Accessing shared mobility impacts on urban traffic networks through discrete event simulations

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Abstract

Many on-demand transportation services are gaining attention in recent years, in the field of shared mobility. However, there is little evidence on how they affect congestion. Thus, this paper aims to provide evidence based on simulations for the impacts of an expanding ride-sourcing system over traffic conditions and *vice-versa*. The main findings indicate that there might be an optimal number of vehicles to operate ride-sourcing, which can only be accessed considering the effect of congestion in the modeling process (with a Macroscopic Fundamental Diagram, for instance). Results also indicate that increasing the availability of vehicles mainly leads to more total traveled kilometers and higher congestion.

Keywords: Shared mobility; Discrete event simulation; Macroscopic Fundamental Diagram.

1. Introduction

Rapid population growth in modern cities has caused extensive degradation of mobility in central districts, because of high vehicle accumulation in limited road space. In such a situation, maximizing the level of service of collective transport modes appears as a direct way to improve traffic network performance and reduce the number of vehicles in congested areas, by motivating commuters to use these modes more frequently instead of private vehicles. Nevertheless, public transport systems cannot adjust to fast changes in the demand due to their scheduling features. New trends in shared transportation completely change the landscape and our understanding of mobility. The rapid adoption of these systems creates immense challenges for city mobility operators and policymakers, as there is limited information on the decision trends, the safety implications, and the impact on vehicle ownership, the travel patterns and their effect of congestion. On-demand transportation services are gaining attention in recent years. Many of these became possible due to the expansion of smartphones and the increasing connectivity they provide. One of the most prominent of these services are ride-hailing and dial-a-ride (referred as ride-sourcing in the remaining of the text) services provided by Transportation Network Companies (TNCs), such as Uber and Lift. TNCs grew despite the debate over the regulations they are subject and complains about unfair competition (National Academies of Sciences, Engineering, and Medicine, 2016; Rayle et al., 2016).

Emerging on-demand transportation services sound a promising direction to improve mobility, fighting car ownership. Moreover, most TNCs allow multiple people to share a ride, like UberPOOL. This shared mobility advance might ensure efficiency and sustainability if applied in large-scale (Mora et al., 2017). Nowadays, these new services operate in a business model, where drivers provide their own vehicle and pay a fee to the central operator per trip. They try to attract more demand by having lower prices than taxis and a very large fleet size, so that waiting time is very small. Their market share for mobility follows a positive trend, but there is no evidence that it can contribute efficiently towards collective mobility. In a recent survey across ride-hailing users (Rayle et al., 2016), in a question "How would you have made this trip if RH service was not available?", 40% answered by taxi, 33% by bus and only 6% by car. Thus, RH can be an attractive alternative for public transport users and if this is combined with the large number of empty vehicles, it can create additional congestion problems.

However, these advantages might not arise naturally. For instance, nowadays these TNCs' business models rely on attracting more drivers (with their own vehicles) and more passengers. Thus, they are much like to create single-passenger trips and many 'empty' vehicles traveling around in congested city centers. Especially due to empty circulating vehicles, the congestion situation is likely to worsen. Rayle et al. (2016) also suggested that ride-sourcing induces traveling, and a considerable competition with public transportation modes (busses and rails). In the other hand, Santi et al. (2014) achieved a significant reduction in the total vehicle traveled distance by considering sharing trips on New York taxi data.

It is still unclear how the expansion of ride-sourcing services will affect urban traffic as their share in all trips also raises (Jin et al., 2018). For the best of our knowledge, papers on the field did not address this impact and did not consider traffic conditions – for example, Santi et al. (2014) and Mora et al. (2017). There is also little knowledge and evidence of how passengers willingness to share their rides can influence the performance of the system. Therefore, there is a lack of analytical or semi-analytical models in this direction yet. Given this, simulation emerges as an option for modeling the ride-sourcing system, supported by Macroscopic Fundamental Diagrams (MFDs) for modeling traffic conditions. The MFD provides a unimodal, low-scatter, demand-insensitive relationship between basic traffic measures (accumulation, speed, and completion flow), and it enables low complexity modeling of whole cities (Sirmatel and Geroliminis, 2018).

Therefore, this paper aims to provide evidence based on simulations for the impacts of an expanding ride-sourcing system over traffic conditions and *vice-versa*. Simulations work in a discrete event framework, and they capture traffic conditions through an MFD.

The structure of this paper is as follows. Section 2 presents a brief literature review on ride-sourcing (focused on TNC based services). Section 3 describes the simulation and the collected indicators. Section 4 presents the main computational results and discussion. Finally, Section 5 closes with some final considerations and further research suggestions.

2. Literature review

As responsible for transformations on urban life, ride-sourcing produces effects over different aspects as urban efficiency and sustainability. Jin et al. (2018) presented a recent review of ride-sourcing operations. In summary, ride-sourcing can improve economic efficiency, but it is still unclear the impacts on congestion in city centers and its reductions on energy consumption and emissions. Hall et al. (2018) evaluated the relationship between ride-sourcing and public transportation in metropolitan areas in the U.S. Contreras and Paz (2018) used a linear regression analysis to measure the effects of ride-sourcing over the taxicab industry in Las Vegas, Nevada. Schwieterman and Smith (2018) used multiple regression analysis and found reductions on trip times between neighborhoods and customers' savings for sharing their trips. Nie (2017) analyzed GPS data from Shenzhen, China, and found that the loss of the taxicab industry to ride-sourcing tends to stabilize, also, ride-sourcing mildly worsened congestion. Zha et al. (2016) investigated ride-sourcing through an economic point-of-view, considering scenarios with different competitiveness and regulations. Vinayak et al. (2018) used a generalized heterogeneous data model to find social dependency effects of shared mobility service usage.

In a different direction, there has been already efforts to improve the quality of ride-sourcing operations by improving matching strategies, or relocation of empty vehicles, or vehicles' route choices. Santi et al. (2014) and Mora et al. (2017) are two recent efforts that seek to provide efficient ways to match passengers by building shareability networks based on graph theory and develop iterative local search algorithms. On dynamic vehicle routing literature, Berbeglia et al. (2010) reviewed dynamic pick-up and delivery problems, like a dial-a-ride problem. Molenbruch et al. (2017) reviewed dial-a-ride problems their solution methods creating classifications for them. Masmoudi et al. (2018) presented a dial-a-ride problem for electric vehicles and battery swapping stations. Another studied direction was continuous approximations, as reviewed in Ansari et al. (2018) for logistics and transportation problems.

Note that this revision did not consider traditional ride-sharing problems. Those interested in such problems are encouraged to read Furuhata et al. (2013) and the references therein.

3. Simulation description

Discrete-event simulation is responsible for model a generic ride-sourcing (ride-hailing, dial-a-ride) system. The simulated urban region is a 4-by-4km square. Distances are measured using Manhattan distances in a continuous space. Three objects compose this system: 1) serving vehicle (for simplicity, called TNCs in the remaining of the text); 2) passengers; and 3) private cars. TNCs are responsible for pick-up passengers and take them to their destination. Private cars appear the moment they start their trip and disappears the moment they reach the destination (they park or enter a garage, thus do not affect traffic anymore). Passengers arrive with specific origins and destinations and then leave when reach destination.

Arrivals follow a Poisson process. Once an arrival occurs, it can become either a passenger or a private car. This choice is random with predefined fractions (10, 20, 30, …, 100%, for instance). If the arrival becomes a private car, it starts its trip immediately. If it becomes a passenger, it waits for an assigned TNC. Passengers might abandon the system if their waiting time exceeds 10 minutes. Both origins and destinations are generated uniformly across the region and are at least 1 km far from each other.

TNCs drive randomly through the region when empty. All TNCs are capable of carrying two passengers. However, some passengers are not willing to share their rides. Passengers choose to share their rides randomly with predefined fractions. Those passengers that accept to share their rides are subject to a 20% detour from the initial travel time prediction. This deviation only occurs upon an assignment to a second passenger; otherwise, TNCs will travel through the shortest path to the destination. The assignment of TNCs and passengers is a greedy heuristic based on the shortest distance.

All vehicles (private cars and TNCs) travel at the same speed. The region has a well-defined MFD. Equation 1 defines speed as a function of the total accumulation ($n = \text{private cars} + \text{TNCs}$). The simulation updates the speed at each step. Figure 1 illustrates $v(n)$. The critical accumulation for this MFD is around 3100 vehicles.

$$v(n) = \begin{cases} 18.48e^{\frac{0.322n}{1000}}, & \text{if } n < 5400 \\ 5.4 - \left(\frac{n}{1000} - 5400\right)1.578, & \text{if } 5400 \leq n < 9000 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

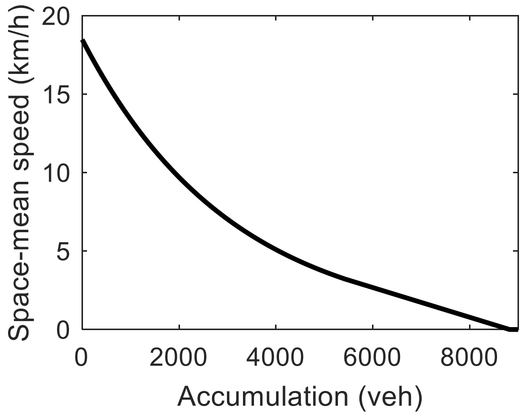

Figure 1 – Simulation speed *vs* accumulation function.

Therefore, the simulation uses the following exogenous settings: 1) Total arrival rate; 2) Number of TNCs; 3) fraction of trips served by TNCs; 4) fraction of passengers that are willing to share their ride (this parameter is called 'willingness to share' in the remaining of the paper); and 5) Total number of arrivals. Arrival rate and the total number of arrivals are set so that the simulation runs for 4 hours, approximately. The analysis considers the first 1.5 hours as a warm-up period.

Finally, simulation captures performance measures instantaneously, event-based, and single measurements. The instantaneous measures include average waiting times, accumulation, speed, utilization, and total traveled distances. Event-based measures include trip-lengths, trip duration, and initial trip length prediction. The only single measurement is the fraction of abandonment (the fraction of passengers that waited more than 10 minutes). These measures may be combined to generate aggregate measures as average time spent in the system (waiting times + time inside a TNC), for instance.

4. Computational results and discussion

This section briefly presents some of the computational results for simulations. All simulations ran on MATLAB™ r2018b on a Windows 10 Pro with 16GB of RAM memory and an Intel® Core™ i7-8700 CPU.

4.1 Single simulation analysis

The first analysis include only fixed parameters runs of the simulation. The objective at this point is to reach steady-state conditions and evaluate the quality of the indicators from the simulation. The mean of the measurements was chosen as an indicator for its simplicity and closeness to the most frequent value, as simulation showed only unimodal distributions. The settings for these simulations were:

1) Total arrival rate: 6000 arrivals/hour;
2) Number of TNCs: 200;

3) Fraction of trips served by TNCs: 10% (arrival rate for TNCs is 600 passengers/hour);
4) Willingness to share: 60%;
5) Total number of arrivals: 24000;

Figure 2 presents a histogram and the measurements for the average waiting times. It is important to note that waiting time measurements are continuous in time, not event-based (when a TNC picks-up a passenger). Thus, at each time step, the simulation calculates, on average, the amount of time each passenger is waiting for a TNC. This choice was to avoid mismeasurements that might raise when TNCs end up only picking-up recently arrived passengers. One could argue that, on the other hand, now the simulation captures neither long nor short waiting times, but that is the reason for collecting abandonments measurements. Finally, the histogram shows a unimodal distribution, as mentioned before with a mean value close to the most frequent one. In addition, the actual measurements show a steady-state condition, where variations occur around the mean value through the time. In this scenario, the fraction of passengers that abandoned the system was 0.0095, which one could expect, as the mean value for the measurements was below 2 minutes, so, more than five times smaller than the abandonment limit.

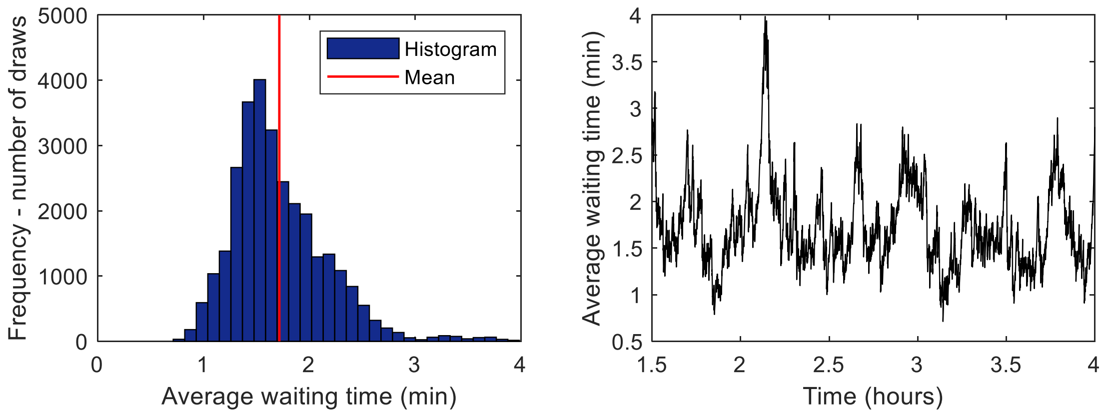

Figure 2 – Histogram of average waiting times (left) and average waiting times (right).

4.2 Fixed demand analysis

For this analysis, the demand was fixed at 50% (3000 passengers/hour), whereas the number of TNCs ranged between 600 and 2000 with steps of 200 vehicles. Simulations also considered three different willingness to share 0%, 20%, and 60%. Moreover, additional simulations ran with the same parameters but at constant speeds (non-MFD simulations). The main objective at this point is to show how congestion can affect indicators, and, therefore, it is imperative to consider when planning ride-sourcing systems.

Figure 3 illustrates the main differences between MFD and non-MFD simulations. Most notoriously, the time inside the system (dashed lines) has very distinct behaviors. In MFD simulations, there is a slight slope at the lowest numbers of vehicles, and then it starts to increase as the number of TNCs raise. One could argue that the system is under hyper-congestion. However, the system only achieves this state when there are 2000 TNCs (with accumulation around 3200 vehicles, and the critical accumulation is around 3100 vehicles). In the other hand, these indicators are decreasing in non-MFD simulations, as one could expect. Another interesting finding, in MFD simulations, is that waiting times seem to reach a lower limit and will not decrease any further. Moreover, it seems that the willingness to share plays an influential role in the definition of such limit as one can observe that waiting times become higher for higher willingness to share. Once more, non-

MFD simulations present decreasing average waiting times indicators, which do not reach a lower limit. Willingness to share look as a relevant parameter only for MFD simulations with different lower limits and distinct curves for average waiting times and average time in the system, respectively; whereas non-MFD simulations show its indicators converging as the number of TNCs raise. Finally, the slope present on average time in the system indicates that one can find an optimal number of vehicles for the ride-sourcing operation. It is worth mentioning that fractions of abandonments are higher than 0.01 only for scenarios with 600 TNCs, thus considered as an irrelevant indicator for this analysis.

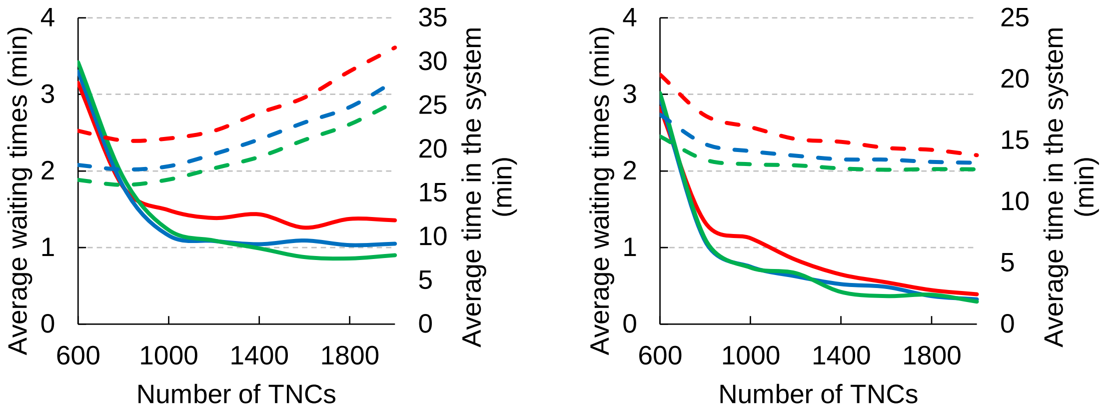

Figure 3 – Comparison of average waiting times (continuous lines) and Average times in the system (dashed lines) for different willingness to share (0% - green; 20% - blue; 60% - red) and different number of TNCs. Varying speeds according and MFD (Left) and Constant speeds (Right).

Figure 4 presents a comparison for Total Kilometers Traveled (TKT) and the Space-mean speed variation on different scenarios. Extra kilometers traveled are the difference between TKT for the different scenarios and a single scenario considering that all arrivals become private cars and no TNCs are operating. Firstly, it is clear that after 800 TNCs, the main responsible for the increase in TKT are empty TNCs as both curves converge. Therefore, even if waiting times might decrease (as seen in Figure 3) with increasing available TNCs, most additional drivers would drive empty and have fewer trips. These situations will result in less profit for drivers (fewer rides and, probably lower fares due to the increased availability). These results also indicate that ride-sourcing requires careful decision making to become environmentally sustainable, as only with 600 TNCs the TKT is lower than the no TNCs scenarios (dashed lines in the figure on the left). Moreover, as one would expect, the simple increase in the number of TNCs has a negative relationship on space-mean speeds, which were higher only for the 600 TNCs scenarios. Finally, it is also worth mentioning that the different willingness to share had no effects on these traffic indicators.

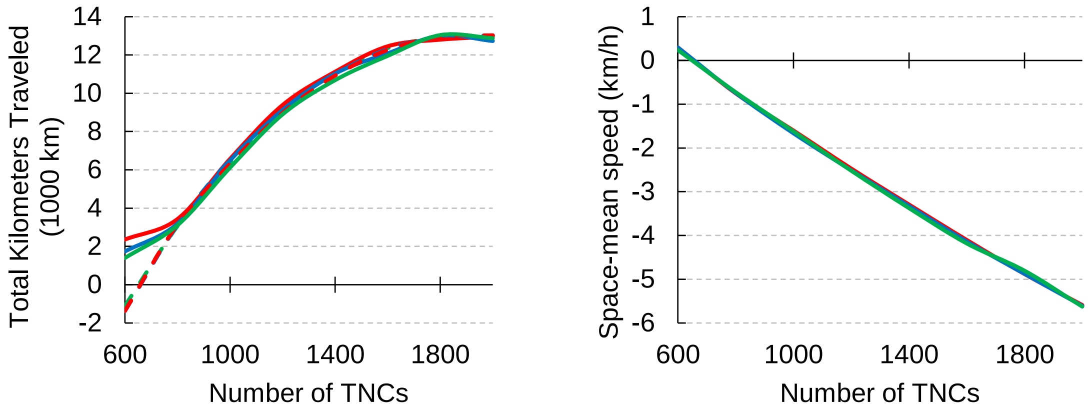

Figure 4 – Traffic impacts. (Left) Comparison of extra Total Kilometers Traveled (dashed lines) and Total Kilometers Traveled by empty TNCs (continuous lines); (Right) Space-mean speed variation compared to no TNCs scenarios for different willingness to share (0% - green; 20% - blue; 60% - red).

It is important to note that these results are not conclusive as there is no guarantee on the efficiency of the matching heuristic used on the simulation.

5. Final considerations

This paper provided initial evidence on the impacts expansion of ride-sourcing services over traffic conditions and *vice-versa*. Discrete-event simulations obtained this evidence. These simulations captured traffic conditions using an MFD. The main findings indicate that there might be an optimal number of vehicles to operate ride-sourcing, which can only be found considering congestion in the modeling process. Results also indicates that increasing the availability of vehicles mainly leads to more total traveled kilometers and higher congestion.

Further research could focus on improving simulations to obtain insights that are more accurate for ride-sourcing problems. Furthermore, these insights should lead to the development of new analytical and semi-analytical approaches proper for optimization and control.

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