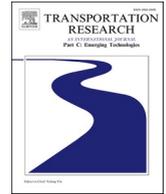




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On the inefficiency of ride-sourcing services towards urban congestion

Caio Vitor Beojone, Nikolas Geroliminis^{*}

Urban Transport Systems Laboratory (LUTS), École Polytechnique Fédérale de Lausanne (EPFL), Lausanne CH-1015, Switzerland

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ABSTRACT

The advent of shared-economy and smartphones made on-demand transportation services possible, which created additional opportunities, but also more complexity to urban mobility. Companies that offer these services are called Transportation Network Companies (TNCs) due to their internet-based nature. Although ride-sourcing is the most notorious service TNCs provide, little is known about to what degree its operations can interfere in traffic conditions, while replacing other transportation modes, or when a large number of idle vehicles is cruising for passengers. We experimentally analyze the efficiency of TNCs using taxi trip data from a Chinese megacity and an agent-based simulation with a trip-based MFD model for determining the speed. We investigate the effect of expanding fleet sizes for TNCs, passengers' inclination towards sharing rides, and strategies to alleviate urban congestion. We observe that, although a larger fleet size reduces waiting time, it also intensifies congestion, which, in turn, prolongs the total travel time. Such congestion effect is so significant that it is nearly insensitive to passengers' willingness to share and flexible supply. Finally, parking management strategies can prevent idle vehicles from cruising without assigned passengers, mitigating the negative impacts of ride-sourcing over congestion, and improving the service quality.

1. Introduction

One of the most prominent innovations seen throughout streets around the world is the ubiquitous presence of drivers using their vehicles for on-demand transportation services. Companies use mobile applications connected through the internet to match these drivers and their passengers in real-time. Due to the nature of their operations, these companies are called Transportation Network Companies (TNCs), but the service itself is called ride-sourcing, e-hailing, and ride-sharing, for instance (Rayle et al., 2016). Ride-sourcing services have revolutionized mobility concepts for on-demand transportation as a result of the advantages they provide, such as convenience, door-to-door rides, low fares, etc. On-demand transportation services sound as a promising direction to improve mobility and fight car ownership. Moreover, many TNCs offer, among the service options, shared rides (called ridesplitting). These services try to match passengers with a reasonably similar trip within a time window. For TNCs and drivers, this service may yield increased profits if it is capable of matching passengers and drivers efficiently. For the passengers, this service presents a cheaper option, but they might face longer travel distances/times. Passengers may also have almost the same advantages as those from a taxi service as door-to-door rides and no need to search for parking. In general, these services seem to have a positive impact on economic efficiency (Jin et al., 2018; Tachet et al., 2017).

^{*} Corresponding author.

E-mail addresses: caio.beojone@epfl.ch (C.V. Beojone), nikolas.geroliminis@epfl.ch (N. Geroliminis).

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Naturally, all this expansion raised several concerns regarding TNCs' operations. Oppositely to taxis, TNCs face no limitation, in most cities, on the fleet size that can operate, no price control, service requirements, and other legal obligations faced by the taxi industry. Moreover, as these services base their operations on mobile applications connected to the internet, there are concerns over issues of data privacy and security (Jin et al., 2018). Rogers (2017) adds other social costs, such as diminished safety and lack of professional training. Proper planning and regulation have vital importance in the development of shared transportation for the near future (Narayanan et al., 2020). Another point of concern is the surge pricing models used, which may considerably increase the fares in moments that driver availability is insufficient (Schwieterman and Smith, 2018). On the other hand, surge pricing mitigates the potential chaos of a bargaining process. Notably, it handles the spatial-temporal imbalances between driver supply and rides demand (Dong et al., 2018). Moreover, recent results point out that it can increase drivers' revenues but make customers worse during highly surged periods (Zha et al., 2018).

Although it is not clear whether ride-sourcing is beneficial or unfavorable (or whether it causes anything significantly) for traffic congestion, the path to clear it is to understand how it is replacing traditional transportation modes. In case ride-sourcing trips are directly substituting private vehicles or taxis trips then, they should have a secondary influence on congestion (Erhardt et al., 2019). However, if ride-sourcing competes with public transportation modes (buses, trains, metro) or inducing latent demand, then the effects on congestion should be significant. Additionally, it might increase vehicle kilometers traveled (VKT) when vehicles cruise for passengers or when it induces latent demand (Vinayak et al., 2018). A probable scenario for Tirachini and del Río (2019) and Tirachini and Gomez-Lobo (2019) has ride-sourcing extensively substituting transit but only inducing latent demand to a small extent. In a recent survey across TNC users in San Francisco (Rayle et al., 2016), in a question "How would you have made this trip if TNC service was not available?", 40% answered by taxi, 33% by bus, and only 6% by car. Thus, TNC can be an attractive alternative for public transport users, and, combined with a large number of empty vehicles, it can create additional congestion problems. The consequences of such non-cooperative interactions can be catastrophic for urban traffic (Çolak et al., 2016; Olmos et al., 2018; Roughgarden, 2005). For instance, reductions in demand for buses can cause imbalances making them miss their schedule, dropping their capacity because of bus bunching (Sirmatel and Geroliminis, 2018; Saw et al., 2019). The transportation literature observes these effects for decades (Vickrey, 1969).

Hence, it is imperative to understand how TNCs' operations can interfere in traffic conditions while replacing other transportation modes to seek improvements in urban mobility. Foremost, this understanding must cover the performance of traffic and operations. It is critical to relate the fleet size with the average speeds and service level, which are related to mobility and accessibility measures (Hanson and Giuliano, 2017; Páez et al., 2012). The literature already presents evidence of traffic improvements from the use of curbside parking for idle drivers (Xu et al., 2017). Hall et al. (2018) shows that ride-sourcing can complement public transport activities, and speculates that users avoiding the limitations of fixed-route and schedule modes are the reason behind the complementary effect. Moreover, the matching process shall have a place, and thus the impact of passengers' behavior too, in a ridesplitting scenario. For this reason, Wei et al. (2020) used logit models to detail the decisions of drivers and passengers in a multi-modal setting and showed that ride-sourcing has the potential to decrease traffic performance. Much of the literature on ride-sourcing relies on surveys (Rayle et al., 2016; Vinayak et al., 2018; Alemi et al., 2018; Lavieri and Bhat, 2019; Dong et al., 2018), economics (Zha et al., 2016; Zha et al., 2018; He and Shen, 2015; Xu et al., 2017), and data regressions (Contreras and Paz, 2018). These studies became available because of the availability of large datasets on human mobility, which enabled studies not only for ride-sourcing but for all transportation modes, such as buses (Bassolas et al., 2020) and taxis (Hamedmoghadam et al., 2019; Riascos and Mateos, 2020). Even though some surveys, such as Wenzel et al. (2019), Tirachini and Gomez-Lobo (2019), Zha et al. (2016), link ride-sourcing services with increased traffic, they do not consider the dynamics of congestion directly nor how these services affect urban mobility and influence congestion. Nourinejad and Ramezani (2020) applies pricing strategies in a dynamic non-equilibrium model that tracks riders and drivers and the respective market performance measures.

However, one must acknowledge the research efforts towards modeling the dispatch of taxis and shared taxis operation. Lee et al. (2004) improved the dispatch of taxis using actual travel distance instead of Euclidean distances to passengers. Wong and Bell (2006) added traffic congestion to the dispatch process. More recently, Ramezani and Nourinejad (2018) used a macroscopic model to control taxi fleets in a multi-region setting. Martinez et al. (2015) used an agent-based simulation to show the potential of shared-taxis for improving mobility management in urban areas. Santi et al. (2014) developed shareability networks to enable the operation of shared-taxis in New York City. Hosni et al. (2014) presented a formulation for the problem of assigning passengers to taxis and computing the optimal routes of taxis. Jung et al. (2016) used hybrid-simulated annealing for dynamic shared-taxi dispatch. Research efforts also focused on ride-sharing systems. Alonso-Mora et al. (2017) further developed the use of shareability networks to allow real-time dispatch in ride-sharing systems. Stiglic et al. (2016) assessed the impacts of riders' and drivers' flexibility to foster the use of ride-sharing. Nourinejad and Roorda (2016) showed that a decentralized approach for ride-sharing could have higher user cost savings and vehicle kilometers traveled (VKT) savings. Vazifeh et al. (2018) presented a real-time minimum fleet problem for on-demand urban mobility using New York City taxi data. In Long et al. (2018), the authors address the problem of travel time uncertainty in ride-sharing services. Furuhashi et al. (2013) and Agatz et al. (2012) present insightful literature reviews on ride-sharing services. Finally, other researchers worked on pick-up and delivery problems, and, more specifically, dial-a-ride problems. Cortés et al. (2010) formulated a pick-up and delivery problem with transfers. Berbeglia et al. (2010) reviewed dynamic pick-up and delivery problems, as dial-a-ride problems. Masmoudi et al. (2018) presented a dial-a-ride problem with battery swapping. Bongiovanni et al. (2019) proposed a variant of dial-a-ride problems for electric-autonomous vehicles. Molenbruch et al. (2017) and Ho et al. (2018) reviewed dial-a-ride problems, their solution methods, and classifications. Nonetheless, these problems do not correlate TNCs' fleet size to traffic conditions, nor the passengers' behavior yet. Ignoring the effect of congestion in the operation of ride-sourcing and ridesplitting services can influence the conclusions made. Alonso-Mora et al. (2017) showed that it is possible to serve the taxi demand of

Manhattan, with reductions of 30% on the current fleet. The paper assumed that all passengers were willing to share a ride with others and that the system had perfect information about future demand. They also did not consider the effect of congestion due to different demand conditions or the compliance of the taxi companies to decrease their fleet size.

It is worth mentioning that other studies contributed to the understanding of labor supply related to surge pricing (Zha et al., 2018) and multi-modal traveler decision making (Wei et al., 2020; Su and Wang, 2019). However, given the complexity of real-time matching algorithms and the dynamic nature of traffic, they usually avoid a spatial representation of the urban network and the ridesplitting matching process. Instead, they rely on equilibrium models.

Therefore, this paper aims to investigate the effect of expanding fleet sizes for TNCs, passengers with different willingness to share, and operational strategies over congestion conditions under a sustainable perspective. The investigation considered a trip-based MFD traffic model integrated into an event-based simulation to tackle the dynamics of congestion. The traffic model considers private vehicles and TNCs' vehicles. The dynamics of the system are based on an aggregated dynamic traffic model, the network Macroscopic Fundamental Diagram (MFD) (Geroliminis and Daganzo, 2008; Loder et al., 2019), to avoid the computational burden of micro-simulation and the lack of sufficient data for proper calibration. We model interactions between travelers and vehicles with an efficient matching algorithm. It is beyond the scope of the paper, the mode-choice modeling. Hence, we focus on the supply of rides and its participation in traffic dynamics testing several fleet sizes and willingness to share to cover a wide range of scenarios with various values of these critical variables defined externally. Our findings show that ride-sourcing can lose attractiveness to public transport when fleets are large enough to cause negative traffic externalities. Nevertheless, a higher willingness to share can minimize waiting and travel times. This paper contributes to the literature in the following ways: i) To the best of our knowledge, this is among the first works to quantitatively relate the TNCs' fleet size, willingness to share with a dynamic traffic congestion model; ii) It investigates the effect of the previously mentioned features and 'empty' vehicles (number of cruising vehicles without passengers) on the performance of the system; iii) It develops a parking management policy for cruising vehicles that can mitigate negative congestion externalities while maintaining the same quality of service; and iv) It shows that, if drivers adapt their participation in a day-to-day basis due to low profit for certain wage thresholds, the number of drivers can be above the ideal for traffic and service quality.

In the remainder of the paper, Section 2 describes the methodological framework, including the simulator architecture, the real data, the matching process for passengers, and a parking-oriented strategy to decrease the circulation of empty vehicles. Then, Section 3 presents numerical results on the effect of fleet size, willingness to share, and parking policies in the quality of service and on network congestion. Discussion and future work are summarized in the last section.

2. Data and Methodology

2.1. Data description

The original data contain GPS coordinates of 199'819 trips, with their respective origins and destinations, of 20'000 taxis every 30 s for 20 h in the city of Shenzhen, China. Shenzhen is immediately north of Hong Kong, in the southern province of Guangdong. Due to a rapid growth period, the population was close to 11 million inhabitants in 2014 (Ji et al., 2014). The development of Shenzhen came with massive foreign investments after it became a special economic zone in 1979. The growth resulted in complex road topology and high traffic demand, leading to traffic congestion problems that propagate over time and space, creating large clusters of congested links (Lopez et al., 2017; Bellocchi and Geroliminis, 2020). The data comprises most of the Futian and the Luohu Districts in Shenzhen, the location of the Central Business District. The considered network consists of 1,858 intersections connected by 2,013 road segments

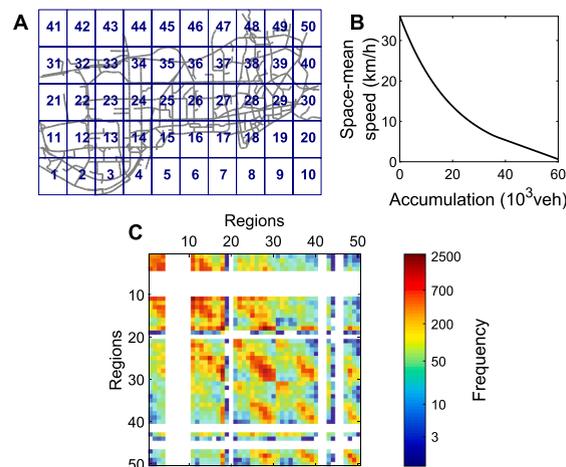


Fig. 1. The simulation of a ride-sourcing service in Shenzhen used data of detailed network, demand, and traffic to provide accurate measurements on operations of ride-sourcing services. (A) Map of Shenzhen and its demand regions. (B) Space-mean speed vs Accumulation for Shenzhen. (C) Demand density per Origin-Destination pair (in a log scale).

(Fig. 1A). As shown in Fig. 1A, 50 regions form the demand data. Fig. 1C shows the demand in an OD matrix. The colormap represents the frequency of each OD pair in the sample. White points represent OD pairs without entries in the sample.

An MFD represents the traffic congestion and computes the average speeds in the network as a function of the accumulation of private and ride-sourcing vehicles. Note that while speed is represented by an MFD, vehicles are moving following the actual network topology and roads. The MFD used on Shenzhen is based on the one obtained in Ji et al. (2014) for the same data of taxi trips. To approximate the jam accumulation for all moving vehicles in the network, we used the total road length (both ways, in case of multiple lanes) using OpenStreetMap data. We assumed that congestion is homogeneous in the region. Hence, a single MFD is capable of measuring congestion. Another reason for such simplifying assumption is the computation of shortest paths - which remain unaltered during the simulation - and, consequently, the route choice. Eq. (1) shows the Accumulation n vs. speed $v(n)$ relationship and Fig. 1B is the graphical representation. While this simplification created an elegant model with small computational effort, it can still well represent the distribution of trip lengths as in real settings (Section 3 provides more details).

$$v(n) = \begin{cases} 36e^{\left(\frac{29}{600}m\right)}, & \text{if } m \leq 36 \\ 6.31 - 0.28(m - 36), & \text{if } 36 < m \leq 60 \\ 0, & \text{if } m > 60 \end{cases}, \quad \text{where } m \equiv \frac{n}{1000} \quad (1)$$

2.2. State description and Congestion dynamics

Four different entity classes populate the simulation environment: private vehicles (PVs), waiting passengers (WPs), traveling passengers (TPs), and ride-sourcing vehicles (RSVs). Each of the classes has properties to define them, shown in Table 1.

Vehicles move in the network following a trip-based model with an accumulation vs speed MFD (Arnott, 2013). For every new trip (a PV or an RSV), the model computes its total distance to the destination and updates the remaining distance for each vehicle based on Lamotte et al. (2018). One way to introduce it starts from the simple observation that a vehicle with trip length l_0 , which entered at a time t_0 , should exit after traveling l_0 , i.e., after a time interval τ_0 satisfying Eq. (2).

Table 1
Nomenclature of tuple elements for each entity.

Entity	Property	Description
PV (Private Vehicle)	PV_i^{id}	Identification
	PV_i^{at}	Arrival time
	PV_i^o	Origin
	PV_i^d	Destination
	PV_i^{rd}	Remaining distance
WP (Waiting Passenger)	WP_j^{id}	Identification
	WP_j^{at}	Arrival time
	WP_j^o	Origin
	WP_j^d	Destination
	WP_j^{wts}	Willingness to share
	WP_j^{dr}	Assigned driver ID
TP (Traveling Passenger)	TP_j^{id}	Identification
	TP_j^{pt}	Pick-up time
	TP_j^o	Origin
	TP_j^d	Destination
	TP_j^{wts}	Willingness to share
	TP_j^{dr}	Assigned driver ID
	TP_j^{td}	Distance traveled
RSV (Ride-Sourcing Vehicle)	RSV_k^{id}	Identification
	RSV_k^i	Last passed intersection
	RSV_k^{cd}	Current destination
	RSV_k^{rd}	Remaining distance to the current destination
	RSV_k^{np}	Number of passengers inside the vehicle
	RSV_k^{PID}	ID of assigned passengers (in order of activity)
	RSV_k^{PAC}	List of activities (in order of execution)

$$l_0 = \int_{t_0}^{t_0 + \tau_0} v(n(k)) dk \tag{2}$$

The main difference with a classical trip based MFD model with an input the trip length distribution of vehicles (see for example, Lamotte and Geroliminis (2018)), is that we estimate trip length for each trip based on the instantaneous shortest path between origin and destination in the real network. We also estimate the trip length between the points in the network that will change the state of a vehicle as described in more details later in Fig. 2. While we are currently using a single MFD for the whole network, this work can be extended in multi-region MFD networks.

The population of PVs fluctuates as every PV has a specific arrival time. Furthermore, we assume that once a PV reaches its destination ($PV_i^{td} = 0$), it enters a garage or parking lot, leaving the system. Note that RSVs and PVs move in the network at every time step at variable speeds, varying according to the traffic conditions summarized in the MFD (Fig. 1B).

WPs are the passenger entities that were not served yet by an RSV. If a WP j is willing to share his ride (i.e., hires the ridesplitting service), his willingness to share WP_j^{wts} is set to 1. Otherwise, it is set to $WP_j^{wts} = 0$. The choice for sharing is the result of a single Bernoulli trial for each traveler generated in the system. Nevertheless, it requires a good quality shared service for the system to accomplish it; otherwise, the user will travel alone even in a ridesplitting service. Service quality constraints are described later in Section 2.3. Finally, once s/he has an assigned RSV to pick-up, it cannot change, and the property WP_j^{dr} links it to the passenger. Note that WPs may assume two states, waiting for an assignment ($WP_j^{dr} = 0$) and waiting for pick-up ($WP_j^{dr} \neq 0$).

Once an RSV picks-up a WP, the last becomes a TP (leaves the list of WPs and adds a new member to the list of TPs). The new TP inherits most of the data from the WP, said: identification, origin, destinations, willingness to share, and assigned driver. However, TPs have new properties, said: time of pick-up and traveled distance. As the speeds might vary a lot during a trip, a traveling passenger has no information about the delivery time, which is informed once the passenger reaches the destination.

The central entity of the ride-sourcing service is the RSV, which is responsible for the pick-up and delivery of passengers according to their preferences. Different from the PVs, RSVs have their positioning tracked all the simulation long. They also may assume different states depending on their current activity. Every RSV has an identification RSV_k^{id} , a last passed node RSV_k^l (node in the network, updated at every time step), a current destination RSV_k^{cd} (node in the network, such as a WP's origin, or a TP's destination, or a parking lot), and a remaining distance to the current destination RSV_k^d , to keep track of their position. To keep track of their activities, they have the destinations' ID RSV_k^{pid} (identification of the passenger - waiting or traveling one), and number of passengers inside the vehicle RSV_k^{pp} . We assume that RSVs have a limited capacity of two passengers. A supporting argument for such an assumption is found in Li et al. (2019). The authors identified that only 6–7% of trips were shared, and more than 90% of them had at most two passengers in a study in Chengdu, China; shared trips with 3 or more passengers is in the range of 0.7% or even less.

RSVs perform different activities as they move through the network. Fig. 2 shows how RSVs change their states during the simulation breaking the activities for both available services. The states refer to the current activity of the RSV. For each activity of an RSV, the path choice follows the Floyd-Warshall algorithm (the shortest path) in terms of distance. In general, an RSV can perform seven different activities:

- Cruising for passenger: the vehicle has no passengers and is driving around his current location, waiting for an assignment of a new passenger (WP);
- Driving to park or to a hot-spot: the vehicle has no passengers and is driving to a hot-spot near high demand areas and then circulates randomly in this area until a request arrives (in case the parking strategy from Section 2.5 is active, the hot-spot becomes a parking lot);
- Parked: the vehicle has no passenger, reached a parking lot near high demand areas, and waits there for the next assignment (only possible when the parking strategy from Section 2.5 is active);
- Picking-up a first passenger: the vehicle received the location of a waiting passenger (assignment), and it is moving towards the passenger's pick-up position (origin);
- Delivering a single passenger: after picking-up the passenger, the vehicle drives him/her towards the final destination;

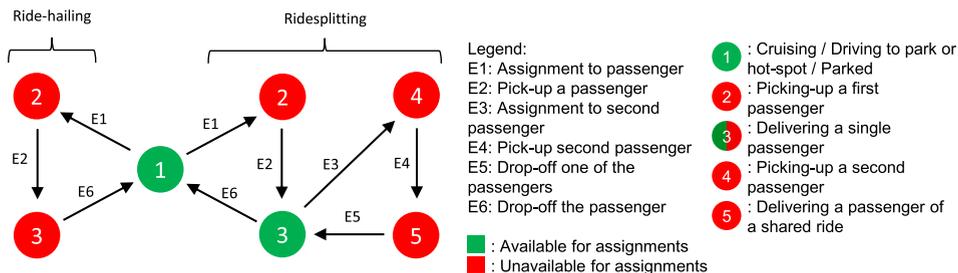


Fig. 2. Simplified RSV activity flow framework for ride-hailing and ridesplitting services.

- Picking-up a second passenger (exclusive for ridesplitting): the vehicle has one passenger and is moving towards a second passenger that matched the current ride; and
- Delivering a passenger of a shared ride (exclusive for ridesplitting): the vehicle has two passengers and is moving towards the destination of one of them.

2.3. Matching passengers and drivers

Here, we present the matching process used inside the simulation and its assumptions regarding driver choice and passengers' matching requirements.

Defining a trip determines the order of the points which the vehicle will visit. The matching process is responsible for determining RSVs' trips. WPs admit waiting 1 min to receive an assignment (a designated RSV available to pick-him/her-up) that fulfills the requirements for maximum waiting time and detour. After this time, travelers leave the WP list and choose a new mode of transportation (busses, bike, walk, taxis, private vehicle) in an event called 'abandonment'. Busses, bike, and walking are considered secondary to the accumulation, and, therefore, the simulation does not keep track of their activities. Passengers in these modes transfer with a fixed travel time to their destination. In the case of an abandoning passenger who decides to travel by taxi, it is modeled similarly to PVs. While a mode-choice module could integrate the simulation, this is beyond the scope of the paper that focuses on the supply side. The interest of this work is to analyze the effect of ride-sourcing services in congestion for different fleet sizes and willingness to share. For demand-oriented work, the reader could refer to Tirachini and Gomez-Lobo (2019), Tirachini and del Río (2019), Zha et al. (2016), Wei et al. (2020). The effect of mode choice and socioeconomic characteristics in the ride-sourcing literature is a research priority.

In general, the matching process assigns the RSV with the smallest extra trip length among the five closest RSVs that fulfill all requirements to perform the ride. We define the smallest extra trip length as the distance that the new assignment will make the RSV travel, in addition to any ongoing activity. It means that even an RSV that fulfills all requirements (capable) and may save some more Vehicle Kilometers Traveled (VKT) will not get the passenger if there are other five capable RSVs closer, for instance.

Despite that the system could benefit from optimization in the dispatching and matching processes, we are interested in evaluating such a system as an operation with human agents and their limited rationality (the system is not centrally optimized). For instance, Hanna et al. (2016) points out that services such as Uber and Car2Go assign the nearest vehicle on a first-come-first-served basis. Future research could investigate the effect of more advanced matching optimization techniques on the performance of the system.

2.3.1. Assignment in ride-hailing

Requirements for matching passengers and drivers in ride-hailing derive from our assumptions about passengers' tolerances towards waiting and service definition. The RSV must be idle and able to reach the passenger in less than Δ minutes under current traffic conditions (Eq. (3)). Any vehicle that fulfills the latter is capable of serving ride-hailing passengers. The matching process uses the distance between two points ($p(\cdot, \cdot)$) and the current speed ($v(t_{clock})$) to compute its requirements. Recall that RSV_k^l and WP_j^o refer to the RSV's last passed intersection and the passenger's origin, respectively.

$$p(RSV_k^l, WP_j^o) \leq v(t_{clock}) \cdot \Delta \tag{3}$$

In summary, the matching process for ride-hailing (single rides, without the option to share) searches the closest available RSV. It occurs because the extra traveled distance for idle RSVs is simply the summed distance to pick-up and deliver the passenger.

2.3.2. Assignment in ridesplitting

There is no predefined priority for assigning partially busy RSVs when a ridesplitting passenger arrives. Instead, the matching process looks for the five nearest capable vehicles, including idle ones and those delivering another ridesplitting passenger.

Defining a ridesplitting trip depends on the chosen RSV's current activity. If it is empty, the defined trip is similar to a ride-hailing one. However, when evaluating a shared ride match (a vehicle with one passenger matches with a second passenger), two types of trip schemes arise. Fig. 3 illustrates both types of trips ($j-i-j$ and $j-j-i$ sequences) and direct route ($i-i$ sequence). Note that the process only assigns one passenger per run, immediately at the passenger's arrival or when a new RSV becomes available. It means that the algorithm does not wait for a pool of passengers to form after some time. Based on the previous statements, assigning an empty RSV to an arriving ridesplitting passenger will not prevent him/her from sharing the ride later. For this reason, the evaluation of matched rides,

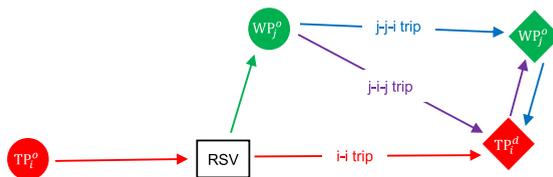


Fig. 3. Ridesplitting trip options scheme. The 'RSV' box indicates the current position of the vehicle in the illustrative network. ' $i-i$ ' trip refers to a direct trip from TP_i^o to TP_i^d (en-route trip at the moment of the evaluation). ' $j-j-i$ ' trip refers to a ridesplitting trip that will deliver passenger j first, and then passenger i . ' $j-i-j$ ' trip refers to a ridesplitting trip that will deliver passenger i , and then passenger j .

such as the one from Fig. 3, only happens with an en-route RSV.

A shared trip contains two passengers if both are willing to share and the first one, who is already on-board, has a similar trip (with a small detour) with the second one. Thus, considering all nearest vehicles during the assignment will also potentially increase (when demand for shared rides is high) the number of circulating vehicles with one passenger who is willing to share. This will result in more shared rides during the peak hour when the system needs them. It will also result in better quality of matching because if we force shared rides, this might result in higher waiting times. This is evident in Figs. 8 and 9, where in the beginning of the simulation the number of ride-splitting with one passenger is more than with two passengers, but as demand increases a higher number of matches occurs and the system performs many shared rides. If matches are forced by only searching the 5 nearest vehicles already with a passenger (who is willing to share), this might create lower quality of service or infeasible solutions.

The requirement for an empty vehicle to serve ridesplitting passengers is the same as for ride-hailing (Eq. (3)). Additionally, requirements for a shared ride match derive from passengers' tolerances towards deviating from their original path and service definition. Firstly, all involved passengers must have hired ridesplitting rides ($WP_j^{wts} = TP_i^{wts} = 1$). In the 'j-i-j' trip from Fig. 3, it is not allowed to add more than a maximum relative detour Ω to the trip distance of TP 'i'. Thus, the detour of picking-up the WP 'j' must be acceptable for 'i' (Eq. (4)); the same applies to 'j' regarding the delivery of 'i' (Eq. (5)). Finally, for the sequence 'j-j-i', the detour of picking-up and delivering 'j' must be acceptable for 'i' (Eq. (6)). Note that, in this sequence, there is no detour for 'j'. In case both sequences ('j-i-j' and 'j-j-i') are possible, the shortest one in distance is chosen.

$$TP_i^{td} + p(RSV_k^l, WP_j^o) + p(WP_j^o, TP_i^d) \leq p(TP_i^o, TP_i^d) \cdot (1 + \Omega) \tag{4}$$

$$p(WP_j^o, TP_i^d) + p(TP_i^d, WP_j^d) \leq p(WP_j^o, WP_j^d) \cdot (1 + \Omega) \tag{5}$$

$$TP_i^{td} + p(RSV_k^l, WP_j^o) + p(WP_j^o, WP_j^d) + p(WP_j^d, TP_i^d) \leq p(TP_i^o, TP_i^d) \cdot (1 + \Omega) \tag{6}$$

Note that the matching requirements share many similarities with the shareability networks presented in Santi et al. (2014). Moreover, our matching process occurs online, as seen in Alonso-Mora et al. (2017). However, these processes share some key differences: 1) we do not allow to change the vehicle that will pick-up a passenger, and 2) fully occupied vehicles are not options for assignments. Readers can refer to Martinez et al. (2015), Jung et al. (2016), Hosni et al. (2014), Stiglic et al. (2016), Nourinejad and Roorda (2016), Long et al. (2018), Zeng et al. (2020), Furuhashi et al. (2013), and Agatz et al. (2012) for other matching strategies for on-demand transportation services.

2.4. Moving idle vehicles to hot-spots

It is unfruitful for RSV drivers to remain in a location that would yield lower revenues. Cruising around the destination of the last assignment might lead to longer vacant times. Hence, we assume drivers prefer to move to areas of high demand after delivering a passenger. Currently, some TNCs test surge pricing schemes to attract vehicles to high demand areas (Lu et al., 2018). Nevertheless, we do not investigate the consequences of surge pricing on ride-sourcing services, drivers repositioning, nor labor supply.

Drivers have *a priori* a list of areas of high demand, called hot-spots. We assume that drivers will move to the closest hot-spot once they become idle and then randomly circulate in this region. Once drivers reach the nearest hot-spot, they cruise, awaiting the next assignment. Note that RSVs are available for new assignments during the 'driving to park or to hot-spot' state. We will briefly comment in Section 3 the case that drivers do not relocate in hot spots but cruise near the areas of the last drop-off.

The locations of hot-spots are the result of a simplified p-median problem (Owen and Daskin, 1998) in two stages. The first stage defines the intersections with the shortest average distances to other nodes in their respective demand regions (Fig. 1A). The second stage solves the p-median problem for the defined nodes and the demand values for each region. Fig. 4 summarizes the positions of hot-spots, their closest intersections, and their demand shares (solution of the p-median problem).

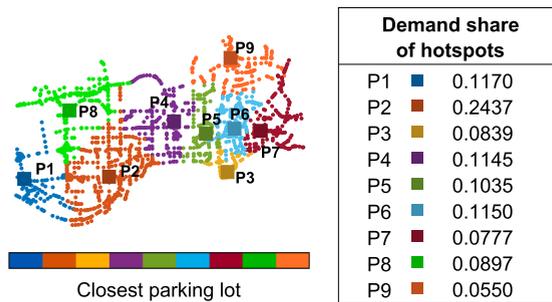


Fig. 4. Geographical position of hot-spots and the set of nearest intersections. The legend brings the results of the p-median problem (demand share of each hot-spot, used for the parking strategy).

2.5. Parking strategy

TNCs' attractiveness depends significantly on the fast response on picking-up passengers when a request arrives (similar to other types of response systems, see, for example, a vast literature for emergency response systems, based on location theory). To succeed in this objective and attract higher demand from other modes of transport, TNCs try to increase the number of registered drivers (see an economic analysis for a static model in [Tirachini and Gomez-Lobo \(2019\)](#)). While an increased fleet size could decrease the waiting time for passenger pick-up, it creates a mass of idle circulating vehicles. As the numerical study of Section 3 shows, strong congestion effects might appear in the network. Nevertheless, this congestion affects other modes of transport that move in the same part of the network. Thus, if there is no intervention from the government to penalize the negative externalities of these actions (e.g., through pricing or creating additional opportunities for public transportation), TNCs can have advantage over other modes of transport. If there is spare parking capacity, the development of simple strategies could decrease the circulation of idle vehicles without significantly increasing the waiting time. The purpose of such is that by leaving on the side demand interactions and mode choice, we can still show with a dynamic model of congestion that smart parking strategies can have a positive effect on the overall system. Whereas the implementation and pricing of such systems can influence mode interactions, this is yet another further research direction in transport economics. This paper focuses more on the supply interactions and dynamics of congestion as a function of fleet sizes and parking strategies that try to decrease the number of circulating idle TNC vehicles.

Idle RSVs cruise, in a random walk, near their last destination waiting for their next assignment. Such behavior has the potential to increase empty kilometers traveled and degrade traffic conditions. For this reason, we propose a parking strategy where we assign idle vehicles to parking lots near high demand areas. The added value of parking lots is that parked vehicles do not contribute to the MFD accumulation and, thus, congestion levels are lower.

[Xu et al. \(2017\)](#) presented an optimal parking provision for ride-sourcing vehicles. The authors focus on managing the trade-off of restraining road capacity, creating curbside parking, and removing idle ride-sourcing vehicles from the streets because it explicitly had cruising RSVs as a source of additional VKT. The framework, however, did not consider ridesplitting nor other spatial network effects directly, such as matching of multiple customers and an RSV.

The locations of parking lots are the same as the hot-spots (from Section 2.4). We consider off-street parking lots at these locations. These parking lots have a limited in-park capacity. Therefore, although every idle driver receives a request to move to a parking lot, some of them will not find an in-park spot and will cruise nearby the assigned parking lot. Once the driver reaches the parking lot entrance, the queue to enter follows a first-come-first-served discipline. At the same time, to leave the parking lot, there is a last-come-first-served discipline. Note that RSVs are available for new assignments while in a 'driving to park' or a 'parked' state. The number of in-park spots and assignable spots (in-park spots plus the number of vehicles that will cruise nearby) of each parking lot is proportional to the demand share of the respective hot-spot. We assume, in most scenarios, that in-park capacity is limited to half of the fleet size of RSVs. We discuss in Section 3.2 the effect of parking lot capacity in system performance.

Assignment of idle RSVs for parking lots uses a color system to prioritize emptier parking lots. Colors (classifications) are a reference to their usage level, i.e., a parking lot with fewer vehicles have a higher priority to get an assigned vehicle. The parking strategy considers the proximity between RSV and parking lot as a secondary classification. The Drum-Buffer-Rope method inspired this process ([Cox and Schleier, 2010](#)). The highest priority goes to green parking lots, which have more than 70% of available spots. Then, yellow ones have more than 30%, but less than 70%; red ones have less than 30%; and, finally, black ones (lowest priority) have all of them assigned to drivers. In summary, the process sends drivers to the nearest parking lot with the highest priority at the moment of the decision (flags change according to the instantaneous number of available assignable spots of each parking lot). Section 3.2 provides the dynamics of vehicle occupancy in parking lots during the simulation. Note that drivers can receive a request to move to the area of a full parking lot (represented with a 'black' flag). These drivers will cruise near the parking lot until they receive a new assignment (passenger), or a in-park spot becomes available.

2.6. Congestion and transit

Passengers' choice for ride-sourcing service depends on waiting times, fares, and journey duration. Once congestion rises, journey duration becomes less appealing. In such situation, passengers become more likely to change to public transportation.

As mentioned earlier, in Section 2.2, we consider that transit move at constant speeds as there were dedicated bus lanes that did not interact with traffic. Another approach would have been to utilize a 3D MFD to model car-bus interactions (similar to [Geroliminis et al. \(2014\)](#)), but this is beyond the scope of this work. A passenger can change her choice in case travel times become too long in ride-sourcing. The estimates for journey duration in ride-sourcing and transit consider a waiting time and a time inside the vehicle. Every passenger computes these estimates before joining the system. In case transit presents a lower estimate for journey duration, some passengers change transportation mode. Hence, when the system becomes very congested, more passengers might shift to public transport. Differently of abandonments, these passengers do not wait for a driver. They leave the ride-sourcing system immediately at their arrival. One can expect that this takes more passengers from ridesplitting than from ride-hailing since we are only accounting for traveling times, not costs. The opposite is expected from waiting time abandonments, since more vehicles will be available for a ridesplitting service.

Eq. (7) computes the estimated journey duration of transit. One can relate it with what a passenger expects to wait plus the amount of time walking plus the transit time-table assumed to travel around a $u_r = 10$ km/h (walking and in-vehicle average). Although ridesplitting passengers can accept up to the maximum detour tolerance (Ω), they expect only half of it to be used (we show evidence for this assumption later in [Fig. 7B](#)). Eq. (8) computes the estimated journey duration of a ride-sourcing passenger based on current

traveling speeds in the network ($v(n(t))$). One can relate such an estimate with what customers see on the application screen before booking a ride. Note that the passenger has a predefined willingness to share, e.g., the service s/he will hire.

$$T_{\text{transit}} = E[W_{\text{transit}}] + \frac{p(WP_j^o, WP_j^d)}{u_{cr}} \tag{7}$$

$$T_{\text{TNC}} = E[W_{\text{TNC}}] + \frac{p(WP_j^o, WP_j^d)}{v(n(t))} \times \left(1 + WP_j^{ms} \frac{\Omega}{2}\right) \tag{8}$$

3. Computational results

We analyzed several metrics, with different ride-sourcing fleet sizes (from 1000 to 7000 in increments of 500 vehicles – based on the operating number of taxis in Ji et al. (2014) for Shenzhen), and willingness to share (fraction of passengers hiring ridesplitting: 0%, 30%, 60%, and 90%). We assumed that the number of drivers remains unchanged for the time of a single simulation run based on the findings of Zha et al. (2018), where drivers might spend more than six hours working per day (more than double of a simulation run). However, the number of drivers can change daily. Section 3.3 presents a discussion in this direction. Further research efforts could analyze within-day dynamics on the number of active drivers, which requires a more careful analysis of pricing and investigation of equilibrium and the trade-off between supply and demand. Note that, in the case of such an application, we expect that fewer drivers would join in off-peak hours. However, the demand peak would surely bring more drivers, specifically if surge pricing schemes are applied, causing similar congestion issues.

The maximum waiting time, Δ , and the maximum detour, Ω , were set to 10 min and 20% of the trip length (shortest path from origin to destination), respectively. Expected waiting time for buses ($E[W_{\text{transit}}]$) is also set to 10 min according to Fu et al. (2020), while the expected waiting for ride-sourcing ($E[W_{\text{TNC}}]$) is pre-computed using the simulation. From all waiting abandonments, about half choose to travel by buses or bike or walk. The other half call a taxi or pick-up a private vehicle (see Rayle et al. (2016)). As the number of abandonment trips is small for fleet sizes above 2000 vehicles (1–4% from all trips, including PVs and ride-sourcing), variations in the fraction of these trips between public and private modes do not influence the numerical results, and conclusions remain unchanged. There are separate scenarios to evaluate the parking strategy from those where it is deactivated.

A Poisson process describes the arrival process of both PVs and WPs. They had piece-wise constant rates in a 3-h long simulation with a low–high-low demand profile lasting one hour for each period. In the low-demand profile, private vehicles and ride-sourcing passengers split in 34'000 and 6'000 trips per hour for each, respectively. In the high-demand profile, arrival rates double.

Our results show that encouraging ridesplitting is not enough to decrease the VKT, a measure associated with worse congestion, fuel consumption, and safety issues. Furthermore, traffic congestion worsens as ride-sourcing fleets grow. Finally, the findings acknowledge that it is necessary to restrain idle ride-sourcing vehicles from cruising to decrease impacts on VKT.

As this is a trip based simulation, with an MFD representation of speed dynamics in the network, it is necessary to test whether this parsimonious model, without link speed variations and detailed traffic assignment, provides realistic traffic characteristics. To do so, we compare trip length distributions from the real taxi trips in Shenzhen with the ones produced by the simulator. We sampled 2'000 trip lengths between 7:00 and 10:00 from the taxi trips with passengers from Shenzhen and 2'000 trips from an instance of the simulation, to ensure that the simulation could provide a realistic representation. Fig. 5 summarizes the probability density functions for both samples and compares their cumulative density functions. Graphically, both samples have similar shapes. Furthermore, a Kolmogorov–Smirnov test evaluated the similarity between the samples and did not reject the null hypothesis for a confidence level of 5%. The use of the shortest path and aggregating demand data in regions (see Fig. 1A) did not generate a significant distinction between samples such that the simulator could represent trip lengths accurately.

3.1. The effect of willingness to share and fleet size on service quality

Evaluating the ride-sourcing service requires a multi-dimensional look. Performance measurements include waiting times, journey duration, and abandonments regarding the perspective of passengers. While the fraction of travelers that are willing to share a trip is an input to the simulator (ranging from 0 to 90%), the quality of the matching could influence the actual number of travelers that share a

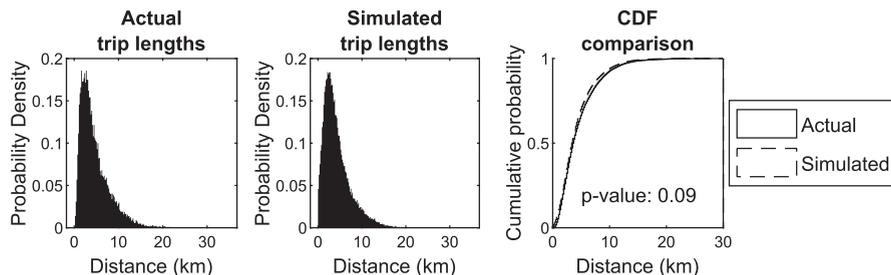


Fig. 5. Histograms and CDF of trip lengths. Result of a Kolmogorov–Smirnov test comparing both samples.

trip. It depends on the extra detour for both travelers that potentially match, as described in Section 2.

We consider that a complete journey of a passenger starts the moment s/he orders the service and ends the moment s/he reaches his destination. However, passengers that abandon the ride-sourcing service may lead to unrealistic results. Furthermore, waiting and traveling times may underestimate the consequences of abandonments since served trips will concentrate near main demand centers, whereas those far from them will abandon unserved. For instance, abandonments range between 15% and 33% (for willingness to share of 90% and 0%, respectively) for a fleet size of 1500 ride-sourcing vehicles and decrease to negligible values for larger fleets. For this reason, abandonments penalize the measurements proportionally to the ratio of abandoned passengers using Eqs. (9) and (10).

$$E[W'] = E[W] \cdot (1 + f_{ab}) \cdot (1 - f_{trs}) + \Delta \cdot f_{trs} \tag{9}$$

$$E[T^{pr}] = (E[W] + E[T^{tr}]) \cdot (1 + f_{ab}) \cdot (1 - f_{trs}) + E[T_{transit}] \cdot f_{trs} \tag{10}$$

Here, $E[W']$ represents the average waiting time subject to a penalty, and $E[T^{pr}]$ describes average journey duration calculated from the average waiting time ($E[W]$), the average travel time ($E[T^{tr}]$), the waiting tolerance (Δ), the average transit journey duration ($E[T_{transit}]$), the abandonments (as a ratio f_{ab} ranging between 0 and 1), the losses to transit (as a ratio f_{trs} ranging between 0 and 1).

As mentioned, the quality of service of transportation services (TNCs, taxis, metros or buses) significantly depends on the passengers' waiting times, which is zero for private cars. Bringing passengers into the service requires planning on the business model, comprising fleet sizes, service availability, fares, so on. An on-demand transportation service, such as a ride-sourcing service, has to manage the dispatching process of its fleet in real-time, accounting for the route choice and chances to match passengers. Operators may reposition drivers establishing fares dynamically through the city. Once dispatching and repositioning policies are well defined and operational, decreasing the waiting times of passengers requires increases in the fleet sizes unavoidably. For example, a passenger may wait between 4 and 9 min when only 1000 vehicles are operating (Fig. 6A). For some fleet sizes, a passenger may wait between 2 and 3 min, on average. Such short waiting times can make ride-sourcing services more appealing compared to public transport (Hensher and Rose, 2007). This can be problematic from a system's point of view because the minimum waiting times occur in fleets larger than those that minimize the average journey duration, and the difference is higher for lower willingness to share. Such an inconsistency can become a problem because companies might prefer to have larger fleets than the optimum (in terms of average journey duration), so they can attract more customers with lower waiting times and increase their revenues. We must point here that it would only materialize depending on the TNCs' capacity of attracting drivers, which need an admissible income from this activity. However, the penalties on the average waiting times increase more due to raises in 'losses to transit' (f_{trs}) than it decreases due to the additional drivers becoming closer to passengers, at large fleet sizes. Note that these losses are a consequence of ride-sourcing becoming less attractive because passengers expect low traveling speeds (see Eqs. (7) and (8)). It is interesting to observe that nearly the same fleet sizes minimize both waiting times and journey durations when the parking strategy is active.

It is interesting to indicate that scenarios without vehicles moving to hot-spots (not shown in the figures) had lower waiting times than the scenarios shown in Fig. 6A. They even lowered to values under one minute (lower than the minimum when using the parking

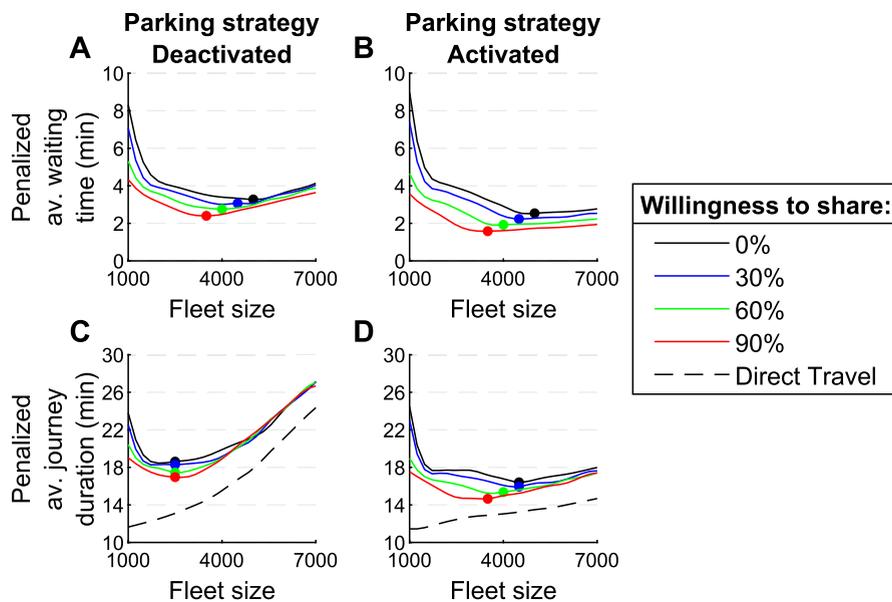


Fig. 6. Optimum fleet sizes minimize the average journey duration of passengers. (A, B) Series of average waiting times for different fleet sizes and willingnesses to share. (C, D) Series of average journey duration. A and C show results for instances without use of the parking strategy. B and D show results for instances using the parking strategy. Markers indicate the fleet size with minimum journey duration. The results were corrected with a penalty to abandonments. Direct travel time represents the in-vehicle time for a direct service with no detour.

strategy). The reason for such finding is in Fig. 1C. Origins and destinations have high correlation, thus, remaining near the last delivery point created decent chances of getting a new assignment.

After picking up a passenger, the ride-sourcing service must plan and execute the delivery. Planning includes setting a proper path/route according to a specific strategy, such as minimize travel time for the driver. As a trip-based single region MFD dynamic model is used, once establishing the shortest path, traveling times would only decrease upon higher movement speeds, but the routes would remain unchanged. There resides the conflict of managing fleet sizes for ride-sourcing services. Since traveling speeds depend on traffic conditions, increasing fleet sizes significantly influence average travel speeds. For instance, Fig. 6C presents the result of combining shorter waiting times and longer traveling times, producing a well-defined minimum on each case. We define with a marker the fleet sizes at the minimum average journey duration as optimum fleets. Note that higher willingnesses to share lowered the average journey duration and the fleet sizes in the optima. The line “direct travel” indicates the in-vehicle travel time for immediate service, excluding waiting, detour, and abandonment penalty. It represents the aggregated congestion model of the city, based on the MFD of Fig. 1B, and it emphasizes the importance of integrating a congestion model in the analysis. Movie S1 shows how the identification of the optimum fleets relates to the number of idle vehicles at peak-hour getting close to zero.

The parking strategy helps to control congestion and to avoid unnecessary vehicle presence in the streets. The average journey duration and waiting times reach a minimum, and they rise slowly for larger fleet sizes (Fig. 6B and D). For instance, observing the minimums marked with a circle in Fig. 6, the activation of the parking strategy lowered the average journey duration by 2.3 min, for a willingness to share of 90% (red circles in Figs. 6C and D at fleet sizes of 2500 and 3500 vehicles, respectively). With fewer vehicles on the streets (but available in a parking lot), distances to pick-up passengers did not increase, and average waiting times became approximately 1 min shorter for all values of willingness to share (comparing the minimums – circles – in Fig. 6A and B).

Ridesplitting has two major uncertainties when trying to get more customers. On the one side is the uncertainty of matching passengers, while on the other side is the extra time and distance that they will deviate from their initially designed trip. In Fig. 7 we explore these concerns in a growing fleet size perspective. Although small fleets may provide higher chances for matching passengers, they face long detours and waiting times that increase abandonments. The reasoning behind such result is simple. For a given demand, having smaller fleet size means that serving vehicles will be very busy. As a result, the number of vehicles with no passengers will be smaller and in some cases when a new demand arrives, only vehicles with passengers might be in the proximity, pushing the system to create more matches to avoid abandonments. In summary, when fleet sizes are small, customers of ridesplitting have higher chances of being served because of the shortage of empty RSVs. On the other hand, large fleets provide the opposite situation without significant decreases in the matched rides, showing that the matching process indeed favors shared rides to save some VKT. Additionally, the detours decrease for larger fleet sizes because the matching algorithm could match passengers with more similar requests more frequently. All the previous indicates that fleet size is vital in identifying potential matches. Note also that because abandonment rate decreases with fleet size, there is a slight increase for large values due to high level of congestion. The loss of RSV demand to public

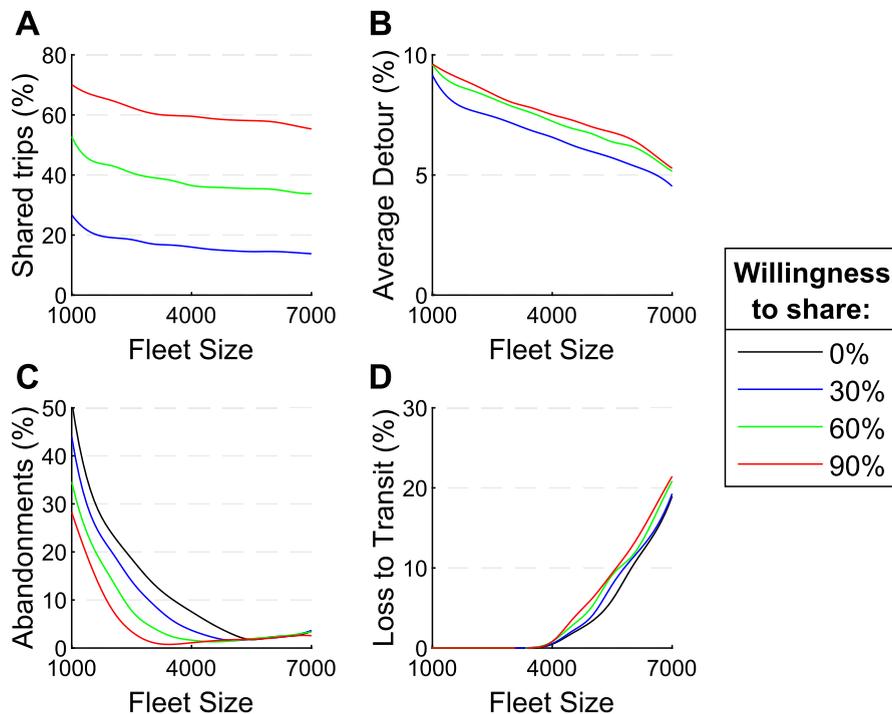


Fig. 7. (A) Shared trips fraction (accounting only for ridesplitting hired trips), (B) average detours for increasing fleets, (C) fraction of abandonments, and (D) loss to public transport.

transport happens only for very large fleet sizes when the network reaches high level of congestion.

To understand these outcomes, we need a more extensive examination of these instances. With a fixed fleet size, we can observe the situation of ride-sourcing vehicles through time and evaluate how it may influence service performance. Fig. 8 illustrates the system conditions through the number of vehicles in each state. One can readily note the effect of the peak-hour over the system. Firstly, idle vehicles rapidly become busy. Secondly, in their absence, the number of vehicles working with shared trips ('2nd pick-up' and 'Drop-off shared' states) rises substantially. The parking strategy holds empty vehicles from cruising, accelerating the system recovery from the peak hour. Note that, during off-peak hours, a few vehicles were allowed to cruise without compromising service performance (from Fig. 6). The use of the parking strategy enabled shared rides earlier than in scenarios where is deactivated (see 'Drop-off shared' state when willingness to share is 90%). However, it did not succeed in fostering more shared rides. Table 2 shows the VHT used to pick-up and Drop-off shared rides is smaller, especially for larger willingness to share. In general, VHTs for busy vehicles do not change in order, but they fall about four times when observing empty vehicles ('Cruising' and 'Driving to park' states).

System congestion may produce changes in the participation of each service (ride-hailing and ridesplitting) in the number of served passengers. Fig. 9 illustrates the allocation of passengers between each service, highlighting shared rides of ridesplitting for scenarios with a fleet size of 3000 vehicles. Note that we did not plot the results for willingness to share of 0% because all passengers hire ride-hailing services (without ridesplitting option). Mainly, ride-hailing demand remains constant for most of the simulation time. The exception is the peak-hour, where ride-hailing loses space for ridesplitting beyond the willingness to share. The reduction in ride-hailing trips occurs between 1.5 h and 2 h when demand is high, and the number of idle vehicles is small (see Fig. 8). At the same time, only shared rides become available, another reason for increasing their proportions. Noticeably, shared ridesplitting rides build up once the matching algorithm is capable of finding partially busy vehicles. Thus, shared trip percentage does not increase instantly with the increase in demand. The later indicates that shared trips require a pool of vehicles with a single passenger to form before starting to share. Once the pool of drivers for ridesplitting is big enough, about half of arriving ridesplitting customers have a shared ride. This illustrates the potential VKT savings at a ride level, from the perspective of the matching algorithm.

3.2. Traffic and TNCs relation

Ride-sourcing vehicles compose urban traffic, influencing traffic performance depending on their actions. Fig. 10 reveals that traveling speeds take longer times to recover from the peak-hour for larger fleet sizes. Parking idle ride-sourcing vehicles enhanced the recovery speed from the peak-hour, therefore, increasing the overall resilience of the system (Zhang et al., 2019). Under a fleet size of 3000 ride-sourcing vehicles, instances without the parking strategy reached the critical speed (speed which maximizes flow in the MFD) 35 min after the start of the peak-hour and entered a hyper-congested state for another 35 min. On the other hand, with the same fleet size with the parking strategy active, they reached the critical speed after 41 min after the beginning of the peak-hour and entered a hyper-congested state for 26 min. Furthermore, the speeds worsen faster for larger fleets when the parking strategy is inactive (Fig. 10).

Next, we explore, in Fig. 11, the reachable area from an intersection in the central business district as a function of time. As time advances, the driver can travel longer distances until reaching the whole network modeled. A 0.5 h difference in departure time changes significantly in the reachable area. For example, a driver departing 1.5 h after the simulation start can reach a distance of 5.4 km, comprising 48% of the simulated network, in 30 min, and this reachable area will extend to 60% if departing 0.5 h later. However, traffic conditions recover faster when using the parking strategy, allowing a driver to travel 4.6 km more by departing 0.5 h later, whereas only 3.0 km more without the parking strategy (45 min travel). Movie S2 shows the evolution of reachable areas and speeds in the simulation.

Fig. 12 shows the number of assigned vehicles to each parking lot. Firstly, most parking lots empty following a similar trend until

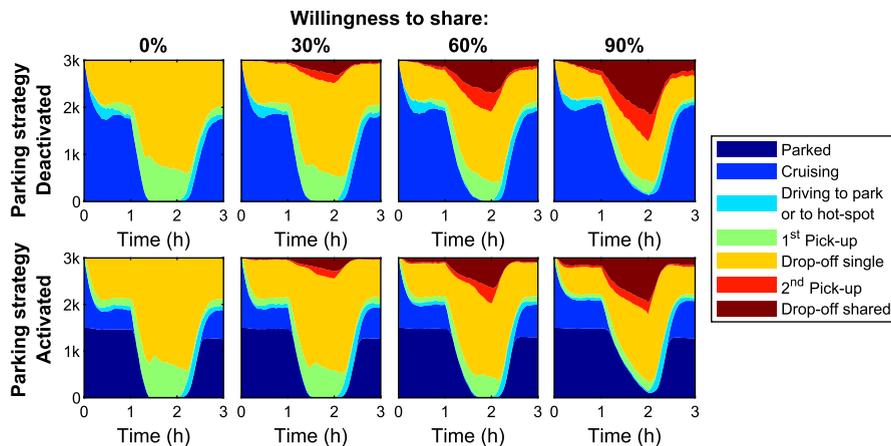


Fig. 8. Number of vehicles in each state for instances with a fleet size of 3000 ride-sourcing vehicles, and varying willingness to share and use of the parking strategy.

Table 2

Vehicle Hours Traveled (VHT) for private vehicles and for each state of ride-sourcing vehicles (fleet size of 3000 vehicles).

Parking strategy	Willingness to share	Private vehicles	VHT per state					
			Cruising	Driving to park or to hot-spot	1st pick-up	Drop-off single	2nd pick-up	Drop-off shared
Deactivated	0%	31503	3144	350	1066	4439	0	0
	30%	31192	3282	362	889	3928	189	350
	60%	30528	3597	377	638	3136	401	852
	90%	29957	4054	376	382	2253	566	1370
Activated	0%	29475	802	297	1069	4270	0	0
	30%	28466	862	304	912	3879	126	290
	60%	28046	962	300	649	3362	227	701
	90%	26995	1156	299	371	2696	264	1064

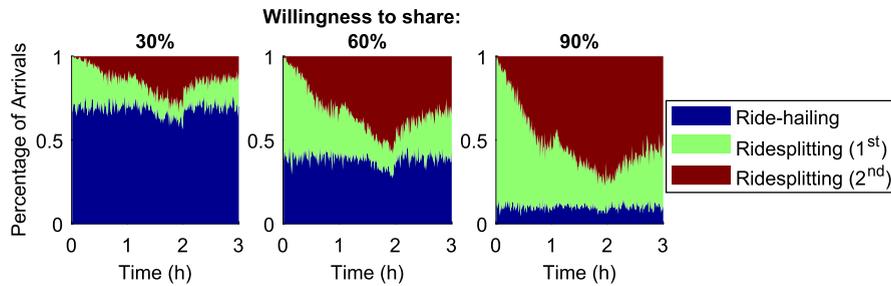


Fig. 9. Instantaneous percentage of arrivals (out of all served requests) for each service (ride-hailing and ridesplitting) at different willingness to share. Scenarios with a fleet of 3000 ride-sourcing vehicles.

the point they reach a green flag. At peak-hour, all except parking lot P9 reach this flag. Parking lots P3 and P5 have no vehicles around 2 h after the simulation start. Except for parking lot P9, which kept nearly 30% of its capacity, very few vehicles remained parked. Yet, this strategy could yield positive results for traffic conditions (Figs. 10 and 11). The period after peak-hour illustrates the effects of the parking assignment algorithm, where those parking lots that reached the flag thresholds have a lag before receiving new assignments. Only parking lot P5 did not have drivers waiting for a parking spot (black flag) after the peak hour. The opposite happens to parking lots P8 and P9. They are far from the central business district, and, thus, most of the drivers around them were idle by the end of the simulation.

VKT is a fundamental measure for transportation systems since it is associated with worse congestion, fuel consumption, and safety issues. Ride-sourcing vehicles generate VKT not only when transporting passengers, but also when they are searching for them, resembling taxis. Hence, we explore through Fig. 13 how ride-sourcing fleets generate additional VKT to the city. In a scenario with enlarging fleets of ride-sourcing, the only alternative to curb the growth of VKT is to take idle ride-sourcing vehicles from the streets, as, for example, with the parking management strategy. We show through the results of Eq. (11) how ride-sourcing generated additional VKT (VKT⁺) compared to a scenario where all travelers would travel alone to their destinations without the service (assuming no issues with parking).

$$\text{VKT}^+ = \underbrace{\int_{t_i}^{t_f} (N_{\text{RSV}}^{\text{NP}}(t) + N_{\text{PV}}(t))v(t) dt}_{\text{VKT of all vehicles}} - \underbrace{\sum_{\text{TP}} p(\text{TP}_j^o, \text{TP}_j^d)}_{\text{Sum of passengers' shortest paths}} - \underbrace{\sum_{\text{PV}} p(\text{PV}_i^o, \text{PV}_i^d)}_{\text{Sum of private vehicles' shortest paths}} \tag{11}$$

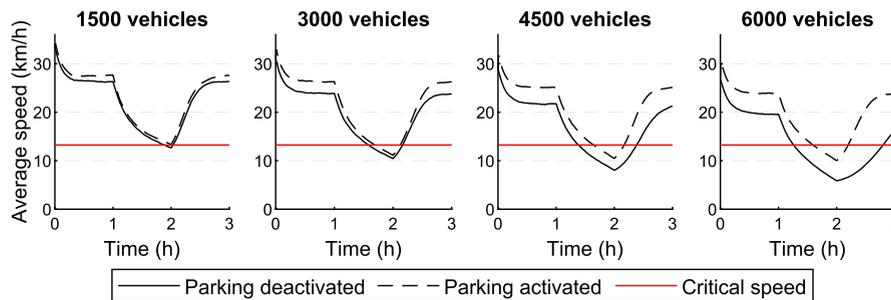


Fig. 10. Growing fleets deteriorate average speeds and their restoration after the peak-hour. Parking idle vehicles enhances average speeds independently of the fleet size.

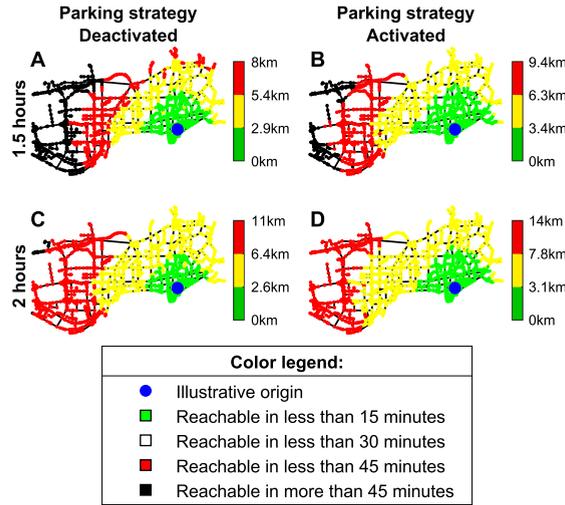


Fig. 11. Taking idle vehicles from the streets enhances the area a traveler can reach in a certain time window and enhances the resilience of the system, in general. Dynamic reachable area in the modeled network (scenarios with 4000 ride-sourcing vehicles and 30% willingness to share). Starting from an intersection in the central business district of Shenzhen (marked as a blue circle), the reachable area (and distance) that one can access within a certain time window (i.e., 15 min, 30 min, and 45 min) at certain simulated times (A and B 1.5 h after simulation starts, C and D 2 h after simulation starts). See [Movie S2](#) for a complete observation of reachable areas over time.

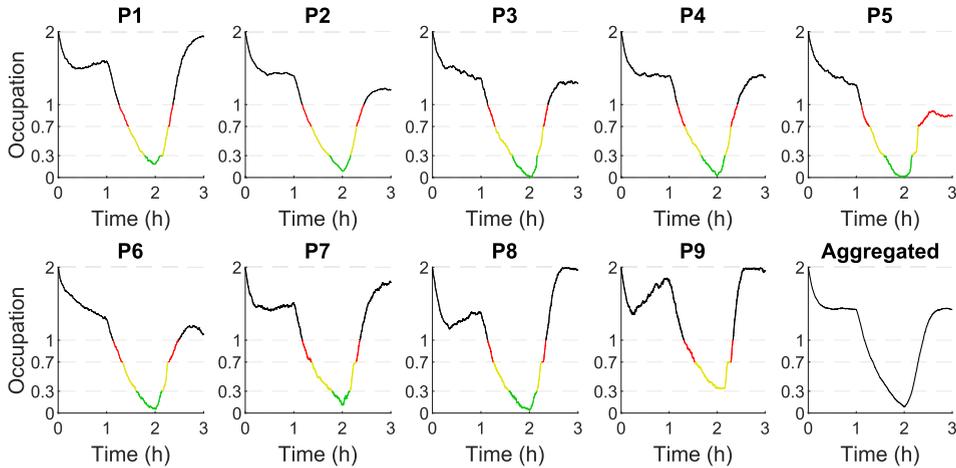


Fig. 12. Parking lot occupation level and their instantaneous color flags.

Here t_i and t_f indicate the beginning and the end of a simulated instance. $N_{RSV}^{NP}(t)$ refers to the number of ride-sourcing vehicles on the streets (not parked), N_{PV} refers to the number of private vehicles on the streets, and $v(t)$ refers to the speed on the network at time t . $p(\cdot, \cdot)$ is the shortest path distance between two points in the network. TP is the group of all served passengers of the ride-sourcing service, and TP_j^o and TP_j^d are the origins and destinations of a passenger j , respectively. PV is the group of all travelers that used private cars (or taxis in case of abandonments), and PV_i^o and PV_i^d are the origins and destinations of a traveler i from this group, respectively. Remember that, private vehicles are assumed to use the shortest path, and to leave the system once reaching their destinations, thus Eq. (12) holds.

$$\int_{t_i}^{t_f} N_{PV}(t)v(t) dt = \sum_{PV} p(PV_i^o, PV_i^d) \tag{12}$$

Thus, Eq. (11) may be simplified to Eq. (13).

$$VKT^+ = \int_{t_i}^{t_f} N_{RSV}^{NP}(t)v(t) dt - \sum_{TP} p(TP_j^o, TP_j^d) \tag{13}$$

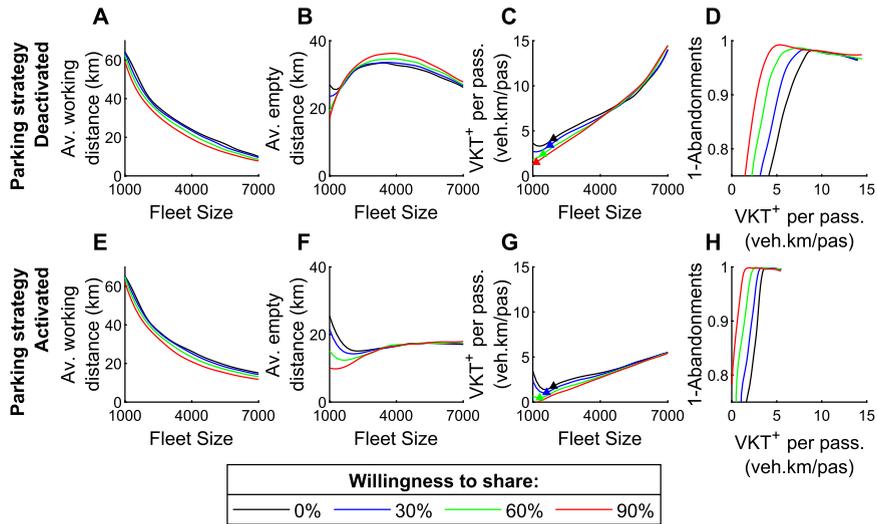


Fig. 13. TNCs can increase the chances of serving passengers at the expense of adding extra kilometers traveled to the system. (A and E) average working distance traveled per RSV. (B and F) average empty distance traveled per vehicle (C and G) Relationship between the additional kilometers traveled per served passenger and the fleet size. (D and H) Fraction of served passengers as result of additional VKT. All VKT measures are normalized by the fleet size or the number of served passengers. Triangular markers in C and G indicate the fleets capable of serving 75% of the passengers for each willingness to share.

We separated the VKT that RSVs produced according to their activities. For instance, ‘Working VKT’ refers to those produced when RSVs are assigned to pick up passenger(s) or driving with passenger(s) to destination(s); ‘Empty VKT’ refers to those produced when RSVs are circulating without a passenger on-board or without a request to pick-up a passenger. Then, we plot on Fig. 13 the relation between the fleet size and the Working VKT and Empty VKT divided by the fleet size. The latter variables are equivalent to the average distance traveled per vehicle during the simulation being in one of ‘working’ or ‘empty’ states (recall Fig. 2). We also plot the additional VKT (VKT^+) per passenger served as a function of fleet size and the abandonment rate. More specifically, on Fig. 13A and E, one can note that RSVs travel approximately the same working distance for a given fleet size with or without the parking strategy. Moreover, in both cases, a smaller value of Working VKT per vehicle (meaning average working distance) is observed as the fleets become larger, which can have an impact on the revenues (as we discuss in Section 3.3). On the other hand, the parking strategy had a significant impact on the amount of Empty VKT that each vehicle produced, i.e., average distance without passengers traveled per vehicle during the simulation (Figs. 13B and F). RSVs travel longer distances without passengers while fleets grow until congestion decreases traveling speeds. It is worth noting that, for small fleets (1000 vehicles, for instance), there is the opposite effect, which is related to Wild Goose Chase effect, even with a limited search radius (as suggested in Xu et al. (2020)). Moreover, activating the parking strategy keeps the empty distance traveled near 18 km for all willingness to share. Fig. 13C and G show the relationship between growing fleet sizes and the added VKT to the system per passenger served. At the same time, the parking strategy significantly decreased this growth. Note that the markers indicate the fleet sizes capable of serving 75% of the demand and that willingness to share allows fewer vehicles to handle the same number of passengers while producing fewer added VKT. Finally, Fig. 13D and H present an interesting finding related to demand served, which is directly connected to potential benefit for these services. Instead of showing the fleet size, we investigate the relation between served rate ($1 - \text{abandonment rate}$) and added VKT per passenger served. These figures show that there is always a ‘price to pay’ to serve more passengers, and this is related to further extra kilometers traveled by an increased fleet size. Nevertheless, this graph highlights that significantly higher fleet sizes do not contribute to serving more passengers but only

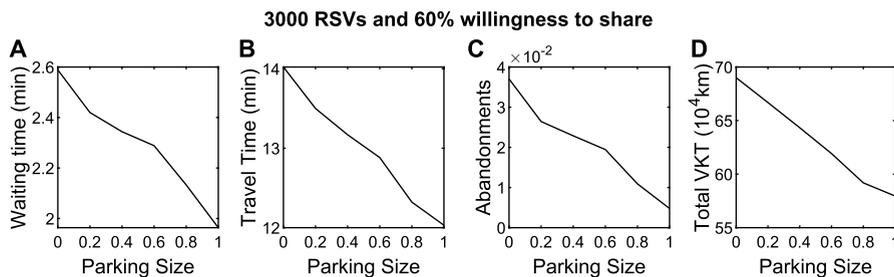


Fig. 14. Increasing parking capacity (as a fraction of RSVs that can use in-park spot) decreases waiting times (A), travel times (B), abandonments (C) and VKT(D).

create wasted extra kilometers in the system that result in more emissions, environmental impacts, and safety issues.

To further decrease VKT and VHT, parking lots can increase their capacities. Fig. 14 summarizes the effects of parking capacity over the system for fixed fleet size and willingness to share. Note that traffic congestion did not increase sufficiently to make ride-sourcing less attractive than public transport in any of these scenarios. Increasing the number of available parking spots exhibits an option to improve service quality, decreasing waiting times, travel times, and serving more passengers. These improvements result from higher traveling speeds after removing cruising vehicles from the roads (recall the speed vs accumulation relationship from the MFD). Furthermore, it improves traffic congestion, reducing VKT. Finally, note that gains in performance appear in even for small capacities. Nevertheless, parking capacity comes with an infrastructure cost that has to be investigated in a future direction (possibly together with parking pricing schemes).

3.3. Revenues and Day-to-Day Adjustments

In the previous section we considered that the number of drivers is fixed externally and does not change from day to day. Nevertheless, in the supply side of ride-sourcing, there is an inherent feedback mechanism that each driver based on his/her reserve costs and gains from the market join or leave the market dynamically. In other words, the fleet size can vary from day to day. TNC can control the maximum registration of RSV, or apply a cap on maximum active RSV, but the actual active RSV depends on the market, fare, and wage. This section tries to shed some light in this direction by considering a straightforward day to day evolution.

The previous section showed that while larger fleet sizes decrease waiting time for passengers, this creates a higher congestion level and lower quality of service for all private modes of transport. It is known that in competitive markets where different jurisdictions have not the same objective function, the system can reach states far from optimal welfare (see, for example, Douglas (1972) and Lamotte et al. (2017)). While our work does not analyze equilibrium conditions between competitive players, we intend to show that TNCs may end with a pool of active drivers larger than the optimum fleet. However, the negative outcomes of large fleets over congestion will make only a few drivers get a revenue above a minimum wage. Therefore, large fleets do not pose as a potential equilibrium for reasonable minimum wages.

In general, a ride-sourcing service can attract drivers as far as these drivers can profit from offering rides. Both drivers and TNCs can only profit if drivers complete trips. So far, we observed how several settings were able to improve the service perception of customers and their effects on congestion. We assume that the maximum revenue the system can make is to serve all presented ride requests before facing abandonments or loss of attractiveness to public transport. We consider booking fees of US\$ 2.20 (F_{book}^{rh}) and US\$2.00 (F_{book}^{rs}) and fares per kilometer of US\$ 1.00 (F_{dist}^{rh}) and US\$ 0.80 (F_{dist}^{rs}), for ride-hailing and ridesplitting, respectively (Uber, 2019). Under such assumptions, it is straightforward to compute the potential revenue for the system (R_{sys}^p) with the number of passengers (approximately 24'000 passengers before abandonments or losses to transit) and their willingness to share. Eq. 14 illustrate the estimation of potential revenues.

$$R_{sys}^p = N_{req} \cdot [(1 - \beta) (F_{book}^{rh} + E[T_{length}] F_{dist}^{rh}) + \beta (F_{book}^{rs} + E[T_{length}] F_{dist}^{rs})] \tag{14}$$

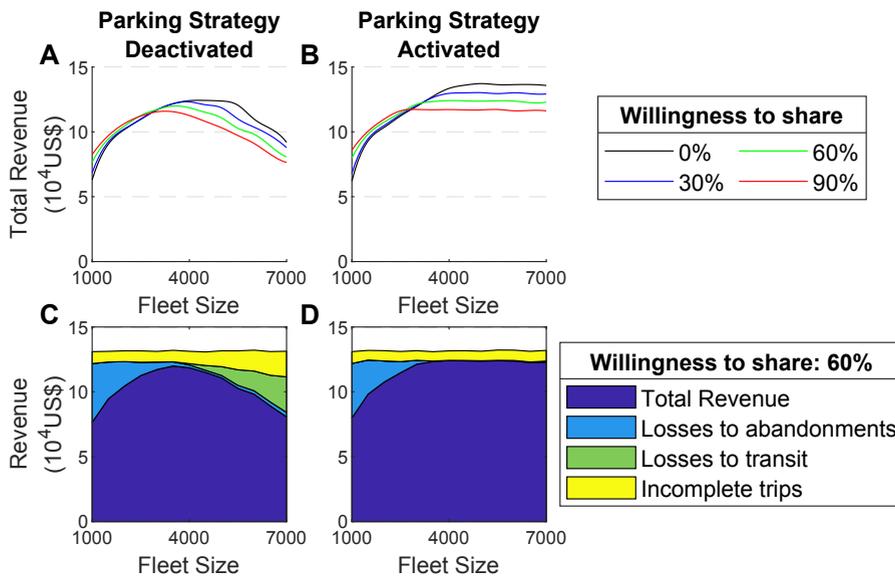


Fig. 15. The system’s revenues peak for particular fleet sizes and decrease due to congestion losses yielding higher revenues for lower willingness to share. (A and B) Total revenue of the system for increasing fleet sizes. (C and D) Potential revenues and summary of losses for scenarios with willingness to share 60%.

Here, N_{req} is the number of requests without any abandonments or losses to transit, β is the willingness to share (in percentage), and $E[T_{length}]$ is the average trip length of passengers at their shortest path.

The service faces inefficiencies and randomness that reflect in the difficulty of producing the potential revenue. Although the inefficiencies (such as service design, internal policies, and other subjective activities) are hard to enumerate completely, one can do it for most of its impacts over the final revenue. In Fig. 15, we explore the revenues the system produces in a single day, as a function of fleet size. Revenues peak at smaller fleet sizes once willingness to share increases (Fig. 15A). However, a lower willingness to share yields higher revenues. With an inactive parking strategy, the revenues start to drop immediately after the peak. Note that the peaks occur between 3500 (90% willingness to share) and 4500 (0% and 30% willingness to share) vehicles, depending on the willingness to share. Fig. 15C clarifies the impacts of inefficiencies over the potential revenues showing the losses and actual system revenues. For smaller fleet sizes, most of the losses are due to the incapacity to serve all passengers, that finally abandon the system. However, as more drivers become available, they cover these losses up to the point which the system starts to lose demand for transit. Hence, one can expect that the ridership of transit would increase as the number of drivers for ride-sourcing services rise. The 'Incomplete trips' entry stands for the revenue from ongoing rides at the end of the simulation. It is arguably a loss since the system will produce the revenue once these passengers are delivered. However, its growth for large fleet sizes exposes the problems with longer journey durations. Revenues for the system peaks and remains when the parking strategy is active because it avoided the losses to transit, even when fleet sizes were large. However, one can expect revenues losses to transit in case parking lots were smaller. It should be highlighted that we do not propose to increase the fleet size of RSVs to attract more passengers to public transport, as this creates a problematic state for the system with high congestion.

Hall et al. (2018) showed the ambiguous effect of ride-sourcing over transit, which depended on its quality and the city they operate. Our results from Fig. 15C presents a complementary perspective for the previous. Ride-sourcing's positive effects over transit may be a direct reflection of the negative externalities of ride-sourcing fleets over congestion. Hence, in areas where ride-sourcing appears to foster transit ridership, one should look for traffic congestion worsening and its causes.

Using the same assumption from Zha et al. (2018), we consider that ride-sourcing drivers decide, about offering rides, daily. In general, drivers compete for passengers. In case the number of drivers is too large, very few will have satisfactory revenues that day, and most of the drivers will not drive the next days. Fig. 16 explores drivers' revenues after a 'day' (3 h) of work. We assume that the revenue for a driver is 75% of what the passenger paid (the remaining 25% is the commission of the TNC). We set an illustrative minimum wage of US\$14.50, which drivers consider, after a workday, in their decision to remain working in the next days. The minimum wage is for illustration purposes only; we do not claim it to be realistic. The \$14.50 is a base value, which is equivalent to the American minimum wage (US\$7.25 per hour) for a two-hour job. In other words, that is a case where drivers expect to be busy for about 2 h. Willingness to share created higher variability in drivers' revenues and lower averages. In general, the average revenue ranges from US\$21.24 and US\$23.15. There were around 700 more drivers with revenues higher than the illustration when willingness to share is 0%, compared to it at 90%. The parking strategy, however, increased the average revenue by US\$2.00 for a willingness to share of 0%. At the same time, only 2'896 drivers had higher revenues than the illustration threshold, 600 fewer drivers than the scenario where it is deactivated. Such findings point that the last-come-first-served basis for the queue inside the parking lot causes higher variability and, therefore, fewer drivers with satisfactory revenues. Note that many drivers had no revenue at all for a higher willingness to share.

Finally, in Fig. 16C, we can see that the system has plenty of scenarios for which the number of drivers with adequate revenues (the illustration wage threshold) is larger than the fleet size that minimizes journey durations (from Fig. 6C). There can be 1'200 more drivers than at these minimums. Furthermore, this number can increase even more if drivers' value of time (e.g., minimum wage threshold/wage reservation) is smaller. The previous indicates that more vulnerable areas may have more active drivers and more traffic issues (given that people still have access to private cars). Differently, the parking strategy made it less attractive to drivers, since only a few will have an acceptable wage (Fig. 16D). It is interesting to note that the number of drivers with satisfactory revenues becomes less sensitive to the starting fleet size. For all the previous, a policy suggestion would be to limit the number of simultaneous active drivers a TNC can have in the city.

Tirachini and Gomez-Lobo (2019) analyzed for static conditions without congestion how incentives of the company and pricing strategies can influence the number of drivers that register for TNC services. Analyzing this type of equilibrium game for similar settings as our problem (with congestion dynamics, empty kilometer traveled) can reach additional interesting insights. This should be a research priority.

Finally, results throughout the paper indicate the 'Wild Goose Chase' effect (Castillo et al., 2018; Xu et al., 2020) for small fleet sizes, decreasing drivers revenues (Fig. 16) and a high number of drivers moving to pick-up passengers, compared to the number of drivers delivering them (Fig. 8 and Movie S1). Further investigation is needed in this direction.

4. Final considerations

In this paper, we investigated the effect of expanding fleet sizes for TNCs, passengers with different willingness to share, and operational strategies over congestion conditions. We highlight that, by omitting the dynamics of congestion in rides-sourcing studies to focus on matching strategies or rebalancing vehicles in static environments, different conclusions with possibly unrealistic performance measures are obtained.

Results show that sharing (allowing ridesplitting with a large pool of passengers) by itself is not capable of decreasing the system's VKT if there is no control over the fleet (its size and operation). To reduce emissions (by reducing VKT), TNCs should change their

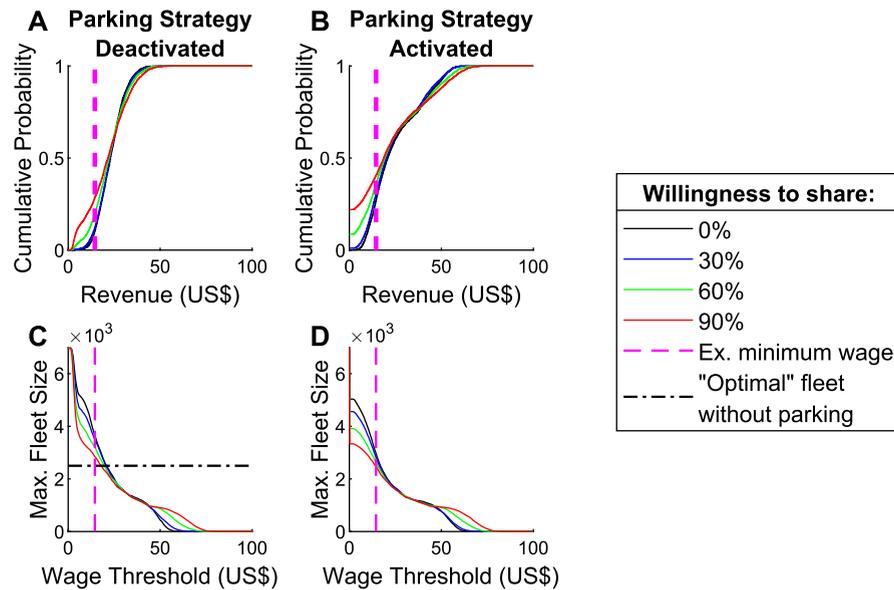


Fig. 16. Analysis over drivers' revenue after one 'day' of work. (A and B) Cumulative probability of drivers' revenue for a fleet size of 4000 RSVs. (C and D) Maximum number of drivers with revenues higher than the wage threshold, i.e., drivers' sensitivity to wage thresholds. "Optimal" fleet stands for the fleet the minimizes the average journey duration in Fig. 6C.

modus operandi; in a way to avoid that their fleet cruises without an assigned passenger. On the other hand, sharing decreases the number of vehicles needed to maximize coverage and minimize service times. Furthermore, in case it is not possible to avoid TNCs' fleets cruising for passengers, increases in the willingness to share can minimize both waiting times and service times. For adequately sized fleet sizes, the adoption of sharing is related to higher revenues (for the system and the driver). Therefore, so that ride-sourcing becomes a sustainable service, it must change its operations to remove vehicles without passengers from the streets, and passengers must become more receptive to ridesplitting at the same time. Furthermore, our findings show that TNCs' operations with large fleet sizes can lose attractiveness to public transportation as a result of high traffic congestion, and drivers can have attractive revenues even in such situations. Nevertheless, we considered no interactions between these modes, and, even with dedicated bus lanes, there would be interactions and problems on intersections. Moreover, it is outside the scope of this paper to combine surge pricing policies and market equilibrium, but this can be a future direction. Therefore, we do not cope with the detailed modeling of decisions on the mode choice for travelers.

Additional results expand the perception of how efficient matching algorithms can boost the presence of shared rides and further decrease VKT. Moreover, recent advancements in the process of matching passengers requires complex optimization formulations and heuristics. Further research can shed more light in this direction.

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