Regulating Ride-Hailing Service Operations: Impact of Idle Distance Charge and Demand Distribution on Network Performance

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SHORT SUMMARY

The increase of ride-hailing vehicles' presence on roads has significantly reshaped transportation network dynamics. In the absence of regulations, there is a potential for a decline in service quality and overall network efficiency due to ride-hailing operations. This study employs simulation to investigate the efficiency of a specific regulation penalizing rides without passengers, aiming to mitigate the negative effects of ride-hailing services. Various simulation scenarios are developed, integrating the proposed regulation, and evaluated using the MnMs (multimodal network modeling and simulation) framework from the LICIT-Eco7 research laboratory (Gustave Eiffel University, France). Results indicate that the regulation positively impacts service quality by reducing user waiting times but increasing the cancellation rate. Notably, system performance is significantly enhanced by decreasing idle kilometers traveled by vehicles. Furthermore, we show that the regulation's effectiveness is influenced by factors such as the proportion of a company's fleet size and the level of demand.
Keywords: Mobility Management, Regulations, Ride-hailing, Simulation, Traffic Flow Theory, Transport Policy.

1. INTRODUCTION

In recent years, the emergence of ride-hailing services has brought significant changes in the transportation network performance of many cities (Erhardt et al., 2019). The increased presence of ride-hailing vehicles on roads has been identified as a contributing factor to traffic congestion (Sun et al., 2019). Companies try to increase their fleet sizes to minimize waiting times, attracting customers from competing services by providing enhanced service quality (Gindrat, 2021). However, the absence of regulations in ride-hailing operations might lead to an extra traffic burden and consequently lead to a decline not only in service performance but also affecting other road users. Scientific studies and governmental policies address the challenge of mitigating the negative impact of ride-hailing on the transportation system. Proposed policies fall into categories such as pricing regulation (e.g., congestion charges (Vignon et al., 2021)), restrictive measures (fleet cap (Ke et al., 2021), wage constraints (Li et al., 2019), fare commission cap (Vignon et al., 2021), etc.), and other interventions (fare regulations (Yu et al., 2020), parking strategies (Beojone and Geroliminis, 2021), etc.).

This study employs agent-based simulation to assess the effectiveness of a potential regulation strategy implemented by local authorities to mitigate the adverse effects of ride-hailing operations. The local authority aims to regulate ride-hailing services by imposing restrictive policies. The primary research questions addressed in this work include:

- Does the regulation reduce the negative externalities of ride-hailing operations on the network?

- How does the regulation impact ride-hailing operations, system performance, and service quality?

Multiple simulation scenarios are created, incorporating the regulation, using a Manhattan generic network to calibrate settings. This approach enables the observation of behavioral patterns within ride-hailing services and an examination of the regulatory scheme. The system encompasses two modes of transport: vehicles from two ride-hailing companies and private vehicles.

For the sake of brevity, we excluded from this short paper profit analysis, the analysis of decentralized and centralized operations of companies as well as the impact of different demand distribution patterns on the efficiency of the regulation. Those additional results will be included in the final conference presentation.

2. METHODOLOGY

To model ride-hailing operations within the network, we utilize an agent-based simulation framework called MnMs (Multimodal Network Modeling and Simulation), developed by the LICIT-Eco7 research laboratory (Gustave Eiffel University, France). This simulator adopts the trip-based MFD concept for the multimodal motion of users and vehicles (Paipuri and Leclercq, 2020).

The city's local authority regulates the ride-hailing market by imposing operational restrictions or charges on private companies. Consequently, private companies and drivers must adapt their operational behaviors to comply with these regulations and sustain profitability. Considering that idle trip is the travel that a vehicle drives to pick up a customer and service trip is the travel with a passenger onboard, below we present the notation (**Table 1**) used for the modeling where $I, i \in I$, is a set of all possible trips:

Table 1: Notation

P_i^d	net trip profit of a driver
p_i^s	profit from a service trip
p_{min}	minimum driver profit from a trip
p_{km}	profit per service km
X_i	total expenses
x_{km}	expenses per km
l_i^s	service trip length
l_i^e	idle trip length
L_i	total trip length
w	drivers' minimum wage per hour
t_i^e	duration of idle trip
t_i^s	duration of service trip

Drivers autonomously determine their operational strategy, and the company does not interfere with individual driver decision-making regarding whether to accept a trip request. A driver accepts a trip if their earning from the trip is more or equal to the minimum driver's hourly wage multiplied by the total trip time (**Equation 1**):

$$P_i^d \geq (t_i^e + t_i^s)w \qquad (1)$$

In **Equation 2**, we compute the driver's net profit by deducting the expenses. **Equation 3** represents the trip profit acquired by the driver, **Equation 4** calculates the total trip expenses, and

Equation 5 determines the total trip length, including both idle distance and service distance. It is important to note that we incorporate a minimum price in **Equation 3**, denoted as p_{min}, that the driver will receive from serving a trip if $l_i^s p_{km} < p_{min}$, i.e., when the service distance is too small. This consideration aligns with the implementation of minimum prices by on-demand service companies in many countries.

$$P_i^d = p_i^s - X_i \tag{2}$$

$$p_i^s = \max\left(l_i^s p_{km}, p_{min}\right) \tag{3}$$

$$X_i = L_i x_{km} \tag{4}$$

$$L_i = l_i^e + l_i^s \tag{5}$$

In our simulation, when a new demand request appears, we attempt to match it with the nearest vacant vehicle. Drivers accept a trip based on the anticipated profitability, which depends on the idle distance they need to travel. Consequently, each driver implicitly establishes an idle distance threshold. For instance, if the idle distance is excessively high, the driver incurs more expenses for the trip, potentially leading to rejection if the trip lacks sufficient profitability. Therefore, the dependence of drivers' decisions on idle distance is integrated into profit formulation, making idle distance a key factor in the matching process.

Users in our simulation accept any service price but have specific waiting time tolerances for being matched and picked up by a driver. If a user is not matched from the first try, they enter a buffer and we attempt to match them in the next timestep. If the waiting time limits are exceeded without a successful match, the user abandons the ride-hailing request by canceling it. Our simulation assumes a user's waiting time tolerance for being matched is 3 minutes, and for being picked up, it is 10 minutes. Each user is loyal to a specific ride-hailing company and cannot be served by the opponent. Elastic or transferable demand requests will be considered in future studies. Rebalancing strategies are not employed, and while waiting to be matched, the vehicles do not cruise.

The increase in total kilometers traveled by ride-hailing vehicles has an impact on the network speed and, consequently, traffic conditions. Since we exclude rebalancing and cruising, the total kilometers traveled by ride-hailing vehicles consist of both idle and service (with a passenger on board) distances. The service distance depends on the network size and the demand distribution, factors beyond the control of regulatory authorities. Thus, we focus on the regulation that can impact the idle distance. Based on our previous findings regarding the adverse effects of idle distance on traffic conditions (Hryhoryeva and Leclercq, 2023.), we opt for the implementation of an idle kilometer charge as a pricing regulation.

This regulation is conceptualized as an additional cost borne by the driver for each kilometer traveled without a passenger on board. It is noteworthy that the drivers know the trip destination before deciding to accept or reject it, enabling them to evaluate the trip's potential profitability in advance. We consider this extra cost burden lies on drivers' shoulders and is not subsidized by the company. If c_e represents the charge per idle kilometer and C_i is the total charge paid per given trip (**Equation 7**), then **Equation 6** represents the net profit of the driver per trip after deducting the fixed expenses and the idle charge.

$$P_i^d = p_i^s - X_i - C_i \tag{6}$$
$$C_i = l_i^e c_e \tag{7}$$

3. RESULTS AND DISCUSSION

We use a Manhattan generic network of 9 kilometers per 9 kilometers, with link lengths set at 3 kilometers, resulting in a total of 16 nodes (4 nodes per 4 nodes) within the network. Each node corresponds to one demand area, and these demand regions are classified into three categories: low-demand (5 regions), medium-demand (6 regions), and high-demand (5 regions). **Figure 1** illustrates the categories of regions: red are high-demand regions, orange are medium, and yellow are low.

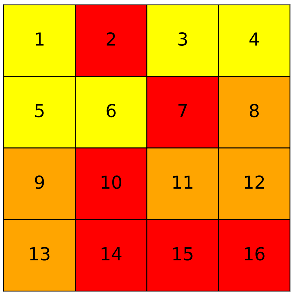

Fig. 1: Categories of regions according to the demand level

We consider having two ride-hailing companies (Company1 and Company2, or simply C1 and C2) and private vehicles (PV). Among 5000 demand requests that arrive between 5pm (17:00) and 8pm (20:00), 20% of it belongs to C1 (1000 demand requests), 20% is attributed to C2 (1000 requests), and the rest 60% belongs to PV (3000 requests). The peak hour is from 6pm to 7pm, and 50% of all demand requests arrive during this time. The rest 25% arrive between 5pm and 6pm, and another 25% arrive between 7pm and 8pm. **Figure 2** visualizes the demand distribution over time.

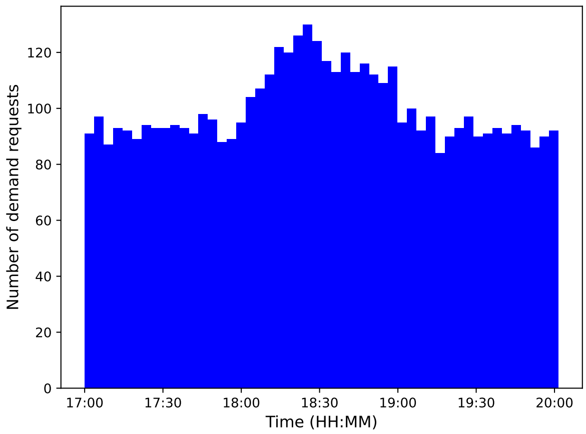

Fig. 2: Demand requests distribution over the simulation horizon

The initial positions of ride-hailing vehicles in the network are randomly assigned with a uniform distribution. The minimum driver profit from a trip p_{min} is 7 euros, profit from each service kilometer p_{km} is 1.7, expenses per kilometer x_{km} is 0.3, and drivers' minimum wage per hour w is 18.

To analyze the system response to the imposed charge, we conduct tests with nine charge prices ranging from 0 to 4 in increments of 0.5. These charge prices are applied in scenarios where companies operate with six distinct fleet sizes: 50, 100, 150, 200, 250, and 300 vehicles for each company. By varying the fleet size while maintaining a constant number of demand requests assigned to each company, we explore different ratios of demand flow to the company size. These ratios represent key parameters influencing idle distance (Hryhoryeva and Leclercq, 2023). In other words, while having the same demand, the fleet of 50 vehicles might be not enough to meet all demand requests, while a fleet of 300 vehicles is more sufficient.

Given that the companies operate independently without direct interaction, and users as well as drivers remain loyal to a specific company, our findings indicate that the charge does not impact the competition's outcome when both companies have the same fleet size and market share. Thus, for the sake of simplicity, we take the mean value of the outcome metrics for the two companies for the following analysis of the charge price.

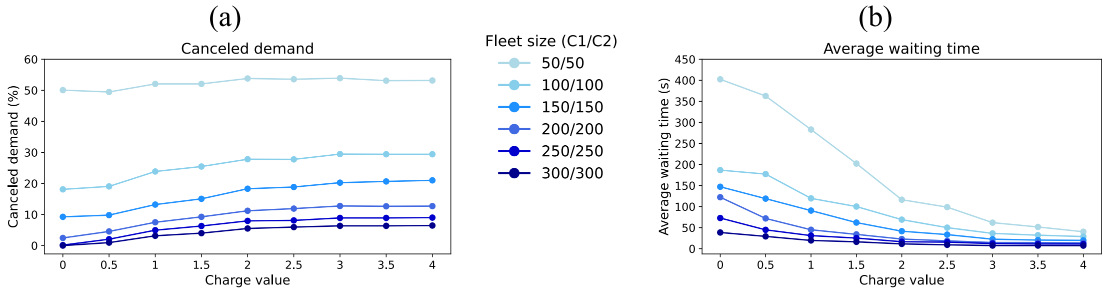

Fig. 3: Influence of the charge price on (a) cancelation rate; (b) average user waiting time;

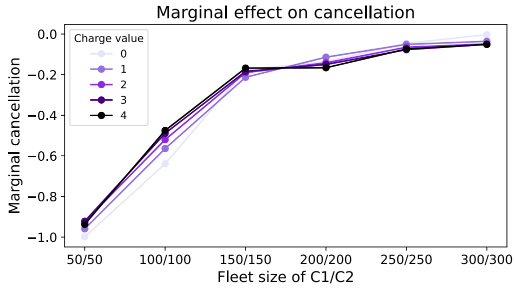

Fig. 4: Marginal effect of fleet size on cancelation

From the user perspective, we observe a rise in demand cancellation rates corresponding to an increase in the charge value, which reaches a plateau at the charge value equal to 2 (**Figure 3a**). Notably, for fleets with 50 vehicles, we observe drastic cancelation values that go above 50% and have a gap of about 25-30% with the subsequent fleet size of 100 vehicles. Concurrently, the impact of increasing charge values on the cancellation rate for the 300-vehicle fleet is less significant compared to other fleet sizes. This increase in cancellations is attributed to drivers refusing trips involving extended idle distances, making users unreachable.

Figure 4 shows the marginal effect of increasing fleet size on cancellation rates under various charge values. Notably, starting from a fleet size of 200 vehicles, the change in cancellation rate becomes less significant with further increases in fleet size under any charge value. This inflection point can be explained as follows. When the fleet size is small, vehicles prioritize the most profitable users in terms of idle distance. As additional vehicles are introduced to the fleet, they easily find profitable trips that were previously unserved. I.e., in the beginning, adding more vehicles to the fleet has a big impact on the system quality improvement. However, as the fleet size reaches 200 vehicles, there is a sufficient number of vehicles to serve the majority of requests, leading to the cancelation rate being less influenced by the increase in the fleet size.

In terms of waiting time (time between sending a trip request and being picked up), the charge increase has more influence on smaller fleets (**Figure 3b**). This is caused by the reduction in the average idle distance covered by each vehicle per trip request. The cancellation of trips with the longest waiting times contributes to the smoothing of curve slopes. Thus, the profile of the average idle distance is similar to that of the waiting time curve (**Figure 5a**). It is noteworthy that considering canceled trips as equivalent to the nominal 15-minute waiting time and incorporating them into the average waiting time data produces a similar curve trend to the total idle distance (**Figure 5b**). Thus, the regulatory strategy effectively filters out long distances that do not contribute to the overall system benefit. So, the canceled trips added to waiting times represent the idle distances that have been eliminated.

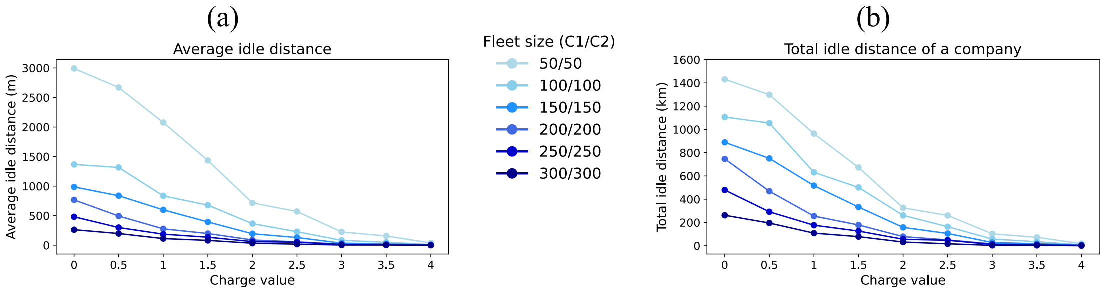

Fig. 5: Influence of the charge price on (a) average idle distance; (b) total idle distance

From the system's perspective, the total idle distance for each company diminishes as the charge increases across all fleet sizes (**Figure 5b**). However, the reduction in total idle distance is more significant for smaller fleets, characterized by steeper slopes. Thus, the drivers begin canceling trips with big idle distances due to their unprofitability, resulting in an overall decrease in total idle distance.

It is noteworthy that while the curve profiles of average idle distance and total idle distance follow a similar pattern, they are not identical. The total idle distance is formed by multiplying the average idle distance by the fleet size and the number of served requests, while the latter depends on the cancelation rate. Thus, the cancelation rate influences the scalability of the curves. As the cancelation rate is significantly higher for a fleet of 50 vehicles compared to 100 vehicles, the total idle distance curve for 50 vehicles tends to approach that of 100 vehicles more closely than the corresponding curves for average idle distance. This occurs because the serving rate of 50 vehicles is low, resulting in a lower contribution to total idle distance, despite having a high average idle distance.

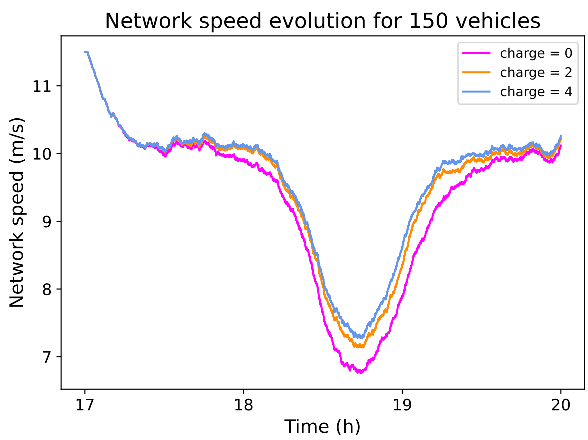

Fig 6: Network speed under different charge values

In **Figure 6**, the network speed profile is presented under three different charge values, with each company operating 150 vehicles. Thus, the charge implicitly influences the network speed. The variations in the speed evolution under different charges can be attributed to the reduction in total idle distance. As the charge increases, drivers accept requests with smaller idle distances to maintain their revenue. This reduction in total idle distance leads to a decrease in the contribution of ride-hailing vehicles to traffic, resulting in an improvement in network speed.

During the peak hour in the simulation, an increase in network speed is noticeable under charges equal to 2 and 4 compared to the absence of a charge. Thus, the reduction in idle distance caused by the charge mitigates the congestion and consequently has a positive impact on the total travel time. However, the difference in speed between a charge equal to 2 and a charge equal to 4 is less significant due to the marginal reduction in total idle distance.

4. CONCLUSIONS

We showed that the policy can effectively reduce the total idle distance traveled by vehicles and user waiting time. Although the implementation of this policy leads to an increase in the cancellation rate, the loss in service quality caused by the moderate increase in cancelation is less significant than the improvements in waiting time and idle distance. We could also observe that the impact of charge varies depending on the proportion of a company's available fleet size and the demand level.

For the sake of brevity, we excluded from this short paper profit analysis, the analysis of decentralized and centralized operations of companies as well as the impact of different demand distribution patterns on the efficiency of the regulation. Those additional results will be included in the final conference presentation.

Future research includes testing the regulation on the real transportation network using a simulation with realistic demand and supply information.

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