
Set LZs, traffic light phases, calculate shortest paths and Manhattan distances
repeat
    if t = warmUp then
        for k = 1 to numDV
            Create a DV
            Assign a random number of customers
            Create delivery route using GRASP
            Insert DV to the network and to queue arrays
        next k
    end if
    Set DV On/Out of delivery
    Inflow DV from queue arrays
    Inflow PV with probability p_insertion^critical and P_insertion
    Lane changes
    Motion
    Update traffic light phases
increment t until t = simulationTime
return density, speed, flow
```

Although some authors assumed that DVs do not cruise for parking (Amer and Chow, 2015; Romano Alho et al., 2018; Simoni and Claudel, 2018), recent studies have shown the opposite (Dalla Chiara & Goodchild, 2020). When a DV reaches a LZ that is not available, then: ***Alternative LZ*:** it starts cruising by finding the shortest return loop. If after one loop the LZ is still unavailable, it modifies the delivery by finding the shortest path to the closest LZ. If this LZ is already in the delivery route, the customers are joined, and CPLEX is used to solve the TSP for the new, joint second-level trip. If the LZ is not in the route, is added as a new delivery, the second-level trip is re-optimised using CPLEX, and the first-level trip is modified to reflect the insertion of the new LZ. When the DV reaches the new LZ is determined to park: *(a)* illegally if the LZ is unavailable or, *(b)* cruising until the LZ or one of its illegal parking spaces becomes available. ***Illegal parking:*** it immediately tries to park illegally at the rear or front of the LZ. If the illegal parking is also unavailable, it starts the same process as the *Alternative LZ* strategy, first circling and then finding the closest LZ. ***Last delivery:*** it puts the delivery at the end of the "list" with the intention to park legally or illegally. This implies changes in the first-level trip by finding the shortest path to the last LZ and from the last LZ to the outflow edge.

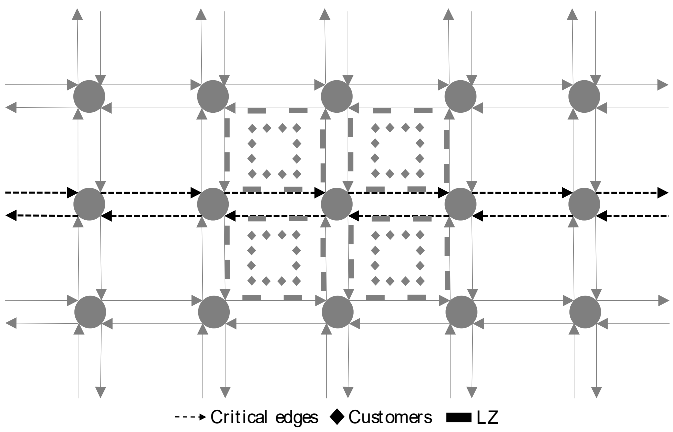

Figure 2. Network representation

Fig. 3 shows the results for the Macroscopic Fundamental Diagram (MFD) for each strategy and for the case without DVs. The blurry points are the median flow results for each street, while the bold points are the median flow results for the entire network. The MFD describes the relationship between network accumulation and production where three phases can be identified: *(i)* an uncongested phase, with low density and increasing flow, *(ii)* a saturation or full capacity phase, and *(iii)* a congested or flow reduction phase. Although the introduction of DVs take the network to congestion, there are important differences. The *illegal Parking* strategy seems to show fewer flow median values on the congested phase for critical streets (bold green points) with all the flow median values for non-critical streets in the uncongested phase (red bold and blurry). Albeit the *Alternative LZ* and *Last Delivery* strategies show flow median values for individual streets in the congested phase in both critical (green blurry) and non-critical streets (red blurry), the *Alternative LZ* strategy seems to be less congested.

Although the MFD allows to make a visual inspection of boundary traffic states and the capacity of urban networks, it does not provide a general measure of performance. To achieve this, we use the interquartile coefficient of variation (IQRcv) of traffic flow. The interquartile range is considered a more robust measure of spread and the median a more robust measure of central tendency. The boxplot for the IQRcv is shown in Fig.

4 and validate the results obtained with the MFDs. The *Illegal parking* strategy shows the best results by having a significant lower median IQRcv and lower variation. These results could demonstrate that: *(i)* the current LZs number is insufficient and/or *(ii)* the allocation of parking space does not meet the demand. Since the traffic flow and density are not negatively affected by the presence of illegal parking, allocating more LZs to popular delivery areas seems to be a viable option. Even though this result contradicts the common perception about capacity reductions caused by DVs, a major difference is that we are considering the cruising effect of DVs over the traffic network, which caused significant flow reductions. The fact that the LZs are located closer to the centre than to the intersections with limited illegal parking, significantly reduces the network performance deterioration caused when the congestion reaches the intersection, affecting the flow in adjacent streets.

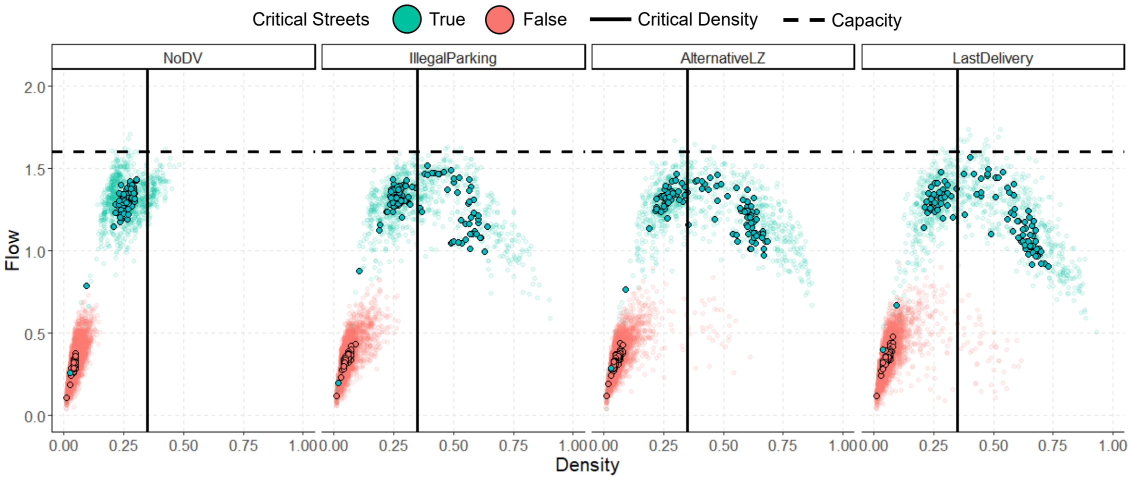

Figure 3. Results for the MFDs. Flow is given in [vehicles/second] while density is normalised

The comparison between *Alternative LZ* and *Last Delivery* strategies shows that although the difference in median values is not significant, the distribution of IQRcv for *Alternative LZ* seems to have lower kurtosis and a higher probability to produce lower IQRcv values than *Last Delivery*. Therefore, for reducing network flow variations it might be preferred that DVs make a small deviation from the optimal route by selecting a closer LZ, rather than leaving the delivery for the end of the route and having to return to the "optimal" LZ.

5. CONCLUSIONS

This study aims to shed some light by developing a realistic hybrid tool to evaluate the impact of different delivery strategies over the network traffic flow. Whilst the results conclude that to minimise the effect of DVs the best strategy is to park illegally, important considerations need to be addressed. For instance, we are not considering the effect of pedestrians and/or public transport into the model, as well as the possible consequences of DVs' illegal parking over bicycle lanes. These aspects should certainly be included in future. Additionally, the location of the LZs in the study network were equally spread over an edge, with two illegal parking areas. This aspect certainly limited the well-known congestion consequences of illegal parking. For example, LZs that are located close to up- or down-stream intersections with more illegal parking will certainly spread the congestion shockwave to adjacent edges, attaining different results. A similar situation occurs when DVs parked illegally are blocking access to buildings, side streets or public transport. The fact that the Illegal Parking strategy derived better results is certainly controversial. However, a logical interpretation is that the city might be better-off by relaxing restrictions and/or adding more LZs to popular delivery sites. This decision will help DVs to finish their route faster, reducing cruising time and possible congestion. Besides, since the benefits and responsibility for the implementation of more relaxed illegal parking measures lies entirely in the city's hands, is an additional incentive to consider it as a feasible traffic management policy.

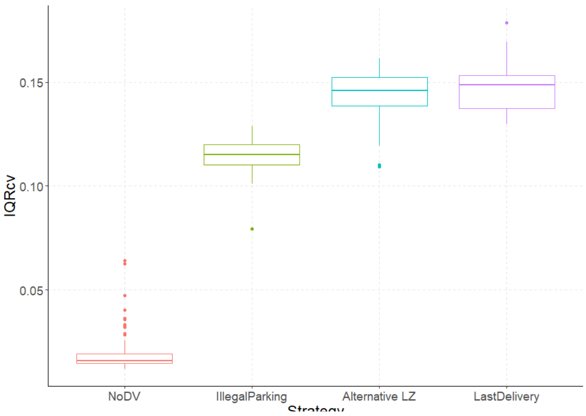

Figure 4. Results for the IQRcv

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